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Optimization and Management in Manufacturing Engineering

Resource Collaborative Optimization and Management through the Internet of Things

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Preface

Scientific and technological achievements of the mobile internet, cloud computing, and the Internet of Things (IoT) have emerged with the rapid development and increased utilization of the internet and big data. The emerging information technologies, IoT and big data are comprehensively permeating into manufacturing industries and therefore promoting the industrial development of digitalization, intellectualization, networking, and service orientation. The IoT and big data are involved in various fields, making them very important social resources. This wave of development has brought rare historic opportunities but unprecedented challenges for the transformation and upgrading of traditional modes of engineering and management.

The collection, storage, integration, and sharing of big data, however, face serious security risks during the operation and management processes typically found in the manufacturing industry. Information errors and leakage frustrate both enterprises and customers, and definitely impede the pace of transformation and upgrading of traditional manufacturing industries. Furthermore, traditional organization theory and system evolution theory no longer apply to the evolution of intelligence- and service-oriented manufacturing industries. Self-organizing and intelligent decision modes of innovation in manufacturing units contribute to the improvement of the organizational hierarchical relationships as well as manufacturing and service efficiency. The wide adoption of the IoT and big data in manufacturing industries enhances product life cycle management. Collaborative optimization and scheduling of the manufacturing chain and service chain help to improve the self-adaptive ability and serviceability of manufacturing systems, and can effectively facilitate the value and utility of a manufacturing network. Optimization of manufacturing life-cycle process management is promoted through data integration, fusion, and collaboration, therefore improving the adaptability of the scheduling system, achieving the manufacturing processes of close-loop control and optimization, and collaboratively allocating manufacturing and service resources. Since enterprises' internal and external information can be real-time detected and traced, studies on business process information quality management model and service data quality control theory under the environment of IoT and big data can significantly improve the quality of both life cycle product and service. Manufacturing process information quality management and product quality control have received significant academic and practical attention. Based on the considerations given above, it is important to inspect and verify the application ability of theoretical engineering management systems by evaluating the organizational operation efficiency of service-oriented and networked engineering and manufacturing systems, collaborative optimization utility and value improvement of the supply chain and service chain, self-adaptive dynamic scheduling and collaborative allocation of manufacturing and service resources, and quality of data, product, and services during the manufacturing process.

1. By deploying RFID technologies and sensors in the IoT environment, enterprises can acquire real-time data during business operations. In order to obtain the most value from these data, enterprises need to share some information with each other. Since enormous amounts of data are transmitted through wireless channels in the IoT environment, firms' information systems are more liable to be attacked. Therefore, the application of IoT is inseparable from information sharing and also introduces some information security issues.
2. Structural reorganization and business process re-engineering have significantly improved the operational efficiency of manufacturing enterprises and are crucially important under IoT environment. Specifically, manufacturers should properly reduce their hierarchical levels to make an efficient and flat organizational structure due to the more precise, comprehensive, and faster acquisition of the product life-cycle information inside and among cooperative enterprises. Also, firms' decision-making authority should be reallocated to improve the decision speed and accuracy.
3. The potential of IoT systems to improve the management of manufacturing resources is enormous. The operators and managers of smart manufacturing systems can take corrective and timely actions to avoid damage and inefficiency via the collaborative considerations of allocating and dispatching. A new challenge is how individuals think the IoT will affect the traditional management process of manufacturing resources. Novel models of manufacturing systems can be built based on the combinatorial problem (as traditionally done), by extending beyond the limits of individual factories to connect multiple factories throughout value chain can be a challenge. Specifically, manufacturing jobs like cutting or other batch processes are scheduled integrally and robustly in collaborative manufacturing. Another example is the transportation and storage management of distributed inventories that are optimally coordinated through the monitoring and tracking of convey tools and individual products.
4. With the IoT, companies can monitor real-time product operating information after selling products, and provide customers with personalized service based on

this information. Customer satisfaction with this kind of service has been gradually integrated into the product quality, but it is based on the customer's willingness to establish a long-term relationship with the business. In addition, quality is not just a matter of concern between the enterprise and customer. The sustainability of the product is also a part of its quality. The acquisition and analysis of the full life cycle quality data will drive the further development of the re-manufacturing industry, which is of great importance to a product's life-cycle quality improvement. The development of new information technology requires us to redefine the concepts of quality and quality management to promote the healthy and sustainable development of enterprises and society.

5. The internet and IoT have changed the relationships between humans, organizations, society, and the environment in a product's life-cycle management. The value chain of products has been extended, while big data has improved the life-cycle assessment of a product. In service-based manufacturing, a challenge is how to construct the life-cycle assessment structure based on the massive amounts of complex data being derived from the IoT. Compared with traditional assessments, which are relatively static and closed, the assessment based on IoT data is dynamic and open. In traditional assessments, data must be obtained by the program in advance, while data derived from IoT devices can be extracted in real-time from the massive and unrelated data flow.

Based on the above challenges regarding information security, organizational management, production scheduling, quality management, and the evaluation of manufacturing enterprises, we focused on the core issues of enterprise information and organization with the IoT and big data. We studied the problem of information sharing and risk management, as well the challenge of the optimal allocation of the decision-making authority, in an IoT environment. We then took into consideration the problems of the operation and management of enterprises in three dimensions. We examined coordinated scheduling for parallel-batching machines, hybrid manufacturing distributed inventory management with sharing logistics, and the cutting stock problem. Finally, we proposed the concept and tool of the Life Cycle Assessment and Total Quality Management of the Product Life Cycle to solve the problem of quality management and assessment with the IoT and big data.

In Chap. 1, Xinbao Liu, Jun Pei, and Xiaofei Qian present some valuable insights on information sharing and risk management. Xinbao Liu, Jun Pei, and Zhiping Zhou conduct novel research on the optimal match of information and decision-making power in Chap. 2. A dynamic coordinated supply chain scheduling problem is studied by Jun Pei and Min Kong in Chap. 3. Panos M. Pardalos and Tianji Yang explore the problem of hybrid manufacturing distributed inventory management with sharing logistics in Chap. 4. Chapter 5 deals with the cutting stock problems in the IoT environment, which is investigated by Hao Cheng, Lin Liu, and Siwen Liu.

In Chap. 6, Xinbao Liu, Lin Liu, Shaojun Lu, and Peiya Zhu introduce some novel views on the total quality management of the product life cycle in the IoT environment. Mi Zhou and Xinbao Liu give an elaborate life cycle assessment on mobile phones in the IoT environment in Chap. 7.

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Contents

1 Information Sharing and Risk Management 1
1.1 Introduction 1
1.1.1 The Benefits and Risks Resulting from IoT 1
1.1.2 Information Sharing and Information Security Investment 2
1.2 Literature Review 3
1.2.1 Just Considering Security Investment 3
1.2.2 Considering Both the Security Investment and Information Sharing 5
1.3 Model Setting 6
1.3.1 Previous Game in Traditional Environment 8
1.3.2 Our Game in the Environment of IoT 8
1.4 Non-cooperative Game 9
1.4.1 Firms' Strategies in the Non-cooperative Game 10
1.4.2 Parameters Analyses 11
1.4.3 Economical Analysis 13
1.4.4 Numerical Experiments 14
1.5 Totally Cooperative Game 18
1.5.1 Firms' Strategies in the Totally Cooperative Game 18
1.5.2 Parameters Analyses 19
1.5.3 Economical Analysis 22
1.5.4 Numerical Experiments 23
1.6 Optimum Analysis and Coordination Mechanism 27
1.6.1 Optimum Analysis 28
1.6.2 Coordination Mechanism 30
1.7 Conclusion and Future Research 32
1.7.1 Conclusion 32
1.7.2 Future Research 33

2 Optimal Allocation of Decision-Making Authority in IoT-Based Manufacturing Enterprises 35
2.1 Introduction 35
2.2 Literature Review 38
2.3 Optimization Model for Decision Authority Distribution 41
2.3.1 The Multi-objective Optimization Model 42
2.3.2 Numerical Study 47
2.4 Sequential Game Model for Centralization Behavior 53
2.4.1 The Sequential Game Model 53
2.4.2 Numerical Study 58
2.5 Conclusion and Further Research 60
2.5.1 Conclusion 60
2.5.2 Future Research 61

3 Dynamic Coordinated Supply Chain Scheduling in an IoT Environment 63
3.1 Introduction 63
3.2 Literature Review 64
3.2.1 The Applications of the IoT in Industrial Manufacturing 64
3.2.2 The Development of Supply Chain Scheduling 65
3.2.3 The Development of Batch Scheduling 65
3.2.4 The Applications of the IoT in Supply Chain Scheduling 67
3.3 Problem Description 67
3.4 A Mixed Integer Programming Formulation 68
3.5 Heuristic for Batch Formation and Scheduling in Single Machine 71
3.6 Key Steps in SFLF-PR 76
3.6.1 Coding and Encoding 76
3.6.2 Basic Shuffled Frog Leaping Algorithm (SFLA) 77
3.6.3 Basic Path-Relinking Algorithm 78
3.6.4 SFLA-PR Algorithm 78
3.7 Computational Experiments 87
3.8 Conclusion and Future Research 90
3.8.1 Conclusion 90
3.8.2 Future Research 90

4 Hybrid Manufacturing Distributed Inventory Management with Sharing Logistics 91
4.1 Introduction 91
4.1.1 Background 91
4.1.2 Inventory Routing Problem in Hybrid Manufacturing 93

4.2 Literature Review 94
4.2.1 Vehicle Routing Problem 94
4.2.2 Inventory Routing Problem 95
4.2.3 Crossing Field Literature 96
4.2.4 Our Contribution 96
4.3 Model Descriptions 97
4.3.1 Model with One Retailer and Ignorance of Transportation 98
4.3.2 Model with Multiretailers and the Consideration of Transportation 99
4.4 The Proposed Solution Method 101
4.4.1 The Main Structure of Algorithm 102
4.4.2 Improvement Neighborhood Structure 103
4.4.3 Perturbation Mechanism 106
4.4.4 Adaptive Selection Mechanism 110
4.4.5 Subproblem of Delivery and Pickup Plan 110
4.4.6 Acceptance and Termination Condition 113
4.5 Computational Results 113
4.5.1 Construction of Instances 113
4.5.2 Algorithm Setting 113
4.5.3 Lower Bound 115
4.5.4 Upper Bound 116
4.5.5 Comparison with Upper Bound and Lower Bound 116
4.5.6 The Performance of Heuristic in the Subproblem of Delivery and Pickup Plan 118
4.5.7 The Effect of Novel Neighborhood Structures 120
4.5.8 The Sensitivity Analysis of Vehicle Capacity 120
4.5.9 Sensitivity Analysis of $\boldsymbol{l_i}$ and $\boldsymbol{C}$ 122
4.6 Conclusion and Future Research 124
4.6.1 Conclusion 124
4.6.2 Future Research 124

5 Cutting Stock Problem with the IoT 127
5.1 Introduction 127
5.1.1 The Cutting Stock Problem 127
5.1.2 Notation of the Cutting Stock Problem 128
5.1.3 Cutting Stock in Manufacturing 128
5.1.4 The Cutting Stock Problem with the IoT 128
5.2 Literature Review 129
5.2.1 One-Dimensional Cutting Stock Problem 130
5.2.2 Two-Dimensional Cutting Stock Problem 132
5.2.3 Applications of the Cutting Stock Problem 133

5.3 Variable Cross-Sectional Cutting Stock Problem . . . 134
5.3.1 Background and Model of the Problem . . . 135
5.3.2 The Improved Algorithm for Solving Circular Truncated Cone Cutting Stock Problem . . . 139
5.4 CSP in the Internet of Things . . . 148
5.4.1 Product Cutting Status and Position Monitoring . . . 148
5.4.2 The Model of CSP in Internet of Things . . . 149
5.4.3 Improved SHP Algorithm . . . 153
5.4.4 Simulation and Analysis . . . 157
5.5 Conclusion and Future Research . . . 159
5.5.1 Conclusion . . . 159
5.5.2 Future Research . . . 160

6 Total Quality Management of the Product Life Cycle in an IoT Environment . . . 163
6.1 Introduction . . . 163
6.1.1 Total Quality Management . . . 163
6.1.2 Product Life Cycle Quality Management . . . 164
6.1.3 Quality of Service (QoS) in a Cloud Manufacturing Environment . . . 164
6.2 Literature Review . . . 165
6.2.1 The Application of TQM to Realize Continuous Quality Improvements . . . 165
6.2.2 The TQM Approach . . . 166
6.2.3 Meeting Customer Requirements with Cloud Manufacturing . . . 167
6.3 Entire Life Cycle Quality Management . . . 169
6.3.1 Difference of Quality Management Under Internet and Big Data . . . 169
6.3.2 Entire Life Cycle Quality Management Concepts System . . . 170
6.3.3 Life Cycle Quality Assurance System and Methods for Its Implementation . . . 177
6.3.4 Life Cycle Quality Management System . . . 182
6.4 A Quality Management Model Considering Service Level . . . 195
6.4.1 Model Description . . . 195
6.4.2 Equilibrium Analysis . . . 197
6.5 Conclusion and Future Research . . . 208
6.5.1 Conclusion . . . 208
6.5.2 Future Research . . . 208

7 Life Cycle Assessment in an IoT Environment . . . 209
7.1 Introduction . . . 209
7.1.1 Life Cycle Assessment . . . 209
7.1.2 LCA in an IoT Environment . . . 210

7.2 Literature Review 211
7.2.1 Inventory Analysis and Impact Assessment 212
7.2.2 Life Cycle Cost 214
7.2.3 Social Life Cycle Assessment 215
7.2.4 LCA Methods 215
7.3 Life Cycle Assessment of Mobile Phone from Environmental Dimension 216
7.3.1 Summary of Life Cycle of Mobile Phone 217
7.3.2 Construction of LCA System Model 218
7.4 Inventory Analysis 221
7.4.1 Production Capacity of iPhone4S 221
7.4.2 Components Inventory of iPhone4S 222
7.4.3 Energy Consumption and Emissions of Material Production and Mobile Phone Manufacturing for iPhone4S 223
7.4.4 Inventory in the Transportation Phase 230
7.4.5 Inventory in the Use Phase 231
7.4.6 Inventory in the Recycling Phase 232
7.4.7 Inventory in the Whole Life Cycle 232
7.5 Impact Assessment and Improvement Analysis 233
7.5.1 Impact Assessment 233
7.5.2 Improvement Analysis 235
7.6 Social Life Cycle Assessment to iPhone 4S 236
7.6.1 Construction of S-LCA Structure 236
7.6.2 Brief Introduction of Yang's ER Approach 237
7.6.3 Assignment of Belief Degrees and Attribute Weights 240
7.6.4 Generating the Overall Belief Degrees 241
7.7 Conclusion and Future Research 244
7.7.1 Conclusion 244
7.7.2 Future Research 245

Appendix: Materials of the Main Components of iPhone4S 247

References 251

Abbreviations

1D-CSP	One-dimensional cutting stock problem
2D-CSP	Two-dimensional cutting stock problem
ACOS	Ant colony optimization selection
ADP	Approximate dynamic programming
AHP	Analytic hierarchy process
ALNS	Adaptive large neighborhood search
ASes	Autonomous systems
BFD	Best fit decreasing
BPR	Business process reengineering
BRP	Bin packing problem
BSC	Balanced score card
C&P	Cutting and packing problems
CMfg	Cloud manufacturing
CRM	Customer relationship management
CSP	Cutting stock problem
DPR	Diversity-based path-relinking
ERM	Employee relationship management
ERP	Enterprise resource planning
FFD	First fit decreasing
GA	Genetic algorithm
GPR	Greedy-based path-relinking
GPS	Global position system
HCUS	Heuristic constraining the utilization of the stored bars
HCUSO	Heuristic constraining the utilization of stored and ordered bars
HIE	Healthcare information exchanges
IoT	Internet of things
IRP	Inventory routing problem
IRPSDPD	Inventory routing problem with simultaneously delivery-pickup and purchasing decision
LNS	Large neighborhood search

MES	Manufacturing execution systems
PL	Production logistics
PLC	Product life cycle
PR	Path relinking
QoS	Quality of service
RFID	Radio frequency identification devices
SA	Simulated annealing
SCOS	Service composition and optimal selection
SESG	Synergistic elementary service group
SFLA	Shuffled frog leaping algorithm
SFLA-PR	Hybrid shuffled frog leaping algorithm and path relinking algorithm
SHP	Sequential heuristic procedure
TQM	Total quality management
VMI	Vender managed inventory
VNS	Variable neighborhood search
VRP	Vehicle routing problem
WSAN	Wireless sensor and actuator network

Chapter 1
Information Sharing and Risk Management

1.1 Introduction

The manufacturing industry plays an important role in the economy and society. In traditional environment, the manufacturing industry is at a standstill or even in recession in the United States [1]. Thus, it is crucial to identify new drivers to boost the manufacturing industry. In recent years, the development of Internet of Things (IoT) has brought a great opportunity as well as a challenge for modern manufacturing enterprises. The application of IoT in manufacturing industry not only brings economic benefits for manufacturing enterprises, but also promotes the upstream and downstream industries. Unfortunately, the employment of the wireless transmission technologies in the IoT environment also introduces significant information security issues.

1.1.1 The Benefits and Risks Resulting from IoT

In the manufacturing industry, the application of IoT can simplify the initialization and reconfiguration tasks, reduce the complexity of the tasks performed by humans, and lead to faster response time for the adaptations required, while at the same time minimizing configuration errors and the associated system downtime [2]. Manufacturing enterprises can obtain real-time production data and inventory data by deploying radio-frequency identification (RFID) technology and sensors, which enables decision makers to make rapid and data-driven decisions. In addition, by embedding sensors in machines and products, manufacturers can acquire massive amounts of data generated throughout the production life cycle. By analyzing these data, firms can obtain valuable information and make better decisions. For instance,

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an automobile manufacturer can improve the product design by collecting and analyzing the running data of all its vehicles.

The economic benefits brought by IoT are enormous. Whereas, the application of IoT also introduces some risks. Due to the adoption of RFID and wireless sensors, most data in the IoT environment are transmitted wirelessly, which make firms more liable to be attacked by hackers. Take RFID technology as an example, it is well known that a RFID system is composed of tags, readers, and a backend server. The reader communicates with the tag through a wireless channel. By eavesdropping, intercepting, or modifying the messages transmitted between the tag and the reader, a RFID system is vulnerable to various attacks [3].

1.1.2 Information Sharing and Information Security Investment

Successful IoT applications require firms to cooperate with each other. A typical cooperation between firms occurs through information sharing. For instance, if a supplier shares its inventory and transportation information of the raw material to the manufacturer, it will help the manufacturer arrange its production plan. Similarly, it will also benefit the supplier if the manufacturer shares order, production, and logistics information. Information sharing can decrease the risk brought by information asymmetry, which intensifies the coordination between firms and increases the overall competitiveness of all firms.

The adoption of some IoT technologies will result in some information security issues, and information sharing will exacerbate this problem further. Although information sharing can bring significant profits for manufacturing enterprises, excessive information sharing is costly and may lead to the leakage of confidential data. Thus, it is important for a firm to determine the appropriate level of information sharing. If a firm suffers from frequent cyber attacks, the partnering firms may terminate their cooperation relationships since the breached firm may cause the leakage of their information. Thus, the firm victimized by cyber attacks will obtain notoriety and suffer a great loss. Hence, it is significant for a firm to prevent hackers' attacks and protect its information system from being breached. The firm should invest in information security technologies to reduce the probability of being breached. Therefore, sharing a suitable level of information and investing an appropriate amount in information security is of tremendous significance for a firm in the IoT environment.

1.2 Literature Review

Based on a traditional view that information security comes down to technical measures, many enterprises will spend a lot of money on developing or purchasing various information security technologies to protect their information systems. However, Anderson [4] proposed a different view that information insecurity was at least as much due to perverse incentives. The author thought many security issues could be explained using the language of microeconomics and advocated that information security required an economic approach beyond the traditional security technologies. In 2006, Anderson and Moore [5] published a paper in *Science* in which they indicated that the economics of information security had become a thriving and fast-moving discipline. Many researchers have examined information security from the economic perspective and most of these studies can be classified into two major categories: those that only consider security investment and those that consider both the security investment and information sharing.

1.2.1 Just Considering Security Investment

In 2002, Gordon and Loeb [6] proposed an economic model to determine the optimal amount to invest for protecting a given set of information. They considered the vulnerability of the information to a security breach and the potential loss if such a breach occurred. Some vulnerability probability functions regarding information security investment were proposed by them. Shirtz and Elovici [7] demonstrated that exhausting the information security budget did not ensure a higher level of security required by an organization. They proposed a practical and easily implementable framework for optimizing investment decisions with organizational budget constraints while maintaining a required level of security. Huang and Behara [8] developed an analytic model for information security investment allocation of a fixed budget, in which concurrent heterogeneous attacks with distinct characteristics were considered. The relationships among the major variables were investigated via analytical and numerical analyses subject to various boundary conditions. They showed how a firm should allocate its limited information security budget to defend against two kinds of security attacks (targeted and opportunistic). Using game theory, Wu et al. [9] showed that the optimal security investment level of an interconnected firm against targeted attacks was different from that against opportunistic attacks. They found that not all information security risks were worth fighting against. Considering the characteristics of the effects of information security investment, Kong et al. [10] analyzed the information security investment strategies and performance relationships from a balanced score card (BSC) perspective. They found that the BSC perspective investment strategies could positively affect the improvement of a company's investment performance. Companies having already set up and executed investment strategies for information security could also use BSC to assess the existing strategies and measure their information security system. Since the economic incentives of the ISPs and the network effects of security measures could result in an under-investment, Khouzani et al. [11] investigated the potential gains in a network's social utility when a regulator implemented a monitoring and penalizing mechanism on the outbound threat activities of autonomous systems (ASes). They demonstrated that free-riding behaviors made the regulations trashy if the subset of ASes under the regulator's authority was smaller than a certain threshold. Then they analyzed how the regulator could improve the overall effectiveness of different security policies. From the perspective of a risk-averse decision maker, Huang et al. [12] presented an economic analysis of the optimal information security investment. They found that the maximum security investment increased with, but never exceeded, the potential loss from a security breach. Their analysis showed that the information security investment did not always increase with the level of risk aversion of the decision maker. After analyzing several approaches enabling the assessment of the necessary investment in security technologies from the economic point of view, Bojanc and Jerman-Blažič [13] proposed a procedure enabling the selection of the optimal investment of the necessary security technologies based on the quantification of the values of the protected systems. Further in 2012, based on a quantitative analysis of the security risks and a digital-assets assessment in an organization, Bojanc [14] et al. proposed a mathematical model for evaluating an optimal security-technology investment and providing suggestions on the selection of the best solution and associated decision-making. Taking into account the vulnerability of an agent to a security breach and the potential loss if a security breach occurred, Lelarge [15] investigated the security investment for a network of interconnected agents subject to epidemic risks. The author demonstrated that when agents were strategic, the security investments were always socially inefficient because of the network externalities. As it was difficult to measure the return on an IT security investment, which was a critical obstacle for firms in making such investment decisions, Chai et al. [16] explored the value of an investment in IT security by utilizing event methodology, according to stock market investors' behavior toward a firms' IT security investment announcements. They conducted an empirical study and found that information security investment would lead to positive abnormal returns for firms. Bandyopadhyay et al. [17] examined the impact of network security vulnerability and supply chain integration on firms' incentives to invest in information security. They found that an increase in the degree of network vulnerability or the degree of supply chain integration increased the security risk, while the degree of network vulnerability and the degree of supply chain integration had different impacts on firms' incentives to invest in security. If the degree of supply chain integration was low, then an increase in network vulnerability induced firms to reduce their security investments. Otherwise, firms would have an incentive to increase their investments when the network vulnerability is higher. Then a liability mechanism was designed to induce each firm to invest at the socially optimal level. To address the research question "how much and what financial resources should be allocated to IT security", Eisenga et al. [18] analyzed different practices and techniques used for determining the investments in IT security and provided some suitable methods for the decision-making process. After modeling the Healthcare Information Exchanges (HIE) based on its network characteristics, Huang et al. [19] applied classical economic decision analysis techniques to obtain some insights on determining the optimal information security investment. They found that for an organization in a HIE, not all security events were worth protecting and only those with the potential loss reaching a critical value needed to be protected. Based on value-at-risk methods and operational risk modeling from financial economics, Lee et al. [20] proposed a profit optimization model for customer information security investments and then provided some recommendations on the trade-offs between the risk and return in customer information security investments. According to the topology of a given data center network and the risk-neutral assumption, Wang et al. [21] presented a probability-based model to calculate the insecurity probability of each protected resource and the optimal investment for each security protection device. Two algorithms were designed to calculate the probability of threat and the optimal investment for data center security. The studies mentioned above mainly focused on the security investment and few researchers took the information sharing into consideration.

1.2.2 Considering Both the Security Investment and Information Sharing

In 2003, Gordon et al. [22] proposed a model considering both the information sharing and security investment to examine firms' information security strategies. Their analyses showed that information sharing reduced each firm's amount spent on information security activities. However, information sharing can enhance the security level of a firm. Gal-Or and Ghose [23] developed an analytical framework to investigate firms' information sharing levels and investments in security technologies under Bertrand competition. Their research results suggested that information sharing was more valuable in more competitive industries, and the benefits from such information-sharing alliances increased with the size of the firms. Hausken [24] investigated the information sharing and security investment for two substitutive firms. The author first analyzed firms' strategies when making decisions individually. Then a social planner was introduced for controlling information sharing, security investment, or both, in simultaneous and two-period games. The author found that a social planner would over-invest in security (over-share information) in the simultaneous game. Liu et al. [25] examined the relationship between decisions made by two firms in terms of knowledge sharing and investment in information security. Their study demonstrated that the nature of information assets possessed by the two firms (complementary or substitutable) had a significant influence on firms' decisions. In the complementary case, firms had a natural incentive to share security knowledge. While in the substitutable case, a firm would share no information in the equilibrium. In 2014, Gao et al. [26] investigated the information sharing and security investments for two complementary firms. The term "complementary" meant that the two firms' combined information assets were of significant value and the information asset of a single firm was no value to an attacker. They obtained the equilibrium choices for firms when they made decisions individually and also analyzed the effect of a social planner on total costs when the social planner could determine strategies for both firms. In 2015, Gao et al. [27] applied an alternative well-accepted security breach probability function to analyze the security investment and information sharing strategies for two firms. Their analyses showed that although aggregate attack, aggregate defense, and the security breach probability remained unchanged, a greater intervention from the social planner would give rise to higher social welfare. However, all these references mainly considered the sharing of information security knowledge, and this kind of information sharing was another type of security investment since sharing security knowledge can reduce the vulnerability of firms' information systems. Most researchers merely considered the benefit of information sharing and few of them took the risk into account. In addition, no researcher investigated the information security strategies for firms in the IoT environment. In view of that sharing business-related information enhances commercial interests but introduces the risk of information leakage, this chapter conducts research on the business information sharing levels and security investments for two firms in the IoT environment.

1.3 Model Setting

We consider two similar firms in traditional environment intending to deploy the IoT technologies and restructure their business process. The term "similar" means that the two firms share the same benefit function and cost function. They have drawn up a N-period IoT plan and want to clarify whether this plan is economical. Thus, we need to make a comparative analysis between the strategies in the environment of IoT and traditional environment. In both environments, firms need to share some information with each other to obtain cooperation benefit. Apparently, firm i' benefit increases with firm j's information sharing level (i,j = 1,2; $i \neq j$). Whereas, firm i' information sharing also has a positive impact on its own period benefit. For example, if the manufacturer share its finished goods inventory information with the retailer, then the retailer can make a fast decision on whether to sell some goods to the customer and then place a timely order, which benefits the manufacturer, the retailer, and the customer. The extent of a firm's information sharing benefiting itself depends on the interdependence between the two firms. In traditional environment, firms' cooperation is relatively simple and thus the interdependence is small. Hence, in this chapter, we assume that the interdependence between firms in traditional environment is 0 and the interdependence in IoT environment is represented by γ. A higher value of γ

Table 1.1 Notations

Order	Notation	Definition	Range of values
1	L	The period benefit firm i can obtain if firm j's information sharing level is 1 in traditional environment. (i, j=1, 2; $i \neq j$)	$L > 0$
2	S	Loss of a firm when a security breach occurs in both environments	$S > 0$
3	C	The fixed cost to construct the IoT environment	$C > 0$
4	c	The IoT maintenance cost in each period	$c > 0$
5	v	The probability of a breach without any investment in traditional environment	$0 < v \ll \frac{1}{2}$
6	β	The efficiency of information security investment	$\beta > 0$
7	ε	The importance of the shared information for a firm	$\varepsilon \in [0, 1]$
8	n	Period number	$n = 1, 2, \cdots, N$
9	θ	Used to measure the growth rate of period benefit in IoT environment, a larger value means a smaller growth rate	$0 < \theta < 1$
10	k	Coefficient difference of a firm's period benefit between the first period and the stable state in IoT environment	$k > 0$
11	w	Coefficient of a firm's period benefit in the stable state in IoT environment	$w > k + 1$
12	μ	Used to measure the growth rate of breach probability in IoT environment, a larger value means a smaller growth rate	$\mu < 1$
13	t	Coefficient difference of a firm's breach probability between the first period and the stable state in IoT environment	$t > 0$
14	z	Coefficient of a firm's breach probability in the stable state in IoT environment	$z > t + 1$
15	ρ	The constant discount rate	$0 < \rho < 1$
16	γ	The interdependence between firms i and j	$\gamma > 0$
17	α_i	Information sharing level of firm i in each period in traditional environment	$\alpha_i \in [0, 1]$
18	$\alpha_{i,n}$	Information sharing level of firm i in period n in IoT environment	$\alpha_{i,n} \in [0, 1]$
19	x_i	Information security investment of firm i in each period in traditional environment	$x_i \geq 0$
20	$x_{i,n}$	Information security investment of firm i in period n in IoT environment	$x_{i,n} \geq 0$

means that a firm's information sharing level has a greater effect on its own period benefit. In this chapter, we do not consider the propagation of security breaches from one firm to another one. The notations that occur in this chapter are listed in Table 1.1. Games in the two environments are described as follows.

1.3.1 Previous Game in Traditional Environment

In traditional environment, it is rational to assume that firms' benefit and cost are identical in each period since they have reached the stable state. Then the information sharing level and security investment of firm i (i=1,2) in traditional environment is denoted by α_i and x_i. Since firm i's benefit f_i increases with the information sharing level of firm j, we have $\frac{df_i}{d\alpha_j} > 0$. Due to the declining marginal utility, we also have $\frac{d^2 f_i}{d{\alpha_j}^2} < 0$. This chapter assumes that the period benefit of firm i is $f_i = (2\alpha_j - {\alpha_j}^2)L$.

Besides the benefit, information sharing will also bring the risk of information leakage. Firms need to invest in information security to decrease the probability of being breached. We use the function $p(x) = v^{\beta x+1}$ of Gordon and Loeb [6] as the breach probability function, where x is the information security investment and β represents the efficiency of the security investment. The parameter v is the initial probability of being breached when the security investment is 0. In this chapter, we assume that it is a low probability event that a firm is successfully breached by hackers. A firm's breach probability asymptotically approaches zero but will never reach zero with the increase of security investment. This is because an absolutely secure information system does not exist even investing a lot of money to protect the system. As firm i's investment is x_i, its breach probability is $p_i = p(x_i) = v^{\beta x_i+1}$.

Firm i suffers a loss of S if its information system is breached by hackers. In addition, even though firm i is not breached, it will also cause firm i a loss when firm j is breached due to the information sharing of firm i. This kind of loss relates to the importance of the shared information of firm i. Thus, the expected cost of firm i is $x_i + p_i S + \varepsilon\alpha_i(1 - p_i)p_j S$, where ε represents the importance degree of the shared information.

Taking into consideration of the constant discount rate ρ, the objective function of firm i is

$$\text{Max } F_{i,tra} = \sum_{n=1}^{N} \frac{(2\alpha_j - {\alpha_j}^2)L - x_i - p_i S - \varepsilon\alpha_i(1 - p_i)p_j S}{(1+\rho)^{n-1}}$$

1.3.2 Our Game in the Environment of IoT

We use $\alpha_{i,n}$ and $x_{i,n}$ to represent the information sharing level and investment of firm i in period n in the IoT environment. It will cost firm i a fixed cost C to deploy IoT technologies and construct the IoT environment. Ceteris paribus, a firm will get a larger benefit in the IoT environment than in the traditional environment due to the application of advanced technologies and the restructuring of business process. Besides, a firm's benefit will increase with the period number n since the firm becomes more skillful in using the new technologies over time and the benefit increasing rate decreases with n. When n takes a large value, the increment is not obvious. Similar to the traditional environment, the period benefit of firm i in the IoT environment increases with $\alpha_{j,n}$. Because of the interdependence between the two firms in the IoT environment, firm i' period benefit also increases with $\alpha_{i,n}$. Hence, we assume that firm i' benefit of period n in the IoT environment is $f_{i,n} = [(2\alpha_{j,n} - {\alpha_{j,n}}^2) + \gamma(2\alpha_{i,n} - {\alpha_{i,n}}^2)](w - k\theta^{n-1})L$. Apparently, provided that the security investment and information sharing level are identical in each period, we have $f_{i,n} > f_{i,n-1}$ and $f_{i,n+1} - f_{i,n} < f_{i,n} - f_{i,n-1}$, which consists with our analysis. $w - k > 1$ is in compliance with that a firm's period benefit will be larger in the IoT environment. We also have $\frac{d^2 f_{i,n}}{d{\alpha_{i,n}}^2} < 0$ and $\frac{d^2 f_{i,n}}{d{\alpha_{j,n}}^2} < 0$ because of the declining marginal utility.

Due to the adoption of RFID and wireless transmission technology, a firm's system is easier to be breached by hackers in the IoT environment. Furthermore, hackers become more knowledgeable with the new technologies over time, which implies that a firm's breach probability increases in n provided that other conditions are the same. Similar to the benefit increasing rate, the probability increasing rate also decreases in n. Thus, we have the assumption that in period n, firm i's breach probability is $p_{i,n} = (z - t\mu^{n-1})v^{\beta x_{i,n}+1}$. We have $z - t > 1$ to ensure that a firm's information system is more vulnerable in IoT environment.

Similar to the traditional case, it will cause firm i a loss of S if hackers have successfully attacked its information system. Because of information sharing, firm i also suffers a loss if firm j's system is breached. Besides, it will take firm i a cost of c to maintain the IoT devices in each period. Hence, in period n, the expected cost of firm i in IoT environment is $x_{i,n} + p_{i,n}S + \varepsilon\alpha_{i,n}(1 - p_{i,n})p_{j,n}S + c$.

1.4 Non-cooperative Game

In terms of our game in the IoT environment, suppose that the two firms make decisions non-cooperatively and just consider their own profits in this section. Assume that each firm can acquire the other firm's strategy based on the same decision rule. The objective of each firm is to maximize the total benefits of all periods. Thus, taking into consideration of the constant discount rate ρ, the objective function of firm i in IoT environment is

$$\text{Max}\, F_{i,iot} = -C + \sum_{n=1}^{N} \frac{\begin{array}{c}[(2\alpha_{j,n} - {\alpha_{j,n}}^2) + \gamma(2\alpha_{i,n} - {\alpha_{i,n}}^2)](w - k\theta^{n-1}) \\ L - x_{i,n} - p_{i,n}S - \varepsilon\alpha_{i,n}(1 - p_{i,n})p_{j,n}S - c\end{array}}{(1+\rho)^{n-1}} \tag{1.1}$$

Similarly, the objective function of firm j is

$$\text{Max } F_{j,iot} = -C + \sum_{n=1}^{N} \frac{\begin{array}{c}[(2\alpha_{i,n} - \alpha_{i,n}{}^2) + \gamma(2\alpha_{j,n} - \alpha_{j,n}{}^2)](w - k\theta^{n-1}) \\ L - x_{j,n} - p_{j,n}S - \varepsilon\alpha_{j,n}(1 - p_{j,n})p_{i,n}S - c\end{array}}{(1+\rho)^{n-1}} \tag{1.2}$$

In the following parts of this section, firms' strategies and an analysis on each firm's strategy are given.

1.4.1 Firms' Strategies in the Non-cooperative Game

We first consider firm i's strategy. In this chapter, firms' solutions are assumed to be interior, i.e., $x_{i,n} > 0$ and $0 < \alpha_{j,n} < 1$. To maximize the benefit, $x_{i,n}$ and $\alpha_{i,n}$ should satisfy the first order condition, i.e., $\frac{\partial F_{i,iot}}{\partial x_{i,n}} = \frac{-1 - S\beta\ln v \cdot p_{i,n} + \varepsilon\alpha_{i,n}S\beta\ln v \cdot p_{i,n}p_{j,n}}{(1+\rho)^{n-1}} = 0$ and $\frac{\partial F_{i,iot}}{\partial \alpha_{i,n}} = \frac{2\gamma(1-\alpha_{i,n})(w-k\theta^{n-1})L - \varepsilon(1-p_{j,n})p_{i,n}S}{(1+\rho)^{n-1}} = 0$. As firms i and j are similar, it can be easily derived that the two firms' strategies are the same in the equilibrium, i.e., $x_{i,n} = x_{j,n} = x_{E,n}$ and $\alpha_{i,n} = \alpha_{j,n} = \alpha_{E,n}$, where $x_{E,n}$ and $\alpha_{E,n}$ refer to the security investment and information sharing level in the equilibrium in period n. Then we have $p_{i,n} = p_{j,n} = p_{E,n}$, where $p_{E,n}$ is the breach probability when security investment is $x_{E,n}$. Thus, we can get the following two equations:

$$-1 - S\beta\ln v \cdot p_{E,n} + \varepsilon\alpha_{E,n}S\beta\ln v \cdot p_{E,n}^2 = 0 \tag{1.3}$$

$$2\gamma(1 - \alpha_{E,n})(w - k\theta^{n-1})L - \varepsilon(1 - p_{E,n})p_{E,n}S = 0 \tag{1.4}$$

Define $I(p) = \varepsilon S\beta\ln v \cdot p^2\left(1 - \frac{\varepsilon p(1-p)S}{2\gamma(w-k\theta^{n-1})L}\right)$. Based on Eqs. 1.3 and 1.4, we can express the interior solution as

$$p_{E,n} = I^{-1}(1 + S\beta\ln v \cdot p_{E,n})$$

$$x_{E,n} = \frac{\ln \frac{p_{E,n}}{(z-t\mu^{n-1})v}}{\beta\ln v}$$

$$\alpha_{E,n} = 1 - \frac{\varepsilon p_{E,n}(1 - p_{E,n})S}{2\gamma(w - k\theta^{n-1})L}$$

Omitting the analytical process, we also give the solution of the non-cooperative game in traditional environment for comparison. We find that firms' strategies are identical in each period. We use x_E and α_E to denote the security investment and information sharing level of each period in traditional environment. Then we have

$$p_E = \frac{-1}{S\beta \ln v}$$
$$x_E = \frac{\ln \frac{-1}{S\beta v \ln v}}{\beta \ln v}$$
$$\alpha_E = 0$$

1.4.2 Parameters Analyses

We first explore the impact of period number n on firms' strategies. Define $\varphi = w - k\theta^{n-1}$. Then Eq. 1.4 can be expressed as

$$2\gamma\varphi(1-\alpha_{E,n})L - \varepsilon\left(1-p_{E,n}\right)p_{E,n}S = 0 \tag{1.5}$$

Take the derivative of Eq. 1.3 with respect to φ, then the following equation can be obtained

$$\varepsilon S\beta \ln v \cdot p_{E,n}^2 \frac{d\alpha_{E,n}}{d\varphi} + S\beta \ln v \cdot \left(2\varepsilon\alpha_{E,n}p_{E,n} - 1\right)\frac{dp_{E,n}}{d\varphi} = 0 \tag{1.6}$$

Similarly, based on Eq. 1.5, we have

$$2\gamma\varphi L \frac{d\alpha_{E,n}}{\varphi} + \varepsilon S\left(1-2p_{E,n}\right)\frac{dp_{E,n}}{d\varphi} = 2\gamma(1-\alpha_{E,n})L \tag{1.7}$$

Combining Eqs. 1.6 and 1.7, we can yield

$$\begin{cases} \dfrac{d\alpha_{E,n}}{d\varphi} = \dfrac{2\gamma LS\beta lnv \cdot (1-\alpha_{E,n})\left(2\varepsilon\alpha_{E,n}p_{E,n}-1\right)}{2\gamma\varphi LS\beta lnv \cdot \left(2\varepsilon\alpha_{E,n}p_{E,n}-1\right) - \varepsilon^2 S^2\beta \ln v \cdot \left(1-2p_{E,n}\right)p_{E,n}^2} \\ \dfrac{dp_{E,n}}{d\varphi} = \dfrac{2\varepsilon\gamma LS\beta lnv \cdot (1-\alpha_{E,n})p_{E,n}^2}{\varepsilon^2 S^2\beta \ln v \cdot \left(1-2p_{E,n}\right)p_{E,n}^2 - 2\gamma\varphi LS\beta lnv \cdot \left(2\varepsilon\alpha_{E,n}p_{E,n}-1\right)} \end{cases} \tag{1.8 \& 1.9}$$

It can be easily derived that $\frac{d\alpha_{E,n}}{d\varphi} > 0$ and $\frac{dp_{E,n}}{d\varphi} > 0$. Since φ increases with n, based on Eqs. 1.8 and 1.9, the following proposition can be obtained.

Proposition 1 *For each firm, the information sharing level and the probability of being breached will increase over time in the non-cooperative game.*

Proposition 1 states that when firms make decisions individually, each firm will share more information over time, which consists with our intuition. This is because the two firms become more skillful as time goes on and thus they will gain more benefits over time, which encourages firms to share more information to obtain more profits. Besides, the breach probability of each firm also increases progressively over time, which is caused by the following two factors: (1) Since a firm's information sharing level increases as time goes on, the firm will suffer more losses if its partner's information system is breached, which decreases the firm's incentive to maintain a high security level for its own information system. (2) Hackers become more knowledgeable over time, thus, each firm's information system is more vulnerable. Though we can make sure that a firm's breach probability increases over time, we can not decide whether the firm decreases its security investment as time goes on. The reason is that the firm's breach probability will increase originally due to the increase of hackers' knowledge. Even if the security investment increases, the breach probability may also increases. We can't clarify whether the increase of the breach probability is caused by the decrease of security investment or by the increase of hackers' knowledge.

Next, the effect of the interdependence between firms will be examined. Take the derivative of Eqs. 1.3 and 1.4 with respect to γ, then the following two equations are obtained.

$$\varepsilon S\beta \ln v \cdot p_{E,n}^2 \frac{d\alpha_{E,n}}{d\gamma} + S\beta \ln v \cdot \left(2\varepsilon\alpha_{E,n}p_{E,n} - 1\right)\frac{dp_{E,n}}{d\gamma} = 0 \tag{1.10}$$

$$2\gamma\left(w - k\theta^{n-1}\right)L\frac{d\alpha_{E,n}}{d\gamma} + \varepsilon S\left(1 - 2p_{E,n}\right)\frac{dp_{E,n}}{d\gamma} = 2(1 - \alpha_{E,n})\left(w - k\theta^{n-1}\right)L \tag{1.11}$$

Based on Eqs. 1.10 and 1.11, we have

$$\begin{cases} \dfrac{d\alpha_{E,n}}{d\gamma} = \dfrac{2LS\beta\ln v \cdot (1 - \alpha_{E,n})\left(w - k\theta^{n-1}\right)\left(2\varepsilon\alpha_{E,n}p_{E,n} - 1\right)}{2\gamma LS\beta lnv \cdot \left(w - k\theta^{n-1}\right)\left(2\varepsilon\alpha_{E,n}p_{E,n} - 1\right) - \varepsilon^2S^2\beta\ln v \cdot \left(1 - 2p_{E,n}\right)p_{E,n}^2} \\ \dfrac{dp_{E,n}}{d\gamma} = \dfrac{2\varepsilon LS\beta lnv \cdot (1 - \alpha_{E,n})\left(w - k\theta^{n-1}\right)p_{E,n}^2}{\varepsilon^2S^2\beta\ln v \cdot \left(1 - 2p_{E,n}\right)p_{E,n}^2 - 2\gamma LS\beta lnv \cdot \left(w - k\theta^{n-1}\right)\left(2\varepsilon\alpha_{E,n}p_{E,n} - 1\right)} \end{cases} \tag{1.12 \& 1.13}$$

It can be easily obtained that $\frac{d\alpha_{E,n}}{d\gamma} > 0$ and $\frac{dp_{E,n}}{d\gamma} > 0$. Since $p_{E,n} = (z - t\mu^{n-1})v^{\beta x_{E,n}+1}$, we get $\frac{dx_{E,n}}{d\gamma} < 0$. Then the following proposition can be obtained.

Proposition 2 *In the non-cooperative game, each firm will share more information and invest less in information security in each period with a larger interdependence between firms.*

Proposition 2 reveals that when the interdependence between firms becomes larger, firms will increase their information sharing levels, which is intuitive. A greater interdependence means that a firm can benefit more for a certain level of information sharing, which stimulates firms to share more information with each other. Since the increase of the information sharing level will increase the information leakage risk for firms, from intuition, we may think that firms should invest more in information security to cut down the losses brought by security breaches. However, Proposition 2 shows that firms will reduce their security investments when their interdependence increases, which deteriorate the security performance further. They reason causing this counter-intuitive result is that firms make decisions individually and just consider their own benefits. The increase of a firm's information sharing level will lead to more losses if his partner's information system is breached, which cuts down the firm's incentive to protect its own information system. Even though a firm's information system is very safe, the firm will also suffer some losses due to its partner's security breach. Hence, each firm will invest less when the interdependence between firms increases.

1.4.3 Economical Analysis

In this section, we will explore that whether the N-period IoT plan is economical since it will cost a lot of money to construct the IoT environment. Thus, the following two questions need to be addressed.

(a) In which period, the period net benefit of a firm in the IoT environment starts to be larger than or equal to that in traditional environment?
(b) In which period, the total profits in the IoT environment become larger than or equal to that in traditional environment?

To address the first question, we assume that in period N_{E1} a firm starts to have more period net benefit in IoT environment than in traditional environment, which means that the period net benefit before period N_{E1} is greater in traditional environment compared to in IoT environment. Thus, we have the following two mathematical expressions.

$$\frac{\begin{array}{c}[(2\alpha_{E,N_{E1}} - {\alpha_{E,N_{E1}}}^2) + \gamma(2\alpha_{E,N_{E1}} - {\alpha_{E,N_{E1}}}^2)]\left(w - k\theta^{N_{E1}-1}\right) \\ L - x_{E,N_{E1}} - p_{E,N_{E1}}S - \varepsilon\alpha_{E,N_{E1}}\left(1 - p_{E,N_{E1}}\right)p_{E,N_{E1}}S - c\end{array}}{(1+\rho)^{N_{E1}-1}}$$

$$\geq \frac{(2\alpha_E - {\alpha_E}^2)L - x_E - p_E S - \varepsilon\alpha_E(1-p_E)p_E S}{(1+\rho)^{N_{E1}-1}} = \frac{-\frac{\ln\frac{-1}{S\beta v\ln v}}{\beta\ln v} - \frac{-1}{\beta\ln v}}{(1+\rho)^{N_{E1}-1}}$$

and

$$\frac{\begin{array}{c}[(2\alpha_{E,N_{E1}-1} - {\alpha_{E,N_{E1}-1}}^2) + \gamma(2\alpha_{E,N_{E1}-1} - {\alpha_{E,N_{E1}-1}}^2)]\left(w - k\theta^{N_{E1}-2}\right) \\ L - x_{E,N_{E1}-1} - p_{E,N_{E1}-1}S - \varepsilon\alpha_{E,N_{E1}-1}\left(1 - p_{E,N_{E1}-1}\right)p_{E,N_{E1}-1}S - c\end{array}}{(1+\rho)^{N_{E1}-2}}$$

$$< \frac{(2\alpha_E - \alpha_E{}^2)L - x_E - p_E S - \varepsilon\alpha_E(1-p_E)p_E S}{(1+\rho)^{N_{E1}-2}} = \frac{-\frac{\ln\frac{-1}{S\beta v\ln v}}{\beta\ln v} - \frac{-1}{\beta\ln v}}{(1+\rho)^{N_{E1}-2}}$$

For the second question, we assume that in period N_{E2} each firm starts to earn more money in the IoT environment. Similar to the first question, we can also get the following two expressions.

$$-C + \sum_{n=1}^{N_{E2}} \frac{\begin{array}{c}[(2\alpha_{E,n} - \alpha_{E,n}{}^2) + \gamma(2\alpha_{E,n} - \alpha_{E,n}{}^2)]\left(w - k\theta^{n-1}\right)\\ L - x_{E,n} - p_{E,n}S - \varepsilon\alpha_{E,n}\left(1 - p_{E,n}\right)p_{E,n}S - c\end{array}}{(1+\rho)^{n-1}}$$

$$\geq \sum_{n=1}^{N_{E2}} \frac{(2\alpha_E - \alpha_E{}^2)L - x_E - p_E S - \varepsilon\alpha_E(1-p_E)p_E S}{(1+\rho)^{n-1}} = \sum_{n=1}^{N_{E2}} \frac{-\frac{\ln\frac{-1}{S\beta v\ln v}}{\beta\ln v} - \frac{-1}{\beta\ln v}}{(1+\rho)^{n-1}}$$

and

$$-C + \sum_{n=1}^{N_{E2}-1} \frac{\begin{array}{c}[(2\alpha_{E,n} - \alpha_{E,n}{}^2) + \gamma(2\alpha_{E,n} - \alpha_{E,n}{}^2)]\left(w - k\theta^{n-1}\right)\\ L - x_{E,n} - p_{E,n}S - \varepsilon\alpha_{E,n}\left(1 - p_{E,n}\right)p_{E,n}S - c\end{array}}{(1+\rho)^{n-1}}$$

$$< \sum_{n=1}^{N_{E2}-1} \frac{(2\alpha_E - \alpha_E{}^2)L - x_E - p_E S - \varepsilon\alpha_E(1-p_E)p_E S}{(1+\rho)^{n-1}} = \sum_{n=1}^{N_{E2}-1} \frac{-\frac{\ln\frac{-1}{S\beta v\ln v}}{\beta\ln v} - \frac{-1}{\beta\ln v}}{(1+\rho)^{n-1}}$$

It can be easily derived that $N_{E1} \leq N_{E2}$. For any period before N_{E1} (i.e., $n < N_{E1}$), firms are in the process of adapting themselves to the IoT environment, and their period net benefits in IoT environment are less than traditional environment. From period N_{E1}, a firm's period net benefit starts to be greater than or equal to that in traditional environment. Whereas, the total profits of a firm are still smaller in IoT environment until period N_{E2} (i.e., $N_{E1} \leq n < N_{E2}$). In period N_{E2}, a firm will get greater total profits in IoT environment. Therefore, for the two firms in the non-cooperative game, the N-period IoT plan is economical if $N > N_{E2}$. Otherwise, the IoT plan will not be cost-efficient. Although we can't give the analytical solutions of N_{E1} and N_{E2} based on the above expressions, some numerical solutions can be obtained when the values of some parameters are given. For better analyses, we will conduct some numerical experiments in the next section.

1.4.4 Numerical Experiments

Some numerical experiments are conducted for better illustrating the aforementioned analyses. The primary purposes of these experiments are:

1. Verifying the variation trends of the information sharing level ($\alpha_{E,n}$), security investment ($x_{E,n}$) and breach probability ($p_{E,n}$) in the equilibrium point when period number (n) or interdependence between firms (γ) increase.
2. Assessing the impact of γ on the period net benefit (without considering the discount rate ρ).
3. Giving the numerical solutions of N_{E1} and N_{E2} and making some relative analyses.

The basic principle on how to take values for some parameters in our experiments is that the value-taking should ensure that the solutions are interior, i.e., ($0 < \alpha_{E,n} < 1\,, x_{E,n} > 0$). In this chapter, our experiments just consider a 10-period plan, i.e., $N = 10$. For better presenting the properties stated in Propositions 1 and 2, the parameter values in our experiments are set as: $L = 2$, $S = 7$, $C = 2$, $c = 0.1$, $v = \frac{1}{3e}$, $\varepsilon = 1$, $\beta = 0.8$, $w = 2$, $k = 0.9$, $\theta = 0.9$, $z = 2$, $t = 0.5$, $\mu = 0.2$, and $\rho = 0.05$.

First, an experiment is conducted to achieve purposes (1) and (2). Since we want to analyze the effect of γ on a firm's strategies and period net benefit, the values of γ is chosen in the following 5 cases: $\gamma = 0.2$, $\gamma = 0.4$, $\gamma = 0.6$, $\gamma = 0.8$, and $\gamma = 1.0$. The experiment results are shown in Table 1.2.

Table 1.2 presents that both the information sharing level $\alpha_{E,n}$ and the breach probability $p_{E,n}$ increase with n from 1 to 10 for any $\gamma \in \{0.2,0.4,0.6,0.8.1.0\}$, which consists with Proposition 1. Whereas, $x_{E,n}$ does not have this kind of monotonicity. For instance, when $\gamma = 0.2$, $x_{E,n}$ increases with n from 1 to 4 and decreases with n from 4 to 10, respectively. Hence, we can't decide whether the security investment in the equilibrium point will increase with n, which is in accordance with our analysis under Proposition 1. From Table 1.2, we also find that in any period n ($1 \le n \le 10$), the information sharing level increases and the security investment decreases with γ from 0.2 to 1.0, which meets with Proposition 2.

Besides verifying the theoretical analyses in above sections, the experiment results can also help us explore the impact of the interdependence between firms on a firm's period net benefit. From Table 1.2, we get that the period net benefit of any period increases with γ from 0.2 to 1.0. Hence, we can conjecture that a greater interdependence between firms will bring more benefits for each firm in the non-cooperative game, which consists with our intuitive knowledge.

To accomplish purpose (3), we conduct another numerical experiment to compare the period net benefit and total profits in IoT environment with in traditional environment. Except for the value of γ, the values of other parameters are identical to the aforementioned experiment. We have shown that a greater γ will bring more benefits for firms, thus, γ needs to take a smaller value to prevent that in the first period the period net benefit of a firm will be larger in the IoT environment compared to in traditional environment (i.e., prevent $N_{E1} = 1$). Here, we choose $\gamma = 0.125$. The experiment results are presented in Figs. 1.1 and 1.2, respectively.

Figure 1.1 shows that in the non-cooperative game, a firm's period net benefit is always a negative value in traditional environment. This is because firms will share no information with each other in traditional environment and they will get no benefit. It should be noted that in Fig. 1.1 the graph of traditional environment is a

Table 1.2 The experiment results of the non-cooperative game

γ	n	$\alpha_{E,n}$	$x_{E,n}$	$p_{E,n}$	Period net benefit (without considering the discount rate)
0.2	1	0.3623271	0.4398933	0.0878890	0.2080679
	2	0.4082399	0.5781102	0.0882711	0.3298934
	3	0.4442278	0.6006259	0.0885754	0.5364929
	4	0.4730535	0.6037619	0.0888223	0.7362483
	5	0.4965444	0.6033544	0.0890256	0.9169655
	6	0.5159581	0.6024125	0.0891950	1.0785629
	7	0.5321888	0.6014985	0.0893377	1.2228959
	8	0.5458900	0.6006988	0.0894589	1.3519149
	9	0.55755045	0.6000105	0.0895626	1.4673641
	10	0.56754280	0.5994177	0.0896518	1.5707642
0.4	1	0.6722744	0.4217351	0.0906096	1.2054265
	2	0.6963786	0.5610486	0.0908362	1.3253614
	3	0.7152248	0.5844432	0.0910149	1.5344442
	4	0.7302893	0.5882958	0.0911589	1.7392564
	5	0.7425448	0.5884808	0.0912767	1.9264812
	6	0.7526589	0.5880342	0.0913744	2.0953227
	7	0.7611046	0.5875386	0.0914563	2.2471772
	8	0.7682268	0.5870950	0.0915256	2.3837004
	9	0.7742828	0.5867119	0.0915847	2.5064488
	10	0.7794685	0.5863820	0.0916355	2.6168275
0.6	1	0.7792957	0.4150408	0.0916337	1.7379980
	2	0.7956654	0.5547961	0.0917947	1.8873126
	3	0.8084505	0.5785413	0.0919212	2.1235996
	4	0.8186613	0.5826774	0.0920228	2.3534060
	5	0.8269622	0.5830951	0.0921057	2.5634774
	6	0.8338087	0.5828421	0.0921743	2.7531291
	7	0.8395230	0.5825092	0.0922318	2.9238914
	8	0.8443398	0.5822034	0.0922803	3.0775619
	9	0.8484341	0.5819382	0.0923217	3.2158397
	10	0.8519389	0.5817098	0.0923571	3.3402674
0.8	1	0.8335977	0.4115510	0.0921722	2.2053239
	2	0.8459957	0.5515456	0.0922970	2.3886370
	3	0.8556729	0.5754797	0.0923949	2.6557581
	4	0.8633978	0.5797679	0.0924734	2.9134720
	5	0.8696754	0.5803101	0.0925374	3.1487680
	6	0.8748514	0.5801604	0.0925903	3.3611978
	7	0.8791703	0.5799141	0.0926345	3.5525148
	8	0.8828101	0.5796817	0.0926718	3.7247243
	9	0.8859033	0.5794790	0.0927036	3.8797165
	10	0.8885507	0.5793043	0.0927309	4.0192092

(continued)

Table 1.2 (continued)

γ	n	$\alpha_{E,n}$	$x_{E,n}$	$p_{E,n}$	Period net benefit (without considering the discount rate)
1.0	1	0.8664472	0.4094079	0.0925045	2.6554286
	2	0.8764257	0.5495526	0.0926064	2.8739890
	3	0.8842114	0.5736048	0.0926862	3.1729224
	4	0.8904246	0.5779879	0.0927502	3.4593272
	5	0.8954725	0.5786077	0.0928022	3.7204859
	6	0.8996336	0.5785223	0.0928453	3.9562209
	7	0.9031052	0.5783298	0.0928812	4.1685332
	8	0.9060304	0.5781429	0.0929116	4.3596535
	9	0.9085160	0.5779789	0.0929374	4.5316765
	10	0.9106433	0.5778375	0.0929595	4.6865053

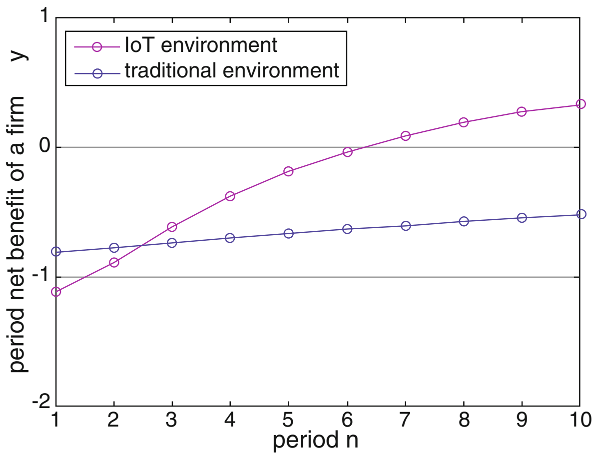

Fig. 1.1 The period net benefit of a firm in IoT environment and traditional environment when firms determine their strategies individually

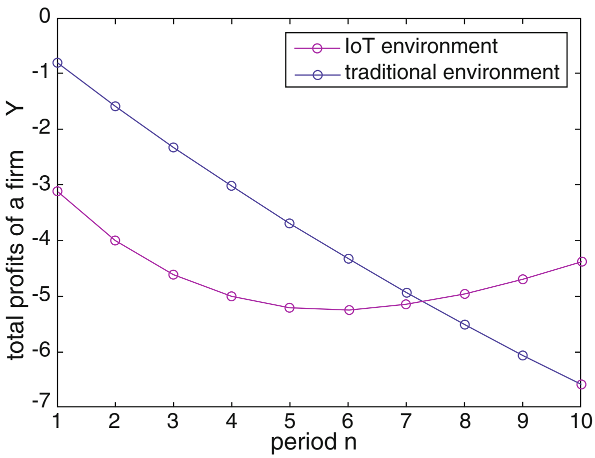

Fig. 1.2 The total profits of a firm in IoT environment and traditional environment when firms determine their strategies individually

little upward since we consider the discount rate here. In Fig. 1.1, we find that the graph of the IoT environment is under the line $y = 0$ from period 1 to period 6 and becomes above the line $y = 0$ since period 7, which means that the firm is under deficit from period 1 to period 6 and achieves profitability since period 7. In the first two periods (i.e., $n = 1, 2.$), the graph of the IoT environment is under the traditional environment. Whereas, the graph of the IoT environment is above the traditional environment from period 3 to period 10, which implies that $N_{E1} = 3$.

In Fig. 1.2, it can be obtained that $N_{E2} = 8$ as the graph of IoT environment becomes above the graph of traditional environment in period 8. The graph of traditional environment is downward since firms are under deficit in any period in traditional environment. The graph of IoT environment is downward from period 1 to periods 6 and upward from period 6 to 10. This is because firms achieve profitability in period 7, which is demonstrated in Fig. 1.1. In period 10, even though a firm will suffer some losses in both the IoT environment and traditional environment, the firm will have a smaller loss in the IoT environment, which means that the 10-period IoT plan is economical. Due to the limit of period number in this experiment, firms can't earn money in the 10-period plan if they don't cooperate their strategies. However, it is rational to conjecture that the total profits will be a positive value with a greater period number.

1.5 Totally Cooperative Game

In the totally cooperative game, we assume that both of the two firms will cooperate their strategies, which means that each firm intends to maximize the total benefit of the two firms. Thus, the objective function of them is

$$
\begin{aligned}
\text{Max } F_{iot} = \quad & -2C + \sum_{n=1}^{N} \frac{\begin{array}{c}[(2\alpha_{j,n} - {\alpha_{j,n}}^2) + \gamma(2\alpha_{i,n} - {\alpha_{i,n}}^2)](w - k\theta^{n-1}) \\ L - x_{i,n} - p_{i,n}S - \varepsilon\alpha_{i,n}(1 - p_{i,n})p_{j,n}S - c\end{array}}{(1+\rho)^{n-1}} \\
& + \sum_{n=1}^{N} \frac{\begin{array}{c}\left[(2\alpha_{i,n} - {\alpha_{i,n}}^2) + \gamma\left(2\alpha_{j,n} - {\alpha_{j,n}}^2\right)\right]\left(w - k\theta^{n-1}\right) \\ L - x_{j,n} - p_{j,n}S - \varepsilon\alpha_{j,n}\left(1 - p_{j,n}\right)p_{i,n}S - c\end{array}}{(1+\rho)^{n-1}}
\end{aligned}
\tag{1.14}
$$

1.5.1 Firms' Strategies in the Totally Cooperative Game

We also first analyze the strategy of firm i. To satisfy the first order condition, we have $\frac{\partial F_{iot}}{\partial x_{i,n}} = \frac{-1 - S\beta \ln v \cdot p_{i,n} + \varepsilon\alpha_{i,n}S\beta \ln v \cdot p_{i,n}p_{j,n} - \varepsilon\alpha_{j,n}S\beta \ln v \cdot \left(1 - p_{j,n}\right)p_{i,n}}{(1+\rho)^{n-1}} = 0$ and

$\frac{\partial F_{iot}}{\partial \alpha_{i,n}} = \frac{2(\gamma+1)\left(1-\alpha_{i,n}\right)\left(w-k\theta^{n-1}\right)L-\varepsilon\left(1-p_{j,n}\right)p_{i,n}S}{(1+\rho)^{n-1}} = 0$. Due to the similarity of the two firms, we have $x_{i,n} = x_{j,n} = x_{O,n}$ and $\alpha_{i,n} = \alpha_{j,n} = \alpha_{O,n}$, the parameters $x_{O,n}$ and $\alpha_{O,n}$ represent the security investment and information sharing level of the cooperative game in period n. Then we have $p_{i,n} = p_{j,n} = p_{O,n}$, where $p_{O,n}$ is the breach probability when security investment is $x_{O,n}$. Thus, the following two equations can be obtained.

$$1 + S\beta \ln v \cdot p_{O,n} + \varepsilon \alpha_{O,n} S\beta \ln v \cdot p_{O,n}\left(1 - 2p_{O,n}\right) = 0 \tag{1.15}$$

$$2(\gamma + 1)(1 - \alpha_{O,n})\left(w - k\theta^{n-1}\right)L - \varepsilon\left(1 - p_{O,n}\right)p_{O,n}S = 0 \tag{1.16}$$

Define $H(p) = \varepsilon S\beta \ln v \cdot p(1 - 2p)\left(1 - \frac{\varepsilon p(1-p)S}{2(\gamma+1)\left(w-k\theta^{n-1}\right)L}\right)$. Combining Eqs. 1.15 and 1.16, we express the optimal solution of the totally cooperative game as follows.

$$p_{O,n} = H^{-1}\left(-1 - S\beta \ln v \cdot p_{O,n}\right)$$

$$x_{O,n} = \frac{\ln \frac{p_{O,n}}{(z-t\mu^{n-1})v}}{\beta \ln v}$$

$$\alpha_{O,n} = 1 - \frac{\varepsilon p_{O,n}\left(1 - p_{O,n}\right)S}{2(\gamma + 1)\left(w - k\theta^{n-1}\right)L}$$

Similar to the non-cooperative game, we also give the solution of the totally cooperative game in traditional environment (the analytical process is omitted). Firms' strategies are the same in each period in traditional environment. The parameters x_O and α_O are used denote the security investment and information sharing level of each period in traditional environment in the totally cooperative game. Define $H'(p) = \varepsilon S\beta \ln v \cdot p(1 - 2p)\left(1 - \frac{\varepsilon p(1-p)S}{2L}\right)$. Then we get

$$p_O = H^{'-1}(-1 - S\beta \ln v \cdot p_O)$$

$$x_O = \frac{\ln \frac{p_O}{v}}{\beta \ln v}$$

$$\alpha_O = 1 - \frac{\varepsilon p_O(1 - p_O)S}{2L}$$

1.5.2 Parameters Analyses

Corresponding to the analyses in the non-cooperative game, we also analyze the impact of the period number n and the interdependence γ on firms' strategies in the totally cooperative game. We first examine the effect of the period number. Plugging $w - k\theta^{n-1} = \varphi$ into Eq. 1.16, we get

$$2\varphi(\gamma+1)(1-\alpha_{O,n})L - \varepsilon\left(1-p_{O,n}\right)p_{O,n}S = 0 \tag{1.17}$$

Take the derivative of Eq. 1.15 with respect to φ, we obtain the following equation.

$$\begin{aligned} &\varepsilon S\beta \ln v \cdot p_{O,n}\left(1-2p_{O,n}\right)\frac{d\alpha_{O,n}}{d\varphi} \\ &+ S\beta \ln v \cdot \left[\varepsilon\alpha_{O,n}\left(1-4p_{O,n}\right)+1\right]\frac{dp_{O,n}}{d\varphi} = 0 \end{aligned} \tag{1.18}$$

Analogously, based on Eq. 1.17, we have

$$2\varphi(1+\gamma)L\frac{d\alpha_{O,n}}{\varphi} + \varepsilon S\left(1-2p_{O,n}\right)\frac{dp_{O,n}}{d\varphi} = 2(\gamma+1)(1-\alpha_{O,n})L \tag{1.19}$$

Combining Eqs. 1.18 and 1.19, we can yield

$$\begin{cases} \dfrac{d\alpha_{O,n}}{d\varphi} = \dfrac{-2LS\beta \ln v \cdot (\gamma+1)(1-\alpha_{O,n})\left[\varepsilon\alpha_{O,n}\left(1-4p_{O,n}\right)+1\right]}{\varepsilon^2 S^2\beta \ln v \cdot p_{O,n}\left(1-2p_{O,n}\right)^2 - 2\varphi LS\beta lnv \cdot (1+\gamma)\left[\varepsilon\alpha_{O,n}\left(1-4p_{O,n}\right)+1\right]} \\ \dfrac{dp_{O,n}}{d\varphi} = \dfrac{-2\varepsilon LS\beta lnv \cdot (\gamma+1)(1-\alpha_{O,n})p_{O,n}\left(1-2p_{O,n}\right)}{2\varphi LS\beta lnv \cdot (1+\gamma)\left[\varepsilon\alpha_{O,n}\left(1-4p_{O,n}\right)+1\right] - \varepsilon^2 S^2\beta \ln v \cdot p_{O,n}\left(1-2p_{O,n}\right)^2} \end{cases} \tag{1.20 \& 1.21}$$

It is easy to derive that $-2LS\beta \ln v \cdot (\gamma+1)(1-\alpha_{O,n})[\varepsilon\alpha_{O,n}(1-4p_{O,n})+1]$ 0 and $-2\varepsilon LS\beta \ln v \cdot (\gamma+1)(1-\alpha_{O,n})p_{O,n}(1-2p_{O,n}) > 0$. Based on Eq. 1.17, we have $2\varphi(\gamma+1)L = \frac{\varepsilon\left(1-p_{O,n}\right)p_{O,n}S}{\left(1-\alpha_{O,n}\right)}$. Then it can be obtained that $2\varphi LS\beta \ln v \cdot (1+\gamma)\left[\varepsilon\alpha_{O,n}\left(1-4p_{O,n}\right)+1\right] - \varepsilon^2 S^2\beta \ln v \cdot p_{O,n}\left(1-2p_{O,n}\right)^2 = \frac{\varepsilon S^2\beta \ln v \cdot p_{O,n}}{\left(1-\alpha_{O,n}\right)}\left[\left(1-p_{O,n}\right)\left[\varepsilon\alpha_{O,n}\left(1-4p_{O,n}\right)+1\right] - \varepsilon(1-\alpha_{O,n})\left(1-2p_{O,n}\right)^2\right]$. Define $(1-p_{O,n})[\varepsilon\alpha_{O,n}(1-4p_{O,n})+1] - \varepsilon(1-\alpha_{O,n})(1-2p_{O,n})^2$ as $h(\alpha_{O,n}, p_{O,n})$. Then we have $\dfrac{\partial h}{\partial \alpha_{O,n}} = \varepsilon\left(2-9p_{O,n}+8p_{O,n}^2\right)$, which means $h(\alpha_{O,n}, p_{O,n})$ is a linear function of α_O. Since $p_{O,n} \in \left(0, \frac{1}{2}\right)$, it can be easily derived that $h(0, p_{O,n}) = (1-p_{O,n}) - \varepsilon(1-2p_{O,n})^2 \geq (1-p_o) - (1-2p_o)^2 > 0$ and $h(1, p_{O,n}) = (1-p_{O,n})[1+\varepsilon(1-4p_{O,n})] > 0$. Thus, we can get that $h(\alpha_{O,n}, p_{O,n}) > 0$. Then we have $2\varphi LS\beta \ln v \cdot (1+\gamma)[\varepsilon\alpha_{O,n}(1-4p_{O,n})+1] - \varepsilon^2 S^2\beta \ln v \cdot p_{O,n}(1-2p_{O,n})^2 < 0$. The denominator terms of Eqs. 1.20 and 1.21 are opposite. Therefore, it can be obtained that $\frac{d\alpha_{O,n}}{d\varphi} > 0$ and $\frac{dp_{O,n}}{d\varphi} < 0$. As φ and $(z - t\mu^{n-1})$increase with n, we have the following proposition.

Proposition 3 *In the totally cooperative game, the information sharing level and security investment of each firm will increase over time and the breach probability of each firm will decrease with time goes on.*

From Proposition 3, we note that firms will increase their information sharing level with time goes on in the totally cooperative game, which is intuitive and similar to the non-cooperative case. Whereas, contrary to the non-cooperative game, the breach probability of each firm decreases over time in the totally cooperative game. This is because firms will suffer greater loss when firms sharing more information with each other. In order to cut down the total losses, each firm needs to decrease the breach probability. In the non-cooperative game, we can't decide whether a firm will increase or decrease its security investment. While in the totally cooperative game, since a firm's information system becomes more vulnerable with time goes on, the firm should increase the security investment to cut down its breach probability over time.

Next, we will explore the effect of the interdependence between firms on each firm's strategy. Take the derivative of Eqs. 1.15 and 1.17 with respect to γ, then we obtain the following two equations.

$$\varepsilon S\beta \ln v \cdot p_{O,n}\left(1-2p_{O,n}\right)\frac{d\alpha_{O,n}}{d\gamma}+S\beta \ln v\cdot\left[\varepsilon\alpha_{O,n}\left(1-4p_{O,n}\right)+1\right]\frac{dp_{O,n}}{d\gamma}=0 \quad (1.22)$$

$$2(1+\gamma)\varphi L\frac{d\alpha_{O,n}}{\gamma}+\varepsilon S\left(1-2p_{O,n}\right)\frac{dp_{O,n}}{d\gamma}=2\varphi(1-\alpha_{O,n})L \quad (1.23)$$

Base on Eqs. 1.22 and 1.23, we get

$$\begin{cases} \dfrac{d\alpha_{O,n}}{d\gamma}=\dfrac{-2LS\beta \ln v\cdot\varphi(1-\alpha_{O,n})\left[\varepsilon\alpha_{O,n}\left(1-4p_{O,n}\right)+1\right]}{\varepsilon^2S^2\beta \ln v\cdot p_{O,n}\left(1-2p_{O,n}\right)^2-2\varphi LS\beta lnv\cdot(1+\gamma)\left[\varepsilon\alpha_{O,n}\left(1-4p_{O,n}\right)+1\right]} \\ \dfrac{dp_{O,n}}{d\gamma}=\dfrac{-2\varepsilon LS\beta lnv\cdot\varphi(1-\alpha_{O,n})p_{O,n}\left(1-2p_{O,n}\right)}{2\varphi LS\beta lnv\cdot(1+\gamma)\left[\varepsilon\alpha_{O,n}\left(1-4p_{O,n}\right)+1\right]-\varepsilon^2S^2\beta \ln v\cdot p_{O,n}\left(1-2p_{O,n}\right)^2} \end{cases} \quad (1.24\ \&\ 1.25)$$

We have proved that $2\varphi LS\beta \ln v\cdot(1+\gamma)[\varepsilon\alpha_{O,n}(1-4p_{O,n})+1]-\varepsilon^2S^2\beta \ln v\cdot p_{O,n}(1-2p_{O,n})^2<0$. It can be derived that $-2LS\beta \ln v\cdot\varphi(1-\alpha_{O,n})[\varepsilon\alpha_{O,n}(1-4p_{O,n})+1]0$ and $-2\varepsilon LS\beta \ln v\cdot\varphi(1-\alpha_{O,n})p_{O,n}(1-2p_{O,n})>0$. Then we can get $\frac{d\alpha_{O,n}}{d\gamma}>0$ and $\frac{dp_{O,n}}{d\gamma}<0$. Thus, the following proposition can be obtained.

Proposition 4 *In the totally cooperative game, each firm will share more information and invest more in information security in each period when the interdependence between firms increases.*

Proposition 4 shows that when the interdependence become larger, the information sharing levels and security investments of both firms will increase in each period. A greater interdependence means a firm's information sharing will bring more benefits for the firm, thus, it is easy to understand that each firm will increase their information sharing levels to obtain more profits. Similar to the analysis on Proposition 3, because of the increased information sharing levels, firms need to invest more in information security to decrease each firm's breach probability.

1.5.3 Economical Analysis

Similar to Sect. 1.4.3, we will also explore that whether the N-period IoT plan is economical when firms cooperate their strategies. Hence, the two questions in the non-cooperative game also need to be addressed here.

We assume that in period N_{O1} the period net benefit of a firm starts to be greater in IoT environment compared to in traditional environment, which implies that the period net benefit before period N_{O1} is greater in traditional environment than in IoT environment. Hence, we have the following two mathematical expressions.

$$\frac{\begin{array}{c}\left[\left(2\alpha_{O,N_{O1}}-{\alpha_{O,N_{O1}}}^2\right)+\gamma\left(2\alpha_{O,N_{O1}}-{\alpha_{O,N_{O1}}}^2\right)\right]\left(w-k\theta^{N_{O1}-1}\right)\\ L-x_{O,N_{O1}}-p_{O,N_{O1}}S-\varepsilon\alpha_{O,N_{O1}}\left(1-p_{O,N_{O1}}\right)p_{O,N_{O1}}S-c\end{array}}{(1+\rho)^{N_{O1}-1}} \geq \frac{(2\alpha_O-{\alpha_O}^2)L-x_O-p_OS-\varepsilon\alpha_O(1-p_O)p_OS}{(1+\rho)^{N_{O1}-1}}$$

and

$$\frac{\begin{array}{c}\left[\left(2\alpha_{O,N_{O1}-1}-{\alpha_{O,N_{O1}-1}}^2\right)+\gamma\left(2\alpha_{O,N_{O1}-1}-{\alpha_{O,N_{O1}-1}}^2\right)\right]\left(w-k\theta^{N_{O1}-2}\right)\\ L-x_{O,N_{O1}-1}-p_{O,N_{O1}-1}S-\varepsilon\alpha_{O,N_{O1}-1}\left(1-p_{O,N_{O1}-1}\right)p_{O,N_{O1}-1}S-c\end{array}}{(1+\rho)^{N_{O1}-2}} < \frac{\left(2\alpha_O-{\alpha_O}^2\right)L-x_O-p_OS-\varepsilon\alpha_O(1-p_O)p_OS}{(1+\rho)^{N_{O1}-2.}}$$

For the second question, we assume that in period N_{O2} each firm starts to earn more money in the IoT environment. Similarly, we get the following two expressions.

$$-C+\sum_{n=1}^{N_{O2}}\frac{\begin{array}{c}[(2\alpha_{O,n}-{\alpha_{O,n}}^2)+\gamma(2\alpha_{O,n}-{\alpha_{O,n}}^2)]\left(w-k\theta^{n-1}\right)\\ L-x_{O,n}-p_{O,n}S-\varepsilon\alpha_{O,n}\left(1-p_{O,n}\right)p_{O,n}S-c\end{array}}{(1+\rho)^{n-1}} \geq \sum_{n=1}^{N_{O2}}\frac{(2\alpha_O-{\alpha_O}^2)L-x_O-p_OS-\varepsilon\alpha_O(1-p_O)p_OS}{(1+\rho)^{n-1}}$$

and

$$-C+\sum_{n=1}^{N_{O2}-1}\frac{[(2\alpha_{O,n}-\alpha_{O,n}{}^2)+\gamma(2\alpha_{O,n}-\alpha_{O,n}{}^2)]\left(w-k\theta^{n-1}\right)}{(1+\rho)^{n-1}}$$
$$<\sum_{n=1}^{N_{O2}-1}\frac{(2\alpha_O-\alpha_O{}^2)L-x_O-p_OS-\varepsilon\alpha_O(1-p_O)p_OS}{(1+\rho)^{n-1}}$$

Analogous to the non-cooperative game, we have $N_{O1} \leq N_{O2}$. For any period before N_{O1} (i.e., $n < N_{O1}$), firms' period net benefits in IoT environment are less than traditional environment. From period N_{O1} to period $N_{O2} - 1$, the period net benefit of a firm is greater than or equal to that in traditional environment. Whereas, the total profits of a firm are still smaller in IoT environment. After period N_{O2}, a firm will get greater total profits in IoT environment. Therefore, for the two firms in the totally cooperative game, the N-period IoT plan is economical if $N > N_{O2}$. Otherwise, the IoT plan will not be cost-efficient. Just like the non-cooperative case, we can't give analytical solutions of N_{O1} and N_{O2}, some numerical solutions can be obtained when the values of some parameters are given. Thus, we also conduct some numerical experiments for the totally cooperative game.

1.5.4 Numerical Experiments

Similar to the non-cooperative case, in order to demonstrate the aforementioned analyses better, we conduct some numerical experiments in this section.

The basic principle on how to taking values for some parameters is identical to the experiments conducted in the non-cooperative game, i.e., the value-taking should ensure that the solutions are interior, i.e., $(0 < \alpha_{O,n} < 1\ , x_{O,n} > 0)$. To make a comparative analysis with the non-cooperative game, most parameters take the same values with the experiments conducted in the non-cooperative game. Hence, we also consider a 10-period plan, i.e., $N = 10$. The parameter values are set as: $L = 2$, $S = 7$, $C = 2$, $c = 0.1$, $v = \frac{1}{3e}$, $\varepsilon = 1$, $\beta = 0.8$, $w = 2$, $k = 0.9$, $\theta = 0.9$, $z = 2$, $t = 0.5$, $\mu = 0.2$, and $\rho = 0.05$.

First, a numerical experiment is conducted to verify the variation trends of the information sharing level ($\alpha_{O,n}$), security investment ($x_{O,n}$) and breach probability ($p_{O,n}$) in the totally cooperative game when period number (n) or interdependence between firms (γ) increase. Besides, the effect of γ on period net benefit (without considering the discount rate ρ) is also evaluated based on our experiment results, which are shown in Table 1.3.

Table 1.3 presents that for any value of γ, the information sharing level of a firm ($\alpha_{O,n}$) increases and the breach probability ($p_{O,n}$) decreases with n, which complies with Proposition 3. As time goes on, security investment will increase, which is

Table 1.3 The experiment results of the totally cooperative game

γ	n	$\alpha_{O,n}$	$x_{O,n}$	$p_{O,n}$	Period net benefit (without considering the discount rate)
0.2	1	0.9419939	0.8273949	0.0458558	1.0942250
	2	0.9464987	0.9695716	0.0457500	1.1687540
	3	0.9499936	0.9952029	0.0456682	1.3380683
	4	0.9527701	1.0008421	0.0456035	1.5078212
	5	0.9550177	1.0024798	0.0455511	1.6639966
	6	0.9568651	1.0032318	0.0455082	1.8052485
	7	0.9584026	1.0037367	0.0454726	1.9325274
	8	0.9596955	1.0041366	0.0454427	2.0471186
	9	0.9607923	1.0044707	0.0454173	2.1502659
	10	0.9617295	1.0047551	0.0453956	2.2431070
0.4	1	0.9504861	0.8299866	0.0456567	1.5329613
	2	0.9543160	0.9719529	0.0455675	1.6435906
	3	0.9572891	0.9974219	0.0454984	1.8453825
	4	0.9596523	1.0029329	0.0454437	2.0443569
	5	0.9615661	1.0044673	0.0453994	2.2268258
	6	0.9631396	1.0051346	0.0453631	2.3917382
	7	0.9644494	1.0055693	0.0453329	2.5403085
	8	0.9655512	1.0059103	0.0453075	2.6740600
	9	0.9664859	1.0061945	0.0452860	2.7944502
	10	0.9672848	1.0064364	0.0452677	2.9028086
0.6	1	0.9568083	0.8319096	0.0455096	1.9720203
	2	0.9601394	0.9737212	0.0454324	2.1187238
	3	0.9627264	0.9990709	0.0453726	2.3529731
	4	0.9647834	1.0044875	0.0453252	2.5811530
	5	0.9664497	1.0059457	0.0452869	2.7899028
	6	0.9678201	1.0065506	0.0452554	2.9784650
	7	0.9689610	1.0069334	0.0452292	3.1483181
	8	0.9699209	1.0072309	0.0452072	3.3012226
	9	0.9707353	1.0074782	0.0451885	3.4388493
	10	0.9714315	1.0076886	0.0451726	3.5627199
0.8	1	0.9616983	0.8333931	0.0453963	2.4112924
	2	0.9646456	0.9750863	0.0453284	2.5940530
	3	0.9669353	1.0003445	0.0452757	2.8607465
	4	0.9687564	1.0056887	0.0452339	3.1181216
	5	0.9702320	1.0070884	0.0452001	3.3531437
	6	0.9714456	1.0076453	0.0451723	3.5653488
	7	0.9724563	1.0079883	0.0451492	3.7564790
	8	0.9733066	1.0082522	0.0451297	3.9285316
	9	0.9740282	1.0084713	0.0451133	4.0833909
	10	0.9746451	1.0086574	0.0450992	4.2227701

(continued)

Table 1.3 (continued)

γ	n	$\alpha_{O,n}$	$x_{O,n}$	$p_{O,n}$	Period net benefit (without considering the discount rate)
1.0	1	0.9655934	0.8345724	0.0453066	2.8507126
	2	0.9682362	0.9761721	0.0452458	3.0695185
	3	0.9702900	1.0013579	0.0451987	3.3686471
	4	0.9719237	1.0066447	0.0451613	3.6552100
	5	0.9732477	1.0079981	0.0451311	3.9164988
	6	0.9743369	1.0085170	0.0451062	4.1523419
	7	0.9752440	1.0088284	0.0450855	4.3647452
	8	0.9760072	1.0090658	0.0450681	4.5559427
	9	0.9766549	1.0092623	0.0450534	4.7280316
	10	0.9772087	1.0094293	0.0450408	4.8829170

caused by the fact that a firm's information system gets more vulnerable over time while $p_{O,n}$ decreases with n. In Table 1.3, we find that in the same period, a firm's information sharing level and security investment increase with γ from 0.2 to 1.0, which consists with Proposition 4. As to the impact of γ on period net benefit, we find that in the same period, the period net benefit of a firm will be greater with the increase of γ from 0.2 to 1.0, which signifies that the interdependence between firms has a positive effect on the period net benefit in the totally cooperative game. Thus, in the process of deploying IoT technologies and redesigning the business process, firms should endeavor to increase the interdependence between them.

Next, we will compare firms' strategies in the non-cooperative game and in the totally cooperative game. From Tables 1.2 and 1.3, we find that for the same γ and n, it can be obtained that $\alpha_{O,n} > \alpha_{E,n}$ and $x_{O,n} > x_{E,n}$, which indicates that firms will share more information and invest more in information security in the totally cooperative game compared to in the non-cooperative game. This is because that in the non-cooperative game, each firm's objective is to maximize its own profits. Sharing too much information will make a firm suffer more losses (if his partner's system is breached) than the benefits it can bring. While in the totally cooperative game, each firm aims to maximize the total profits of the two firms. Compared to the non-cooperative case, even though sharing more information can't bring more benefits for the firm itself, it can increase the benefits of the other firm, which contributes to the total profits of the two firms. Hence, firms will share more information with each other when they cooperate their strategies. As to security investment, in the totally cooperative game, increasing the investment to an appropriate level will reduce the breach probability of a firm and thus decrease the partner's expected loss due to information leakage. In addition, as firms share more information in the totally cooperative game, in order to cut down the losses caused by information leakage, firms will choose to increase the security investments to reduce the breach probability. Thus, each firm will invest more in information security in the totally cooperative game. Tables 1.2 and 1.3 also demonstrate that a firm will get a greater period net benefit if they determine their

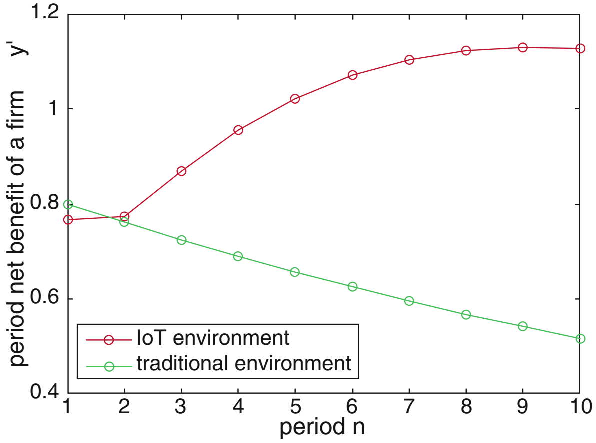

Fig. 1.3 The period net benefit of a firm in IoT environment and traditional environment when firms cooperate their strategies

strategies jointly. Furthermore, we find that the difference in the period net benefits when firms coordinate their strategies and when they do not is higher at a smaller value of γ. This confirms the greater need for cooperating strategies when the interdependence between firms is small. Therefore, it is significant for firms to coordinate their decisions, especially when the interdependence is small.

In order to give the numerical solutions of N_{O1} and N_{O2} and make some relative analyses, we conduct another numerical experiment. In this experiment, we will compare the period net benefit and total profits in the IoT environment with in traditional environment when firms cooperate their strategies. The parameter values in this experiment are identical to previous experiments except for the value of γ. As we have shown that a greater γ means a greater period net benefit, we choose $\gamma = 0.05$ in this experiment to prevent that in the first period a firm's period net benefit in the IoT environment will be larger than in traditional environment. It should be noted that the discount rate is considered in this experiment. Figures 1.3 and 1.4 present the experiment results.

In traditional environment, firms are in a steady state and thus the period net benefit of a firm will be the same in each period. Whereas, in Fig. 1.3, the graph of traditional environment is downward since we have considered the discount rate. We find that the graph of IoT environment is above the graph of traditional environment from period 2 to period 10 and the gap between the two graphs increases over time. Hence, we have $N_{O1} = 2$.

In Fig. 1.4, we find that before period 2, the graph of IoT environment is under the line $Y' = 0$, which means that firms have not recouped their IoT constructing cost (C) in the first two periods. From period 8 to period 10, the total profits of a firm in the IoT environment are greater than in traditional environment, which implies that $N_{O2} = 8$. When firms cooperate their strategies, the IoT plan is cost-efficient if $N \geq N_{O2}$. In this experiment, we have $N = 10 > N_{O2} = 8$. Hence, it is an advisable

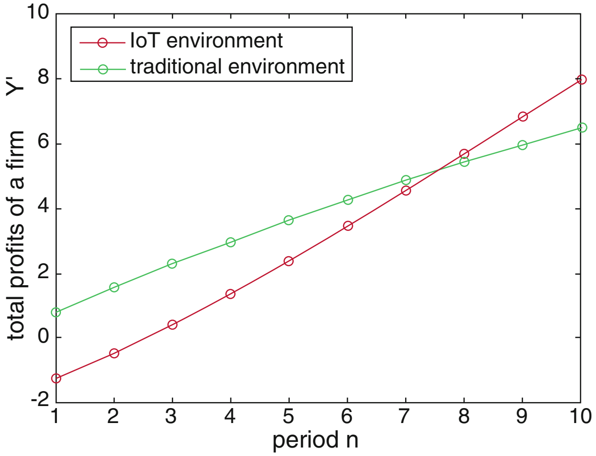

Fig. 1.4 The total profits of a firm in IoT environment and traditional environment when firms cooperate their strategies

choice for the two firms to deploy the IoT technologies and redesign the business process. If $N < N_{O2} = 8$, then firms will get more profits in traditional environment in the N periods. Suppose firms can't endure that in N periods they obtain less profits in the IoT environment compared to in traditional environment, then firms need to give up the N-period IoT plan or modify the IoT plan to make they can earn more profits in IoT environment.

1.6 Optimum Analysis and Coordination Mechanism

We have demonstrated that firms will share more information and invest more in information security when they coordinate their decisions. They will get more profits when determining their strategies jointly compared to when making decisions individually. Then a natural question appears: is the solution obtained in the totally cooperative game the optimal solution? We have known that all the variables of the solution in the totally cooperative game (i.e., $\alpha_{O,n}$ and $x_{O,n}$; $n = 1, 2 \cdots N$.) satisfy the first order condition, which is a necessary condition for getting the optimal solution. The solution $(\alpha_{O,n}, x_{O,n})$ can be a minimum, maximum or saddle point. For our problem, the solution $(\alpha_{O,n}, x_{O,n})$ is an optimal solution if and only if $(\alpha_{O,n}, x_{O,n})$ is a maximum point. In order to prove the optimality of the solution $(\alpha_{O,n}, x_{O,n})$, we make an optimum analysis on $(\alpha_{O,n}, x_{O,n})$ in this section. Then a coordination mechanism is proposed to encourage firms to increase their information sharing levels and security investments to the optimal point when they make decisions individually.

1.6.1 Optimum Analysis

Firms need to determine the information sharing levels and security investments for each period. We find that firms' strategies of different periods are independent with each other. For instance, firms' information sharing levels and security investments in period 4 will not affect their strategies in period 5 and vice versa. Thus, for our problem, maximizing the total profits of firms in all periods equals maximizing the period net benefit for each period. The period net benefits of the two firms in period n is represented as $y'_{iot,n}$. Therefore, our problem can be expressed as:

$$\text{Max } y'_{iot,n} = \frac{\begin{array}{c}[(2\alpha_{j,n} - \alpha_{j,n}{}^2) + \gamma(2\alpha_{i,n} - \alpha_{i,n}{}^2)](w - k\theta^{n-1}) \\ L - x_{i,n} - p_{i,n}S - \varepsilon\alpha_{i,n}(1 - p_{i,n})p_{j,n}S - c\end{array}}{(1+\rho)^{n-1}}$$

$$+ \frac{\left[\left(2\alpha_{i,n}-\alpha_{i,n}{}^2\right)+\gamma\left(2\alpha_{j,n}-\alpha_{j,n}{}^2\right)\right]\left(w-k\theta^{n-1}\right)L-x_{j,n}-p_{j,n}S-\varepsilon\alpha_{j,n}\left(1-p_{j,n}\right)p_{i,n}S-c}{(1+\rho)^{n-1}}\ (n = 1, 2\cdots N.)$$

The gradient of $y'_{iot,n}$ is

$$\nabla y'_{iot,n} = \left(\frac{\partial y'_{iot,n}}{\partial \alpha_{i,n}}, \frac{\partial y'_{iot,n}}{\partial \alpha_{j,n}}, \frac{\partial y'_{iot,n}}{\partial x_{i,n}}, \frac{\partial y'_{iot,n}}{\partial x_{j,n}}\right) = (A_1, A_2, A_3, A_4)$$

where $A_1 = \frac{2(\gamma+1)\left(1-\alpha_{i,n}\right)\left(w-k\theta^{n-1}\right)L-\varepsilon\left(1-p_{j,n}\right)p_{i,n}S}{(1+\rho)^{n-1}}$,

$A_2 = \frac{2(\gamma+1)\left(1-\alpha_{j,n}\right)\left(w-k\theta^{n-1}\right)L-\varepsilon\left(1-p_{i,n}\right)p_{j,n}S}{(1+\rho)^{n-1}}$,

$A_3 = \frac{-1-S\beta\ln v\cdot p_{i,n}+\varepsilon\alpha_{i,n}S\beta\ln v\cdot p_{i,n}p_{j,n}-\varepsilon\alpha_{j,n}S\beta\ln v\cdot\left(1-p_{j,n}\right)p_{i,n}}{(1+\rho)^{n-1}}$,

and $A_4 = \frac{-1-S\beta\ln v\cdot p_{j,n}+\varepsilon\alpha_{j,n}S\beta\ln v\cdot p_{i,n}p_{j,n}-\varepsilon\alpha_{i,n}S\beta\ln v\cdot\left(1-p_{i,n}\right)p_{j,n}}{(1+\rho)^{n-1}}$.

Since $y'_{iot,n}$ is a continuously differentiable function, $\nabla y'_{iot,n} = 0$ is one of the necessary conditions for obtaining the optimal solution. Hence, we have $A_1 = 0$, $A_2 = 0$, $A_3 = 0$, and $A_4 = 0$. Based on $A_1 = 0$ and $A_2 = 0$, it can be derived that

$$2(\gamma+1)\left(\alpha_{i,n} - \alpha_{j,n}\right)\left(w - k\theta^{n-1}\right)L + \varepsilon\left(p_{i,n} - p_{j,n}\right)S = 0 \tag{1.26}$$

Based on $A_3 = 0$ and $A_4 = 0$, we can get

$$S\beta\ln v\cdot\left(p_{i,n} - p_{j,n}\right) - \varepsilon S\beta\ln v\cdot\left(\alpha_{i,n}p_{j,n} - \alpha_{j,n}p_{i,n}\right) = 0 \tag{1.27}$$

From Eq. 1.27, we obtain

$$p_{i,n} = \frac{1 + \varepsilon\alpha_{i,n}}{1 + \varepsilon\alpha_{j,n}}p_{j,n} \tag{1.28}$$

Substituting Eq. 1.28 into Eq. 1.26 yields

$$\left[2(\gamma+1)\left(w-k\theta^{n-1}\right)L+\frac{\varepsilon^2 Sp_{j,n}}{1+\varepsilon\alpha_{j,n}}\right]\left(\alpha_{i,n}-\alpha_{j,n}\right)=0 \tag{1.29}$$

As $2(\gamma+1)\left(w-k\theta^{n-1}\right)L+\frac{\varepsilon^2 Sp_{j,n}}{1+\varepsilon\alpha_{j,n}}>0$, we have $\alpha_{i,n}=\alpha_{j,n}$. Then it can be obtained that $p_{i,n}=p_{j,n}$. Then we get $x_{i,n}=x_{j,n}$. Therefore, the strategies of the two firms are identical in the optimal solution. Hence, our problem can be changed to

$$\text{Max } y'_{iot,n}=2\frac{(1+\gamma)(2\alpha_n-\alpha_n{}^2)(w-k\theta^{n-1})L-x_n-p_nS-\varepsilon\alpha_n(1-p_n)p_nS-c}{(1+\rho)^{n-1}}$$

where α_n, x_n and p_n represent the information level, security investment, and breach probability of the two firms in period n, respectively. Then the gradient of $y'_{iot,n}$ can be represented as

$$\begin{aligned}\nabla y'_{iot,n}&=\left(\frac{\partial y'_{iot,n}}{\partial\alpha_n},\frac{\partial y'_{iot,n}}{\partial x_n}\right)\\&=\left(2\cdot\frac{2(\gamma+1)(1-\alpha_n)\left(w-k\theta^{n-1}\right)L-\varepsilon(1-p_n)p_nS}{(1+\rho)^{n-1}},\right.\\&\quad\left.2\cdot\frac{-1-S\beta\ln v\cdot p_n+\varepsilon\alpha_nS\beta\ln v\cdot p_n{}^2-\varepsilon\alpha_nS\beta\ln v\cdot(1-p_n)p_n}{(1+\rho)^{n-1}}\right)\end{aligned}$$

Based on $\nabla y'_{iot,n}=0$, we have $2(\gamma+1)(1-\alpha_n)(w-k\theta^{n-1})L-\varepsilon(1-p_n)p_nS=0$ and $-1-S\beta\ln v\cdot p_n+\varepsilon\alpha_nS\beta\ln v\cdot p_n{}^2-\varepsilon\alpha_nS\beta\ln v\cdot(1-p_n)p_n=0$.

The Hessian Matrix of $y'_{iot,n}$ is

$$\begin{aligned}H(y'_{iot,n})&=\begin{bmatrix}\frac{\partial^2 y'_{iot,n}}{\partial\alpha_n{}^2}&\frac{\partial^2 y'_{iot,n}}{\partial\alpha_n\partial x_n}\\\frac{\partial^2 y'_{iot,n}}{\partial x_n\partial\alpha_n}&\frac{\partial^2 y'_{iot,n}}{\partial x_n{}^2}\end{bmatrix}\\&=\begin{bmatrix}\frac{-4(\gamma+1)\left(w-k\theta^{n-1}\right)L}{(1+\rho)^{n-1}}&\frac{-2\varepsilon S\beta\ln v\cdot p_n(1-2p_n)}{(1+\rho)^{n-1}}\\\frac{-2\varepsilon S\beta\ln v\cdot p_n(1-2p_n)}{(1+\rho)^{n-1}}&\frac{-2S\beta^2ln^2v\cdot p_n[1+\varepsilon\alpha_n(1-4p_n)]}{(1+\rho)^{n-1}}\end{bmatrix}\end{aligned}$$

For any point M(α_n, x_n) satisfying $\nabla y'_{iot,n}=0$, we assume $H(M)=\begin{bmatrix}B_{11}&B_{12}\\B_{21}&B_{22}\end{bmatrix}$. Apparently, we have $B_{11}<0$ and $B_{22}<0$. $B_{11}B_{22}-B_{12}B_{21}$ $=\frac{8(\gamma+1)\left(w-k\theta^{n-1}\right)LS\beta^2\ln^2v\cdot p_n[1+\varepsilon\alpha(1-4p_n)]-4[\varepsilon S\beta\ln v\cdot p_n(1-2p_n)]^2}{(1+\rho)^{2(n-1)}}=$

$\frac{4\beta \ln v p_n\left[2(\gamma+1)\left(w-k\theta^{n-1}\right)LS\beta \ln v\cdot[1+\varepsilon\alpha(1-4p_n)]-\varepsilon^2S^2\beta\ln v\cdot p_n(1-2p_n)^2\right]}{(1+\rho)^{2(n-1)}}$. Referring the derivation process of Proposition 3, we can obtain that $2(\gamma+1)(w-k\theta^{n-1})LS\beta\ln v\cdot[1+\varepsilon\alpha(1-4p_n)]-\varepsilon^2S^2\beta\ln v\cdot p_n(1-2p_n)^2<0$. Then it can be derived that $B_{11}B_{22}-B_{12}B_{21}>0$. Thus, $H(M)$ is a negative definite matrix, which indicates that $y'_{iot,n}(M)$ is a local maximum. Since any point satisfying $\nabla y'_{iot,n}=0$ is a local maximum and $y'_{iot,n}$ is a continuously differentiable function, we can conclude that there just exists one local maximum and the local maximum is the optimal solution. It can be easily derived that the solution $(\alpha_{O,n}, x_{O,n})$ we obtained in the totally cooperative game satisfies $\nabla y'_{iot,n}=0$. Therefore, $(\alpha_{O,n}, x_{O,n})$ is the optimal solution.

1.6.2 Coordination Mechanism

We have known that firms will share the optimal level of information and invest the optimal amount in information security when they coordinate their decisions. However, the strategies obtained in the totally cooperative game is not stable if each firm intends to maximize its own profits. Thus, a coordination mechanism is needed to encourage firms to share more information and invest more in information security when they make decisions alone. We design a compensation mechanism below to help firms choose the optimal strategies even though they make decisions individually. The mechanism is described as follows:

1. In period n, firm i will get a reward of $[(2\alpha_{i,n}-\alpha_{i,n}{}^2)](w-k\theta^{n-1})L$ from firm j and pay a compensation of $[(2\alpha_{j,n}-\alpha_{j,n}{}^2)](w-k\theta^{n-1})L$ to firm j.
2. In period n, firm i will pay $\varepsilon S\left(1-\frac{1}{2}p_{i,n}-\frac{\varepsilon S}{2(1+\gamma)\left(w-k\theta^{n-1}\right)L}p_{i,n}\left(\frac{1}{2}-\frac{2}{3}p_{i,n}+\frac{1}{4}p_{i,n}{}^2\right)\right)$ to firm j if the information system of firm i is breached. Similarly, firm i will acquire $\varepsilon S\left(1-\frac{1}{2}p_{j,n}-\frac{\varepsilon S}{2(1+\gamma)\left(w-k\theta^{n-1}\right)L}p_{j,n}\left(\frac{1}{2}-\frac{2}{3}p_{j,n}+\frac{1}{4}p_{j,n}{}^2\right)\right)$ from firm j if firm j is breached.

Next, we will give an analysis to prove that the proposed mechanism can coordinate firms' strategies when making decisions alone. Under our mechanism, firm i's objective can be expressed as

$$\text{Max } F_{i,iot}=-C+\sum_{n=1}^{N}\frac{\begin{array}{c}(1+\gamma)(2\alpha_{i,n}-\alpha_{i,n}{}^2)\left(w-k\theta^{n-1}\right)\\ L-x_{i,n}-p_{i,n}S-\varepsilon\alpha_{i,n}\left(1-p_{i,n}\right)p_{j,n}S-c\end{array}}{(1+\rho)^{n-1}}$$

$$-\varepsilon S p_{i,n}\left(1-\frac{1}{2}p_{i,n}-\frac{\varepsilon S}{2(1+\gamma)\left(w-k\theta^{n-1}\right)L}p_{i,n}\left(\frac{1}{2}-\frac{2}{3}p_{i,n}+\frac{1}{4}{p_{i,n}}^2\right)\right)$$

$$+\sum_{n=1}^{N}\frac{+\varepsilon S p_{j,n}\left(1-\frac{1}{2}p_{j,n}-\frac{\varepsilon S}{2(1+\gamma)\left(w-k\theta^{n-1}\right)L}p_{j,n}\left(\frac{1}{2}-\frac{2}{3}p_{j,n}+\frac{1}{4}{p_{j,n}}^2\right)\right)}{(1+\rho)^{n-1}}$$

Firm i's decisions are determined by $\frac{\partial F_{i,iot}}{\partial \alpha_{i,n}}=\frac{2(1+\gamma)\left(1-\alpha_{i,n}\right)\left(w-k\theta^{n-1}\right)L-\varepsilon\left(1-p_{j,n}\right)p_{i,n}S}{(1+\rho)^{n-1}}=0$ and $\frac{\partial F_{i,iot}}{\partial x_{i,n}}=\frac{-1-S\beta\ln v\cdot p_{i,n}+\varepsilon\alpha_{i,n}S\beta\ln v\cdot p_{i,n}p_{j,n}-\varepsilon S\beta\ln v\cdot\left[1-\frac{\varepsilon S}{2(1+\gamma)\left(w-k\theta^{n-1}\right)L}p_{i,n}\left(1-p_{i,n}\right)\right]p_{i,n}\left(1-p_{i,n}\right)}{(1+\rho)^{n-1}}=0.$
Due to similarity of the two firms, they will make the same decisions in the equilibrium point. We use $\alpha'_{E,n}$, $x'_{E,n}$, and $p'_{E,n}$ to represent the information sharing level, security investment, and breach probability in the equilibrium point under the compensation mechanism, respectively. Then, we have

$$2(1+\gamma)(1-\alpha'_{E,n})\left(w-k\theta^{n-1}\right)L-\varepsilon(1-p'_{E,n})p'_{E,n}S=0 \tag{1.30}$$

$$\begin{aligned}&1+S\beta\ln v\cdot p'_{E,n}-\varepsilon\alpha'_{E,n}S\beta\ln v\cdot {p'_{E,n}}^2\\&+\varepsilon S\beta\ln v\cdot\left[1-\frac{\varepsilon S}{2(1+\gamma)\left(w-k\theta^{n-1}\right)L}p'_{E,n}(1-p'_{E,n})\right]p'_{E,n}(1-p'_{E,n})=0\end{aligned} \tag{1.31}$$

Base on Eq. 1.30, it can be derived that $\alpha'_{E,n}=1-\frac{\varepsilon S p'_{E,n}\left(1-p'_{E,n}\right)}{2(1+\gamma)\left(w-k\theta^{n-1}\right)L}$. Then substituting $\alpha'_{E,n}=1-\frac{\varepsilon S p'_{E,n}\left(1-p'_{E,n}\right)}{2(1+\gamma)\left(w-k\theta^{n-1}\right)L}$ into Eq. 1.31, we obtain

$$1+S\beta\ln v\cdot p'_{E,n}+\varepsilon\alpha'_{E,n}S\beta\ln v\cdot p'_{E,n}(1-2p'_{E,n})=0 \tag{1.32}$$

We find that Eqs. 1.30 and 1.32 share the identical form with Eqs. 1.15 and 1.16, thus, it can be obtained that $\alpha'_{E,n}=\alpha_{O,n}$, $p'_{E,n}=p_{O,n}$, and $x'_{E,n}=x_{O,n}$. Therefore, firms will make the optimal decisions under the coordination mechanism when they determine their strategies individually. This mechanism has a great significance for firms to choose the optimal information sharing levels and security investments if they intend to deploy IoT technologies and redesign their business process, even though each firm just wants to maximize its own benefit.

1.7 Conclusion and Future Research

1.7.1 Conclusion

The development of IoT technologies promotes many industries and brings numerous profits for firms. By deploying IoT technologies and redesigning business process, firms will obtain greater competitive advantage compared to traditional environment. The application of wireless transmission technologies in IoT environment will lead firms' information systems to be more vulnerable than in traditional environment. Information sharing is indispensable for firms to acquire the great economic benefits in IoT environment, whereas, it will also introduce some information leakage risks. This chapter deals with a problem that whether firms need to deploy the IoT technologies and proposes a multiple-period game of information sharing and security investment between two firms in the IoT environment. Based on our meticulous theoretic analyses, we find that the breach probability of a firm increases over time when firms determine their decisions individually. While each firm's breach probability will decrease with time goes on when making decisions jointly. Firms will invest less in information security with a greater interdependence between firms in the non-cooperative game. While in the totally cooperative game, firms will aggrandize their security investments when the interdependence increases. Some numerical experiments are conducted for both the non-cooperative game and the totally cooperative game. The experiment results have verified our theoretic analyses and illustrated whether an IoT plan is economical. Besides, based on the experiment results, we find some other properties which are not theoretically analyzed. We list some key findings as follows: (1) Firms will share more information and invest more in information security in the totally cooperative game compared to in the non-cooperative game. (2) A greater interdependence between firms will bring more benefits for each firm in both the non-cooperative game and totally cooperative game. (3) A firm will get a greater period net benefit if they determine their strategies jointly. (4) The difference in the period net benefits when firms coordinate their strategies and when they do not is higher at a smaller value of γ. This confirms the greater need for cooperating strategies when the interdependence between firms is small. According to these findings, it is significant for firms to coordinate their decisions, especially when the interdependence is small. Through a careful theoretic analysis, we demonstrate that the solution obtained in the totally cooperative game is the optimal solution. At last, a coordination mechanism is proposed to encourage each firm to increase its information sharing level and security investment to the optimal point even though when firms make decisions individually.

1.7.2 Future Research

In spite of the contributions, this study has some limitations and can be extended in the future. First, this chapter just considers a game of two firms. One can extend our model to multiple firms. Second, the propagation of security breaches is not considered in this chapter and can be incorporated with our model. Third, some other breach functions and benefit functions can be considered to extend our study. Lastly, this study just conducts some numerical study and one can verifies our work with empirical data in the future.

Chapter 2
Optimal Allocation of Decision-Making Authority in IoT-Based Manufacturing Enterprises

2.1 Introduction

Global economic integration and information network have brought radical changes to the operational management of business processes. Emerging information technologies, such as the Internet of Things (IoT) and big data, have fostered customers' changing personalized demands and accelerated the product updating speed, thereby impacting traditional production patterns. Empirical studies found that the IoT infrastructure can effectively support information systems of next-generation manufacturing enterprises [28]. More specifically, the requisition and sharing of a product's life cycle (e.g., market demand, usage, and recycling) information in an IoT-based manufacturing enterprise have the following advantages over traditional manufacturing scenarios: (1) more comprehensive acquisition of product life cycle information, which would be impossible in a traditional manufacturing environment, (2) precise detection and analysis of on-site data through the perceptual and application layers of the condensed sensing network, and (3) faster information transmission in an intelligent manufacturing environment, so different hierarchies can conveniently access the needed information.

Scholars have studied the adoption mechanisms of RFID technology and found that it can practically improve manufacturing efficiency [29, 30]. However, few considered the adjustment of the internal governance structure from the perspective of decision-making authority optimization, which may lead to heterogeneous firm performances. To survive fierce market competition, managers must focus on the decisions they make when facing the intricate options offered by their cooperative partners, manufacturing strategies/tactics, and operational skills [31]. Accordingly, a reasonable distribution of enterprise resources is required. For instance, human resources can combine personal experience and knowledge with IoT data to make quick and accurate decisions. We should thus comprehensively consider information transmission, knowledge occupation, and organizational resources when

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making effective decisions [32]. Such types of organization include flexible business alliances, market-oriented virtual enterprises, and long-term strategic networks.

Decision efficiency is of such vital importance to enterprises that decision errors in key areas can result in severe losses [33]. Rapid decisions contribute to enterprises' agility and flexibility in seizing transient market opportunities and the improvement of the customer experience, while decision accuracy is another guarantee of success. While highlighting the importance of rapid and accurate enterprise decision making, recent studies have systematically proposed various skills or abilities professional managers should master, or performed analysis about frequent decision errors to support the improvement of decision efficiency [34]. In this chapter, we focus on the allocation structure of decision-making authority in an IoT-based manufacturing enterprise that considers both decision speed and accuracy by matching decision items with resource occupations. A game theory model is then put forward concerning a specific organization level to demonstrate to what extent the optimal allocation of the decision authority can be implemented. After that, we discuss how decision-making efficiency is affected by organizational change, e.g., management levels and span.

Manufacturing enterprises will inevitably be challenged by numerous decision items with different degrees of emergency and importance in operational processes. The organizational designer considers the decision items and makes a trade-off to regulate its structure and policy [35]. This chapter develops a satisfactory allocation mechanism for the decision-making authority and an evaluation method of the decision efficiency in an IoT-based manufacturing enterprise under the framework of a multi-objective optimization model. The objectives of our optimization model are to minimize the total expected loss of unscheduled decision items, maximize the total decision benefits, and minimize the maximum completion time of decision items. Based on analyses of existing studies, the application of information technology does not necessarily lead to the decentralization or flattening of the organizational structure. Rather, decentralization can result in the decline of the service level, management control level, and ever-increasing manufacturing costs [36]. Our game theory model analyzes the evolutionary trend of centralization toward different types of decision items in each organizational level from a microcosmic point of view. In addition, we also analyze how the allocation mechanism of the decision-making authority changes with the organizational structure in an intelligent manufacturing environment. Figure 2.1 shows the framework and technical outline of this chapter.

The hierarchical centralization decision game model in Fig. 2.1 was proposed to analyze to what degree different levels should reveal their centralization toward the various decision items for the purpose of personal benefit maximization. We verified if the optimal decision-making authority allocation solution can be fully implemented through the sequential game model. We also developed an effective incentive mechanism for the implementation of the optimal solution and proposed suggestions for organizational change in an intelligent manufacturing environment. The main contributions of this chapter can be concluded as follows:

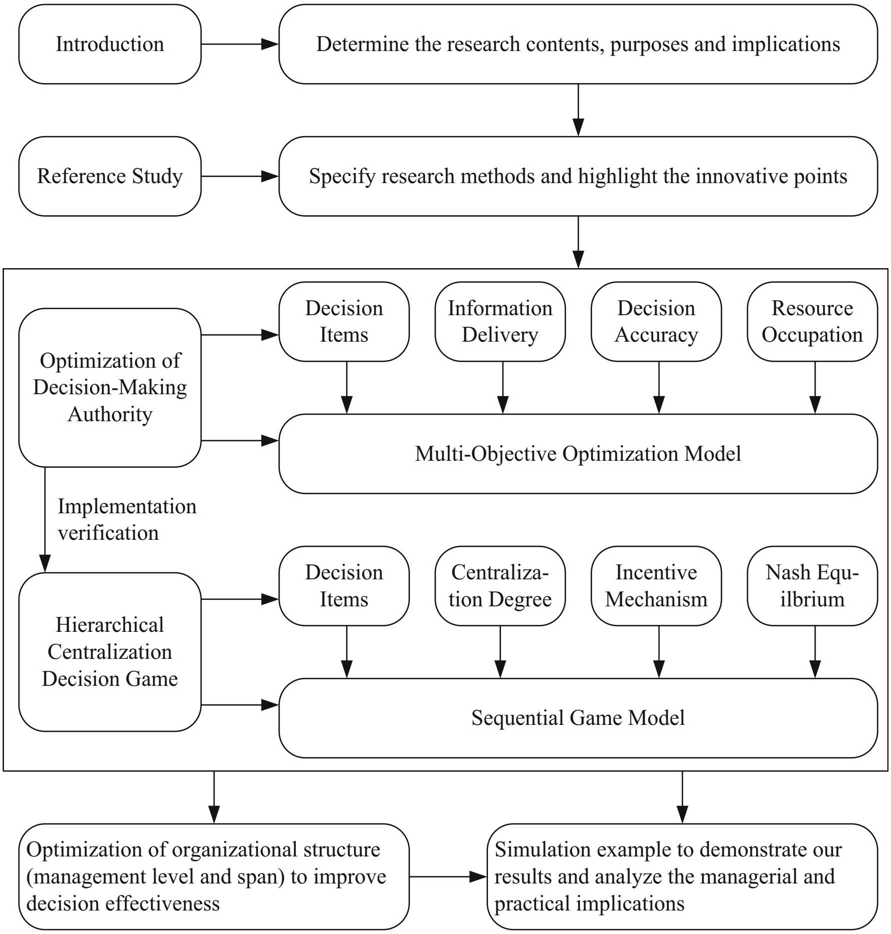

Fig. 2.1 The framework and technical route of the current chapter

(1) we put forward optimization methods for the quantization of the decision-making authority, which can further be extended to the internal governance of the organizational structure; (2) our results are meaningful for IoT-based manufacturing enterprises to improve their decision efficiency and cultivate core competitiveness, thus ensuring flexibility and adaptation toward changing market opportunities; and (3) the models established here are closer to actual manufacturing practices since the main technical advantages of the IoT are refined and taken into consideration.

The rest of this chapter is organized as follows. Section 2 reviews some recent literature related to this work and highlights our innovative points. The multi-objective optimization model of decision-making authority allocation is established in Sect. 3. Section 4 further discusses the optimal centralization degrees of each organization level toward different types of decision items. The effects of organizational change on the decision effectiveness are considered in Sects. 3 and 4. Our results are also demonstrated in a numerical example. Finally, we discuss and summarize the conclusions of this chapter and put forward some suggestions for further study.

2.2 Literature Review

With the development of emerging information technology, recent research has sufficiently considered the new operating characters and information transmission problems under manufacturing environment or in supply chain management. Yan and Huang [37] indicated that the application of RFID technology in supply chain management can help enterprises to share information and get out of the "bullwhip effect." They proposed an IoT-based supply chain information transmission model for better information transmission and satisfy demands of both enterprises and customers. By extending the IoT to manufacturing field, Zhang et al. [38] presented a real-time information capturing and integration architecture of the Internet of Manufacturing Things (IoMT). A real-time manufacturing information integration service (RTMIIS) was also designed to achieve seamless dual-way connectivity and interoperability among enterprise layer, workshop layer, and machine layer. Li et al. [39] provided a theoretical framework which classifies IoT strategies into four archetypes from two dimensions of manager's strategic intent and industrial driving force. They found that industry information sharing can efficiently contribute to the enhancement of market-based and technology-based exploratory and exploitative capabilities. Inspired by these studies, the information delivery and sharing within IoT-based enterprises are considered faster, more accurate, and comprehensive. However, we also emphasize the role of knowledge resource that support decision making through information analysis.

With respect to the organization resource, scholars stressed on different aspects according to their different research backgrounds. Kehoe and Wright [40] explored the relationships between employees' perception of high-performance HR practice, willing to stay within the organization and citizenship behavior. The results indicated that affective organizational commitment fully mediated the relationship between HR practice perceptions and intention to remain with the organization. Tseng and Lee [41] empirically studied how firms' knowledge management capabilities and uniquely dynamic capabilities can be applied or developed to provide quick response to the market competition. Knowledge management capabilities were found to enhancing dynamic capability of organizations and in turn increasing organizational performance and providing competitive advantages. Based on a sample of 226 Spanish firms, Beltrán-Martín et al. [42] explored the mediating variables between high-performance work systems (HPWS) and organizational performance, and that this mediating role was confirmed to be the firm's human resource (HR) flexibility. Foss et al. [43] proposed that interactions with external knowledge sources were often involved when realizing opportunities. Their analysis also indicated that the strength of this association was significantly influenced by organizational designs. Although occupation of organization resources including information, knowledge, and human resource were often considered in the extant literature on factors that affect performance improvement, the effects of organizational resources on allocation of decision-making authority remain to be investigated.

Decision items were often classified according to their relative degree of importance. Correct major decisions made by enterprises can intuitively generate more benefits, while more knowledge and time are required. Citroen [44] investigated how information was obtained, analyzed, judged, and applied by executives in industries that have to make strategic decisions. Moreover, the crucial role of high-quality information played in reducing uncertainty during the structured decision-making process was stressed. Ivanov [45] developed a framework to increase the efficiency, consistency, implacability, and sustainability of decisions on supply chain strategy, design, tactics, and operations, which were interlined and dispersed over different supply chain structures (functional, organizational, informational, financial, etc.). Sivak and Schoettle [46] investigated the effects of decisions that a driver can make to influence on-road fuel economy of light-duty vehicles. Drivers' decisions were classified into strategic decisions (vehicle selection and maintenance), tactic decisions (route selection and vehicle load), and operational decisions (driver behavior). Ivanov et al. [47] considered different value chain strategies as an integrated framework where supply chain management served as a basis for integration, cooperation, and coordination, with the managerial integration classified into strategic, tactical, and operative decision-making levels. Manufacturing enterprises will encounter a huge number of stochastic decision items with different importance and emergency degrees during daily management. The allocation problem of decision-making authority can be considered as a dynamic scheduling problem with random-arrival decision items. Similar to the existing literature, decision items are categorized into strategic, tactic, and operational levels. However, we consider a constant number of decision items in a certain period instead of random-arrival feature for simplification.

Intraorganizational decision mechanisms, including factors that influence the allocation of decision-making authorities, were extensively explored, and some achievements were achieved. Bester [48] studied how the preferences of the organization's members affected the optimal allocation of decision rights using a mechanism-design approach and found that decentralized control rights may enhance organizational efficiency. Harris and Raviv [49] studied an empirical model to analyze when the CEO would choose to allocate decision-making authority over an investment decision to a division manager. The probability of delegation was shown to increase with the importance of the division manager's private information while decrease with that of the CEO. On the study of authorization preferences, Graham et al. [50] investigated the degree to which executives delegate financial decisions and the circumstances that drive variation in delegation.

The authorization preferences were shown to be related to both corporate policies and personal characteristics of the executives. Colombo and Delmastro [51] focused on the determinants of the allocation of decision-making power through the estimates of ordered probit models with random effects. Factors that prominently explained the authority delegation were shown to include complexity of plants' operations, communication technologies, ownership status of plants, and nature of decisions considered. Although many factors were found to significantly influence the allocation of firm's decision-making authorities and decentralization behavior of executives, this chapter attempts to combine the optimization of organizational resources with the allocation of decision-making authorities in an IoT-based manufacturing enterprise. Particularly, the optimization model established provides a new thought for the organizational governance.

The balance of decision-making objectives and performances is another concern that practitioners focus on when facing dynamic market opportunities. The effect of strategic decision speed on subsequent firm performance was explored, and environmental and organizational characteristics that related to decision speed were identified [52]. It was proposed that strategic decision speed could mediate the relationship between environmental/organizational characteristics and performance. Moreover, fast strategic decision making implied subsequent firm profit growth and mediated the relation of dynamism, centralization, and formalization with firm performance. Bogacz et al. [53] considered the optimal decision making in two-alternative forced-choice (TAFC) tasks by analyzing six models of TAFC decision making. They concerned both decision accuracy and speed in a statistically optimal algorithm and proved that there was always an optimal trade-off between speed and accuracy that maximized various reward functions. For the inherent compromise between two or more objectives in many natural and artificial decision-making systems, Marshall et al. [54] built an optimization model to examine the trade-off between speed and accuracy and concluded that noise and time cost of assessing alternative choices were likely to be significant, which meant that increasing the willingness of individuals to change their decisions cannot improve collective accuracy overall without impairing speed. Shang and Seddon [55] focused on the benefits that organizations might achieve from their investment in enterprise systems (ES) and provided five detailed benefits of dimensions through the investment decisions. The managerial benefit of resource management and decision making was noted that accurate and time-effective information delivered to managers could improve the speed and quality of decision making and assisted with cost control. It is obvious that previous research highlighted both the accuracy and speed of decisions that managers make. Some literature also took the decision cost control or achieved benefit into consideration. The major limitation was concluded to be the secondhand data (e.g., provided by website), which was believed to be unreliable or misinterpreted. Considering the rapidly changing market opportunities, the objectives of decision-making authority allocation in this chapter include maximization of decision benefit and minimization of average decision time and unscheduled decision items (also can be interpreted as potential loss due to unprocessed decision items).

Previous study also explored the change of organizational structure (such as organizational hierarchical and management range) in situations supported by information technologies. Further research is required to find a trade-off between decision efficiency and agent supervision costs. Dewett and Jones [56] described two principal performance-enhancing benefits of IT, information efficiencies and information synergies, and then discussed the role that IT plays in moderating the relationship between organizational characteristics (including structure, size, learning, culture, and interorganizational relationships) and organizational efficiency and innovation. Bloom et al. [57] studied the impact of information and communication technology on the autonomy and control span of plant manager. Analysis of data set of American and European manufacturing firms confirmed that advanced information technologies were associated with more autonomy and a wider control span, whereas communication technologies decreased the autonomy for workers and plant managers. Rajan and Wulf [58] investigated the relationship between reporting relationships, compensation structure, and information technology and found that firm hierarchies are becoming flatter. This meant that the number of positions reporting directly to the CEO had gone up significantly while the number of organizational levels between the division heads and the CEO had decreased, reflecting a delegation of authority. Mookherjee [59] concerned the costs and benefits of delegated decision making in hierarchical organizations or contracting networks with regard to problems of incentives and coordination. The communication costs that restrict the performance of centralized arrangements relative to delegation were introduced, which had to be traded off against possible control losses of delegation. In IoT-based manufacturing enterprises, information acquired is undoubtedly more comprehensive and accurate than traditional scenarios. The relationship between characteristics of information and decision accuracy and speed still remains to be explored. The directions of organizational transformation, or how the hierarchies or control span should be adjusted, urgently need to be investigated for IoT-based manufacturing enterprises to maximize their decision efficiency.

2.3 Optimization Model for Decision Authority Distribution

Taking the advantage of the Internet of Things (IoT), manufacturing enterprises have significantly improved their operational efficiency when facing uncertain market opportunities. Recent studies gradually emphasized the application of IoT in promoting production process efficiency, while the crucial roles of "decision-making factors" in determining firms' success were often ignored. The exploration of microcosmic governance within the enterprise, such as structure reorganization and business process reengineering, is getting recognized by the theoretical research and manufacturing practices. This section mainly discusses the optimal allocation of the decision-making authorities among organizational hierarchies within an IoT-based manufacturing enterprise. A multi-objective optimization model is first established considering both information delivery and resource constrains with the purpose of maximizing the decision efficiency and minimizing the total decision time and the opportunity losses. We try to analyze how the allocation of enterprise's decision-making authority is affected by factors including distortion rate of decision information delivery, subjective weights of enterprise's objectives, etc. The changing tendency of enterprise's organizational structure under IoT environment is further explored compared to that of traditional manufacturing contexts. Our numerical research illustrates that the enterprise's objectives are significantly affected by the inter-layer distortion rate of information delivery, while independent from the waiting time of information delivery and the enterprise's subjective weights of objectives. The number of hierarchical level of the IoT-based manufacturing enterprise is suggested to be reduced to make a more efficient and flatter organizational structure.

2.3.1 The Multi-objective Optimization Model

Suppose an IoT-based manufacturing enterprise faces dynamic market opportunities and has to make rapid but accurate decisions toward a total number of K decision items within a certain period of time. The decision can be made at any level of its hierarchy but have to be implemented at the basic level. We classify the decision items into three categories, including K_1 strategic decision items, K_2 tactic decision items, and K_3 operational decision items according to their importance to the enterprise with $\sum_{i=1}^{3} K_i = K$. Empirically, we also have $K_1 < K_2 < K_3$, which means that most of the decision items the enterprise faces are operational type. Generally, the relationship between K_i $(i = 1, 2, 3)$ can be approximately summarized according to previous experience. In addition, we define the importance of the decision items by γ_i $(i = 1, 2, 3)$, respectively, with $\gamma_1 > \gamma_2 > \gamma_3$.

For the convenience of model establishment and further analysis, we assume the organization of discussed manufacturing enterprise to be inverted pyramid structure. Moreover, the differences between functional divisions are blurred and ignored. The simplified organizational structure of the enterprise is shown in Fig. 2.2. It has N hierarchical levels with the most basic staff level 1 and the top executive level N. Other hierarchical level can be represented as $(n = 1, 2, \ldots, N)$. The average management span is defined as m, which means that each staff in level n will be directly reported to by m staffs in level $(n - 1)$.

Although sometimes a strategic decision item can be gradually split into several tactic or operational decision items, they are repetitively computed for the decision authority of the split tactic, or operational decision items can also be allocated.

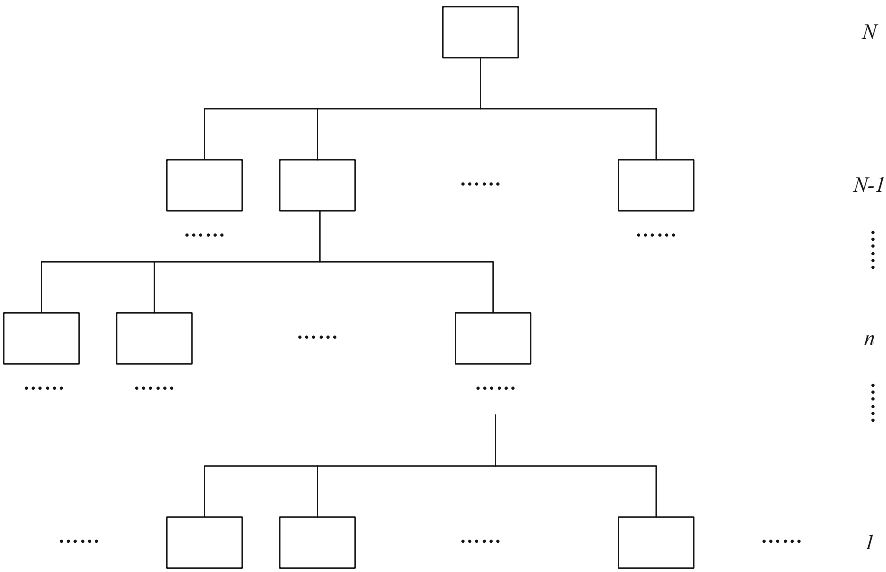

Fig. 2.2 The organizational structure of the IoT-based manufacturing enterprise

Moreover, we assume that each decision item can only be allocated to one staff. Instead of concerning whom in a certain level the decision authority of an item is allocated to, we only care about the average allocation condition. Let k_{ni} denote the number of item i which decision authority is allocated to level n. For instance, k_{11} means the number of strategic decision items allocated to the most basic staff. We have $\sum_{n=1}^{N} k_{ni} \leq K_i$. This means the sum of type i decision items allocated to each hierarchical level will not exceed the total number that the enterprise encountered. Besides, it is obvious that $\sum_{i=1}^{3} k_{ni}$ represents the total number of different types of decision items allocated to level n.

Under the intelligent manufacturing environment, product life cycle information can be real-time detected and transparently shared through firm's sensing network. The decision maker can get access to the accurate information he needs freely and conveniently when permitted to the intranet or information management system of the enterprise, which is the main difference compared to that of traditional scenario. It is worth noting that the decision maker will combine the information acquired with his own knowledge to make a defective decision. Since the knowledge/experience can be explained as the ability to process information, more accurate decision will be made based on abundant knowledge. Let $f(n)$, $g(n)$, and $h(n)$ denote level n's knowledge on strategic, tactic, and operational decision items, respectively. Intuitively, $f(n)$ is an increasing function of n, i.e., the knowledge of strategic decision increases with hierarchical level. $g(n)$ is a concave function of n, i.e., the middle management level has more information on tactic decision items. $h(n)$ is a decreasing function of n, i.e., lower level has more knowledge on operational decision items. In addition, we have $0 \leq f(i), g(i), h(i) \leq 1$, with the extreme situations of no knowledge and full knowledge.

When the decision is made in level n, it will be transmitted downward to level 0 (e.g., workers) for implementation. Let p $(0 < p < 1)$ be the distortion rate of decision information during each transmission between adjacent hierarchical levels. The delivery time of decision information is denoted by s, namely, waiting time of decision information in every intermediate transmission level. The processing time of the decision items is defined as t_i $(i = 1, 2, 3)$, respectively. Since strategic decision items are generally much more complicated and require prudent treatment, we have $t_1 > t_2 > t_3$. Each staff in level n has an available time T_n for decision making, which can be regarded as an important organizational resource of the manufacturing enterprise. We also assume that $T_n > T_{n+1}$, that is, staffs in lower hierarchical level have more time available for decision making. Moreover, it is obvious that $\sum_{i=1}^{3} k_{ni} t_i \leq m^{N-n} T_n$.

From the description above, the notations used in this section are listed in Table 2.1.

Table 2.1 Notations of the optimization model

Notation	Description	Constraints
K	Total number of the decision items	–
i	Index of category of the decision items	$i \in \{1, 2, 3\}$
K_i	Number of decision items in category i	$\sum_{i=1}^{3} K_i = K$, $K_1 < K_2 < K_3$
γ_i	The importance of the decision items	$\gamma_1 > \gamma_2 > \gamma_3$
N	Total hierarchical levels of the organizational structure	–
n	Index of the hierarchical level	$n \in \{1, 2, \ldots, N\}$
m	The average management span	$\sum_{i=1}^{3} k_{ni} t_i \leq m^{N-n} T_n$
k_{ni}	The number of decision items in category i allocated to staffs in level n	$\sum_{n=1}^{N} k_{ni} \leq K_i$
$f_1(n)$	Level n's knowledge on strategic decision items, an increasing function of n	$0 \leq f_1(n) \leq 1$
$f_2(n)$	Level n's knowledge on tactic decision items, a concave function of n	$0 \leq f_2(n) \leq 1$
$f_3(n)$	Level n's knowledge on operational decision items, a decreasing function of n	$0 \leq f_3(n) \leq 1$
p	Distortion rate of cross level transmitted information	$0 < p < 1$
s	Information delivery time in each intermediate level	–
t_i	Processing time of i type decision item	$t_1 > t_2 > t_3$
T_n	Available time of each staff in level n for decision making	$T_n > T_{n+1}$

From Table 2.1, we can calculate enterprises' benefit if a decision item is made and implemented. For example, the benefit is $\gamma_1 f(n)p^n$ when a strategic decision item is made in level n. Here γ_1 directly represents enterprise's benefit under ideal conditions. Therefore, the total benefit of the IoT-based manufacturing enterprise is given as follows:

$$TB = \sum_{n=1}^{N} p^n \left[\sum_{i=1}^{3} \gamma_i k_{ni} f_i(n) \right] \tag{2.1}$$

When the decision-making authority of an item is not allocated to any level, however, the enterprise will lose a market opportunity since no actions are taken. As such, the enterprise should make the best of its organizational resource to reduce the potential opportunity loss. Here γ_i is also used to represent the unit relative loss, and we have the total opportunity loss:

$$OL = \sum_{i=1}^{3} \gamma_i \left(K_i - \sum_{n=1}^{N} k_{ni} \right) \tag{2.2}$$

In order to make a rapid response to the market, the optimal allocation of the decision-making authority should ensure a sufficiently short time span. The total time for decision making and transmission of decision information in level n is calculated as $\sum_{i=1}^{3} k_{ni}(t_i + ns)$. As the number of staffs in level n is m^{N-n}, thus we have the average decision time in level n:

$$DT_n = \frac{\sum_{i=1}^{3} k_{ni}(t_i + ns)}{m^{N-n}} \tag{2.3}$$

From Eqs. 2.1, 2.2, and 2.3, we can further propose the objectives of our model: (1) improve the overall level of decision accuracy to maximize the total benefit, (2) make full use of firm's resources to minimize the total opportunity loss, and (3) minimize the maximum average decision time in level n. The allocation of decision-making authority requires to be optimized to satisfy these three objectives, or in other words, the optimal k_{ni} need to be solved. Thus, the multi-objective model is shown as follows:

$$\max \sum_{n=1}^{N} p^n \left[\sum_{i=1}^{3} \gamma_i k_{ni} f_i(n) \right] \tag{2.4}$$

$$\min \sum_{i=1}^{3} \gamma_i \left(K_i - \sum_{n=1}^{N} k_{ni} \right)$$

$$\min \max_n \frac{\sum_{i=1}^{3} k_{ni}(t_i + ns)}{m^{N-n}}$$

$$s.t. \qquad k_{ni} \in D$$

$$D = \left\{ k_{ni} \in Z^{N\times 3} \left| \begin{array}{l} \sum_{i=1}^{3} K_i = K; K_1 < K_2 < K_3; T_n > T_{n+1}; 0 < p < 1; t_1 > t_2 > t_3; \gamma_1 > \gamma_2 > \gamma_3; \\ \sum_{n=1}^{N} k_{ni} \le K_i; \sum_{i=1}^{3} k_{ni} t_i \le T_n; 0 \le f_i(n) \le 1; \ \sum_{i=1}^{3} k_{ni} t_i \le m^{N-n} T_n \end{array} \right. \right\}$$

To solve the analytical solution of this multi-objective programming directly is difficult and complex. Here we declare the method and process so that we acquire its non-inferior solution. We first unify different objective functions into comparable normalized form.

Take $\min OL(k_{ni})$ as an example, let $OL^* = \min_{k_{ni} \in D} OL(k_{ni})$ and $OL^{\Delta} = \max_{k_{ni} \in D} OL(k_{ni})$, take the linear transformation of the objective function $OL(k_{ni})$, and we have

$$ol(k_{ni}) = \frac{OL(k_{ni}) - OL^*}{OL^{\Delta} - OL^*} \tag{2.5}$$

Similarly, the objective function $\max TB(k_{ni})$ is equivalent to $\min[-TB(k_{ni})]$. Thus, we can obtain the linear transformation of $-TB(k_{ni})$ as

$$-tb(k_{ni}) = \frac{-TB(k_{ni}) + TB^*}{-TB^{\Delta} + TB^*} \tag{2.6}$$

where $TB^* = \min_{k_{ni} \in D} TB(k_{ni})$ and $TB^{\Delta} = \max_{k_{ni} \in D} TB(k_{ni})$.

With respect to the objective function of $\min \max_n DT_n$, let $DT(k_{ni}) = \max_n DT_n(k_{ni})$, and we have the linear transformation of the objective function $\max_n DT_n$ as

$$dt(k_{ni}) = \frac{DT(k_{ni}) - DT^*}{DT^{\Delta} - DT^*} \tag{2.7}$$

where $DT^* = \min_{k_{ni} \in D} DT(k_{ni})$ and $DT^{\Delta} = \max_{k_{ni} \in D} DT(k_{ni})$.

From Eqs. 2.5, 2.6, and 2.7, we turn problem (2.4) into a normalized form of multi-objective minimization problem:

$$\begin{aligned} &\min ol(k_{ni}), -tb(k_{ni}), dt(k_{ni}) \\ &s.t. \quad k_{ni} \in D \end{aligned} \tag{2.8}$$

In fact, our objectives are mutually independent. Give the weight coefficients of the normalized objectives and turn problem (2.8) into a single-objective minimization problem

$$\min w_1 ol(k_{ni}) - w_2 tb(k_{ni}) + w_3 dt(k_{ni}) \tag{2.9}$$

where w_1, w_2, and w_3 are the subjective weights of the three objectives with $w_1, w_2, w_3 > 0$ and $w_1 + w_2 + w_3 = 1$. The pareto-optimal solution of problem (2.9), i.e., subjective preference solution of problem (2.4), can be easily solved by means of simplex method if all the related parameters are given.

Proposition 1 *Solve the minimization of the weighted sum function (2.9) and obtain the optimal solution $\widetilde{k_{ni}}$. Then $\widetilde{k_{ni}}$ is also an efficient solution of problem (2.4).*

Proof Since $\widetilde{k_{ni}}$ is the optimal solution of the weighted single-objective problem (2.9), for any $k_{ni} \in D$, we have $w_1 ol\left(\widetilde{k_{ni}}\right) - w_2 tb\left(\widetilde{k_{ni}}\right) + w_3 dt\left(\widetilde{k_{ni}}\right) \leq w_1 ol(k_{ni}) - w_2 tb(k_{ni}) + w_3 dt(k_{ni})$. Suppose $\widetilde{k_{ni}}$ is not an efficient solution of problem (2.4), then there exists at least one $\overline{k_{ni}} \in D$ that satisfies $OL\left(\overline{k_{ni}}\right) \leq OL\left(\widetilde{k_{ni}}\right), -TB\left(\overline{k_{ni}}\right) \leq -TB\left(\widetilde{k_{ni}}\right), DT\left(\overline{k_{ni}}\right) \leq DT\left(\widetilde{k_{ni}}\right)$, and at least one strict inequality holds. Since $w_1, w_2, w_3 > 0$. It is obvious that $w_1 OL\left(\overline{k_{ni}}\right) - w_2 TB\left(\overline{k_{ni}}\right) + w_3 DT\left(\overline{k_{ni}}\right) \leq w_1 OL\left(\widetilde{k_{ni}}\right) - w_2 TB\left(\widetilde{k_{ni}}\right) + w_3 DT\left(\widetilde{k_{ni}}\right)$. Take the linear transformation of it and we find the contradiction. Thus Proposition 1 is proved. ∎

2.3.2 *Numerical Study*

Now we give the default values of the parameters in this chapter as follows: $K = 2220$, $K_1 = 20$, $K_2 = 200$, $K_3 = 2000$; $\gamma_1 = 0.9$, $\gamma_2 = 0.2$, $\gamma_3 = 0.05$; $N = 4$, $m = 4$; $f_1(n) = \left(\frac{n}{N}\right)^2, f_2(n) = 1 - \frac{\left(n - \frac{N}{2}\right)^2}{\left(\frac{N}{2}\right)^2}, f_3(n) = \frac{1}{n^2}$; $p = 0.9$, $s = 1$; $t_1 = 10$, $t_2 = 8$, $t_3 = 6$; $T_1 = 100$, $T_2 = 80$, $T_3 = 60$, $T_4 = 40$. The given defult values of the parameters satisfy the constraints in set D. We obtain the optimal allocation of decision-making authority as shown in Fig. 2.3.

In Fig. 2.3, the decision authority of strategic items is allocated to top managers of level 3 and level 4. All the strategic decision items are allocated. It is intuitive

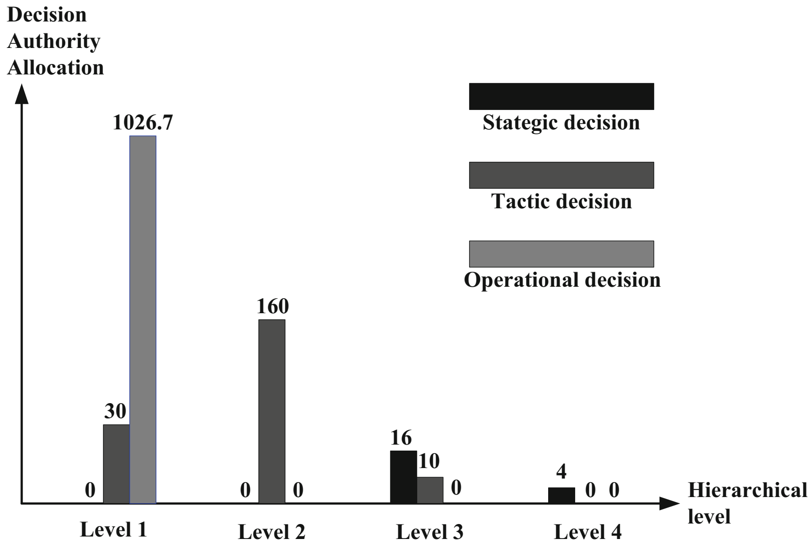

Fig. 2.3 The optimal allocation of decision-making authority

that top managers have more knowledge about strategic items and can definitely make comparatively accurate and high-quality decisions. It should be noted that strategic items are quite important to manufacturing enterprises, accurate decisions on this type items can bring more benefit, and the enterprise will suffer greater opportunity loss if a strategic decision is unallocated or unscheduled, namely, the strategic items should be allocated in high priority. Further, most decision authority of strategic items is allocated to level 3. This can be explained by level 4's limited available time and staffs, although level 4 is more knowledgeable. The decision authority of tactic items is mainly allocated to level 2. Also, in our example, all the tactic decision items are allocated. This is because the enterprise may encounter more market opportunities that need tactic decisions. On the other side, tactic items also bring high payoffs. Since the human resource is mainly distributed in middle level and low level, and middle-level staffs are believed to have more expertise in tactic item, it is obvious that middle-level managers mainly focus on tactic decision items. Finally, staffs from level 1 also participate in the rest tactic items. Although staff from level 1 has little knowledge about tactic items, the tactic items are far more important than operational items. On this account, the decision authority of the rest tactic items is allocated to level 1 in priority. It's worth noting that the operational decision items are only allocated to staffs in level 1. This is because most human resource is distributed in level 1 and thus results in adequate available time for decision. Moreover, staffs in level 1 are regarded as most experienced and knowledgeable in operational items. However, compared to the overall time efficiency, the benefit brought by operational items is negligible.

Table 2.2 The effects of the waiting time on the optimal allocation of decision-making authority

	k_{11}^{*}	k_{12}^{*}	k_{13}^{*}	k_{21}^{*}	k_{22}^{*}	k_{23}^{*}	k_{31}^{*}	k_{32}^{*}	k_{33}^{*}	k_{41}^{*}	k_{42}^{*}	k_{43}^{*}	TB^{*}	OL^{*}	DT^{*}
$s = 0.5$	0	30	1026.7	0	160	0	16	10	0	4	0	0	85.53	48.67	90
$s = 1$	0	30	1026.7	0	160	0	16	10	0	4	0	0	85.53	48.67	100
$s = 1.5$	0	30	1026.7	0	160	0	16	10	0	4	0	0	85.53	48.67	110
$s = 2$	0	30	1026.7	0	160	0	16	10	0	4	0	0	85.53	48.67	120
$s = 2.5$	0	30	1026.7	0	160	0	16	10	0	4	0	0	85.53	48.67	130

With the optimal scheme of decision authority allocation, the total benefit, potential loss of opportunity, and total decision time can be calculated according to Eqs. 2.1, 2.2, and 2.3 as 85.53, 48.67, and 100, respectively. In the following, we analyze the changing tendency of the optimal allocation scheme and objectives with groups of important parameters, such as the information distortion rate p and the waiting time of decision information delivery s, the subjective weights of the multi-objectives, and the total hierarchical levels N and the average management span m which reflect the tendency of organizational structure under IoT environment. Finally, we analyze our results and further conclude some managerial and practical significances.

More importantly, the acquisition and delivery of product life cycle information under IoT environment are considered to have three typical characters as discussed in Sect. 1. However, how the related parameters can be affected by the information acquisition and transformation characters remains to be explored, which is further related to the change tendency of allocation of different decision-making authority in each hierarchical level of the IoT-based manufacturing enterprise.

Table 2.2 illustrates the influence of the waiting time s, i.e., the information delivery time at each hierarchical level, on the optimal allocation of decision-making authority. From Table 2.2, it is intuitive that the waiting time almost has no effect on the optimal allocation scheme. Specifically, the total benefit of the enterprise TB and the expected loss of market opportunities OL are independent from s, and s is only a constant term of $DT = \max_{n} DT_n = \max_{n} \frac{\sum_{i=1}^{3} k_{ni}(t_i + ns)}{m^{N-n}}$ given the default values. Thus, the optimal allocation scheme is not affected by the waiting time. Note that the increase of s enlarges the average delivery time of decision information, the maximum decision time under the optimal allocation scheme increases with s. In fact, s reflects the efficiency of information delivery in each hierarchical level and executive capacity of the staffs, which cannot be simply improved under the environment of information technology.

The optimal allocation scheme of decision-making authority and the corresponding values of enterprise's objectives are shown in Table 2.3 when the distortion rate of information delivery p changes. From Table 2.3, we can see that higher levels will be allocated less decision items when the distortion rate decreases. This is because the accuracy of decision information made by staffs in

Table 2.3 The effects of the distortion rate on the optimal allocation of decision-making authority

p	k_{11}^*	k_{12}^*	k_{13}^*	k_{21}^*	k_{22}^*	k_{23}^*	k_{31}^*	k_{32}^*	k_{33}^*	k_{41}^*	k_{42}^*	k_{43}^*	TB^*	OL^*	DT^*
0.9	0	30	1026.7	0	160	0	16	10	0	4	0	0	85.53	48.67	100
0.8	0	30	1026.7	0	160	0	16	10	0	4	0	0	71.54	48.67	100
0.7	0	40	1013.3	0	160	0	16	0	13.3	4	0	0	59.01	48.67	100
0.6	0	40	1013.3	0	160	0	16	0	13.3	4	0	0	47.75	48.67	100
0.5	0	30	1026.7	0	160	0	20	0	6.7	0	0	6.7	37.60	48.67	100

Table 2.4 The effects of the objective weights on the optimal allocation of decision-making authority

w	k_{11}^*	k_{12}^*	k_{13}^*	k_{21}^*	k_{22}^*	k_{23}^*	k_{31}^*	k_{32}^*	k_{33}^*	k_{41}^*	k_{42}^*	k_{43}^*	TB^*	OL^*	DT^*
$\left(\frac{1}{3},\frac{1}{3},\frac{1}{3}\right)$	0	30	1026.7	0	160	0	16	10	0	4	0	0	85.53	48.67	100
$\left(\frac{1}{2},\frac{1}{4},\frac{1}{4}\right)$	0	30	1026.7	0	160	0	16	10	0	4	0	0	85.53	48.67	100
$\left(\frac{1}{4},\frac{1}{2},\frac{1}{4}\right)$	0	30	1026.7	0	160	0	16	10	0	4	0	0	85.53	48.67	100
$\left(\frac{1}{4},\frac{1}{4},\frac{1}{2}\right)$	0	62.8	646.1	0	127.2	0	16	10	0	4	0	0	67.52	67.69	79.5

higher level decreases sharply with a very low information distortion rate. It should be pointed that when p decreases, the decision authority of items with higher importance will be gradually allocated to lower hierarchical levels, even though staffs in higher level have more knowledge on these items. Since the distortion rate p is only related to the objective of enterprise's total benefit, the objectives of potential opportunity losses and the maximum average decision time are not affected by p. Moreover, the distortion rate p under IoT environment is significantly larger than traditional manufacturing scenarios according to the information acquisition and transformation characteristics. In this way, the decision authority of important decision items is more likely to be allocated to higher levels due to their abundant knowledge and the high information distortion rate, thus generating more total benefits.

Table 2.4 indicates the effects of subjective weights of enterprise's objective functions on the optimal allocation scheme of decision authority. In our example, there is a big difference between γ_i, the importance of different types of decision items. When the objective of total benefit maximization is given a large weight, the higher hierarchical level should be allocated the decision authority of items with higher importance considering the high distortion rate under the constraint of available time. Thus, the optimal allocation scheme remains unchanged. Similarly, when the objective of potential opportunity loss minimization is given a large weight, considering the far low importance of the operational decision items, the items of high importance should be allocated to higher level in priority. However, when the maximal decision time is given a large weight, the total expected benefit and potential opportunity loss will be less important. In this way, it is optimal to allocate the decision authority of less decision items with the purpose of saving total decision time, which leads to less total benefit and more expected opportunity losses.

The optimal organizational structure of the enterprises is always changing due to dynamic market and improvement in information technology. In order to accelerate the information delivery and reduce distortion of decision information result in redundant middle levels, enterprises need to reduce the decision levels accordingly. However, the reduction of decision levels implies more potential opportunity losses. It is significant and interesting to analyze the optimal hierarchy of enterprises and its changing tendency based on the three characteristics under the IoT environment. From Eqs. 2.1, 2.2, and 2.3, it is difficult to judge how the enterprise's objectives will be changing with the hierarchical level and the management span. In our example, when the organizational designer chooses to reduce the hierarchical level to $N = 3$, then we have the management span $m = 8.68$, that is, no staffs are dismissed or newly recruited. Also, when the hierarchical level is increased to $N = 5$, we have $m = 2.71$. We conclude the optimal allocation of decision-making authority in Table 2.5. We use the same default values of the parameters. In addition, we define $T_5 = 20$.

It is obvious that the decrease of the hierarchical level will significantly increase the management span of the organization. In our numerical example, the decision-making authority of strategic items is always mostly allocated to higher levels and operational items allocated to the lower levels. However, when there are less hierarchical levels, the division of responsibilities is much clearer. This helps different layers to concentrate on less types of decision items. Our results show that when the hierarchical level increases, staffs in the higher level will have less available time for decision making. The higher level will be allocated less decision authority of items, especially items with high importance. Other than the available time, the high delivery distortion of decision information due to more interlayers is another factor that influences the enterprise's expected total benefit. It should be noted that there will be less staffs in each level when N is larger; thus less decision authority of items will be allocated to each level when N increases.

Furthermore, Table 2.5 shows that enterprise's expected total benefit decreases with N. A possible explanation is the high distortion rate of decision information that makes a low accuracy of decision information. In addition, the increase of hierarchical levels implies more losses of market opportunities. In this way, the organizational structure with more levels operates inefficiently since the management span is too small. More time are wasted in the information delivery between interlayers. Under the intelligent manufacturing environment based on the Internet of Things, the information is more accurately delivered to the bottom level for implementation due to a larger information distortion rate. Based on the analysis of Table 2.5, it is suggested that the organizational designer should reduce the hierarchical levels to make an efficient and flat organizational structure.

Table 2.5 The effects of hierarchical level on the optimal allocation of decision-making authority

N	k_{11}^*	k_{12}^*	k_{13}^*	k_{21}^*	k_{22}^*	k_{23}^*	k_{31}^*	k_{32}^*	k_{33}^*	k_{41}^*	k_{42}^*	k_{43}^*	k_{51}^*	k_{52}^*	k_{53}^*	TB^*	OL^*	DT^*
3	0	130.7	1081.4	14	69.3	0	6	0	0	–	–	–	–	–	–	88.03	45.93	99.19
4	0	30	1026.7	0	160	0	16	10	0	4	0	0	–	–	–	85.53	48.67	100
5	0	0	898.93	0	199	0	7.16	0.97	60.21	10.84	0	0	2	0	0	78.25	52.04	100

2.4 Sequential Game Model for Centralization Behavior

In this section, a sequential game model is proposed to analyze the centralization behavior of each hierarchy from a microcosmic perspective. We solve the optimal centralization behavior of each hierarchical level toward different types of items through a multivariate layer optimization model. Some suggestions are finally proposed to adjust incentive mechanism which guides staffs to behave closely to the optimal allocation scheme of decision-making authority. Our effort creatively quantifies enterprise's decision authorities, which also has great practical significance for IoT-based manufacturing enterprises to adjust the organizational structure and design incentive mechanisms.

2.4.1 The Sequential Game Model

Although the optimal allocation of the decision-making authority is solved by minimizing the average decision time and opportunity losses and maximizing firm's total benefits, the full implementation of this scheme can be difficult. In fact, each hierarchical level will also balance the benefits and contributions from its own perspective to choose an optimal rate for centralization or decentralization. In this way, enterprise's optimal allocation of decision authority can be meaningless for practice. In this section, we consider the centralization mechanism of different levels from microcosmic perspective using sequential game theory to study how enterprise's optimal allocation scheme can be implemented. Furthermore, an incentive mechanism is designed for levels to choose the centralization rate that is close to enterprise's optimal allocation scheme.

Figure 2.4 illustrates the structure of the sequential game which describes the decision process of level's centralization or decentralization. With regard to each type of decision item, each level n can choose to implement the decision authority with the limitation of its available time or delegate the decision authority to lower

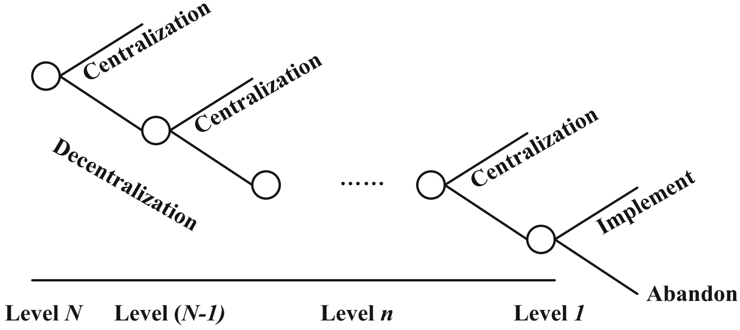

Fig. 2.4 Structure of the sequential game

level. However, when the decision authorities of different items are decentralized to the bottom level 1, it only has two choices including implementing the decision items and abandoning them.

Let x_{ni} be the decentralization probability of level n toward items of type i, where $x_{ni} \in [0, 1]$, $n \in \{1, 2, \ldots, N\}$, and $i \in \{1, 2, 3\}$. Then its centralization probability is $(1 - x_{ni})$. AC_{ni} denotes level n's expected benefit oriented from decision item of i type when it chooses the centralization behavior, and AD_{ni} represents its expected benefit oriented from i type decision item when it chooses the decentralization behavior. Each level will benefit B_i when an i type decision item is accurately decided and implemented. In addition, level n will generate a unit decision cost C_i if it chooses the centralization behavior. This can be explained as labor cost, time cost, and so on. To encourage the centralization behavior, level n is rewarded a bonus M_{ni} if it chooses the centralization behavior and the decision is accurately made, delivered, and implemented. We conclude the notations used in this section in Table 2.6 as follows. Other used notations can be found in Table 2.1.

Firstly, level n will not always have the opportunity to decide its behavior of centralization or decentralization. When and only when all the higher levels of level n choose the decentralization decision can level n have the opportunity. When level j $(j > n)$ takes the decision authority of an i type item, level n's expected benefit oriented from an i type item can be derived as

$$RA_{ni} = B_i \sum_{j=n+1}^{N} f_i(j) p^j \left[x_{ji} \prod_{k=j+1}^{N} (1 - x_{ki}) \right] \tag{2.10}$$

We explain Eq. 2.10 as follows: when the decision is made in level j $(j \in \{n + 1, n + 2, \ldots, N\})$, level n will also get a benefit of B_i if the item is accurately decided and implemented. $x_{ji} \prod_{k=j+1}^{N} (1 - x_{ki})$ denotes the probability that the decision

Table 2.6 Notations of the sequential game model

Notation	Description
x_{ni}	Level n's centralization probability toward i type items, $x_{ni} \in [0, 1]$
B_i	Each level's benefit if an i type item is perfectly implemented
C_i	Unit decision cost of an i type item
M_{ni}	Level n's unit bonus if its decision on an i type item is perfectly implemented
RA_{ni}	Level n's expected benefit oriented from an i type decision item when the authority is taken by levels higher than n
AC_{ni}	Level n's expected benefit oriented from an i type decision item when level n chooses the centralization behavior
AD_{ni}	Level n's expected benefit oriented from an i type decision item when the authority is taken by levels lower than n
A_{ni}	Level n's expected benefit oriented from an i type decision item
TA_n	Average total benefit of level n oriented from all decision items

authority of the i type level is taken in a level higher than n. $f_i(j)$ represents the knowledge of level j on i type decision item, which can also be understood as the decision accuracy. p^j denotes the distortion rate of decision information when it is delivered from level j to level 0. Thus, when level j chooses the centralization behavior and takes the decision authority of an i type item, the accuracy of implementation is $f_i(j)p^j$. Thus Eq. 2.10 is derived.

When level n has the choice of centralization and decentralization behaviors, it also implies that the decision authority of a i level item is given up by levels higher than n simultanesously. We derive the expected benefit oriented from an i type decision item when it chooses the centralization behavior as follows:

$$AC_{ni} = (B_i + M_{ni} - C_i)\left[\sum_{j=n+1}^{N}\left(1 - x_{ji}\right)\right]x_{ni}f_i(n)p^n \tag{2.11}$$

In Eq. 2.11, $\sum_{j=n+1}^{N}\left(1 - x_{ji}\right)x_{ni}$ denotes the probability that levels higher than n take the decentralization decision simultaneously. $f_i(n)$ represents the knowledge of level n on i type decision item, which can also be understood as the decision accuracy. p^n denotes the distortion rate of decision information when it is delivered from level n to level 0. Thus when level n chooses the centralization behavior and takes the decision authority of an i type item, the implementation accuracy is $f_i(n)p^n$. In addition, when an i type item is accurately implemented, the expected benefit is $(B_i + M_{ni} - C_i)$.

Also, when level n chooses the decentralization behavior and delegates the decision authority of an i type item to lower level, the expected benefit can then be derived as

$$AD_{ni} = B_i\left[\sum_{j=n}^{N}\left(1 - x_{ji}\right)\right]\sum_{u=1}^{n-1}f_i(u)p^u\left[x_u\prod_{v=u+1}^{n-1}\left(1 - x_v\right)\right] \tag{2.12}$$

In Eq. 2.12, $\sum_{j=n}^{N}\left(1 - x_{ji}\right)$ means that all the levels higher than n (included) choose the decentralization behavior. $x_u\prod_{v=u+1}^{n-1}\left(1 - x_v\right)$ further represents the probability that the decision authority is allocated to level u, $(u \in \{1, 2, \ldots, n-1\})$. When the decision authority of an i type decision item is taken by level u, and the decision information is delivered and implemented in level 0, the implementation accuracy is $f_i(u)p^u$. In addition, level n will receive a benefit B_i no matter in which level the authority of an i type item is accurately taken and implemented.

Based on Eq. 2.10, 2.11, and 2.12, we derive the expected unit benefit A_{ni} of level n oriented from an i type item as follows:

$$\begin{aligned}A_{ni} &= RA_{ni} + AC_{ni} + AD_{ni} \\ &= B_i \sum_{j=n+1}^{N} f_i(j)p^j \left[x_{ji} \prod_{k=j+1}^{N} (1 - x_{ki}) \right] \\ &\quad + (B_i + M_{ni} - C_i) \left[\sum_{j=n+1}^{N} \left(1 - x_{ji}\right) \right] x_{ni} f_i(n) p^n \\ &\quad + B_i \left[\sum_{j=n}^{N} \left(1 - x_{ji}\right) \right] \sum_{u=1}^{n-1} f_i(u) p^u \left[x_u \prod_{v=u+1}^{n-1} (1 - x_v) \right]\end{aligned} \tag{2.12}$$

As we have derived the expected unit benefit A_{ni} of level n oriented from an i type item when it is decided at any level, however, note that the enterprise will encounter K_i items of i type and each level has $m^{(N-n)}$ staffs. We derive the average total benefit of a staff in level n as

$$TA_n = \frac{1}{m^{(N-n)}} \sum_{i=1}^{3} K_i A_{ni} \tag{2.13}$$

In Eq. 2.13, $\sum_{i=1}^{3} K_i A_{ni}$ represents the total benefits that level n gets from the $K_i i$ type decision items ($i = 1, 2, 3$). In fact, TA_n is the average total benefit of level n oriented from all decision items. Since TA_n reflects the total benefits that each staff in level n can get, it is also important that each staff will choose its own preferences/probabilities of centralization toward each type of decision item x_{ni} to maximize TA_n.

It is worth noting that the preferences of level n's centralization are restrained by its available time. Since the probability that level n takes the decision authority of an i type decision item is $x_{ni} \prod_{j=n+1}^{N} \left(1 - x_{ji}\right)$, the total time that level n spends on all decision items is $\sum_{i=1}^{3} \left[K_i t_i x_{ni} \prod_{j=n+1}^{N} \left(1 - x_{ji}\right) \right]$. Thus the restraints of available time can be derived as follows:

$$\frac{1}{m^{(N-n)}} \sum_{i=1}^{3} \left[K_i t_i x_{ni} \prod_{j=n+1}^{N} \left(1 - x_{ji}\right) \right] \le T_n \tag{2.14}$$

Note that the sum of each type of decision items should not exceed the total numbers of decision item that the enterprise encounters. Since the centralization probability of level n toward items of i type is x_{ni}, it is obvious that the number of i type items that staffs in level n will take the decision-making authority is $K_i x_{ni} \prod_{j=n+1}^{N} \left(1 - x_{ji}\right)$. Thus, we have $\sum_{n=1}^{N} K_i x_{ni} \prod_{j=n+1}^{N} (1 - x_{ji}) \le K_i$. In other words, we have

$$\sum_{n=1}^{N} x_{ni} \prod_{j=n+1}^{N} \left(1 - x_{ji}\right) \leq 1 \tag{2.15}$$

From Eqs. 2.13, 2.14, and 2.15, our problem can eventually be induced into a multi-objective (or can be regarded as single-objective) and multivariate optimization problem as follows:

$$\max TA_n = \frac{1}{m^{(N-n)}} \sum_{i=1}^{3} K_i A_{ni} \tag{2.16}$$

$$\begin{aligned} s.t. \quad & \frac{1}{m^{(N-n)}} \sum_{i=1}^{3} \left[K_i t_i x_{ni} \prod_{j=n+1}^{N} \left(1 - x_{ji}\right) \right] \leq T_n \\ & \sum_{n=1}^{N} x_{ni} \prod_{j=n+1}^{N} \left(1 - x_{ji}\right) \leq 1 \\ & x_{ni} \in [0, 1] \end{aligned}$$

where $A_{ni} = B_i \sum_{j=n+1}^{N} f_i(j) p^j \left[x_{ji} \prod_{k=j+1}^{N} (1 - x_{ki}) \right] + (B_i + M_{ni} - C_i) \left[\sum_{j=n+1}^{N} \left(1 - x_{ji}\right) \right]$ $x_{ni} f_i(n) p^n + B_i \left[\sum_{j=n}^{N} \left(1 - x_{ji}\right) \right] \sum_{u=1}^{n-1} f_i(u) p^u \left[x_u \prod_{v=u+1}^{n-1} (1 - x_v) \right].$

Proposition 2 *The staff in level* n *is more likely to choose centralization behavior toward a type* i *decision item when the difference between the bonus given by the enterprise and the decision cost* $M_{ni} - C_i \geq B_i \left(\frac{\left[\sum_{j=n}^{N} \left(1 - x_{ji}\right) \right] \sum_{u=1}^{n-1} f_i(u) p^u \left[x_u \prod_{v=u+1}^{n-1} (1 - x_v) \right]}{\left[\sum_{j=n+1}^{N} \left(1 - x_{ji}\right) \right] x_{ni} f_i(n) p^n} - 1 \right)$.

Proof When level n has the opportunity to choose the centralization or decentralization behavior toward a type i item, it is obvious that the decision-making authority of the item is delegated by levels higher than n. Thus, the staff in level n will make a decision that maximizes the expected benefit. When $AC_{ni} > AD_{ni}$, it is better to keep the decision-making authority and make a centralization behavior. Substitute $AC_{ni} = (B_i + M_{ni} - C_i) \left[\sum_{j=n+1}^{N} \left(1 - x_{ji}\right) \right] x_{ni} f_i(n) p^n$ and $AD_{ni} = B_i \left[\sum_{j=n}^{N} \left(1 - x_{ji}\right) \right] \sum_{u=1}^{n-1} f_i(u) p^u \left[x_u \prod_{v=u+1}^{n-1} (1 - x_v) \right]$, and simplify the inequation, and Proposition 2 is proved. ∎

Proposition 2 gives the relationship between the enterprise's incentive bonus and the decision cost. Given the decision cost and the optimal probabilities of level n's centralization behavior $n \in \{1, 2, \ldots, N\}$, the organization designer can then make an incentive bonus for staffs to guide their behavior according to the optimal allocation scheme of decision-making authorities.

Proposition 3 *If level* n *has enough available decision time and is required to make a choice of centralization or decentralization behavior toward* i *type items and* j *type items, where* $\mathrm{i} \neq \mathrm{j}$ *and* $\mathrm{i}, \mathrm{j} \in \{1, 2, 3\}$*, then the staff in level* n *will keep the decision-making authority of* i *type items in priority if and only if* $\dfrac{B_i + M_{ni} - C_i}{B_j + M_{nj} - C_j} \geq \dfrac{t_i}{t_j}\dfrac{f_j(n)}{f_i(n)}$.

Proof In fact, when a staff in level n is confronted with the choice of centralization behavior between i type items and j type items, the only judgment is to generate more benefit within the same decision time. If the staff chooses the i type items, then the profit is $(B_i + M_{ni} - C_i)f_i(n)p^n$, and the decision time of an i type item is t_i. Thus, the profit generated per time unit can be derived as $\frac{(B_i+M_{ni}-C_i)f_i(n)p^n}{t_i}$. The profit generated per time unit of the j type item can then be derived as $\frac{\left(B_j+M_{nj}-C_j\right)f_j(n)p^n}{t_j}$ similarly. Therefore, when $\frac{(B_i+M_{ni}-C_i)f_i(n)p^n}{t_i} > \frac{\left(B_j+M_{nj}-C_j\right)f_j(n)p^n}{t_j}$, i.e., $\frac{B_i+M_{ni}-C_i}{B_j+M_{nj}-C_j} \geq \dfrac{t_i}{t_j}\dfrac{f_j(n)}{f_i(n)}$, a staff in level n will keep the decision authority of i type items in priority. ∎

From Proposition 3, we can further propose that when the staffs in hierarchical level n are confronted by multiple types of decision items within their available time, they will definitely choose to keep the decision authority of the type which can generate the largest profit per decision time unit. When staffs in level n take all the decision authority of this type of decision item and they still have available decision time, they will then choose to keep the decision authority of the type of item which can generate the second largest profit per decision time unit, by that analogy until no available decision time left. From Proposition 3, on the other hand, the organization designer can also make an inventive scheme that leads to the optimal allocation of decision authority that maximizes enterprise's multi-objectives.

2.4.2 Numerical Study

In problem (2.16), we should solve the optimal probabilities of centralization of level n toward decision item i, where $n = \{1, 2, \ldots, N\}$ and $i = 1, 2, 3$, to maximize the total profit of each staff in level n under the restraints of available time. To solve the exact analytical solution of problem (2.16) can be extremely difficult and complex. Similarly, we also try to solve the optimal numerical solution given default values of related parameters in Sect. 3. In addition, the default value $B =$

$[3, 1, 0.2]$, $C = [3, 2, 1]$. Moreover, we define that $M_{ni} = 9$, $M_{ni} = 5$, and $M_{ni} = 2$. This means that the organization designer will make no difference on which level takes the decision authority of the i type decision items.

In fact, problem (2.16) is a sequential game theoretic model that higher level can make a decision of its own centralization probability to maximize its own expected total profit. It should be noted that there can be free-riding behavior. For example, sometimes a specific layer will benefit more if he delegates the decision authority to lower layer since the higher layer has little knowledge on the decision items. Moreover, it is a waste of available time that should be spent on the items that it has more knowledge. By solving the multivariate layer planning model of problem (2.16), we get the optimal centralization probabilities of each level toward different types of decision items as follows:

$$x_{ni}^* = \begin{bmatrix} x_{11}^* & x_{12}^* & x_{13}^* \\ x_{21}^* & x_{22}^* & x_{23}^* \\ x_{31}^* & x_{32}^* & x_{33}^* \\ x_{41}^* & x_{42}^* & x_{43}^* \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0.51 \\ 1 & 0.69 & 0.02 \\ 0.86 & 0.11 & 0 \\ 0.2 & 0 & 0 \end{bmatrix}$$

From the levels' subjective centralization probabilities toward different types of decision items, we can see that the highest level will keep the decision authority of the strategic decision items at the restriction of its available time. In our example, this is mainly because the highest level has the most knowledge on the strategic items, making the items more accurately implemented, despite the lower distortion rate. Also, when a strategic decision item is accurately implemented, the layer will be awarded a high bonus. At the third level, however, the knowledge on strategic decision items decreases, while its knowledge on the tactic increases. Thus, it will keep the decision authority of more tactic items. Specifically, the lowest level has the most knowledge on operational items. However, the profit brought by the operational decision is comparatively low. Considering its limited available decision time, it should choose the tactic decision items in priority.

To regulate the centralization behavior of different levels with the purpose of maximizing enterprise's multi-objectives, we first deduce the optimal centralization probabilities of each level toward different items according to Fig. 2.3 as follows:

$$\tilde{x}_{ni}^* = \begin{matrix} \tilde{x}_{11}^* & \tilde{x}_{12}^* & \tilde{x}_{13}^* \\ \left[\begin{matrix} \tilde{x}_{21}^* \\ \tilde{x}_{31}^* \end{matrix}\right. & \begin{matrix} \tilde{x}_{22}^* \\ \tilde{x}_{32}^* \end{matrix} & \left.\begin{matrix} \tilde{x}_{23}^* \\ \tilde{x}_{33}^* \end{matrix}\right] \\ \tilde{x}_{41}^* & \tilde{x}_{42}^* & \tilde{x}_{43}^* \end{matrix} = \begin{bmatrix} 0 & 1 & 0.51 \\ 0 & 0.84 & 0 \\ 1 & 0.05 & 0 \\ 0.2 & 0 & 0 \end{bmatrix}$$

In fact, there is minor difference between x_{ni}^* and $\tilde{x}_{ni}^*$ that the highest level still only keeps the decision authority of strategic items. No significant conflicts exist between the enterprise's benefit and the highest level's benefit in the centralization behavior toward strategic items. From Proposition 3, the lowest level will choose to keep the decision authority of tactic items in priority for the larger $\frac{B_2+M_{12}-C_2}{t_2}pf_2(1)$, the profit brought by tactical items per time unit. The most difference is that the interlayers hesitate in concentrating more in strategic items or tactic items for they have high knowledge on both types of items. The organizational designer should make an efficient incentive bonus of M_{ni} with the purpose of guiding different layers to behave in preferences that are most close to the optimal allocations of the enterprise's decision items. Let the x_{ni} in problem (2.16) be known variables as given $\widetilde{x}^*_{ni}$, and solve the multivariate layer planning model, and we have

$$M^*_{ni} = \begin{bmatrix} 0 & 2 & 0.8 \\ 0 & 6.74 & 0 \\ 10.31 & 3.87 & 0 \\ 9 & 0 & 0 \end{bmatrix}$$

M^*_{ni} is the minimum incentive bonus that the organization designer needs to pay for staffs in different levels toward different decision items. However, there will be multiple feasible solutions. In our example, M^*_{ni} shows that the organizational designer should make a scheme of incentive bonus considering the benefit of different layers. For example, to encourage the centralization behavior of level 2 toward tactic items, the incentive bonus should be specifically increased. However, to encourage the decentralization behavior of level 3 toward tactic items, both the incentive bonus of the level toward strategic and tactic items should be adjusted accordingly.

2.5 Conclusion and Further Research

2.5.1 Conclusion

The emerging information technologies of the IoT and big data have changed customers' personalized demands and accelerated the information transformation between and inside enterprises. Also, traditional production patterns of manufacturing enterprises have changed. According to the previous literature, we conclude that there are three advantages of information acquisition and delivery in IoT manufacturing enterprises compared to that of traditional manufacturing scenarios: (1) more comprehensive acquisition of product life cycle information, (2) precise detection and analysis of on-site data, and (3) faster information transmission inside and among cooperative enterprises.

Despite the technical convenience and advantages that the IoT brought to the manufacturing process, this chapter mainly concentrates on the optimal allocation of decision-making authority of strategic, tactic, and operational decision items with the objectives of maximization of total profit and minimization of expected opportunity losses and maximal decision time. After we solve the optimal allocation scheme of decision-making authority, we explore the centralization behavior of different layers from a microcosmic perspective. The problems are analyzed and solved in an established multi-objective optimization model and a multivariate layer planning model, respectively. Due to the complexity of analytical solution, our results are solved and tested in a numerical example. Finally, we propose suggestions for change of organizational structure and incentive mechanism for organization planer.

We find that the optimal allocation of decision-making authority toward different types of decision items is significantly affected by the distortion rate of decision information delivery, while independent from the waiting time of information delivery in interlayers and enterprise's preference of the objectives. Most importantly, the hierarchical levels under IoT environment are suggested to be reduced to make an efficient and flat organizational structure. Then, we propose that the knowledge functions, incentive mechanism, decision costs, and the decision time have synthetic influences on the centralization behavior of different levels toward decision items.

2.5.2 Future Research

Our work creatively introduces methods to quantify the decision authority and the decision information transformation and solve the optimal allocation scheme under the restrictions of enterprise's resources. Our work contributes for the new directions to look into the governance of internal organizational structure, which is also significantly effective to propose directions for the allocation of decision authority and organizational change under IoT environment. However, our results are mostly analyzed from a numerical example due to the complexity of solving analytical solutions of the multi-objective optimization mode. Further study could consider the optimal hierarchical level and management span according to the characteristics of information acquisition and delivery under intelligent manufacturing environment. Moreover, how can the decision efficiency of an IoT-based manufacturing enterprise be improved can be interesting and meaningful.

Chapter 3
Dynamic Coordinated Supply Chain Scheduling in an IoT Environment

3.1 Introduction

The Internet of Things (IoT) refers to the networking of physical items through the use of embedded sensors and other devices that gather and convey information about the items. The data collected from these devices can be used to optimize products, services, and operations. One of the earliest and best-known applications of such technology appears in the area of energy optimization: sensors deployed across the electricity grid can help utilities remotely monitor energy usage and make responses to account for peak times and downtimes. The IoT is also widely used in manufacturing enterprises to optimize production. For example, in factories, sensors enhance production efficiency by providing a constant flow of data to optimize production processes. The data collected from equipment can be used to determine the operating state of the equipment. This can greatly improve the accuracy of the equipment maintenance plan, reduce maintenance costs, and reduce unplanned downtime. The data collected from vehicles can be used to predict the arrival time of raw materials and product components.

Increasing numbers of enterprises and organizations have realized the importance of the IoT for industrial production. Although IoT sensors have been deployed in some enterprises and organizations, most data generated by existing IoT sensors are overlooked. In addition to connecting interoperable devices, companies must integrate and customize the analytical software that can help derive business insights (e.g., prediction and optimization) from real-time streams of data. For example, there are over 30,000 sensors on a modern oil platform, and many of the components on such a platform are now connected. However, less than 1 % of the data generated by these sensors are currently used for decision-making [60]. This chapter focuses on a parallel-batching scheduling problem in a two-stage supply chain that incorporates data gathered from IoT sensors. Multiple parallel-batching machines process the jobs ordered by multiple customers in the

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first stage, where machine breakdown and job dynamic arrival are considered. The sensors embedded in the machines provided information about the machines' conditions in real time, and allowed us to propose timely and effective scheduling solutions. The jobs' dynamic arrival information was obtained by sensors inserted in the vehicles. In the second stage, the finished jobs were transported by vehicle from the manufacturers to the customers.

3.2 Literature Review

3.2.1 The Applications of the IoT in Industrial Manufacturing

The development of on-board sensors and Industrial Internet sensor technology, such as RFID and GPS, has resulted in their increased use in manufacturing processes. Manufacturers are obtaining increasing amounts of original, reliable data from these industrial sensors. It is possible to use these real-time data to optimize the manufacturing process. Many researchers have discussed RFID-enabled scheduling in the literature. For example, to handle dynamic situations in production logistics (PL) processes, Qu et al. [61] integrated Cloud Manufacturing (CM) and IoT technologies to design a smart production logistics synchronization control mechanism with multi-level dynamic adaptability. Khaleel et al. [62] described an IoT platform for the car manufacturing industry that utilized RFID tags and a wireless sensor and actuator network (WSAN). Ghimire et al. [63] proposed an IoT-based situational awareness framework to help manufacturers reduce the time needed for decision-making in real-time project management. Zhang et al. [64] proposed a multi-agent architecture for real-time production scheduling that consisted of a Machine Agent, Capability Evaluation Agent, Real-time Scheduling Agent Process, and Monitor Agent. This architecture can realize the collection and processing of real-time shopfloor data, optimally schedule/re-schedule manufacturing tasks based on real-time feedback, and track and trace the manufacturing execution according to a critical event structure. Zhong et al. [65] presented an RFID-enabled real-time manufacturing execution system (RT-MES) to deal with shop-floor uncertainty and complexity for Mass-customization Production (MCP) companies. They also illustrated a case study to evaluate the efficiency and effectiveness of the proposed RT-MES of this system, with the goal of improving the control processes through real-time scheduling.

3.2.2 The Development of Supply Chain Scheduling

The global manufacturing revolution and the limitation amount of resources available intensify the strength of competition between manufacturing enterprises. Manufacturing enterprises are not dominant when they participate in market competition as individuals, so they tend to take part in the market competition as whole supply chains. Supply chain scheduling is an important way to optimize the allocation of resources. Hall and Potts [66] found that although the research about supply chains is extensive, no scholars have focused on relating decision making to supply chain scheduling. Motivated by industry practices, Chen and Vairaktarakis [67] investigated a series of integrated production and distribution scheduling models and designed an algorithm and a heuristic algorithm to solve them. They also described the importance of the proposed integrated model. Chen [68] provided a detailed review of supply chain scheduling; he proposed the five-field notation, $\alpha|\beta|\pi|\delta|\gamma$, to describe supply chain scheduling models. α specifies the machine situation in the manufacturing plant(s). β represents the characteristics of the job ordered by the customer(s). π describes the features of the delivery process and γ represents the number of customers. Chen and Hall [69] considered supply chain scheduling models where suppliers and manufacturers coordinate production in assembly systems, and designed a practical mechanism for decision making. Hall et al. [70] examined the coordination of scheduling and batch deliveries; they considered several scheduling models and designed the corresponding DP algorithm for each model.

3.2.3 The Development of Batch Scheduling

Batch production is the core model of the modern manufacturing industry. Originally, batch production was widely applied in the detection process of semiconductor manufacturing. In recent decades, researchers have become more interested in studying batch scheduling problems. Melouk et al. [71] utilized a simulated annealing algorithm to solve the single machine batch processing problem whose objective function minimized the makespan. Cheng et al. [72] designed a heuristic algorithm for the problem of single batch machine scheduling with deliveries and proved that the worst-case performance ratio of the heuristic algorithm is 11/9. Motivated by the product challenges of semiconductor manufacturing, Jula and Leachman [73] proposed a variety of optimization-based algorithms and greedy heuristics-based algorithms to coordinate the multistage scheduling of parallel batch-processing machines. Lee [74] examined the problem of minimizing the makespan on a single batch processing machine where dynamic job arrivals were taken into account. Several polynomial and pseudopolynomial-time algorithms were proposed for special cases, and efficient heuristics were presented for the general problem. Their performance was evaluated by extensive computational experiments. Zhang et al. [75] studied the problem of minimizing the makespan on a single batch processing machine with non-identical job processing time and size. They proposed an approximation algorithm with a worst-case ratio of 7/4 for the general case. Kashan et al. [76] proposed two different Genetic Algorithms (GA) to deal with the single batch processing machine with non-identical job sizes. Kashan and Karimi [77] proposed an improved mixed integer linear formulation and lower bounds for the problem of minimizing the makespan on flowshop batch processing machines. Li et al. [78] provided an efficient algorithm to solve the problem of scheduling with agreeable release times and due dates on a single batch processing machine by considering two different objective functions: minimizing the maximum tardiness and minimizing the number of tardy jobs. Chung et al. [79] proposed a mixed integer linear programming (MILP) model to optimize the scheduling problem of parallel batch processing machines with non-identical ready times and arbitrary job sizes. Chang et al. [80] studied the problem of scheduling semiconductor burn-in operations, where the burn-in oven was seen as a batch processing machine, and presented an efficient heuristic algorithm that solved this problem rapidly with satisfactory performance. Chou et al. [81] proposed a hybrid genetic algorithm for refining the solution obtained by the LPT-BFF heuristic algorithm for solving a single batch processing machine dynamic scheduling problem. Damodaran et al. [82] presented a Simulated Annealing (SA) algorithm to minimize the makespan of parallel batch processing machines with unequal job ready times. A hybrid genetic heuristic algorithm was proposed by Kashan et al. [83] for scheduling parallel batch processing machines with arbitrary job sizes. Zhou et al. [84] developed an effective discrete differential evolution algorithm for the scheduling problem of uniform parallel batch processing machines that have non-identical capacities and speeds with arbitrary job sizes. Jiang [85] proposed a hybrid discrete particle swarm optimization (DPSO) algorithm and genetic algorithm (GA) to address the scheduling problem of uniform parallel batch machines that took transportation into account. Cheng and Kovalyov [86] investigated the problem of scheduling serial batching machines with batch set-up times. A variety of polynomial time algorithms were developed for different objective functions. Su et al. [87] considered a two-stage scheduling problem with parallel machines and batch delivery; they proposed a new heuristic algorithm, MH3, to solve the problem. Chou et al. [88] considered a single batch-processing machine problem with arbitrary job sizes, and proposed a joint GA and dynamic programming (DP) algorithm as a solution. Sung et al. [89] considered a scheduling problem for a semiconductor burn-in oven (which was seen as a batch processing machine). They proposed the DP algorithm to solve the problem in a reasonable amount of time when the number of job families was small. Chang et al. [90] developed a SA approach to minimize the makespan for batch-processing parallel machines.

3.2.4 The Applications of the IoT in Supply Chain Scheduling

The development of internet technology has achieved information sharing between the various parts of the supply chain, so that the cooperation between the different members of the supply chain is more efficient. However, there are still unresolved issues, such as industrial machinery fault predictions and the real-time monitoring and tracking of industrial transport vehicles. Some researchers have studied supply chain scheduling in an IoT environment. Pei et al. [91] presented a novel two-phase heuristic (TP-H) algorithm for solving a supply chain scheduling problem with non-identical job sizes and release times. They considered the influence of the IoT and performed computational experiments to evaluate the proposed approach. Pei et al. [92] investigated a serial-batching scheduling model where the time-dependent set-up time and effects of deterioration and learning on a single machine were considered, and developed three optimization algorithms. Pei et al. [93] also studied a single serial-batching scheduling problem and considered some features of dynamic job arrival and the set-up time because of the influence of the IoT. They developed a two-phase hybrid algorithm (TPHA) to solve this problem.

3.3 Problem Description

In this section, we assume that there are M decentralized manufacturers which located at different locations and G decentralized customers. These manufacturers should produce n jobs totally for these customers. Each manufacturer only has a parallel batching machine with capacity of B. Machine breakdown is also taken into consideration in this chapter. Once a batch starts processing and machine breakdown does not happened in the process of the batch, no interruption is allowed until all the jobs in it are completely processed, that is, the processing time of batch is decided by the longest processing time in this batch. If machine breakdown occurs in the process of the batch, then the batch needs to be continually processed until the machine have been repaired, where the processing time of manufacturers is decided by the longest processing time in this batch and the repair time of the machine.

In our model, each job must be assigned to one of the decentralized manufacturers. All of the machines which belong to different manufacturers are non-identical, where the processing time of each job on different machine is different. Once the jobs which ordered by a customer have finished the process in one machine, they would be transported to the customer by a vehicle with unlimited capacity. The processing time of the job j_j which is processed on machine M_m is denoted by p_{jm}, where $j = 1, \ldots, n, m = 1, \ldots, M$. And the arrival time of each job to decentralized manufacturers is also different. The arrival time of the job j_j which is processed on machine M_m is denoted by r_{jm}, where $j = 1, \ldots, n, m = 1, \ldots, M$.

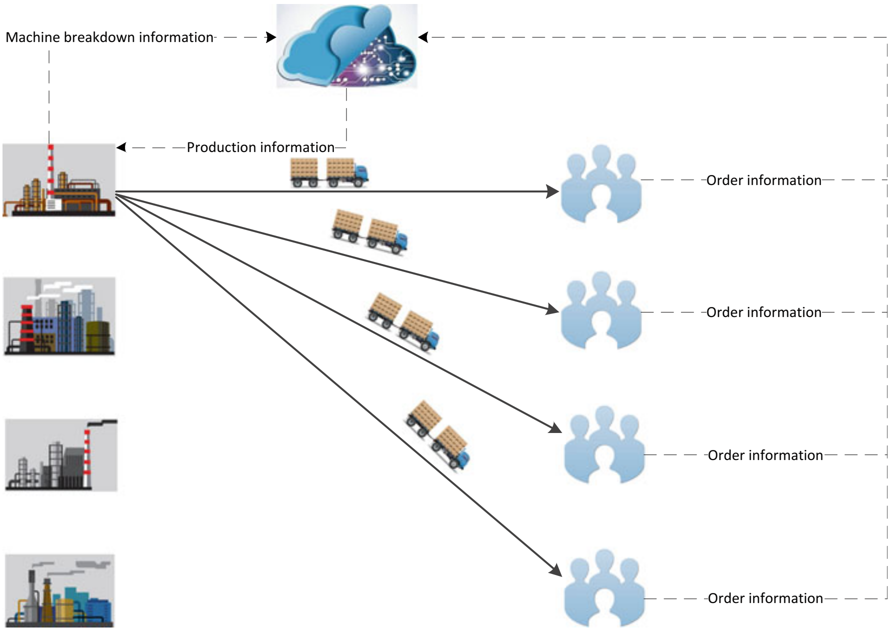


Fig. 3.1 Problem description

The size of job j_j is denoted by s_j. The objective is to find a joint schedule of production and distribution to improve service levels. Figure 3.1 illustures the problem as follows.

3.4 A Mixed Integer Programming Formulation

- **Indices**

  j job index $j = 1, 2, \cdots, n$,
  h batch index $h = 1, 2, \cdots, H$,
  k, f batch index $k = 1, 2, \cdots, H, f = 1, 2, \cdots, H, k \neq f$,
  m machine index $m = 1, 2, \cdots, M$,
  g customer index $g = 1, 2, \cdots, G$.

- **Parameters**

  N total number of jobs,
  B the capacity of machines,
  M number of machines,
  H total number of batches,
  s_j the sizes of job j,

r_{jm} the arrival time of job j to manufacturer m,
p_{jm} the processing time of job j on the machine of manufacturer m,
pt^{hm} the processing time of batch h on the machine of manufacturer m,
T_{mg} the delivery time from manufacturer m to customer g,
BR_m total number of the machine breakdowns in manufacturer m,
bt_{lm} the begin time of lth breakdown on the machine of manufacturer m,
et_{lm} the end time of lth breakdown on the machine of manufacturer m,
LM a large positive integer.

- **Decision variables**

$$x_{jh} = \begin{cases} 1, & \textit{If job j is assigned to batch h}, \\ 0, & \textit{otherwise}; \end{cases}$$

$$y_{kfm} = \begin{cases} 1, & \textit{If batch f is scheduled following batch k on machine m}, \\ 0, & \textit{otherwise}; \end{cases}$$

$$z_{hm} = \begin{cases} 1, & \textit{If batch h is assigned to machine m}, \\ 0, & \textit{otherwise}; \end{cases}$$

$$D_{jmg} = \begin{cases} 1, & \textit{If job j which is ordered by customer g is assigned to machine m}, \\ 0, & \textit{otherwise}; \end{cases}$$

$$u_{lmh} = \begin{cases} 1, & \textit{If lth breakdown of the machine which belongs to the manufacturer m happens} \\ & \textit{when batch h to be processed on it}, \\ 0, & \textit{otherwise}; \end{cases}$$

t_{hm} the release time of batch h to be processed on machine m,
S_{hm} the start time of batch h to be processed on machine m,
C_{hm} the completion time of batch h to be processed on machine m,
C_{max} the maximum completion time (makespan).

$$\textit{Minimize } C_{max}$$

Subject to

$\sum_{h=1}^{H} x_{jh} = 1$	$\forall j$	(1)
$\sum_{m=1}^{M} z_{hm} = 1$	$\forall h$	(2)
$\sum_{j=1}^{n} x_{jh} \times s_j \leq B$	$\forall h$	(3)
$pt^{hm} \geq p_{jm} \times x_{jh} \times z_{hm}$	$\forall j, h, m$	(4)

(continued)

$t_{hm} \geq r_{jm} \times x_{jh} \times z_{hm}$	$\forall j, h, m$	(5)
$S_{hm} \geq \max\{C_{(h-1)m}, t_{hm}\}$	$\forall l, h, m$	(6)
$C_{hm} \geq S_{hm} + pt^{hm} + u_{lmh} \times (et_{lm} - bt_{lm})$	$\forall l, h, m$	(7)
$C_{max} \geq (C_{hm} + T_{mg}) \times x_{jh} \times z_{hm} \times D_{jmg}$	$\forall j, h, m, g$	(8)
$\sum_{m=1}^{M} y_{kfm} + \sum_{m=1}^{M} y_{fkm} = 1$	$\forall k, f \neq k$	(9)
$C_{km} + pt^{km} - S_{fm} + LM(y_{kfm} - 1) \leq 0$	$\forall k, m, f \neq k$	(10)
$u_{lmh} \times (bt_{lm} - S_{hm}) \times (C_{hm} - et_{lm}) \geq 0$	$\forall l, h, m$	(11)
$z_{km} + z_{fm} + LM \times (1 - (y_{kfm} + y_{fkm})) \geq 2$	$\forall k, m, f \neq k$	(12)
$y_{kfm} + y_{fkm} - LM(z_{km} + z_{fm} - 2) \geq 1$	$\forall k, m, f \neq k$	(13)
$x_{jh} \in \{0, 1\}$	$\forall j, h$	(14)
$z_{hm} \in \{0, 1\}$	$\forall h, m$	(15)
$y_{kfm} \in \{0, 1\}$	$\forall k, m, f \neq k$	(16)
$D_{jmg} \in \{0, 1\}$	$\forall j, m, g$	(17)

The objective function (1) is to minimize the makespan. Constraint set (1) promises that one job should be accommodated by only one batch. Constraint set (2) guarantees that each batch is only assigned to one machine. Constraint set (3) guarantees that the total size of all jobs assigned to the same batch cannot exceed the capacity of the parallel batching machine. Constraint set (4) enforces that the processing time of each batch is decided by the longest processing time in it. Constraint set (5) reveals that the release time of a batch is decided by the arrival time of last arrive job in this batch. Constraint set (6) promises that the start processing time for each batch is no less than the release time of the current batch and the completion time of the previous batch. Constraint set (7) indicates that the completion time of each batch is no less than the sum of its start processing time, processing time and machine repair time if machine breakdown happens during the batch process. Constraint set (8) indicates that the makespan is no smaller than the sum of each batch processing and shipping time. Constraint set (9) gurantees the chronological order of batches. Constraint set (10) guarantees that the overlapping situation between any two different batches is not exist. Constraint set (11) reveals that the batch cannot be processed if machine breakdown happens. Constraint set (12) guarantees that if two batches are not assigned to machine m or one is assigned to machine m and another not, then $y_{kfm} + y_{fkm} = 0$. Constraint set (12) also ensures that if two batches are assigned to machine m, then $y_{kfm} + y_{fkm} \leq 1$. Constraint set (13) guarantees that if two batches are assigned to machine m, then $y_{kfm} + y_{fkm} \geq 1$. Constraint set (12), (13) are the primacy constraints proposed by Pearn et al. [94] The ranges of the variables are defined by constraint sets (14), (15), (16), (17).

3.5 Heuristic for Batch Formation and Scheduling in Single Machine

In this section, we propose a heuristic algorithm to scheduling the dynamic arrival jobs which be assigned to the same machine with the consideration of machine breakdown. Before giving the detail of this algorithm, we introduce the concept of waste and idle space (*WIS*) which was proposed by Xu et al. [95]. The batch can be viewed as a rectangle whose width is the longest processing time in this batch and height is the capacity of this batch. The waste space of batch h (WS^h) indicates the remaining space of batch h except that space which was occupied by jobs that had been already assigned to it. Let P^h denote the processing time of batch h. WS^h can be calculated as following formula.

$$WS^h = B \times P^h - \sum_{j \in h} s_j \times p_j$$

Because the machine could process batch h only when all of the jobs in it have arrived, so the idle space of batch h (IS^h) is generated. Let S^h denote the starting time of batch h. IS^h is calculated as following formula, which is equal to the idle time before batch start processing multiplied by the capacity of batch.

$$IS^h = B \times \left(S^h - C^{h-1}\right)$$

The waste and idle space of batch h (WIS^h) include waste space of the batch and idle space of the batch. WIS^h is calculated as following formula.

$$WIS^h = WS^h + IS^h$$

The waste and idle space of a feasible schedule (*WIS*) is made up by the waste and idle space of each batch in it. *WIS* is calculated as following formula.

$$WIS = \sum_{h \in s} WIS^h$$

A simple example for a feasible batch schedule is proposed as follows, where batch capacity is equals to 4 (Table 3.1).

An illustration of this problem as follows (Fig. 3.2):

Xu et al. [95] proves that solving $1|p - batch, r_j, s_j|C_{max}$ can be converted to minimize *WIS* of schedule *S*. They proposed a FFWIS-ERT algorithm for above problem. Based on the concept of *WIS*, we divide our problem as two stages: (i) batch formation (ii) batch scheduling. We design corresponding algorithm for each stage in this chapter.

Firstly, we develop a hybrid heuristic and dynamic programming algorithm to solving the batch formation problem based on lemma 1 as follows.

Table 3.1 A simple example for a feasible batch schedule

Batch	Jobs	r_j	p_j	s_j	WS^h	IS^h	WIS^h
1	Job 1	1	2	1	4	8	12
	Job 2	2	1	2			
2	Job 3	2	3	1	5	4	9
	Job 4	3	2	1			
	Job 5	5	1	2			
3	Job 6	8	2	3	2	0	2

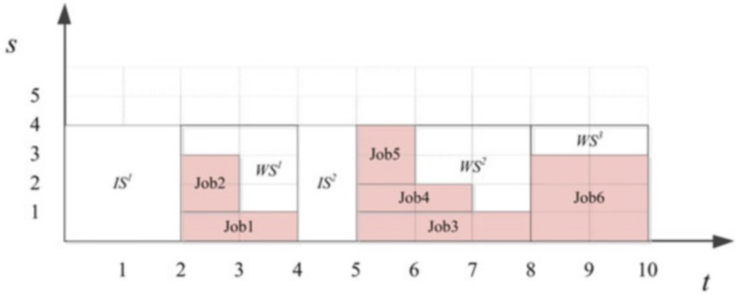


Fig. 3.2 An illustration of the example

Lemma 1 If the job j and batch h meet the condition as $r_j \geq r$, $p_j \leq p$ *and* $(r_j - r - p) \geq 0$, or $r_j \geq r, p_j \leq p$ *and* $(r_j - r - p_j) \leq 0$, then the job j should not be assigned to the batch h, where r is the maximum value of the arrival time of jobs in batch h, and p is the maximum value of the processing time of jobs in batch h.

Proof If the job j is assigned to the batch h, then the contribution of job j to WIS^h is calculated as $\Delta WIS^h = \max\{r_j - r, 0\} \times B + \max\{p_j - p, 0\} \times B - s_j \times p_j$. If the job j is assigned to a new batch which denoted by $h+1$ separately, and processed following batch h. The contribution of job j to $WIS^h + WIS^{h+1}$ is $\Delta WIS^{h,h+1} = \max\{r_j - r - p, 0\} \times B + p_j \times B - s_j \times p_j$. Now we discuss the following situations.

Situation 1: $p_j - p \leq 0$

Case 1: $r_j - r \leq 0$

The contribution of job j to WIS^h is $\Delta WIS^h = -s_j \times p_j$, and the contribution of job j to $WIS^h + WIS^{h+1}$ is $\Delta WIS^{h,h+1} = p_j \times B - s_j \times p_j$. It's obviously that $\Delta WIS^{h,h+1} \geq \Delta WIS^h$, and assigning the job j to batch h is better for our objective than assigning the job j to batch $h+1$.

Case 2: $r_j - r \geq 0$ and $r_j - r - p \geq 0$

The contribution of job j to WIS^h is $\Delta WIS^h = (r_j - r) \times B - s_j \times p_j$, and the contribution of job j to $WIS^h + WIS^{h+1}$ is $\Delta WIS^{h,h+1} = (r_j - r - p) \times B + p_j \times B - s_j \times p_j = (r_j - r) \times B + (p_j - p) \times B - s_j \times p_j$. It's obviously that inequality $\Delta WIS^{h,h+1} \leq \Delta WIS^h$ is always established, and assigning the job j to batch h is worse choice for our objective.

Case 3: $r_j - r \geq 0$ and $r_j - r - p \leq 0$

The contribution of job j to WIS^h is $\Delta WIS^h = (r_j - r) \times B - s_j \times p_j$, and the contribution of job j to $WIS^h + WIS^{h+1}$ is $\Delta WIS^{h,h+1} = p_j \times B - s_j \times p_j$. The difference between $\Delta WIS^{h,h+1}$ and ΔWIS^h is $\Delta WIS^{h,h+1} - \Delta WIS^h = (r_j - r) \times B - p_j \times B = (r_j - r - p_j) \times B$. We obtain that if $r_j - r - p_j \leq 0$, then assigning the job j to batch h is worse choice for our objective.

Situation 2: $p_j - p \geq 0$

Case 1: $r_j - r \leq 0$

The contribution of job j to WIS^h is $\Delta WIS^h = (p_j - p) \times B - s_j \times p_j$, and the contribution of job j to $WIS^h + WIS^{h+1}$ is $\Delta WIS^{h,h+1} = p_j \times B - s_j \times p_j$. It's obviously that $\Delta WIS^{h,h+1} \geq \Delta WIS^h$, and assigning the job j to batch h is better for our objective than assigning the job j to batch $h+1$.

Case 2: $r_j - r \geq 0$ and $r_j - r - p \geq 0$

The contribution of job j to WIS^h is $\Delta WIS^h = (r_j - r) \times B + (p_j - p) \times B - s_j \times p_j$, and the contribution of job j to $WIS^h + WIS^{h+1}$ is $\Delta WIS^{h,h+1} = (r_j - r - p) \times B + p_j \times B - s_j \times p_j = (r_j - r) \times B + (p_j - p) \times B - s_j \times p_j$. It's obviously that equality $\Delta WIS^{h,h+1} = \Delta WIS^h$ is always established.

Case 3: $r_j - r \geq 0$ and $r_j - r - p \leq 0$

The contribution of job j to WIS^h is $\Delta WIS^h = (r_j - r) \times B + (p_j - p) \times B - s_j \times p_j$, and the contribution of job j to $WIS^h + WIS^{h+1}$ is $\Delta WIS^{h,h+1} = p_j \times B - s_j \times p_j$. The difference between $\Delta WIS^{h,h+1}$ and ΔWIS^h is $\Delta WIS^{h,h+1} - \Delta WIS^h = -(r_j - r - p) \times B$. We obtain that assigning the job j to batch h is better for our objective.

From above discussion, we can conclude that if current batch h and job j meet following relationship:

(i) $r_j \geq r, p_j \leq p$ *and* $(r_j - r - p) \geq 0$ or (ii) $r_j \geq r, p_j \leq p$ *and* $(r_j - r - p_j) \leq 0$, then the job j should not be assigned into batch h.

We also proposed a DP algorithm as a part of the batch formation algorithm, the procedure of the DP algorithm is formally described as follows.

Step 1: Create a new empty batch and put the first job in the job list into this batch.
Step 2: Value function: define $H(j, v)$ as the minimum WIS^h value of batch h with capacity of v when the first j jobs in the job list are taken into consideration.
Step 3: Initialization:

For each $j = 1, 2, \cdots, n, v = 0, 1, \cdots, B$,

$$H(j, v) = \begin{cases} (B - s_j) \times p_j + r_j \times B & \textit{if } j = 1 \textit{ and } s_1 \leq v \leq B \\ +\infty & \textit{otherwise} \end{cases}$$

Step 4: Recursive relations:

For each $j = 2, \cdots, n, v = 0, 1, \cdots, B$,

$$H(j,v) = \begin{cases} \min\{H(j-1,v), H(j-1,v-s_j) + (\max\{0, r_j - R\} + \max\{0, p_j - P\}) \times B - s_j \times p_j\}, & s_j \le v \le B \\ H(j-1,v), & 0 \le v < s_j \end{cases}$$

When the state is $H(j-1, v-s_j)$, a set of jobs which are denoted by $S_{j-1,v-s_j}$ has been assigned into the batch, we can obtain it by backtracking. In above recursive relations, R can be calculated as following formula.

$$R = \max\{r_i | i \in S_{j-1,v-s_j}\}$$

P can be calculated as following formula.

$$P = \max\{P_i | i \in S_{j-1,v-s_j}\}$$

Step 5: Optimal solution: $\min\{H(n,v) | v = 0, 1, \cdots, B\}$

Lemma 2 The running time complexity of DP algorithm is $O((n-1)B)$ time.

Proof We calculate the running time complexity of algorithm DP as follows. The number of different states of the recursive relations is $(n-1)B$. For each state, the right-hand side of recursive relations can be calculated in $O(1)$ time. Thus, the overall time computational complexity of the algorithm is $O((n-1)B)$.

Based on the discussion for Lemma 1 and DP algorithm, we propose Algorithm 1 to solve the batch formation problem, and the procedure of the Algorithm 1 is formally described as follows.

Algorithm 1

Step 1. A set of jobs is assigned to a machine, we view these jobs as unscheduled job set (UJS) on this machine, and current batch h is empty
Step 2. Applying DP algorithm for UJS to obtain a scheduled job set (AJS) which is assigned to the batch h, and delete AJS from UJS, that is $UJS = UJS/AJS$
Step 3. Calculate ΔWIS^h for each job in UJS
Step 4. Check each job in UJS by the non-decreasing order of ΔWIS^h in turn. If job can be accommodated by the batch and meet the rule which state in Lemma 1, then put the job into the current batch h and transfer the job to AJS from UJS; Otherwise, go to step 6
Step 5. Update the state of current batch h and go to the step 3
Step 6. Output the current batch h

The procedure of the batch scheduling algorithm is formally described as follows.

Table 3.2 Parameters of the simple example

Batch capacity	Jobs	r_j	p_j	s_j
8	Job 1	1	2	3
	Job 2	2	3	3
	Job 3	6	2	3
	Job 4	2	1	4
	Job 5	9	4	4
	Job 6	8	2	3

Table 3.3 The process of DP algorithm

Jobs	r_j	p_j	s_j	1	2	3	4	5	6	7	8
Job 1	1	2	3	$+\infty$	$+\infty$	18	18	18	18	18	18
Job 2	2	3	3	$+\infty$	$+\infty$	18	18	18	18	18	18
Job 3	6	2	3	$+\infty$	$+\infty$	18	18	18	18	18	18
Job 4	2	1	4	$+\infty$	$+\infty$	18	18	18	18	18	18
Job 5	9	4	4	$+\infty$	$+\infty$	18	18	18	18	18	18
Job 6	8	2	3	$+\infty$	$+\infty$	18	18	18	18	18	18

Batch Scheduling Algorithm

Step 1. Give initial job set *IJS*, and let $UJS \leftarrow IJS$, *set* $h = 1$, $C^{i-1} = 0$, where h is the index of batch and C^h denotes the completion time of batch h
Step 2. Apply the Algorithm 1 for UJS to obtain batch h
Step 3. Assign batch h to be processed on the machine. If the breakdown is not happens during the process of batch h, then updated the completion time of batch h as $C^h = \max\{r^h, C^{h-1}\} + p^h$, and update the arrival time of jobs in the UJS as $r'_j = \max\{r_j - C^h, 0\}$; Otherwise continued the processing of batch h after the breakdown was repaired. Then update the completion time of batch h as $C^h = \max\{r^h, C^{h-1}\} + p^h + BT$ and update the arrival time of jobs in the UJS as $r'_j = \max\{r_j - C^h, 0\}$. Where r^h and p^h represent the release time and processing time of batch i respectively and BT is the machine repair time
Step 4. If UJS $\neq \varnothing$, then let $h = h + 1$ and go to step 2; Otherwise, output the C^h

Now a simple example with six jobs is as follows. The initial job set is $IJS = \{J_1, J_2, J_3, J_4, J_5, J_6\}$ and $UJS \leftarrow IJS$, $AJS = \varnothing$ (Table 3.2).

Applying the DP algorithm for UJS is show as following table (Table 3.3).

From above table, we obtain that $AJS = AJS \cup J_1$, $UJS = UJS \backslash J_1$. Base on lemma 1, J_4 should not be assigned to the batch. Then calculate the ΔWIS^b for other unscheduled job as 7, 34, 64, 50, so put J_2 into the batch, that is $AJS = AJS \cup J_2$, $UJS = UJS \backslash J_2$. There is no job could be accommodated by the batch. We assume that the machine breakdown is not happens during the process of the batch. Thus calculate the $C^1 = 2 + 3 = 5$. Update r'_j as $r'_3 = 1, r'_4 = 0, r'_5 = 4$, $r'_6 = 3$. Applying the DP algorithm for UJS again, the result is as follows (Table 3.4).

From above table, we obtain $AJS = AJS \cup J_3 \cup J_4$, $UJS = UJS / J_3, J_4$. And there is no job could be accommodated by the batch. We assume that the machine breakdown is happens during the process of the batch and the machine repair

Table 3.4 The process of DP algorithm

Jobs	r_j	p_j	s_j	1	2	3	4	5	6	7	8
Job 3	1	2	3	$+\infty$	$+\infty$	18	18	18	18	18	18
Job 4	0	1	4	$+\infty$	$+\infty$	18	18	18	18	14	14
Job 5	4	4	4	$+\infty$	$+\infty$	18	18	18	18	14	14
Job 6	3	2	3	$+\infty$	$+\infty$	18	18	18	18	14	14

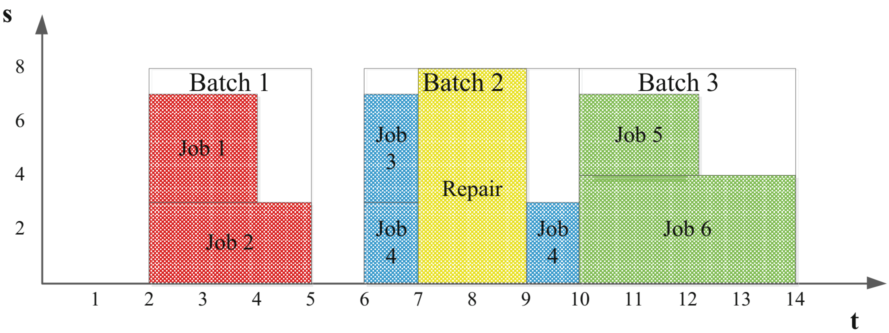


Fig. 3.3 An illustration of example

Fig. 3.4 The way of coding

2	3	*	1	4	5	*	6

time is 2. Thus calculate the $C^2 = 5 + 1 + 2 + 2 = 10$. Update r''_j as $r''_3 = 0, r''_4 = 0, r''_5 = 0, r''_6 = 0$. Similarly, J_5, J_6 should be assigned to a batch. Therefore calculate the $C^3 = 10 + 4 = 14$ when we assume there is no machine breakdown during the process of J_5, J_6.

An illustration of example as follows (Fig. 3.3).

3.6 Key Steps in SFLF-PR

3.6.1 Coding and Encoding

In this chapter, the solution of problem is denoted by a permutation of the index of n jobs and m-1 *. Figure 3.4 illustrates an example of coding as follows with six jobs and three machines.

In above example, job 2 and jobs 3 are assigned to the machine 1, jobs 1, 4, 5 are assigned to the machine 2, and job 6 is assigned to machine 3.

3.6.2 Basic Shuffled Frog Leaping Algorithm (SFLA)

SFLA was first proposed by Eusuff in 2006 [96]. It's a meta-heuristic algorithm to solve the discrete optimization problems. This algorithm combines the basic idea of SCE (Shuffled Complex Evolution) and PSO (Partical Swarm Optimization).

The description of SFLA is as below:

Step1: Initialize parameters of SFLA: number of virtual frog (N_SFLA), number of memeplexes (S_ SFLA), number of iterations of each memeplex (i_SFLA).
Step 2: Generate initial population of SFLA (P_SFLA) randomly.
Step 3: Calculate the fitness of each frog in P_SFLA, and sort the frog in P_SFLA in non-increasing order of their fitness.
Step 4: Partition P_SFLA into S_ SFLA memeplexes.
Step 5: Execute search process within each memeplex.
Step 6: Execute shuffling operation for memeplexes which have been updated.
Step 7: If the termination condition is met, output the best solution of SFLA, otherwise go to step 3.

The detail of Step 4 is as follows: the first frog is assigned to memeplexes M_1, the second frog is assigned to memeplexes M_2, the $(S\_SFLA)th$ frog is assigned to memeplexes M_{S_SFLA}, the $(S\_SFLA + 1)th$ frog is assigned to memeplexes M_1 again and so on. The procedure of partition is described as the following formula.

$$M_k = \left\{X_{k+S\_SFLA\times(l-1)} \in P\_SFLA | 1 \le l \le N\_SFLA/S\_SFLA\right\}, 1 \le k \le S\_SFLA$$

The detail of Step 5 is as follows: the best and worst solution of memeplexe M_k are denoted by x_{bk} and x_{wk} respectively, and the global solution is denoted by x_g. The new solution is generated by the following formula.

$$x'_{wk} = x_{wk} + Rand \times (x_{bk} - x_{wk})$$

Where $Rand$ is a random number following uniform distribution on $[0, 1]$.

If the fitness of x'_{wk} is better than the fitness of x_{wk}, then the x_{wk} is replaced by x'_{wk}. Otherwise, generate new solution using x_g and x_{wk} as following formula.

$$x'_{wk} = x_{wk} + Rand \times \left(x_g - x_{wk}\right)$$

If fitness of x'_{wk} is better than the x_{wk}, then the worst solution x_{wk} is replaced by x'_{wk}. If above two steps cannot produce better solution, then generate a new solution randomly and directly replace the worst solution x_{wk}. Repeat above process until the termination condition is met.

The detail of Step 6 is as below: The solutions of these memeplexes which have been updated are combined together and generate a new population.

3.6.3 Basic Path-Relinking Algorithm

The Path Relinking (PR) is proposed by Glover [97, 98]. PR, an effective algorithm for balancing search intensification and search diversification, has been applied successfully in many combinatorial optimization problems, such as assembly bandwidth coloring problem [99], single batch-processing machine scheduling problem [100], line balancing problem [101], and rural road network development problem [102].

The detail of the basic PR is as follows:

Step 1: Give a pair of solutions (S_{begin}, S_{end}), S_{begin} is the initial solution and S_{end} is the guiding solution.

Step 2: Find the difference between S_{begin} and S_{end}, $DI = \left\{ l | s^l_{begin} \neq s^l_{end}, l = 1, 2, \cdots, n \right\}$, where s^l_{begin} represents the value of lth position of S_{begin}.

Step 3: Set $S_l \leftarrow S_{begin}$, $SDI = DI$, Replace the value of the lth position about S_l with the one about S_{end}, and delete l from SDI, $SDI = SDI/l$, where S_l represents the solution about which the value of the lth position is replaced by the one about S_{end}.

Step 4: Repeat step 3 until $SDI = \varnothing$.

Step 5: Select a solution as new S_{begin} among $S_l, l \in DI$ according to certain rules, and record the best solution be found so far as S_{best}.

Step 6: If $S_{begin} = S_{end}$, then output S_{best}, otherwise, let $DI = \varnothing$, and go to step2.

We provide a simple example about above processes.

We assume that there are two solutions $S_{begin} = \{1, 2, 3, 4, 5\}$ and $S_{end} = \{2, 4, 3, 5, 1\}$. The difference between S_{begin} and S_{end} is $DI = \{1, 2, 4, 5\}$. According to Step 3, we obtain $S_1 = \{2, 1, 3, 4, 5\}$, $S_2 = \{1, 4, 3, 2, 5\}$, $S_3 = \{1, 2, 3, 5, 4\}$, $S_4 = \{5, 2, 3, 4, 1\}$. If the S_1 is selected as next S_{begin}, then repeat above process until stop condition is met. Figure 3.5 illustrates above process.

3.6.4 SFLA-PR Algorithm

In this section, we proposed SFLA-PR algorithm to solve our problem. The SFLA-PR has following distinguishing features: a novel way of partition memeplex base on stochastic universal sampling, a path relinking operator to produce new solutions in local search, a global search process to generate better solutions.

A framework of SFLA-PR algorithm is given in the form of pseudo code. In the framework, P_{SP} represents the population of the algorithm, and the population will be part into S_SP memeplexs, s_{ki} is the ith frog in kth memeplex M^k_{sp}.

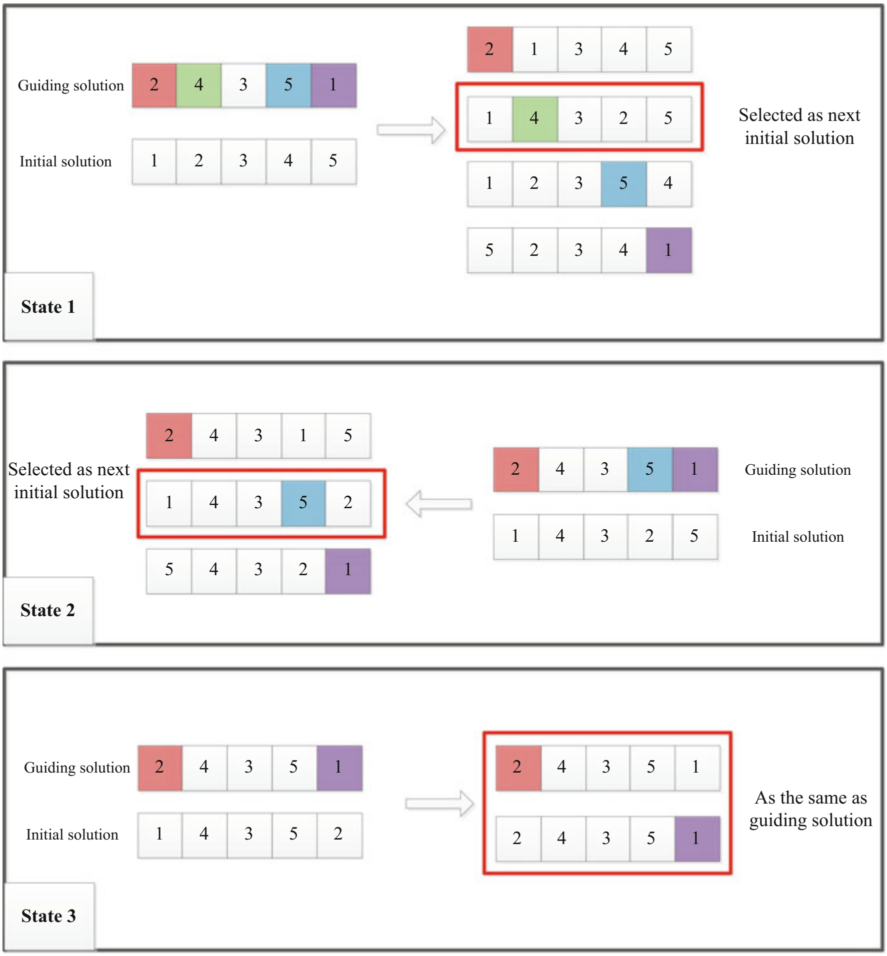


Fig. 3.5 The process of basic PR

- **Algorithm framework**

Pseudo-Code of Our SFLA-PR Algorithm

1.	**Input:** the given parameter of problem
2.	**Output:** a solution about the problem
3.	$P_{SP} = \{s_1, s_2, \cdots, s_n\} \leftarrow$ population_initialization() /* population initialization*/
4.	**While** stop condition is not met **do**
5.	$M_{sp}^{k} \leftarrow$partition_memeplex (P_{SP}), $k = 1, 2, \cdots, S\_SP$ /* partition memeplex for P_{SP} */
6.	**For** each $M_{sp}^{k} \in P_{SP}$ **do**

(continued)

For each $s_{ki} \in M_{sp}^{k}$ **do**
$s_{ki} \leftarrow$ local_search (s_{ki}) /* execute local search process for each frog in memeplex M_{sp}^{k} */
End for
$s_{new} \leftarrow$ global_search (s_a, s_b) /* execute global search process for frog s_a and s_b in memeplex M_{sp}^{k} to obtain new frog s_{new} */
$M_{sp}^{k} \leftarrow$ APU (M_{sp}^{k}, s_{new}, s_w)
While stop condition is not met **do**
Preform Diversity path_relinking operator
End while
End for
$P_{SP} \leftarrow \text{shuffle}\left(M_{sp}^{k} \mid k = 1, 2, \cdots, S_{SP}\right)$ /* shuffle all of memeplexes which have evolved
While stop condition is not met **do**
Preform Greedy path_relinking operator
End while
End while

- **Partition memeplex**

In above section, we introduce the way of partition memeplex in basic SFLA. In order to enhance optimization ability of the algorithm, we design a novel method of partition memeplex. This method is inspired by the stochastic universal sampling, and the detail of it is as follows:

Step 0: Set m = 1 , k=1

Step 1: Sort the frog in population P_{SP} with their fitness by the non-increasing order.

Step 2: Calculate the select probability of each frog, $p_{s_i} = \frac{fitness_{s_i}}{\sum fitness_{s_i}, s_i \in P_{SP}}$, set $p_{s_0} = 0$

Step 3: Generate a random number $Rand$ on [0,1], and if $\sum_{i=1}^{x-1} p_{s_i} \leq Rand < \sum_{i=1}^{x} p_{s_i}$, then put s_x into M_{sp}^{k}

Step 4: If $m \times k = n$, then algorithm stop; otherwise, if $k = n/m$, then $m = m + 1$, $k = 1$ and go to step 2; otherwise, $k = k + 1$ and go to step 2.

- **Local search process**

In this chapter, we adopt integer coding for each frog, so traditional local search strategy no longer applies. In this section, we propose three neighborhood structures, swap, insert, ruin and restructure, respectively. Based above neighborhood structures, we design a novel local search strategy(NLS) which is described as follows (Figs. 3.6, 3.7, and 3.8):

Swap: Randomly swap two different position of a frog to form a new frog.

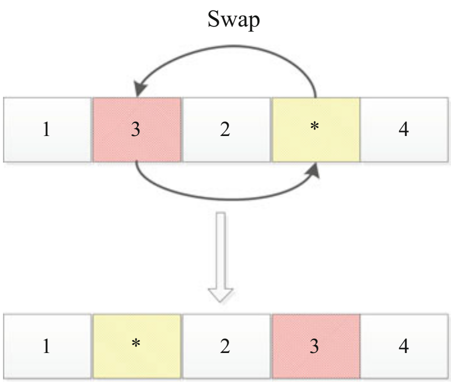


Fig. 3.6 Neighborhood structure-swap

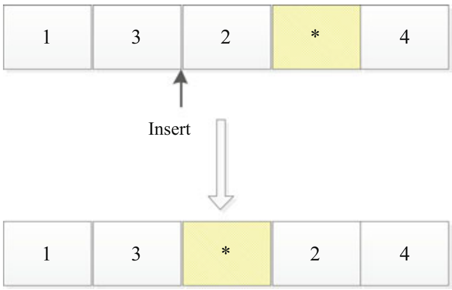


Fig. 3.7 Neighborhood structure-insert

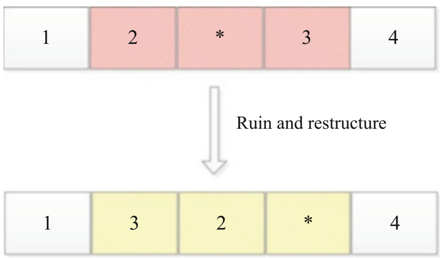


Fig. 3.8 Neighborhood structure- ruin and restructure

Insert: Randomly select one position of a frog insert after another position of the frog.

Ruin and restructure: Randomly select and restructure a length of frog, and retain the remaining part of the frog.

Pseudo-Code of NLS

1.	**Input:** solution s, maximum iterations $imax$
2.	**Output:** solution s
3.	$i \leftarrow 1$
4.	**While** $i \leq imax$ **do**

(continued)

$s_{news} \leftarrow swap(s, rands)$ /*repeat *rands* swap operation for solution s, when *rands* is a random integer*/
$s_{newi} \leftarrow insert(s, randi)$ /*repeat *rands* insert operation for solution s, when *randi* is a random integer*/
If s_{news} is better than s_{newi} **than**
$s_{new} \leftarrow s_{news}$
Else
$s_{new} \leftarrow s_{newi}$
End if
If s_{new} is better than s **than**
$s \leftarrow s_{new}$
else
$s_{new} \leftarrow ruin\,\&\,restructure(s_{new})$
If s_{new} is better than s **than**
$s \leftarrow s_{new}$
End if
End if
$i{+}{+}$
End while
Output s

- **Global search process**

In this section, we applied a procedure of global search which proposed by Mattfeld and Bierwirth [103]. Staring the first position of s_a, s_b, randomly generate a random number *Rand*, if *Rand* is less than the given threshold, then select the first position of s_a as the first position offspring; otherwise the first position of s_b is selected. Then delete the position which is selected from s_a, s_b. Repeat above process until s_a, s_b is empty. An illustration of this procedure is as follows (Fig. 3.9):

The Adaptive Population Updating (APU) for Global Search is also given in this subsection.

Pseudo-Code of APU (Adaptive Population Updating for Global Search)

Input: solution s, current the worst solution s_w in M_{sp}^k and M_{sp}^k
Output: updated M_{sp}^k
If solution s is better than s_w **then**
$s_w \leftarrow s$
Else

(continued)

6.	**If** $exp\left(\frac{cal\_fitness(s_w) - cal\_fitness(s)}{T}\right) \geq Rand$ **then** /* T is the current number of iterations
7.	$s_w \leftarrow s$
8.	**End if**
9.	**End if**

- **Path-relinking current: GPR and DPR**

Greedy path-relinking operator is common and intuitional in path-relinking algorithm [99]. The basic idea of greedy path-relinking operator can be summarized that always keep the best solution among all of generated solution during iterative process, we also propose tournament-based algorithm when we select two different initial solutions for greedy path-relinking operator from a certain memeplex. For the sake of easy, we call this greedy-based path-relinking operator as GPR operator.

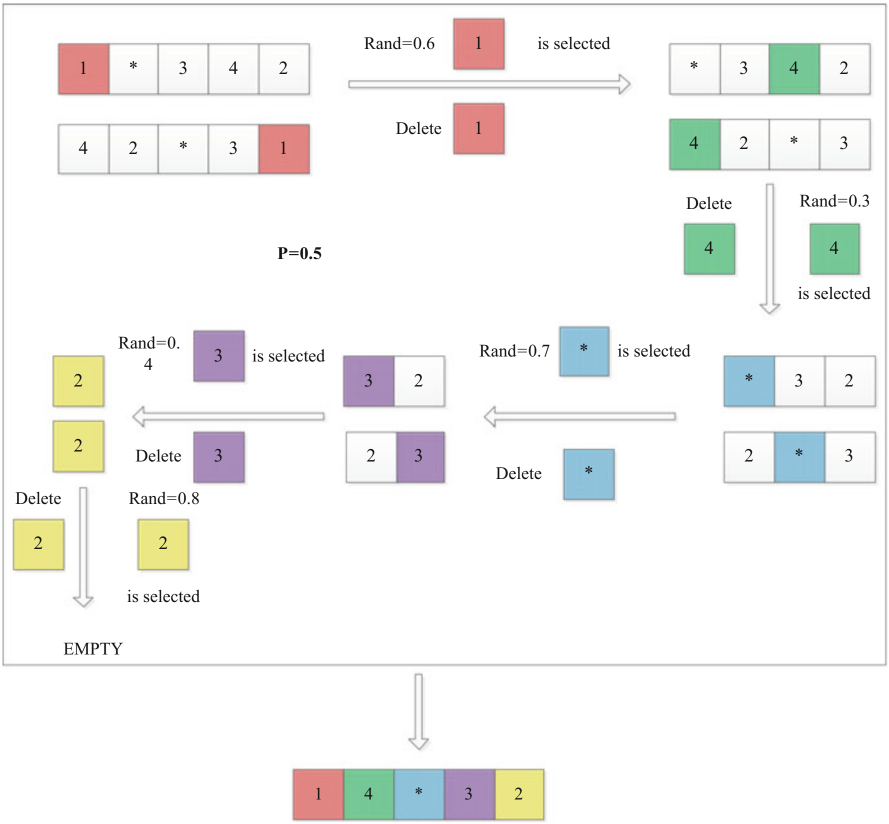


Fig. 3.9 The procedure of global search

The detail of GPR operator and tournament-based algorithm are described as follows:

Pseudo-Code of Our GPR Operator

Input: P_{SP}
Output: updated P_{SP}
$(s_c, s_d) \leftarrow tournament\_select(P_{SP})$ /* select two different solution from P_{SP} */
$DI \leftarrow Find\_difference\ (s_c, s_d)$ /* find the positions in which s_c, s_d have different value */
$s(0) \leftarrow s_c$, $r \leftarrow 0$, $SDI \leftarrow DI$, $l_* = 1$, $CS1 \leftarrow \varnothing$
While $SDI \neq \varnothing$ **do**
$\min = +\infty$
For each $l \in SDI$ **do**
$s_{temp1} \leftarrow f(s(r) \otimes l)$ /* the lth position of $s(r)$ is replaced by the value of the same position of s_d */
$CS1 = CS1 \cup s_{temp1}$
If $cal\_fitness(s_{temp1}) \leq \min$ **then**
$s_{temp2} \leftarrow s_{temp1}$
$\min = cal\_fitness(s_{temp1})$
$l_* = l$
End if
End for
$r \leftarrow r + 1$
$s(r) = s_{temp2}$
$SDI \leftarrow SDI \backslash l_*$
End while
$P_{SP} \leftarrow RPU(P_{SP}, CS1)$

In above algorithm, the detail of $tournament\_select(P_{SP})$ is described as follows:

Step 1: Randomly divide the solution pond into two groups (each group has different numbers of solutions)

Step 2: Calculate the fitness for each solution in each group, and sort the solution by non-increasing order with their fitness

Step 3: Select the first solution from each group as s_a and s_b respectively

In above algorithm, the detail of $RPU(P_{SP}, CS1)$ is described as follows:

Pseudo-Code of RPU (Random Population Updating for Greedy Path-Relinking)

Input: candidate solutions CS1 and P_{SP}
Output: updated P_{SP}
Decided the best solution s in CS1 and the worst solution s_w in P_{SP}
If $cal\_fitness(s) \le cal\_fitness(s_w)$ **then**
$s_w \leftarrow s$
Else
Randomly select a solution Rs from the candidate solutions CS1
If $exp\left(\frac{cal\_fitness(s_w) - cal\_fitness(Rs)}{T}\right) \ge Rand$ **then** /* T is the current number of iterations
$s_w \leftarrow Rs$
End if
End if

Except for GPR operator, we also proposed a diversity-based path-relinking operator to maintain the diversity of solution during iterative process. For simplification, we call this diversity-based path-relinking operator as DPR operator. A novel method of diversity accounting is also proposed. The detail of DPR operator and tournament-based algorithm are described as follows:

Pseudo-Code of Our DPR Operator

Input: M_{sp}^k
Output: updated M_{sp}^k
$(s_e, s_f) \leftarrow Random\_select\ (M_{sp}^k)$ /* select two different solutions from M_{sp}^k */
$DI \leftarrow Find\_difference\ (s_e, s_f)$ /* find the positions in which s_e, s_f have different value */
$s(0) \leftarrow s_e$, $r \leftarrow 0$, $SDI \leftarrow DI$, $l_* = 1$, $CS2 \leftarrow \varnothing$
While $SDI \ne \varnothing$ **do**
$diversity = 0$
For each $l \in SDI$ **do**
$s_{temp1} \leftarrow f(s(r) \otimes l)$ /* the lth position of $s(r)$ is replaced by the value of the same position of s_f */
$CS2 \leftarrow CS2 \cup s_{temp1}$
If cal_$diversity(s_{temp1}) \ge diversity$ **then**
$s_{temp2} \leftarrow s_{temp1}$
$l_* = l$
End if
End for

(continued)

$r \leftarrow r+1$
$s(r) = s_{temp2}$
$SDI \leftarrow SDI \setminus l_*$
End while
$M_{sp}^k \leftarrow DPU\left(M_{sp}^k, CS2\right)$

In above algorithm, the detail of cal_*diversity*(s_{temp1}) is described as follows:

Pseudo-Code of cal_*diversity*(*S*)

Input: solution s and P_{SP}
Output: the value of diversity about solution s
$Di = 0, Di1 = 0, Di2 = 0$
For each $k \leq m$ **do**
If $s \in M_{sp}^k$ **then**
For each $s_v \in M_{sp}^k$ and $s_v \neq s$ **do**
For each $i \leq N$ **do**
If $s[i] \neq s_v[i]$ **then/*** $s[i]$ represents the value in the *it*h position of solution s
$Di1{+}{+}$
End if
End for
End if
Else
For each $s_v \in M_{sp}^k$ **do**
For each $i \leq N$ **do**
If $s[i] \neq s_v[i]$ **then**
$Di2{+}{+}$
End if
End for
End else
End for
$Di = \alpha \times Di1 + (1-\alpha) \times Di2$

In above algorithm, the detail of $DPU\left(M_{sp}^k, CS2\right)$ is described as follows:

Pseudo-Code of DPU (Diversity Population Updating for Diversity Path-Relinking)

1.	**Input:** candidate solutions CS2 and M_{sp}^{k}
2.	**Output:** updated M_{sp}^{k}
3.	Decided the best solution s in CS2 and current the worst solution s_w in M_{sp}^{k}
4.	**If** $cal\_fitness(s) \leq cal\_fitness(s_w)$ **then**
5.	$s_w \leftarrow s$
6.	**Else**
7.	Select the solution Ds which have the largest value of diversity from the candidate solutions CS2
8.	**If** $exp\left(\frac{cal\_fitness(s_w) - cal\_fitness(Ds)}{T}\right) \geq Rand$ **then** /* T is the current number of iterations
9.	$s_w \leftarrow Ds$
10.	**End if**
11.	**End if**

3.7 Computational Experiments

In this section, we present computational experiments to evaluate the performance of our proposed algorithm SFLA-PR which is compared with Variable Neighborhood Search(VNS) and SA. Experiment parameters are listed in following table (Table 3.5).

Following figures show the convergence behaviors of SFLA-PR, VNS, and SA for each instance. In each figure, ten tests were executed and the best individual in each iteration was listed. All the algorithms were implemented in C++ and carried out on a Lenovo computer running Window10 with a dual-core CPU Intel i5-6200U@2.30 GHz and 8 GB RAM. From Figs. 3.10 and 3.11, we can conclude

Table 3.5 Experiment parameters

Parameter	Description	Value
N	The number of jobs	30,40,50,200,300,400
C	The capacity of the batching machines	8
M	The number of machines	4,5,6
s_j	Job size	U [1, 8]
p_{jm}	The processing time of job j on m machine	U [1, 10]
r_{jm}	The arrival time for job j to machine m	U [1, 10]
T_{mg}	The delivery time for machine m to customer g	U [20, 30]
BT	Machine breakdown time	U [2, 5]

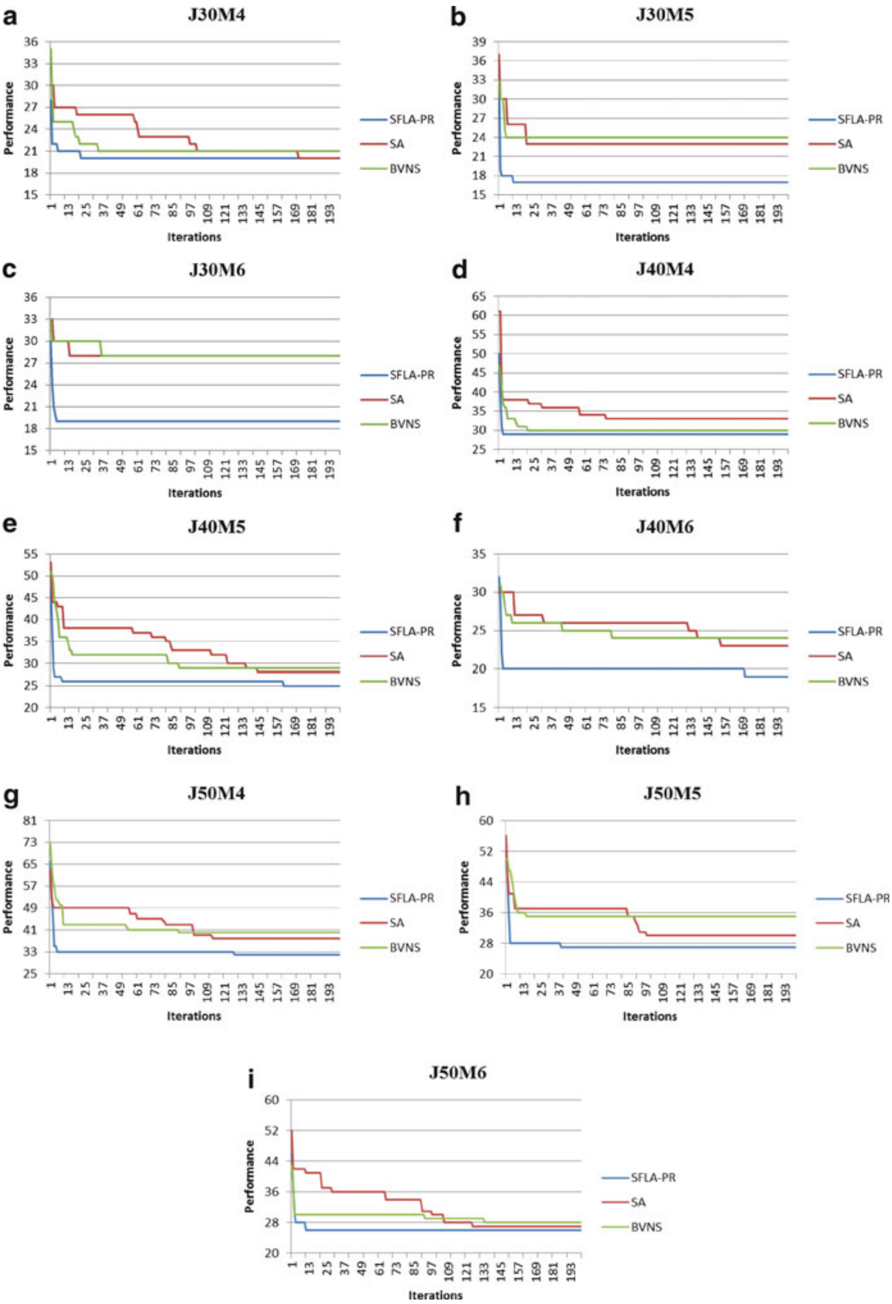


Fig. 3.10 Convergence curves for the problem with small size. (**a**) Convergence curve for J30M4. (**b**) Convergence curve for J30M5. (**c**) Convergence curve for J30M6. (**d**) Convergence curve for J40M4. (**e**) Convergence curve for J40M5. (**f**) Convergence curve for J40M6. (**g**) Convergence curve for J50M4. (**h**) Convergence curve for J50M5. (**i**) Convergence curve for J50M6

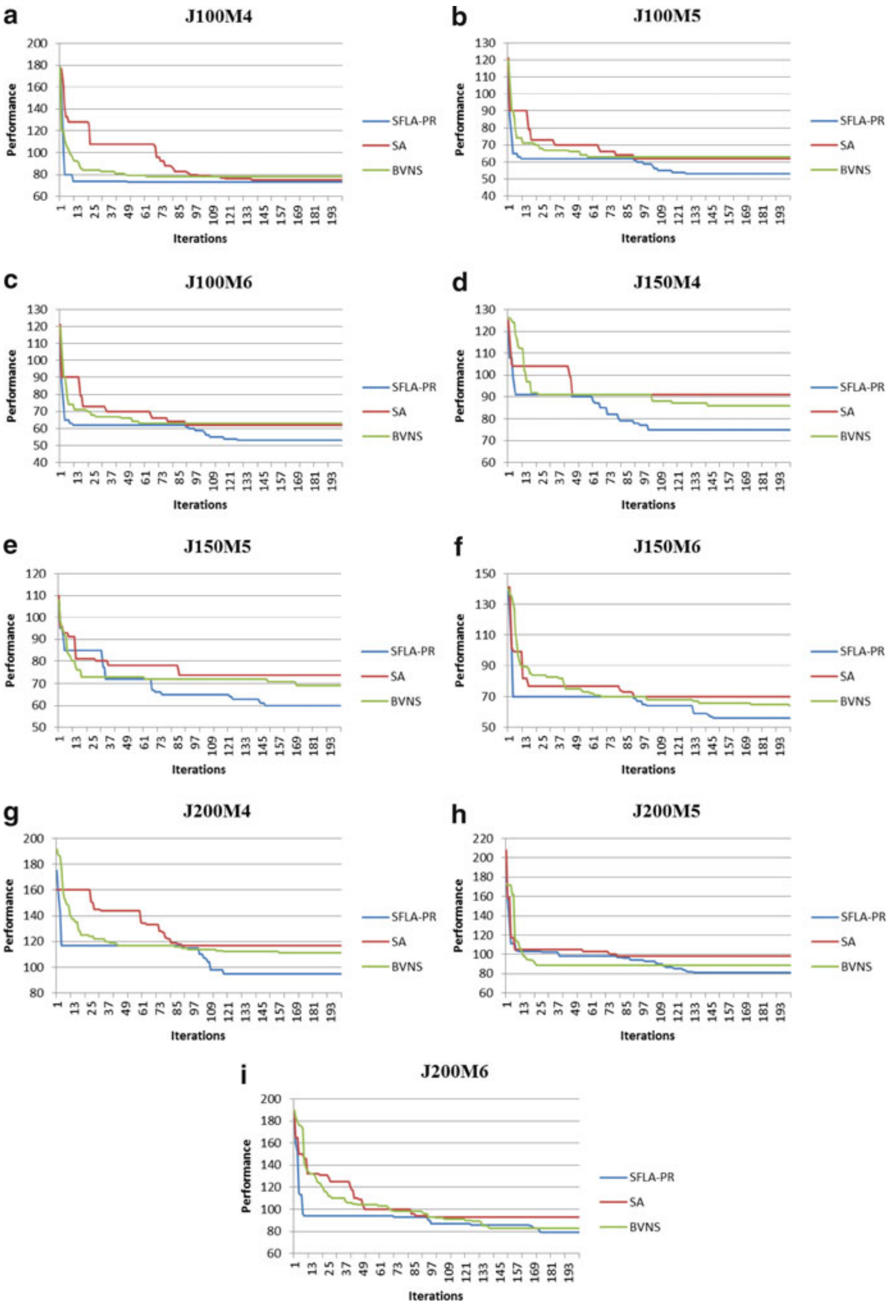


Fig. 3.11 Convergence curves for the problem with large size. (**a**) Convergence curve for J100M4. (**b**) Convergence curve for J100M5. (**c**) Convergence curve for J100M6. (**d**) Convergence curve for J150M4. (**e**) Convergence curve for J150M5. (**f**) Convergence curve for J150M6. (**g**) Convergence curve for J200M4. (**h**) convergence curve for J200M5. (**i**) Convergence curve for J200M6

that the SFLA-PR has better performance than other algorithms, since compared with VNS and SA, SFLA-PR has faster convergence rate and better solution's quality in all the cases. In small scale experiments, proposed algorithm has obvious advantages in terms of the convergence rate and solution's quality. In large scale experiments, proposed algorithm still better than the other two algorithms.

3.8 Conclusion and Future Research

3.8.1 Conclusion

This chapter studies a multiple parallel batching machine scheduling problem under the environment of the IoT, we built the model in which jobs ordered by several customers need to be processed and delivered by decentralized manufacturers located at different places. Specifically, each job with dynamic arrival time which has been known from the IoT sensors must be assigned to one of the decentralized manufacturers to process on its single batching machine. Then, the job is delivered to the customer directly without intermediate inventory. The objective is to find a joint schedule of production and distribution to optimize the customer service level. A batch formation algorithm based on DP algorithm and SFLA-PR algorithm are developed to solve above problem. Finally, experiment results show the effectiveness and efficiency of the proposed SFLA-PR compared with VNS and SA.

3.8.2 Future Research

Future research will focus on supply chain scheduling based on real data with consideration of other realistic objective functions. In addition, we need to design more efficient meta-algorithm to solve the complex problems.

Chapter 4
Hybrid Manufacturing Distributed Inventory Management with Sharing Logistics

4.1 Introduction

4.1.1 Background

Manufacturing companies cannot focus only on tradition manufacturing modes if they want to ensure profitability and competitiveness. Business process reengineering (BPR) is helpful for manufacturing companies who hope to benefit from new approaches to business. Manufacturers are confronted by two problems: defining what technology is important to the manufacturing company for reconstructing their processes and improving their mode and how to improve their management method to maximizing the benefit of the new mode. In this chapter, we highlight a new manufacturing mode, hybrid manufacturing, and propose a coordination management model that takes into consideration inventory and transportation as part of the comprehensive goal. We emphasize the innovational role of the IoT in these areas.

The development of recycling economics and the implementation of environmental protection laws have caused enterprises to choose to use hybrid manufacturing modes; these modes combine the processes of manufacturing and remanufacturing. This trend has become more apparent with the reevaluation of sustainability in global supply chains [104]. In hybrid manufacturing, the manufacturer has the option to choose the material sources, new or recycled, for producing products. The type of material we discuss here is reusable, such as that used to make beverage bottles, constant temperature preservation boxes for perishable products, gas containers, and reusable medical equipment. While recycled materials are also utilized by manufacturers, they are outside of the scope of this chapter. The benefits of hybrid manufacturing are obvious. First, the alteration cost is negligible for the manufacturing company. In many industries, the recycled material can be reused with some polishing, cleaning, or inspection. For example,

X. Liu et al., *Optimization and Management in Manufacturing Engineering*,
Springer Optimization and Its Applications 126,
DOI 10.1007/978-3-319-64568-1_4

Mason et al. [105] gave an example of an inventory management system for reusable gas cylinders. Based on the RFID and wireless sensor network technology, the tags from their system detected the states of information and actively transmitted these data to the database. Second, the quality of the recycled material is not worse than new material, so customers are not aware of whether the products were made with new or remanufactured materials. Third, the tracing and monitoring of in-use products by manufacturers provide whole life cycle information for improving the service level and operational efficiency. For example, an electric car company can trace customer usage and provide professional advice about the repair and replacement of parts. However, the reusable material is more expensive than the single-use materials due to its durability and traceability. Thus, the inventory management of reusable material is critical to efficiency. Reusable material requires backward logistics in transportation, which is a challenging problem in supply chain logistics management. In this chapter, we discuss a coordination management method that takes into consideration inventory and transportation.

Coordination optimization of the supply chain can substantially reduce costs and help the competitiveness of a business in the global marketplace. Novel information and sensor technologies enable the visibility and transparency of inventory, transportation, and other aspects of the supply chain. However, the most commonly used methods and models are still constrained to a single domain. It has been challenging for researchers to contribute to the coordination and optimization of the larger part of supply chains compared with approaches developed for traditional models.

The vendor-managed inventory (VMI) system is a kind of coordination relationship in the supply chain. In such a system, the upstream manufacturer takes the responsibility for the transportation and storage of products. The downstream retailer(s) is (are) in charge of selling and marketing. The participants in the supply chain share its private information with others. When there are multiple retailers distributed in separate locations, the manufacturer constructs vehicle routes based on the inventory and vehicle information. Downstream retailers are open to accepting reusable materials and keeping them until the manufacturer takes them back because this provides some convenience for customers. The manufacturer needs to take the responsibility for the transportation and storage of reusable materials because only the manufacturer benefits. In this environment, sharing logistics can reduce the transportation cost by combining the delivery of products and pickup of reusable material on the same route. The inventory and route coordination plan become more complicated when the stochastic demand, stock-out cost, simultaneous delivery and pickup, and multiple retailers are involved.

Information plays an important role in the transportation and inventory management of hybrid manufacturing. Many studies have shown the effect of acquiring item-level information [106] and information sharing [107]. The development of sensor technology has allowed the manufacturer to obtain the item-level information of products in the whole life cycle, even after its service life has expired. For example, the sensor on a gas container can monitor the pressure and transmit this information to the manufacturer. If the gas is used up or the pressure drops to some level, the manufacturer would recognize that it has become a reusable material waiting to be picked up. Furthermore, RFID and GPS provide the tracking information that depicts the availability and location of the product and material. Information technology and information sharing provide accurate inventory information for multiple distributed retailers that are specific to the type of inventory management discussed in this chapter. Unlike some traditional models where the information is assumed to be perfect, the information acquired in this model is not assumed to be perfect. The required information is unknown when the decision is made. Compared with the "blind" situation where the information of return and inventory level are unavailable, this information reduces the stochastic character of the problem and enables the modeling and solution of this problem.

4.1.2 Inventory Routing Problem in Hybrid Manufacturing

In this chapter, the problem is formulated as the inventory routing problem (IRP) with features of hybrid manufacturing. The IRP generalizes the vehicle routing problem (VRP), which is a well-studied combinatorial optimization and integer programming problem. The VRP considers a group of distributed retailers and satisfies their demands with a fleet of vehicles by composing route plans. The IRP is different from the VRP in that the demands of the IRP are not satisfied by the delivery but by the inventory stored by the customers. Thus, the IRP problem is a coordination optimization of transportation and inventory management in the context of the VMI, where the manufacturer takes care of both. This model also has several features that differ from the standard model. First, the demands are stochastic. Second, the demands can be divided into the delivery of products and pickup of reusable material. Third, the processes of delivery and pickup are simultaneous. Fourth, the model considers the decision of purchasing new material for guaranteeing the continuity of production. In this chapter, we also discuss the simultaneous delivery-pickup and purchasing decision (IRPSDPD).

Theoretically, the IRPSDPD as an extension of the IRP is also an NP-hard problem. Related analysis in other papers indicates that the stochastic IRP problem with multiple periods is quite complicated due to the fact that the calculated amount of the n-state Markov decision process increases exponentially and the problem quickly becomes intractable. In this chapter, we only tackle a realistically sized problem: we consider the single-period aspect of the IRPSDPD and the control of the inventory level of reusable material by the inventory level policy. A novel solution method based on adaptive neighborhood searching was proposed for this problem.

The structure of this chapter is organized as follows. In Sect. 2, we review the related literature and highlight our contribution. In Sect. 3, we formulate the model. Our proposed algorithm is based on adaptive large neighborhood searching and is given in detail in Sect. 4. Section 4.1 provides the simulation and sensitivity analysis for evaluating the performance of our proposed algorithm. In Sect. 4.2, we provide our conclusions and recommend future research directions.

4.2 Literature Review

Although IRPSDPD is encountered in the practical environment of manufacturing companies, it is not well studied in the academic literature. IRPSDPD is located in the crossing field of inventory management of closed-loop supply chain and inventory routing problem. In this section, we briefly introduce the characters and methodologies of the previous works related to IRP and VRP due to the fact that IRPSDPD is an extension of IRP and VRP. Then the existing literature in the crossing field is reviewed and compared with this chapter. The academic contribution of this chapter is discussed in the end.

4.2.1 Vehicle Routing Problem

VRP is a classic combinatorial optimization problem which generates the traveling salesman problem. Its formulation is first proposed by Dantzig and Ramser [108]. There are many variations of VRP. For the connection of this chapter, I highlight two variations of VRP. The first variation is called VRP with simultaneous delivery and pickup. In the VRP with simultaneous delivery and pickup, the vehicles are utilized to deliver and collect the demands in one route simultaneously. The connection with IRPSDPD is that the roles of vehicles are same in both problems. The difference is that the demands of VRP with simultaneous delivery and pickup have to be satisfied, where the satisfaction of demands is more flexible in IRPSDPD. VRP with simultaneous delivery and pickup is solved by exact algorithm [109], heuristic algorithm [110–112], and meta-heuristic algorithm [113–116]. The second variation I want to demonstrate is called VRP with stochastic demand. In the VRP with stochastic demand, the planner cannot know the information of demands except for the stochastic distribution of demand [117]. There are two perspectives for the VRP with stochastic demand, static and dynamic. In the static view, the planner makes the decision of routing plan with maximum match of all possible scenarios. In the dynamic view, the planner can realize the demands when the routing has begun and communicates with vehicle to adjust the routes. The static VRP with stochastic demand is solved by exact algorithm [118], meta-heuristic algorithm [119], and hybrid metaheuristic [120]. The dynamic VRP with stochastic demand is much more complex because the possible scenarios are exponentially exploded with the number of retailers. For tackling the calculation challenge, sampling strategy generates scenarios by randomly realizing of stochastic parameter [121]. The other method is building the stochastic model of VRP with stochastic demand mostly by Markov decision process [122–124]. For solving the problems within reasonable time, approximate dynamic programming (ADP) is utilized to reduce the complexity and obtain the approximate results of state evaluation [125]. Some other researchers propose rollout algorithm to solve this problem such as Secomandi [126] and Goodson et al. [127]. Rollout algorithm obtains the approximate cost by optimal cost to go with one-step look-ahead policy, which is easy to implement. The challenge of dynamic VRP with stochastic demand is also faced by all IRP problem with stochastic demand, including IRPSDPD. In the end of this section, we will discuss our choice of tackling this challenge.

4.2.2 Inventory Routing Problem

The inventory routing problem is also a classic combinatorial optimization problem, which generates VRP by allowing unsatisfied or overfilled demand. Recently, IRP problem has attracted a lot of interests from academic. The variants of IRP are expanded by the previous work. In structural, the variant of IRP can be composed of one-period or multi-period, one or multiple vehicles, homogeneous or heterogeneous vehicle, maximum level or Order-Up-To inventory policy, etc. The determined IRP where the planner makes the decision based on certain demand information is a class of variation [128–131]. In some cases, the demand is given by forecast algorithm which transmits the stochastic problem into determined one [132]. However, Bertazzi et al. [133] argued that the ignorance of stochastic feature of demand in IRP results in a very bad performance of inventory and routing coordination. Different with the above models, this chapter treats the demand as the stochastic parameter with known distribution. IRP with stochastic also encounters the challenge of exponential explosion of states, which leads to a difficult and even intractable problem. Some researches solve this problem by utilizing ADP [134–136]. Other researches utilized rollout algorithm to estimate the value of solution, like Bertazzi et al. [133] or Bertazzi et al. [137]. However, the rollout problem need calculate a group of optimal solution of the determined counterpart by exact algorithm, which is also very time-consuming. Thus the rollout algorithm has to constrain the problem with less complexity like single-vehicle or Order-Up-To inventory policy. Similarly, scenario tree heuristic utilized by Hvattum et al. [138] has also too much calculation requirement, which hedges the application of the algorithm. For reducing the complexity of the problem, Nolz et al. [139] handled the stochastic demand in IRP by sampling the scenarios of demand pattern. For the same purposes, Yu et al. [140] built the stochastic IRP model with conditional constraint of service level. Different with them, the model proposed by this chapter reduces the complexity of the problem by considering the single-period IRP with stochastic demand. It is inspired by the reactive model and algorithm of Coelho et al. [141] and the work of Juan et al. [142]. In the former one, one retailer was added into itinerary only when its inventory level was lower than the inventory level. In the later one, the routing strategies and inventory cost were estimated by Monte Carlo simulation algorithm. Different from them, this chapter calculates the expected inventory cost with known distribution.

4.2.3 Crossing Field Literature

The inventory management in closed-loop supply chain is a vibrant research area. However, not many papers directly bridge the fields of inventory management in closed-loop supply chain and IRP. Among them, Liu and Chung [143] and Li et al. [144] just considered the situation of determined demand. Van Anholt et al. [145] built an IRP with simultaneous delivery and pickup based on the real case on automated teller machine. However, due to the special circumstance of their case, the capacity constraint of vehicle was not considered. For the same reason, their goods (cash) for delivery and pickup were homogenous, and the transmission between machines was allowed. The other exception in the crossing field is the work of Brinkmann et al. [146] in which they proposed the special cases of bike sharing in the area of IRP with simultaneous delivery and pickup. The most closed paper related to this chapter is the work of Soysal [147]. In his work, the reusable transportation items (like panel or container) have to be collected by the vehicle, which is different from our work. In our model, the reusable material can also be stored at retailers with specific holding costs. Meanwhile, his solution algorithm is based on the sampling scenarios of demands, which is similar to the work of Nolz [139]. As far as we know, there is no existing work about IRP with simultaneous delivery-pickup and purchasing decision in the environment of hybrid manufacturing. One part of the contribution this chapter chasing is filling the research gap in this area.

4.2.4 Our Contribution

Our work firstly bridges the field of inventory management in closed-loop supply chain and IRP problem. This job extends the research of inventory management in hybrid manufacturing mode. For the real-life hybrid manufacturing companies who have the need of coordination optimization in transportation and inventory, our work guides their operation by optimization the routing, transporting, and purchasing plan. Secondly, the simplification of model by considering single-period model and the expected cost of inventory are firstly utilized in the IRP with simultaneous delivery and pickup. Thirdly, the adaptive large neighborhood searching is improved with some improvements of dynamic routing optimization. Meanwhile, a high-performance heuristic algorithm is proposed for the subproblem of delivery and pickup plan. This part of work can guide the other researchers about neighborhood searching algorithm when applied on a similar problem.

4.3 Model Descriptions

The graphical presentation of model is given in Fig. 4.1. The solid black line is the process of forward logistics. The broken line is the backward logistics. The forward and backward logistics are shared by the vehicle. The manufacturer utilizes the hybrid manufacturing mode to provide products by new and recycling reusable materials. We make these assumptions for building this model. The recycled material is assumed as good as new one. The reusable material is collected by the retailers and transported to the manufacturer at the end of period. The back order is allowed in retailers. The process time of production is ignored. It is assumed that the production of products needs one unit of material (reusable or new). The quantity of products is constrained by the sum quantity of reusable materials and new ordering materials. The occurrence order of this model is defined as this:

1. The manufacturer recognizes the inventory information of himself and retailers.
2. The manufacturer makes the decision of purchasing new materials, delivery quantity of product, and the pickup quantity of recycling material.
3. The routes start and finish in an instant.
4. The retailers satisfy the demand of customer with the product in hand; the unsatisfied demand is backlogged.
5. The retailers accept the reusable material from customers.

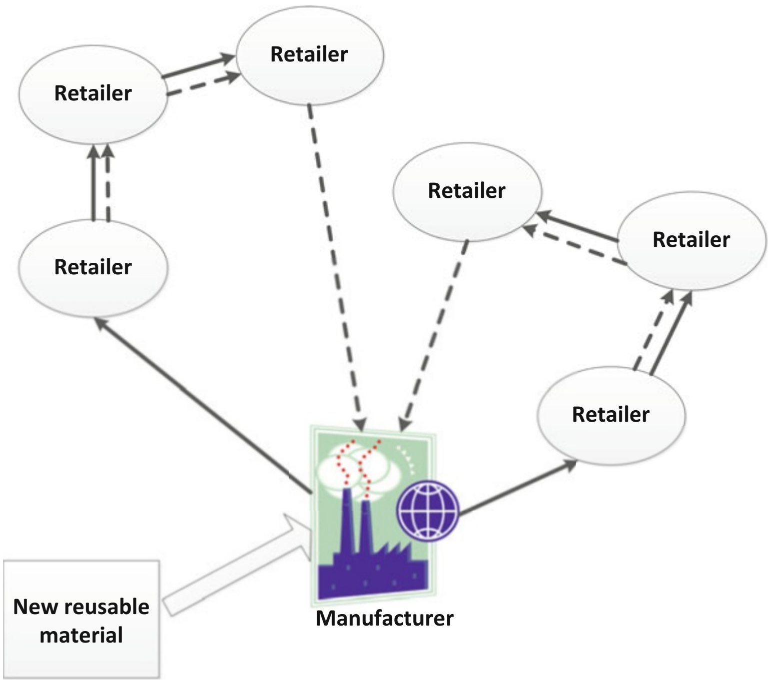


Fig. 4.1 The graphical presentation of model

6. The purchasing of new materials is satisfied at the end of one period and delivered to the manufacturer.
7. The period is ended.

4.3.1 *Model with One Retailer and Ignorance of Transportation*

Let's first consider a simplified supply chain model with infinite transportation capacity. This supply chain consists of one manufacturer and one retailer who provide signal-kind products. For the simplification of modeling, we only consider the inventory-related costs, which involved the cost of holding products, holding reusable materials, and punishment of lost sale, at the first step. Two inventory levels are considered in the model. S_I is the inventory level of products served in the retailer. S_φ is the inventory level of reusable materials served in the manufacturer. $S_{I+\varphi}$ is the total inventory level of products and reusable materials, where $S_{I+\varphi} = S_I + S_\varphi$. $S_{I+\varphi}$ is the total inventory level of products and reusable materials, where $S_{I+\varphi} = S_I + S_\varphi$. This chapter utilizes the Order-Up-To level policy or (s, s) policy to control the inventories of products and reusable materials. Under this policy, the manufacturer will deliver the products and purchase new reusable materials when the inventory levels are below some critical points. The expected cost of one period C_{S_I} is calculated below. $\rho(d_t)$ represents the distributed probability function of demand d_t in the future period t. h_p is the holding cost of products, and h_m is the holding cost of reusable materials. l is the unit penalty cost of lost sale.

$$C_{S_I} = \sum_{d=0}^{S_I} (h_p - h_m) \cdot (S_I - d) \cdot \rho(d) + \sum_{d=S_I+1}^{\infty} l \cdot (d - S_I) \cdot \rho(d)$$

The optimal inventory level ${S_I}^*$ of products maximizes the value of C_{S_I}. Then the expected cost of two periods $C_{S_{I+\varphi}}$ is calculated below. k is the extra inventory level when $d = r - k$.

$$C'_{S_{I+\varphi}} = \sum_{d_1=0}^{S_{I+\varphi}} \rho(d_1) \cdot \Big(h_p(S_I - d_1) + h_m(S_{I+\varphi} - S_I) \Big)$$

$$+ \sum_{d_1=S_{I+\varphi}+1}^{\infty} \rho(d_1) \cdot \Big(l(d_1 - S_I) + h_m(S_{I+\varphi} - S_I) \Big)$$

$$+\sum_{d_1=0}^{S_{I+\varphi}-S_I}\rho(d_1)\cdot\left(\sum_{d_2=0}^{S_I}\rho(d_2)\cdot\Big(h_p(S_I-d_2)+h_m(S_{I+\varphi}-S_I-d_1)\Big)\right.$$

$$\left.+\sum_{d_2=S_I+1}^{\infty}\rho(d_2)\cdot\Big(l(d_2-S_I)+h_m(S_{I+\varphi}-S_I-d_1)\Big)\right)$$

$$+\sum_{d_1=S_{I+\varphi}-S_I+1}^{\infty}\rho(d_1)\cdot\left(\sum_{d_1=0}^{S_{I+\varphi}-d_1}\rho(d_1)\cdot h_p(S_{I+\varphi}-d_1-d_2)\right.$$

$$\left.+\sum_{d_2=S_{I+\varphi}-d_1+1}^{\infty}\rho(d_2)\cdot l(d_1+d_2-S_{I+\varphi})\right)$$

$$C_{S_{I+\varphi}}=\Big(1-\sum_{d=0}^{r-1}\rho(d)\Big)\cdot C'_{S_{I+\varphi}}+\sum_{k=1}^{r}\rho(r-k)\cdot C'_{S_{I+\varphi+k}}$$

The optimal inventory level ${S_{I+\varphi}}^{*}$ of the sum of products and reusable materials will maximize the value of $C_{S_{I+\varphi}}$. The discussion and analysis of inventory levels can be seen in the previous work of authors.

4.3.2 Model with Multiretailers and the Consideration of Transportation

Single-period IRPSDPD can be defined as follows: let $G=(M,E)$ be a graph where M is the vertex set and E is the edge set. M consisted of M' and the depot point $\{0\}$. M' represents the set of retailers who are responsible for selling products and collecting reusable products. Depot point $\{0\}$ is the main base of manufacturer who produces the products by recycling or new materials. All transportation vehicles (like trucks) are assumed to start and finish their routes at the depot point. Each vehicle finishes its route and hand overs reusable materials at the end of period. Every retailer in M' has to face the stochastic demands of product and returns of reusable material. Meanwhile every retailer maintains the inventories of product and reusable materials with corresponding costs. The cost of transportation is associated with the edge of E. In this model, the cost of transportation is linearly dependent with the traveling distance, where $c_{ij}=c_{ji}$, and the triangle inequality is always satisfied. Each retailer can be visited by at most one vehicle. Each vehicle cannot visit the same retailer twice in one route. One unit of reusable material takes the same space as one unit of product does. Due to the scale effect in the manufacturer, we assume that the holding cost in manufacturer is less than the holding cost in any retailer. The maximum load of each route cannot exceed the capacity of vehicle. All vehicles are homogeneous. Besides these, all assumptions in the model with one retailer are retained.

When the multiretailers are involved in the model, the inventory control policy and transportation plan become more complicated. The Order-Up-To level of reusable materials is determined as ${S_{I+\varphi}}^{*} - {S_I}^{*}$ for guaranteeing the producing of products. The max-level inventory policy, which means the delivery quantity can be any positive value but the inventory level cannot exceed a maximum level, is applied to control the product inventory in the multiple retailers. The formulation for IRPSDP is given as below:

$$\text{Min} \sum_{i \in M'} \sum_{d_i=0}^{I_i} hp_i \cdot (I_i - d_i) \cdot \rho(d_i) + \sum_{i \in M'} \sum_{d_i=I_i+1}^{\infty} l_i \cdot (d_i - I_i) \cdot \rho(d_i) + \sum_{i \in M} hm_i \cdot \varphi_i + \sum_{i,j \in M} \sum_{k \in V} c_{ij} \cdot x_{ijk} + C_{new} \cdot n_0$$

$$I_i = I_{i0} + \sum_{k \in K} m_{ik} \qquad \forall i \in M' \tag{4.1}$$

$$\varphi_i = \varphi_{i0} + r_i - \sum_{k \in K} n_{ik} \qquad \forall i \in M' \tag{4.2}$$

$$I_i \leq U_i \qquad \forall i \in M' \tag{4.3}$$

$$\sum_{i \in M'} \sum_{k \in K} m_{ik} \leq \varphi_{00} \tag{4.4}$$

$$n_{ik} \leq z_{ik} \cdot \varphi_{i0} \qquad \forall i \in M' \forall k \in K \tag{4.5}$$

$$\varphi_0 = \varphi_{00} + \sum_{i \in M'} \sum_{k \in K} n_{ik} + n_0 - \sum_{i \in M'} \sum_{k \in K} m_{ik} \tag{4.6}$$

$$\varphi_0 \geq {S_{I+\varphi}}^{*} - {S_I}^{*} \tag{4.7}$$

$$\sum_{j \in M} \sum_{k \in V} y_{ijk} - \sum_{j \in M} \sum_{k \in V} y_{jik} = \sum_{k \in K} n_{ik} - \sum_{k \in K} m_{ik} \quad \forall i \in M' \tag{4.8}$$

$$\sum_{i \in M} y_{0ik} = \sum_{i \in M'} m_{ik} \qquad \forall k \in K \tag{4.9}$$

$$y_{ijk} \leq Q_k \qquad \forall i,j \in M \forall k \in K \tag{4.10}$$

$$\sum_{j \in M} x_{ijk} + \sum_{j \in M} x_{jik} = 2 z_{ik} \qquad \forall i \in M \forall k \in K \tag{4.11}$$

$$\sum_{k \in K} z_{ik} \leq 1 \qquad \forall i \in M' \tag{4.12}$$

$$\sum_{k \in K} \sum_{i \in S} \sum_{j \in S} x_{ijk} \leq |S| - 1 \qquad \forall S \subseteq M' \tag{4.13}$$

$$x_{ijk}, z_{ik} \, \epsilon \{0, 1\} \qquad \forall i,j \in M \forall k \in K \tag{4.14}$$

$$m_i k, n_i k, n_0, y_i jk \in Z^{+} \{0\,1\,2\ldots\ldots\} \qquad \forall i,j \in M \forall k \in K \tag{4.15}$$

The objective of model is to minimize the sum cost of expected holding cost of products, expected punishing cost of lost sales, holding cost of reusable materials, traveling cost, and purchasing cost of new materials. Constraints (4.1) and (4.2) define the inventory levels of products and reusable materials in retailers, respectively. Constraint (4.3) confines the maximum value of inventory level. The sum of products delivered to the retailers should be no more than the quantity of reusable materials in the depot (Constraint (4.4)). The pickup of reusable materials in one retailer should be no more than the initial inventory level if one vehicle visits it (Constraint (4.5)). In Constraint 4.6, the material flow balance of reusable materials in the depot is depicted. The inventory level of reusable materials should be no less than the determined Order-Up-To level (Constraint (4.7)). Constraints (4.8 and 4.9) are flow conservation equations. Constraint (4.10) guarantees the vehicle load does not exceed the vehicle capacity. Constraint (4.11) ensures the consecutiveness of routes. z_{0k} is defined to 1 for every vehicle. Constraint (4.12) imposes that one retailer can at most be visited by one vehicle. Constraint (4.13) is subtour elimination constraint. Constraints (4.14 and 4.15) define the types of decision variables.

For solving the multiple-period aspect of this problem, the model needs to implement the above single-period model periodically by updating the parameters I_{i0} with I_i, φ_{i0} with φ_i, and φ_{00} with φ_0. Due to the independence of inventory Order-Up-To level and time-varying parameters, the Order-Up-To level of reusable materials would not change during the periods.

4.4 The Proposed Solution Method

We proposed to solve IRPSDPD with adaptive large neighborhood search (ALNS) heuristic, which is firstly introduced by Pisinger and Ropke [148]. ALNS is based on large neighborhood search (LNS) brought by Shaw [149] to solve capacitated VRP. In the work of Shaw [149], the initial routing plan is destroyed and repaired repeatedly to improve the cost. Many researchers solved VRP and its variation by LNS, such as Bent and Hentenryck [150], Li et al. [144], Goel and Gruhn [151], Hong [152], Drexl [153], and Lee et al. [154]. As for solving IRP, Goel et al. [155], Song and Furman [156], and Liu et al. [157] utilized LNS as the solution method. When compared with LNS, ALNS randomly selects one among many kinds of neighborhood structures according to their performance in a phase of searching histories. ALNS has successfully tackled a variety of VRP, such as VRP with backhauls [148], capacitated VRP with stochastic demands and time windows [158], vehicle routing problem with stochastic demands and split deliveries [159], VRP with multiple routes for one vehicle in one operation [160], and VRP with stochastic demand and weight-related cost [161]. As an extension of VRP, ALNS is also applied to solve the variations of IRP, such as IRP with transshipment between retailers [141], selective and periodic IRP [162], IRP with stochastic demand [139], and short sea IRP with multi-product [163]. In this chapter, we utilize ALNS with two modifications. At first, two novel kinds of neighborhood structure are created for improving the routes besides several standard neighborhood structures appearing in other researches. Secondly, a greedy insertion algorithm in perturbation action for improving the efficiency of load is designed. Meanwhile, a heuristic algorithm is designed for solving the subproblem of delivery and pickup plan. The detail structure of ALNS is described below.

4.4.1 The Main Structure of Algorithm

The proposed algorithm is constructed in Algorithm 1. It starts from an initial solution s_0. Iteratively, the algorithm improves the current solution s_c with selected neighborhood structure and gets the temporary solution s_t. If s_t satisfies the acceptance condition, it replaces s_c. If otherwise, s_t is abandoned. If the fitness value of s_t is less than the fitness value of overall best solution s_b, s_t replaces s_b as the new overall best solution. If s_c cannot be improved in τ times of iterations, a perturbation action is chosen to be applied on the s_c for diversifying the solution. Note that the neighborhood and perturbation action are both selected by adaptive mechanism. When the termination condition is satisfied, the algorithm stops and returns s_b as the optimal solution.

Algorithm 1 The Proposed Algorithm (ALNS)

Generating the initial solution $s_0 s_b \leftarrow s_c \leftarrow s_0$
Do while the termination condition is not satisfied
  If the s_c is improved in $iter1$ times of iterations then
    Select a neighborhood structure by adaptive selection mechanism
    $s_t \leftarrow$ improve s_c with the selected neighborhood structure
    If s_t satisfies the acceptance condition then
      $s_c \leftarrow s_t$
    End if
    If fitness $(s_t) < \text{fitness}(s_b)$
      $s_b \leftarrow s_t$
    End if
  Else
    Select a perturbation action by adaptive selection mechanism
    $s_c \leftarrow$ improve s_c with the selected perturbation action
  End if
Loop
Return s_b

The initial solution is constructed by the cost-saving heuristic algorithm proposed by Clark and Wright [164]. The cost-saving algorithm maintains a table of distance saving values, denoted as CV_{ij}. $CV_{ij} = c_{0i} + c_{0j} - c_{ij}$. Then it orders CV_{ij} in nonincreasing order. Link i and j with the biggest CV_{ij} if possible, and then delete CV_{ij}. Cost-saving algorithm is purely designed for optimizing the route plan.

4.4.2 Improvement Neighborhood Structure

During the algorithm, two groups of neighborhood structure are utilized for improving routes which are inter-route and intra-route. Nine traditional neighborhood structures are depicted in Fig. 4.2. They are:

Random swap: Random swap is conducted by swapping two random retailers in the same route. Shown in Fig. 4.2b, retailers (2) and (3) are selected randomly and swapped in the same route. Its computational complexity is $O(n^2)$ according that n represents the amount of retailers.

Add: Add is conducted by inserting an unconnected retailer into a random route. Shown in Fig. 4.2c, retailers (5) are added in the route of "(1)—(2)—(3)—(4)." Note that this neighborhood structure cannot be applied when there is no unconnected retailer. Its computational complexity is $O(n^2)$.

Drop: Drop is conducted by deleting a connected retailer from its route. Shown in Fig. 4.2d, retailer (4) is deleting from its route and becomes an unconnected retailer. Its computational complexity is O(n).

Segment Revise: Segment revise is conducted by revising the sequence of a segment in the same route. Shown in Fig. 4.2e, the sequence of "(1)—(2)—(3)" is revised to "(3)—(2)—(1)." Its computational complexity is $O(n^2)$.

Shift 0–1: Shift 0–1 is conducted by dropping a retailer from its original route and inserting it into a random position of another route. Shown in Fig. 4.2g, retailer (4) is shifted to the other route after retailer (3). Its computational complexity is $O(n^2)$.

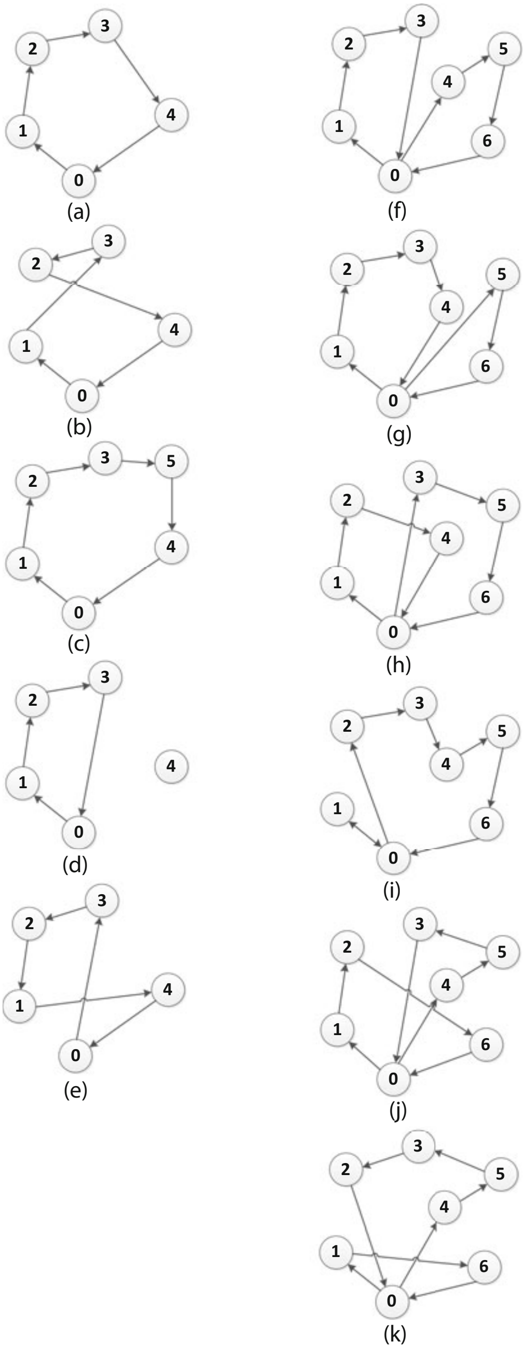
Shift 1–1: Shift 1–1 is conducted by swapping the positions of two retailers at different routes. Shown in Fig. 4.2h, the position of retailers (3) and (4) is swapped. Its computational complexity is $O(n^2)$.

Shift 0–2: Shift 0–2 is conducted by dropping two consecutive retailers from their original route and inserting then into a random position of another route. Shown in Fig. 4.2i, retailers (2) and (3) are shifted to the other route. Its computational complexity is $O(n^3)$.

Shift 2–2: Shift 2–2 is conducted by swapping the positions of two groups of consecutive retailers at two different routes. Shown in Fig. 4.2j, the positions of retailers (4)–(5) and retailers (1)–(2) are swapped. Its computational complexity is also $O(n^2)$.

Exchange: *Exchange* is conducted by breaking two routes at random points and cross-linking the rest parts of the routes. Shown in Fig. 4.2k, two routes are broken after retailers (1) and (5), respectively, and cross-link the rest of routes. Its computational complexity is also $O(n^2)$.

Fig. 4.2 The examples of neighborhood structures



Among these nine neighborhoods, *random swap, add, drop,* and *segment revise* are intra-route. *Shift 0–1, Shift 1–1, Shift 0–2, Shift 2–2,* and *exchange* are inter-route. Besides these, two novel structures are proposed based the special feature in IRPSDPD. Here we initially introduce Lemma 1 for analyzing the special feature in IRPSDPD.

Lemma 1 *If swapping retailer i and j in the same route, the load of vehicle during the arcs between i and j increases (when* $m_i + n_j - m_j - n_i > 0$*) or decreases (when* $m_i + n_j - m_j - n_i < 0$*) by at most* $|m_i + n_j - m_j - n_i|$.

Proof: Assuming there is no limitation of vehicle load between i and j, the delivery and pickup quantity, m_i, n_i, m_j, and n_j, is unchanged. By deleting retailer i, the load of vehicle during the arcs between i and j increases by n_i. By deleting retailer j, the load of vehicle during the arcs between i and j decreases by m_j. By adding retailer i into the original position of j, the load of vehicle during the arcs between i and j increases by m_i. By adding retailer j into the original position of i, the load of vehicle during the arcs between i and j increases by n_j.

Assuming there is the limitation of vehicle load, denoted as Q, we define one arc between i and j with load L. If $L < Q$ and $m_i + n_j - m_j - n_i + L < Q$, the constraint of vehicle load does not apply. *Lemma 1* still stands.

If $L < Q$ and $m_i + n_j - m_j - n_i + L \geq Q$, the increasing load is less than $|m_i + n_j - m_j - n_i|$ due to that $L \leq Q$ always stand for any mutation.

If $L \leq Q$ and $m_i + n_j - m_j - n_i < 0$, i, j or other retailers in the route will increase their delivery and pickup quantity due to the decreasing trend of vehicle load. The decreasing load is no more than $|m_i + n_j - m_j - n_i|$.

If $L = Q$ and $m_i + n_j - m_j - n_i > 0$, the increasing load is 0. ∎

Lemma 1 provides the upper bound of the load change when swapping retailers and indicates the condition of decreasing vehicle load. It is obvious that swapping two retailers which may increase the vehicle load is not beneficial for improving the efficiency. Meanwhile the vehicle load in one route is the constraint for its capacity only when it contains arcs with full capacity. Thus the neighborhood structure *load-swap* is proposed according to Lemma 1.

Load-swap: Load-swap chooses a route which contains arcs with full load and swaps two retailers i and j which locate at the both sides of the arc with full load, satisfy $m_i + n_j - m_j - n_i < 0$, and maximize $m_j + n_i - m_i - n_j$. Its computational complexity is $O(n^2)$.

Load-swap just improves the load efficiency by decreasing the loads of tight arcs. However, it does not achieve the optimal configuration for minimizing the load of route. Here we introduce Proposition 1 for the optimal configuration in this circumstance.

Proposition 1 *For minimizing the load of vehicle, the optimal schedule can be obtained after placing all retailer in nonincreasing order of* $m_i - n_i$.

Proof If placing all retailer in nonincreasing order of $m_i - n_i$ in one route, $m_i + n_j - m_j - n_i < 0$ always stand for any i who is prior to j.

Utilizing *Lemma 1*, the load of vehicle in the route cannot increase if the condition is satisfied. ∎

Proposition 1 is consistent with intuition. The vehicle should visit the retailers with the most delivery and the least pickup in the first place. Then it should visit the retailer which increases the least load during the route. Based on Proposition 1, we proposed *segment-reorder* for obtaining the optimal configuration.

Segment-Reorder: Segment-reorder chooses a segment which contains the arcs with full load and reorders the retailers in nonincreasing order of $m_i - n_i$. Its computational complexity is $O(nlogn)$.

Load-swap can be conducted under the condition that the solution includes at least one arc which carries full load ($y_{ijk} = Q_k$), and this arc is not from or in the manufacturer (i *and* $j \neq 0$). *Segment-reorder* can be conducted under the condition that the solution includes the arcs which carry full load. In the case of these neighborhood structures cannot be applied, ALNS skips this iteration.

Load-swap and *segment-reorder* are designed to improve the load efficiency when the vehicle capacity hinders the delivery and pickup decision. However, these two neighborhood structure do not consider the route transportation efficiency. The overall optimal solution is the trade-off of both load efficiency and transportation efficiency. Thus all these neighborhood structures are mixed and used in ALNS. The perturbation actions are introduced in the next section.

4.4.3 Perturbation Mechanism

The above neighborhood structure can only cover a small scope of searching space. Thus when the algorithm is trapped into local optima, we need to diversify the solution by more drastic changes of solution. ALNS utilizes broken-and-insertion actions to perturb the local optimal when the current solution has not been improved or replaced during a period of iterations. The broken actions disconnect a group of the connected retailers from the route plan of the current solution, enumerated as *random*, *relatedness*, *long-arc broken*, *and tight-load broken*. *Random* broken action selects a group of connected retailers randomly for disconnecting. *Relatedness* broken action selects one retailer and a random number of the most closed retailers from it. *Long-arc broken* action selects two consecutive retailers which form the longest arc in each route. *Tight-load broken* action will be introduced later. The next step is to insert the disconnected retailers into the route plan back. We firstly propose *distance greedy insertion* heuristic algorithm as insertion action whose pseudo-code is shown in Algorithm 2.

Algorithm 2 Distance Greedy Insertion Heuristic Algorithm

```
For iϵset of unconnected retailers
  p → +⋈
  For kϵset of routes
    For rϵk
```

(continued)

`If` $(dc(r, i, r+1) > th_{dgi})$
`Abandon` r
`End if`
`If` $(dc(r, i, r+1) < p)$
$p \to ds(r, i, r+1)\ r^* \to r\ k^* \to k$
`End if`
`End`
`End`
`If` $(p \neq +\bowtie)$
`Insert` i `into` r^*, r^*+1 `in` k^*
`End if`
`End`

In Algorithm 2, *distance greedy insertion* heuristic algorithm iteratively selects an unconnected retailer, denoted as i. Then it searches all the possible insertion in the route plan for minimizing the distance cost $dc(^*, i, ^*)$. $dc(^*, i, ^*)$ is calculated by the extra distance by inserting i into the route. If $dc(^*, i, ^*)$ is bigger than a given threshold th_{dgi}, i cannot be inserted. In the simulation, this threshold is given by a quarter of diagonal distance of the smallest rectangle that contains every retailer. Finally, the algorithm inserts i into the optimal position if it has been found.

Distance greedy heuristic algorithm is assumed to achieve the optimal transportation plan. However, it is not reasonable when the loads of some vehicles are tight. Here we introduce Lemma 2 and Proposition 2 for explaining the effect of inserting retailer on vehicle load.

Lemma 2 *If one retailer increases one unit of delivery and others do not increase any delivery or pickup, then the load of routes before this retailer increases at most one unit; if one retailer increases one unit of pickup and others do not increase any delivery or pickup, then the load of routes after this retailer increases at most one unit.*

Proof Note that the load of route before one retailer always contains the delivery of this retailer; the load of routes after one retailer always contains the pickup of this retailer.

We define the load of any routes before retailer i as L_{bi}. Assumed one retailer increases one unit of delivery and others do not increase any delivery or pickup. We define the new load of any routes before retailer i as $L_{bi}^{'}$.

$L_{bi}^{'} < L_{bi}$ is controversial to the statement that addition delivery is contained in the load of routes before one retailer.

$L_{bi}^{'} \geq L_{bi} + 2$ is controversial to the assumption that others do not increase any delivery or pickup.

Thus $L_{bi} + 1 \geq L_{bi}^{'} \geq L_{bi}$.

Define the load of any routes after retailer i as L_{ai}. Assumed one retailer increases one unit of pickup and others do not increase any delivery or pickup.

$L_{ai}^{'} < L_{ai}$ is controversial to the statement that addition pickup is contained in the load of routes after one retailer.

$L_{ai}^{'} - 2 \geq L_{ai}$ is controversial to the assumption that others do not increases any delivery or pickup.

Thus $L_{ai} + 1 \geq L_{ai}^{'} \geq L_{ai}$. ∎

Proposition 2 *If inserting one retailer into a route, then the load of route before this retailer increases by at most* $U_i - I_{i0}$*, and the load of route after this retailer increases by at most* φ_{i0}.

Proof Assuming there is a retailer in the position where the retailer will be inserted, its delivery and pickup quantities are 0.

If there is no violation of vehicle load constraint, the load of route before this retailer increases m_{ik}, and the load of route after this retailer increases by n_{ik} by utilizing *Lemma 2*.

If there is the violation of vehicle load constraint, call it L_{arc}.

$L_{arc} + m_{ik} > Q_k$ if the arc is prior to the inserting retailer i.

$L_{arc} + n_{ik} > Q_k$ if the arc is not prior to the inserting retailer i.

Therefore the load of route before this retailer increases by m_{ik} at most, and the load of route after this retailer increases by n_{ik} at most.

Note that for one retailer, $m_{ik} \leq U_i - I_{i0}$ and $n_{ik} \leq \varphi_{i0}$. ∎

Based on Proposition 2, we propose *load greedy insertion* heuristic algorithm as another insertion action whose pseudo-code is shown in Algorithm 3.

Algorithm 3 Load Greedy Insertion Heuristic Algorithm

For $i \epsilon$ *set of unconnected retailers*
  $p \rightarrow +\bowtie$
  For $k \epsilon$ *set of routes*
    If k contains arcs with full load
      Abandon k
    End if
    For $r \epsilon k$
      If $(maxaddload(r, i, r+1)/(Q_k - maxload(k)) > th_{lgi})$
      Abandon r
    End if
    If $(maxaddload(r, i, r+1)/(Q_k - maxload(k)) < p)$
      $p \rightarrow maxaddload(r, i, r+1)$ $r^* \rightarrow r$ $k^* \rightarrow k$
      End if
    End
  End
  If $(p \neq +\bowtie)$
    Insert i into r^*, r^*+1 in k^*
  End if
End

Two insertion heuristic algorithms are similar in structure. As shown in Algorithm 3, *load greedy insertion* heuristic algorithm iteratively selects an unconnected retailer, denoted as i. Then it searches all possible insertion in the route plan for minimizing the ratio between the added load caused by insertion, denoted as $maxaddload(r, i, r+1)$ and the minimum available capacity. $maxaddload(r, i, r+1)$ is calculated by Proposition 2. Note that if the route contains the arcs with full load, it cannot be utilized to insertion. The upper-bound threshold of ratio is given.

Similar with Lemma 2 and Proposition 2, we introduce Lemma 3 and Proposition 3 to discuss the effect of removing one retailer from a route.

Lemma 3 *If one retailer decreases one unit of delivery and others do not decrease any delivery or pickup, then the load of routes before this retailer decreases at most one unit; if one retailer increases one unit of pickup, then the load of routes after this retailer decreases at most one unit.*

Proof Similar with *Lemma 2*. ∎

Proposition 3 *If removing one retailer from a route, the load of route before this retailer decreases at most* $\sum_{k \in K} m_{ik}$ *, and the load of route after this retailer decreases at most* $\sum_{k \in K} n_{ik}$.

Proof Similar with *Proposition 2*. ∎

Based on Proposition 3, we construct *tight-load broken* action. *Tight-load broken* action selects an arc with the maximum load in the route. Then it disconnects the retailer which can decrease the load of this arc in the most. *Tight-load broken* action is repeated until the amount of broken retailer reaches a certain level. An example of *tight-load broken* is shown in Fig. 4.3. In this case, the maximum vehicle load of this route occurs during arc (2, 3). The retailer 2 is disconnected because deleting it from the route can decrease the load during arc (2, 3) by 15 units which is the most.

With the different combination of broken action and insertion algorithm, many perturbation methods are constructed. In the next section, the selection mechanism is introduced for selecting neighborhood structures and perturbation methods.

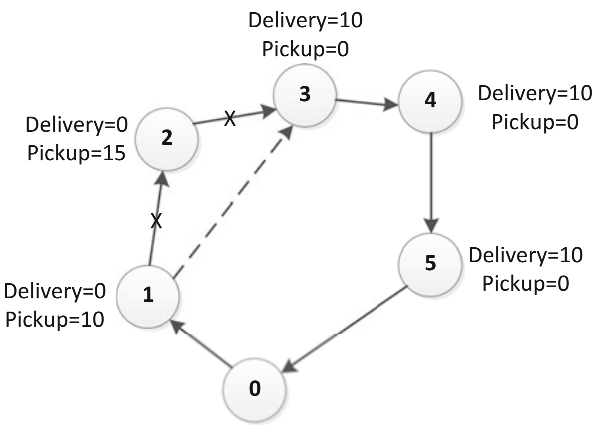


Fig. 4.3 The example of *tight-load broken*

4.4.4 Adaptive Selection Mechanism

Due to the property of the problem and the character of solution, the outcome of neighborhood structures and perturbation methods is different in situation and different during the searching. Normally, we assumed that the mutation method has more potential to improve the solution if it performs better than others in the searching history. We adopt adaptive selection mechanism to encourage more potential mutations. The selection mechanism utilizes a score system to trace their performances. Through the scores they take in a certain period, the possibility of selecting mutation is updated. In every cycle, the neighborhood structure or perturbation method is selected by roulette wheel. This method is first proposed by Ropke et al. [165].

In the score system, the mutation can add its score in three conditions, θ_1 for the new overall best solution, θ_2 for the better solution than current, and θ_3 for the new solution which has never been searched before. Normally, $\theta_1 > \theta_2 > \theta_3$. During the searching, θ_3 is increasing in the searching because the new solution is more valuable with the expansion of searching space. There are three kinds of the selective scores, for neighborhood structure, broken action in perturbation method, and insertion action in perturbation method, respectively. The selecting possibility is determined by ratio between its weight and total weight, namely, ${}^{w_{z*}}\!/\!\sum_{t=1}^{t} {}^{w_{t*}}$ (* respects for the types of mutation, including neighborhood structure, broken action, and insertion action).

At the beginning of the algorithm, the weight values are same for each mutation. In every period of the searching of the given length *iter*2, the weighted values are updated with the following equation:

$$w_{z*}{}^{p} = (1 - \mu) w_{z*}{}^{p-1} + \mu \frac{\gamma_{z*}}{\sigma_{z*}}$$

where $w_{z*}{}^{p-1}$ is the weight value in the last period, γ_{z*} is the total score mutation z got in the last period, σ_{z*} represents the total times of applying mutation z got in the last period, and $\mu \in (0, 1)$ indicate the learning rate. The learning rate μ controls the speed of weight value changing during the algorithm.

4.4.5 Subproblem of Delivery and Pickup Plan

The fitness value of solution with the delivery and pickup plan, plus the routing plan and the purchasing decision, is evaluated by the objective value. However, the above ALNS can only provide the routing plan. With one specific routing, the original problem becomes a delivery and pickup problem which determined m_{ik} and n_{ik} according to the routing plan. This subproblem must be solved in the iteration where a new routing plan is founded. In ALNS, we design a heuristic method mixed dynamic programming and greedy algorithm to solve this delivery and pickup problem.

In the first step, we compose the optimal pickup plan with no delivery job. It is obvious that the pickup problem can be divided by vehicle, and it is a knapsack problem for each vehicle. If the sum of the remaining material is less than the vehicle capacity, namely, $\varphi_{i0} \cdot z_{ik} \leq Q_k$, n_{ik} is equal to φ_{i0} due to the assumption that the holding cost in manufacturer is less than the holding cost in any retailer. Otherwise, we utilize the dynamic programming to obtain the optimal plan. Define that state $f_k(i, n_{ik}, L_k)$ denotes the optimal cost when vehicle k pick ups n_{ik} units of reusable material in retailer i with the total load L_k. The state can be update by

$$f_k(i+1, n_{i+1k}, L_k) = min_{n_{ik}} f_k(i, n_{ik}, L_k - n_{i+1k}) + n_{i+1k} \cdot hm_{i+1} \qquad \forall k, n_{i+1k}, L_k$$

$$f_k(0, n_{ik}, L_k) = 0 \qquad \forall k, n_{ik}, L_k$$

$$f_k(i, n_{ik}, L_k) = 0 \qquad \text{if } L_k > Q_k \text{ or } n_{ik} > \varphi_{i0}$$

where i is iterated by the sequence of vehicle visiting. After the updating, the optimal cost $f_k{}^*(i, n_{ik}, L_k)$ is equal to $f_k(i_{last}, n_{i_{last}k}, Q_k)$. The optimal plan is obtained in inverted order:

$$n^*{}_{i_{last}k} = \text{arg}min_{n_{i_{last}k}} f_k(i_{last}, n_{i_{last}k}, Q_k)$$

$$L^*{}_k = Q_k - n^*{}_{i_{last}k}$$

$$n^*{}_{i_{last-1}k} = \text{arg}min_{n_{i_{last-1}k}} f_k(i_{last-1}, n_{i_{last-1}k}, L^*{}_k)$$

$$\ldots\ldots$$

$$n^*{}_{ik} = \text{arg}min_{n_{ik}} f_k{}^*(i, n_{ik}, L^*{}_k)$$

$$L^*{}_k = L^*{}_k - n^*{}_{i+1k}.$$

$$\ldots\ldots$$

The complexity of dynamic programming is determined by the updating process. The total number of state is $O(C_1C_2nk)$ where n is for the number of retailers and k for the number of vehicles. The complexity of updating one state is $O(C_1)$ where C_1 is the amount of maximum φ_{i0} and C_2 is equal to vehicle capacity Q_k. Thus the total complexity is $O(nk)$.

In the next step, the delivery plan is inserted into the optimal pickup plan by greedy criterion. Define that $Invc_i(m_{ik})$ denotes the inventory cost when delivering m_{ik} units of products to retailer i. Define that $Decost_i$ is the decreasing cost when adding one unit of delivery to retailer i:

$$
Decost_i = \begin{cases} 0 \\ \text{if} \sum \mathrm{m_{jk}} > \mathrm{Q_k} (\mathrm{j}\ \textit{belongs to the same route with}\ \mathrm{i}) \\ Invc_i(m_{ik}) - Invc_i(m_{ik}+1) + hm_0 \\ \textit{if adding one unit of delivery to retailer i does not violates the capacity constraint} \\ Invc_i(m_{ik}) - Invc_i(m_{ik}+1) + 2 \cdot hm_0 - min_j\, hm_j\ (k\ \textit{visits j before i in the route and}\ n_{jk} > 0) \\ \textit{otherwise} \end{cases},
$$

and $Decost_i = Decost_i - c$, *if* $\varphi_{00} + \sum\limits_{i \in M'} \sum\limits_{k \in K} n_{ik} - \sum\limits_{i \in M'} \sum\limits_{k \in K} m_{ik}$ is no more than the inventory level.

In the first condition, the delivery plan is full in this route; thus $Decost_i$ is 0. In the second condition, $Decost_i$ is the sum of decreasing cost in product inventory and the decreasing cost of holding one unit of reusable material in manufacturer. In the third condition, we have to shrink one unit of pickup before i if adding one unit of delivery, $Decost_i$, needs to be added with one unit of holding cost in manufacturer and minus with one unit minimum holding cost in retailers who are prior to i. Whenever adding one unit of delivery causes one unit of new ordering material, $Decost_i$ decreases by new purchasing cost c.

The greedy algorithm begins with the empty delivery plan. During the iteration, $Decost_i$ is updated. If all $Decost_i$ are no more than 0, the iteration is stopped. Otherwise, add one unit of delivery to the retailers with the biggest $Decost_i$. Meanwhile, decrease one unit of pickup if the capacity constraint is violated. The iteration is stopped when the source of reusable material in manufacturer is exhausted. The calculating complexity is $O(C_3 n^2)$ where C_3 is for the smaller value between φ_{00} and $\sum\limits_{k \in K} Q_k$. The pseudo-code is shown in Algorithm 4. The performance of this heuristic algorithm is shown by comparing with CPLEX software in Sect. 4.5.6.

Algorithm 4 Heuristic Algorithm for Delivery and Pickup Subproblem

Utilizes dynamic programming to obtain the optimal pickup plan $\overline{n_{ik}}$
While (φ_{00} is not zero)
Update $Decost_i$
If $\mathrm{Max}(Decost_i) \leq 0$
Return $\overline{n_{ik}}$ and $\overline{m_{ik}}$
End if
$m_{ik}{+}{+}$ with $\mathrm{Max}(Decost_i)$
If the capacity constraint is violated
$n_{jk}{-}{-}$ with $\min_j hm_j$ among j who k visits prior to i in the route and $n_{jk} > 0$
End if
$\varphi_{00}{-}{-}$
Loop
Return $\overline{n_{ik}}$ and $\overline{m_{ik}}$

4.4.6 Acceptance and Termination Condition

ALNS handles a new solution in a simulated annealing fashion. If the new solution $S^{'}$ precedes the current solution S, $S^{'}$ is accepted; if $S^{'}$ does not precede S, $S^{'}$ is accepted with a possibility $e^{-(fittness(S')-fittness(S))/T}$ where T is the current temperature. Temperature T is cooling in the rate of τ. This mechanism broadens the searching space by accepting the nondominated solution.

ALNS is terminated when T is cooled to a certain temperature, which means it is ended within a specific number of iterations $iter3$.

4.5 Computational Results

The algorithm is coded in Visual Studio 2010 by C# language. It is running on a laptop computer with an Intel Core i5-6300HQ 3.2GHz CPU, 8GB RAM, and Windows 10. CPLEX is applied by IBM ILOG CPLEX Optimization Studio 12.5.1.0. version. In the following sections, we introduce the construction of instances and parameter settings.

4.5.1 Construction of Instances

The instances are constructed based on 27 public-capacitated VRP instances, from Set A by Augerat et al. [166]. The coordinates of nodes and the capacity of vehicle are same. The demands in simulation follow Poisson distribution with expectation values λ_i equal to the defined demands in Augerat et al. [166]. The characters of instances are shown in Table 4.1. For simplification of the simulation, φ_{00} and $S_{I+\varphi}{}^{*}-S_{I}{}^{*}$ are determined as $\sum\limits_{k\in K} Q_k$. For each instance, we construct ten cases with the stochastic settings described in Table 4.2. Other parameters are defined as $hm_0 = 0.4$ and $C_{new} = 15.0$. The distance cost c_{ij} is defined as Euclidean distance, equal to $2.0 \cdot \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$.

4.5.2 Algorithm Setting

The parameter settings in proposed solution are determined for the trade-off between calculation efficiency and solution quality. There are three kinds of parameters: the parameters involved in the adaptive selection mechanism, including the scores θ_1, θ_2, θ_3, the original weighted values $w_{z*}{}^{0}$, and the learning rate μ; the parameters of perturbation mechanism, including the threshold in *distance*

Table 4.1 The characters of instances

Instance no.	Retailers no.	Vehicles no.	Vehicle capacity
1	31	5	100
2	32	5	100
3	32	6	100
4	33	5	100
5	35	5	100
6	36	5	100
7	36	6	100
8	37	5	100
9	38	5	100
10	38	6	100
11	43	7	100
12	44	6	100
13	44	7	100
14	45	7	100
15	47	7	100
16	52	7	100
17	53	7	100
18	54	9	100
19	59	9	100
20	60	9	100
21	61	8	100
22	62	9	100
23	62	10	100
24	63	9	100
25	64	9	100
26	68	9	100
27	80	10	100

Table 4.2 Stochastic parameter settings in instances

Parameter	Distribution
I_{i0}	$U[-5, 5]$
φ_{i0}	$U\left[0, \left\lfloor \frac{4}{3} \cdot \frac{\sum_{i \in M'} \lambda_i}{\lvert M' \rvert} \right\rfloor\right]$
hp_i	$U[1.0,2.0]$
hm_i	$U[0.5,1.0]$
l_i	$U[15.0,30.0]$

greedy insertion th_{dgi} and the threshold in *load greedy insertion* th_{lgi}; and the parameters of main algorithms, including the iteration condition of applying perturbation $iter1$, the length of updating weighted values $iter2$, the total iteration times $iter3$, the initial temperature $T_{initial}$, and its cooling rate τ. The final value of

Table 4.3 The parameter setting for algorithm

Parameter	Value
θ_1	2.0
θ_2	1.1
θ_3	$1.0 \cdot \frac{\text{current iteration}}{iter3}$
${w_{z*}}^0$	1.0 for all z^*
μ	0.5
th_{dgi}	$0.25 \cdot \sqrt{(x_{max} - x_{min})^2 + (y_{max} - y_{min})^2}$
th_{lgi}	1.5
$iter1$	$\lvert M' \rvert$
$iter2$	100
$iter3$	$\begin{cases} 6000 & \lvert M \rvert \le 45 \\ 7500 & 45 < \lvert M \rvert \le 60 \\ 9000 & 60 < \lvert M \rvert \le 75 \\ 10500 & 75 < \lvert M \rvert \end{cases}$

parameter settings is shown in Table 4.3. $|M|$ denotes the number of total nodes including manufacturer and retailers.

4.5.3 Lower Bound

Lower bound is the level which is less than the optimal result of the optimization programming. In order to examine the performance of algorithm in this NP-hard problem, we utilize the calculating result from CPLEX as the lower bound. The gap between the lower bound and the objective value of overall best solution provided by the algorithm shows the maximum space for further improvement. We relax the original problem in two ways. Firstly, the subtour elimination constraints for more than four nodes are relaxed. Namely, constraint (4.13) is revised to

$$\sum_{k \in K} \sum_{i \in S} \sum_{j \in S} x_{ijk} \le |S| - 1 \qquad \forall S \subseteq M' \; and \; |S| \le 3 \tag{4.13$'$}$$

Therefore, the subtour including no less than four nodes is admitted as lower bound. The subtour caused by this relaxation also relaxes the constraint of vehicle capacity in constraint (4.8) and (4.9). For enforcing the constraint of vehicle capacity, we add an additive constraint (4.9b) as a supplement:

$$\sum_{i \in M} y_{i0k} = \sum_{i \in M'} n_{ik} \qquad \forall k \in K \tag{4.9b}$$

The other relaxation is that we use the lower bound created by CPLEX in limited calculating time as the lower bound if the optimal result cannot be obtained. This relaxation improves the calculating efficiency of lower bound. The calculating time limitation is set as 300 s. During the simulation, no optimal result is obtained in this time limitation. At last, the gap is calculated below:

$$gap = \frac{fittness(overall\ best\ solution) - Lower\ Bound}{fittness(overall\ best\ solution)} \times 100\%$$

4.5.4 Upper Bound

In the simulation, we propose a new heuristic algorithm as the upper bound of the problem. Different with the flexible delivery policy in the proposed algorithm, the delivery quantity is fixed to the optimal inventory level minus the current product quantity. Thus, this policy can be called as Order-Up-To policy. The pickup decision is determined to pick up as much as possible, namely, the minimum value of the remaining capacity and reusable material inventory. The routing plan and the purchasing decision are also made by ALNS. Due to the character of Order-Up-To policy, the routing plan after mutation is not always feasible. Therefore, the initial routing is modified with the consideration of delivery quantity constraint. Meanwhile, a penalty factor π is added if the routing plan is infeasible. In the upper-bound heuristic, $fittness(S) = fittness'(S) \cdot \pi^u$ where $fittness'(S)$ is the fitness value regardless violation and u is the times of violation. In the simulation, π is given to 0.3.

The Order-Up-To policy actually adds the constraint of the problem. Thus the objective value with Order-Up-To policy is no more than the optimal value obtained by the proposed algorithm. However, the calculation complexity of delivery and pickup subproblem in Order-Up-To policy is constant rather than $O(n^2)$ in proposed algorithm. The calculation time of upper bound is much faster than ALNS. During the simulation, the objective value and CPU time of Order-Up-To policy are also provided for comparison. The improvement is calculated as below:

$$improvement = \frac{Upper\ Bound - fittness(overall\ best\ solution)}{fittness(overall\ best\ solution)} \times 100\%$$

4.5.5 Comparison with Upper Bound and Lower Bound

The simulation result for all 27 instances is depicted in Table 4.4. The CPU time is recorded in second. The load tightness is the ratio of total delivery/pickup and the

Table 4.4 Simulation results for all 27 instances

Instance no.	Objective value (ALNS)	Routing cost	CPU time (ALNS)	Load tightness (ALNS)	Lower bound	Gap (%)	Upper bound	Improvement (%)	Load tightness (upper bound)	CPU time (upper bound)
1	5053.185938	1619.204797	88.14114855	1.1104	4362.56892	13.82339	8280.145557	64.24364448	1.086	5.820698
2	4896.430322	1468.148059	103.3883498	1.2862	4328.07761	11.84532	8415.034277	72.74632514	1.1972	6.286346
3	5634.606348	1626.859119	150.255732	1.326	4980.23831	11.76608	9568.040625	70.58790028	1.149666667	7.050482
4	5451.439355	1650.114478	128.7460678	1.2772	4780.3907	12.5332	8976.222754	65.27143359	1.1518	7.404717
5	5768.745068	1667.411829	141.4481982	1.19	5043.15708	12.67131	9288.667578	61.51619196	1.028	9.86236
6	4900.640723	1473.350098	137.5398943	1.1574	4402.63503	10.30232	8043.413721	64.67415094	1.1624	9.47845
7	6426.32749	1979.721851	166.5344054	1.354	5498.19199	14.57212	10,944.02139	70.51257193	1.157166667	7.729171
8	5639.978467	1642.775049	154.1710638	1.3666	4913.6415	12.86739	9680.192773	71.76310062	1.2284	9.155397
9	5812.843262	1726.514062	154.5149645	1.264	5096.37529	12.34948	9582.533398	65.34070551	1.1624	10.83043
10	5630.980518	1734.299622	160.0003022	1.069166667	4933.03064	12.51735	9492.153418	69.1402626	1.026833333	10.11764
11	6911.714697	2096.937756	222.8166723	1.139714286	5993.24028	13.35699	11,655.00244	68.72705877	1.180428571	13.62401
12	7366.123291	2159.513037	232.4239386	1.353833333	6449.10498	12.44554	12,375.04199	68.68711472	1.115666667	12.00849
13	7796.194434	2438.270605	246.4786562	1.246857143	6556.76636	16.01985	12,679.38545	63.07966113	1.218285714	13.59181
14	7418.956396	2055.809863	309.472053	1.196428571	6506.55497	12.43135	12,453.24697	68.54507446	1.171714286	18.44887
15	7623.858838	2068.724585	323.8600188	1.192142857	6730.68179	11.79947	12,371.71367	62.82668591	1.100571429	19.05923
16	7806.286475	2367.525781	482.0191661	1.378285714	6714.5938	14.09497	13,784.34023	76.79942489	1.135857143	24.36036
17	8411.708887	2510.997778	420.3044199	1.288714286	7058.3939	16.18289	14,141.96211	68.72006059	1.093714286	25.68165
18	9467.826074	2548.881738	518.3188287	1.311555556	8159.39883	13.93574	16,414.89023	73.77739549	1.170111111	24.4819
19	10,085.98447	2860.066699	561.6260622	1.251	8553.12195	15.30748	17,097.63955	69.81067538	1.153444444	30.35633
20	9719.975098	2528.145313	821.6078013	1.345888889	8501.15485	12.54422	17,149.77813	70.79073131	1.198571762	39.24404
21	8815.181934	3007.914844	637.5896237	1.281	7314.94082	16.99738	15,244.35127	73.12496245	1.1355	34.8823
22	10,598.02881	3508.065503	722.6853151	1.330111111	8516.93203	19.75156	18,385.76846	66.6807568	1.136666667	37.70397
23	10,577.49131	2999.409814	810.520406	1.2931	8926.16631	15.6961	18,544.96133	76.01945043	1.0878	38.88526
24	10,732.80381	3266.320752	753.4435408	1.271888889	8892.92705	17.18304	18,137.84473	68.05297269	1.044555556	39.00919
25	9576.32373	2814.605298	888.0011891	1.367	8102.26904	15.42516	17,525.71309	83.28116417	1.170666667	43.79189
26	10,145.36875	2874.790991	1047.894929	1.326	8693.11118	14.40931	17,790.64005	75.63519059	1.22230145	52.3995
27	12,458.09326	3994.430127	1414.882979	1.2567	10,090.5567	19.01468	20,762.33887	66.78387463	1.1479	85.13666
Avg.	**7804.707324**	**2321.807757**	**436.9883602**	**1.267821752**	**6670.304515**	**14.14235889**	**13,288.33497**	**69.52364968**	**1.141986016**	**23.570413**

capacity of vehicle, namely, $\sum_{i \in M'} \sum_{k \in K} (m_{ik} + n_{ik}) / \sum_{k \in K} Q_k$. The calculations of lower bound and upper bound are depicted above.

During all the 27 instances, the average result of objective value from ALNS algorithm is 7804.707324. The routing cost is 2321.807757, about one third of total cost. Compared with the lower bound, the average gap is 14.14235889 %. However, this result varies a lot during the simulations. The biggest gap is found in instance 27 which has the most complexity. It is partially because that the lower-bound calculation time is insufficient when the scale of instance is too big. Another finding is in the instance 14. Compared with instance 13, the gap is reduced from 16 % to 12 % because the total iteration number *iter*3 is increasing by 1500. At the same time, the CPU time of instance 14 is much bigger than the CPU time of instance 13. Thus, we can find that the improvement performance of ALNS is better with more generations of searching by sacrificing the calculation time. Compared with upper-bound algorithm, ALNS has average 69.52364968 % of improvement. ALNS also performs better in the load tightness, which means the solution obtained by ALNS algorithm is more efficient in vehicle utilization. This result conforms to our expectation due to the fact that the upper-bound algorithm is fixed in the delivery quantity and loses the flexibility of load utilization. In contrast, upper-bound algorithm performs better in the CPU time. This result shows that more than 90 % time of ALNS is exploited by the heuristic algorithm of subproblem.

4.5.6 The Performance of Heuristic in the Subproblem of Delivery and Pickup Plan

In this section, we evaluate the heuristic algorithm proposed in Sect. 4.4.5 by comparing with the optimal solution. The optimal solution is obtained by CPLEX. Meanwhile CPU time (in second) is also provided for comparison. We utilize instances 1, 14, and 20 as the examples. The routes are constructed randomly. One hundred examples are created randomly for each instance. The average results are depicted in Table 4.5.

Through Table 4.5, it is obvious that the performance of heuristic we proposed is almost near optimal. The maximum gap is 0.261019 %. Meanwhile, the calculating time of heuristic is much less than CPLEX's. The calculating time ratio between heuristic and CPLEX is almost one sixth. It is noted that the time consumption of heuristic is increasing slowly with the number of retailers. This character is important when the practical problem consists of many retailers.

Table 4.5 Solving the subproblem of delivery and pickup plan (heuristic vs. optimal)

Instance no.	Heuristic result	CPU time (heuristic)	Optimal result	CPU time (CPLEX)	Gap (%)
1	8045.66301757812	0.0157009885	8031.65971191406	0.049159184799	**0.191203654758215**
14	10,882.4525400391	0.0374036075	10,855.5139912109	0.1936279688	**0.261019214751832**
20	15,188.6538964844	0.07329286099	15,224.8485039063	0.5932877755	**0.249592681733822**

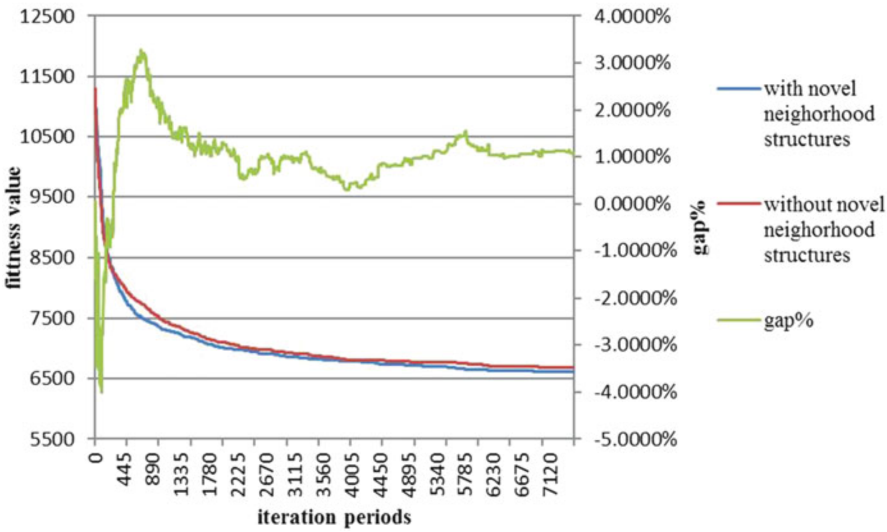


Fig. 4.4 The effect of novel neighborhood structures

4.5.7 The Effect of Novel Neighborhood Structures

This chapter proposes two novel neighborhood structures, *load-swap* and *segment-reorder*. We hope to examine the improvement effect of these two novel neighborhood structures by comparing the convergences with and without them. The instance is also constructed based on instance 11 and repeated for ten times. The average results are depicted in Fig. 4.4.

As shown in Fig. 4.4, the convergence with novel neighborhood structures is more rapid when comparing with the counterpart. The final gap between two situations is 1.0074 %. In the first 500 iterations, the convergences are matched. The biggest gap is found at about 750th iteration. This result shows that the novel neighborhood structures cannot increase the convergence when the searching just begins. With the iteration going, the effect of novel neighborhood structures is stable due to the local optima. Even if the variance of results is actually big, the designation of novel neighborhood structures is still meaningful for improving ALNS in the problem with simultaneous delivery and pickup.

4.5.8 The Sensitivity Analysis of Vehicle Capacity

During the simulation, we find that the optimal solution by ALNS usually does not fully exploit the vehicles. This fact raises our interests in the effect of total vehicle capacity on the algorithm when the transportation is insufficient. Two factors

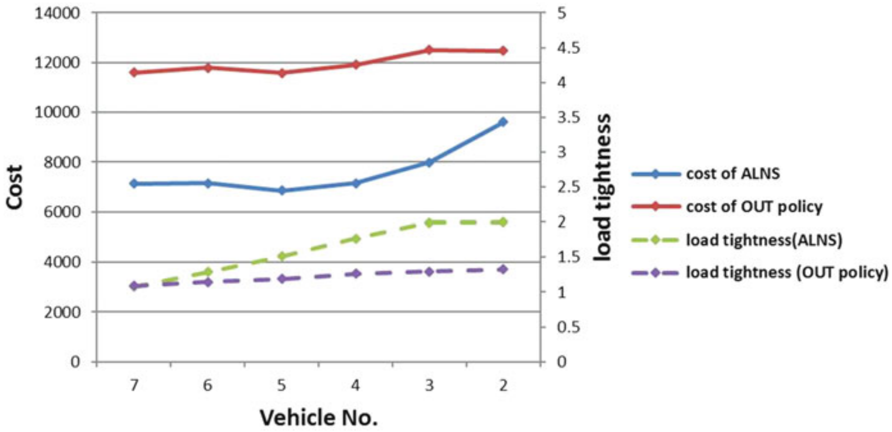


Fig. 4.5 The sensitivity analysis of vehicle number on cost and load tightness

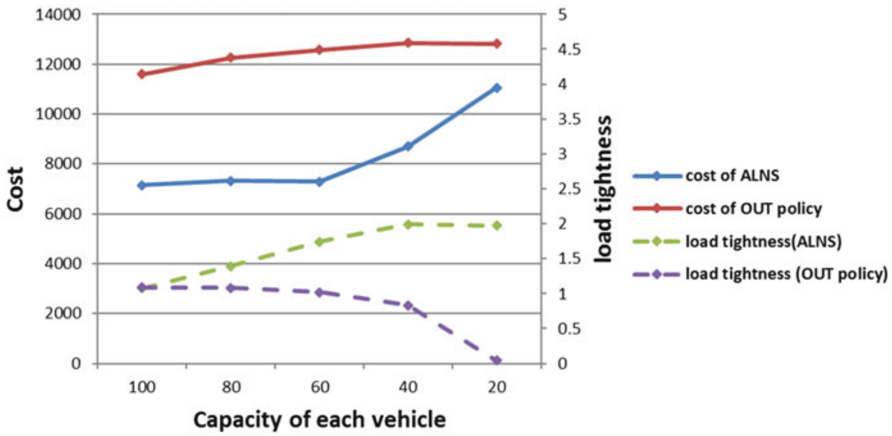


Fig. 4.6 The sensitivity analysis of vehicle capacity on cost and load tightness

related to the vehicle are studied, the quantity of vehicles and the capacity of each vehicle. In this sensitivity analysis, we utilize instance 11 as the example. The quantity of vehicles ranges from two to seven, where it is seven originally. The capacity of each vehicle ranges from 20 to 100, where it is 100 originally. The φ_{00} and ${S_{I+\varphi}}^* - {S_I}^*$ are fixed to the optimal result in Sect. 4.3.1 during the simulation. These two factors are motivated by the practical contradiction that the manufacturer chooses to utilize the less number of vehicles with bigger capacity or the more number of vehicles with smaller capacity. The result is depicted in Figs. 4.5 and 4.6.

Shown in Fig. 4.5, the total cost of ALNS is stable when the vehicle number is decreasing from seven to four. However, it rises quickly to the upper bound when the vehicle number is decreasing to three or two. The rising cost also can be viewed to occur on condition that the load tightness reaches nearly to the maximum level. Due to the definition of load tightness, the maximum level is 2. A similar result is also found in Fig. 4.6; the cost rises quickly when the load tightness of solution is almost the maximum level. For the Order-Up-To policy, we can find that the load tightness is slowly increasing when the vehicle number is shrinking in Fig. 4.5. At the same time, the load tightness of Order-Up-To policy is rapidly decreasing when the vehicle load is decreasing in Fig. 4.6.

This result provides the management insight that the total vehicle capacity has effect on the cost if the total vehicle capacity does not match the demand of transportation. Otherwise, the capacity of each vehicle does not affect the cost. Thus, the manufacturer can choose the configuration of its vehicle for optimizing their investment efficiency. However, it is obvious that the capacity of vehicle cannot be too small to satisfy the demand of one retailer. We make an extreme example with 70 vehicles with the capacity of ten units. The result shows that the cost soars to over 10,000. This phenomenon is caused by the prohibition of split delivery in the model.

4.5.9 Sensitivity Analysis of l_i and *C*

The penalty cost of lost sale l_i is increasing when the manufacturer hopes to increase the customer service level. The increasing l_i affects the inventory level in the retailer and the reusable material level in the manufacturer. Thus, it seems that increasing l_i has a positive influence on the delivery quantity. However, it is not clear about the effect on the pickup quantity. We can surmise that the increasing l_i has a positive influence on the pickup quantity, which will be examined in this sensitivity analysis. The purchasing cost C is increasing when the new reusable material becomes more expensive. C has no influence on the inventory level, although the delivery and pickup quantity is affected by C. We can surmise that C has a positive influence on the pickup quantity because the recycling reusable material is more valuable in this condition. It will be also examined in the sensitivity analysis. The sensitivity analysis also takes instance 11 as the example. We define $\sum_{i\in M'}\sum_{k\in K} m_{ik}/\sum_{k\in K} Q_k$ as the delivery tightness for describing the delivery quantity. Similarly, $\sum_{i\in M'}\sum_{k\in K} n_{ik}/\sum_{k\in K} Q_k$ is defined as the pickup tightness. The result is shown in Figs. 4.7 and 4.8.

As shown in Fig. 4.7, the tendency of delivery quantity is increasing with l_i, which conforms to the intuition. However, the tendency of pickup quantity is stable with l_i, which does not conforms to our surmise. It is an interesting result. We want to explain this in two aspects. Firstly, the pickup plan does not have to yield to the tight delivery plan because of the reasonable routing. Thus, the pickup quantity has no decreasing tendency with l_i. Secondly, the existence of purchasing new reusable material provides the threshold of recycling cost. The recycling cost is the marginal

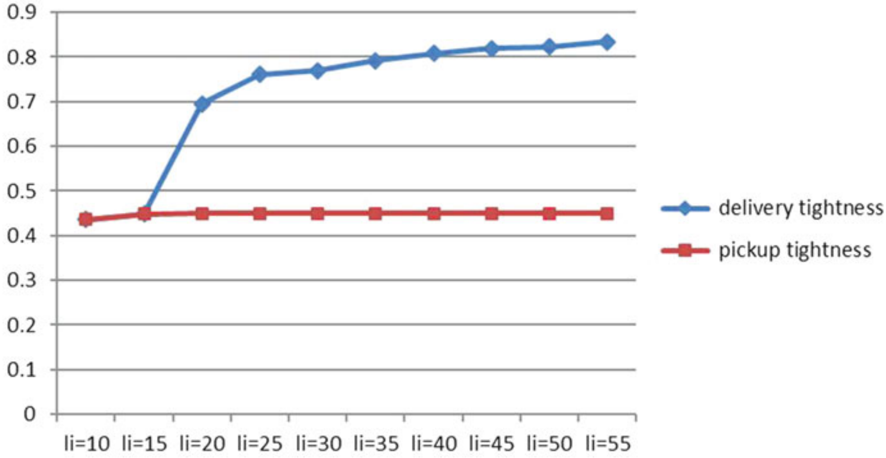


Fig. 4.7 The sensitivity analysis of l_i on delivery and pickup tightness

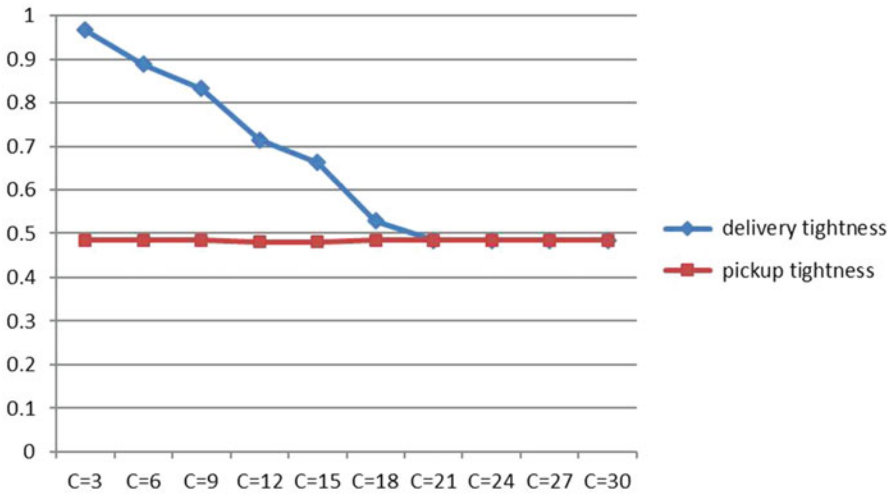


Fig. 4.8 The sensitivity analysis of C on delivery and pickup tightness

cost of adding one recycling reusable material according to the current routing plan. Because the capacity of new reusable material is unlimited, the pickup quantity must be less than the threshold determined by C. Thus pickup quantity has also no increasing tendency with l_i.

In Fig. 4.8, the tendency of delivery quantity is decreasing with C until the delivery quantity is exactly equal to the pickup quantity. The pickup quantity is almost unchanged with C during the simulation. This result also does not conform to our surmise that the pickup is encouraged by the increasing C. We can explain it by this way. The reusable material is more valuable when the purchasing cost is increasing. The model tends to shrink the product delivery for avoiding the potential loss of materials even if it causes the penalty in the part of retailers. When there is no new purchasing, the threshold of recycling cost is not affected by C as in the surmise we made. It is anti-intuitional that the high-valued reusable material discourages the product delivery instead of encouraging the recycling reusable material.

4.6 Conclusion and Future Research

4.6.1 Conclusion

This chapter discusses the optimization method for hybrid manufacturing in the environment of Internet of Things. The main attention is focused on the coordination of inventory and transportation by sharing the forward and backward logistics. For the manufacturer, this mode is very efficient but difficult in making the corresponding decisions. Firstly, this chapter formulates the model of inventory routing problem with simultaneous delivery-pickup and purchasing decision (IRPSDPD) which is extended by IRP. In the model, the technology of IoT provides the accurate inventory information about products and reusable materials to the planner as the input information. Then, the solution algorithm is proposed based on adaptive large neighborhood searching. According to the dynamic constraint of vehicle load in this model, we proposed two new neighborhood structures, *load-swap* and *segment-reorder*, in the neighborhood mutation phase, one new greedy insertion action, *load greedy insertion*, and one new broken action, *tight-load broken* as the modification of traditional ALNS. *Load-swap* and *segment-reorder* can improve the quality of solution by about 1 % in the simulation study. For solving the subproblem of delivery and pickup plan, we design a high efficient heuristic algorithm which blends the dynamic programming and greedy algorithm. This heuristic is near optimal compared with CPLEX but much faster. The performance of the algorithm is evaluated in the simulations consisted of 27 standard instances of capacitated VRP. The lower and upper bound is also provided for comparison. Finally, a serial of sensitivity analysis experiments is undertaken for management insights in this problem.

4.6.2 Future Research

In this chapter, we simplify the problem with the limitation of single period. The long-term effect of inventory policy is also important for the planner. However, the transportation plan has no long-term effect because the routing is cyclic. Thus, for the hybrid manufacturer, there is a trade-off between long-term inventory optimization and short-term routing optimization when applying the coordination of both. Future studies can focus on the multi-period model with the coordination optimization and compare the features of single-period model and multi-period model.

For the problem of IRP with simultaneous delivery and pickup, it has many variants waiting to be researched. The future work can study the variants with distance constraint, with split delivery, with multiple depots, with weight-related cost, and etc. The application work of this problem is also very important to examine the practical value of this new class of problems.

Chapter 5
Cutting Stock Problem with the IoT

5.1 Introduction

5.1.1 The Cutting Stock Problem

The cutting stock problem is representative of the combinatorial optimization problems that arise in industries such as steel, furniture, paper, glass, and leather. In a cutting plan, we must obtain the required set of smaller pieces (items) by cutting large pieces (objects) that are in stock. The objective is usually to minimize waste. In a real-life cutting process, there are some further criteria, e.g., the number of different cutting patterns (setups), capacity of the cutting equipment, and due dates. With the increasing scarcity of resources in the world, researchers are paying more attention to resource utilization.

The assortment problem and bin packing problem are collectively referred to as the cutting stock problem. They belong to cutting and packing problems (C&P), which is a branch of operational research. The cutting stock problem is a mixed problem of the combinatorial problem and production scheduling problem. The cutting stock problem is a large-scale problem due to the explosiveness of the combinatorial problem and proves to be an NP-hard problem. The main objective of the cutting stock problem is to make certain projected goals optimal or approximately optimal by determining the cutting pattern and execution times under certain process constraints.

In manufacturing, the cutting stock problem can be divided into the one-dimensional cutting stock problem (1D-CSP) and two-dimensional cutting stock problem (2D-CSP). The 1D-CSP is a problem about how to optimize cutting to maximize the usage rate with the given raw materials and customer demand for billets. The 1D-CSP can be classified into a single profile's 1D-CSP and multipiece profiles' 1D-CSP, depending on the differences between the raw materials. The 1D-CSP can be grouped into either uniform sections' 1D-CSP or variable sections'

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1D-CSP based on the transformation of the sections of raw materials. The most common materials of the variable sections are truncated cone-shaped ingots. The 2D-CSP exists in many industries. The 2D-CSP can be divided into the single profile's 2D-CSP and multipiece profiles' 2D-CSP, depending on the varieties of the raw materials. The 2D-CSP can be partitioned into rectangle bars' 2D-CSP and profiled bars' 2D-CSP, depending on the shapes of the sheet parts. The 2D-CSP can be sorted into rectangular cut, guillotine cut, two-stage cut, direction cut, one-dimensional cut, non-rectangular cut, and profiled bars cut, depending on the differences in the cutting constraints. In the manufacturing industry, the cut pattern is always a multi-rectangular cut with multiple limits.

5.1.2 Notation of the Cutting Stock Problem

A cutting stock problem is described by a tripler $n/\alpha/\beta/\gamma$ [167]. Let n field describe the dimensional of the cutting stock problem. $n = 1$ indicates a one-dimensional cutting stock problem, while $n = 2$ means a two-dimensional cutting stock problem. The α-field provides the kind of assignment. $\alpha = \mathrm{V}$ represents a selection of items, and $\alpha = \mathrm{B}$ represents all objects as a selection of items. The β-field is used to describe an assortment of large objects. $\beta = \mathrm{D}$, $\beta = \mathrm{I}$, and $\beta = \mathrm{O}$ represent different figures, identical figures, and one object, respectively. The γ-field describes an assortment of small items. $\gamma = \mathrm{C}$ denotes congruent items, $\gamma = \mathrm{F}$ denotes few items with different figures, $\gamma = \mathrm{M}$ denotes many items of many different figures, and $\gamma = \mathrm{R}$ denotes many items of relatively few different figures.

5.1.3 Cutting Stock in Manufacturing

Some algorithms for solving the cutting stock problem can be completed by a computer. The algorithm usually integrates with the MES (manufacturing execution systems), and the production orders are made after the MES gets the sales orders from the ERP (enterprise resource planning) system. Based on the production orders, available stock objects, technology parameters of the machines, and alterations of the blank specifications, the MES can work out the cutting plan. Finally, after auditing, the manager releases the cutting plan to the workers in the workshop.

5.1.4 The Cutting Stock Problem with the IoT

The traditional cutting stock problem mainly takes objects and items into account. The objective is usually to minimize waste or the number of used stock.

The objective of the traditional cutting stock problem cannot satisfy the need for production management in the modern age. Modern production management pursues business cooperation and total optimization. The objective of modern production management includes minimizing waste and minimizing the processing cost and production balance of the cutting equipment. In addition, the influences caused by the changed cut blank during the process must be considered. To achieve these goals, the status information of the cutting equipment and processing information of the blank must be obtained in real time. The IoT enables modern enterprises to meet the new needs of the cutting stock problem. Some new characteristics arise in regard to the cutting stock problem with the implementation of the IoT:

1. More optimization space. Accurate data cannot be obtained in a traditional manufacturing environment. While the application of the IoT enables enterprises to obtain accurate data (like precise information about the material stock, material on order, and material that is recyclable), the optimization space of the cutting stock problem is expanded.
2. Realizing the establishment of the cutting scheme. In a real productive process, when a cutting plan is not finished, some issues (like equipment failure, the insertion of a rush order, or the delay of some in-transit material) may occur. The IoT can provide related data, so a new cutting plan can be made to replace the old cutting plan.
3. Make the optimization model of the cutting stock problem more suitable for actual production. In traditional patterns, since the condition of the cutting equipment and the machining condition in a productive process cannot be obtained in a timely fashion, the optimization objectives of the cutting stock problem mostly consider the minimization of material waste and setup cost; the balance of the productivity, the influence caused by the change of product, cannot always be taken into account. Manufacturers utilizing the IoT find that these problems can be easily dealt with. The optimization model presented here is more practical than the traditional model.

5.2 Literature Review

Dyckhoff [167] proposed a typological method to analyze cutting stock problem systematically. The common research method can be divided into the production-based method and the cutting-based method. The production-based method involves assigning small pieces (blank) to some large pieces (material) continuously until the cutting pattern is formed. This method includes dynamic programming, the first fit decreasing (FFD) algorithm, and the sequential heuristic procedure (SHP) algorithm. The cutting-based method involves determining the cutting pattern of the large pieces first and then assigning small pieces to the large pieces. It mainly includes an algorithm based on linear programming. The cutting-based method is effective only when there is a single specification for the materials or there are only a few kinds of materials. When the specifications for the materials are all different, the only method that can be used is the production-based method. All the solution algorithms for solving the cutting stock problem can be divided into two algorithms. The first algorithm is based on linear programming or integer programming, and the second is the heuristic algorithm.

5.2.1 One-Dimensional Cutting Stock Problem

The cutting stock problem with a single bar and uniform section materials has been widely studied. However, the cutting stock problem with multiple bars and variable section materials has received little attention due to its complexity. Kantorovich [168] proposed the first one-dimensional cutting stock problem model using a linear programming model, but it was not practical since all the cutting patterns are needed in a simple method. Gilmore and Gomory [169] proposed the delay column-generation algorithm. This algorithm generated the required column after each circulation by using an improved simplex algorithm, so all the cutting patterns were not needed. It also divided the main problem into many subproblems. The cutting pattern for a new improved feasible basis for linear programming was made by solving the assistant knapsack problem.

In cutting stock problems, the waste loss can be decreased by using the linear programming method, but this method is only appropriate for situations where there is only a single specification or few specifications for the material, and the derived blank is always more than the real demand, which causes unnecessary waste. In addition, the solution derived by linear programming is not an integer solution. The traditional optimization method relaxes the integer programming problem into a linear programming problem that can be solved by a simplex algorithm, and then the result needs to be processed. The optimal solution is not absolutely obtained in this way. After the process, one or more productions may be excessive or insufficient, so further processing must be done. Gilmore and Gomory [170] proposed to round down the decimal of the non-integer solution first and then deal with the rest of the unfinished production. However, this method is only suitable for a small-scale one-dimensional cutting stock problem. For the large-scale problems that exist in practical manufacturing, obtaining reasonable cutting patterns for the rest of the productions is difficult. Stadtler [171] proposed a method that rounds up the largest number of a non-integer in the solution vector to an integer first and then optimizes it using a simplex algorithm until all elements in the solution vector are integers. This method replaces the inequalities $x_j \geq |x_j|$ and $x_j \leq |x_j|$ of the branch-and-bound method with the equation $x_j = |x_j|$. For $x_j \geq |x_j|$, the increased constraints along with the number of variables appear to result in exponential growth. For $x_j \leq |x_j|$, the increased constraints appear to result in linear growth with a fast solving speed and good-quality solution. The column-generation algorithm converges slowly when factors like degeneration are considered. Based on a simplex algorithm and sub-gradient optimization algorithm, Degraeve and Peeters [172] solved the linear programming relaxation problem in the one-dimensional cutting stock problem to speed up the column-generation algorithm. Lee [173] proposed a local search heuristic algorithm that was based on an integer programming problem to improve the quality of the column-generation algorithm. The branch-and-bound method for solving integer programming problems is only applied when there are few variables. Many cutting compound modes and the solving speed may decrease if the length ratio of the raw material and blank is greater than the certainty value. Vance [174], Vanderbeck [175], and Peeters [176] combined the column-generation algorithm and branch-and-bound method to solve the one-dimensional cutting stock problem. Yanasse and Lamosa [177] proposed a one-dimensional and multi-specification cutting stock problem using the sequence constraints of the integer linear programming model.

Cutting stock problems are, in reality, mostly NP-hard problems. The heuristic algorithm is easily combined with optimization objectives and constraints, so it is widely applied. The most common heuristic algorithm is the SHP algorithm proposed by Haessler [178]. An extension of this work was proposed by Sweeney and Haessler [179]. They adopted the two-stage SHP algorithm to solve the one-dimensional cutting stock problem in which the raw materials and blanks are divided into different quality grades. This algorithm's efficiency is low when the ratio of the grades is great.

The linear programming method can reduce the loss of waste, while the SHP algorithm can avoid the rounding process and manage many kinds of product objectives and constraints (including cutting patterns). A mixed algorithm (combined approach) was proposed by Gradisar et al. [180]. Scholl et al. [181] proposed a mixed method, BISON, which was a combination of the MTPR, FFD, best-fit decreasing (BFD), double tabus, and the branch-and-bound methods. They used BISON to solve the off-line one-dimensional bin packing problem (BRP). Sung et al. [182] used a two-stage optimization algorithm, which was a combination of pre-selected elimination methods and the tabu search method, to solve the one-dimensional cutting stock problem.

Antonio et al. [183] proposed two types of heuristic algorithms that were based on dynamic programming to solve the multi-objective one-dimensional cutting stock problem: heuristic constraining the utilization of the stored bars (HCUS) and heuristic constraining the utilization of stored and ordered bars (HCUSO). Chu and Antonio [184] also proposed a heuristic dynamic programming method to obtain the approximate solution of the multi-criteria one-dimensional cutting stock problem. Gilmore and Gomory [170] introduced a two-stage algorithm to solve the one-dimensional cutting stock problem.

When the scale of the problem is great, it is difficult to obtain a solution in a limited amount of time just using the heuristic algorithm, so some meta-heuristic algorithms were proposed. Vahrenkmp [185] proposed a random search for the one-dimensional cutting stock problem based on a heuristic algorithm. Wagner [186] presented a solution to the one-dimensional bundled stock cutting stock problem using a genetic algorithm. Liang et al. [187] adopted an evolutionary algorithm that only contained a mutation search to solve the cutting stock problem.

Yang et al. [188] proposed an improved tabu search approach algorithm to solve the one-dimensional cutting stock problem with raw materials of uniform lengths. Gracia et al. [189] proposed a hybrid approach based on the genetic algorithm and different search strategies to solve the problem of cutting structural beams identified in a metalwork company with the objective of minimizing the waste produced during the cutting process. Yang et al. [190] solved the one-dimensional cutting stock problem based on the ant colony optimization algorithm. Kazuki, Shunji, and Hiroshi [191] investigated the one-dimensional cutting stock problem of the paper tube industry using a combination of the tabu search algorithm and FFD heuristic algorithm. Vacharapoom and Sdhabhon [192] researched the one-dimensional cutting stock problem with minimum trim loss and the number of stocks used; since the problem has a strong heterogeneous assortment of demand items, they developed new solution procedures that resulted in more efficient cutting plans. Their procedures are implemented in three steps. The intensive search algorithm, genetic algorithm, and BFD algorithm is used in the different steps.

5.2.2 Two-Dimensional Cutting Stock Problem

The common cutting patterns in the two-dimensional cutting stock problem include rectangle cutting, truncation cutting, two-stage cutting, and direction cutting. Accurate methods are still widely used in small- and medium-sized problems. Christofides and Whitlock [193] proposed a tree search algorithm for the two-dimensional truncation cutting problem without stage limits that restricts the largest number of every production from top to bottom. The upper bound was obtained through dynamic programming, and the nodes' evaluations were based on the transport route; the search scale was limited by special conditions. Agrawal [194] solved the two-dimensional rectangle truncation cutting problem without limits based on the branch-and-bound method. The branch-and-bound method can ensure the acquisition of the easiest cutting method, but it also has a high time complexity.

Lindecrantz [195] first put forward an algorithm based on dynamic programming to solve the uniform rectangle cutting problem. Gilmore and Gomory [196] proposed a dynamic programming to solve the two-dimensional unrestrained cutting stock problem. Tarnowski [197] proposed a polynomial time algorithm to solve the two-dimensional guillotine cutting problem. Cui [198] pointed out that although the algorithm proposed by Tarnowski had a high efficiency of time, the cutting plan was too complicated. He also proposed a dynamic programming algorithm to solve the truncation cutting problem with uniform rectangular bars.

Dagli [199] proposed a combinational method of artificial intelligence and operational research to solve the two-dimensional cutting stock problem whose optimization objective is minimizing waste. Lai and Chan [200] proposed a simulated annealing algorithm to solve the two-dimensional non-truncation cutting stock problem. Based on the research of Jakobs et al., they [201] used the generation search and simulated annealing algorithm to solve the two-dimensional non-truncation cutting problem. A combination of simulated annealing and linear programming was proposed by Gomes and Oliveira [202] to solve the bin packing problem with irregular two-dimensional bar types. Elsa et al. [203] proposed an integer programming model for the two-dimensional rectangle cutting stock problem. The objective of this problem is to minimize the total raw material and consider the value of the surplus stock. Weng [204] designed a two-dimensional cutting stock system for irregular production using AutoCAD.

Cui et al. [205] considered the two-dimensional cutting stock problem of round production; its objective was to minimize the total raw materials and cutting cost. The cutting stock procedure was a two-stage procedure. First, they adopted the guillotine-type cutting method to cut band bars from plate metals and then pressed rounded products using the band bars. The cut way was obtained by the column-generation method.

5.2.3 Applications of the Cutting Stock Problem

The decision-making method for solving complicated cutting stock problems in most enterprises is still traditional and performed manually. The traditional way produces much waste and takes a significant amount of calculation time; it is also prone to error. There are some enterprises making cutting decision with computer assisted, but these decisions are mostly for simple problems. The algorithm they use cannot simultaneously guarantee the utilization and computational efficiency for more complex cutting stock problems. We have seldom seen the application of a cutting stock system in the supply chain environment.

The Optimum Cut-1D procedure from the Optimum Cut software solves the calculation issues of the one-dimensional cutting stock problem. Huaruan Technology Development Co., Ltd. worked with Tsinghua University's Institute of Civil Water Conservancy and developed the "cutting stock optimization system of rebar," which is mainly used to calculate the cutting stock problem in construction reinforcement. This type of software does have certain problems. Since this type of software is applied in professional fields, it typically only has a single function. Some software packages do not have an intuitive interface, so they are not widely used in manufacturing.

Xia et al. developed the optimization cutting stock management system of angled steel (an optimization management system for OMS material). Huang et al. developed a one-dimensional cutting stock computer-aided system for precision machinery manufacturing. Zhao et al. combined cutting stock management, manufacturing management, procurement, manufacturing store issue, and inventory management to create a total management system for the cutting stock problem in pylon.

The special sheet metal parts and structural parts design process software CADCAM developed by RADAN in 1976 and the JETCAM Expert (metal plate stamping and cutting software) developed by JETCAM are both two-dimensional cutting stock systems. In China, some colleges, universities, scientific research institutions, and software companies are developing stock layout software. The general automatic layout system PyCAD developed by Wuhan Sanyi Hi-tech Co., Ltd. can lay out products according to an optimization scheme on arbitrarily shaped plates with arbitrary dimensions; the software lays out two-dimensional components on definite plates and makes efficient use of raw materials. Rao et al. at the Huazhong University of Science and Technology developed an integrated metal plate optimization system, AutoCut, which possesses an autonomous copyright and uses automatic positioning and programming to address the structural metal cutting stock problem. Our research group developed a cutting stock system for multiple products with a one-dimensional uniform section and variable sections for the Magang steel wheel company in 2008 [206].

Based on the above literature review, our research experience, and the investigation of some commercial enterprises, we conclude that the development tendency of the cutting stock problem will be formulated along the following five points: the environment of the supply chain, multi-aspect collaboration, multi-objective optimization, complicated constraints, and intelligence.

5.3 Variable Cross-Sectional Cutting Stock Problem

Masteel Wheel Company Co., Ltd. is an oversize enterprise which mainly manufactures monobloc rolled steel wheel and tire for the train in China. The company sells more than 1300 types of products which include tires, ring parts, wheels, bearing washers, forgings, etc. The productions are applied in different areas, like rolling stock, machine, chemical industry, petroleum, textile, metallurgy, mining, astronautics, ports, subways, and so on. The blanks need to be cut from a type of frustum of cone-shaped steel ingot (Fig. 5.1). Because this kind of material has a variable cross section, the cutting lengths of the blank with the same weight in different parts are different; this problem is more complex than the problem of cutting the raw materials with a uniform section. Furthermore, due to the thickness of the cutting blade, a blade slot of certain width will be generated when cutting the frustum of cone-shaped steel ingot. As a result, the diameter of item cut is different from the immediate one. Therefore, when cutting the bars, the impact of the blade slots on the computation of the cutting stock plans is an issue that cannot be ignored. The blanks having already been cut still have to be heated, forged, and rolled until they are finally finished. So the process requirements like forging ratio and height-diameter ratio in later procedure have to be considered in cutting patterns. It is complicated and important to schedule the cutting pattern in order to minimize the raw materials or leftover materials.

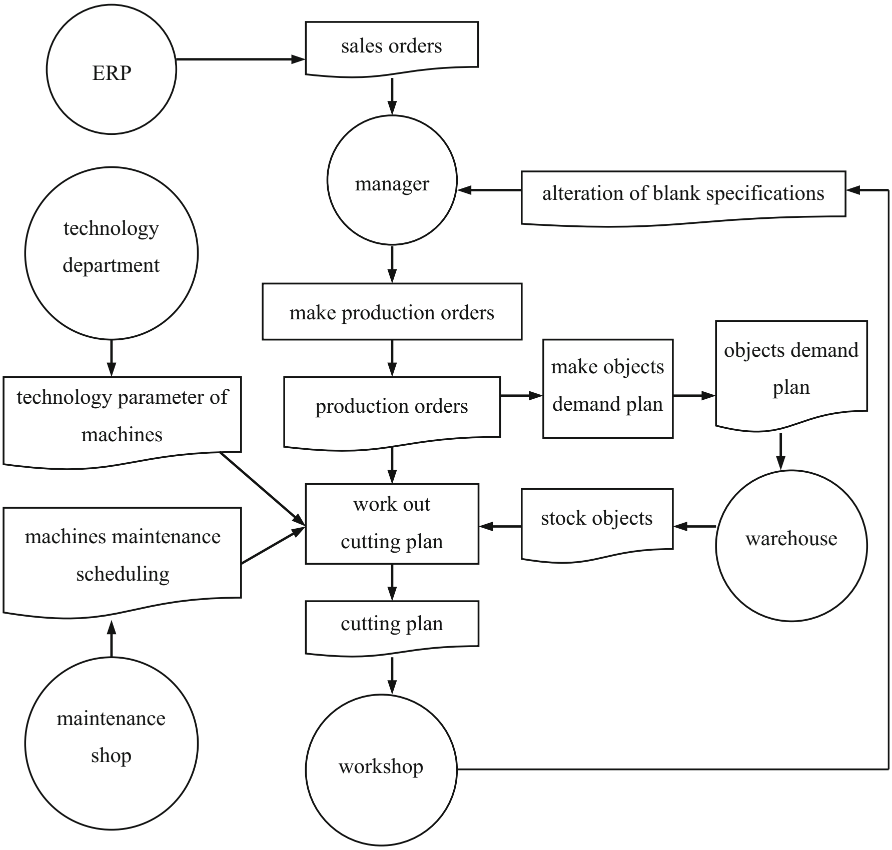


Fig. 5.1 Business process diagram in a manufacturing system

5.3.1 Background and Model of the Problem

In order to facilitate the remove of pouring production from die cavity, mold is usually designed to be a special stage shaped which is thick on the head (denoted as big side) and thin (denoted as small side) on the end. This means that the pattern draft (i.e., the angle of the subface and the side face) is not 90°.

Suppose the area of big side is S, the area of small side is s, and the height is L, then the pattern draft α of raw material is derived as follows:

$$\alpha = \frac{\sqrt{\mathrm{S}}\text{-}\sqrt{s}}{L}$$

The pattern draft α of uniform variable cross section which has round-shaped cross section can be derived using the diameters of sides and height. Suppose the diameter of big side and small side is D and d, respectively, and the height is L, then the pattern draft α of raw material is presented as follows:

$$\alpha = \frac{\mathrm{D}\text{-}d}{2L}$$

The pattern draft is related to many factors, such as shape, size, material, cooling shrinkage rate, the friction coefficient between product and mold, and so on. In general, the harder of the production, the more complex of the shape, the longer of the production, and the smaller of the shrinking ratio, the larger the pattern draft is. As for metal material, the pattern draft is between 0.004 and 0.08.

The cutting stock problem using raw material of various thicknesses is called CSP with homogenous variable cross-sectional raw materials. This material is different from column material with uniform thicknesses, its raw material is nonlinear, and degrees of thicknesses at different positions are also different. The cutting length is different when the same blanks are cut at different positions. Therefore, the cutting pattern of certain blank is determined according to the weight of production. The products will be heated and then rolled until they are finally finished. When the raw material is variable cross section, besides the product demands and the length of material, the cutting sequence and position of product also need to be considered.

The number of blades that can be loaded on tool post is limited in actual production. If K blades can be installed on tool post at most, K-1 blanks can be cut on one raw material at most (both ends are left).

Consumption always happened when cutting the materials because the blades have certain thicknesses. Therefore, thicknesses of blades have to be taken into account. For example, the blades on the cutting machine of Masteel Wheel Company have 16 mm width cutting space. When cutting cylinder-shaped raw material, the thickness can be considered into the length of the cutting product. Thus the waste caused by blades' thickness can be ignored when designing the algorithm. When cutting variable cross-sectional material, the waste is different according to the position of cutting space, so the width and position of cutting space have to be taken into account.

The blanks using variable cross-sectional material have different degrees of thickness, so they still need to be heated, forged, and rolled until they are finally finished. The technological requirements such as height-diameter ratio and forging ratio in later period have to be taken into account. Height-diameter ratio has to satisfy certain condition. Unsuitable height-diameter ratio will influence the quality of final product. Forging ratio also has to be within limits.

Suppose there are m variable cross-sectional raw materials. The area of big side is S_i, area of small side is s_i, the length of the raw material is L_i, the weight of raw material is $W_i(i = 1,2,\ldots m)$, and there are enough materials (density of steel ingot is ρ). The raw material needs to be cut into n kinds of pieces. The weight of small blank is w_j; the number is $q_j(j = 1,2,\ldots n)$. Suppose K blades can be installed on each tool rest at most (there can exist at most K-1 products in a cutting pattern). The

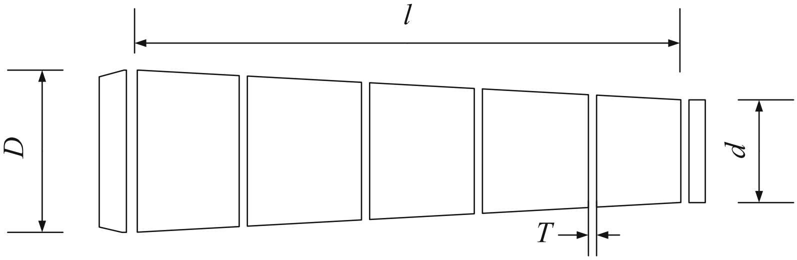


Fig. 5.2 The figure of variable cross-sectional material

width of cutting space is T, forging ratio is no less than HH, and height-diameter ratio is no more than HD. The figure of variable cross section is shown in Fig. 5.2. The objective is to arrange the cutting in order to minimize the steel ingots' weight after all the products have been cut. The model can be formulated as follows:

$$\min = \sum_{i=1}^{m} \sum_{p} W_i x_{ip}$$

$$\sum_{i=1}^{m} \sum_{p} a_{ipj} x_{ip} \geq q_j \tag{5.1}$$

$$\sum_{p} a_{ipj} w_{ip} \leq W_i \tag{5.2}$$

$$\sum_{p} a_{ipj} \leq K - 1 \tag{5.3}$$

$$h_{ipk} = f\left(\sum_{l=1}^{k} (h_l + T), w_{\delta ipl}\right) \tag{5.4}$$

$$\sum_{k=1}^{K-1} h_{ipk} + T \leq L_i \tag{5.5}$$

$$\frac{h_{ipk}}{d_i + \dfrac{\sqrt{S_i} - \sqrt{s_i}}{L} h_{ipk}} \leq HD \tag{5.6}$$

$$\frac{h_{ipk}}{h_{\delta ipl}} \geq HH \tag{5.7}$$

The notation used in the model is described as follows:

m: The number of steel ingots.
n: The number of products.
S_i: The big side's area of the ith steel ingot, $i = 1,2\ldots m$.
s_i: The small side's area of the ith steel ingot, $i = 1,2\ldots m$.

d_i: The small side's diameter of the ith steel ingot, $i = 1,2...m$.
L_i: The length of the ith steel ingot, $i = 1,2...m$.
W_i: The weight of the ith steel ingot, $i = 1,2...m$.
ρ: The density of the steel ingot.
w_j: The weight of the jth product, $j = 1,2...n$.
h_j: The final height of the jth product, $j = 1,2...n$.
q_j: The demand of the jth product, $j = 1,2...n$.
K: The number of blades on the tool rest, each steel ingot can be cut into K-1 products (both ends are abandon).
T: The thickness of blade (the width of blade's cutting space).
HH: The lower bound of forging ratio. The forging ratio is the ratio of height of blank and height of final blank. The forging ratio must be greater than or equal to less than HH.
HD: The upper limit of the height-diameter ratio. The height-diameter ratio must be less than or equal to HD.
a_{ipj}: The number of cutting product j for ith steel ingot in cutting pattern p.
x_{ip}: The number of ith steel ingot in cutting pattern p.
δ_{ipk}: The product to be cut in position k of ith steel ingot in cutting pattern p. For example, suppose the pth cutting pattern of ith steel ingot is (2, 4, 1, 3) which shows that the first product is cut into two pieces, the second product is cut into four pieces, the third product is cut into one piece, and the fourth product is cut into three pieces. It is obvious that the product to be cut in position 6 is product 2, so $\delta_{ip6} = 4$.
h_{ipk}: The length of kth product of ith steel ingot in the cutting pattern p. The δ_{ik} can be computed according to formula (5.4). If the weight of product is known, we can get the length of the product according to the transform formula of weight and length. When the problem is to get the length of all products in one cutting pattern, the length of the first product has to be known, then the length of the second product needs to be solved, and so on; with this, the length of all the products can be obtained.

The optimization objective is to minimize the total weight of material in the cutting pattern.

Constraint (5.1) indicates that the total count of jth product has to be larger than the demand of product j for all steel ingots in all cutting patterns.

Constraint (5.2) is the constraint for weight; it indicates that the total weight of all products in each cutting pattern has to be less than the weight of the steel ingot.

Constraint (5.3) requires that the total number of items cut by one pattern cannot exceed the bar number K.

Constraint (5.4) gives the recursive algorithm to calculate the length of kth product of ith steel ingot in cutting pattern p. $f(l,w)$ is the transfer function of weight and length which means that in order to obtain the cutting length of a product weighed w, one can cut in the position l near the small head end. The cutting length will be discussed in the next passage. The distance to small side end is T when product one is cut. According to distance and weight of a product, we can derive the cutting length of product one. The rest can be done in the same manner until the cutting lengths of all products are obtained.

Constraint (5.5) is the constraint for length; it requires that the sum of total length of all products and the knife seam width is no more than the length of the steel ingot.

Constraint (5.6) is the constraint for forging ratio. The forging ratio is the ratio of height of blank and height of final blank. The forging ratio must be greater than or equal to HH.

Constraint (5.7) is the constraint for height-diameter ratio. The height-diameter ratio must be less than or equal to HD.

5.3.2 *The Improved Algorithm for Solving Circular Truncated Cone Cutting Stock Problem*

5.3.2.1 Length Conversion Algorithm

Because the steel ingots used as materials have variable cross section, even some identical products will get different length of cutting if being cut in different position on the same variable cross-sectional material. For this problem, cutting pattern should be determined by the weight of a product instead of the length. However, when the cutting pattern is finally made, the weight has to be transferred into length so the distance of blades can be determined when adjusting the cutters. Therefore, the transformational relation among position on steel ingot, weight, and length should be studied first.

Suppose the length of material is L, a blank-weighed w is cut from this material in random position. The cutting position is defined as the distance between the small side end of the blank and the small side end of the material. The cutting position is denoted as l. The cutting length is defined as the distance between the big side end of the blank and the small side end of the blank. The cutting length is denoted as $f(l, w)$. The length transform relationship of variable cross section is shown in Fig. 5.3.

There are two ways to transform weight to length: manual ruler method and formula method. Manual ruler method is an approximation algorithm which is also

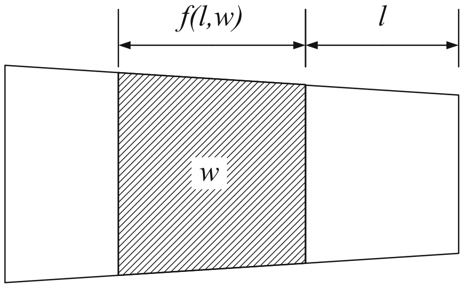


Fig. 5.3 The figure of variable cross-sectional length calculation

Table 5.1 The product weight data of manual ruler

Ruler		Ruler		Ruler		Ruler	
Number	Weight (kg)	Number	Weight (kg)	Number	Weight (kg)	Number	Weight (kg)
1	53	5	57	9	61	13	65
2	54	6	58	10	62	14	66
3	55	7	59	11	63	15	67
4	56	8	60	12	64		

frequently applied in real production practice. This method is easy to be calculated, whereas it is also likely to produce large errors. It is suited for the manual computation of blanking worker. Formula method has large calculated amount and high accuracy and is suitable for the calculation of computer programs.

Manual Ruler Method

By manual ruler method, steel ingot is divided into several 100-mm-long small pieces. Every small piece is regarded as a cylinder. The weight of the cylinder is calculated in advance and drawn into a form. Table 5.1 shows the transformation between length and weight for a 0.9 t-weighed steel ingot.

If the steel ingot is cut starting from the smallest side end, the small cylinder to be cut can be obtained by the cutting position and weight. Because the length of each small cylinder is already known, the cutting length can be estimated. For the section which is not heavy enough (suppose it is the ith section and differs from the total weight Δw), the length of this section can be derived by linear formula $l_i = \frac{\Delta w}{w(i)} \times 100$, and the total length of this blank can be expressed by $L = (i-1) \times 100 + l_i$.

Suppose the steel ingot is cut and the position is l apart from the small side end, the weight of the first section can be represented as $w' = \frac{100-l_1}{100} \times w_i$.

As shown in the table above, the counting process for the length of f (224,120) is shown as follows:

Because the position 224 is on the third piece of steel ingot and the position on it is 224–100-100 = 24 mm,

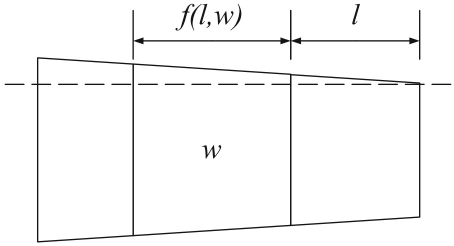
$$l_i = \frac{100-24}{100} \times 55 = 41.8\,\text{kg}$$

Select a 100-mm-long steel ingot from the fourth piece, and the total weight is $41.8 + 56 = 97.8$ kg <120 kg, so the cutting process continues.

Select a 100-mm-long steel ingot from the fifth piece, and the total weight is $97.8 + 57 = 154.8$ kg >120 kg, so we can only take a part of this piece.

$\Delta w = 120–97.8 = 22.2$,$w(5) = 57$, so $l_i = \frac{\Delta w}{w(i)} \times 100 = \frac{22.2}{57} \times 100 = 38.95$

Fig. 5.4 The figure of variable cross section length calculation



In conclusion, we can start to cut at the position which is 224 mm near from the small side end; the weight of blank is 120 kg and the cutting length is $f(224{,}120) = 100–24 + 100 + 38.95 = 214.95$ mm.

Formula Method

For the circular truncated steel ingot, if the weight and the distance to the small side end are already known, it is easy to derive the cutting length by the cubature formula of circular truncated cone. Suppose the diameters of the big side end and the small side end are D and d, the length is L and the density is ρ. If the w-weighed product is cut starting from position l, the length $f(l,w)$ can be derived by the cubature formula of circular truncated cone. The reasoning process is presented as follows:

Through the center of circle of the top side and bottom side of the circular truncated cone product, we can get a trapezoid with maximum cross section of this circular truncated cone product. The sketch diagram is shown in Fig. 5.4. We make a vertical line from an apex of the top to the bottom; then a triangle is formed and the slope of which is $\alpha = \frac{(D-d)}{2L}$.

Because the diameters of big side end and small side end are D and d, the diameters of big side end and small side end of the w-weighed blank are calculated as below:

$$\begin{aligned} D_w &= d + 2[l + f(l,w)]\alpha \\ d_w &= d + 2l\alpha \end{aligned}$$

According the cubature formula of circular truncated cone, we can get

$$\begin{aligned} V_w &= \frac{S_{dw} + S_{Dw} + \sqrt{S_{dw}S_{Dw}}}{3} h \\ &= \frac{\pi\left(\frac{d+2l\alpha+2f(l,w)\alpha}{2}\right)^2 + \pi\left(\frac{d+2l\alpha}{2}\right)^2 + \sqrt{\pi\left(\frac{d+2l\alpha+2f(l,w)\alpha}{2}\right)^2 \pi\left(\frac{d+2l\alpha}{2}\right)^2}}{3} \end{aligned}$$

as $V_w \rho = w$; then we have

$$\frac{\pi\left(\frac{d+2l\alpha+2f(l,w)\alpha}{2}\right)^2+\pi\left(\frac{d+2l\alpha}{2}\right)^2+\sqrt{\pi\left(\frac{d+2l\alpha+2f(l,w)\alpha}{2}\right)^2\pi\left(\frac{d+2l\alpha}{2}\right)^2}}{3}\rho=w$$

Based on the above equation, we can get that

$$f(l,w)=\frac{\sqrt[3]{\alpha\frac{3w}{\pi\rho}+\left(l\alpha+\frac{d}{2}\right)^3}-\left(l\alpha+\frac{d}{2}\right)}{\alpha}$$

The cutting length can be derived by this formula according to the cutting position and cutting weight. The final result of the cutting length can be accurate to the millimeter. Because the cutting process will unavoidably produce some errors, and the influence caused by larger product can be omitted, the result should be rounded up to an integer slightly. The cutting formula can be expressed as follows:

$$f(l,w)=\left\lceil\frac{\sqrt[3]{\alpha\frac{3w}{\pi\rho}+\left(l\alpha+\frac{d}{2}\right)^3}-\left(l\alpha+\frac{d}{2}\right)}{\alpha}\right\rceil$$

Relation Between Position and Length

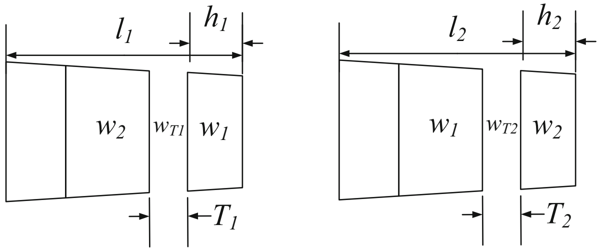
When cutting on uniform variable cross-sectional material, considering the effect caused by the thickness of blade and the difference of diameters of big side end and small side end, the lengths of steel ingot will be different even for the same products with different cutting order. In consideration of the influence caused by cutting order, only with a suitable sequence can the product waste length be minimized. In order to analyze how the cutting order influences the waste length, the following theorem is given:

Theorem *Suppose the distance of blade between two blanks is T. When cutting two blanks with different weights consecutively on the same steel ingot (suppose the weights of the blanks are $w_1$and w_2, $w_1 < w_2$), the waste length of steel ingot is less when the light-weighed blank is near to small side end.*

Proof The cutting positions of these two blanks are shown in Fig. 5.5. As $w_1 < w_2$, it is easy to derive that $h_1 < h_2$ through the cubature formula of circular truncated cone. According to $T_1 = T_2 = T$ and $h_1 < h_2$, we can derive that $w_{T1} < w_{T2}$. Combining $w_1 + w_{T1} + w_2 < w_2 + w_{T2} + w_1$ and cubature formula of circular truncated cone, we can now have $l_1 < l_2$.

By the above theorem and induction method, we find that when cutting the blanks with different weights on the same steel ingot, if the distance of blade between adjacent blanks is T, then the total waste length of steel ingot is minimized

Fig. 5.5 The relation of variable cross-sectional length and position



provided that the sequence of the products from small side end to big side end is a nondecreasing order of weights.

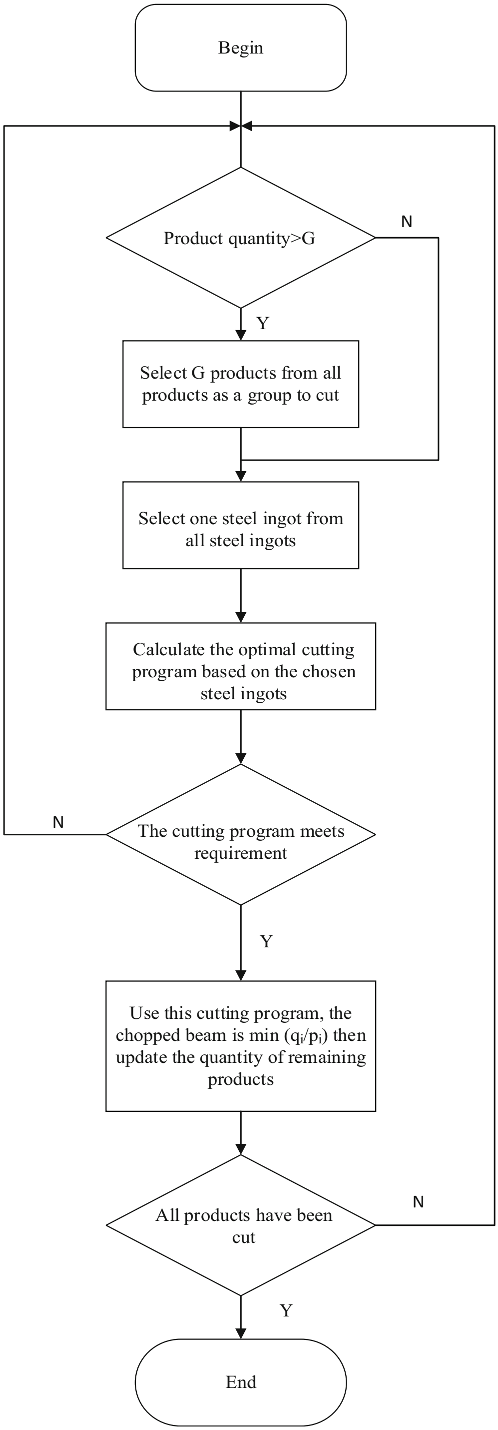
5.3.2.2 SHP Algorithm

The basic algorithm flow of SHP algorithm is as follows: first, obtain all the cutting plans for cutting on single steel ingot, and do not take the number of products into account. Second, select the best of these cutting plans, and suppose it is $P = (p_1, p_2, \ldots p_n)$. p_i is used to denote the number of blanks i. For instance, $P = (2,3,0,5)$ represents cutting two pieces of the first product, three pieces of the second product, and five pieces of the forth product consecutively. After one cutting process using this pattern, the chopped beam is denoted as min (q_i/p_i), at least one product can be finished. Repeat the above process constantly until all the products are cut.

When there are different types of products, the cutting plan of all products on single steel ingot is hard to obtain; we choose G products as a group and operate on this group in order to reduce the search space and save the operation time. The flow of the algorithm is shown in Fig. 5.6.

The SHP algorithm is widely used in actual production because of the following advantages: (1) the time complexity of the SHP algorithm is low. Compared with the purposes of column-generation method, cutting plane method, and branch-and-bound method, the purpose of the SHP algorithm is not to obtain optimal solution, so we can use the SHP algorithm to obtain satisfactory solution for large-scale problem in finite time. (2) For the solution obtained by the SHP algorithm, the number of cutting plans is not bigger than the types of products. This is very helpful to reduce the regulating times of knife rest. (3) The cutting ratio and operation time of the SHP algorithm are controllable. We can improve the cutting ratio by adjusting parameters or increasing operation time. The disadvantages of the SHP algorithm are given as follows: this algorithm is lack of theoretical support, only can obtain satisfactory solution in reasonable time, and cannot find the optimal solutions. We even don't know the distance between our solution and optimal solution.

Fig. 5.6 The SHP program flowchart



5.3.2.3 Group Selection and Local Optimization

When there are many different types of products, we have to choose G products as a group to cut first and replace all products with the chosen group in order to reduce time complexity.

The chosen group has much influence on the cutting ratio. If we do not choose appropriate products, the following sequences may happen: (1) the cutting ratio of other products may decrease, which will influence all products' cutting ratio in the entire cutting plan, and (2) the types of the remaining products may decrease. As a consequence, the cutting ratio of the remaining products may decrease. There are many algorithms for selecting products; cutting workers even can manually select what they need. However, these selection algorithms are optimal in certain aspects; it may have different effects on different products. Besides, these algorithms are lack of theoretical analysis.

Quantity-Based Selection Algorithm

Haessler proposed SHP algorithm to solve one-dimensional cutting stock problem in 1971 and gave a selection plan which was based on quantity [178]. The flow of this selection plan is given as follows:

Let $k_{max} = \max q_i$
For $k = k_{max}$ down to 1

Let $n_1 = L_{sum} = 0$
For $i = 1$ to m

Let $b_i = [u_i/k]$

if $b_i > 0$, then let $n_1 = n_1 + 1$ and $L_{sum} = L_{sum} + b_i l_i$

Next i

if $n_1 > =G$ and $L_{sum} > \mu L$, then let $k_0 = k$ and exit from the procedure
Next k
Let $b_i = u_i$ and $k_0 = 1$

In this selection algorithm, let q_i denote the quantity of uncut products, b_i is used to denote the chosen products, n_1 represents the number of type, the length of the chosen product is denoted as Lsum, and μ denotes the controls parameter of cutting ratio and means the ratio of chosen product's length and ingot's length. When the ratio is larger than μ, the cutting ratio reaches certain demand and the search process is end.

This algorithm selects products by the number and the length of products; it solves the blindness of random selection method, which improves the result of product selection. But this algorithm doesn't deal with the terminal condition so when there are less products, the cutting ratio is sharply decreasing.

Sorting-Based Selection Algorithm

Gradisar proposed a selection plan in 2005 [180]. He, respectively, sorted the length, number of uncut products, and product of length and demanded quantity of products in ascending orders first. Then select G products from these three ranks, and choose the plan which has the highest cutting ratio. The selection flow is shown in Fig. 5.7.

Compared with selection algorithm based on quantity, the selection algorithm based on sorting has better effect because it selects from three aspects, respectively. However, it cannot solve the terminal condition problem either.

After the raw materials and products are determined, we have to consider how to cut the products on chosen raw material and generate a partial cutting plan. Then we need to deal with how to arrange the cutting plan to cut a L-long steel ingot into small pieces whose length are $l_i(i = 1\ldots G)$ in order to maximize the total length of the products. The model can be defined as

$$\begin{aligned}&\max \sum_{j=1}^{G} l_j x_i\\ &\sum_{j=1}^{G} l_j x_j \le L\\ &x_j \ge 0, \text{integer}\end{aligned}$$

This is a typical one-dimensional knapsack problem, and the optimal solution can be obtained by the following recursion formula. In the dynamic recursion formula, let l denote the length of the remaining raw material and n denote the product type. The initial value of l is L; the initial value of n is 1:

$$\mathrm{R}(\mathrm{l}, \mathrm{n}) = \begin{cases} \left. \max\limits_{0<i<\lfloor L/l_i \rfloor} R(l - l_i{}^{*} i, n+1) + l_i{}^{*} i \right) & n \le G \\ 0 & n > G \end{cases}$$

We can realize the recursion formula by recursive function when we are programming to obtain partial optimal cutting plan. During the recursive process, we can record the max value of n and i in each step; the final max value of n and i is the optimal cutting plan.

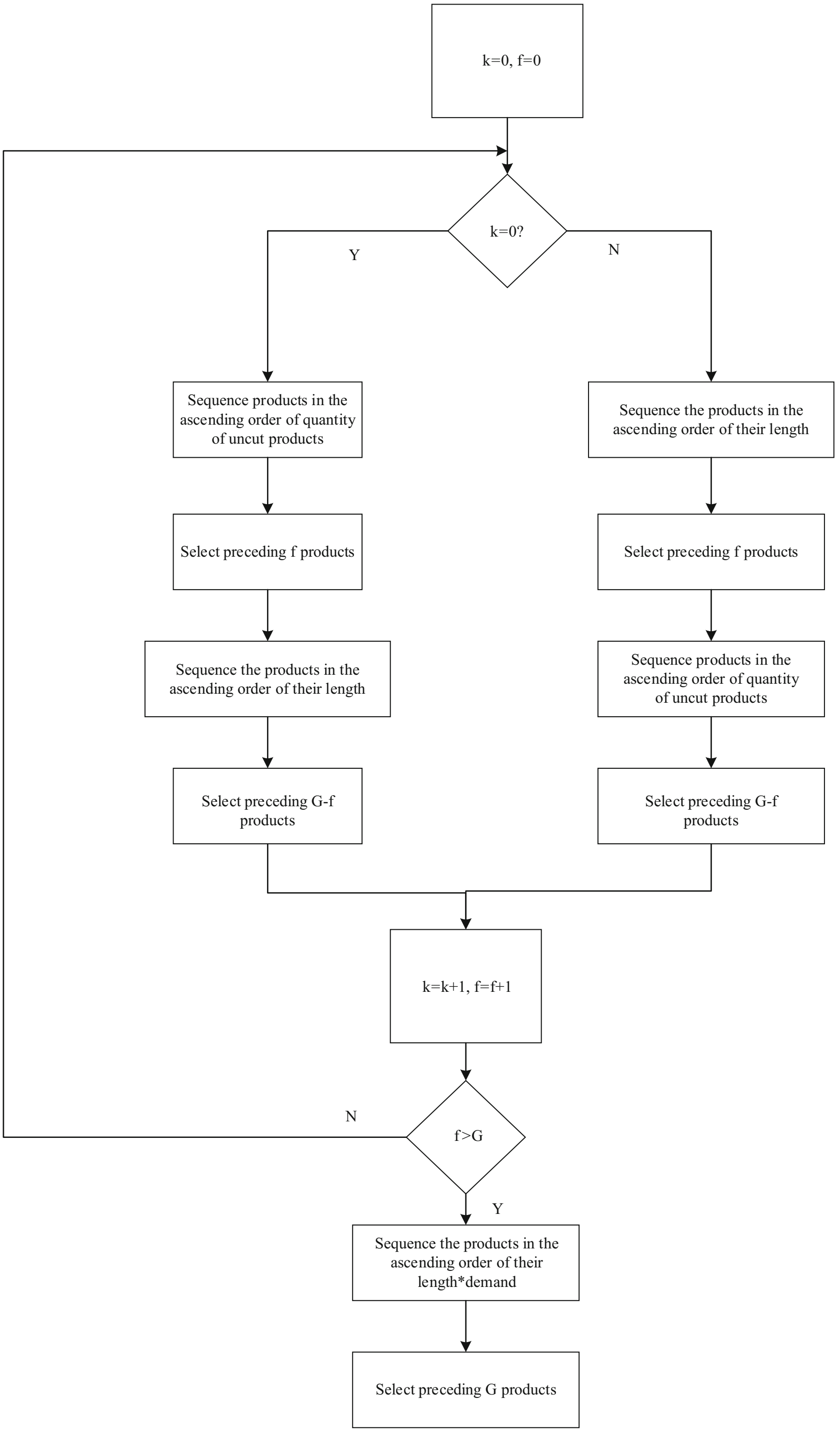


Fig. 5.7 The subset selection algorithm based on sequence

5.4 CSP in the Internet of Things

Traditional cutting stock problem aims to improve the utilization rate of raw materials and is regarded the cutting stock problem as a simple optimization problem. However, the cutting stock problem is a segment in real production and needs to be cooperatively optimized with other working procedures. The real-time status of product on production line, the operational aspect of machines, and the change of orders always influence the cutting process. The application of the Internet of Things enables the acquirement of these information.

5.4.1 Product Cutting Status and Position Monitoring

The cutting stock problem in the environment of Internet of Things not only considers the cutting ratio and stock utilization but also considers the distribution and optimization of all kinds of resources in a unified way. The involved resources not only include the steel ingot and raw materials but also contain all relevant resources. In order to manage these resources more efficiently, the relevant resources are listed below.

For example, there are hundreds of different resources on the production line of Masteel Wheel Company. These resources include finished product, semifinished product, and all kinds of machines. The machines on the production line can be replaced with each other, and some of them are correlative front and back. Besides, different products need different machines, so the whole process can be divided into a number of sub-operations according to the functions and the sequence of the process of managing machines. The complete production line of Masteel Wheel Company is shown in Fig. 5.8.

Each product probably goes through certain parts of the whole process; the technology which a single product goes through is called process route. No matter how the process route is, the product has to go through cutting process and rolling process. Before the cutting process is completed, the match ruler table can be adjusted, canceled, or remade at any time. All products between the cutting process

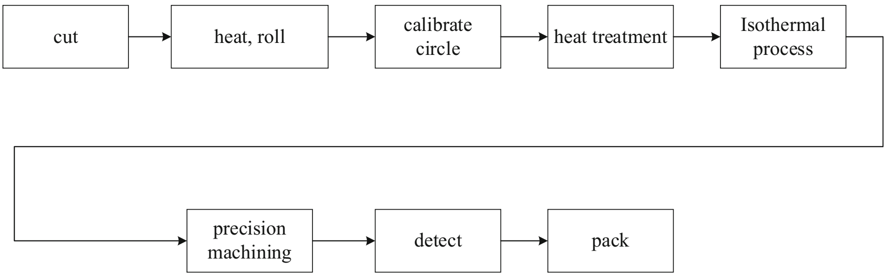


Fig. 5.8 The complete production line of Masteel Wheel Company

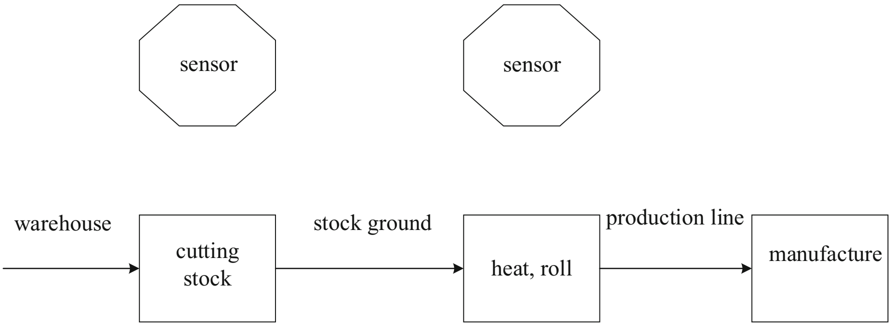


Fig. 5.9 Simplified working flowchart

and rolling process cannot be rearranged, but can be adjusted according to practical situation. For instance, product A is originally cut, products A and B are made up of same material, and product B is lighter than product A. In the latter procedure, product B can be made using blanks of product A under the condition that forging ratio and height-diameter ratio are satisfied. Similarly, product A also has to be recut in cutting process.

The product position has to be known in order to distinguish the position of different products. The whole process can be splitted into three parts: (1) before cutting process, the form of product is steel ingot. (2) During cutting process and rolling process, the form of product is blank. (3) After the rolling process, the form of product is semifinished product. To obtain the form and position of product in time, we can install label reader on the cutting and rolling machines. When products go through these two procedures, the product can be recognized and stored into database (Fig. 5.9).

5.4.2 *The Model of CSP in Internet of Things*

Under the traditional production environment, the information is not shared and timely, so the cutting process is separated. The product information in other batches, the process condition, and the date of delivery are unknown. The cutting stock problem is separately considered from the whole production process without considering the relationship among cutting, manufacturing, and the condition of production themselves.

Under the environment of Internet of Things, because the raw materials, products, and manufacturing resources are shared, the machines, products, and materials on the production line can be intelligently identified, positioned, tracked, monitored, and managed, the cutting clerk should know the position and condition of

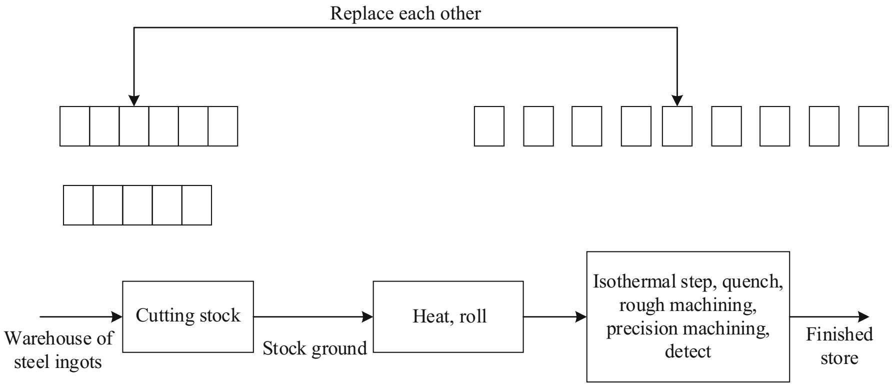


Fig. 5.10 The cutting process in the environment of Internet of Thing

products and position and condition of bars when he makes the cutting plan. Also, the cutting clerk should track and control the product timely and precisely, so the completion time, precise position, and condition can be adjusted or recut according to different conditions.

This chapter divides the product into three types according to the condition of cutting and different positions of products. The three types of steel ingots include uncut state, already cut not suppressed state, and already rolled state. Under the environment of Internet of Things, we can easily get to know the current state of product.

The real production line of Masteel Wheel Company is a jobshop process. The whole process is made up of several steps like cutting process, heating process, rolling process, isothermal process, quenching process, rough machining process, finish machining process, examining process, and so on. The whole cutting process under the environment of Internet of Thing is shown in Fig. 5.10.

The cutting process is the first step of the whole process, which means all products have to go through the cutting process. After the rolling process, all products are manufactured in order on the production line; thus, the productive process after rolling process is a flowshop problem. Therefore, the rolling process and the process after it can be regarded as one process and can be called rolling process.

Rolling is the bottleneck in the whole productive process. The cutting process is much faster than the rolling, so between the cutting process and rolling process, there is a buffer area called workblank field. The workblank which is cut but not rolled yet will be stored in this field.

There is an ingot warehouse before the cutting process to store uncut raw materials. And there is a finished store after all processes to store are finished product.

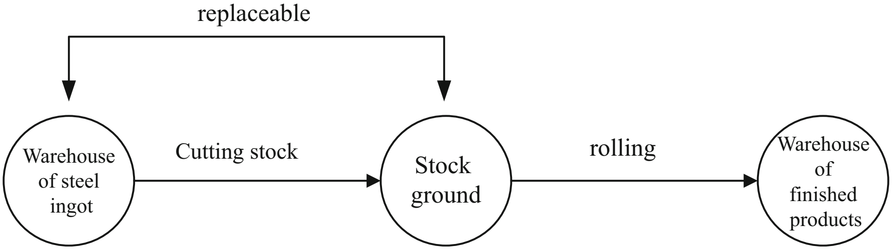


Fig. 5.11 Substitution of workblank in the environment of Internet of Things

For simple research, the whole production line can be simplified into three buffer areas and two processes: ingot warehouse, workblank field, finished store, cutting process, and rolling process. The simplified picture is shown in Fig. 5.11.

In the cutting process, the uncut products in the ingot warehouse and the already cut but not rolled products in the stock ground can replace each other. If we have to cut a product with urgent date of delivery, and there is a replaceable product in the stock ground whose weight is equal to or slightly heavier than current product and date of delivery is looser, we can replace current product with the product in the stock ground and recut the replaced product. In this situation, the cutting ratio of the replaced product will decrease or remain unchanged, but the completion time of current product will shorten. So this situation will meet the requirement of the date of delivery better.

Suppose the weight of raw steel ingot is W and the quantity is unlimited. The preliminary goal is to cut these raw materials into m kinds of products p_i whose weight is w_i, quantity demanded is $d_{i,}$ and the date of delivery is $T_i(i = 1,2...m)$. Suppose there are n kinds of already cut and unrolled product sp_j whose weight is sw_j, quantity is sd_j, and date of delivery is $ST_j(j = 1,2...n)$. Moreover, the already processed time is $st1_j$; surplus completion time is $st2_j$. Based on the objective of minimizing the total cost of raw materials and satisfying the date of delivery of products, we give the model of cutting stock problem as follows:

$$\min Z_1 = \sum_k W x_k$$

$$\max Z_2 = \sum_{i=1}^{m} C_{ij}\delta_{ij}$$

$$\sum_k a_{ik}x_k \geq d_i \tag{5.8}$$

$$\sum_{i=1}^{m} a_{ik}w_i^{'} \leq W \tag{5.9}$$

$$\delta_{ij} = \begin{cases} 1 & w_i \le sw_j \le w_i{}^*\sigma \text{ and } d_i \le sd_j \text{ and } ST_j > T_i \max j \\ 0 & other \end{cases}$$
$$w_i^{'} = \begin{cases} w_i & \delta_{ij} = 0 \\ sw_j & \delta_{ij} = 1 \end{cases}$$
$$f(t) = \begin{cases} C_1 t & t \ge 0 \\ -C_2 t & t < 0 \end{cases}$$
$$C_{ij} = d_i\left[f\left(T_i - st2_j\right) + f\left(ST_j - st1_j - st2_j\right) - f\left(T_i - st1_j - st2_j\right) - f\left(ST_j - st2_j\right)\right]$$
$$x_j \ge 0, \text{integer}$$
$$a_{ij} \ge 0, \text{integer}$$

W, the weight of raw material
m, the number of type of uncut products
w_i, the weight of uncut product i
d_i, the quantity demanded of uncut product i
n, the number of type of already cut products on the stock ground
sw_i, the weight of already cut product i on the stock ground
sd_i, the quantity of already cut product i on the stock ground
x_j, the number of chopped beam in the jth cutting program;
a_{ik}, the quantity of cut product i in the kth cutting program
δ_{ij}, whether the product i and product j are exchanged
C_1, the storage cost of product
C_2, the penalty cost of delayed order
$f(t)$, product cost which is storage cost or penalty cost of delay, t denotes the advanced completion time
C_{ij}, the cost saved after exchanging i with j

In this model, the first objective is to minimize the total weight of used raw materials. The second objective is to maximize the saved cost after exchanging. Constraint (5.8) expresses the total number of each product after cutting process meets the requirement for it. Constraint (5.9) ensures that the total length of all products cut by one material is less than the length of raw material (Fig. 5.12).

Let SP_j in stock ground replace P_i in warehouse of steel ingots; the number of SP_j is d_i. In the replace process, production time is $st1_j + st2_j$, date of delivery is T_i, the completion time fulfilled ahead of schedule caused by replacement is T_i- $st1_j$-$st2_j$, and the cost is $f(T_i\text{-}st1_j\text{-}st2_j)$. In the process to produce SP_j, production time is $st2_j$, date of delivery is ST_i, the completion time fulfilled ahead of schedule is T_i-$st2_j$, and the cost is $f(ST_i\text{-}st2_j)$.

After the replacement, the production time of P_i is $st2_j$, the date of delivery is T_i, the completion time fulfilled ahead of schedule is T_i-$st2_j$, and the cost is $f(T_i\text{-}st2_j)$. The production time of SP_j is $st1_j + st2_j$, the date of delivery is ST_j, the completion time fulfilled ahead of schedule is ST_i-$st1_j$-$st2_j$, and the cost is $f(ST_i\text{-}st1_j\text{-}st2_j)$.

It is obvious that the saved cost after replacement is noted as follows:

$$C_{ij} = d_i\left[f\left(T_i - st2_j\right) + f\left(ST_j - st1_j - st2_j\right) - f\left(T_i - st1_j - st2_j\right) - f\left(ST_j - st2_j\right)\right]$$

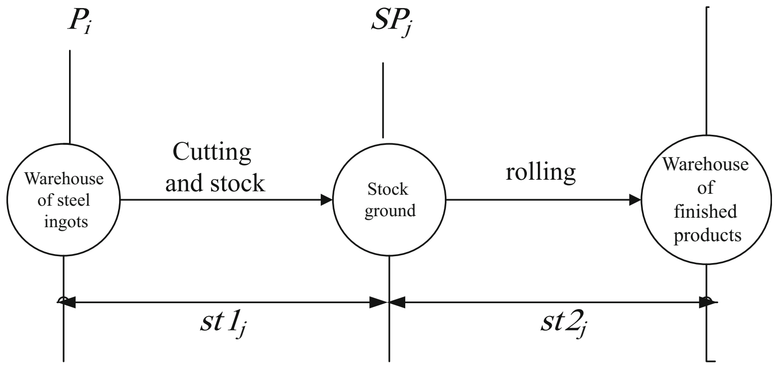


Fig. 5.12 The substitution of blank in different processes

5.4.3 Improved SHP Algorithm

CSP in the environment of Internet of Things is based on the classic CSP and considers the different stages of product substitution, product delivery, store cost, and other factors. There are two optimization objectives: the first objective of minimizing the number of the total consumption of steel ingot when cutting is completed for all products is identical to the objective of traditional CSP. The second objective is minimizing the total cost that contains the loss of delivering delay and the increased cost caused by inventory completing ahead of schedule.

Under the environment of Internet of Things, CSP formally is a multi-objective optimization problem. To solve this problem, one can use the weighed method for transforming this problem into a single-objective problem or find the Pareto solution and then find out the solutions which meet production requirements according to the actual situation.

CSP is an NP-hard problem, and the optimal solution to CSP of single objective in a large scale is hardly found in finite time. The search space of multi-objective problem is much larger than the search space of single-objective problem, which make it more difficult to find the solutions which satisfy the actual needs for the multi-objective problem.

However, when analyzing CSP in the environment of Internet of Things carefully, it is not difficult to find that CSP in the environment of Internet of Things is different from common multi-objective CSP. The two objectives of CSP in IoT environment are not completely mutually exclusive. In addition, the weights of these two objectives are also different in the actual production process. People are more concerned about the first objective that minimizes the use of raw materials, while the second objective is to satisfy the first goal, and the more optimized of the second goal, the better.

Therefore we give priority to the first objective. Firstly use the first objective to generate preliminary cutting plan. Then considering the second objective, replace the emergency products in delivery period with relatively noncritical products from

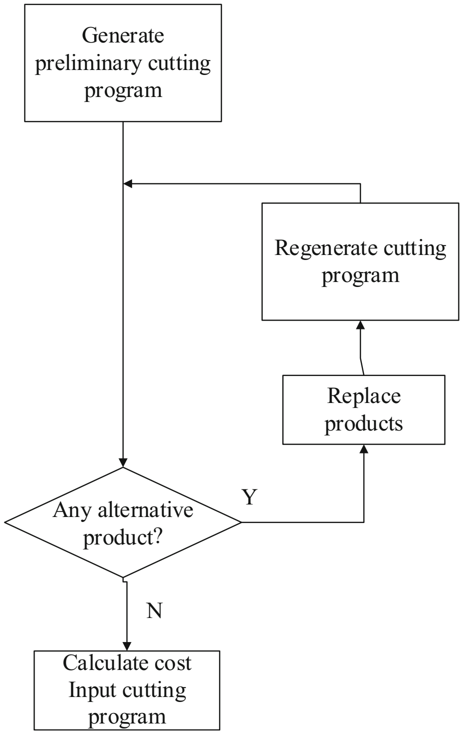


Fig. 5.13 The flowchart of cutting stock algorithm in the environment of IoT

stock field. Next, regenerate cutting program and repeat this process constantly until there is no replaceable product. The flowchart of the algorithm is shown in Fig. 5.13.

5.4.3.1 Generate Preliminary Cutting Plan

To generate preliminary cutting plan, we only consider the first objective and ignore the second objective which means that we only need to minimize the use of raw materials and do not take the date of delivery and preserve cost for finished products into account. The model of the problem is given as follows:

$$\min Z_1 = \sum_k W x_k$$

$$\sum_k a_{ik} x_k \geq d_i$$

$$\sum_{i=1}^{m} a_{ik} w_i \leq W$$

$$x_j \geq 0, \text{integer}$$
$$a_{ij} \geq 0, \text{integer}$$

This is a typical one-dimensional CSP (1, V, O, M). We can use the SHP algorithm discussed in Sect. 5.3.2.2 to solve this problem.

5.4.3.2 Substitution Principle and Algorithm

The products which are not cut in ingot warehouse and the products which have been cut but not rolled in stock field can be replaced by each other. If there is a very urgent product, and in blank material field, there is a replaceable and similar product with looser delivery date, we can replace the urgent product with the replaceable one.

There is a product P_i in current cutting program and a product SP_j in stock field. The replacement of these two products has to meet the following principles: (1) the delivery date of P_i is more emergent than that of SP_j, which is denoted by $T_i < ST_j$; (2) the weight of SP_j is equal to or slightly greater than P_i (meanwhile, the technology requirements need to be satisfied, such as the forging ratio and ratio of height to diameter and so on), which is expressed as $w_i \leq sw_j \leq \sigma w_i$; and (3) the number of SP_j must be greater than or equal to P_i, which can be represented as $d_i \leq sd_j$.

Principle (1) is to look for the products with a relatively nonurgent delivery date from the stock field to produce more urgent products. Readjust the current cutting program, and cut the original product. The principle (2) shows that we can only use heavier products to replace lighter products, because the former can produce the latter by forging, but if the weight is much heavier, there will produce too much waste. Owing to technology limit, heavier products cannot be replaced with lighter products. The principle (3) is to ensure that all emergent products but not a part of the whole products are replaced because only replace a part of the whole products which is not conducive to forwarding the delivery date.

The advantages of replacement can be summarized as follows: adjusting the delivery, reducing cost through producing emergent products, and using blanks those are already cut. In general, the cutting rate of the current cutting will reduce, because the weight of the products is greater than the weight of products in original program. Sometimes it will increase the cutting rate of products. As shown in Fig. 5.14, a heavy product is replaced to the current cutting program, and the cutting rate improves.

Therefore, our objective is to find such a combination of replacement. After replacement, the cutting rate will slightly reduce, remain unchanged, or improve, but it can shorten makespan in order to meet the delivery demands better. Algorithm flow is as follows:

Step 1 For all products $P_i (i = 1,2,\ldots m)$ in the cutting area, find related products $SP_j (j = 1,2,\ldots n)$ from the stock field.

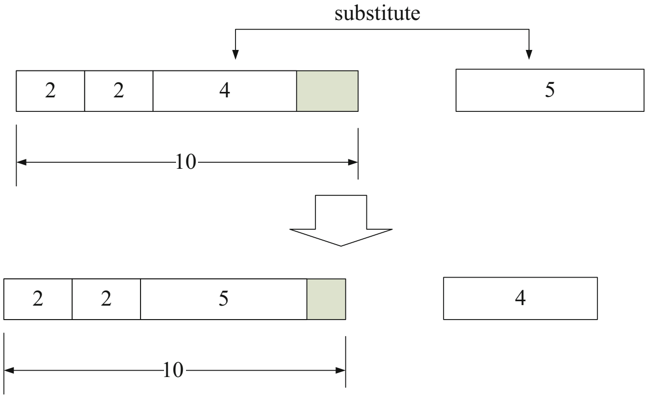


Fig. 5.14 Sketch of the influence of substitution to cutting rate

Step 2 If $T_i < ST_j$, $w_i \leq sw_j \leq \sigma w_i$ and $d_i \leq sd_j$, go to step 3; else go to step 1.
Step 3 Replace products and store two-tuple(i,j)into Φ if the remaining materials which contain all P_i are greater than sw_j in preliminary cutting program.
Step 4 Print all (i,j) in Φ, show P_i can be replaced by SP_j.

5.4.3.3 Regenerating Cutting Program

P_i and SP_j can be exchanged with Φ to regenerate new cutting program. The new program can save more cost than the original program and does not reduce the cutting rate. The mathematical model for solving new cutting program is as follows:

$$\min Z_1 = \sum_k W x_k$$

$$\sum_k a_{ik} x_k \geq d_i \tag{5.10}$$

$$\sum_{i=1}^{m} a_{ik} w_i^{'} \leq W \tag{5.11}$$

$$x_j \geq 0, \text{integer}$$
$$a_{ij} \geq 0, \text{integer}$$

Different from the original program, restriction (5.11) of current cutting program is $\sum_{i=1}^{m} a_{ik} w_i^{'} \leq W$. Due to the limit of above step 3, we don't need to recalculate the cutting stock program as long as we replace P_i with SP_j in the original program.

If there is no limit in step 3, we can use SHP to recalculate this new model for a new solution. Also, the cutting rate of this solution is likely to be smaller than before.

5.4.4 Simulation and Analysis

To analyze the efficiency of the algorithm proposed in this chapter, use Lenovo K29 laptop with the 2.5 G Hz main frequency to simulate the algorithm with Visual C++6.0 development environment. The experimental data are shown in Table 5.4 that gives the ingot and the product data from actual production data. The date of delivery is a random number between 3 and 15.

Suppose the weight of steel ingot is 1000 kg and the quantity is large enough. Tables 5.2 and 5.3 show the information of the weight (unit is kg), the data, and the date of delivery about the products which are going to be cut and have been cut.

Cutting programs of all products are shown in Table 5.4 without replacement. It can be seen from the table that the program needs to change cutting tool 20 times and needs 333 steel ingots, and the cutting rate is 92.64%.

Considering the replacement of products during cutting process, the cutting stock programs are shown in Table 5.5. It can be seen from the table that the

Table 5.2 The data of products which are to be cut

Products				Products			
ID	Length	Quantity	Date of delivery	ID	Length	Quantity	Date of delivery
1	256	31	15	11	323	63	10
2	353	45	10	12	285	52	7
3	278	64	6	13	344	68	15
4	228	64	7	14	396	49	12
5	332	11	6	15	321	23	15
6	499	51	11	16	452	17	7
7	367	26	15	17	293	70	7
8	300	24	3	18	371	48	12
9	315	41	6	19	462	46	10
10	410	43	3	20	343	58	7

Table 5.3 The data of products which are already cut

Products				Products			
ID	Length	Quantity	Date of delivery	ID	Length	Quantity	Date of delivery
1	414	45	7	11	458	61	9
2	331	76	10	12	435	62	6
3	464	62	14	13	211	44	11
4	383	75	5	14	218	52	7
5	328	37	14	15	252	71	12
6	275	65	4	16	207	16	12
7	392	49	14	17	358	49	15
8	497	71	5	18	455	13	14
9	390	37	12	19	263	14	3
10	461	63	8	20	443	47	14

Table 5.4 Cutting programs of SHP algorithm

ID	Quantity	Cutting plan					
		Product	Quantity	Product	Quantity	Product	Quantity
1	11	256	3	228	1		
2	4	332	3				
3	26	499	2				
4	26	353	1	278	1	367	1
5	18	228	3	300	1		
6	10	353	2	278	1		
7	6	278	1	300	1	410	1
8	21	323	3				
9	26	410	1	285	2		
10	21	315	2	344	1		
11	22	278	1	344	2		
12	3	344	1	321	2		
13	6	321	3				
14	11	410	1	293	2		
15	24	396	1	293	2		
16	23	462	2				
17	9	452	2				
18	13	396	2				
19	24	371	2				
20	29	343	2				

number of cutting tool and steel ingot remains unchanged and is 20 and 333 times, respectively. However, the cutting rate increases to 96.78%.

In addition, compared with the original program, new cutting scheme has five products interchanged, and they are 344<−>358, 462<−>497, 452<−>464, 371<−>461, and 343<−>458, respectively. It can be found that the delivery dates of products in the to-be-cut area are relatively slower than before; thus, the new cutting program can meet the requirements of date of delivery better.

Therefore, the new method can improve the cutting rate and meanwhile does not change the consumption of raw materials. It can help to cut the products to meet the requirement of delivery date better and delay the cutting product whose date of delivery is not urgent. Thus, this method can reduce the inventory cost and the loss of opportunity cost caused by delayed delivery.

Table 5.5 Cutting program considering product interchange in environment of IoT

ID	Quantity	Cutting plan					
		Product	Quantity	Product	Quantity	Product	Quantity
1	11	256	3	228	1		
2	4	332	3				
3	26	499	2				
4	26	353	1	278	1	367	1
5	18	228	3	300	1		
6	10	353	2	278	1		
7	6	278	1	300	1	410	1
8	21	323	3				
9	26	410	1	285	2		
10	21	315	2	358	1		
11	22	278	1	358	2		
12	3	358	1	321	2		
13	6	321	3				
14	11	410	1	293	2		
15	24	396	1	293	2		
16	23	497	2				
17	9	464	2				
18	13	396	2				
19	24	461	2				
20	29	458	2				

5.5 Conclusion and Future Research

5.5.1 Conclusion

We have reviewed the common cutting stock problems in real productive process: one-dimensional cutting stock problem of uniform variable section raw material and the cutting stock problem under the environment of Internet of Things. For the one-dimensional cutting stock problem of uniform variable section raw material, we not only have taken the cutting rate and the quantity of cutting programs into account but also have considered the demand for ratio of forging reduction and ratio of height-diameter, the restrict of quantity of blades, the distance of adjacent blades, and so on. For the cutting stock problem in the environment of Internet of Things, we have considered the new features of cutting stock problem such as the position condition of steel ingot, blanks, and the replaceable blanks in different stock ground or machines. Besides, we have proposed improved algorithm based on these conditions.

The problems discussed above are all from practical production process. We have summarized general model of these problems, designed algorithms to solve these problems, and applied these models and algorithms into practice. The cutting stock problem investigated above shows the following properties:

Firstly, the cutting stock problems we solved are large-scale problems with complicated constraints. When modeling the one-dimensional cutting stock problem with uniform variable section raw material, we not only consider the cutting ratio and the quantity of cutting program but also consider the constraints in real production process such as forging ratio, height-diameter ratio, the quantity of blade, the width of blade, and so on. And we increase length transfer algorithm to calculate the cutting length of products when solving problem using improved SHP algorithm. The improved SHP selection algorithm insures the homogeneity of selected products and avoids the decrease of cutting rate when the quantity of products decreases. Considering the constraint for number of blades, we redesign an algorithm to solve knapsack problem and decrease the complexity of this algorithm. We also modify the procedure of SHP for solving small amount products which avoids the disadvantage of terminal condition of SHP. We also make the SHP algorithm to automatically calculate parameters based on users' tolerate degree about the running time. All these improvement and adjustment above are made to meet the requirements in large-scale cutting stock problem.

Secondly, our objective is not to obtain the optimal solution but to obtain the satisfactory solution proceeding from the reality. So we adopt improved SHP algorithm to solve one-dimensional cutting stock problem with uniform variable section raw material and the cutting stock problem in the environment of Internet of Things.

Finally, the problems we investigate are already or about to be applied in practical production. The one-dimensional cutting stock problem with uniform variable section raw material and algorithm we discussed are already used for many years in Magang Steel Wheel Company. The application also gains great effects.

5.5.2 Future Research

The cutting stock problem in real production process is a very complicated and changeable problem. With the change of products, the recombination of production process, the upgrading of machines, and the application of new technology, the cutting stock problem will show new characteristics. So the problems we investigate still need to be extended and completed.

Firstly, it is observed that the cutting stock problem in real production process is mostly multi-objective cutting stock problem, and the objectives are not only improving the cutting ratio. The one-dimensional cutting stock problem with uniform variable section raw material we discussed only considers the single-objective situation. The cutting stock problem in the environment of Internet of Things is a multi-objective problem, whereas we just select one of these objectives as the main objective. Hence, the multi-objective cutting stock problem still needs further investigation.

Secondly, the cutting stock problem in real production process is a part of the whole production process, so the cutting stock problem should be put into the overall situation. Otherwise, some issues may appear, for example, the products need to be produced urgently cannot be cut in time. This is also our direction of further research.

Last but not the least, the cutting stock problem we investigated is proceeded in inner enterprise. However, if considering the cutting stock problem in the whole supply chain, then the model in this chapter will be not very practical. For example, the blank can be delegated out, and the waste produced by cutting process can be melted down and reused instead of throwing away. These issues are worth to be investigated further.

Chapter 6
Total Quality Management of the Product Life Cycle in an IoT Environment

6.1 Introduction

6.1.1 Total Quality Management

Feigenbaum [218] developed the theory of total quality management in 1961. He held that total quality management (TQM) aims at fully satisfying customer requirements through market research, design, production, and services. He integrated the enterprise activities of designing quality, maintaining quality, and improving quality into an effective system. Shewhart [247] promoted the understanding of quality and quality management and accelerated the development of quality management. Johnson and Jack [224] indicated that TQM is "doing the right thing at the right time." Deming [227] noted that the role of quality management in business is to create the constancy of purpose for the improvement of products and to create a system that can produce quality outcomes. Benson et al. [248] pointed out that quality is to "satisfy or delight the customer." All quality improvement initiatives must start from an understanding of customer requirements. Samson and Terziovski [215] indicated that TQM must utilize techniques that improve product quality and processes to help a firm improve its competitive performance. Jeong et al. [240] thought total quality management means making sure everything and everyone in the organization realize continuous quality improvement. Hoanga et al. [244] summarized 11 measurements of the TQM model, including leadership and top management commitment, employee involvement, education and training, teamwork, employee empowerment, customer focus, process management, strategic planning, open organization, information and analysis system, and service. Many researchers systematically summarized the methods for quality management and tried to redefine the concepts of quality management under the specific requirements of certain enterprises.

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6.1.2 Product Life Cycle Quality Management

The product life cycle contains demand analysis, product design, manufacturing, marketing, after-sales service, and remanufacturing. The company should not only make the products themselves meet customers' requirements but also provide customers with continuous service. Companies can now use some new information technologies, such as RFID, cloud computing, and the IoT, to help supervise their products' life cycle quality. However, faced with changing demands and distributed manufacturing, companies cannot fully meet the requirements of their customers. Son [251] considered how to manage and reduce the impact of various sources on product quality during the whole life cycle, as well as assure that the quality of the product was consistent with customer requirements. Compared to traditional quality control activities, which aim at the process quality of an individual enterprise, today's quality management is not only about the process control of the product realization, but it is also a dynamic process of system control throughout the entire life cycle of the product or service. Quality management is a continuous process of maintaining and improving the quality, which encompasses demand analysis, product design, manufacturing, marketing, after-sales service, and the remanufacturing process of products.

6.1.3 Quality of Service (QoS) in a Cloud Manufacturing Environment

Cloud manufacturing integrates cloud computing, the IoT, service-oriented technologies, and advanced management technologies to allocate various manufacturing resources and satisfy changing customer demands. Li et al. [229] thought cloud manufacturing aims to intelligently integrate and provide the best manufacturing resource allocations to customers. In a cloud manufacturing environment, the main manufacturer can be seen as a service organizer that makes decisions based on a large number of service components. Quality of service (QoS) is a set of nonfunctional parameters of a service, such as the service time, service price, location, reliability, and security. Many researchers proposed extended QoS models and designed their algorithms to effectively improve the QoS of composite services and better meet customer requirements.

6.2 Literature Review

6.2.1 *The Application of TQM to Realize Continuous Quality Improvements*

The development of global manufacturing has caused researchers to propose a new definition of quality to help companies realize continuous quality improvements. Cynthia [245] reviewed the definition of TQM and concluded that it should be viewed in manufacturing operations as a collection of processes through a descriptive-qualitative type of research. He indicated that a manufacturing firm must strive to continuously improve these processes by incorporating the knowledge and experiences of workers; the simple objective of TQM is to "Do the right things, right the first time, every time," which means TQM is infinitely variable and adaptable. Beaujean et al. [207] regarded manufacturing companies' objectives as the need to increase the effectiveness and efficiency of their production systems. They combined the customer, management, and operation perspectives and proposed a new definition of quality that contained a holistic description, analysis, and improvement of the whole process and project landscape. Ren and Lin [246] proposed that manufacturing enterprises need to analyze the formation of service quality in the manufacturing process after demand analysis, conceptual design, detailed design, processing and manufacturing, and service support. Then, the enterprise can develop and implement the corresponding improvement countermeasures to realize the continuous improvement of service quality based on the whole life cycle of the product service quality gap model. Feng and Ma [208] developed the life cycle of a virtual enterprise-integrated quality management system model based on system science, preliminary discussion quality diagnosis, and control methods. Feng et al. [252] summarized the influential factors of quality management in the life cycle and designed the life cycle of a virtual enterprise quality management evaluation index system. They used the fuzzy comprehensive evaluation method to evaluate each stage of the entire life cycle. Dominguez et al. [249] proposed a quality evaluation framework to manage quality in model-driven web engineering. Parzinger [209] found that TQM benefits are not equally distributed across adopters. They researched TQM benefits on the product life cycle (PLC) stages of the organization and described how the product life cycle may affect the importance of each of the implementation factors identified in Feigenbaum [218], described the form this effect can take, and provided insight into the successes and failures of TQM. Son [210] indicated that the quality assurance of a designed product plays a very important role during its life cycle in the context of the global and concurrent economies. The designed product runs the risk of being unsatisfactory to customers. He proposed a method that allowed for the management of the quality of a product during its life cycle at the design stage. Feng et al. [211] proposed an integrated quality management system model for the life cycle of a virtual enterprise, which is a complex system. They discussed the model elements, diagnosis, and control, but did not verify the method they proposed. Yan et al. [212]

found that most of the project quality problems are caused by design, which means that the quality of the design has a great impact on the life cycle quality of the project. They first introduced the project life cycle theory in design quality management and proposed a framework of project life cycle design. Bradley [213] thought that software played a critical role in providing much of the advanced functionality of modern telecommunications equipment. He found that the way to achieve significant progress toward TQM in the software development life cycle was via the implementation of a comprehensive defect prevention program.

6.2.2 The TQM Approach

Among modern managerial approaches, the TQM philosophy has enjoyed significant attention. Mitreva and Taskov [214] found that the TQM strategy does not directly measure the success of a company through the financial indicators compared to Six Sigma. The application of the TQM strategy requires that the management personnel in the company have goodwill and perseverance; it also requires that they integrate their knowledge to achieve complete mastery of quality in all processes at the lowest cost of operation. Samson and Terziovski [215] examined the total quality management practices and operational performances of a large number of manufacturing companies in order to determine the relationships between these practices and firm performance, individually and collectively. Suneeta and Koranne [216] reviewed studies on service quality and found that service quality is interdependent and has a direct relationship with customer satisfaction. Barbara [217] examined TQM in relation to the mechanistic, organismic, and cultural models of organization in order to associate TQM practices with management theory. Those models provided diverse analogues for explaining the management of organizations and highlighted the different issues concerning the practice of TQM. Thomas [243] reviewed empirical research on TQM and found that most of the features generally associated with TQM, such as quality training, process improvement, and benchmarking, do not generally produce advantages, but some imitable features such as open culture, employee empowerment, and executive commitment can produce advantages. Hoogervorst and Koopman [219] found that TQM entails a human-centered approach to organization, which is fundamentally incompatible with traditional mechanistic thinking. An organization needs to pay more attention to its organizational culture, management practices, and organizational structures and systems to avoid the failure of TQM. Zhou [220] considered some possible potential in utilizing RFID tracking/tracing identification technology to gain refined and improved information about consumer preferences, which in turn can be beneficially utilized as input for effective strategy design. He proposed an adaptive learning mechanism and showed that marketers can develop effective strategies by using it. Pantouvakisa and Psomasb [221] analyzed data from 87 major shipping companies and revealed four reliable and valid latent factors from the existing ten factors regarding the results achieved through implementing

TQM practices. Those are "customer satisfaction," "financial performance," "service quality performance," and "conformity to rules." Jamison [222] developed a further understanding about the relationship between quality management practices and organizational performance. He considered the role that learning and exploration play in quality/continuous improvement efforts. He drew the conclusion that learning and exploration were mutually beneficial when considered within the context of continuous improvement. Torre [223] held that quality has become one of the most relevant challenges for enterprises that wish to satisfy the requirements of their customers. He studied how information technologies help to ensure a better quality for enterprises and how they influence the concept of quality. Khanam et al. [241] used the Pareto analysis approach to arrange the TQM enablers and IT resources. They proposed that managers use a set of vital factors for the successful implementation of TQM and managers can decide which IT resources are more helpful for implementing TQM. Meryem et al. [225] proposed that Six Sigma had a direct impact on organizational performance rather than being complementary to traditional QM practices. They found a significant path to success from process management (PM). They also found that employee relationship management (ERM) had a direct impact on PM and customer relationship management (CRM), and top management had direct positive links to CRM and ERM. Marek [226] used an affinity diagram to analyze the literature and provided a solid basis for identifying the main changes within the TQM concept. He summarized the tools that clearly indicate parts of the concept. Tahira et al. [242] used the Pareto analysis to analyze the total quality management and concluded that top management commitment is the key critical success factor, with customer focus and satisfaction close behind. Saber and Aasim [228] analyzed different types of information system strategies for implementing TQM in the aviation industry and discussed different examples of the IS support techniques in performing the TQM implementation at Delta Air Lines. They also focused on different information strategies and selected different processes of the TQM implementation for the aviation industry.

6.2.3 Meeting Customer Requirements with Cloud Manufacturing

As the technology of the IoT matures and the quality of products is determined by the life cycle manufacturing services based on cloud platforms, researchers and companies are integrating QoS and new information technology into the cloud manufacturing mode. Geoffrey et al. [230] found cloud patterns are always described in the literature as good practices, without any consideration of the context and interactions with other patterns. They performed a series of experiments with different versions of the cloud-based RESTful application. They assessed the impact of these patterns on the QoS of the application through measurements of the overall response time and the average and maximum number of requests processed by the application per second. They found that these patterns and their combinations can increase the QoS of applications. Jin et al. [231] proposed service composition as an effective way to build a new value-added cloud service by combining existing manufacturing cloud services to meet the demands of manufacturing tasks in cloud manufacturing. Quality correlations among manufacturing cloud services would affect the whole quality of the manufacturing cloud service composition. They proposed a description model to automatically obtain the associated QoS values of the services. José et al. [250] proposed a service correlation-aware QoS description model based on its investigated and service-correlated mapping in order to calculate the QoS of manufacturing cloud service compositions more accurately. Liu and Zhang [232] proposed the synergistic elementary service group-based service composition (SESG-SC) approach, which avoids the assumption of one-to-one mapping between elementary services and subtasks and allows a free combination of multiple functionally equivalent elementary services into a synergistic elementary service group (SESG) to perform each subtask collectively, thereby improving the overall QoS and achieving a more acceptable success rate. Liu et al. [233] proposed the branch-and-bound method for the execution plan selection (BB4EPS) algorithm to solve the QoS-aware service composition problem. A universal QoS model was used to evaluate the QoS parameters for the service composition in their BB4EPS algorithm. Li et al. [234] proposed an extended model containing two kinds of correlation descriptions. A comprehensive candidate service set is established when correlation services are reserved during the matching process through their algorithm, which also avoids the low QoS of the composite service caused by the omission of services that have correlations. Cao [235] established a service selection and scheduling model that considers the criteria of time, quality, cost, and service (TQCS). These four relative superiority degrees are then combined linearly into an overall objective, in which the weight coefficients are calculated through analytic hierarchy process (AHP). They proposed using ant colony optimization selection (ACOS) for the established service selection and scheduling model. Xu et al. [236] presented three kinds of correlations in their correlation-aware QoS model in order to improve the performance of manufacturing service aggregation. They discussed how to select an appropriate service to compose new and optimal performance services from the cloud. They proposed an improved discrete bees algorithm based on the Pareto (IDBA-Pareto) method to solve the problem in that context for cloud manufacturing. Zheng et al. [237] proposed a design preference-based QoS description model of cloud manufacturing and a QoS computation model based on fuzzy theory. They adopted the particle swarm optimization (PSO) algorithm based on the above model to select the optimal service composition. Xiang et al. [238] regarded service composition and optimal selection (SCOS) as key issues for implementing a cloud manufacturing system. In order to provide both a high-quality and low-energy consumption service, they studied the problem of SCOS based on QoS and energy consumption (QoS-EnCon). Panda and Jana [239] dealt with the task allocation problem with uncertainty-based QoS in a heterogeneous multi-cloud system through their proposed algorithm.

6.3 Entire Life Cycle Quality Management

6.3.1 Difference of Quality Management Under Internet and Big Data

1. Impact of the Internet and big data on quality

Generally, we define the quality from the aspects of work quality and product quality, while the introduction of Internet and big data is changing these two aspects. Traditional work quality refers to the quality of all the work in product design, manufacturing, and after-sales service which are done by the companies in order to ensure or improve the quality. Traditional work quality is formed in the design sector, manufacturing sector, service sector, etc. The definition of traditional work quality is put forward under a single enterprise-led production mode. However, enterprises in the environment of Internet and big data have different forms of organization and work process, and the distributed manufacturers and suppliers have brought many changes in the process of quality management. With the development of cloud manufacturing mode and the virtual enterprise, we have to redefine the work quality under the Internet and big data. Traditional product quality refers to the characteristics in the product itself to meet the needs of customers. It contains performance, longevity, reliability, safety, appearance, color, packaging, specifications, cost, price, maintenance period, maintenance costs, delivery, environmental adaptability, etc. Similarly, this definition of the product quality is proposed for traditional products, while the products under Internet and big data have many different characteristics compared to traditional products. New product quality should also include quality of suppliers, providing users with constantly improved quality service, the quality of user participation in the design process, the information exchange in the process of using products, product status real-time monitoring, brand reputation, scrap, and remanufacturing quality.

2. Impact of the Internet and big data on quality management

The full personnel, the whole process, comprehensive concept in the total quality management has changed in the environment of Internet and big data. Customers will be involved in the product life cycle service process and jointly optimize the quality of service with companies. The full personnel concept not only includes full personnel within the enterprise, but customers, logistics, suppliers, and all other participants in the product life cycle. The whole process not only includes the design, manufacturing, service processes, but includes supplier collaboration process, market analysis, user participation in the design, marketing, and business users to participate in the service process, the remanufacturing process. Besides, comprehensive concept contains statistical methods, integrated approach, new methods of data mining, and other large data environments.

3. The meaning of the entire life cycle quality management

First of all, ensuring the interests of organizations and customers is the fundamental goal of quality management; implementation of entire life cycle quality management is conducive to safeguarding the long-term interests of the organization and improving the product entire life cycle quality. Second, entire life cycle quality management can achieve a wide range of users and suppliers involved in product design. Third, manufacturing service selection in the cloud manufacturing mode plays a decisive role in reducing the cost and improves the quality of service, and following the life cycle quality management is conducive to optimizing the manufacturing cloud service selection and improving organizational efficiency. Besides, improving the entire life cycle quality will bring continued improvement on product value and service levels and reduction on the quality cost. And the application of Internet and big data will help organizations respond faster to market demands. What's more, consistent high quality of service will help improve customer loyalty and reduce customer churn. Real-time monitoring for product status would eliminate a major accident and may greatly reduce the loss of customers. Finally, remanufacturing process will enhance the quality and improve resource utilization, thereby enhancing the environmental benefits of products, and continue to improve the quality of life cycle, which will continually increase the competitiveness of enterprises.

6.3.2 Entire Life Cycle Quality Management Concepts System

Life cycle quality management concepts system can guide the quality management under Internet and big data environments. The concepts system should contain the concepts of life cycle quality, life cycle quality management, and life cycle quality cost. These concepts are the comprehensive reflection of life cycle quality management's objectives and significances.

6.3.2.1 Concepts and Composition of Entire Life Cycle Quality

Entire life cycle quality under Internet and big data environment includes generalized life cycle quality and narrow life cycle quality. Narrow life cycle quality refers to the degree of social products to meet customer needs in the design, manufacture, service, remanufacturing, and other whole life cycle process. Generalized life cycle quality includes life cycle work quality and life cycle product quality. Life cycle product quality refers to how the characteristics of the product itself can meet the needs of the community and the customer in the product life cycle process. Life cycle work quality refers to the quality of all systematic work in order to improve and ensure product quality in the product life cycle process.

1. Life cycle product quality

We divide product quality under Internet and big data environments into four aspects of design quality, manufacturing quality, service, and remanufacturing quality. Product design quality includes customer engagement, targeting advertising design and service design quality, etc. In the environment of the Internet and big data, the rise of crowd innovation and crowdsourcing mode allows users to directly participate in product design more frequently, which will make the product design more innovative, fresher, and unique. Besides, the general application of Internet technology and big data product can make advertising more accurate and more personalized. Manufacturing quality is formed during the manufacturing process, and manufacturing quality can no longer be altered after fabrication. Manufacturing quality includes internal attributes that contained product performance, safety, durability, reliability, economy, etc. and appearance properties that contained product shape, color, finish, and packaging. Internal property is the most important part in manufacturing quality. External quality is not the most important attribute in the manufacturing quality but also essential. On the basis of ensuring product internal attributes, external quality attributes are particularly important for enhancing the competitiveness of products. In the environment of Internet and big data, we are able to use a lot of product quality data and use data mining techniques for proposing manufacturing process improvement strategies so as to enhance the quality of the product. Also, we can better meet the needs of users relying on the customer data in the environment of Internet and e-commerce. What's more, personalizing the external quality attributes can be easily achieved. Quality of service is directly reflected during product usage. Quality of service includes warranty, maintenance costs, frequency of maintenance, continuous service process satisfaction, value-added services, etc. Quality of services is relatively easily overlooked by organizations. In the environment of Internet and big data, enterprises can use data to anticipate the damage of the product so as to inform the customer that the product should repair in advance. And based on big data, enterprises can design more reasonable continuous service plan for customers, which can enhance the customer experience and increase customer loyalty. Remanufacturing quality includes the environmental waste, scrap and residue treatment, and remanufacturing process product quality. These quality factors are relative to each other. The good life cycle quality needs the full participation and high-quality service. So, enhancing the quality of the life cycle is a systematic process, which a single enterprise or a single sector cannot achieve.

2. Life cycle work quality

Traditional enterprises regard product quality as a fundamental objective to implement quality management. They hold that the product quality is determined by the quality of work, that is, high work quality brings high product quality. So, they think that the fundamental task of companies to improve product quality is to ensure the quality of operations. The traditional work quality will be assigned to various departments within the enterprise which are responsible for quality promotion. The traditional work quality requires clear division of labor. However, the work quality in the environment of Internet and big data will be assigned to various enterprises besides the main manufacturing enterprise. Work quality is determined by the corporation of decision-making companies, supplier companies, designed companies, manufacturing companies, logistics companies, marketing departments, continuous service departments, and remanufacturing enterprises during product life cycle process. The pursuit of traditional quality management thinking is the simple superposition of the quality work in various departments, while life cycle quality management system requires all enterprises to provide complete life cycle high-quality services to customers at a common organizational goal. In the environment of Internet and big data, work quality has different status and functions compared to the past on multiple levels. First, work quality is not just limited to the quality of work in design, manufacture, and service process. As the development of production-service-oriented manufacturing model, the work quality is reflected throughout the product life cycle. Second, the work quality will jump out of the traditional main manufacturing enterprise and need multiparty joint efforts. Third, boundaries between work quality and product quality will become increasingly blurred. Since service has gradually developed into the core competitiveness of a modern enterprise, life cycle work quality becomes an important quality evaluation criterion. Finally, work quality and reputation in the market are playing an increasingly important role in determining the status of the enterprise, and work quality will directly determine the consumers' purchase options. Work quality in the environment of Internet and data is becoming more important compared to the conventional meaning.

6.3.2.2 Concepts of Life Cycle Quality Management and Its Development

Life cycle quality management refers to the activities that contained planning, organization, coordination, control, decision making, innovation, etc. which are done by all individual members in the corresponding departments of the design, manufacturing, service, remanufacturing, and logistics companies in order to ensure and improve the quality of the whole life cycle. Life cycle quality management under Internet and big data requires the combination of new methods for data analysis and traditional management technology. The cooperation of all personnel involved in the life cycle including customer is of great significance too. Organization should consolidate and maintain long-term relationships with its customers through providing good service. Only in this way can organization improve the whole life cycle of customer satisfaction, social benefits, and organizational benefits. Concepts of quality management and their development in the environment of Internet and big data are shown in Table 6.1.

In traditional quality management, quality manager intends to find the key point of quality improvement for his company from the sample data, and many companies hold the point that the quality is determined in the process of product design

Table 6.1 Concept development of quality management

Items	Quality management in product life cycle	Total quality management	Statistical process control	Quality inspection
Support technology	IoT, cloud computing, virtual reality, big data, data mining, deep learning	Information technology, automation, mechanization, mathematical statistics	Technical inspection, mathematical statistics	Technical inspection
Target	The fusion of management methods and big data technologies, total participation in product life cycle, continued to provide customer satisfaction services, long-term cooperation with customers, cyclic utilization of organization earnings, and improving social benefits	Total enterprises total participation, the whole process to meet customer needs, pursuit of excellence	Mass production meets quality standards	Small-scale production meets product standards
Executive	Organizer	Manufacturer	Quality management department	Quality inspector
Quality formation	Including market analysis, ordering, crowdsourcing design, manufacturing service selection, marketing, after-sales service, interaction with the users, continuous service and remanufacturing processes in product life cycle	Market analysis, design, ordering, manufacturing, marketing, after-sales service, scrapping	Before production	After production

and manufacturing process. However, we can have full data under IoT environment and big data. And customer can participate in the quality improvement process from the demand analysis to the end of the life cycle. The company also needs real-time information provided by customers to improve the service quality. In another word, quality is not only shown in the information feedback by customers who have purchased the product, but cooperate level of enterprises and users in the whole life cycle. So it is necessary for companies to reconsider quality and quality management in demand analysis, product design, manufacturing, marketing, continuously service, and remanufacturing. And the goal of quality management is no longer confined to maximize the customer satisfaction. Enterprises have to consider the common goal of the organization, customers, and community so as to realize management innovation and continuous quality improvement in the new environment.

6.3.2.3 Concepts and Components of Quality Cost

Feigenbaum [218] put forward that quality is a comprehensive concept, where the strategy, quality, price, cost, productivity, services and human resources, energy, and environmental studies need to be considered together. We need to recognize the breadth of the quality in the modern economy. The purpose of quality management is to achieve complete customer satisfaction, effective human resource management, and low cost at the same time. Quality cost is caused from ensuring the quality and the dissatisfaction of customers.

The entire life cycle quality cost refers to the cost of management in order to ensure and improve life cycle quality, as well as the loss incurred when products can't meet the customer satisfaction and social quality standards in the entire life cycle of the product. Life cycle costs contain the quality of design quality costs, collaborative manufacturing cost of quality, service quality and costs, recycling costs and other manufacturing quality, etc. It is the sum of enterprises' internal and external quality costs which are tangible or intangible.

In the concept of traditional quality cost, the quality cost is just the sum of control costs and the failure costs. Quality cost is formed in product design, manufacturing phase, and traditional after-sales service stage. And control cost refers to prevention and appraisal fees in order to ensure customer satisfaction. Failure cost refers to the cost of failure before or after delivery when quality doesn't satisfice the customer. With the enhancement of the quality level, control costs increase, while the failure cost reduces when quality level is enhanced. As shown in Fig. 6.1, total quality cost is lowest when the quality level reaches the point P. In the environment of Internet and big data, enterprises will gradually put into real-time

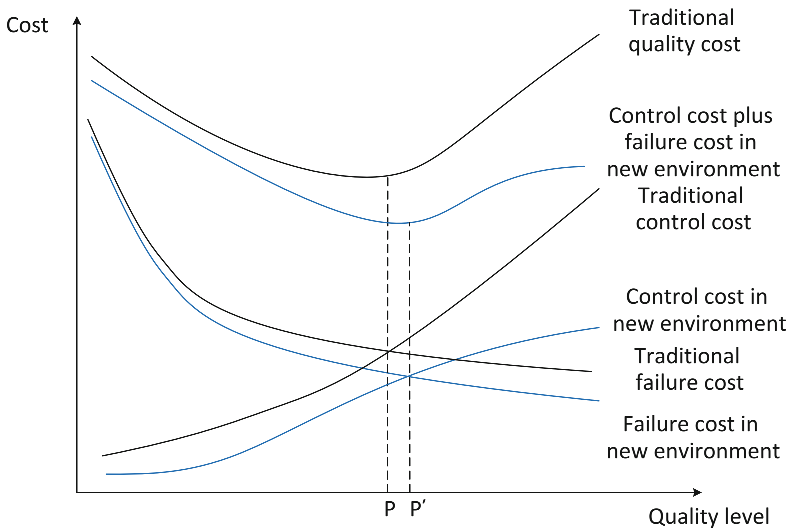

Fig. 6.1 Control cost plus failure cost

monitoring equipment and data analysis platform, which cause the increase of service quality costs. On the one hand, it can help enterprise realize timely detection of quality problems in design and production process, which greatly reduces the labor costs, rework costs, and management costs caused in prevention and detection of defective products. On the other hand, it can forecast downtime of products and inform customers when the product needs maintenance. Then they can guarantee quality of use, extend product life, and reduce product quality failure, which will reduce failure cost finally. In this condition, total quality cost is lowest when the quality level reaches the point P′. Compared to the traditional condition, optimum cost value has decreased substantially, while the corresponding level of quality has improved.

Compared with traditional quality cost models, life cycle quality cost under Internet and big data should also include the cost of continuous service throughout the product life cycle and social recovery cost of remanufacturing stage.

In the environment of Internet and big data, customer satisfaction is not only a direct result due to the purchase of the product, but perception of the service provided by enterprises in the product life cycle. Quality of service not only includes the cost of the enterprise to purchase networking equipment, collaborative service management platform and big data analytic platform, and other service equipment so as to improve product competitiveness and customer satisfaction, but includes the loss due to poor customer service. Accordingly, good quality of service not only brings customer satisfaction and good reputation, but helps enterprises to establish a good long-term relationship with customers. Customers will be involved in quality management to further improve service quality and provide enterprises with continued earnings. As shown in Fig. 6.2, the increase of quality service input costs will reduce the quality loss cost. However, marginal utility of quality input costs for quality level reduced when the quality inputs contained service equipment,

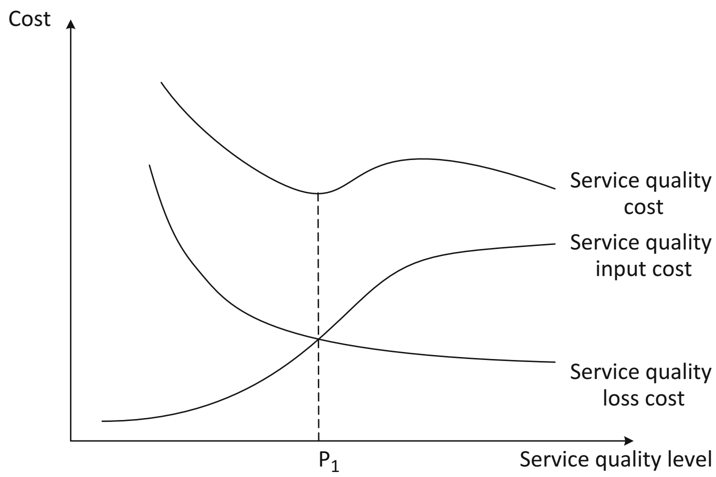

Fig. 6.2 Service quality cost

systems, and high-level personnel to ensuring the quality is as much as necessary. Service quality inputs at this time are mainly used to maintain and operate the entire service system. Meanwhile, the service quality loss costs continue to decrease with the improvement of service quality levels. Therefore, the total cost of the service quality will no longer grow or slowly decline when the system and equipment related to service quality are mature in the enterprise. In this condition, the best value of service quality cost and its corresponding most suitable areas may be more than one.

Product social quality refers to the effectiveness of reducing environmental pollution and improving the profit of the society in the process of residual scrap recycling and product remanufacturing stage. For example, quantity of recycling parts and extent of impact on the environment can be regarded as an important index for social quality. Similarly, social cost of quality composed of social input fee and social loss due to the failure of social quality. With the increasing of the quality level, the social input costs should increase, while the social loss cost would decrease. From Fig. 6.3, we can get that social quality cost is the lowest when the quality level reaches the point P_2. In the environment of Internet and big data, social cost of quality can be affected by the service quality cost. For instance, with the use of service system, product operation and maintenance data during the usage phase can be collected in real time. And real-time big data analysis for the product provides an effective basis for the quality classification. Also, social input cost can be effectively reduced in this way.

So compared to quality traditional cost model, the life cycle quality cost under Internet and big data should consider control costs, failure costs, service costs, and social costs as well as relationship between them. As shown in Fig. 6.4, we need to seek the best points or the most suitable areas for life cycle quality cost.

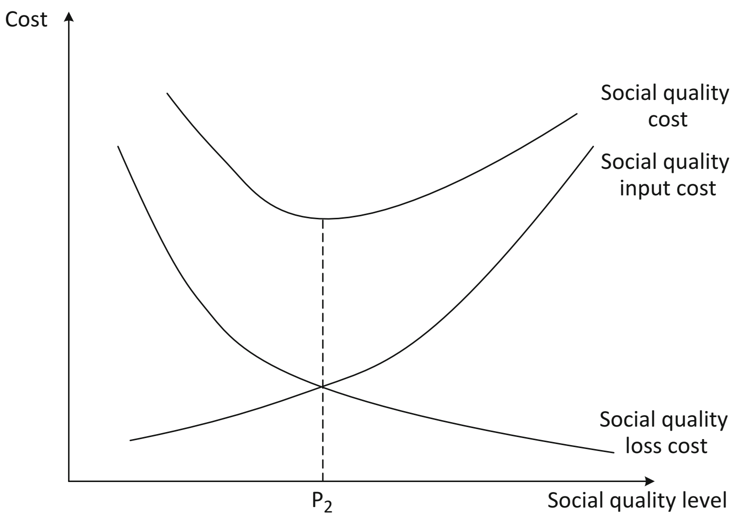

Fig. 6.3 Social quality cost

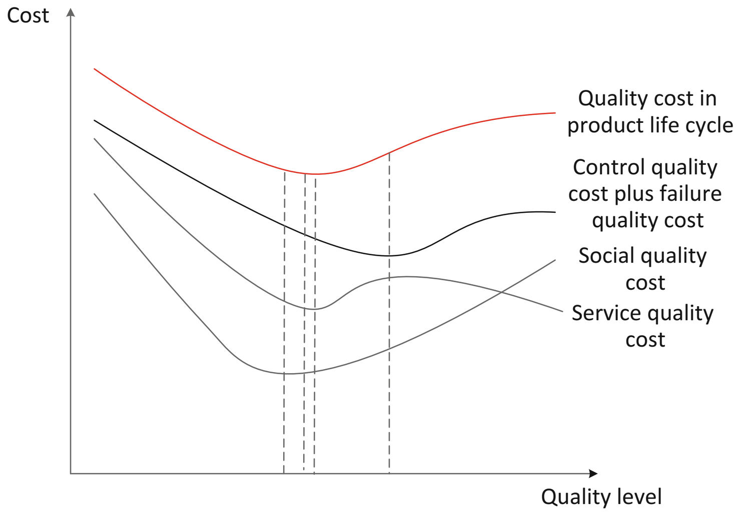

Fig. 6.4 Quality cost in product life cycle

We hold that life cycle quality management needs to follow the following ideas:

1. Strengthen the level of customization, provide different continuous services improvement programs for different customers, establish long-term relationships with customers, absorb customers into one of the quality workers in the enterprise, and achieve mutual benefit and win-win situation.
2. Optimize social benefits and ensure sustainable development. Design services for customers and dispose of scrap or remanufacture the products during after-sales stage from the perspective of product life cycle. Benefit both the customer and the society, and then realize sustainable development in the entire life cycle.
3. Promote quality improvement through establishment of multi-partnership. Manufacturing process under big data is often done by several companies; the relationship should be a full coordination between the various participating companies, and strengthen the links between the various enterprises and customers and provide various types of continuous service.

6.3.3 Life Cycle Quality Assurance System and Methods for Its Implementation

Life cycle quality assurance system is organized to produce products that meet customer and social needs, as well as quality control and certification requirements. In the system, the basic principles of quality management, quality improvement methods, and life cycle management functions should be established. Organization tightly organized quality management activities through the establishment of organization's quality management system, where all aspects of the product design, manufacturing, service, and remanufacturing process that affect the overall quality of products can be considered. Then the organization can become an outstanding quality management group with clear mandate, responsibilities, authority, mutual coordination, and mutual promotion.

6.3.3.1 Life Cycle Quality Management Principles

With the development of the Internet and big data, quality management is playing an increasingly important role in attracting consumers. So in the environment of Internet and big data, in order to create a life cycle quality management system to ensure providing customers with high-quality products, the following principles should be followed:

Regard contacting the customer communication as an important daily work of enterprises. Faced with continues changing customer needs in the Internet and big data environment, enterprises have to maintained daily communication with customers and realize real-time control of customer service satisfaction and timely processing of abnormal situations. Organization should ensure that all members in the product life cycle obtain the real demands of customer; coordinate common interests of multi-business, customers, and society; ensure that the whole industry chain grows with customers together; and achieve sustained coordination.

Give full play to the role of participating companies in the entire life cycle. The main decision-making enterprises play a crucial role in the whole life cycle, while the member enterprise is the main service provider. Equal and open communication among all businesses and a high degree of information sharing must be guaranteed. Organization needs to make decision according to different members' interests and the interests of customers, so as to ensure the participation of all members as well as distribute them with enough profit.

All are involved in the entire life cycle. Participants in quality life cycle are the fundamental of total quality management system. Only in their efforts can continuous quality improvement be achieved. In the environment of Internet and big data, all participating companies' common goal is to improve the customer experience in order to ensure the quality of the whole life cycle.

Quality process control is based on full data. In the environment of Internet and big data, we have more resources and process data in process control. Predictability product quality and more efficiently product quality improvement can be achieved. Enterprise can get various plans in advance for each unusual circumstance through data mining and knowledge discovery. Then they can ensure the effectiveness of manufacturing process, reduce costs, reduce waste, and shorten production time.

Integrate innovative management methods and Internet. Integrating the traditional management methods with the Internet and big data can help improve management efficiency. Today's enterprises can establish knowledge system to store knowledge which may be used for the daily management. They can also use big data analytics to help understand the inherent correlation between the various management practices and help realize the business goals with making more effective management decisions.

Continuously improve customer service experience. In total quality management, continuous improvement is an important target for enterprise. It is also suitable in the environment of Internet and big data. In order to achieve continuous improvement of customer service experience, enterprises can apply the theory in big data environments, real-time supervision, and evaluation and establish data warehousing, which will also form a solid foundation for service improvement.

Decision method is based on data. Effective decision making is based on scientific analysis for real data and information. Real data and information contain important decision-making reference. So, enterprises should establish and improve the production with use of IoT, collect full real-time data and information, and obtain the significant knowledge for important business decisions.

Long-term cooperate with customers. The whole production system keeps a long-term mutually beneficial relationship with the customer. Organizations should enhance its ability to create value and enhance customer value. Organizations should help customers to better understand the business goals, but also allow enterprises to better understand the individual needs of the customer. Enterprises need to provide customers with continuous service to win more loyal customers.

6.3.3.2 Life Cycle Quality Improvement Methods

To maintain the continuous improvement of the quality assurance system in product life cycle, classic PDCA methods are still suitable. Furthermore, we can combine PDCA methods with big data technology, realize the innovation of the management methods, and improve the quality assurance system. The PDCA method based on big data combines big data analysis and classical management methods in product life cycle, which can continue to find the product life cycle process problems, make improvement suggestions, optimize improvement program, and ensure continuous improvement of product quality. As data volumes grow, big data analytics will play an increasingly important role in the long-term business practice, and the accumulated great amounts of data will also create a greater value. These data come from communication processes and the actual production process, finally feedback on the production process quality and customer service experience, and create a good cycle of sustainable development mechanism. To achieve the establishment of full life cycle quality management system, the quality accountability must be clear. Each participating enterprise is responsible for the functions themselves. Their responsibilities, rights, and interests should be cooperated in a suitable way. They need to choose leaders, engineers, and technicians as well as different levels of customer personnel from each of the participating companies to form quality control (QC) team, who responds for guaranteeing the effectiveness of the entire quality system, improving relationship between the customer and the enterprise, and monitoring and promoting the continuous upgrading of product quality and service (Fig. 6.5 and Table 6.2).

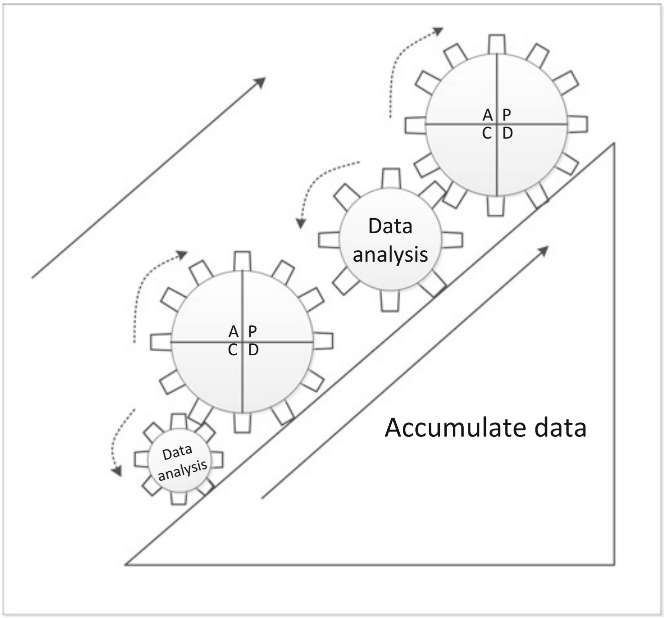

Fig. 6.5 The PDCA cycle based on Internet and big data

Table 6.2 The task of each phase in PDCA cycle

Phase	Task
P	Identify the problem (data mining, data analysis of big data); problem analysis (Ishikawa); making plans
D	Implementation plan
C	Use big data analysis techniques to check completion
A	Summarize and archive data, establish data warehousing, standardize some valuable activities

To establish a complete quality management system, all activities related to quality formation in the environment of internet and big data must be systematically improved. These activities contain the product's entire life cycle process from market research to product recycling or remanufacturing. Enhancing the quality of life cycle processes should focus on these factors. Quality improvement activities not only play a role between major manufacturers and suppliers of business but also play an important role in the product life cycle between the other participants. All participants in the entire life cycle are quality builders. It takes a long time for enterprises to improve quality of service and data storage capacity. In the environment of Internet and big data, real user data is a prerequisite for providing high-quality service and high-quality products. In other words, the quality improvement process and data are interlocking, and quality improvement must be based on data. In the upgrade process of quality, enterprises can be possible to get more detailed

Fig. 6.6 Life cycle quality management function

user data with the user's trusting in the enterprise more. And big data analysis will play an increasingly important role in promoting product quality. So, PDCA cycle will be shortened; PDCA cycle speed will continue to accelerate. Then the organization can provide users with better service to form a mutually beneficial situation of long-term cooperation (Fig. 6.6).

Total quality management (TQM) and traditional quality management (QM) are generally considered to include market research, design, manufacturing, and after-sales service processes. However, life cycle quality management covers a wider range of functions. The goal of life cycle quality management is not only to meet customer needs, but to improve the overall interests of community, customers, and organization. The market research process not only relies on the survey, but also extends to a multichannel information collection process. The design process becomes open to the customer, and the manufacturing process refers to no longer a single enterprise internal problem. What's more, the continuous service process is indispensable in the quality function cycle. The product's service process will guide the design and manufacturing process, while the manufacturing process will also affect the service process of the product. These changes require us to reestablish the quality functional cycle. As shown above, the revenue of customers, society, and organizations will increase with time again and again, so the organization should follow the new quality function cycle to ascertain the responsibility and position of all member enterprises and customers in the quality cycle and to ensure the effectiveness of the quality functions. In addition, we should strengthen the connection between enterprises and customers and create an active organizational culture of communication and cooperation between enterprises and customers, form a perfect organization quality assurance system, promote the cycle of product quality in an orderly way, and then create continuous improvement for customers, society, and organizations.

6.3.4 Life Cycle Quality Management System

The old seven tools of quality control proposed in the 1960s include permutation diagram, histogram, control chart, causal diagram, correlation diagram, hierarchical method, and the questionnaire. The new seven tools proposed in the 1970s include association diagram, KJ method, system diagram, matrix diagram, PDPC method, matrix data analysis, and arrow diagram. None of these tools can directly support the entire process of quality management, but they can support different stages of quality management. The old seven tools are mainly used to deal with the digital information, and the new seven tools are language-based and graphics-based research methods. The development of Internet and big data has a great impact on the whole life cycle quality management methods. In order to better adapt to the new quality management environment, the traditional quality management tools based on mathematical statistics will be gradually substituted by big data-based quality management methods. We discuss the new methods for quality management under Internet and big data from the following seven aspects.

6.3.4.1 Correlational Analysis Method

In the environment of Internet and big data, the traditional causal relationship is gradually replaced by correlativity. There are a variety of correlations between management behavior, customer service choice behavior, management decision, and customer satisfaction, and we can use rich data to find these correlations and provide customers with better service portfolio. Typical data mining methods such as Apriori and FP-growth algorithm can help achieve good association rules. Take Apriori algorithm, for example, assume that there are five services 1, 2, 3, 4, and 5, and customer history information is shown in the following table (Table 6.3 and Fig. 6.7).

Table 6.3 Customer service selection records

Customer	Service selection
1	134
2	235
3	1,235
4	25

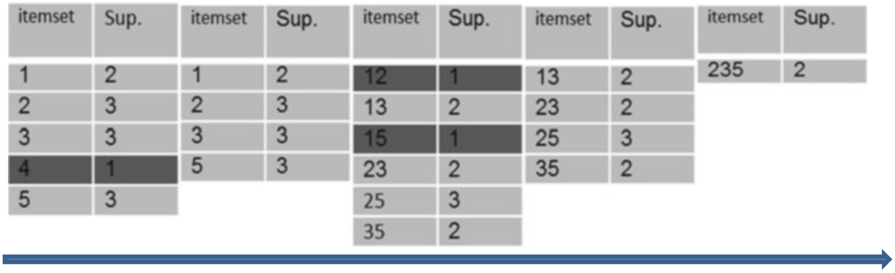

Fig. 6.7 Process of Apriori algorithms

According to Apriori algorithm's general procedure, first find all frequent item sets, excluding infrequent item set; then we can generate association rules from the frequent item sets, which can obtain that customers tend to choose 2,3,5 three services at the same time. Thus, companies can improve customer satisfaction by rationally designing service composition model. In the environment of Internet and big data, we can use a variety of such similar association rule discovery algorithms to provide organizations with important data-based decision-making references; in addition, these methods can be applied to find and solve quality problems of the whole life cycle.

6.3.4.2 Cause and Effect Analysis Method

In the practical quality management process, the correlations tell companies what to do. However, they also need a reason based on the results. Among the methods for determining cause and effect relationship, fishbone invented by Mr. Ishikawa, Japanese management guru, is still a simple and practical method. First, find all kinds of problems in quality management, and then find the factors that influence these issues through brainstorming, and last use the fishbone diagram to graphically represent these factors and seek improvements (Fig. 6.8).

In the environment of Internet and big data, traditional six determinants of quality, which contain manpower, machinery, materials, methods, environments, and measurement, are broadened conceptually. Manpower expands to all members of the entire product life cycle. Machinery include not only production machines; it also includes all the machines for data analysis and data processing. And after broadening the concept of methods, measurement methods and quality testing

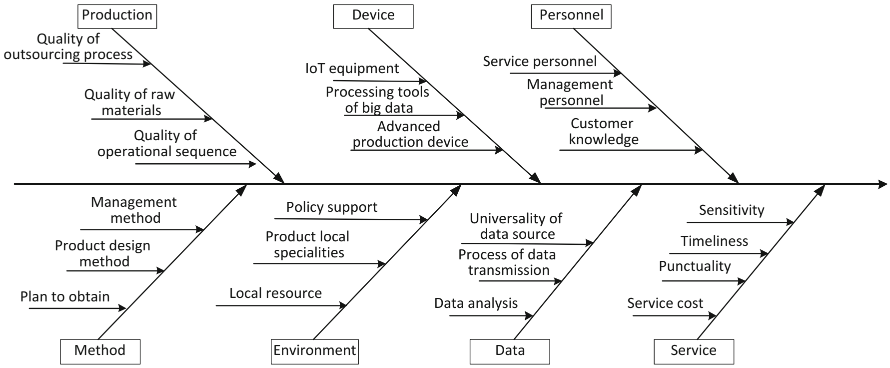

Fig. 6.8 The fishbone chart analysis of quality management

methods are also included. In addition, data and services have a significant impact on quality. On the data side, how extensive and effective of data sources, the rationality and completeness of data analysis determine the quality of decision making. Information obtained from the correct data can help organizations better serve customers, but the information obtained from inappropriate data will mislead the customer and the organization, resulting in organizational behaviors going against organizational goals, decreasing of customer satisfaction, and impairing product life cycle quality. For services, the relationship between enterprises and customers has been transformed from one-time transaction into long-term cooperation. Customers pay more attention to the service quality in the long-term cooperation. So organizations should correspondingly coordinate all the members to provide customers with timely, on-time, and advanced services, lower service costs, increase social benefits, ensure customer benefits, and enhance organizational competitiveness through technological and management innovation.

6.3.4.3 Quality System Assessment

Based on four aspects of product quality—design quality, manufacturing quality, service quality, and remanufacturing quality—we can design quality evaluation system of the entire life cycle as shown in Fig. 6.9. Quality evaluation indexes in the environment of Internet and big data include design quality (customer engagement degree in design process, reasonable degree of advertising design, service design quality, etc.), manufacturing quality (appearance, durability, performance, etc.), service quality (timeliness of repair services, service innovative level, completion of services, etc.), and remanufacturing quality (remanufacturing process quality, environmental costs, social costs, etc.). Then based on the above indicators, we can use AHP or other methods to evaluate the product life cycle quality. Specific indicators can be obtained through the Internet platform and the company’s internal supplements. And the crawler technology is applied to get data for evaluation.

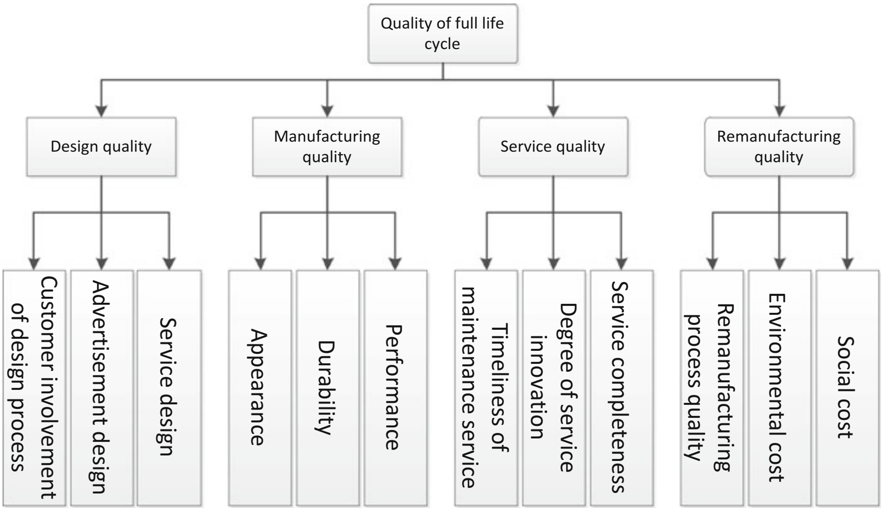

Fig. 6.9 Evaluation indicators of quality in product life cycle

Meanwhile, in the environment of Internet and big data, the evaluation process gradually transformed from the original periodic activities into the daily activities of the enterprise. Through analysis of real-time streaming data, companies can obtain real-time evaluations of products or services and find quality problems of products according to these evaluations. Then they can determine the best solution based on comprehensive analysis, which really makes the product quality keep up with the times (Fig. 6.9).

Because there are many unquantifiable quality indicators in the quality assessment indicator system, we can use fuzzy comprehensive evaluation and evidential reasoning to handle this problem. Take fuzzy comprehensive evaluation method, for example, we give the evaluation process of entire life cycle as follows:

1. Set first-grade index (design quality, manufacturing quality, service quality, remanufacturing quality) and second-grade index (customer engagement degree in design process, reasonable degree of advertising design, service design quality, appearance, durability, performance, timeliness of repair services, service innovative level, completion of services, remanufacturing process quality, environmental costs, social costs).
2. Get the mentioned times of each indicator in many kinds of internet websites with the use of crawler technology; then combine it with expert appraisal results and determine the weight vector.
3. Establish factors' membership matrix through data analysis.
4. Realize gradual synthesis from low grade to high grade, obtain evaluation vector for each product.
5. Analyze the evaluation vector of every specific product to find the quality gap and implement quality improvement.

6.3.4.4 The Quality Improvement Method in Design Phase

According to the general ASI (four-stage) model of QFD, the new product development process includes planning phase, design phase, process phase, and production phase. By applying the QFD method, we first establish the quality house of various stages, then convert it into demand, and finally form clear production requirements. But traditional QFD is built on the basis of customer perception, and the perception of customers is mainly obtained through market research. So when survey results are wrong, subsequently all the analysis results will lead the astray of organization. This method is still applied in the environment of Internet and big data. However, we cannot obtain customer merely on the basis of market research; we should collect more extensive data through the Internet platform before determining to develop a new product. Thus, fully grasping the market situation provides reliable actual support for the establishment of the quality house. Meanwhile, service process should also be taken into account in the quality planning process, and quality function deployment should be carried out in service stage (Fig. 6.10).

6.3.4.5 Multi-vendor Collaborative Manufacturing Quality Control Methods

In the environment of Internet and big data, the manufacturing process is still the key to the formation of product quality. The intrinsic quality of the product largely depends on the quality of the manufacturing process on the premise of ensuring the accuracy of market analysis and product development. Process control refers to the scientific and systematic process management activities for achieving product quality in manufacturing process. Its purpose is to ensure the effectiveness and stability of the production process, improve product intrinsic quality, and avoid error generation. Traditional statistical process control is a technology that applies statistical methods to monitor and assess the production process at all stages, maintain the production process at an acceptable and stable level, and thus ensure products conforming specified requirements. The representative methods for traditional statistical process control contain process capability indices and process diagram method; its main role is to analyze and determine whether a process is stable and in normal working condition. Actual production data collected from Internet and big data environment are often polygene and heterogeneous, and the amount of data is much larger than that of traditional process, so the quality control of the manufacturing process will become more complicated; judging the quality of the manufacturing process can be converted into classification problems. With the introduction of IoT, we can get all the data of each product at any step. Then we can analyze these data to identify defective products and reverse traceability to find the reasons for failure, which provides timely solutions to the problems in the production process. In addition, quality prediction and multi-information sharing ensure

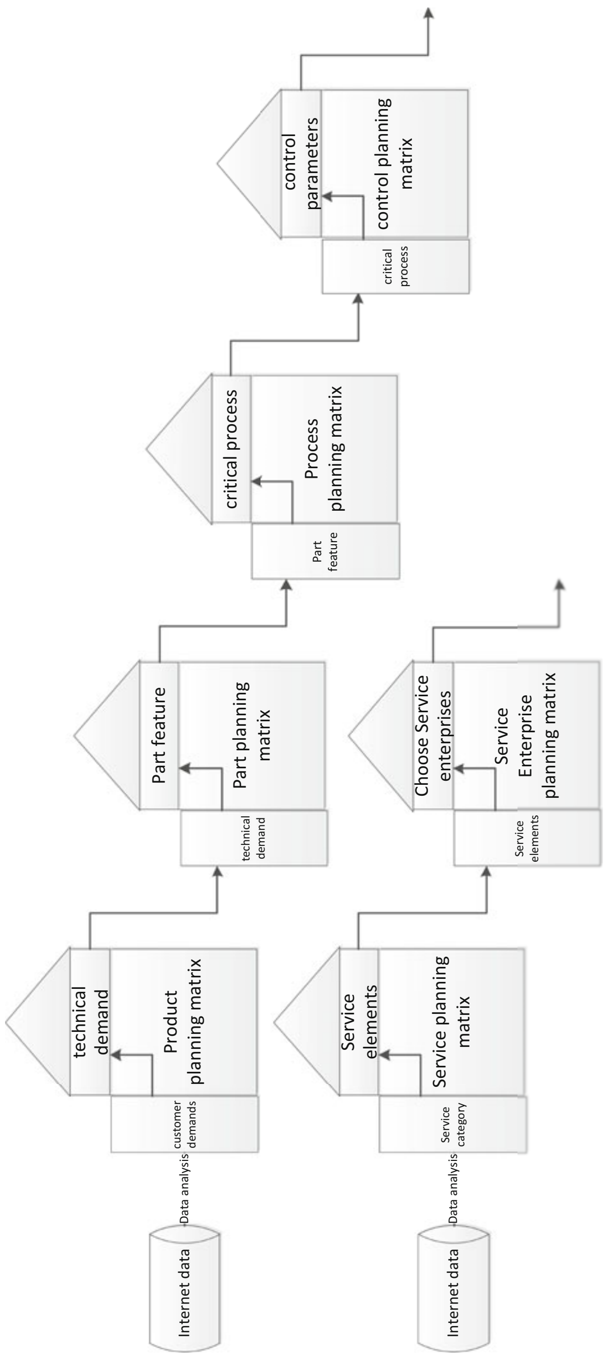

Fig. 6.10 Quality function deployment

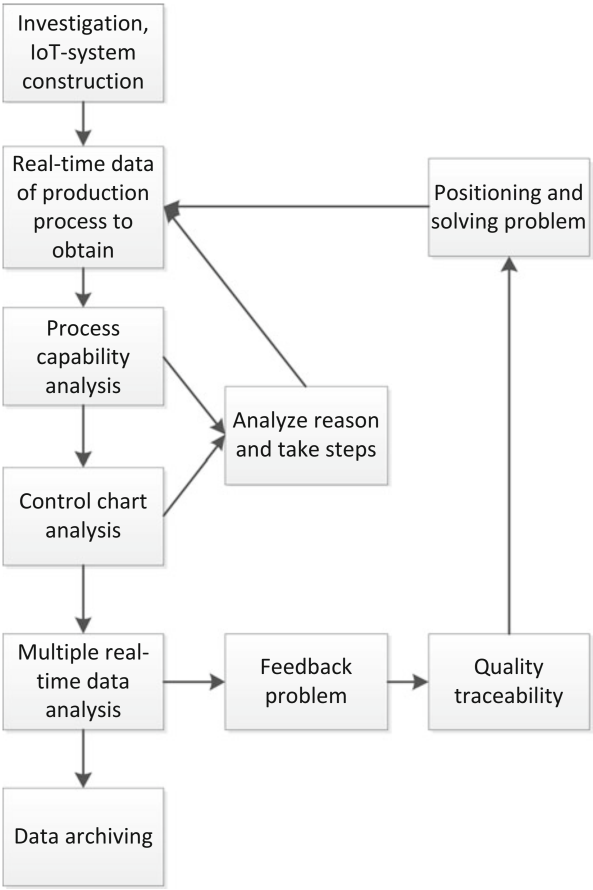

Fig. 6.11 Quality control of manufacturing process

that all members of the organization understand the quality of the manufacturing process and then develop a reasonable plan based on the quality of the manufacturing process. The following figure shows the manufacturing process quality control in the environment of Internet and big data (Fig. 6.11).

First, a sound IoT system should be established for the manufacturing process to ensure the completeness of the information. Then apply process capability analysis and control chart analysis to determine whether the production status is at a steady state. We can use multivariate analysis of semifinished products at each production step based on real-time status data. If defective product is found, we should timely handle it to avoid the invalidity of the next stage and meanwhile trace back to find the source of quality failure. Finally, archive all the data generated to form an organization repository for guiding the manufacturing process later. With the development of networked manufacturing mode, supply chain quality management and manufacturing service quality have drawn organizations' much attention. Incenting suppliers and manufacturers play a very important role to ensure

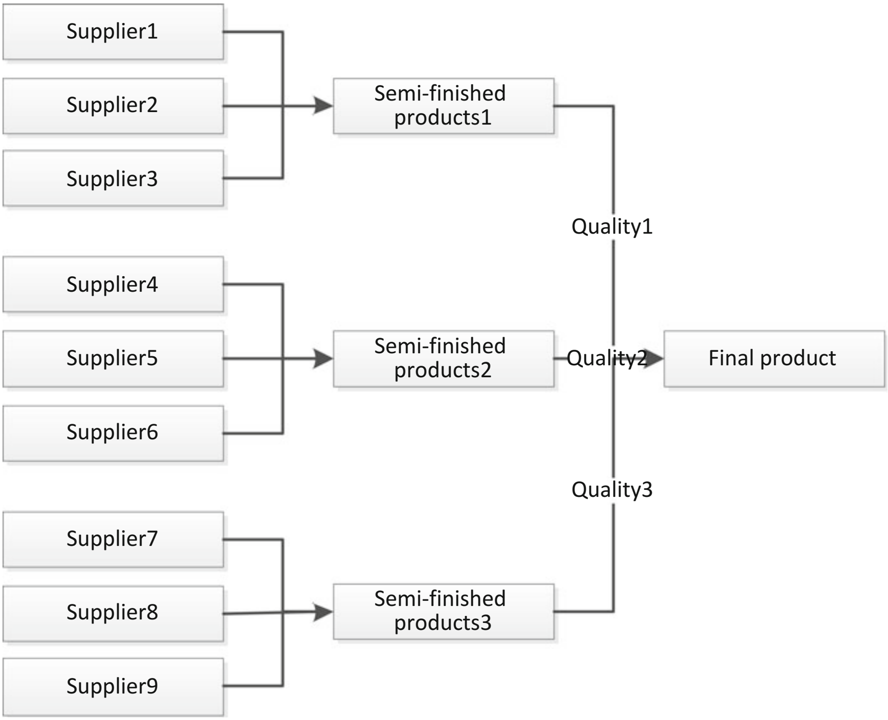

Fig. 6.12 Collaborative manufacturing supply chain

objective quality of products in the environment of Internet and big data. As shown below, for the quality management of collaborative manufacturing mode, it is necessary to establish a sound quality assurance system in each member within the organization. The organization also needs to apply game theory and operational research methods for effective quality collaboration contract design of complex supply chain and rational decision making so as to ensure the quality management implementation at organizational level (Fig. 6.12).

6.3.4.6 Service Quality Gap Improvement Methods

In service science theory, the quality of service is an important prerequisite factor affecting customer satisfaction. From the consumer's point of view, the traditional service quality evaluation factors include the following five points: function, economy, safety, timeliness, and comfort. In the environment of Internet and big data, along with the development of the servitization of manufacturing, quality of service is increasingly important in the quality of the entire life cycle. For instance, the quality of service processes directly determines customer satisfaction and whether they will maintain a good and long-term business relationship with the company in the future. From the perspective of the life cycle, in addition to the above indicators, predictability is also an important contributor to the quality of service in manufacturing industry. Because if you can predict the occurrence of mechanical failure in advance, customer loss cost will be greatly reduced. Companies, who predict problems of products or services before the customer's perception via the Internet and big data technology give targeted solutions and coordinate the time and place of service with customers, would greatly improve customer satisfaction and minimize the loss of customers. Moreover, service should have sensitivity to market changes; in the Internet and big data environment, continuously updating service is crucial for customer retention. If the service cannot keep up with the customer needs and market standards, the customer will lose patience soon in comparison and then choose a different product, ceasing cooperation with the original enterprise. To help companies analyze service problems and improve the quality of service in the environment of Internet and big data, we provide a service quality gap model as follows (Fig. 6.13).

In the analysis process of service gap, customer expectations for services, perception of services, and real-time accurate feedback information can be obtained via the Internet. In order to accurately locate the service gap and develop solutions to eliminate the gap, companies should establish a good platform for information exchange within the enterprise, strengthen linkages between company members of overall organization, and focus on the role of data analysis in management decision. Enterprises should analyze the current service gaps according to their capabilities and then improve service quality of the entire product life cycle through breakthroughs in key technologies, intelligent manufacturing, employee training, customer relation consolidation, strategic target revision, and so on. In the above service quality gap model, the service gap is mainly produced in the following six aspects.

The first gap: gaps between product positioning and customer perception from the actual advertising. Excessive advertising and inappropriate publicity, organizations overly pursuing of the ornamental and performance of advertising, and blindly exaggerating of the product's advantages result in high customer expectations for the product.

The second gap: gaps between the actual feedback and the feedback gathered by the organizations. This is due to the noise in feedbacks that makes organizations more difficult to obtain useful information from a large amount of feedback information.

The third gap: gaps between the customer expectations of service and the awareness of service personnel. The uncertain qualities of service personnel and inadequate communication make contributions to the misunderstanding of customer demands.

The fourth gap: gaps between the customer expectations of service and the organization recognition. Organization's capacity constraints and its insufficient attention to the customer expectations of service result in that organization cannot accurately estimate customer expectations and reflected in the actual decision-making process of the enterprise.

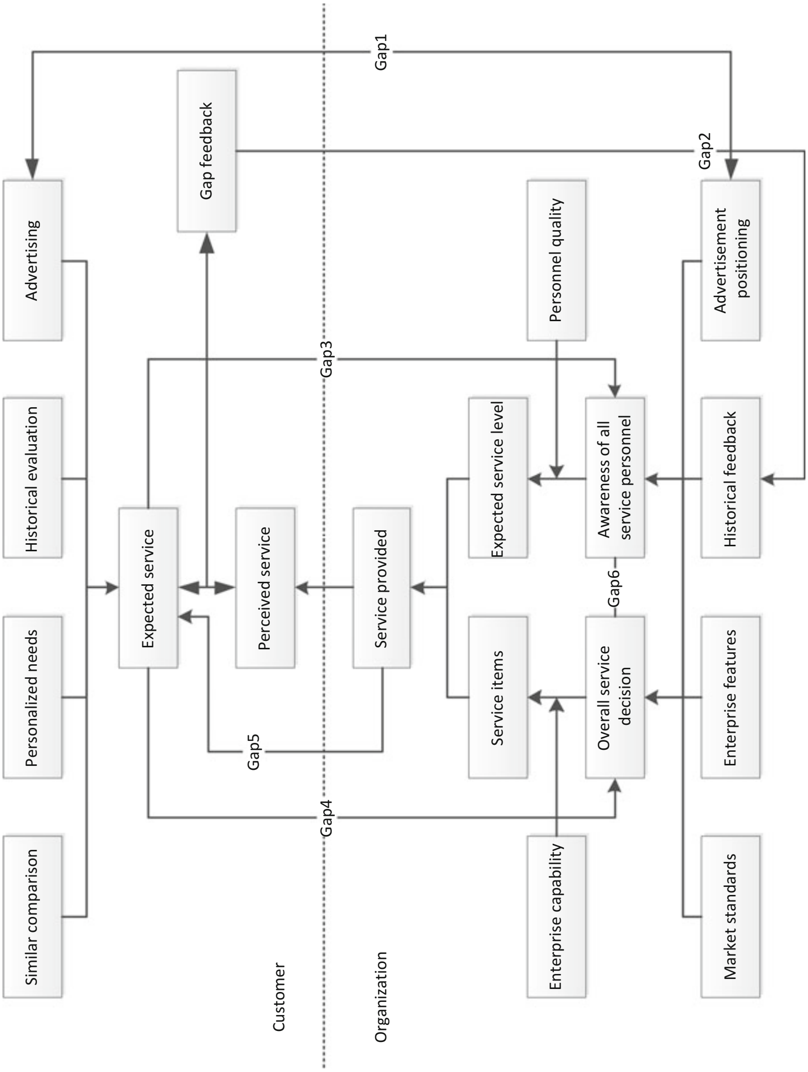

Fig. 6.13 Service gap model

The fifth gap: gaps between the actual provision of service and the desired service. The lack of personalized service and technical bottlenecks results in the presence of service gap compared to similar competitors.

The sixth gap: gaps between the organization recognition and staff recognition, which are induced by insufficient internal communication, too many organizational levels, and the distortion of information transmission.

The presence of service gap results in customer dissatisfaction. In the environment of Internet and big data, we have more technology and tools to identify and determine these gaps. In order to eliminate service gaps and improve customer satisfaction, organizations should do the following:

1. Recognize the fact that different consumers have different acceptance degree of advertising, and guide them reasonably. Understand what customer needs and select the appropriate platform for targeted advertising. Then design advertising mode from the customer's point of view to both retain the old customers and attract new customers. Moreover, strengthen communications with customers, and promptly make adjustments to advertising when the customer perception deviates from the organization's purpose to avoid misleading customers, and ultimately lead to mismatching between expectations and reality.
2. Establish an effective communication mechanism to ensure that customer information can be effectively transferred to the organization. Make use of both traditional information collection methods such as questionnaires, interviews, and call tracking forms and new information acquisition methods through Internet platform such as data crawler technology, etc. In addition, strengthen customer relationship management. Vigorously carry out customer relationship marketing, give adequate attention to customer feedback information, and then apply big data technology to find useful information to guide the organizational decision making in the next phase.
3. Improve personnel training system, and comprehensively improve the quality of staff. Encourage the participants in all classes of whole life cycle to actively communicate with customers, directly understand customer needs and expectations, and consult with the customer, thus achieving the best service together and providing customers with timely solution.
4. Establish a good organizational system that transfers information well from the perspective of maximizing customers satisfaction, design the most appropriate portfolio of services, improve organizational learning capacity, and enhance organizational strength to break barriers encountered.
5. Maintain timely communication with customers, and let customers understand that what types of services and the level of service organizations can provide for them. Then try to make customer expectations be consistent with the service provided.
6. Improve operations within the organization, and try to convey the organization's wishes and ideas to all service participants as soon as possible. Then avoid leading the decline in service quality and lower customer satisfaction in terms of the lack of coordination within the organization.

6.3.4.7 Decision-Making Method of Remanufacturing Quality

Remanufacturing is the mass production of old high-end equipment for professional repair. The remanufacturing products need the same quality and performance as the original ones. There will be a long-term development of remanufacturing in China. With the development of economy and society, remanufacturing is essential for green development. So in recent years, remanufacturing industry has been the worldwide attention. Remanufacturing process is a key step in the product life cycle; the importance of its quality assurance for product life cycle quality is self-evident. Remanufacturing and general production processes have different characteristics, and remanufacturing process can be represented by the following figure (Fig. 6.14).

Compared with the general manufacturing products, recycled products have complete different status due to the use of life and the use of different environments and their aging situation is uneven, leading to difficulty in matching new and old parts. So the remanufacturing process has a greater uncertainty and is more complex compared with the general manufacturing process.

The first step in remanufacturing quality control is to identify nonreusable and reusable parts in the disassembled part. For reusable parts, we need to carry out rigorous test to ensure the safety of remanufactured products. And nonreusable parts should be scrapped under the premise that without harming the environment. These nonreusable parts are replaced by the new parts from original manufacturer or the remanufacturing parts with strict quality standards. For the production and assembly of remanufactured products, they should be upgraded to a certain extent to meet the modern production requirements. After assembly, remanufacturing products need overall and rigorous testing of performance before delivery. In product usage period, the quality is under real-time control. Remanufacturing process is an indispensable part of product life cycle. The quality of

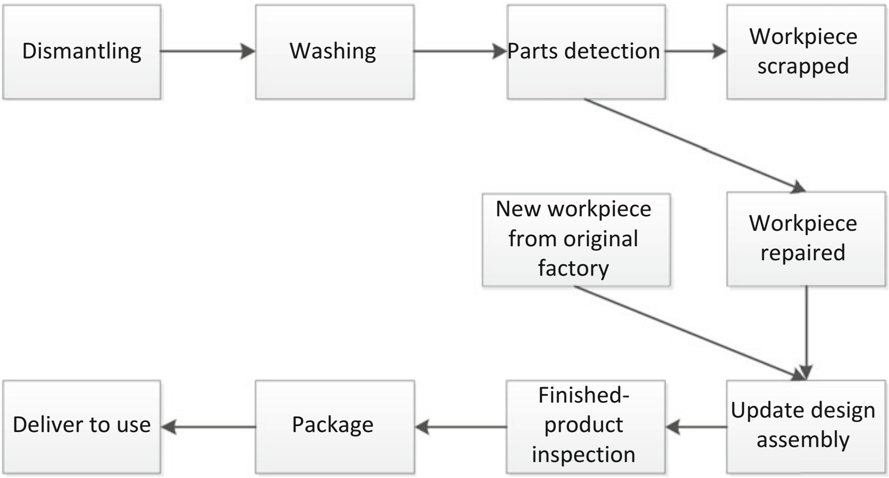

Fig. 6.14 Remanufacturing flow process

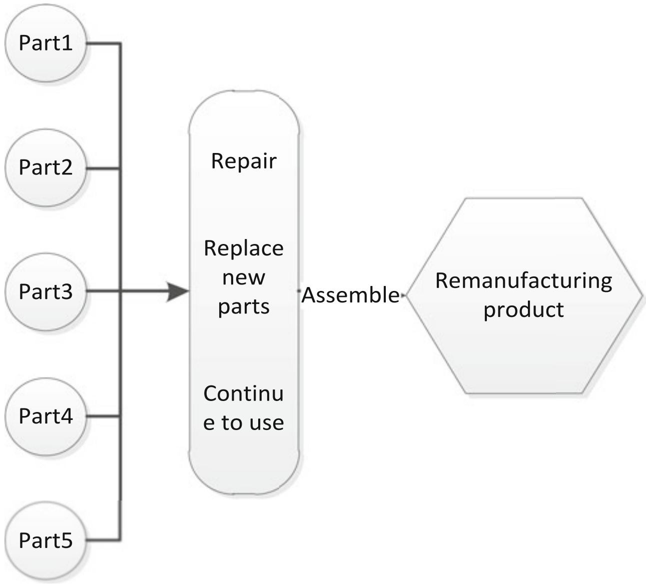

Fig. 6.15 Remanufacturing decision process

remanufacturing process determines the social benefit of the product, but the relatively high remanufacturing cost is not conducive to the realization of the remanufacturing process. Meanwhile, the perfect remanufacturing system is of great significance to improve customer satisfaction and improve the quality of the entire life cycle. Therefore, the core enterprises in the organization should give encouragement and support to the remanufacturing enterprises.

As shown in Fig. 6.15, remanufactured products are generally composed of multiple components, and the treatment of these various components can be continued to be used after being repaired and replaced by new pieces. To ensure the quality of remanufactured products, we must consider the damage situation of all old parts in remanufacturing process to make the relevant decisions. In the environment of Internet and big data, we can get the damage situation of used products according to the detailed historical data and determine the quality level of repaired parts. Assume that a remanufactured product consists of a total of n components. After dismantling and cleaning, the damage rate is $S = (s_1, s_2, s_3, \ldots, s_i, \ldots, s_n)$ through the existing data; s_i represents the degree of damage of the ith component, and $0 < s_i < 1$. The remanufacturing decision is $X = (x_1, x_2, x_3, \ldots, x_i, \ldots, x_n)$ where

$$x_i = \begin{cases} 1, \textit{represent} \text{ that the ith component continues to be used} \\ 2, \text{represents that the ith component is reused after maintenance} \\ 3, \text{represents that the ith component is replaced by a new one} \end{cases},$$ the

unit cost of continuing to use, repairing to use, and replacing a new component, respectively, Cr_1, Cr_2, Cr_3; let $Cr_1 < Cr_2 < Cr_3$. Total remanufacturing cost is $C = aCr_1 + bCr_2 + cCr_3 +$ assembly cost, where a_r, b_r, c_r represent the number of parts that continue to use, repair to use, and replace to use, respectively. Thus we have $a_r + b_r + c_r = n$. If all the components are replaced by new ones, the total cost is $Cr_0 = nC_3 +$ assembly cost. Taking that the more use of continuous used parts and repaired parts into account, the relative waste of social resources will be less and achieves higher social benefits. Thus the target of manufacturing quality can be expressed by $\min_X \left(\prod_1^n s_i, \frac{C}{Cr_0}, \frac{n}{a_r + b_r} \right)$. The multi-objective problem can be transformed to a single-objective problem or Pareto-optimal problem, and the concrete solving process can be realized by the relevant intelligent algorithm. The solution results of the problem can be used to guide the remanufacturing enterprise to make the optimal remanufacturing decision. The above process reflects the principle of the life cycle quality management in complex remanufacturing circumstance. The benefits of society, customers and organizations are all taken into consideration, which promote the quality of the entire life cycle in the environment of Internet and big data.

6.4 A Quality Management Model Considering Service Level

6.4.1 Model Description

Nomenclature

a The supplier's quality investments, $0 < a \leq 1$

p, q The supplier's quality and service investments, $0 < p, q \leq 1$

E_i The benefit manufacturer can obtain if the product is of good quality ($i = 1,2$), $E_1 > E_2$

R The price of the semi-manufactured goods

H The loss causted by the inferior-quality products in some certain conditions

L The penalty cost whenever a nonconforming product is found

C The cost of inspecting the product

$C(a), C_1(p), C_2(q)$ The supplier's and the manufacturer's unit production cost

Pa_j Path describing the meteria flow within a supply chain

θ_j Likelihood of occurrence of path Pa_j, $0 < \theta_j < 1$

k_i The undetermined coefficient, $0 \leq i < 3, k_i > 0$

π_m^e, π_s^e Expected profit function of the manufacturer and the supplier

We assume that in the first stage, the supplier sells semi-manufactured goods to the manufacturer. The state of the production process, in turn, determines the likelihood that the goods are of good quality, and the probability that a good product is produced is a. Specifically, in order to generate a probability a, $0 < a \leq 1$, that the production process is of high type, the supplier must invest an amount $C(a)$.We assume that a semi-manufactured good of bad quality is certain to result in a final

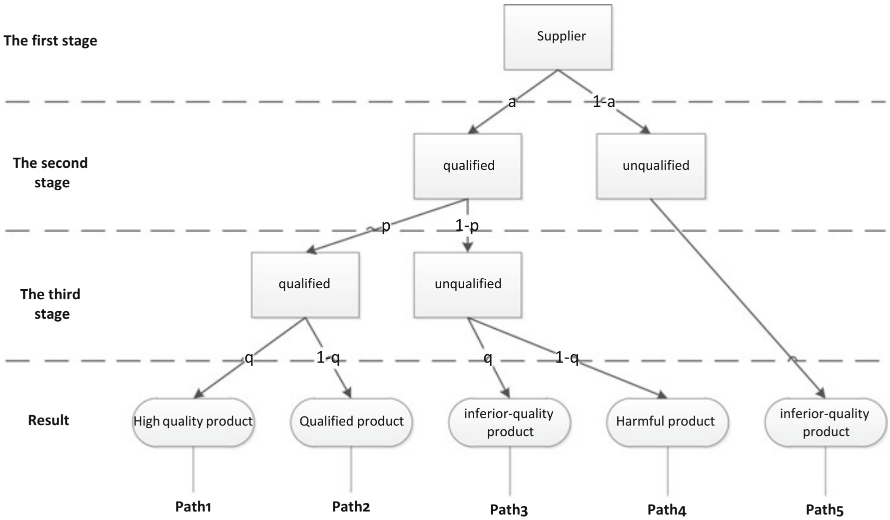

Fig. 6.16 Tree presentation of material flow on the supply chain

Table 6.4 Illustration of the enumerated paths Pa_j, the supplier's profit π_s, and the manufacturer's profit π_m associated with each Pa_j

Pa_j / π_i	Pa_1	Pa_2	Pa_3	Pa_4	Pa_5
θ_j	apq	$ap(1-q)$	$a(1-p)q$	$a(1-p)(1-q)$	$1-a$
π_s	$R-C(a)$	$R-C(a)$	$R-C(a)$	$R-C(a)$	$R-C(a)$
π_m	$E_1 - C_1(p) - C_2(q) - R$	$E_2 - C_1(p) - C_2(q) - R$	$-C_1(p) - C_2(q) - R$	$-H - C_1(p) - C_2(q) - R$	$-H - C_1(p) - C_2(q) - R$

product of bad quality. In the second stage, the manufacturer will use the goods to produce the final product. Similarly, the likelihood that the product is qualified is p $(0 < p \leq 1)$, and the manufacturer needs to invest an amount $C_1(p)$. In the third stage, the manufacturer can invest an amount $C_2(q)$ to generate a probability q, $0 < q \leq 1$, which denotes consumers' satisfaction degree to the service of manufacturer (Fig. 6.16).

The combination of these three indicators gives all the paths from the root node to the leaf nodes in the tree structure. We will summarize these enumerated paths $Pa_j(j = 1, 2, 3, 4, 5)$ along with the supplier's profit π_s and the manufacturer's profit π_m on each path Pa_j.On the first path, the supplier will get payment from manufacturer and invest an amount $C(a)$ to generate a probability a, so the supplier's profit function is $\pi_s = R - C(a)$. And the likehood of occurrence of Pa_1 is apq.We assume that the manufacture can get E_1 on the path. So his profit function is $\pi_m = E_1 - C_1(p) - C_2(q) - R$. Similarly, we put the remained information in the Table 6.4 as follows.

In Table 6.4, E_2 represents the profit which manufacturer can get on the second path, H is the loss caused by the inferior-quality products in certain conditions, and θ_j is the likehood of occurrence of Pa_j. We assume that $E_1 > E_2 > k_i > H$, $i = 0, 1, 2$ and $E_1 - E_2 > \mathrm{H}$, which means that improving the service when the product is of good quality can bring more profit. And we assume that $E_1 > \sum_{i=0}^{2} k_i$, which ensures a positive profit of the supply chain. The supplier's unit production cost $C(a)$, the manufacturer's unit production cost $C_1(p)$, and the manufacturer's unit service cost $C_2(q)$ take a quadratic form in their quality investments:

$$C(a) = k_0{}^* a^2, C_1(p) = k_1{}^* p^2, C_2(q) = k_2{}^* q^2 \tag{6.1}$$

So the expected profit function of supplier can be written as follows:

$$\pi_s^e = R - C(a) \tag{6.2}$$

and the expected profit function of the manufacturer is

$$\begin{aligned} \pi_m^e = & \, apq(E_1 - C_1(p) - C_2(q) - R) \\ & + ap(1-q)(E_2 - C_1(p) - C_2(q) - R) \\ & + a(1-p)q(-C_1(p) - C_2(q) - R) \\ & + a(1-p)(1-q)(-H - C_1(p) - C_2(q) - R) \\ & + (1-a)(-H - C_1(p) - C_2(q) - R) \end{aligned} \tag{6.3}$$

Because $\frac{\partial \pi_s^e}{\partial a} < 0$ when $0 < a \leq 1$, it is obvious that the supplier will not invest any amount to generate a high a in this condition without any supervision. In the following, we study the model in three scenarios in order to find the best way to promote the quality of supply chain and increase the profit of supplier and manufacturer. The event sequence of this game is as follows:

(i) The manufacturer invests an amount C alone to inspect all the goods purchansed from supplier.
(ii) The supplier's quality is taken as common knowledge; the q and p are determined by a third party.
(iii) The manufacturer and the supplier cooperate to inspect the semi-manufactured good and bear the cost of generating a together.

6.4.2 Equilibrium Analysis

6.4.2.1 The Manufacturer Invests an Amount C to Inspect All the Goods Purchased from Supplier

We assume that the inspection process is perfectly reliable, which means a nonconforming component would be inspected to be an unqualified good certainly.

Table 6.5 Illustration of the enumerated paths Pa_j, the supplier's profit π_s, and the manufacturer's profit π_m associated with each Pa_j

Pa_j / π_i	Pa_1	Pa_2	Pa_3	Pa_4	Pa_5
θ_j	apq	$ap(1-q)$	$a(1-p)q$	$a(1-p)(1-q)$	$1-a$
π_s	$R-C(a)$	$R-C(a)$	$R-C(a)$	$R-C(a)$	$-L-C(a)$
π_m	$E_1-C_1(p)-C_2(q)-R-C$	$E_2-C_1(p)-C_2(q)-R-C$	$C_1(p)-C_2(q)-R-C$	$-H-C_1(p)-C_2(q)-R-C$	$L-C$

In this condition, manufacturer will not pay any to the supplier for the unqualified goods which have been inspected by manufacturer. In contrast, suppliers would have to pay L to manufacturer as the compensation. And these unqualified goods will not get into the third stage. In this condition, we get Table 6.5 as follows:

So we get the expected profit function of supplier:

$$\pi_s^e = a(R - C(a)) + (1 - a)(-L - C(a)) \tag{6.4}$$

and the expected profit function of manufacturer:

$$\begin{aligned} \pi_m^e = a(-C_1(p) - C_2(q) - R) + apqE_1 + ap(1-q)E_2 \\ - a(1-p)(1-q)H + (1-a)L - C \end{aligned} \tag{6.5}$$

In a supply chain, the members often make their decisions independently. In our model, given the income statement, the supplier and the manufacturer simultaneously maximize the expected profit functions. From Eqs. 6.4 to 6.5, we derive the following equations.

In the Nash game, the optimal pricing strategy is given by

$$a = \frac{R+L}{2k_0}, p = \frac{\alpha_2\alpha_3 - \alpha\alpha_2}{\alpha^2 - \alpha_1\alpha_3}, q = \frac{\alpha_1\alpha_4 - \alpha\alpha_2}{\alpha^2 - \alpha_1\alpha_3} \tag{6.6}$$

$\alpha_1 = -2ak_1, \alpha = aE_1 - aE_2 - aH, \alpha_2 = aE_2 + aH, \alpha_3 = -2ak_2, \alpha_4 = aH.$

So we have the following proposition.

Proposition 1 Given the condition that the manufacturer invests an amount C to inspect all the goods purchased from supplier, then with the increase of price R, penalty cost L, the quality level of the supplier will increase, i.e., $\frac{\partial a}{\partial R} > 0$, $\frac{\partial a}{\partial L} > 0$.

We have assumed that $E_1 - E_2 > H, E_1, E_2, H > 0, 0 < a, p, q <$; it can be derived that $\alpha_1, \alpha_3 < 0, \alpha, \alpha_2, \alpha_4 > 0, \alpha_2\alpha_3 < 0, \alpha\alpha_2 > 0$. And because we have $\alpha_2\alpha_3 - \alpha\alpha_2 < 0$ and $p > 0$,we can get $\alpha^2 - \alpha_1\alpha_3 < 0$, which is equivalent to $4k_1k_2 > (E_1 - E_2 - H)^2$. It can be easily obtained that $\frac{\partial p}{\partial E_1} = \frac{-\frac{\partial \alpha}{\partial E_1}\alpha_2(\alpha^2 - \alpha_1\alpha_3) - (\alpha_2\alpha_3 - \alpha\alpha_2)2\alpha\frac{\partial \alpha}{\partial E_1}}{(\alpha^2 - \alpha_1\alpha_3)^2} > 0$, $\frac{\partial q}{\partial E_1} = \frac{-\frac{\partial \alpha}{\partial E_1}\alpha_2(\alpha^2 - \alpha_1\alpha_3) - (\alpha_1\alpha_4 - \alpha\alpha_2)2\alpha\frac{\partial \alpha}{\partial E_1}}{(\alpha^2 - \alpha_1\alpha_3)^2} > 0$, so we have the proposition as follows:

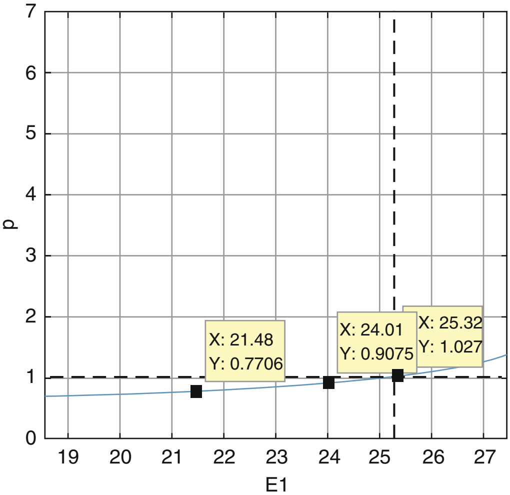

Fig. 6.17 Change trend of p with deferent $E_{1.}$

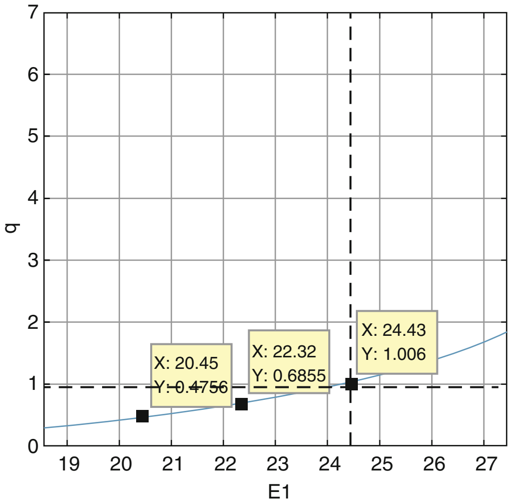

Fig. 6.18 Change trend of q with deferent E_1

Proposition 2 Given the condition that the manufacturer invests an amount C to inspect all the goods purchased from supplier, then with the increase of E_1, the quality level and the service level of the manufacturer will increase, i.e., $\frac{\partial p}{\partial E_1} > 0$, $\frac{\partial q}{\partial E_1} > 0$.

In the Nash game, after the manufacturer invests an amount C, the supplier needs to choose a proper quality level to ensure its profit. Compared to the condition above, the supplier is motivated to undertake quality improvement efforts rather than not to do any effort. The choice of manufacturer can be illustrated in Figs. 6.17 and 6.18 by a numerical example with $E_1 = 24$, $E_2 = 16$, $\mathrm{k}_0 = 4$, $k_1 = 13$, $k_2 = 4$,

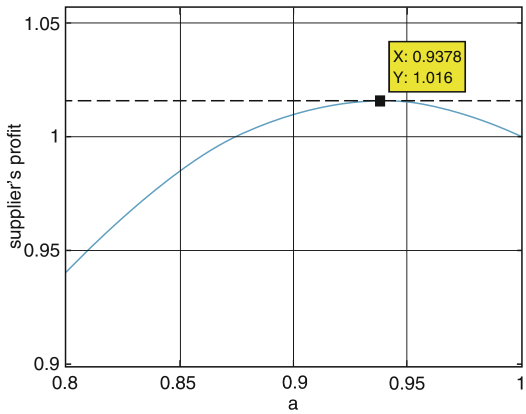

Fig. 6.19 Supplier's yield curve with R = 5

$C = 1$, $L = 2.5$, $H = 2$. We can see from Eq. 6.6 that the supplier's qualified rate is increased with gradually increasing price that he can get from manufacturer, and a linear positive correlation existed between them. A high profit E_1 can motivate the manufacturer to reduce defect rate and improve the service effectively. Similarly, a high price R can motivate the supplier to promote the quality level of semi-manufactured goods. Then we can get supplier's yield curve when the price $R = 5$, and we can find a proper a to maximize π_s^e.The relation between a is illustrated in Fig. 6.19.

Besides, the manufacture and service level for the manufacturer influences the profit he can get. Since we presume a noncooperative game, we assume that the supplier and the manufacturer will choose the best strategy for themselves, respectively. So the supplier's quality level a is given 0.94 here, and we can get the yield curve of manufacturer in Figs. 6.20 and 6.21 with $E_1 = 24$.

Nash equilibrium is given in the first condition, where the introduction of inspection can effectively reduce the probability that any further processing will be done on a defective product, making the further processing more valuable. As a result of these overinvestments, though there is a loss of C in the profit function, the supplier and the manufacturer both have the motivation to reduce the defect rate of the products and improve the service. Note that because of the absence of a specific cooperation, the manufacturer cannot encourage a low-type supplier further more. In terms of the supplier's choices, he will determine the corresponding quality level a according to the price R and the punishment L; the relation between π_s^e and π_m^e is ambiguous. From the consumer's standpoint, they may neither get the products of such high quality nor get the best service, so there are some rooms for improvement to make the supply chain more effective.

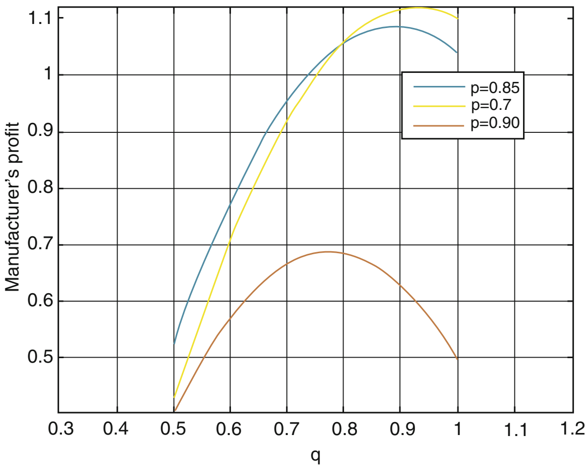

Fig. 6.20 Manufacturer's yield curve based on variable q with $E_1 = 24$ in the first condition

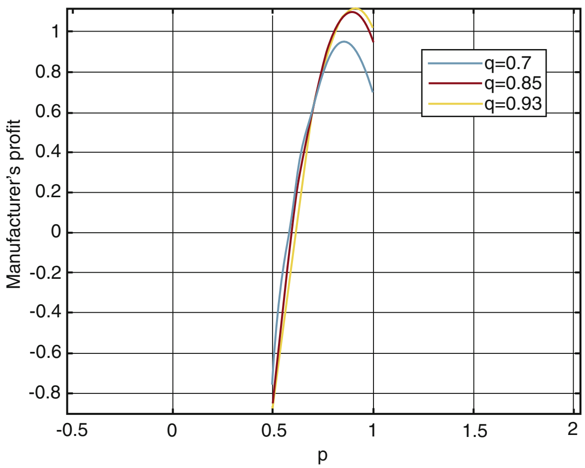

Fig. 6.21 Manufacturer's yield curve based on variable p with $E_1 = 24$ in the first condition

6.4.2.2 The Supplier's Quality Is Taken as Common Knowledge and the q and p Are Determined by a Third Party

Also, we hold the same assumption in this condition, and we introduce third-party supervision into the model where they can make decisions for both firms, and the objective of the third party is to maximize the total benefit of the supply chain. And

Table 6.6 Illustration of the enumerated paths Pa_j, the supplier's profit π_s, and the manufacturer's profit π_m associated with each Pa_j

Pa_j / π_i	Pa_1	Pa_2	Pa_3	Pa_4	Pa_5
θ_j	apq	$ap(1-q)$	$a(1-p)q$	$a(1-p)(1-q)$	$1-a$
π_s	$R-C(a)$	$R-C(a)$	$R-C(a)$	$R-C(a)$	$R-C(a)$
π_m	$E_1-C_1(p)-C_2(q)-R$	$E_2-C_1(p)-C_2(q)-R$	$C_1(p)-C_2(q)-R$	$-H-C_1(p)-C_2(q)-R$	$-H-C_1(p)-C_2(q)-R$

the quality level of supplier is taken as common knowledge. In this condition, we get Table 6.6 as follows:

Then we can get the expected profit function of supplier:

$$\pi_s^e = R - C(a) \tag{6.7}$$

and the expected profit function of manufacturer is

$$\begin{aligned}\pi_m^e = apqE_1 + ap(1-q)E_2 - R - C_1(p) - C_2(q) \\ - ((1-a) + a(1-p)(1-q))H\end{aligned} \tag{6.8}$$

We plus Eqs. 6.7 and 6.8 and get the expected profit function of supply chain as follows:

$$\begin{aligned}\pi_t^e = apqE_1 + ap(1-q)E_2 - C(a) - C_1(p) - C_2(q) \\ - ((1-a) + a(1-p)(1-q))H\end{aligned} \tag{6.9}$$

The first-order conditions for the equilibrium strategies in this game are

$$\frac{\partial \pi_t^e}{\partial p} = aqE_1 + a(1-q)E_2 + a(1-q)H - 2k_1p = 0 \tag{6.10}$$

$$\frac{\partial \pi_t^e}{\partial q} = apE_1 - apE_2 + a(1-p)H - 2k_2q = 0 \tag{6.11}$$

Solving Eqs. 6.10 and 6.11 for p and q gives the equilibrium strategy (p^*, q^*):

$$p^* = -\left(a^2H(E_1 - E_2 - H) + 2ak_2(E_2 + H)\right)/\left(a^2(E_1 - E_2 - H)^2 - 4k_1k_2\right) \tag{6.12}$$

$$q^* = \left(a^2(E_2 + \mathrm{H})^2 - a(aE_1E_2 + aE_1H + 2k_1H)\right)/\left(a^2(E_1 - E_2 - H)^2 - 4k_1k_2\right) \tag{6.13}$$

It can be obtained that $a^2H(E_1-E_2-H)+2ak_2(E_2+H)>a^2H(E_1-E_2)+H(2ak_2-a^2H)>0$. And have got $4k_1k_2>(E_1-E_2-H)^2$. From Eqs. 6.12 to 6.13, we derive the following:

Proposition 3 The equilibrium strategy (p^*, q^*), given in (6.10) and (6.11), maximizes the total profit of the supply chain if $aE_1E_2+aE_1H+2k_1H>a(E_2+\mathrm{H})^2$.

$$\frac{\partial p^*}{\partial a}=-\frac{z_1\left(a^2(E_1-E_2-H)^2-4k_1k_2\right)-(a^2H(E_1-E_2-H)+2ak_2(E_2+H))z_2}{\left(a^2(E_1-E_2-H)^2-4k_1k_2\right)^2} \tag{6.14}$$

$$\frac{\partial q^*}{\partial a}=\frac{\left(a^2(E_1-E_2-H)^2-4k_1k_2\right)z_3-z_2\left(a^2(E_2+H)^2-a(aE_1E_2+aE_1H+2k_1H)\right)}{\left(a^2(E_1-E_2-H)^2-4k_1k_2\right)^2} \tag{6.15}$$

$z_1=2aH(E_1-E_2-H)+2k_2(E_2+H), z_2=2a(E_1-E_2-H)^2$,
$z_3=2\mathrm{a}(E_2+\mathrm{H})^2-(2aE_1E_2+2aE_1H+2k_1H)$.

Based on the assumption of $E_1-E_2>H$, we can get $a^2(E_1-E_2-H)^2-4k_1k_2<0, z_1>0, z_2>0$ *and* $a^2H(E_1-E_2-H)+2ak_2(E_2+H)>0$. Also we can get $z_3=2\mathrm{a}(E_2+\mathrm{H})^2-(2aE_1E_2+2aE_1H+2k_1H)<2\mathrm{a}(E_2+\mathrm{H})^2-(2a(E_2+H)E_2+2a(E_2+H)H+2k_1H)=-2k_1H<0$, $a^2(E_1-E_2-H)^2-4k_1k_2<0$, $z_2>0$ and $a^2(E_2+\mathrm{H})^2-a(aE_1E_2+aE_1H+2k_1H)<0$. Therefore we have $\frac{\partial p^*}{\partial a}>0$, $\frac{\partial q^*}{\partial a}>0$, as revealed in the following proposition:

Proposition 4 If the supplier's quality is taken as common knowledge, the q and p are determined by a third party; then with the increase of a, manufacturer's quality level p, service q, and the profit of the supply chain will increase, respectively, i.e., $\frac{\partial p^*}{\partial a}>0$, $\frac{\partial q^*}{\partial a}>0$.

$$\frac{\partial \pi_t^e}{\partial a}=pqE_1+p(1-q)E_2-2\mathrm{k}_0a+aH-(1-p)(1-q)H \tag{6.16}$$

From Eq. 6.16, we can get $\frac{\partial \pi_t^e}{\partial a}>0$ if $pqE_1+p(1-q)E_2-2k_0a>0$. When $a, p, q\approx 1$ holds and $E_1>\mathrm{k}_0+k_1+k_2>2k_0$, we can get a principle that the total profit of the supply chain will increase with the increasing of supplier's quality level a.

The proposition above can be illustrated in Figs. 6.22 and 6.23 by a numerical example with $E_1=24, E_2=16, \mathrm{k}_0=4, k_1=13, k_2=4, C=1, L=2.5, H=2$.

So we can get a principle that the supplier needs to spare no effort to improve the quality of semi-manufactured goods, which means $a=1$, in order to maximize the profit of the supply chain.

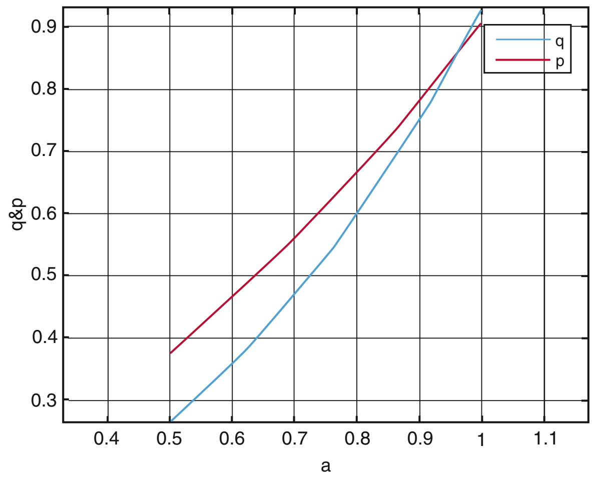

Fig. 6.22 Change trend of $p\&q$ with deferent a

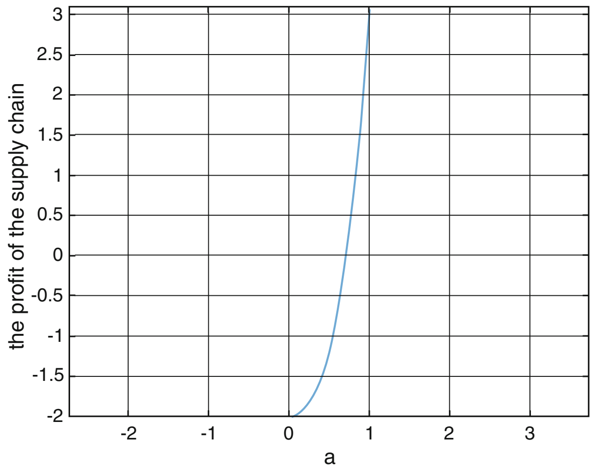

Fig. 6.23 Change trend of π_t^e with deferent a

Proposition 5 The solution we get through the introduction of a third party (p^*, q^*) is the global maximum point when $a = 1$.

When $a = 1$, we can write the objective of the third party as follows:

$$\begin{aligned} \text{Max } \pi_t^e = {} & pqE_1 + p(1-q)E_2 - C(1) - C_1(p) - C_2(q) \\ & - (1-p)(1-q)H \end{aligned} \tag{6.17}$$

The gradient of π_t^e is

$$\nabla\pi_t^e = \left(\frac{\partial\pi_t^e}{\partial p}, \frac{\partial\pi_t^e}{\partial q}\right)$$
$$= (qE_1 + (1-q)E_2 + (1-q)H - 2k_1p, pE_1 - pE_2 + (1-p)H - 2k_2q) \tag{6.18}$$

The Hessian matrix of π_t^e is

$$\mathrm{Hm}\left(\pi_t^e\right) = \begin{bmatrix} \frac{\partial^2\pi_t^e}{\partial p^2} & \frac{\partial^2\pi_t^e}{\partial p\partial q} \\ \frac{\partial^2\pi_t^e}{\partial q\partial p} & \frac{\partial^2\pi_t^e}{\partial q^2} \end{bmatrix} = \begin{bmatrix} -2k_1 & E_1 - E_2 - H \\ E_1 - E_2 - H & -2k_2 \end{bmatrix}$$

It can be easily obtained that $-2k_1 < 0$ and $4k_1k_2 > (E_1 - E_2 - H)^2$. Thus, we can draw a conclusion that (p^*, q^*) is the optimal solution.

6.4.2.3 The Manufacturer Invests an Amount C to Inspect All the Goods and Share the Manufacture Cost of Semi-manufactured Goods with Supplier

Similarly, we hold the assumption that the inspection process is perfectly reliable and introduce another parameter $1-\beta$ to indicate the ratio that manufacturer is willing to share with suppliers; in return,$1-\alpha$ denotes the responsibility that supplier needs to take so that the inspection cost of manufacturer can be reduced. In this condition, we get Table 6.7 as follows:

So we get the expected profit function of supplier:

$$\pi_s^e = aR - (1-\alpha)C - \beta C(a) - (1-a)L \tag{6.19}$$

And the expected profit function of manufacturer is

Table 6.7 Illustration of the enumerated paths Pa_j, the supplier's profit π_s, and the manufacturer's profit π_m associated with each Pa_j

Pa_j / π_i	Pa_1	Pa_2	Pa_3	Pa_4	Pa_5
θ_j	Apq	Ap(1 − q)	a(1 − p)q	a(1 − p)(1 − q)	1 − a
π_s	$R-\beta C(a)-(1-\alpha)C$	$R-\beta C(a)-(1-\alpha)C$	$R-\beta C(a)-(1-\alpha)C$	$R-\beta C(a)-(1-\alpha)C$	$-L-\beta C(a)-(1-\alpha)C$
π_m	$E_1-C_1(p)-C_2(q)-R-\alpha C-(1-\beta)C(a)$	$E_2-C_1(p)-C_2(q)-R-\alpha C-(1-\beta)C(a)$	$-C_1(p)-C_2(q)-R-\alpha C-(1-\beta)C(a)$	$-H-C_1(p)-C_2(q)-R-\alpha C-(1-\beta)C(a)$	$L-\alpha C-(1-\beta)C(a)$

$$\pi_m^e = a(-C_1(p) - C_2(q) - R) + apqE_1 + ap(1-q)E_2 \\ - a(1-p)(1-q)H + (1-a)L - \alpha C - (1-\beta)C(a) \tag{6.20}$$

From Eqs. 6.19 to 6.20, we derive the following:

Proposition 6 Given that the manufacturer and the supplier will share cost for each other, the Nash equilibrium can be given by

$$\mathrm{a} = \frac{R+L}{2\mathrm{k}_0\beta}, \mathrm{p} = \frac{\alpha_2\alpha_3 - \alpha\alpha_2}{\alpha^2 - \alpha_1\alpha_3}, q = \frac{\alpha_1\alpha_4 - \alpha\alpha_2}{\alpha^2 - \alpha_1\alpha_3} \tag{6.21}$$

$\alpha_1 = -2ak_1, \alpha = aE_1 - aE_2 - aH, \alpha_2 = aE_2 + aH, \alpha_3 = -2ak_2, \alpha_4 = aH.$

From Eqs. 6.21, we can see that the manufacturer can choose a proper share ratio β to ensure that the supplier chooses to determine a = 1 in the coordination case. Then manufacturer doesn't have to invest an amount C to inspect the goods purchased from supplier. To maximize the profit of him, the supplier will spare no effort to ensure that all the products are in good condition. So we need to rewrite the expected profit function of supplier as

$$\pi_s^e = R - \beta C(a) \tag{6.22}$$

$$\pi_m^e = (-C_1(p) - C_2(q) - R) + pqE_1 + p(1-q)E_2 - (1-p)(1-q)H \\ - (1-\beta)C(a) \tag{6.23}$$

Subject to

$$\mathrm{a} = 1, \beta = \frac{R+L}{2\mathrm{k}_0} \tag{6.24}$$

In order to obtain the equilibrium strategies for the supplier and the manufacturer, we establish the following first-order conditions:

$$\begin{cases} \dfrac{\partial \pi_m^e}{\partial p} = 0 \\ \dfrac{\partial \pi_m^e}{\partial q} = 0 \end{cases} \tag{6.25}$$

Then we can solve Eqs. 6.25 for the equilibrium strategies (p_0, q_0).

From Eqs. 6.22 to 6.24,we can get the expected profit function of the supply chain as follows:

$$\pi_t^e = pqE_1 + p(1-q)E_2 - C(1) - C_1(p) - C_2(q) - (1-p)(1-q)H \tag{6.26}$$

It can be easily obtained that (p_0, q_0) is also the optimal solution of the supply chain. And we can get $p_0 = p^*, q_0 = q^*$ when a = 1.

Proposition 7 If the supplier and the manufacturer share the cost with each other in the model, we can maximize the profit of the supply chain without any inspection or a third party, i.e., a = 1 , $p_0 = p^*$, $q_0 = q^*$.

The profit of supplier $\pi_s^e = 1.25$ is greater than the best case in the first condition, where $\pi_s^e = 1.016$. And the profit of manufacturer can be illustrated in Figs. 6.24 and 6.25 by the same numerical example as in the first condition with $E_1 = 24$, $E_2 = 16$, $k_0 = 4$, $k_1 = 13$, $k_2 = 4$, $C = 1$, $L = 2.5$, $H = 2$, $R = 5$.

Compared to Figs. 6.22 and 6.23, we can find that manufacturer's profit is greater with the same p and q. So we can draw a conclusion here that this kind of cooperation can effectively increase the profit of the supply chain and improve the quality of products to some degree; cost share is an efficient means of inspiring suppliers to deliver the highest quality. Actually, the loss for inspecting the goods

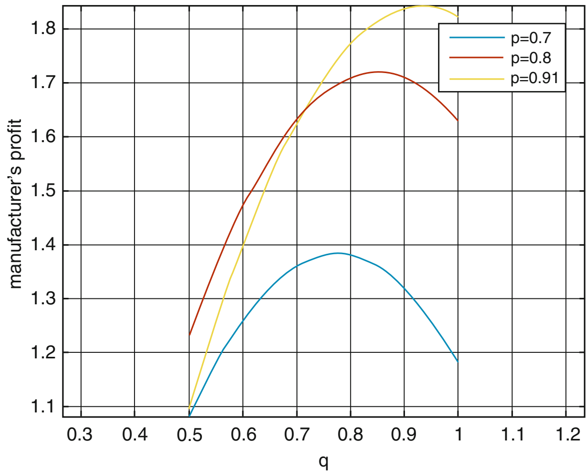

Fig. 6.24 Manufacturer's yield curve based on variable q with $E_1 = 24$

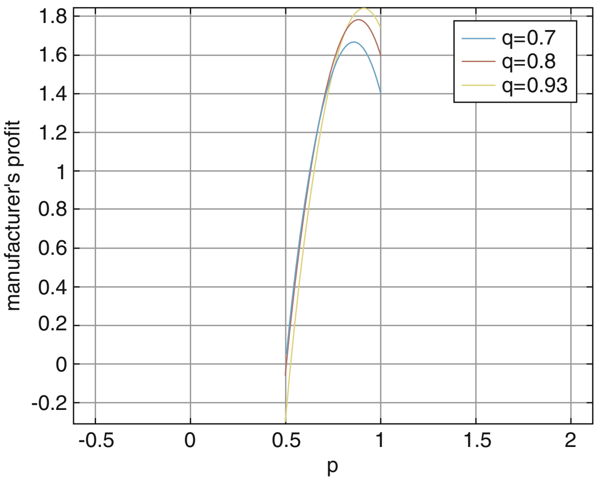

Fig. 6.25 Manufacturer's yield curve based on variable p with $E_1 = 24$

doesn't exist anymore in this condition. And we can find that the total profit of the supply chain is equal to that of the second condition with a more reasonable benefit distribution mechanism.

6.5 Conclusion and Future Research

6.5.1 Conclusion

In this chapter, we propose a new concept of quality management. Also, we put forward the definition of the entire life cycle quality management in the environment of Internet and big data in the hope that quality management can help today's enterprises producing products that can meet requirements of society, customer, and themselves. The impact of Internet and big data on the quality management, new quality management concept system, QAS (quality assurance system), and new methods for quality management are also discussed. Then we study a model considering the impacts of three different conditions on the supply chain, including the manufacturer invests an amount C to inspect all the goods purchased from supplier; if the supplier's quality is taken as common knowledge, the q and p are determined by a third party; and the manufacturer invests an amount C to inspect all the goods and shares the manufacture cost of semi-manufactured goods with supplier. We provide a game theoretical framework from game theory perspectives to explore the effect of the three conditions. Our analysis shows that the supervision mechanism can effectively improve performance of both the supplier and the manufacturer. We also compare their profits in those different scenarios. We find that the introduction of a third party who will inspect the supply chain can motivate the supplier and the manufacturer to improve the quality of their products and maximize the profit of the supply chain. Besides, compared with the first condition, sharing costs helps to yield more profit for the both of them. In addition, compared with the second condition, sharing cost can realize a more reasonable benefit distribution mechanism.

6.5.2 Future Research

Further study can focus on the integration of new information technologies based on the Internet and big data such as big data analysis. And the application of life cycle quality management with the use of new information technology in a certain manufacturing union is worth of study. Also, we can use many other research methods to discuss the function of life cycle quality management from different perspectives. As a whole, we should do more research work on this field in order to help today's enterprises produce the products which can meet the requirements of society, customer, and enterprises themselves.

Chapter 7
Life Cycle Assessment in an IoT Environment

7.1 Introduction

7.1.1 Life Cycle Assessment

Life Cycle Assessment (LCA) is a tool that assesses the environmental impacts and resources used throughout a product's life cycle, i.e., from raw material acquisition to the production and use phases and waste management [263]. Hellweg found that LCA is an important decision-support tool that, among other functions, allows companies to benchmark and optimize the environmental performance of products or for authorities to design policies for sustainable consumption and production [287].

In the future, the assessment of the whole life cycle of products will be in great demand because of sustainable development, especially for complex products such as spacecraft, aircraft, ships, locomotives, cars, and large complex equipment. These complex products have the characteristics of a complex composition, technology, R&D process, manufacturing, and management process. It is an important reflect of the core competitiveness of a country. So through the LCA towards complex product, its value can be more apparent, and management strategies can be better grasped.

The manufacturing industry in China is experiencing the transformation from production-oriented manufacturing to service-oriented manufacturing, and moving from providing a one-time purchase service for consumers to whole life cycle services. Service-oriented manufacturing enables the processing of products in the circulation step, which not only meets the needs of customers better and promotes the efficiency of product circulation, but also increases the profit margins of manufacturing enterprises and service enterprises. Service-oriented manufacturing is based on customer demand management, so the resources of member enterprises in the supply chain are integrated and coordinated. Customers participate in the

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procurement of raw and auxiliary materials, product design, manufacturing, packaging, logistics, after-sales services, recycling, and other integration services, so the added value of the product in the whole life cycle is achieved. LCA in service-oriented manufacturing is quite different from traditional production-oriented manufacturing LCA.

Remanufacturing expanded the life cycle of the product, and the closed-loop system that contains "development – use – scrap – regeneration" is formed. The value of re-manufacturing complex products is high and the industrial chain is long; these re-manufactured products involve complex system engineering. Due to the re-use of a large number of waste parts and components, pollutant emissions in the mining and processing of raw material are avoided to some extent. This fits the strategic needs of global consumers by quietly building a recycling economy. However, the dismantling and cleaning process in re-manufacturing is also accompanied by some pollutant emissions. The overall level of China's current remanufacturing is relatively low, so evaluating the whole life cycle of a product from the aspects of technical, economic, social, and environmental indicators is a challenging issue.

7.1.2 LCA in an IoT Environment

The deep integration of the technology of Internet and Internet of things (IoT) with manufacturing systems is changing the relationship between products, organizations, society, and the environment throughout a product's whole life cycle, which extends the value chain of a product. Product technology and manufacturing technology are complex, and their impact on the economy, society, and environment is more extensive than that of traditional approaches. The IoT provides big data support for LCA of products.

Complex products have the properties of a polymorphic inventory and large intermediate products. There are a large number of suppliers and cooperative and supporting enterprises related to the development of such products. Intelligent components, such as sensors, mobile storage devices, and software systems (such as mobile computing and real-time collaboration), are embedded in complex products. These intelligent components allow manufacturers to acquire real-time data for multiple levels of the entire life cycle of a product, from the raw material processing, production, and use, remanufacturing and scrapping of waste. The tremendous amount of IoT data is multi-sourced, dynamic, heterogeneous, high dimension, and uncertain. In service-oriented manufacturing, how to construct LCA methods of product based on big data which has the features of huge amounts and complexity in the environment of Internet and IoT is an urgent problem to be solved.

Most of the traditional comprehensive evaluation is the choice of static, state and relatively closed object, whereas the evaluation based on big data in the environment of Internet and IoT is dynamic, systematic, open process that object data should be integrated. In traditional comprehensive evaluations, data must be obtained from the procedures in advance, while the evaluation based on big data involves a process of data extraction from large scale data flows that have no obvious associations. The construction of a traditional comprehensive evaluation system mainly depends on literature research, expert consultation and so on. It is always the problem that a lot of data for indicators are unable to be obtained. In a big data environment, data resources increase rapidly, which leads to a change in the method used for evaluating the system's construction, and the reliability and objectivity of the evaluation will be greatly improved.

7.2 Literature Review

The concept of Life Cycle Assessment is proposed in the late 1960s and early 1970s. It has been interpreted by several authorities, such as the Society of Environmental Toxicology and Chemistry (SETAC) [259], the international standard ISO14040 [274] and the United Nations Environment Program (UNEP) [276]. The definition by SETAC is summarized as follows: LCA is a quantitative evaluation process of the environmental loads associated with a certain product system or behavior. It starts with identifying and quantifying the material, energy and environmental emissions, and then evaluating the environmental impact of these uses and emissions.

SETAC has also proposed a basic structure of LCA called SETAC triangle which is now the basis of standardizing activities of ISO [301]. From the SETAC triangle shown in Fig. 7.1, we can see that there are four steps involved in LCA.

- Goal definition and Scoping
- Inventory Analysis
- Impact Assessment
- Improvement Assessment

ISO also provided a structure in the international standard 14040 [273] which is different from SETAC triangle in that the fourth part is called 'Interpretation'(Fig. 7.2).

At present, the studies on LCA are mainly focused on the inventory analysis, life cycle impact assessment (LCIA), LCA approach, Life Cycle Cost (LCC) analysis, Life Cycle Sustainability Assessment (LCSA) and LCA applications. In the following, literatures on the Inventory analysis and impact assessment, Life cycle cost, Social life cycle assessment (S-LCA), LCA methods and LCA applications are reviewed.

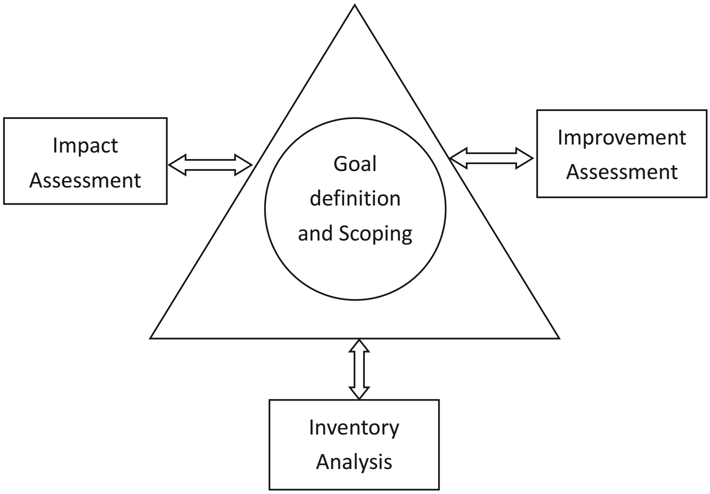

Fig. 7.1 SETAC triangle

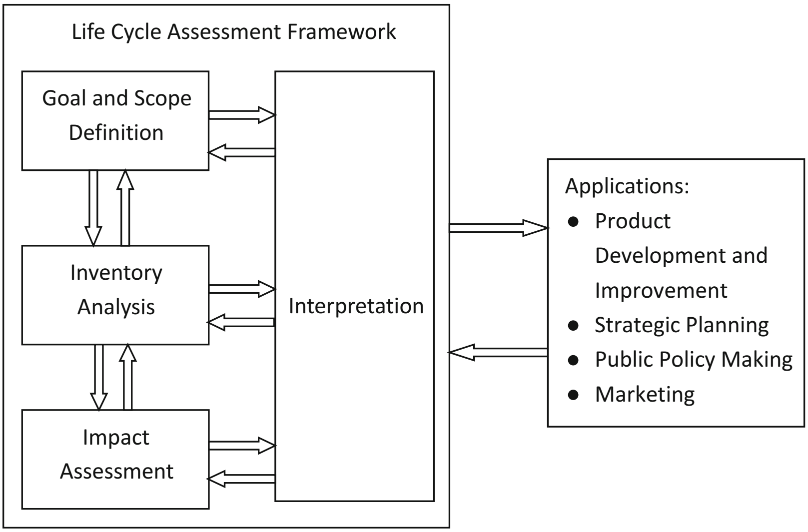

Fig. 7.2 ISO structure of LCA

7.2.1 Inventory Analysis and Impact Assessment

Inventory analysis and impact assessment in the current LCA are to determine all the input and output lists as well as the process of determining the impact of the inventory on environment from the viewpoint of cause and effect chain. Life cycle inventory analysis is the process of quantifying and evaluating the resources and energy requirements and the release to the environment in the whole life cycle of products, technics or activities. Life cycle impact assessment is quantitative or qualitative assessment of the environmental stress identified in the inventory analysis phase, which is to determine the impact to external environment from material and energy exchange of the product system. In fact, all kinds of waste discharged to the environment can be regarded as the basic indicator of environmental based LCA indicator system, while LCIA is to summarize these different emissions into different types of environmental impact. These basic indicators are attached to different types of environmental impact, and it is a network hierarchy. In the technology framework of LCA, LCIA is considered to be the most complex and highest technical content, and the development of LCIA is also on the way. At present, the range of environmental impact is not limited to carbon emissions only, new environmental indicators such as water use, toxicity and biological diversity have already been considered in the process. Hauschild M Z [266] proposed a framework linking elementary flows from the inventory results to indicator results at both midpoint and endpoint level. The Midpoint level is the environmental impact classification which includes 15 categories such as Climate change, Ozone depletion, Human toxicity, Respiratory inorganics, Ionising radiation, Photochemical ozone formation, Acidification, Eutrophication, Ecotoxicity, Land use, Resource depletion. The endpoint level is the area of protection which consists of Human health, Natural Environment and Natural resources. Contreras Moya [260] proposed exergetic LCA that is more efficiency and oriented for assessing four different alternatives for byproducts valorization of the cane sugar process. Bertrand Laratte [254] presented a dynamic indicator for LCA measuring cumulative impacts over time of greenhouse gas emissions from fertilizers used for wheat cultivation and production.

In the life cycle inventory analysis, the UK's Boustead database is the earliest and has great impact. Most of its data are from industrial field that have covered more than 20 countries, and it has become one of the world's largest LCA databases. Other developed databases include GREET, BUWAL 250, Ecoinvent 2000, Input-Output 95, simapro 8, SPINE@CPM and so on. In Asia, Japan, South Korea, China and India have all developed their local LCI databases [280]. Vasilis Fthenakis [290] investigated life cycle inventory analysis of the production of metals used in photovoltaics, including the material flows and emissions in all the stages of production of zinc, copper, aluminum, cadmium, indium, germanium, gallium, selenium, tellurium and molybdenum. Colin W Murphy [258] developed a life cycle inventory for corn production based on average U.S., and then applies three allocation methods including economic allocation, energy-based allocation, and subdivision approach to produce a life cycle inventory for stover. The results shows that the first two methods are more simple to apply, and may be more transparent to interpret, while the third one requires less data to implement. Vincent Moreau [291] proposed a statistical approach to address the lack of data in life cycle inventories and applies it to hydroelectric power plants. These missing data directly affect the quality and reliability of LCA, and is an important source of uncertainty in the results. In China, researches are mainly focused on data types, sources, access methods, data processing and so on.

7.2.2 Life Cycle Cost

Without considering the economic dimension is one of the most important limitations of traditional LCA theory, which leads to the limitation of its applications. One of the service objects of LCA research is enterprise who regards economic factor as the primary consideration when making decisions. In particular, some improvement measures proposed by LCA research often increase the initial investment of the product system. If cost and benefit analysis of the whole life cycle is not properly implemented, the improvement measures will be difficult to be adopted. At present, there are two models for the combination of LCC and LCA. One is to integrate various functions of LCC into LCA system, the other one is to transform the LCA results into the environmental costs which is then added into the LCC analysis procedure. [268] combined LCIA with economic analysis of social life cycle costs (SLCC) to investigate five alternatives for newspaper waste management. In his research, not only the individual benefit and cost which reflect economic dimension are considered, social benefit and cost are also included in the analysis. [299] combined Economic Input-Output LCA (EIO-LCA) and Principal Component Analysis (PCA) to analyze economic and environmental impacts of 276 US manufacturing sectors associated with four transportation modes. In the research, three kinds of environmental impact factors including greenhouse gas emissions, energy use and water consumption are taken into consideration. To compare the private and external costs of two waste disposal facilities including landfill extension and advanced incineration facility in Hong Kong, Kok Sin Woon [277] proposed a eco-efficiency indicator for the combination of LCC and life cycle human health impact. Just as the author described by himself, the method makes the stakeholders in government for a more sustainable management of municipal solid waste disposal. Yi-Hsuan Shih [300] used cost-benefit analysis to explain the economic feasibility of the Sustainable Energy Policy Guidelines of Taiwan for climate change mitigation. The social benefit from emission decrease by using renewable energy product is analyzed. Hao Wang [267] analyzed the LCC of base-isolated reinforced concrete structures in nuclear power plants. Seismic intensity is employed for the estimation of expected damage cost, and a case study is implemented in French Cruas nuclear power plant. E. Ryan [262] proposed a method for the estimation of LCC for Department of Defense programs of U. S, and it has been applied in more than 30 programs.

In summary, there are still many problems in the research of LCC. Since there are some differences in system boundary, research object and assessment approach between LCA and LCC, so there is still not an effective method either by adding the functions of LCC to LCA procedure or calculating LCC using LCA data. Furthermore, economic dimension not only includes the current LCC defined in literature, but also other factors such as benefit and so on. The current LCC are considered from the perspective of enterprise, other stakeholders such as consumer, government have not been included.

7.2.3 *Social Life Cycle Assessment*

The impact from the whole life cycle of a product or service is not merely restricted on environmental and economic dimensions, social dimensions should also be considered. Social aspects are first proposed to integrate into traditional LCA in the 1990s [281], and the guidelines for S-LCA by UNEP and SETAC Life Cycle Initiative can be found in [253]. In Catherine Benoît's opinion, it is necessary to develop database and software in the study of S-LCA, and the stakeholders include worker, consumer, community and all participants should be involved. [283] discussed the necessity of integration of social impacts into LCA framework in the context of food production systems. Three social impacts including human toxicity, occupational health and safety, noise and accidents are analyzed using life-cycling thinking. Catherine Benoit-Norris [255] analyzed the development and characteristics of Social Hotspots Database (SHDB) which is an overarching, global database that supports the data collection in S-LCA procedure. [265] proposed an S-LCIA method that combining performance reference point and impact pathways methods. The author pointed out that the direction for future S-LCIA research is the refinement of SHDB and social hotspot index calculation method.

From the current literatures, we can see that the researches on S-LCA are still not satisfied in many aspects. First of all, because of the regional feature of social impacts, how to construct a general social impact structure is still debatable. Secondly, since the social impacts from the life cycle of a product are not easy to be quantified, how to confirm the assessment criteria for social impacts and acquire the data are complex problems.

7.2.4 *LCA Methods*

At present, there are about 20 kinds of LCA methods considering environmental impacts, such as Eco-indicator 99, CML 2 baseline 2000, Ecopoint 1997, EPS 2000, EDIP and so on. Different methods have certain scope of applications and limitations, and the assessment results are also different. LCA methods could be generally classified into two models, the process-based LCA (PLCA) and the economic input-output analysis-based LCA (EIO-LCA). PLCA maps every process associated with a product within the system boundaries, and associates energy and material inputs and environmental outputs and wastes with each process [256]. It is not easy for the assessment of complex product because a great deal of data are needed and the cost is high. EIO-LCA integrates economic input-output analysis and publicly available environmental databases for inventory analysis of the entire supply chain associated with a product or service [256, 269]. Another method is the hybrid LCA model which is the combination of PLCA and EIO-LCA [282]. According to the author, the hybrid LCA model overcomes the methodological limitations of the above two methods, so the time and execution cost are saved and the accuracy of the research results is improved. [264] used hybrid LCA that combines total environmental impacts and gross value added for the disposal of waste glass-packaging in Swiss, and an eco-efficiency indicator is constructed. Based on the development and comparison of Input-Output-based Hybrid LCA and Integrated Hybrid LCA, [289] took the wind power generation in UK as the case to study the indirect greenhouse gas emissions of energy technologies. For the combination of environmentally extended input-output based life cycle assessment (EE-IO-LCA) model with Intuitionistic Fuzzy Set theory in the process of LCSA includes environmental and socio-economic indicators, [284] proposed the use of TOPSIS method for the selection of the best wind energy alternative where expert judgments are required for both the weighting and sustainability indicator process. In [298], EE-IO-LCA is utilized to calculate energy and carbon footprints throughout the supply chain of alternative delivery trucks.

The existing researches on the LCA method are mainly focused on the environmental dimension, and the discussions on closed-loop LCA method considering remanufacturing are not perfect. Nowadays, IoT technologies have been embedded into all the stages of the complex product life cycle. For instance, Airbus Group has applied IoT technologies to raw material procurement, inventory, product sales and other logistics areas, which leads to the largest and most efficient supply chain system in the global manufacturing industry. The IoT provides a big data platform for the LCA of product including the remanufacturing process. So some new approaches are needed to support the use of these massive, multi-source, heterogeneous data for LCA.

7.3 Life Cycle Assessment of Mobile Phone from Environmental Dimension

With the development of information science and technology, people have been living with electronic products like mobile phones which have become a necessity in people's life. In 2014, the global mobile phone sales have reached to 1.2 billion which caused our concerning on its life cycle process. Here, the iPhone4S is chosen as the representative of the mobile phone, and the LCA to it is conducted for the study of environment impact of mobile phone in its life cycle. Due to the complexity of the mobile phone components and data involved in the process, the research is based on the data in the Apple's report and a simplified model is constructed for the LCA of iPhone4S. First of all, the sales and materials of iPhone4S are counted. Then, inventory analysis to the manufacturing, transportation and waste treatment of key materials are implemented, and the inventory data are analyzed by equivalent model. Finally, the improvement measures are given. From the comparison with other mobile phones, the materials used for the manufacturing of iPhone4S are more environmentally, and energy consumption and pollutant emissions are also relatively lower. Nevertheless, there are still a large amount of emissions such as greenhouse gas, acid gases and fluorinated substances in the manufacturing process. In order to protect our environment, the most effective treatment is to supervising the pollutant emissions of the related industry by government and recycling of waste materials. So with the enjoyment of the convenience from electronic products, we should try to reduce the pollution to the environment.

7.3.1 Summary of Life Cycle of Mobile Phone

In this chapter, the LCA is to be implemented to iPhone4S which is a mobile phone product of Apple. A question arises as why we select the iPhone4S as a representative. The iPhone series are Apple's classic products which opened the era of touch smart phones. In a number of mobile phone series, the performance of iPhone4S is very prominent. IPhone4S came into the market in October of 2011, and the volume of sales in the first quarter is 43.7 million which is more than the original expectation by 17 %. Its appearance had greatly promoted the performance of hardware and software of smart phones, and the configuration and performance provided a reference for the subsequent production of smart phones to all the enterprises. Since the iPhone4S's coming into market, people's habits have been greatly changed and a more colorful life is coming to us. While we are enjoying the convenience of electronic products, we also need to pay attention to some negative impacts of the product on our environment.

Compared with other mobile phone brands, the manufacturing process of Apple's products is more standard, and the production data are more transparent. In the process of designing, Apple has taken into account the environmental protection and energy saving of materials, and the convenience for recycling is also under consideration. With the application of advanced production technology, the performance of product is enhanced, and the responsibility for the entire environment of the earth from a corporation is reflected as well. From the LCA of iPhone4S, we could have a clear understanding of the energy consumption of various components of a mobile phone. Besides, it is also expected to guide the related design and manufacturing enterprises for more environmental design and production, and to help manufacturers improving the process of mobile phone production. The production of iPhone4S has a feature that its manufacturing process is related to the relevant big and small manufacturers from all around the world. For example, the overall design of the product is in the United States, production of key components such as camera is in Japan, core chips is processed in Korea, display screen is designed in the UK. The production of these raw materials is related to the districts such as Africa, China, Australia and so

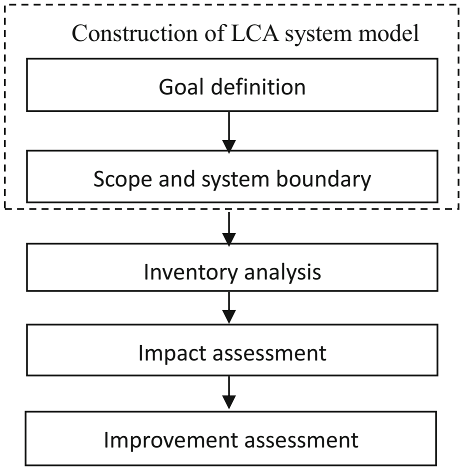

Fig. 7.3 Structure of the chapter

on. Finally all the components are transported to Foxconn's factory to be assembled, and then the final products (iPhone) are sold around the world. Statistically, a total of 31 countries around the world are involved to provide raw materials and components for an iPhone4S, which makes Apple's mobile phone products truly 'from the world's factory'. Due to the fact that China has the largest number of suppliers (more than 300) of iPhone4S, so the main environmental responsibility is also undertaken by China in the mobile phone production process.

The aims of this chapter are summarized as follows:

1. Through the establishment of the model, the LCA of other smart phones can be compared and the impact of the entire smart phone industry on China's environment is to be analyzed.
2. Let enterprises to clearly know the key aspects to improve the environment in the process of manufacturing mobile phones. And the improvement and control can be conducted with the help of government, which is hoped for the improvement to the entire industrial system.
3. Let the government to be more aware of the impact of smart phone products on the environment, so some more practical legal provisions and government policies are expected to be made.
4. Finally, it is hoped for the guidance to the personal use behavior.

The structure of this chapter is shown as follows (Fig. 7.3):

7.3.2 Construction of LCA System Model

In our research, the total production of iPhone4S from its came into market in 2011 to the mid-September of 2014 when it was discontinued is counted. The life cycle

Table 7.1 Greenhouse gas emissions per iPhone 4S

Phase	Greenhouse gas emissions per iPhone 4S (kg CO_2e)
Production	33 (60 %)
Customer use	17.05 (31 %)
Transport	3.85 (7 %)
Recycling	1.1 (2 %)
Total	55

Table 7.2 Material use per iPhone 4S

Material	Material use per iPhone 4S (g)
Glass	47
Stainless steel	40
Battery	25
Circuit boards	16
Display	7
Plastic	3
Others	2

process including the initial production of raw materials, product processing, product use, product recycling and waste treatment are tracked and data are collected. Through quantitative and qualitative analysis and assessment, the environmental impacts of iPhone4S in its life cycle are presented.

Because most of the materials used in the production of iPhone4S are polymer materials and new types of materials, and the technologies used are also the latest, so there is a considerable part of the data cannot be statistically obtained. Our survey is a statistical analysis based on the iPhone4S environmental report [275] provided by Apple in 2012. Tables 7.1 and 7.2 are the data used in the iPhone4S environmental report.

In the report, it has been mentioned that in the design phase, attentions are paid to the following features of materials used in each iphone4S for the purpose to reduce environment impact.

1. The use of arsenic free glass.
2. Mercury free LED backlight display.
3. The use of bromine flame retardant free (BFR-free) materials.
4. The use of polyvinyl chloride free (PVC-free) materials.
5. Most of the packages are made from recycled fiber and bio-based materials.
6. The performance of power adapter is better than the world's most strict energy efficiency standards.

Apple's environmental report on iPhone4S is simple because carbon dioxide is the only emission in its consideration, and there is no interpretation on any other emissions. Apple has only calculated the carbon emissions of mobile phone host in its life cycle. When consumer buys a mobile phone, ancillary products such as the phone's packaging box, adapter, headphone and charging wire are also attached.

These ancillary products also lead to the energy consumption emissions. Because it is difficult to get the data, we will extend the scope and system boundary of LCA on iPhone4s based on the relatively accurate life cycle data of Apple, and a more comprehensive result is to be got.

1. Goal definition

   The general goal is to understand the environmental impacts of iPhone4S from cradle-to-grave in all phases of the life cycle. To achieve the goal, the following issues are to be done.

   (a) The classification of IPhone4S and detailed sales data.
   (b) The production process of iPhone4S.
   (c) The components of IPhone4S, and the detailed inventory data on raw materials of important components.
   (d) Data statistics on energy consumption and pollutant emissions during the exploitation and processing of raw materials in the early stage of production.
   (e) Data statistics on energy consumption during the transportation process in the sales phase
   (f) Data statistics of electricity consumption in the phase of use.
   (g) Data statistics on energy consumption and material been discharged in the phase of waste disposal of used mobile phone.
   (h) Based on the above data and comprehensive statistics, and the environmental impact of iphone4S on the entire life cycle will be given.
   (i) The improvement analysis according to the result is finally conducted.

2. Scope and system boundary

The research object is all iPhone4S mobile phones produced by Apple, and functional unit is the energy consumption and pollutant emissions for one iphone4S mobile phone in the whole life cycle. According to the goal definition, the scope of the assessment is the process including raw materials production, product processing, transportation, use and final disposal of used mobile phones throughout the entire life cycle process. The scope and system boundary are shown in Fig. 7.4.

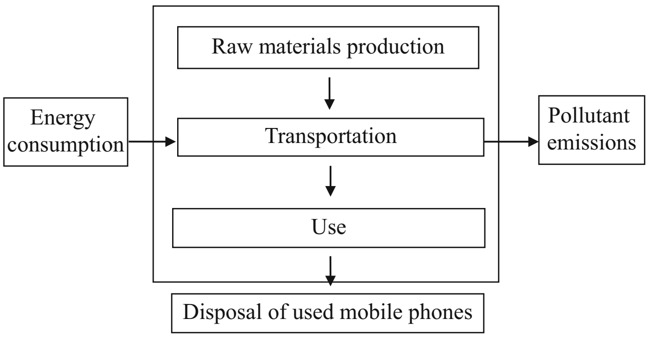

Fig. 7.4 Scope and system boundary

Energy consumption includes various energy sources such as crude oil, raw coal, heavy oil, diesel oil, natural gas and so on. Here, various energy sources are standardized in the form of standard coal. Pollutant emissions are mainly referred to CO_2, SO_2, NO_x, CO, CH_4, C_xF_y, C_xH_y and dust. In the process, the type of environmental impact includes acidification effect, greenhouse effect, non-renewable resource consumption and ozone depletion.

7.4 Inventory Analysis

To carry out the inventory analysis, the scope of assessment is illustrated as follows:

1. The LCA is only limited to hardware of iPhone4S, the software and APP product used in iPhone4S are not included in the LCA process.
2. Because of the limited amount of data, the specific process of materials and components have not been collected. Data on the loss of fixed assets, related water and electricity loss and emissions in the processing phase by factory are not calculated. Water and electricity loss and office materials expenditure of factory workers, management personnel and other related personnel are also not in the research scope. Furthermore, it is supposed that all factories did not conceal the pollutant emissions.

7.4.1 Production Capacity of iPhone4S

Because the manufacturers of iPhone4S do not have accurate data for reference, so it is assumed that the productions and sales are equal. Our assessment is based on the sales data from October of 2011 when it came into market to September of 2014 when it was discontinued. The detailed data on sales time are shown in Table 7.3 which is referred to Wikipedia [270].

The sales data on iPhone4S in each quarter are shown in Table 7.4 as follows.

The sales proportion of iPhone4S 16G, iPhone4S 32G and iPhone4S 64G of are 43 %, 34 % and 23 % respectively when they are all in market. Table 7.5 shows the total sales on each type of iPhone4S.

Table 7.3 Data on sales time of iPhone4S

Starting time	Ending time	Type of mobile phone
14th October, 2011	10th September, 2012	iPhone4S 16G
		iPhone4S 32G
		iPhone4S 64G
11th September, 2012	10th September, 2013	iPhone4S 16G
11th September, 2013	10th September, 2014	iPhone4S 8G

Table 7.4 Sales of iPhone4S

Sales time		Total sales of iPhone (10,000)	Sales of iPhone4S (10,000)	Percentage
14th October–31th December, 2011		3700	3300	89
2012	Q1	3893.5	3193	82
	Q2	2600	1940	74.6
	Q3	2602.8	1620	62.2
	Q4	2690	1740	64.7
2013	Q1	3740	1421	38
	Q2	3743	1347	36
	Q3	3380	1150	34
	Q4	3437	1030	30
2014	Q1	4370	1080	25
	Q2	3534.5	848	24
	Q3	3930	943	24
Total		41,621	19,612	47

Table 7.5 Sales of each type of iPhone4S

Type	iPhone4S 8G	iPhone4S 16G	iPhone4S 32G	iPhone4S 64G
Sales (10,000)	3881	9980	3412	2312
Percentage	19.7	50.8	17.4	12.1

7.4.2 Components Inventory of iPhone4S

Table 7.6 is the main components and materials that summarized from the data of Table 7.2 and a free repair website.

From Table 7.6 and Appendix 7.1, we can see the main materials contained in a mobile phone. The material proportion is estimated based on the previous estimate of the mobile phone dismantling data. Table 7.7 shows the inventory of materials contained in an iPhone4S.

The information in Table 7.7 should be explained in several aspects as follows:

1. The chemical materials used in Apple's mobile phone such as epoxy resin (EP) is embedded into the phone's mainboard as adhesion agent, aluminum and copper are also embedded into the mainboard as metal medium. At present, there is no instrument to show the precise quantity of these materials used in the mobile phone. Therefore, the weights of epoxy resin, aluminum, copper and other materials are estimated according to their proportions.
2. The official report by Apple showed that the chemical materials did not contain bromine flame retardant and PVC which will produce severe contamination in the production.
3. Other metals consist of the metals that have low proportions such as lead, nickel, cadmium, six chromium, gold, silver, tin, and so on.

Table 7.6 Data of iPhone4S's components

Component	Parameter	Material
The host of iPhone4S	Weight:140 g	See Appendix 7.1 for detailed parameters
	Size:115.2 × 58.6 × 9.3 mm	
One base interface turn to the USB cable	Length:1.05 m	Polycarbonate of flame retardant injection molding, thermoplastic elastomer (TPE), copper, aluminum, aluminum magnesium alloy, PVC
One earphone 1	Length:1.1 m	Polycarbonate of flame retardant injection molding, TPE, aluminum magnesium alloy, tin, copper, aluminum
	Size of interface:3.5 mm	
One USB power adapter	Capacity: 330 uF	Polycarbonate of flame retardant injection molding, aluminum magnesium alloy, copper, PVC
	Voltage: 6.3 V	
	Parts: panel, wire, coil, capacitance, resistance	
One USB adapter converter		Polycarbonate of flame retardant injection molding, aluminum magnesium alloy
A copy of the instruction		Paper, pigment ink
One packing box	The carton weight: 120 g	Carton, thermoforming polystyrene, pigment ink
	Weight of thermoforming polystyrene: 11 g	
	Other plastic: 2 g	

4. Official report by Apple showed that the glass does not consist of arsenic, and there are no heavy metals such as mercury contained in the LED backlight display.
5. Due to the complexity of the composition of battery, in order to facilitate the calculation of the LCA process, the compositions of battery are calculated separately.
6. The substance used very little in the production such as polybrominated biphenyls (PBB) and polybrominated diphenyl ether (PBDE) are not included in the table.

7.4.3 Energy Consumption and Emissions of Material Production and Mobile Phone Manufacturing for iPhone4S

1. Data process

Just as depicted above, the materials related to a mobile phone are various, and the suppliers of raw material for Apple are all around the world. From the mineral collection, raw materials refining, semi-finished product processing to finished product assembling process, there are more than 100 large-scale manufacturers

Table 7.7 Inventory of materials contained in an iPhone4S

Main constituent materials	Main parts	Material	Proportion (%)	Weight (g)	Total (kg)
Chemical materials	Frame, metal packaging leather	Polycarbonate (PC) of flame retardant injection molding	8.1	23	4,510,760
		Thermoplastic elastomer (TPE)	1	3	588,360
		Epoxy resin (EP)	2.1	6	1,176,720
		General purpose polystyrene (GPPS)	4.2	12	2,353,440
Metallic materials	Middle frame and chip	Aluminum	8.8	25	4,903,000
		Copper	2.1	6	1,176,720
		Aluminum magnesium alloy	16.6	47	9,217,640
		Other metals	17.7	5	980,600
Glass	Screen and camera	Silicon (glass fiber)	6.4	18	3,530,160
Semiconductor materials	Chip, integrated circuit board	Monocrystalline silicon	3.5	10	1,961,200
Paper fiber	Packing box	Paper fiber	42	120	23,534,400
Battery			4.5	13	2,549,560
Total			100	283	55,501,960

related, not to mention the large number of small-scale manufacturers. Different technics directly influence the processing degree in the mobile phone production stage, which will ultimately lead to the difference in energy consumption and emissions. Here, we will handle the data as the following rules:

(a) Data on raw materials and processing are collected together.
(b) Life cycle data on thermoplastic elastomer (TPE) and epoxy resin (EP) which are the derivative products after the processing of petroleum have not been found. Because these new types of industrial products have not yet been issued on their production and life cycle process authoritatively, the life cycle process of GPPS is selected to replace instead.
(c) Other metals mainly contain the rare metals such as cadmium, six chromium, gold, silver whose explosion and production are complex, so they are replaced by aluminum in the calculation.
(d) For the simplification of energy form, the input of energies are converted to standard coal consumption by standard coal coefficient. The energies used in the process of production include raw coal, diesel oil, heavy oil, crude oil, liquefied petroleum gas and natural gas. The standard coal coefficients are shown as Table 7.8.

Table 7.8 Standard coal coefficient (characterization factor)

	Raw coal	Diesel oil	Heavy oil	Crude oil	Liquefied petroleum gas	Natural gas
Coefficient (kg)	0.7145	1.4601	1.4286	1.4565	1.5903	1.6594

Table 7.9 Environmental load generated by 1 kWh electric power

	Environmental load
CO_2	1.2408 kg
CO	0.0225 kg
SO_2	0.0070 kg
NO_x	0.0033 kg
CH_4	0.0000068 kg
C_xH_y	0.00001 kg
Stive	0.00017 kg
Solid waste	0.000051 kg

(e) According to the China Electric Power Yearbook 2004, the production of 1 kWh electricity needs 0.376 kg standard coal. The environmental load generated by the combustion of 0.376 kg standard coal is then converted into the environmental load generated by 1 kWh electric power which is shown in Table 7.9.

(f) 1 tons of non-metallic mineral mining needs to consume the electricity of 20 KWh, the comprehensive energy consumption is 8.08 kgce.

2. Inventory of manufacturing process for polycarbonate (PC)

(a) Technics

The raw material of polycarbonate is from a biological resource-corncob which is obtained from corn. In the process of producing corn, fertilizers and mechanical operations should be put into. Fertilizers are mainly related to nitrogen fertilizer, phosphate fertilizer and potash fertilizer, while the mechanical operation mainly involves the consumption of diesel oil. The main proportion of fertilizer is nitrogen fertilizer which mainly includes urea (60 %) and ammonium bicarbonate (25 %), and the raw materials of them include coal (62 %), heavy oil (12 %) and natural gas (26 %). Corn products include niblet, corncob and corn straw. Their mass proportion is 1:0.18:1.2, and the emergy is 16,735 KJ/kg, 18,740 KJ/kg, 16,536 KJ/kg respectively. The corncobs are collected and further processed into furfural and furfural residue. Furfural and chlorine can be produced to furfuryl alcohol in conditions of catalytic. Then furan methyl glycidyl ether is produced from the reaction of epoxy chloropropane and furfuryl alcohol under alkaline conditions. To produce epoxy chloropropane, dichloropropanol should be firstly obtained from the reaction of glycerol and hydrogen chloride gas. And then from the epoxidation

Table 7.10 Energy and pollutant emissions from the production of polycarbonate per ton

Energy consumption	Standard coal	kg/t	510.7
Pollutant emissions	CO_2	kg/t	14,823
	SO_2	kg/t	140.1
	NO_x	kg/t	66.142
	CO	kg/t	451.4
	CH_4	kg/t	0.139
	C_xH_y	kg/t	0.21

Table 7.11 Energy consumption and pollutant emissions from the production of GPPS per ton

Energy consumption	Standard coal	kg/t	3111.2
Pollutant emissions	CO_2	kg/t	17,246.12
	SO_2	kg/t	111.602
	NO_x	kg/t	0.317
	CO	kg/t	398.7
	CH_4	kg/t	0.02
	Dust	kg/t	186.49

reaction of dichloropropanol and alkali, epoxy chloropropane is get. Finally, polycarbonate is obtained by furan methyl glycidyl ether and carbon dioxide in the presence of catalyst polymerization.

(b) Data process

Data are collected on the energy consumption and pollutant emissions in the production of corn cob, furfural, furfuryl alcohol, shrink glycerin ether when manufacturing polycarbonate. The use of fossil energy is converted to standard coal consumption. Then energy and pollutant emissions from the production of polycarbonate are obtained as Table 7.10.

3. Inventory of manufacturing process for general purpose polystyrene (GPPS)

(a) Technics

The raw material of GPPS comes from crude oil. Crude oil should be extracted and transported to chemical plant for further processing which includes the refining of crude oil. The refining process of crude oil is as follows: crude oil distillation, cracking of naphtha and light diesel oil, and the separation of cracking gas. A lot of chemical ancillary products such as propylene are produced in the process of refining. The collected chemical substances are further handled with gasoline hydrogenation, aromatics extraction, alkylation and dehydrogenation of ethylbenzene. The final production of polystyrene is then produced by the polymerization reaction of all the above materials.

(b) Data process

The energy consumption and pollutant emissions from the production of GPPS are shown in Table 7.11 as follows. Here, energy consumption is converted to standard coal with the proportion of 29:1.

Table 7.12 Energy consumption and pollutant emissions from the production of industrial silicon per ton

Energy consumption	Standard coal	kg/t	349
Pollutant emissions	CO_2	kg/t	20,602
	SO_2	kg/t	141
	NO_x	kg/t	42
	CO	kg/t	558
	CH_4	kg/t	0.092
	C_xH_y	kg/t	0.133
	Dust	kg/t	66

4. Inventory of manufacturing process for industrial silicon

(a) Technics

The main raw material for processing industrial silicon is silica. First, silica should be explored, and the impurities inside the silica are to be removed. Then carbonaceous reductant is added to produce industrial silicon by smelting. Industrial silicon is further refined for the formation of polycrystalline silicon rod which is then refined and deposited to form single crystalline silicon. According to the requirements of manufacturer, single crystalline silicon will be further processed including coating, developing, etching, implanting ions for lithography, assembling and encapsulation.

(b) Data process

The energy consumption and pollutant emissions from the production of industrial silicon are shown in Table 7.12 as follows. In the calculation, the consumption of ores is converted into standard coal according to standard coal coefficient, and the exploitation of ore is included in the energy consumption and pollutant emissions.

5. Inventory of manufacturing process for glass

(a) Technics

The main raw materials of glass are from different kinds of ores, such as sandstone, feldspar, limestone, dolomite, and so on. The raw materials are firstly crushed into powder, and then all kinds of powder are mixed and stirred into a batch according to the proportion in the batching list plan. The mix of raw materials are poured into the glass melting furnace to melting into glass liquid which is then formed into fixed shape with the corresponding molding device. Finally, all kinds of glass products are sent into the annealing furnace for annealing.

(b) Data process

The energy consumption and pollutant emissions from the production of glass are shown in Table 7.13 as follows.

Table 7.13 Energy consumption and pollutant emissions from the production of glass per ton

Energy consumption	Standard coal	kg/t	236.73
Pollutant emissions	CO_2	kg/t	912
	SO_2	kg/t	6.09
	NO_x	kg/t	16.7
	CO	kg/t	2.14
	CH_4	kg/t	2.14
	Dust	kg/t	13.7

Table 7.14 Energy consumption and pollutant emissions from the production of aluminum ingot per ton

Energy consumption	Standard coal	kg/t	4,525.93
Pollutant emissions	CO_2	kg/t	10,583
	SO_2	kg/t	41.32
	NO_x	kg/t	17.04
	CO	kg/t	0.565
	CH_4	kg/t	14.3
	C_xF_y	kg/t	0.12

6. Inventory of manufacturing process for aluminum

(a) Technics

The main material of aluminum comes from ores which need to be explored firstly. The explored ores are screened and then broken and smelted. The dissolved coarse aluminum and other crystal minerals are separated, and the obtained crystal materials are calcined and roasted to form alumina which is then put into the electrolytic cell to electrolyzing and aluminum ingot will be formed. The consumption of materials is mainly related to the extraction of aluminum, so the energy consumption and emissions in the formation of aluminum ingot are analyzed.

(b) Data process

The energy consumption and pollutant emissions from the production of aluminum ingot are shown in Table 7.14 as follows.

7. Inventory of manufacturing process for copper

(a) Technics

Different technics for copper production lead to different energy consumptions and emissions. Here, flash smelting which has minimum energy consumption and least carbon emissions is taken as the technic to calculate the energy consumption and pollutant emissions in the production of copper. The smelting process of copper is as follows. The first step is the mining of ores, and then the ores are transported to the refinery for processing. The processing of ore includes ore screening, drying, flash smelting, further separation processing in the converted furnace and refining in the electrolytic furnace.

Table 7.15 Energy consumption and pollutant emissions from the production of copper per ton

Energy consumption	Standard coal	kg/t	646.14
Pollutant emissions	CO_2	kg/t	6183.155
	SO_2	kg/t	34.8824
	NO_x	kg/t	16.45
	CO	kg/t	112.122
	CH_4	kg/t	0.03
	C_xH_y	kg/t	0.0498
	Dust	kg/t	1.09

(b) Data process

The electricity consumed in the process of electrolysis is calculated according to the data on electricity emissions, and the use of oxygen comes from the air. So we get the energy consumption and pollutant emissions from the production of copper that are shown in Table 7.15 as follows.

8. Inventory of manufacturing process for lithium iron phosphate battery

(a) Technics

The main components of the lithium iron phosphate battery are complex. It consists of the positive, negative, electrolyte, diaphragm and the shell. The positive and negative electrode active material is lithium iron phosphate and graphite. Positive and negative collectors are aluminum foil and copper foil respectively, and diaphragm is artificial rubber. The main process of lithium iron phosphate is as follows. The first step is to collect and process the raw materials, followed by the drying of iron phosphate and removing of water. Then the iron phosphate is put into rotary furnace and grinding machine for sintering and mixing respectively. The second step is to mix lithium carbonate and iron phosphate for grinding, and the mixture is then put into the machine to carry out the dispersion process. The third step is to dry the material and block by hydraulic press, then the material is put into pushed slab kiln for sintering and superfine grinding by rolling. Finally, sieving and packaging are conducted.

(b) Data process

After the calculation, the energy consumption and pollutant emissions from the production of lithium iron phosphate are shown in Table 7.16 as follows.

9. Inventory of manufacturing process for corrugated paper

(a) Technics

Most of Apple's products are made from recycled fiber and bio based materials. First of all, the recycled raw materials are added to the raw materials of paper for the production of jelly. Then corrugating is operated followed by the cohesion, cutting and printing after forming. Due to the large consumption of water resources and discharged wastewater in the production of paper, if there is reliable sewage

Table 7.16 Energy consumption and pollutant emissions from the production of lithium iron phosphate per ton

Energy consumption	Standard coal	kg/t	812.77
Pollutant emissions	CO_2	kg/t	132
	CO	kg/t	0.049
	SO_2	kg/t	0.265
	NO_x	kg/t	0.148
	CH_4	kg/t	0.196
	Dust	kg/t	0.254

Table 7.17 Energy consumption and pollutant emissions from the production of corrugated paper per square meter

Energy consumption	Standard coal	g/m^2	99.89
Pollutant emissions	CO_2	g/m^2	382.23
	SO_2	g/m^2	2.19
	NO_x	g/m^2	1.24
	Dust	g/m^2	5.27

treatment equipment, the pollutant emissions will be acceptable. Otherwise, if the untreated wastewater is discharged, the impact of pollutant emissions will be serious. Because we did not find the corresponding data in the manufacturing factory of Apple's mobile phone, here the representative production process of corrugated paper is used.

(b) Data process

Energy consumption in the production process is converted to standard coal, and the complex emission components of PM2.5 and PM10 are simplified to dust emissions. Table 7.17 shows the energy consumption and pollutant emissions from the production of corrugated paper.

10. Summary of energy consumption and emission inventory for all the raw materials

The energy consumptions and emissions of various raw materials presented above are summarized and then multiplied by the consumption of various materials in Table 7.7. Here, the consumption of GPPS is the sum of GPPS, TPS and EP. The consumption of aluminum is also the data collected from aluminum, aluminum alloy and other metals that has been mentioned in the beginning of this subsection. The summary data are shown in Table 7.18 (two decimal places).

7.4.4 Inventory in the Transportation Phase

The design of Apple's products is mainly in America, while production and processing phases are implemented by original equipment manufacturers around the world. Specifically, production of key components is in Japan, core chip and display screen are made in Korea. Meanwhile, some parts are supplied by manufacturers in Taiwan, and the final assembling step is in Foxconn. After assembling,

Table 7.18 Summary of energy consumption and pollutant emissions

		PC	GPPS	Silicon	Glass
Unit		kg	kg	kg	kg
Energy consumption	Standard coal	2,303,645.1	13,312,768	684,458.8	835,694.78
Pollutant emissions	CO_2	66,862,995	73,795,834	40,404,642.4	3,219,505.92
	SO_2	631,957.48	477,542.93	276,529.2	21,498.67
	NO_x	298,350.69	1356.4364	82,370.4	58,953.67
	CO	2,036,157.1	1,706,030.1	1,094,349.6	7554.54
	CH_4	627	85.581818	180.4304	7554.54
	C_xH_y	947.26	0	260.8396	
	C_xF_y		0		
	Dust		797,987.32	129,439.2	48,363.19

	Battery	Aluminum	Copper	Corrugated paper	Sum	Average
	kg	kg	kg	kg	kg	kg
Standard coal	2.07E + 08	90,067,870.62	760,325.86	722,886.85	3.16E + 08	1.61
CO_2	33,654,192	210,606,057.6	7,275,842.16	2,766,133.2	4.39E + 08	2.24
SO_2	67,563.34	822,285.0147	41,046.82	15,848.66	2.35E + 06	0.012
NO_x	37,733.49	339,103.0147	19,357.04	8973.67	8.46E + 05	0.00431
CO	12,492.84	11,243.73529	131,936.2		5.00E + 06	0.0255
CH_4	49,971.38	284,575.8971	35.3		3.43E + 05	0.00175
C_xH_y		0	58.6		1.27E + 03	6.46E-06
C_xF_y		2388.044118	0		2.39E + 03	1.22E-05
Dust	64,758.82	0	1282.62	38,138.09	1.08E + 06	0.00551

the product is sent to America for check, and sale to the world. In order to enhance the efficiency of Apple's supply chain which is complex, areophane is used for the main transportation mode. Fuel kerosene is the main energy source of plane, and the main emissions of aviation gas turbine engine are CO_2 and SO_2, NO_x and CH_4. According to the official data about the proportion of carbon emissions provided by Apple in Table 7.1, we can calculate the energy consumption and emissions in the transportation process that are shown in Table 7.19.

7.4.5 Inventory in the Use Phase

In average, an iPhone can be used for 5 years. However, due to the overuse of mobile phone by people nowadays and the increased charge and discharge times, the aging of mobile phone is accelerating that leads to the shortening life of a

Table 7.19 Energy consumption and pollutant emissions

Energy consumption	Standard coal	kg	1,234,433,787
Pollutant emissions	CO_2	kg	755,062,000
	SO_2	kg	26,231,717.98
	NO_x	kg	3,343,258.17
	CO	kg	6,717,377.19
	CH_4	kg	2,160,259,128

mobile phone. Here, 3 years is assumed to be the use time to calculate the power consumption in the life cycle of iPhone4S that is shown as follows:

400MA/h *3.7V=1.48W/h
1.48W/h*12*365*3≈19.5kWh
Converting to the standard coal: 19.5kWh*0.376=7.332Kg

7.4.6 Inventory in the Recycling Phase

Iphone4S is difficult to disassemble as a whole. The depreciation rate of electronic products is high, and the recycled values of most of the electronic components contained in a used mobile phone are low. Since a mobile phone contains a large amount of heavy metals, it will cause great pollution to the environment if the electronic components are discarded at random or handled inappropriately. Heavy metals have certain recycling values, but the cost of recycling is also higher. It will consume energy to disassemble a mobile phone after recycling, and the effective components should be classified and processed carefully. In 2014, Foxconn and Apple started a used mobile phone recycling business. Foxconn registered a wholly owned subsidiary of Jiaxing Ifengpai Business Co., Ltd. (www.ifengpai.com) to construct the sales channel. Fu Lian Internet (www.flnet.com) which is stared at the beginning of October, 2014, became the exclusive on-line sales channel.

Although the concept of recycling business is advanced, it has not been developed to a certain level, so it is difficult to get accurate data. The data provided by Apple that is shown in Table 7.1 is used here and no specific extensions are to be done.

7.4.7 Inventory in the Whole Life Cycle

By the data available in the phase of production, transportation, use and recycling, the final summary of energy consumption and pollutant emissions for each mobile phone are shown in Table 7.20.

Table 7.20 Inventory of iPhone4S in the life cycle

		Production	Transportation	Use	Recycling	Total
Unit		kg	kg	kg	kg	kg
Energy consumption	Standard coal	1.61	6.29	7.3		15.2
Pollutant emissions	CO2	2.24	3.85		1.1	7.19
	SO2	0.012	0.13			0.142
	NOx	0.00431	0.017			0.02131
	CO	0.0255	0.034			0.0595
	CH4	0.00175	11.015			11.01675
	CxHy	6.46E-06				0.00000646
	CxFy	1.22E-05				0.0000122
	Dust	0.00551				0.00551

7.5 Impact Assessment and Improvement Analysis

In the process of impact assessment and improvement analysis, the data collected in inventory analysis needs to be further processed and classified, and the major environmental impacts in the life cycle of iPhone4S need to be identified from the above inventory analysis. Classification of major impacts is then conducted and the characteristic indicators are formed. According to the characteristic indicators, the data of iPhone4S in the life cycle are processed and analyzed again, and the energy consumption and emission load model are generated for iPhone4S in the whole life cycle. Finally, according to the inventory analysis and impact assessment in all the stages and processes, recommendations are given for the government, enterprises and individuals respectively.

7.5.1 Impact Assessment

1 Impact Classification

The main energies used in the life cycle of iPhone4S have already been converted to standard coal in the above. However, the pollutant emissions include CO_2,SO_2, NO_x,CH_4,CO,C_xH_y,C_xF_y and dust. Here, the equivalent model is used to establish the load model of iPhone4S that is to carry out the characteristic operation on inventory data.

According to the international classification of LCA, there are eight impacts which are energy consumption, climate change, acidification, eutrophication, ozone depletion, photochemical pollution, human toxicity, ecological toxicity, land resources and industrial water. Based on the calculated pollutant emissions above, four impacts are selected for the following characterization as Table 7.21 shows.

Table 7.21 Impact classification

Environmental impacts	Inventory	Classification results	Unit
Energy consumption	Standard coal	Energy consumption potential	kg(coal equivalent)
Climate change	CO_2, C_xH_y, CH_4, CO, NO_x, C_xF_y	Global warming potential (GWP)	kg(CO_2 equivalent)
Acidification	SO_2,NO_x	Acidification potential (AP)	kg(SO_2 equivalent)
Ozone depletion	C_xF_y	Ozone depletion potential (ODP)	kg(CFC-11 equivalent)

Table 7.22 Characteristic factor of global warming potential

Substance	Characteristic factor/kg(CO_2 equivalent)
CO2	1
CO	1
CH4	62
CxHy	62
NOx	275
CxFy	3900

Table 7.23 Characteristic factor of acidification potential

Substance	Characteristic factor/kg(SO_2 equivalent)
SO2	1
NOX	0.7

Table 7.24 Characteristic factor of ozone depletion potential

Substance	Characteristic factor/kg(CFC-11 equivalent)
CxFy	1

2 Characterization

Energy consumption potential is measured by the consumption of standard coal, while other forms of energy can be converted into standard coal by characteristic factor. Therefore the characteristic factor is assumed to be the standard coal coefficient, and the result of characterization is the same as Table 7.8.

Global warming potential is measured by carbon dioxide emissions, while other emissions related with the greenhouse effect are converted into carbon dioxide emissions. The result of characterization is shown in Table 7.22.

Acidification potential is measured by the emissions of SO_2, while other gases associated with acidification are converted into the emissions of SO_2. Table 7.23 shows the result of characterization for acid gases.

Table 7.24 shows the characteristic factor of ozone gas consumption.

Table 7.25 Result of characterization for iPhone4S

	Unit	Every one iPhone4S
Energy consumption potential	kg(coal equivalent)	15.2
Global warming potential (GWP)	kg(CO_2 equivalent)	696.15
Acidification potential (AP)	kg(SO_2 equivalent)	0.157
Ozone depletion potential (ODP)	kg(CFC-11 equivalent)	1.22E-05

3 Quantitative Assessment

The data in Table 7.20 are classified according to the calculation method of characterization, and the environmental equivalent model of iPhone4S in its life cycle is generated in Table 7.25.

Although the data in this paper are not collected completely, it is amazing from the result in Table 7.25 that the energy consumption and pollutant emission from a mobile phone is not less than the refining of a ton of copper. The precision parts in a mobile phone include toxic substances such as six chromium and bromide. Free emissions will cause great pollution to the environment. Although a mobile phone is small, it is a collection of a variety of complex components and high accurate technics, so great social resources will be consumed.

7.5.2 Improvement Analysis

Apple has paid more attention on environmental protection in the designing stage compared with other mobile phone companies. For example, the main metal used in Apple's mobile phone is aluminum which produces lower emissions compared with other metals such as copper and iron. On the other hand, in order to give users a better experience, it consumes more energy resources in the production of chip and hard screen glass which leads to a great burden on the environment. So the hard screen glass on the back body of iPhone4S can be changed to metal, which is reflected in the design of Apple's mobile phone in the next generation.

It is worth noting that to the huge amount of affiliate products associated with each mobile phone also has great impact on the environment. If the packaging box of each mobile phone is not recycled effectively, the total carbon emissions will be large. Similarly, the earphone and adapter also contains a lot of electronic components, plastics and metals, if consumers are not aware of the recycling of these parts, it will cause a lot of environmental pollution and waste of resources. Due to the lack of effective statistics on the data consumed during the assembly of mobile phone parts, we have not effectively measure the discharge in the assembly process. In recent years, it has been reported that industrial wastewater that contain exceeded heavy metals and organic solvents was emitted from the assembly Chinese companies such as Foxconn. These emissions made soil and water pollutions in a large area, so great attention should be paid to protect the environment from all stakeholders.

According to the results generated in this chapter, recommendations are proposed to stakeholders including government, enterprises and consumers.

Firstly, the government should play the role of supervision and policy making. The standards for emissions of waste gas, waste water and waste residue need to be made scientifically, and the discharge and recycling of pollutants before emission should be implemented.

Secondly, enterprise should promote retailers to implement the recycling and disposal of used products effectively, and control the use and emissions of heavy metals efficiently. So it is expected that various components in the mobile phone can be recycled and processed appropriately. Manufacturer should discharge waste water and gases after treatment in order to reduce the pollution of metals and chemicals to the environment. The design of product is also need to be improved to increase the reused frequency of each components of mobile phone.

Thirdly, consumers should pay attention to the use of accessories of mobile phone, and it is also hoped that consumers can actively cooperate with the recycling of used mobile phones and accessories by manufacturer.

7.6 Social Life Cycle Assessment to iPhone 4S

Just as introduced in Sect. 7.2.3, environmental dimension is just one of the three impacts that a product system have in its life cycle. Social impact is ought to be considered in the LCA procedure when two kinds of similar product are compared or a decision is to be made which product should be manufactured. In this section, S-LCA is to be conducted on iPhone4S based on some investigations and evidential reasoning (ER) approach is applied to integrate the value of different attributes in the attribute structure.

7.6.1 Construction of S-LCA Structure

S-LCA is a complement for environmental LCA and LCC, and contributes to the full assessment of goods and services within the context of sustainable development [253]. It assesses the social or socio-economic impacts in a product system's life cycle including material extraction, manufacturing, marketing, use, recycling, remanufacturing and disposal. Different from environmental LCA, S-LCA is site-specific which means that some political attributes are needed, and the data used in S-LCA are always subjective judgments. Another difference lies in that all the impacts of environmental LCA are negative while the social impact may be either positive or negative. All the phases are associated with geographic locations where social or socio-economic impacts can be observed in relation with different

Fig. 7.5 Attribute structure of S-LCA to iPhone4S

stakeholders such as worker, consumer, local community and society [253]. So the attribute structure for S-LCA should be constructed according to the impact on the stakeholder category. It has been attained to international agreements on the S-LCA attribute structure which is shown in Fig. 7.5 as follows.

Here, four kinds of stakeholder are considered in the S-LCA procedure, and 15 sub-attributes are included in the attribute structure which could almost reflect the impacts associated with the listed stakeholders. From the attribute structure, we can see that most of the attributes are qualitative ones that means subjective judgments should be inevitably used, so some uncertainties and ignorance may be contained in the assessment. We can also see that the attribute structure consists of both positive and negative attributes that are shown in the third column of Table 7.26. It is obvious a multiple attribute decision making (MADM) problem because the judgments to a list of attributes are to be aggregated. It is appropriate to select a MADM approach that could cope with subjective judgments with uncertainties in a rational way. Here, the ER approach is used to combine the assessment to each attribute for the generation of a general result.

7.6.2 *Brief Introduction of Yang's ER Approach*

The ER approach is well suited to dealing with MADM problem where many qualitative attributes are involved in. The unique characteristics of the ER approach lays in that fuzziness, uncertainties, incompleteness and ignorance can all be tackled with in an appropriate and rational way. It was introduced in 1994 by Yang [295] based on the Dempster-Shafer theory [261, 285] and MADM approach.

Table 7.26 Attribute structure of S-LCA to iPhone4S

Stakeholder	Attributes	Type	Weights	Belief degree				
				H_1	H_2	H_3	H_4	H_5
Worker	Child labor	Negative	0.044				0.7	
	Fair salary	Positive	0.096		0.2	0.3	0.5	
	Working hours	Negative	0.124		0.3	0.6	0.1	
	Forced labor	Negative	0.056	0.1	0.1	0.5	0.3	
	Health and safety	Positive	0.080			0.2	0.5	0.3
Consumer	Health and safety	Positive	0.084			0.1	0.5	0.4
	Feedback mechanism	Positive	0.066			0.6	0.4	
	Consumer privacy	Positive	0.102		0.2	0.5	0.3	
	Transparency	Positive	0.048			0.9		
Local community	Local employment	Positive	0.068				0.2	0.8
	Respect of indigenous rights	Positive	0.032			0.3	0.4	0.2
Society	Contribution to economic development	Positive	0.072			0.6	0.4	
	Technology development	Positive	0.046		0.3	0.7		
	Fair competition	Positive	0.028				0.7	0.3
	Promoting social responsibility	Positive	0.054			0.2	0.8	

It can generate a comprehensive distributed assessment in a sense that no original information is distorted after the aggregation process. In other words, both incompleteness and uncertainties contained in the judgments of experts are preserved in the combination procedure. So it has been applied in many fields such as pre-qualifying construction contractor [286], R&D products assessment [279], new product development [257], consumer preference mapping [297], risk management [288], fault diagnosis [294], medical quality assessment [278] and so on. It is capable of dealing with MADM problems with accurate or fuzzy belief degrees and weights associated with attributes.

In the ER approach, the frame of discernment is first constructed as follows:

$$H = \{H_1, H_2, \cdots, H_N\} \tag{7.1}$$

In Eq. 7.1, $H_n(n = 1, 2, \cdots, N)$ represents the nth linguistic evaluation grades that an alternative may be assessed to. N is the total number of evaluation grades that an expert could distinguish. Then an alternative is assessed to H_n on an attribute can be denoted as follows:

$$\begin{aligned} S(e_i(a_l)) = \; & \left\{\left(H_n, \beta_{n,i}(a_l)\right), n = 1, 2, \cdots, N; H, \beta_{H,i}(a_l)\right\} \\ & (i = 1, 2, \cdots, L; l = 1, 2, \cdots, S) \end{aligned} \tag{7.2}$$

Here, $a_l(l = 1, 2, \cdots, S)$ is the lth alternative to be assessed, $e_i(i = 1, 2, \cdots, L)$ is the ith attribute in the attribute structure, S and L are the number of alternatives and attributes respectively. $\beta_{n,i}(a_l)$ denotes the belief degree to which the state of e_i at a_l is confirmed to H_n, and $\beta_{H,i}(a_l)$ refers to the degree of uncertainty that a_l is assessed on e_i. It is obvious that $0 \le \beta_{n,i}(a_l) \le 1$, $\sum_{n=1}^{N} \beta_{n,i}(a_l) \le 1$. If $\sum_{n=1}^{N} \beta_{n,i}(a_l) < 1$, then the assessment is incomplete and some ignorance is contained in the original information provided by experts. The ER approach provides both recursive [296] and analytical algorithm [293] to combine the distribution of all L attributes for an alternative. The analytical ER algorithm is as follows:

$$m_{n,i}(a_l) = \omega_i \beta_{n,i}(a_l) \tag{7.3}$$

$$m_{H,i}(a_l) = 1 - \sum_{n=1}^{N} m_{n,i}(a_l) = 1 - \omega_i \cdot \sum_{n=i}^{N} \beta_{n,i}(a_l) \tag{7.4}$$

$$\bar{m}_{H,i}(a_l) = 1 - \omega_i, \ \ \tilde{m}_{H,i}(a_l) = \omega_i \left(1 - \sum_{n=1}^{N} \beta_{n,i}(a_l) \right) \tag{7.5}$$

$$m_n(a_l) = k' \left[\prod_{i=1}^{L} \left(m_{n,i}(a_l) + \bar{m}_{H,i}(a_l) + \tilde{m}_{H,i}(a_l) \right) - \prod_{i=1}^{L} \left(\bar{m}_{H,i}(a_l) + \tilde{m}_{H,i}(a_l) \right) \right] \tag{7.6}$$

$$\tilde{m}_H(a_l) = k' \left[\prod_{i=1}^{L} \left(\bar{m}_{H,i}(a_l) + \tilde{m}_{H,i}(a_l) \right) - \prod_{i=1}^{L} \bar{m}_{H,i}(a_l) \right] \tag{7.7}$$

$$\bar{m}_H(a_l) = k' \left[\prod_{i=1}^{L} \bar{m}_{H,i}(a_l) \right] \tag{7.8}$$

$$k' = \left[\sum_{n=1}^{N} \prod_{i=1}^{L} \left(m_{n,i}(a_l) + \bar{m}_{H,i}(a_l) + \tilde{m}_{H,i}(a_l) \right) - (N-1) \prod_{i=1}^{L} \left(\bar{m}_{H,i}(a_l) + \tilde{m}_{H,i}(a_l) \right) \right]^{-1} \tag{7.9}$$

$i = 1, 2, \cdots, L$; $n = 1, 2, \cdots, N$; $l = 1, 2, \cdots, S$

$m_{n,i}(a_l)$ is the basic probability assignment of a_l being assessed to H_n on e_i, $m_{H,i}(a_l)$ is the remaining probability mass unassigned to any individual grade after all the N grades have been considered for assessing the general attribute as far as e_i is concerned. $\bar{m}_{H,i}(a_l)$ denotes the residual support of a_l on e_i while $\tilde{m}_{H,i}(a_l)$ refers to the weighted ignorance of a_l on e_i, and we can see that $m_{H,i}(a_l) = \bar{m}_{H,i}(a_l) + \tilde{m}_{H,i}(a_l)$. After aggregation, the combined probability mass of a_l on H_n denoted by $m_n(a_l)$ is generated. Then the general belief degree that a_l be evaluated on H_n and H which are denoted by $\beta_n(a_l)$ and $\beta_H(a_l)$ could be calculated as follows:

$$\beta_n(a_l) = \frac{m_n(a_l)}{1 - \bar{m}_H(a_l)}, \quad n = 1, 2, \cdots, N \tag{7.10}$$

$$\beta_H(a_l) = \frac{\tilde{m}_H(a_l)}{1 - \bar{m}_H(a_l)} \tag{7.11}$$

where

$$\beta_H(a_l) + \sum_{n=1}^{N} \beta_n(a_l) = 1 \tag{7.12}$$

So, from Eqs. 7.10, and 7.11, we can get the following combined distribution on a_l as Eq. 7.13 shows.

$$S(a_l) = \{(H_n, \beta_n(a_l)), n = 1, 2, \cdots, N; H, \beta_H(a_l)\} \tag{7.13}$$

The ER approach has the feature that if $\forall i = 1, 2, \cdots, L, \beta_{H,i}(a_l) > 0$, then $\beta_H(a_l) > 0$.

7.6.3 Assignment of Belief Degrees and Attribute Weights

In this chapter, AHP is applied for the generation of attribute weights. It is ought to be mentioned that the weight calculated by AHP is relative weight associated with its upper level attribute, so it should be translated to abstract weight for the purpose of attribute aggregation in the next step. The calculated abstract weights are shown in the fourth column of Table 7.26.

Suppose each sub-attribute could be evaluated by the following five linguistic evaluation grades: Worst, Poor, Average, Good, Best. They form the frame of discernment as follows:

$$H = \{H_1, H_2, H_3, H_4, H_5\} = \{\text{Worst, Poor, Average, Good, Best}\} \tag{7.14}$$

Since there is only one alternative (iPhone4S) to be evaluated, $a_l = a_1 (S = 1)$. After some investigations, the belief degrees assigned to the sub-attributes are acquired and shown in the last five columns of Table 7.26. From Table 7.26, a distributed view of the belief degree assignment can be seen clearly. For instance, 'Fair salary' is assumed to be poor, average and good with the belief degree of 0.2, 0.3 and 0.5 respectively. This statement can be denoted by the following distribution:

$$S(\text{Fair salary}) = \{(\text{Poor}, 0.2), (\text{Average}, 0.3), (\text{Good}, 0.5)\} \tag{7.15}$$

In the statement above, the total belief degree for ‘Fair salary’ sums to one, which means the information provided by experts is complete. But this is not always the case for that there is some ignorance contained in the assessment to ‘Child labor’, ‘Transparency’ and ‘Respect of indigenous rights’.

7.6.4 Generating the Overall Belief Degrees

After the assignment of attribute weights and belief degrees, the ER approach is applied to generate the overall belief degrees on iPhone4S from the social aspect as follows:

$S(\text{iPhone4S})=\{(H_1,\ 0.0043),(H_2,\ 0.0874),(H_3,0.4184),(H_4,0.3762),(H_5,\ 0.1002),(H,\ 0.0135)\}$

The incompleteness in the S-LCA to iPhone4S is measured by a belief degree of 0.0135 due to the ignorance in the assessment to attribute ‘Child labor’, ‘Transparency’ and ‘Respect of indigenous rights’. Using the IDS software, the assessment on each evaluation grade can be visually presented as shown in Fig. 7.6. It provides a panoramic view of the overall performance on iPhone4S from the social dimension.

We can also generate the overall belief degrees on iPhone4S from the impacts to the four stakeholders as Figs. 7.7, 7.8, 7.9 and 7.10 shows.

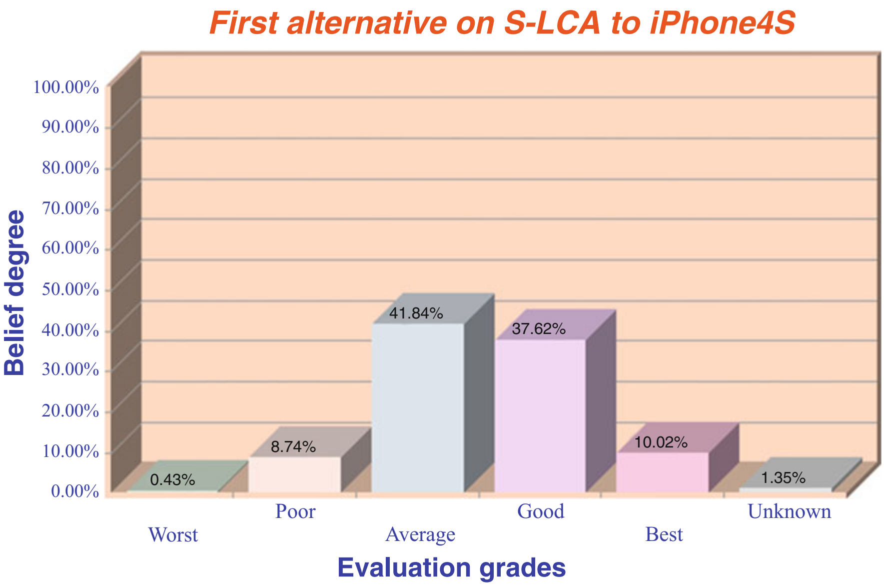

Fig. 7.6 Overall belief degrees on iPhone4S

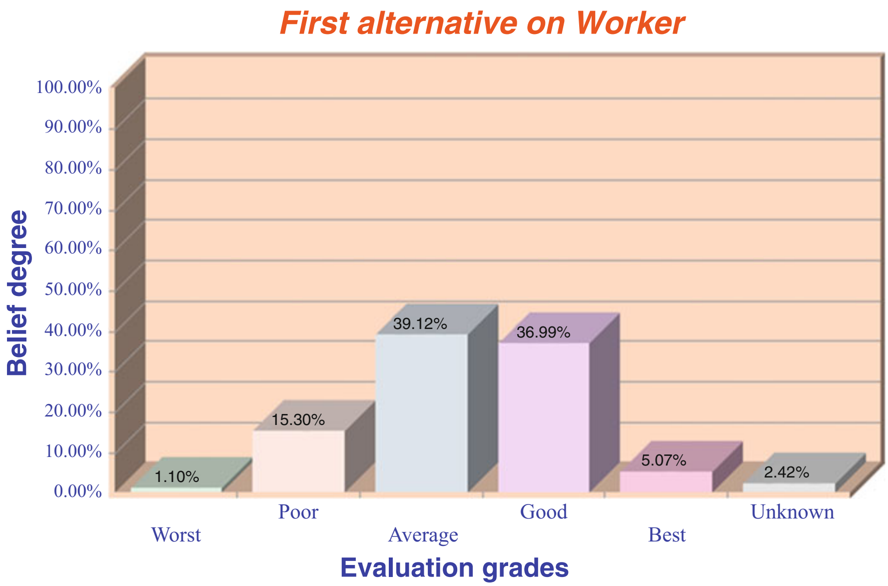

Fig. 7.7 Overall belief degrees on iPhone4S from the impact to worker

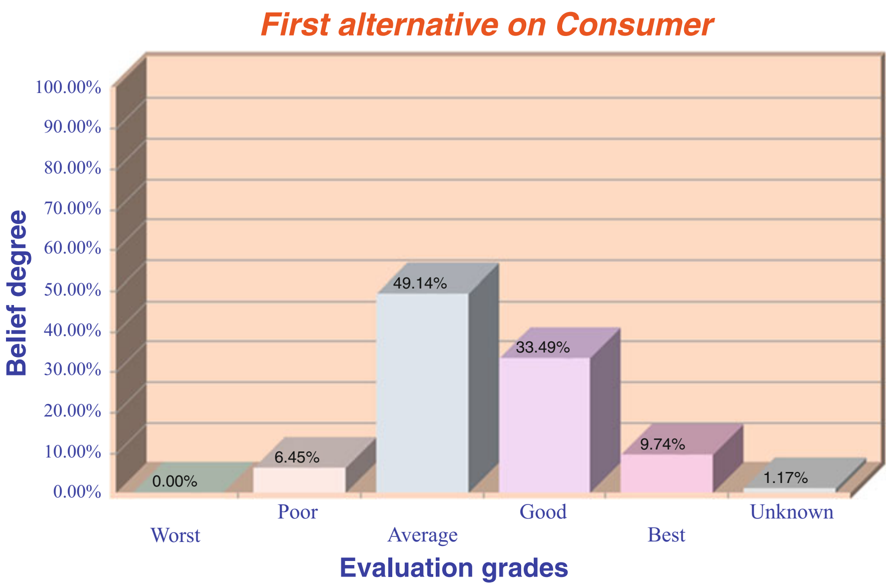

Fig. 7.8 Overall belief degrees on iPhone4S from the impact to consumer

Since there is no ignorance in the assessment to attributes associated with society, the combined belief degree on society is complete. There are some degrees of ignorance in the combination results of other three stakeholders. From Fig. 7.6,

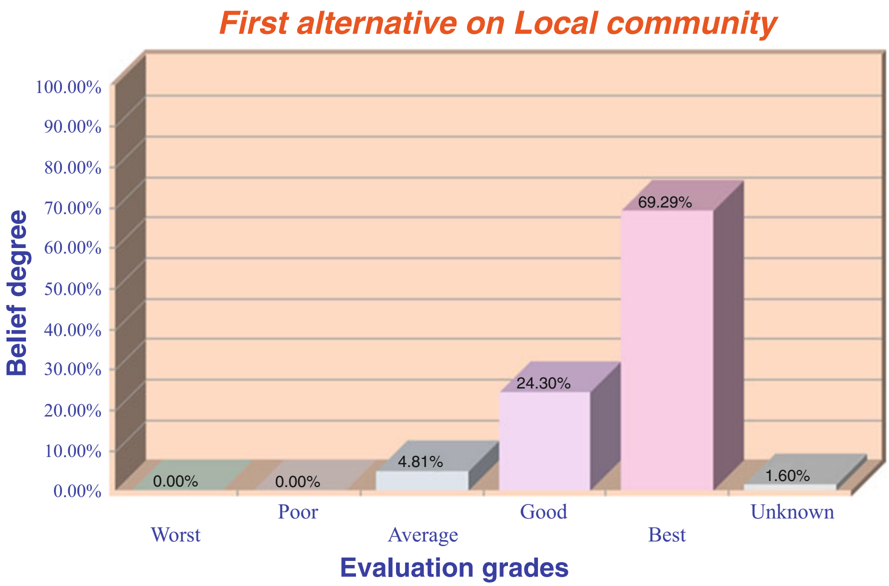

Fig. 7.9 Overall belief degrees on iPhone4S from the impact to community

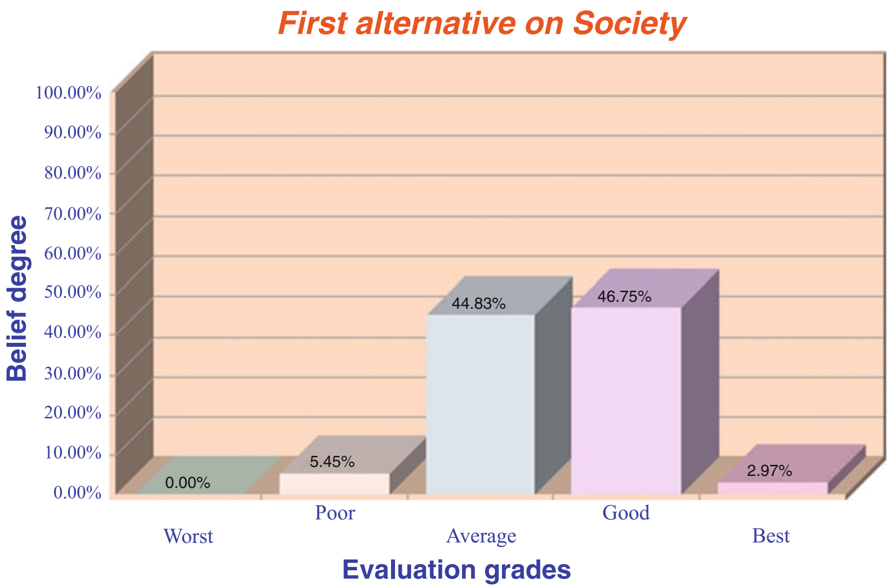

Fig. 7.10 Overall belief degrees on iPhone4S from the impact to society

we can see that iPhone4S is main assessed to average and good from the social dimension. It can be interpreted that the combination results on worker, consumer and society are assessed to average and good with high belief degrees.

7.7 Conclusion and Future Research

7.7.1 Conclusion

In this paper, the environmental and social LCA to iPhone4S are studied based on the iPhone4S environmental report and many investigations, and LCA models for iPhone4S is constructed. In the environmental LCA to iPhone4S, energy consumption and pollutant emissions from the production of main raw materials and components are calculated, followed by the calculation of emissions in the transportation stage. The result is presented from the characteristic indicators. Although environmental friendly materials are used in iPhone4S, considering that it has complex electronic components, great energy consumption and greenhouse and acid gases emissions are generated in the production of raw materials for components. In the pursuit of exquisite and durable products by enterprises, it inevitably brings environmental pollution to our land. In the social LCA to iPhone4S, an assessment structure which considers different stakeholders is used based on some literature review and investigations to experts. AHP method is applied for the generation of attribute weights, and the ER approach is used for the aggregation of subjective judgments to attributes.

Due to the fact that LCA to mobile phone has just begun, a variety of production and manufacturing data is lack which may leads to the deviation of results. In recent years, although the development of mobile phone industry is rapid, the specific industry standards did not form in a unified way. Manufacturers involved in mobile phone production are complex, they may have different production capacity, and the energy consumption and ability to deal with waste are also different. If manufacturers are able to control waste water and gas effectively, the emissions will be greatly reduced in the whole life cycle of product. For example, in the process of producing chip, if the harmful substances such as organic solvent (developer, photoresist, et al.), metal ions (aluminium, nickel, et al.) and inorganic acid (hydrofluoric acid, et al.) are emitted along with the wastewater with no effective disposal by the chip manufacturer, the destruction to environment and human will be greatly increased, and the impact cannot be described merely by the data. If enterprises use a relatively effective waste water recycling system, the waste water discharge will be reduced, and the recycling of materials will also reduce the energy consumption of chip production. Core enterprises should focus on the environmental impact of the whole industry, and develop the standards of energy consumption and pollutant emissions. Meanwhile, the government should also perform well to supervise the enterprises, and strengthen the responsibility of environmental protection to consumers and enterprises.

From the analysis to the social aspect, we should pay more attention to the working hours of workers because some of the original equipment manufacturers (OEM) for Apple have made long working hours for workers, which leads to the unsatisfactory of workers to the manufacturers or society. Consumer privacy should also be paid great attention because it relates to the security of consumer, especially for the developed technology in chip and memory and great number of APP software used by people nowadays. Technology development is another factor that government needs to see because transnational corporations in developed countries are not willing to transfer technology when they establish factories in developing countries. So the core technology is not necessarily obtained by developing countries even if factories are established, whereas the main profit is gained by the parent company.

7.7.2 Future Research

In this chapter, the environmental and social LCA to iPhone4S are conducted individually. It is a complex work to combine these two dimensions together because there are some relations between them. For instance, all the pollutant emissions do have impacts on 'health and safety' in the social LCA structure to some degree. Besides the environmental and social dimensions in the LCA process, economic dimension should also be considered for a more comprehensive assessment. For example, LCC is just one of the factors in the economic dimension. So it is necessary to combine the economic dimension with the environmental and social LCA described in this chapter. Since data in different dimensions have complex type, structure, and internal model, the data acquisition mode and related stakeholders in different dimensions will be quite different. Furthermore, data acquisition methods for the same dimension in different stages of life cycle are also different. The data used in traditional environmental LCA is not real-time, they are mainly collected from literature, yearbook and relevant databases. Data from social networks, mobile devices and sensors will have more proportions in the future research that all the three dimensions are considered in a comprehensive way.

Besides, big data should also be applied for the LCA procedure. The internet and IoT is able to provide big data for the multiple dimensional LCA of product. How to acquire and deal with these assessment data which have the characteristic of massive, high dimensional, multi-sourced, heterogeneous and dynamic is a challenging task. Because of the difference in data acquisition, processing granularity and application requirements, the data in different dimensions and scales have different degrees of uncertainty. The traditional fusion methods which focus on accurate data are not sufficient to deal with big data. So we should also pay attention to the fusion of structured, semi-structured and unstructured assessment data in all phases and dimensions of life cycle, such as real time data, historical data, text data, multimedia data, time series data and so on.

Appendix: Materials of the Main Components of iPhone4S

Components	Details	Materials
CPU	Performance: dual-core Apple A5	Monocrystalline silicon, aluminum, epoxy resin
	Frequency: 800–1000 MHZ	
	Process: 40 nm process of semiconductor process	
	Manufacturer: Samsung	
	Number: APL0498E01	
Auxiliary chips	A: Qualcomm RTR8605 dual-mode multifrequency RF wireless transceiver chip	Monocrystalline silicon, aluminum, epoxy resin
	B: Based on WCDMA network Skyworks 77464-20 load insensitive to power amplifier (LIPA) module	
	C: Avago ACPM-7181 power amplifier	
	D: TriQuint TQM9M9030 multimode four frequency power amplification module	
	E: TriQuint TQM66052 a PA duplexer	
	F: SW SS1830010 chip	
	G: The LCD screen digitizer	
	H: Camera digital signal processor (DSP)	
Integrated circuit board		Monocrystalline silicon, aluminum, copper, lead, gold, silver, tin, epoxy resin

(continued)

X. Liu et al., *Optimization and Management in Manufacturing Engineering*,
Springer Optimization and Its Applications 126,
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Components	Details	Materials
Screen	IPS – LCD: 3.5in, 960 × 640 resolution (kingbox improved glass)	Glass, liquid crystal (silicon, aluminum, calcium, strontium, barium, iron, arsenic, potassium, zinc, titanium, copper, and tin)
The rear camera	800 pixels + LED flash (f/2.4 aperture) components:	Glass
	1. The lens group (sapphire mirror, just the same hardness and sapphire glass)	
	2. The lens base	
	3. Fine cylinder cover	
	4. Infrared filter (sapphire lens)	
	5. Imaging sensor (CMOS, complementary metal oxide semiconductor)	
	6. Digital signal processor (DSP)	
The front camera	300,000 pixels	Glass
Wi-Fi/Bluetooth	Signal transceiver and the antenna, logical component	Aluminum, copper
Flash memory	512 MB	Monocrystalline silicon
Memory	8 GB, 16 GB, 32 GB, 64 GB (24 nm process by Toshiba production)	Monocrystalline silicon
Lithium ion polymer battery (lead-, cadmium-, and mercury-free)	Voltage: 3.7 V	Drill acid lithium, iron, aluminum, copper, nickel, cobalt, and carbon
	Current: 1,420 mah	
	Power: 5.3 Whr	
	Weight: 27.22 g	
	Constitute materials:	
	The anode: aluminum foil, conductive agent, binder	
	The cathode: copper foil, conductive agent, binder	
	Medium: lithium iron phosphate and polymer	
	Shell: aluminum – plastic composite aluminum – plastic packaging film	
Audio accessories	Loudspeaker enclosure	Aluminum-magnesium alloy, copper, PVC
	Handset speaker	
Vibration components	Vibrator	Copper, PVC, aluminum-magnesium alloy
Sensor	Acceleration sensor, the compass, and gyroscope	Magnetic resistance materials, monocrystalline silicon, epoxy resin, aluminum

(continued)

Components	Details	Materials
The middle frame	The borders, the power button, volume buttons, the receiver anti-dust mesh	Aluminum-magnesium alloy
Exterior framework	Home button, front and rear glass flat surface frame	Glass, flame retardant polycarbonate injection level
Cable	Home button row line, the volume button row line, socket cable, photosensitive platoon line, audio line, screen and sensor cable	Copper, PVC
Screw	Main board screw, a full set of screws around 30 or so	Aluminum-magnesium alloy

References

1. Bi, Z., Xu, L.D., Wang, C.: Internet of things for enterprise systems of modern manufacturing. IEEE Trans. Ind. Inform. **10**, 1537–1546 (2014)
2. Houyou, A.M., Huth, H.P., Kloukinas, C., Trsek, H., Rotondi, D.: Agile manufacturing: general challenges and an IoT@Work perspective. In: Proceedings of 2012 I.E. 17th International Conference on Emerging Technologies & Factory Automation, pp. 1–7 (2012)
3. Qian, X., Liu, X., Yang, S., Zuo, C.: Security and privacy analysis of tree-LSHB+ protocol. Wirel. Pers. Commun. **77**, 3125–3141 (2014)
4. Anderson, R.: Why information security is hard—an economic perspective. In: Proceedings of the 17th Annual Computer Security Applications Conference (ACSAC'01), IEEE, pp. 358–365 (2001)
5. Anderson, R., Moore, T.: The economics of information security. Science. **314**, 610–613 (2006)
6. Gordon, L., Loeb, M.: The economics of information security investment. ACM Trans. Inf. Syst. Secur. **5**, 438–457 (2002)
7. Shirtz, D., Elovici, Y.: Optimizing investment decisions in selecting information security remedies. Inf. Manag. Comput. Secur. **19**, 95–112 (2011)
8. Huang, C.D., Behara, R.S.: Economics of information security investment in the case of concurrent heterogeneous attacks with budget constraints. Int. J. Prod. Econ. **141**, 255–268 (2013)
9. Wu, Y., Feng, G., Wang, N., Liang, H.: Game of information security investment: impact of attack types and network vulnerability. Expert Syst. Appl. **42**, 6132–6146 (2015)
10. Kong, H.K., Kim, T.S., Kim, J.: An analysis on effects of information security investments: a BSC perspective. J. Intell. Manuf. **23**, 941–953 (2012)
11. Khouzani, M.H.R., Sen, S., Shroff, N.B.: An Economic Analysis of Regulating Security Investments in the Internet, 2013 Proceedings IEEE INFOCOM, pp. 818–826 (2013)
12. Huang, C.D., Hu, Q., Behara, R.S.: An economic analysis of the optimal information security investment in the case of a risk-averse firm. Int. J. Prod. Econ. **114**, 793–804 (2008)
13. Bojanc, R., Jerman-Blažič, B.: An economic modelling approach to information security risk management. Int. J. Inf. Manag. **28**, 413–422 (2008)
14. Bojanc, R., Jerman-Blažič, B., Tekavčič, M.: Managing the investment in information security technology by use of a quantitative modeling. Inf. Process. Manag. **48**, 1031–1052 (2012)
15. Lelarge, M.: Coordination in network security games: a monotone comparative statics approach. IEEE J. Sel. Areas Commun. **30**, 2210–2219 (2012)

X. Liu et al., *Optimization and Management in Manufacturing Engineering*,
Springer Optimization and Its Applications 126,
DOI 10.1007/978-3-319-64568-1

16. Chai, S., Kim, M., Rao, H.R.: Firms' information security investment decisions: stock market evidence of investors' behavior. Decis. Support. Syst. **50**, 651–661 (2011)
17. Bandyopadhyay, T., Jacob, V., Raghunathan, S.: Information security in networked supply chains: impact of network vulnerability and supply chain integration on incentives to invest. Inf. Technol. Manag. **11**, 7–23 (2010)
18. Eisenga, A., Jones, T.L., Rodriguez, W.: Investing in IT security: how to determine the maximum threshold. Int. J. Inf. Secur. Priv. **6**, 75–87 (2012)
19. Huang, C.D., Behara, R.S., Goo, J.: Optimal information security investment in a healthcare information exchange: an economic analysis. Decis. Support. Syst. **61**, 1–11 (2014)
20. Lee, Y.J., Kauffman, R.J., Sougstad, R.: Profit-maximizing firm investments in customer information security. Decis. Support. Syst. **51**, 904–920 (2011)
21. Wang, S., Chen, J., Stirpe, P.A., Hong, T.: Risk-neutral evaluation of information security investment on data centers. J. Intell. Inf. Syst. **36**, 329–345 (2011)
22. Gordon, L.A., Loeb, M.P., Lucyshyn, W.: Sharing information on computer systems security: an economic analysis. J. Account. Public Policy. **22**, 461–485 (2003)
23. Gal-Or, E., Ghose, A.: The economic incentives for sharing security information. Inf. Syst. Res. **16**, 186–208 (2005)
24. Hausken, K.: Information sharing among firms and cyber attacks. J. Account. Public Policy. **26**, 639–688 (2007)
25. Liu, D., Ji, Y., Mookerjee, V.: Knowledge sharing and investment decisions in information security. Decis. Support. Syst. **52**, 95–107 (2011)
26. Gao, X., Zhong, W., Mei, S.: A game-theoretic analysis of information sharing and security investment for complementary firms. J. Oper. Res. Soc. **65**, 1682–1691 (2014)
27. Gao, X., Zhong, W., Mei, S.: Security investment and information sharing under an alternative security breach probability function. Inf. Syst. Front. **17**, 423–438 (2015)
28. Bi, Z., Xu, L.D., Wang, C.: Internet of things for enterprises systems of modern manufacturing. IEEE Trans. Ind. Inform. **10**, 1537–1546 (2014)
29. Zelbst, P.J., Green, K.W., Sower, V.E., Reyes, P.M.: Impact of RFID on manufacturing effectiveness and efficiency. Int. J. Oper. Prod. Manag. **32**, 329–350 (2012)
30. Qrunfleh, S., Tarafdar, M.: Supply chain information systems strategy: impacts on supply chain performance and firm performance. Int. J. Prod. Econ. **147**, 340–350 (2014)
31. Chakraborty, S.: Applications of the MOORA method for decision making in manufacturing environment. Int. J. Adv. Manuf. Technol. **54**, 1155–1166 (2011)
32. Luis, M., Camarinha-Matos, Afsarmanesh, H., Galeano, N., Molina, A.: Collaborative networked organizations-concepts and practice in manufacturing enterprises. Comput. Ind. Eng. **57**, 46–60 (2009)
33. Plataniotis, G., de Kinderen, S., van der Linden, D., Greefhorst, D., Henderik, A.: Proper. An empirical evaluation of design decision concepts in enterprise architecture. IFIP Working Conference on the Practice of Enterprise Modeling, pp. 24–38. Springer, Berlin (2013)
34. Wiley Phillips, J.K., Klein, G., Sieck, W.R.: Expertise in judgment and decision making: a case for training intuitive decision skills. Blackwell handbook of judgment and decision making, pp. 297–315. Blackwell Publishing, Malden (2004)
35. Felipe, A., Csaszar: An efficient frontier in organization design: organizational structure as a determinant of exploration and exploitation. Organ. Sci. **24**, 1083–1101 (2013)
36. Jones, G.R.: Organizational Theory, Design, and Change. Pearson, Upper Saddle River (2010)
37. Yan, B., Huang, G.: Supply chain information transmission based on RFID and internet of things. ISECS Int. Colloq. Comput. Commun. Control. Manag. IEEE. **4**, 166–169 (2009)
38. Zhang, Y., Zhang, G., Wang, J., Sun, S., Si, S., Yang, T.: Real-time information capturing and integration framework of the internet of manufacturing things. Int. J. Comput. Integr. Manuf. **28**, 811–822 (2015)

39. Li, Y., Hou, M., Liu, H., Liu, Y.: Towards a theoretical framework of strategic decision, supporting capability and information sharing under the context of Internet of Things. Inf. Technol. Manag. **13**, 205–216 (2012)
40. Kehoe, R.R., Wright, P.M.: The impact of high-performance human resource practices on employees' attitudes and behaviors. J. Manag. **39**, 366–391 (2013)
41. Tseng, S.-M., Lee, P.-S.: The effect of knowledge management capability and dynamic capability on organizational performance. J. Enterp. Inf. Manag. **27**, 158–179 (2014)
42. Beltrán-Martín, I., Roca-Puig, V., Escrig-Tena, A., Bou-Llusar, J.C.: Human resource flexibility as a mediating variable between high performance work systems and performance. J. Manag. **34**, 1009–1044 (2008)
43. Foss, N.J., Lyngsie, J., Zahra, S.A.: The role of external knowledge sources and organizational design in the process of opportunity exploitation. Strateg. Manag. J. **34**, 1453–1471 (2013)
44. Citroen, C.L.: The role of information in strategic decision-making. Int. J. Inf. Manag. **31**, 493–501 (2011)
45. Ivanov, D.: An adaptive framework for aligning (re)planning decisions on supply chain strategy, design, tactics, and operations. Int. J. Prod. Res. **48**, 3999–4017 (2010)
46. Sivak, M., Schoettle, B.: Eco-driving: strategic, tactical, and operational decisions of the driver that influence vehicle fuel economy. Transp. Policy. **22**, 96–99 (2012)
47. Ivanov, D., Sokolov, B., Kaeschel, J.: A multi-structural framework for adaptive supply chain planning and operations control with structure dynamics considerations. Eur. J. Oper. Res. **200**, 409–420 (2010)
48. Bester, H.: Externalities, communication and the allocation of decision rights. Econ. Theory. **41**, 269–296 (2009)
49. Harris, M., Raviv, A.: Allocation of decision-making authority. Rev. Finance. **9**, 353–383 (2005)
50. Graham, J.R., Harvey, C.R., Puri, M.: Capital allocation and delegation of decision-making authority within firms. J. Financ. Econ. **115**, 449–470 (2015)
51. Colombo, M.G., Delmastro, M.: Delegation of authority in business organizations: an empirical test. J. Ind. Econ. **52**, 53–80 (2004)
52. Robert, B.J., Wally, S.: Strategic decision speed and firm performance. Strateg. Manag. J. **24**, 1107–1129 (2003)
53. Bogacz, R., Brown, E., Moehlis, J., Holmes, P., Cohen, J.D.: The physics of optimal decision making: a formal analysis of models of performance in two-alternative forced-choice tasks. Psychol. Rev. **113**, 700 (2006)
54. James, A., Marshall, R., Dornhaus, A., Franks, N.R., Kovacs, T.: Noise, cost and speed-accuracy trade-offs: decision-making in a decentralized system. J. R. Soc. Interface. **3**, 243–254 (2006)
55. Shang, S., Seddon, P.B.: Assessing and managing the benefits of enterprise systems: the business manager's perspective. Inf. Syst. J. **12**, 271–299 (2002)
56. Dewett, T., Jones, G.R.: The role of information technology in the organization: a review, model, and assessment. J. Manag. **27**, 313–346 (2001)
57. Bloom, N., Garicano, L., Sadun, R., Van Reenen, J.: The distinct effects of information technology and communication technology on firm organization. Manag. Sci. **60**, 2859–2885 (2014)
58. Rajan, R.G., Wulf, J.: The flattening firm: evidence from panel data on the changing nature of corporate hierarchies. Rev. Econ. Stat. **88**, 759–773 (2006)
59. Mookherjee, D.: Decentralization, hierarchies, and incentives: a mechanism design perspective. J. Econ. Lit. **44**, 367–390 (2006)
60. Bughin, J., Chui, M., Manyika, J.: An executive's guide to the Internet of Things. http://www.mckinsey.com (2015)

61. Qu, T., Lei, S.P., Wang, Z.Z., Nie, D.X., Chen, X., Huang, G.Q.: IoT-based real-time production logistics synchronization system under smart cloud manufacturing. Int. J. Adv. Manuf. Technol. **84**, 147–164 (2015)
62. Khaleel, H., Conzon, D., Kasinathan, P., Brizzi, P.: Heterogeneous applications, tools, and methodologies in the car manufacturing industry through an IoT approach. IEEE Syst. J. **1**, 1–11 (2015)
63. Ghimire, S., Luis-Ferreira, F., Nodehi, T., Jardim-Goncalves, R.: IoT based situational awareness framework for real-time project management. Int. J. Comput. Integr. Manuf. **30** (1), 74–83 (2017)
64. Zhang, Y., Huang, G.Q., Sun, S., Yang, T.: Multi-agent based real-time production scheduling method for radio frequency identification enabled ubiquitous shopfloor environment. Comput. Ind. Eng. **76**, 89–97 (2014)
65. Zhong, R., Dai, Q., Qu, T., Hu, G., Huang, G.: RFID-enabled real-time manufacturing execution system for mass-customization production. Robot. Comput. Integr. Manuf. **29**, 283–292 (2013)
66. Hall, N.G., Potts, C.N.: Supply chain scheduling: batching and delivery. Oper. Res. **51**, 566–584 (2003)
67. Chen, Z., Vairaktarakis, G.L.: Integrated scheduling of production and distribution operations. Manag. Sci. **51**, 614–628 (2005)
68. Chen, Z.: Integrated production and outbound distribution scheduling: review and extensions. Oper. Res. **58**, 130–148 (2010)
69. Chen, Z., Hall, N.G.: Supply chain scheduling: conflict and cooperation in assembly systems. Oper. Res. **55**, 1072–1089 (2007)
70. Hall, N.G., Potts, C.N.: The coordination of scheduling and batch deliveries. Ann. Oper. Res. **135**, 41–64 (2005)
71. Melouk, S., Damodaran, P., Chang, P.: Minimizing makespan for single machine batch processing with non-identical job sizes using simulated annealing. Int. J. Prod. Econ. **87**, 141–147 (2004)
72. Cheng, B., Leung, Y.T., Li, K., Yang, S.: Single batch machine scheduling with deliveries. Nav. Res. Logist. **6**, 470–482 (2015)
73. Jula, P., Leachman, R.C.: Coordinated multistage scheduling of parallel batch-processing machines under multiresource constraints. Oper. Res. **58**, 933–947 (2010)
74. Lee, C.Y.: Minimizing makespan on a single batch processing machine with dynamic job arrivals. Int. J. Prod. Res. **37**, 219–236 (1999)
75. Zhang, G., Cai, X., Lee, C.Y., Wong, C.K.: Minimizing makespan on a single batch processing machine with nonidentical job sizes. Nav. Res. Logist. **48**, 226–240 (2001)
76. Kashan, A.H., Karimi, B., Jolai, F.: Minimizing makespan on a single batch processing machine with non-identical job sizes: a hybrid genetic approach. Nav. Res. Logist. **48**, 226–240 (2001)
77. Kashan, A.H., Karimi, B.: An improved mixed integer linear formulation and lower bounds for minimizing makespan on a flow shop with batch processing machines. Int. J. Adv. Manuf. Technol. **40**, 582–594 (2009)
78. Li, C., Lee, C.Y.: Scheduling with agreeable release times and due dates on a batch processing machine. Eur. J. Oper. Res. **96**, 564–569 (1997)
79. Sung, C.S., Choung, Y.I., Hong, J.M., Kim, Y.H.: Minimizing makespan on a single burn-in oven with job families and dynamic job arrivals. Comput. Oper. Res. **29**, 995–1007 (2002)
80. Chang, P.C., Wang, H.M.: A heuristic for a batch processing machine scheduled to minimize total completion time with non-identical job sizes. Int. J. Adv. Manuf. Technol. **24**, 615–620 (2004)
81. Chou, F.D., Chang, P.C., Wang, H.M.: A hybrid genetic algorithm to minimize makespan for the single batch machine dynamic scheduling problem. Int. J. Adv. Manuf. Technol. **31**, 350–359 (2006)

82. Damodaran, P., Vélez-Gallego, M.C.: A simulated annealing algorithm to minimize makespan of parallel batch processing machines with unequal job ready times. Expert Syst. Appl. **39**, 1451–1458 (2012)
83. Kashan, A.H., Karimi, B., Jenabi, M.: A hybrid genetic heuristic for scheduling parallel batch processing machines with arbitrary job sizes. Comput. Oper. Res. **35**, 1084–1098 (2008)
84. Zhou, S., Liu, M., Chen, H., Li, X.: An effective discrete differential evolution algorithm for scheduling uniform parallel batch processing machines with non-identical capacities and arbitrary job sizes. Int. J. Prod. Econ. **179**, 1–11 (2016)
85. Jiang, L., Pei, J., Liu, X., Pardalos, P.M., Yang, Y., Qian, X.: Uniform parallel batch machines scheduling considering transportation using a hybrid DPSO-GA algorithm. Int. J. Adv. Manuf. Technol. **89**(5–8), 1887–1900 (2017)
86. Cheng, T.C.E., Kovalyov, M.Y.: Single machine batch scheduling with sequential job processing. Eur. J. Oper. Res. **135**, 177–183 (2001)
87. Su, C.S., Pan, C.H., Hsu, T.S.: A new heuristic algorithm for the machine scheduling problem with job delivery coordination. Theor. Comput. Sci. **410**, 2581–2591 (2009)
88. Chou, F.D.: A joint GA+DP approach for single burn-in oven scheduling problems with makespan criterion. Int. J. Adv. Manuf. Technol. **35**, 587–595 (2007)
89. Sung, C.S., Choung, Y.I., Hong, J.M., Kim, Y.H.: Minimizing makespan on a single burn-in oven with job families and dynamic job arrivals. Comput. Oper. Res. **29**, 995–1007 (2002)
90. Chang, P.Y., Damodaran, P., Melouk, S.: Minimizing makespan on parallel batch processing machines. Int. J. Prod. Res. **42**, 4211–4220 (2004)
91. Pei, J., Liu, X., Pardalos, P.M., Fan, W., Wang, L., Yang, S.: Solving a supply chain scheduling problem with non-identical job sizes and release times by applying a novel effective heuristic algorithm. Int. J. Syst. Sci. **47**, 765–776 (2016)
92. Pei, J., Liu, X., Pardalos, P.M., Migdalas, A., Yang, S.: Serial-batching scheduling with time-dependent setup time and effects of deterioration and learning on a single-machine. J. Glob. Optim. (2015). doi:10.1007/s10898-015-0320-5
93. Pei, J., Liu, X., Fan, W., Pardalos, P.M., Migdalas, A., Yang, S.: Scheduling jobs on a single serial-batching machine with dynamic job arrivals and multiple job types. Ann. Math. Artif. Intell. **76**, 215–228 (2016)
94. Pearn, W.L., Chung, S.H., Yang, M.H.: Minimizing the total machine workload for the wafer probing scheduling problem. IIE Trans. **34**, 211–220 (2002)
95. Xu, R., Chen, H., Li, X.: Makespan minimization on single batch-processing machine via ant colony optimization. Comput. Oper. Res. **39**, 582–593 (2011)
96. Eusuff, M.M., Lansey, K.E., Pasha, F.: Shuffled frog-leaping algorithm: a memetic meta-heuristic for discrete optimization. Eng. Optim. **38**, 129–154 (2006)
97. Glover, F.: A template for scatter search and path relinking. European Conference on Artificial Evolution. Springer, Berlin, Heidelberg, pp. 1–51 (1997)
98. Glover, F., Laguna, M., Mart'I, R.: Fundamentals of scatter search and path relinking. Control. Cybern. **29**, 653–684 (2000)
99. Lai, X., Hao, J., Lu, Z., Glover, F.: A learning-based path relinking algorithm for the bandwidth coloring problem. Eng. Appl. Artif. Intell. **52**, 81–91 (2016)
100. Zhang, X., Li, X., Wang, J.: Local search algorithm with path relinking for single batch-processing machine scheduling problem. Neural Comput. Appl. (2016). doi:10.1007/s00521-016-2339-z
101. Yang, Z., Zhang, G., Zhu, H.: Multi-neighborhood based path relinking for two-sided assembly line balancing problem. J. Comb. Optim. **32**, 396–415 (2016)
102. Scaparra, M.P., Church, R.L.: A GRASP and path relinking heuristic for rural road network development. J. Heuristics. **11**, 89–108 (2005)
103. Lei, D., Guo, X.: A shuffled frog-leaping algorithm for job shop scheduling with outsourcing options. Int. J. Prod. Res. **54**, 1–12 (2016)
104. Wible, B., Mervis, J., Wigginton, N.S.: Rethinking the global supply chain. Science. **344**, 1100–1103 (2014)

105. Mason, A., Shaw, A., Al-Shamma'a, A.: Peer-to-peer inventory management of returnable transport items: a design science approach. Comput. Ind. **63**, 265–274 (2012)
106. Zhou, W.: RFID and item-level information visibility. Eur. J. Oper. Res. **198**, 252–258 (2009)
107. Shang, W., Ha, A.Y., Tong, S.: Information sharing in a supply chain with a common retailer. Manag. Sci. **62**, 245–263 (2015)
108. Dantzig, G.B., Ramser, J.H.: The truck dispatching problem. Manag. Sci. **6**, 80–91 (1959)
109. Dell'Amico, M., Righini, G., Salani, M.: A branch-and-price approach to the vehicle routing problem with simultaneous distribution and collection. Transp. Sci. **40**, 235–247 (2006)
110. Salhi, S., Nagy, G.: A cluster insertion heuristic for single and multiple depot vehicle routing problems with backhauling. J. Oper. Res. Soc. **50**, 1034–1042 (1999)
111. Gajpal, Y., Abad, P.: Saving-based algorithms for vehicle routing problem with simultaneous pickup and delivery. J. Oper. Res. Soc. **61**, 1498–1509 (2010)
112. Tasan, A.S., Gen, M.: A genetic algorithm based approach to vehicle routing problem with simultaneous pick-up and deliveries. Comput. Ind. Eng. **62**, 755–761 (2012)
113. Subramanian, A., Drummond, L.M.D.A., Bentes, C., Ochi, L.S., Farias, R.: A parallel heuristic for the vehicle routing problem with simultaneous pickup and delivery. Comput. Oper. Res. **37**, 1899–1911 (2010)
114. Gajpal, Y., Abad, P.: An ant colony system (ACS) for vehicle routing problem with simultaneous delivery and pickup. Comput. Oper. Res. **36**, 3215–3223 (2009)
115. Liu, R., Xie, X., Augusto, V., Rodriguez, C.: Heuristic algorithms for a vehicle routing problem with simultaneous delivery and pickup and time windows in home health care. Eur. J. Oper. Res. **230**, 475–486 (2013)
116. Wang, C., Mu, D., Zhao, F., Sutherland, J.W.: A parallel simulated annealing method for the vehicle routing problem with simultaneous pickup–delivery and time windows. Comput. Ind. Eng. **83**, 111–122 (2015)
117. Bertsimas, D.J.: A vehicle routing problem with stochastic demand. Oper. Res. **40**, 574–585 (1992)
118. Gendreau, M., Laporte, G., Séguin, R.: An exact algorithm for the vehicle routing problem with stochastic demands and customers. Transp. Sci. **29**, 143–155 (1995)
119. Gendreau, M., Laporte, G., Séguin, R.: A tabu search heuristic for the vehicle routing problem with stochastic demands and customers. Oper. Res. **44**, 469–477 (1996)
120. Mendoza, J.E., Rousseau, L.-M., Villegas, J.G.: A hybrid metaheuristic for the vehicle routing problem with stochastic demand and duration constraints. J. Heuristics 1–28 (2015)
121. Mendoza, J.E., Villegas, J.G.: A multi-space sampling heuristic for the vehicle routing problem with stochastic demands. Optim. Lett. **7**, 1503–1516 (2013)
122. Powell, W.B., Sheffi, Y., Nickerson, K.S., Butterbaugh, K., Atherton, S.: Maximizing profits for North American Van Lines' truckload division: a new framework for pricing and operations. Interfaces. **18**, 21–41 (1988)
123. Kim, S., Lewis, M.E., White, C.C.: Optimal vehicle routing with real-time traffic information. IEEE Trans. Intell. Transp. Syst. **6**, 178–188 (2005)
124. Secomandi, N., Margot, F.: Reoptimization approaches for the vehicle-routing problem with stochastic demands. Oper. Res. **57**, 214–230 (2009)
125. Novoa, C., Storer, R.: An approximate dynamic programming approach for the vehicle routing problem with stochastic demands. Eur. J. Oper. Res. **196**, 509–515 (2009)
126. Secomandi, N.: Comparing neuro-dynamic programming algorithms for the vehicle routing problem with stochastic demands. Comput. Oper. Res. **27**, 1201–1225 (2000)
127. Goodson, J.C., Thomas, B.W., Ohlmann, J.W.: Restocking-based rollout policies for the vehicle routing problem with stochastic demand and duration limits. Transp. Sci. **50**, 591–607 (2015)
128. Archetti, C., Bertazzi, L., Laporte, G., Speranza, M.G.: A branch-and-cut algorithm for a vendor-managed inventory-routing problem. Transp. Sci. **41**, 382–391 (2007)
129. Zachariadis, E.E., Tarantilis, C.D., Kiranoudis, C.T.: An integrated local search method for inventory and routing decisions. Expert Syst. Appl. **36**, 10239–10248 (2009)

130. Popović, D., Vidović, M., Radivojević, G.: Variable neighborhood search heuristic for the inventory routing problem in fuel delivery. Expert Syst. Appl. **39**, 13390–13398 (2012)
131. Park, Y.-B., Yoo, J.-S., Park, H.-S.: A genetic algorithm for the vendor-managed inventory routing problem with lost sales. Expert Syst. Appl. **53**, 149–159 (2016)
132. Chen, Y.M., Lin, C.-T.: A coordinated approach to hedge the risks in stochastic inventory-routing problem. Comput. Ind. Eng. **56**, 1095–1112 (2009)
133. Bertazzi, L., Bosco, A., Laganà, D.: Managing stochastic demand in an inventory routing problem with transportation procurement. Omega. **56**, 112–121 (2015)
134. Adelman, D.: A price-directed approach to stochastic inventory/routing. Oper. Res. **52**, 499–514 (2004)
135. Toriello, A., Nemhauser, G., Savelsbergh, M.: Decomposing inventory routing problems with approximate value functions. Nav. Res. Logist. (NRL). **57**, 718–727 (2010)
136. Adulyasak, Y., Cordeau, J.-F., Jans, R.: Benders decomposition for production routing under demand uncertainty. Oper. Res. **63**, 851–867 (2015)
137. Bertazzi, L., Bosco, A., Guerriero, F., Lagana, D.: A stochastic inventory routing problem with stock-out. Transp. Res. Part C Emerg. Technol. **27**, 89–107 (2013)
138. Hvattum, L.M., Løkketangen, A.: Using scenario trees and progressive hedging for stochastic inventory routing problems. J. Heuristics. **15**, 527–557 (2009)
139. Nolz, P.C., Absi, N., Feillet, D.: A stochastic inventory routing problem for infectious medical waste collection. Networks. **63**, 82–95 (2014)
140. Yu, Y., Chu, C., Chen, H., Chu, F.: Large scale stochastic inventory routing problems with split delivery and service level constraints. Ann. Oper. Res. **197**, 135–158 (2012)
141. Coelho, L.C., Cordeau, J.-F., Laporte, G.: Heuristics for dynamic and stochastic inventory-routing. Comput. Oper. Res. **52**, 55–67 (2014)
142. Juan, A.A., Grasman, S.E., Caceres-Cruz, J., Bektaş, T.: A simheuristic algorithm for the single-period stochastic inventory-routing problem with stock-outs. Simul. Model. Pract. Theory. **46**, 40–52 (2014)
143. Liu, S.-C., Chung, C.-H.: A heuristic method for the vehicle routing problem with backhauls and inventory. J. Intell. Manuf. **20**, 29–42 (2009)
144. Li, Y., Lu, M., Liu, B.: A two-stage algorithm for the closed-loop location-inventory problem model considering returns in e-commerce. Math. Probl. Eng. **4**, 1–9 (2014)
145. Van Anholt, R.G., Coelho, L.C., Laporte, G., Vis, I.F.: An inventory-routing problem with pickups and deliveries arising in the replenishment of automated teller machines. Transp. Sci. **50**, 1077–1091 (2016)
146. Brinkmann, J., Ulmer, M.W., Mattfeld, D.C.: Short-term strategies for stochastic inventory routing in bike sharing systems. Transp. Res. Procedia. **10**, 364–373 (2015)
147. Soysal, M.: Closed-loop Inventory Routing Problem for returnable transport items. Transp. Res. Part D: Transp. Environ. **48**, 31–45 (2016)
148. Pisinger, D., Ropke, S.: Large neighborhood search, Handbook of metaheuristics, pp. 399–419. Springer, New York (2010)
149. Shaw, P.: A New Local Search Algorithm Providing High Quality Solutions to Vehicle Routing Problems. APES Group, Dept of Computer Science, University of Strathclyde, Glasgow (1997)
150. Bent, R., Van Hentenryck, P.: A two-stage hybrid local search for the vehicle routing problem with time windows. Transp. Sci. **38**, 515–530 (2004)
151. Goel, A., Gruhn, V.: A general vehicle routing problem. Eur. J. Oper. Res. **191**, 650–660 (2008)
152. Hong, L.: An improved LNS algorithm for real-time vehicle routing problem with time windows. Comput. Oper. Res. **39**, 151–163 (2012)
153. Drexl, M.: Applications of the vehicle routing problem with trailers and transshipments. Eur. J. Oper. Res. **227**, 275–283 (2013)
154. Lee, J., Kim, B.-I., Johnson, A.L., Lee, K.: The nuclear medicine production and delivery problem. Eur. J. Oper. Res. **236**, 461–472 (2014)

155. Goel, V., Furman, K.C., Song, J.-H., El-Bakry, A.S.: Large neighborhood search for LNG inventory routing. J. Heuristics. **18**, 821–848 (2012)
156. Song, J.-H., Furman, K.C.: A maritime inventory routing problem: practical approach. Comput. Oper. Res. **40**, 657–665 (2013)
157. Liu, S.-C., Lu, M.-C., Chung, C.-H.: A hybrid heuristic method for the periodic inventory routing problem. Int. J. Adv. Manuf. Technol. **85**, 2345–2352 (2016)
158. Lei, H., Laporte, G., Guo, B.: The capacitated vehicle routing problem with stochastic demands and time windows. Comput. Oper. Res. **38**, 1775–1783 (2011)
159. Lei, H., Laporte, G., Guo, B.: The vehicle routing problem with stochastic demands and split deliveries. INFOR Inf. Syst. Oper. Res. **50**, 59–71 (2012)
160. Azi, N., Gendreau, M., Potvin, J.-Y.: An adaptive large neighborhood search for a vehicle routing problem with multiple routes. Comput. Oper. Res. **41**, 167–173 (2014)
161. Luo, Z., Qin, H., Zhang, D., Lim, A.: Adaptive large neighborhood search heuristics for the vehicle routing problem with stochastic demands and weight-related cost. Transp. Res. Part E Logist. Transp. Rev. **85**, 69–89 (2016)
162. Aksen, D., Kaya, O., Salman, F.S., Tüncel, Ö.: An adaptive large neighborhood search algorithm for a selective and periodic inventory routing problem. Eur. J. Oper. Res. **239**, 413–426 (2014)
163. Hemmati, A., Stålhane, M., Hvattum, L.M., Andersson, H.: An effective heuristic for solving a combined cargo and inventory routing problem in tramp shipping. Comput. Oper. Res. **64**, 274–282 (2015)
164. Clarke, G., Wright, J.W.: Scheduling of vehicles from a central depot to a number of delivery points. Oper. Res. **12**, 568–581 (1964)
165. Ropke, S., Pisinger, D.: An adaptive large neighborhood search heuristic for the pickup and delivery problem with time windows. Transp. Sci. **40**, 455–472 (2006)
166. Augerat, P., Belenguer, J., Benavent, E., Corberán, A., Naddef, D., Rinaldi, G.: Computational results with a branch and cut code for the capacitated vehicle routing problem. Rapport de recherche- IMAG (1995)
167. Dyckhoff, H.: A typology of cutting and packing problems. Eur. J. Oper. Res. **44**, 145–159 (1990)
168. Kantorovich, L.V.: Mathematical methods of organizing and planning production. Manag. Sci. **6**(4), 366–422 (1960)
169. Gilmore, P.C., Gomory, R.E.: A linear programming approach to the cutting stock problem. Oper. Res. **91**, 849–859 (1961)
170. Gilmore, P.C., Gomory, R.E.: A linear programming approach to the cutting stock problem-part II. Oper. Res. **11**, 863–888 (1963)
171. Stadtler, H.: A one-dimensional cutting stock problem in the aluminium industry and its solution. Eur. J. Oper. Res. **44**, 209–223 (1990)
172. Degraeve, Z., Peeters, M.: Optimal integer solutions to industrial cutting-stock problems: part 2, Benchmark results. INFORMS J. Comput. **15**, 58–81 (2003)
173. Lee, J.: In situ column generation for a cutting-stock problem. Comput. Oper. Res. **34**, 2345–2358 (2007)
174. Vance, P.: Branch-and-price algorithms for the one-dimensional cutting stock problem. Comput. Optim. Appl. **9**, 211–228 (1998)
175. Vanderbeck, F.: Computational study of a column generation algorithm for bin packing and cutting stock problems. Math. Program. Ser. A. **86**, 565–594 (1999)
176. Peeters, M., Degraeve, Z.: Branch-and-price algorithms for the dual bin packing and maximum cardinality bin packing problem. Eur. J. Oper. Res. **170**, 416–439 (2006)
177. Yanasse, H.H., Lamosa, J.P.: An integrated cutting stock and sequencing problem. Eur. J. Oper. Res. **183**, 1353–1370 (2007)
178. Haessler, R.W.: Controlling cutting pattern changes in one-dimensional trim problems. Oper. Res. **23**, 483–493 (1975)

179. Sweeney, E., Haessler, R.W.: One-dimensional cutting stock decisions for rolls with multiple quality grades. Eur. J. Oper. Res. **44**, 224–231 (1990)
180. Gradisar, M., Trkman, P.: A combined approach to the solution to the general one-dimensional cutting stock problem. Comput. Oper. Res. **32**, 1793–1807 (2005)
181. Scholl, A., Klein, R., Jurgens, C.: BISON: a fast hybrid procedure for exactly solving the one-dimensional bin packing problem. Comput. Oper. Res. **24**(7), 627–645 (1997)
182. Sung, T.-C., Weng, W.-C., Yang, C.-T.: A two-stage optimization of piece arrangement for the cutting problem in shipbuilding. J. Mar. Sci. Technol. **12**(3), 175–182 (2004)
183. Antonio, J., Chauvet, F., Chu, C.B., Proth, J.M.: The cutting stock problem with mixed objectives: two heuristics based on dynamic programming. Eur. J. Oper. Res. **114**, 395–402 (1999)
184. Chu, C.B., Antonio, J.: Approximation algorithms to solve real-life multicriteria cutting stock problems. Oper. Res. **47**(4), 495–508 (1999)
185. Vahrenkamp, R.: Random search in the one-dimensional cutting stock problem. Eur. J. Oper. Res. **95**, 191–200 (1996)
186. Wagner, B.J.: A genetic algorithm solution for one-dimensional bundled stock cutting. Eur. J. Oper. Res. **117**, 368–381 (1999)
187. Liang, K.H., Yao, X., Newton, Y., Hoffman, D.: A new evolutionary approach to cutting stock problems with and without contiguity. Comput. Oper. Res. **29**(12), 1641–1659 (2002)
188. Yang, C.-T., Sung, T.-C., Weng, W.-C.: An improved tabu search approach with mixed objective function for one-dimensional cutting stock problems. Adv. Eng. Softw. **37**(8), 502–513 (2006)
189. Gracia, C., Andrés, C., Gracia, L.: A hybrid approach based on genetic algorithms to solve the problem of cutting structural beams in a metalwork company. J. Heuristics. **19**, 253–273 (2013)
190. Yang, B., Li, C., Huang L., Tan, Y., Zhou, C.: Solving one-dimensional cutting-stock problem based on ant colony optimization. Fifth International Joint Conference on INC, IMS and IDC (2009)
191. Matsumoto, K., Umetani, S., Nagamochi, H.: On the one-dimensional stock cutting problem in the paper tube industry. J. Sched. **14**, 281–290 (2011)
192. Vacharapoom, B., Sdhabhon, B.: Three-step solutions for cutting stock problem of construction steel bars. J. Civ. Eng. **5**, 1239–1247 (2014)
193. Christofides, N., Whitlock, C.: An algorithm for two-dimensional cutting problems. Oper. Res. **25**, 31–44 (1977)
194. Agrawal, P.K.: Minimizing trim loss in cutting rectangular blanks of a single size from a rectangular sheet using orthogonal guillotine cuts. Eur. J. Oper. Res. **64**, 410–422 (1993)
195. Lindecrantz, N.: Method for optimum cutting of rectangular sheets. BIT Numer. Math. **4**(1), 30–35 (1964)
196. Gilmore, P., Gomory, R.: Multistage cutting problems of two and more dimensions. Oper. Res. **13**, 94–119 (1965)
197. Tarnowski, A.G., Terno, J., Scheithauer, G.: A polynomial time algorithm for the guillotine pallet loading problem. INFOR. **32**, 275–287 (1994)
198. Cui, Y.D.: Dynamic programming algorithms for the optimal cutting of equal rectangles. Appl. Math. Model. **29**, 1040–1053 (2005)
199. Dagli, C.H.: Knowledge-based systems for cutting stock problems. Eur. J. Oper. Res. **44**, 160–166 (1990)
200. Lai, K.K., Chan, J.W.M.: Developing a simulated annealing algorithm for the cutting stock problem. Comput. Ind. Eng. **32**, 115–127 (1997)
201. Leng, T.W., Yung, C.H., Troutt, M.D.: Applications of genetic search and simulated annealing to the two-dimensional non-guillotine cutting stock problem. Comput. Ind. Eng. **40**, 201–214 (2001)
202. Gomes, A.M., Oliveira, J.F.: Solving irregular strip packing problems by hybridising simulated annealing and linear programming. Eur. J. Oper. Res. **171**, 811–829 (2006)

203. Silva, E., Alvelos, F., Valério de Carvalho, J.M.: An integer programming model for two- and three-stage two-dimensional cutting stock problems. Eur. J. Oper. Res. **205**, 699–708 (2010)
204. Weng, W.-C., Kuo, H.-C.: Irregular stock cutting system based on AutoCAD. Adv. Eng. Softw. **42**, 634–643 (2011)
205. Cui, Y., Xu, D.-y.: Strips minimization in two-dimensional cutting stock of circular items. Comput. Oper. Res. **37**, 621–629 (2010)
206. Lin, L., Liu, X., Pei, J., Fan, W., Pardalos, P.M.: A study on decision making of cutting stock with frustum of cone bars. Oper. Res. **12**, 1–18 (2015)
207. Beaujean, P., Kristes, D., Schmitt, R.: Entrepreneurial quality management—a new definition of quality. Engineering Management Conference, 2008. IEMC Europe 2008. IEEE International. pp. 1–5 (2008).
208. Domínguez-Mayo, F.J., Escalona, M.J., Mejías, M., Ross, M., Staples, G.: A quality management based on the quality model life cycle. Comput. Stand. Interfaces. **34**, 396–412 (2012)
209. Parzinger, M.: A stage-wise application of total quality management through the product life cycle. Ind. Manag. Data Syst. **97**(3), 125–130 (1997)
210. Nguyen, D.S.: Total quality management in product life cycle. IEEE International Conference on Industrial Engineering and Engineering Management. IEEE (2014)
211. Feng, L., Luo, M., Peng, B., Ren, J.: Study on integrated quality management system for the life cycle of virtual enterprise. International Conference on Wireless Communications, NETWORKING and Mobile Computing. pp. 5079–5083 (2007)
212. Luo, Y., Mao, P., Chen, Q.: Innovation of design quality management based on project life cycle. International Conference on Management and Service Science. IEEE. pp. 1–4 (2009)
213. Bradley, T.J.: The use of defect prevention in achieving total quality management in the software life cycle. Communications, 1991. ICC '91, Conference Record. IEEE International Conference on. IEEE. pp. 356–359 (1991)
214. Mitreva, E., Taskov, N.: To apply the six sigma method or the new TQM (Total Quality Management) strategy in the Macedonian companies. (2015)
215. Samson, D., Terziovski, M.: The relationship between total quality management practices and operational performance. J. Oper. Manag. **17**, 393–409 (1999)
216. Suneeta, B., Koranne, S.: Conceptual study of relationship between service quality and customer satisfaction. Int. Res. J. Soc. Sci. (2014)
217. Spencer, B.A.: Models of organization and total quality management: a comparison and critical evaluation. Acad. Manag. Rev. **19**, 446–471 (1994)
218. Feigenbaum, A.V.: Total quality control: engineering and management : the technical and managerial field for improving product quality, including its reliability, and for reducing operating costs and losses. McGraw-Hill, New York (1961)
219. Hoogervorst, J.A.P., Koopman, P.L., Flier, H.V.D.: Total quality management: the need for an employee-centred, coherent approach. TQM Mag. **17**, 92–106 (2005)
220. Zhou, W., Piramuthu, S.: Consumer preference and service quality management with RFID. Ann. Oper. Res. **216**, 35–51 (2014)
221. Pantouvakis, A., Psomas, E.: Exploring total quality management applications under uncertainty: a research agenda for the shipping industry. Marit. Econ. Logist. **18**, 496–512 (2016)
222. Kovach, J.V.: The Role of Learning and Exploration in Quality Management and Continuous Improvement. Quality in the 21st Century. (2016)
223. Torre, T.: Information Technologies and Quality Management. Towards a New Idea of Quality? Information and Communication Technologies in Organizations and Society. Springer International Publishing, (2016)
224. Johnson, J.: TQM and doing the right thing at the right time: the culture clock. BMJ Clin. Res. **2**, 238–239 (1965)
225. Uluskan, M., Godfrey, A.B., Joines, J.A.: Integration of Six Sigma to Traditional Quality Management Theory: An Empirical Study on Organizational Performance. Total Quality Management & Business Excellence. pp. 1–18. (2016)

226. Ćwiklicki, M.: Understanding management concepts through development of their tool box: the case of total quality management. Naše Gospodarstvo/our Econ. **62**, 56–62 (2016)
227. Deming, W.E.: Quality, Productivity, and Competitive Position. Massachusetts Institute of Technology, Center for Advanced Engineering Study (1982)
228. Qasim, S., Zafar, A.: Information system strategy for Total Quality Management (TQM) in aviation industry. Int. J. Comput. Appl. **135**, 37–42 (2016)
229. Li, B.H., Zhang, L., Chai, X., Tao, F., Ren, L., Wang, Y.: Research and Applications of Cloud Manufacturing in China, pp. 224–230. Cloud-Based Design and Manufacturing (CBDM), Springer International Publishing (2014)
230. Hecht, G., Josescheidt, B., Figueiredo, C.D., Moha, N., Khomh, F.: An Empirical Study of the Impact of Cloud Patterns on Quality of Service (QoS). IEEE, International Conference on Cloud Computing Technology and Science. IEEE. pp. 278–283 (2014)
231. Jin, H., Yao, X., Chen, Y.: Correlation-aware QoS modeling and manufacturing cloud service composition. J. Intell. Manuf. 1–14 (2015)
232. Liu, B., Zhang, Z.: QoS-aware service composition for cloud manufacturing based on the optimal construction of synergistic elementary service groups. Int. J. Adv. Manuf. Technol. 1–15 (2016)
233. Liu, M., Wang, M., Shen, W., Luo, N., Yan, J.: A quality of service (QoS)-aware execution plan selection approach for a service composition process. Futur. Gener. Comput. Syst. **28**, 1080–1089 (2012)
234. Li, H.F., Zhao, L., Zhang, B.H., Li, J.Q.: Service Matching and Composition Considering Correlations among Cloud Services. IEEE International Conference on Systems, Man, and Cybernetics. IEEE (2015)
235. Cao, Y., Wang, S., Kang, L., Gao, Y.: A TQCS-based service selection and scheduling strategy in cloud manufacturing. Int. J. Adv. Manuf. Technol. **82**, 1–17 (2016)
236. Xu, W., Tian, S., Liu, Q., Xie, Y., Zhou, Z., Pham, D.T.: An improved discrete bees algorithm for correlation-aware service aggregation optimization in cloud manufacturing. Int. J. Adv. Manuf. Technol. **84**, 17–28 (2016)
237. Zheng, H., Feng, Y., Tan, J.: A fuzzy QoS-aware resource service selection considering design preference in cloud manufacturing system. Int. J. Adv. Manuf. Technol. **84**, 371–379 (2016)
238. Xiang, F., Hu, Y., Yu, Y., Wu, H.: QoS and energy consumption aware service composition and optimal-selection based on Pareto group leader algorithm in cloud manufacturing system. CEJOR. **22**, 663–685 (2013)
239. Panda, S.K., Jana, P.K.: Uncertainty-based QoS min–min algorithm for heterogeneous multi-cloud environment. Arab. J. Sci. Eng. 1–23 (2016)
240. Jeong, B., Jung, H.S., Park, N.K.: A computerized causal forecasting system using genetic algorithms in supply chain management. J. Syst. Softw. **60**, 223–237 (2002)
241. Talib, F., Siddiqui, J., Khanam, S.: Identification of total quality management enablers and information technology resources for ICT industry: a Pareto analysis approach. Int. J. Inf. Qual. **4**, 18–41 (2015)
242. Tahira, R., Ihsanullah, A.-u.-R., Saleem, M.: Studies on variability for quality traits, association and path analysis in Raya (Brassica juncea) germplasm. Int. J. Agric. Biol. **17**, 381–386 (2015)
243. Powell, T.C.: Total quality management as competitive advantage: a review and empirical study. Strateg. Manag. J. **16**, 15–37 (1995)
244. Hoang, D.T., Igel, B., Laosirihongthong, T.: Total quality management (TQM) strategy and organisational characteristics: evidence from a recent WTO member. Total Qual. Manag. Bus. Excell. **21**, 471–473 (2010)
245. Whitney, Gary, Pavett, Cynthia.: Total quality management as an organizational change: predictors of successful implementation. Qual. Manag. J. (1998)

246. Zhang, J., Lin, T., Ren, L.: Dynamic Fuzzy Evaluation for E-Commerce Service Quality Based on the SERVPERF. The International Conference on E-Business and E-Government, ICEE e2010, 7–9 May 2010, Guangzhou, China, Proceedings. pp. 576–579 (2010)
247. Shewhart, W.A.: Economic quality control of manufactured product[J]. Bell Syst. Tech. J. **9**, 364–389 (1930)
248. Benson, P.G., Saraph, J.V., Schroeder, R.G.: The effects of organizational context on quality management: an empirical investigation. Manag. Sci. **37**, 1107–1124 (1991)
249. Kim, D.Y., Kumar, V., Kumar, U.: Relationship between quality management practices and innovation. J. Oper. Manag. **30**, 295–315 (2012)
250. José Tarí, J., Heras-Saizarbitoria, I., Pereira, J.: Internalization of quality management in service organizations. Manag. Serv. Qual. **23**, 456–473 (2013)
251. de Sousa Jabbour, A.B.L., Jabbour, C.J.C., Latan, H., Teixeira, A.A.: Quality management, environmental management maturity, green supply chain practices and green performance of Brazilian companies with ISO 14001 certification: direct and indirect effects. Transp. Res. Part E Logist. Transp. Rev. **67**, 39–51 (2014)
252. Xie, G., Yue, W., Wang, S., Lai, K.K.: Quality investment and price decision in a risk-averse supply chain. Eur. J. Oper. Res. **214**, 403–410 (2011)
253. Benoît, C., Norris, G.A., Valdivia, S., et al.: The guidelines for social life cycle assessment of products: just in time. Int. J. Life Cycle Assess. **15**(2), 156–163 (2010)
254. Laratte, B., Guillaume, B., Kim, J., et al.: Modeling cumulative effects in life cycle assessment: the case of fertilizer in wheat production contributing to the global warming potential. Sci. Total Environ. **418**, 588–595 (2014)
255. Benoit-Norris, C., Cavan, D.A., Norris, G.: Identifying social impacts in product supply chains: overview and application of the social hotspot database. Sustainability. **4**(9), 1946–1965 (2012)
256. Chester, M.V.: Life-cycle Environmental Inventory of Passenger Transportation in the United States. University of California, Berkeley (2008)
257. Chin, K.S., Xu, D.L., Yang, J.B., Lam, J.P.-K.: Group-based ER–AHP system for product project screening. Expert Syst. Appl. **35**(4), 1909–1929 (2008)
258. Murphy, C.W., Kendall, A.: Life cycle inventory development for corn and stover production systems under different allocation methods. Biomass Bioenergy. **58**, 67–75 (2013)
259. Consoli, F., Allen, D., Bousted, I.: Guidelines for Life-Cycle Assessment: A Code of Practice. STEAC, Pensaco-la (1993)
260. Moya, C., Domínguez, R., Van, H., Langenhove, et al.: Exergetic analysis in cane sugar production in combination with life cycle assessment. J. Clean. Prod. **59**, 43–50 (2013)
261. Dempster, A.P.: Upper and lower probabilities induced by a multivalued mapping. Ann. Math. Stat. **38**, 325–339 (1967)
262. Ryan, E., Jacques, D., Colombi, J., Schubert, C.: A proposed methodology to characterize the accuracy of life cycle cost estimates for DoD programs. Proc Comput Sci. **8**, 361–369 (2012)
263. Finnveden, G., Hauschild, M.Z., Ekvall, T., et al.: Recent developments in life cycle assessment. J. Environ. Manag. **91**, 1–21 (2009)
264. Meylan, G., Ami, H., Spoerri, A.: Transitions of municipal solid waste management. Part II: hybrid life cycle assessment of Swiss glass-packaging disposal. Resour. Conserv. Recycl. **86**, 16–27 (2014)
265. Chhipi-Shrestha, G.K., Hewage, K., Sadiq, R.: 'Socializing' sustainability: a critical review on current development status of social life cycle impact assessment method. Clean Techn. Environ. Policy. **17**, 579–596 (2015)
266. Hauschild, M.Z., Goedkoop, M., Guinee, J., et al.: Identifying best existing practice for characterization modeling in life cycle impact assessment. Int. J. Life Cycle Assess. **18**(3), 683–697 (2013)
267. Wang, H., Weng, D., Lu, X., Liang, L.: Life-cycle cost assessment of seismically base-isolated structures in nuclear power plants. Nucl. Eng. Des. **262**, 429–434 (2013)

268. Dahlbo, H., Ollikainen, M., Peltola, S., Myllymaaa, T., Melanen, M.: Combining ecological and economic assessment of options for newspaper waste management. Resour. Conserv. Recycl. **51**, 42–63 (2007)
269. Hendrickson, C., Horvath, A., Joshi, S., Lave, L.: Economic input-output models for environmental life cycle assessment. Environ. Sci. Technol. **32**(7), 184A–191A (1998., American Chemical Society)
270. https://en.wikipedia.org/wiki/IPhone_4S
271. https://www.strategyanalytics.com/
272. https://www.ifixit.com/
273. International Organization for Standardization (ISO). Technical Committee TC 207/Subcommittee SC 5: Environmental management – Life cycle assessment – Principles and framework. International Standard 14040, June 1996
274. International Organization for Standardization (ISO): The New International Standards for Life Cycle Assessment: ISO 14040 and ISO 14044. ISO, Geneva (2006)
275. iPhone4S Environmental Report. September 12, 2012
276. Jolliet, O., Mtiller-Wenk, R., Bare, J., et al.: The LCIA midpoint-damage framework of the UNEP/SETAC life cycle initiative. Int. J. Life Cycle Assess. **9**(6), 394–404 (2004)
277. Woon, K.S., Lo, I.M.C.: An integrated life cycle costing and human health impact analysis of municipal solid waste management options in Hong Kong using modified eco-efficiency indicator. Resour. Conserv. Recycl. **107**, 104–114 (2016)
278. Kong G. L., Xu D. L., Yang J. B., Ma X. M.: Combined medical quality assessment using the evidential reasoning approach. Expert Syst. Appl. **42**, 5522–5530 (2015).
279. Liu, X.B., Zhou, M., Yang, J.B., Yang, S.L.: Assessment of strategic R&D projects for car manufacturers based on the evidential reasoning approach. Int. J. Comput. Intell. Syst. **1**, 24–49 (2008)
280. Curran, M.A., Notten, P.: Summary of global life cycle inventory data resources, report for SETAC/UNEP life cycle initiative, task force 1: database registry. www.epa.gov/NRMRL/lcaccess/pdfs/summary of global lci data resources.pdf (2006)
281. O'Brien, M., Doig, A., Clift, R.: Social and environmental life cycle assessment (SELCA). Int. J. Life Cycle Assess. **1**, 231–237 (1996)
282. Rowley, H.V., Lundie, S., Peters, G.M.: A hybrid life cycle assessment model for comparison with conventional methodologies in Australia. Int. J. Life Cycle Assess. **14**(6), 508–516 (2009)
283. Kruse, S.A.: Ecotrust. Inclusion of Social Aspects in Life Cycle Assessment of Food. Environmental Assessment and Management in the Food Industry, pp. 219–233 (2010)
284. Gumus, S., Kucukvar, M., Tatar, O: Intuitionistic Fuzzy Multi-criteria Decision Making Framework Based on Life Cycle Environmental, Economic and Social Impacts: The Case of U.S. Wind Energy. Sustainable Production and Consumption, In Press. Available online 27 July 2016
285. Shafer, G.: A Mathematical Theory of Evidence. Princeton University Press, Princeton (1976)
286. S'onmez, M., Holt, G.D., Yang, J.B., Graham, G.: Applying evidential reasoning to pre-qualifying construction contractors. J. Manag. Eng. **18**(3), 111–119 (2002)
287. Hellweg, S., Milà i Canals, L.: Emerging approaches, challenges and opportunities in life cycle assessment. Science. **344**(6188), 1109–1113 (2014)
288. Tang, D.W., Yang, J.B., Bamford, D., Xu, D.L., Waugh, M., Bamford, J., Zhang, S.L.: The evidential reasoning approach for risk management in large enterprises. Int. J. Uncertain. Fuzziness Knowl. Based Syst. **20**(1), 17–30 (2012)
289. Wiedmann, T.O., Suh, S., Feng, K., et al.: Application of hybrid life cycle approaches to emerging energy technologies-the case of wind power in the UK. Environ. Sci. Technol. **45** (13), 5900–5907 (2011)
290. Fthenakis, V., Wang, W., Kim, H.C.: Life cycle inventory analysis of the production of metals used in photovoltaics. Renew. Sust. Energ. Rev. **13**, 493–517 (2009)

291. Moreau, V., Bage, G., Marcotte, D., Samson, R.: Statistical estimation of missing data in life cycle inventory: an application to hydroelectric power plants. J. Clean. Prod. **37**, 335–341 (2012)
292. Klöpffer, W.: Life cycle assessment-from the beginning to the current state. Environ. Sci. Pollut. Res. **4**(4), 223–228 (1997)
293. Wang, Y.M., Yang, J.B., Xu, D.L.: Environmental impact assessment using the evidential reasoning approach. Eur. J. Oper. Res. **174**, 1885–1913 (2006)
294. Xu, X.B., Zheng, J., Xu, D.L., Yang, J.B.: Information fusion method for fault diagnosis based on evidential reasoning rule. Control Theory Appl. **32**(9), 1170–1182 (2015)
295. Yang, J.B., Singh, M.G.: An evidential reasoning approach for multiple attribute decision making with uncertainty. IEEE Trans. Syst. Man. Cybern. **24**(1), 1–18 (1994)
296. Yang, J.B., Xu, D.L.: On the evidential reasoning algorithm for multiple attribute decision analysis under uncertainty. IEEE Trans. Syst. Man. Cybern. Part A: Syst. Hum. **32**(3), 289–304 (2002)
297. Yang, J.B., Wang, Y.M., Xu, D.L., Chin, K.S., Chatton, L.: Belief rule-based methodology for mapping consumer preferences and setting product targets. Expert Syst. Appl. **39**, 4749–4759 (2012)
298. Yang, Z., Onat, N.C., Kucukvar, M., Tatari, O.: Carbon and energy footprints of electric delivery trucks: a hybrid multi-regional input-output life cycle assessment. Transp. Res. Part D: Transp. Environ. **47**, 195–207 (2016)
299. Park, Y.S., Egilmez, G., Kucukvar, M.: A novel life cycle-based Principal Component Analysis framework for eco-efficiency analysis: case of the U.S. manufacturing and transportation nexus. J. Clean. Prod. **92**, 327–342 (2015)
300. Shih, Y.-H., Tseng, C.-H.: Cost-benefit analysis of sustainable energy development using life-cycle co-benefits assessment and the system dynamics approach. Appl. Energy. **119**, 57–66 (2014)
301. Klöpffer, W.: Life cycle assessment. Environ. Sci. Pollut. Res. **4**(4), 223–228 (1997)