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School Buildings Rehabilitation

Indoor Environmental Quality and Enclosure Optimization

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Preface

The objectives of this book are to discuss the effect of different strategies for rehabilitation of school buildings on classrooms' indoor environmental quality (IEQ) and to present a multi-objective methodology for enclosure optimization of school buildings, combining artificial neural networks and life cycle cost.

The energy efficiency of buildings, including public buildings, is a major concern for all European governments. The best strategy to reverse this scenario includes efforts on the rehabilitation of those buildings, improving their energy efficiency, without sacrificing the IEQ.

The IEQ within a classroom is linked to the health, comfort and performance of students. It is well established that there are classroom environments where IEQ is poor. Therefore, the rehabilitation of school buildings is assumed as an appropriate strategy. Consequently, some countries have sponsored nationwide programmes for the rehabilitation of school buildings, whose result has been, in some cases, other than the expected. Classrooms performance in service conditions must be evaluated, and from the results, optimized solutions should be established and carefully designed and executed to have the desired effect. Thus, these interventions must be carefully prepared, and the technical decisions must be scientifically supported to guarantee the economic sustainability of the buildings, often neglected during the design process. The rehabilitation of a school building should be regarded as a procedure of combining a number of variables and objectives, sometimes conflicting, including energy, IEQ and costs (initial, operational and maintenance), on a search for an "optimum solution".

The special features of this book are (a) a state of the art of school building rehabilitation; (b) the IEQ assessment of several school buildings, including non-rehabilitated and rehabilitated, according to different strategies; and (c) the proposed multi-objective optimization procedure.

The main benefit of the book is that it discusses the topics related to rehabilitation of school buildings, presents results of the IEQ assessment on nine school buildings and launches a discussion on how the "in-use" performance of schools is key to understand how designed performance is actually experienced. It maps the most used multi-objective algorithms and artificial neural networks architectures and proposes a methodology for combining these numerical tools with building dynamic simulation and life cycle cost analysis for the school enclosure optimization of buildings. This methodology is appealing to both the scientists and the engineers. At the sametime, this book matches the expectations of a variety of scientific and engineering disciplines, such as civil and mechanical engineering, architecture, and mathematics. The book is divided into several chapters that intend to be a synthesis of the current state of knowledge for benefit of professional colleagues.

The authors acknowledge with gratitude the support received from the University of Porto-Faculty of Engineering, Portugal, namely the Laboratory of Building Physics Laboratory (LFC). Finally, the authors welcome reader comments, corrections and suggestions with the aim of improving any future editions.

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Contents

Chapter 1
Introduction

Abstract This chapter introduces the book, including the motivation and the main objectives. The importance of taking into account the particular characteristics of school buildings is highlighted with emphasis on the ventilation system. The importance of the climate conditions are stressed.

Keywords School building · Ventilation · Climate

1.1 Motivation

An education of excellence is a clear aim of any modern society. Several international studies have been conducted to evaluate students' performance and the factors that most influence it, namely classrooms indoor environmental quality. In recent years, an increased interest in this issue can be observed, being subject of analysis for several researchers.

School buildings rehabilitation is a strategic investment, which aims, among others, to improve energy efficiency ensuring proper indoor environmental conditions. Existing school buildings were not designed to meet current legal requirements related to indoor environmental quality. Therefor these buildings do not guarantee the conditions for thermal comfort, nor the indoor air quality, that people nowadays call.

School buildings have some unique features that distinguish them and that significantly influence their performance, namely the occupancy profile. In a school building occupancy can be very high, reaching up to four times more occupants per square meter than in a typical office building. Moreover, occupants spend much of their time inside classrooms, a value that is only exceeded by the time they spend in their homes. Thus, the following aspects must be highlighted and their effect properly accounted for:

- High occupancy rates correspond to very significant internal heat gains;
- High occupancy rates imply more severe ventilation requirements;

R.M.S.F. Almeida et al., *School Buildings Rehabilitation*,
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- To improve natural lighting, classrooms façades have a large glazing area (often over 50 %), with important consequences on the room total heat balance;
- Shading devices arise as key components by protecting the building from solar overheating.

School buildings rehabilitation should be designed regarding energy efficiency requirements and the optimization of teachers and students' thermal comfort. It should be seen as an optimization procedure, with several constraints and objectives. Objectives related to buildings energy efficiency, thermal comfort, indoor air quality and costs of the solutions adopted (initial, operation and maintenance) should be considered. Thus, the search for the optimum constructive solutions corresponds to a multi-objective optimization problem, some conflicting with each other, since we want to ensure the best comfort conditions and indoor air quality, while minimizing energy consumption and costs.

While preparing a rehabilitation intervention a critical decision should be properly discussed: *Which ventilation strategy should be adopted?* Two perspectives can be considered:

- A strategy based on mechanical ventilation and air-conditioning systems, which will control the thermal comfort and the indoor air quality;
- A strategy focused on combining improvement of buildings enclosure thermal properties with a ventilation system that includes a strong natural component.

On the one hand, choosing the first approach will result in tightly controlled indoor conditions at the price of an increased cost to the schools' budget, not only in systems acquisition and installation but also in their operation and maintenance, since high energy consumption is required and systems require expensive period maintenance. Additionally, poor indoor environmental quality will appear when systems are off, since indoor conditions are totally dependent on those. It is also to be noted that these systems durability raises a number of questions.

On the other hand, less stable temperatures will appear in the second option. In these buildings, occupants' ability to adapt is crucial and envelope properties must be adequate. However, a much lower budget is required. The final result is a more sustainable school building throughout its life cycle.

This choice is nowadays undoubtedly constrained by indoor air quality requirements since very strict conditions lead to limited flexibility in the choice. The use of probabilistic criteria for imposing limits on the thermal comfort and indoor air quality can be a way to soften the legislation, making it more suitable to the reality and enabling more sustainable solutions.

Therefore, measuring the in service performance of school buildings is the key to support future decisions and to help establishing realistic comfort and indoor air quality benchmarks.

1.2 Objectives

It is intended that this book presents an integrated approach to the problem of school buildings rehabilitation, focusing on their hygrothermal performance and related areas, such as energy efficiency, thermal comfort and indoor air quality, always emphasizing the economic aspect in the decision making process. Two main objectives were therefore established:

- Characterize the school buildings in service performance: the measuring the real performance of these buildings is crucial. Both rehabilitated and non-rehabilitated must be studied and results will be the basis to launch a discussion regarding the optimization of constructive solutions;
- To propose an optimization methodology, multi-objective, embracing technical and economic aspects, to be used in school buildings rehabilitation. Advanced simulation and optimization computational tools were used.

Yet, it is important to refer that all the analysis and conclusions presented throughout the book were derived considering the scenario of a mild climate country as in most southern European countries. Obviously, different constructive solutions and recommendations would be derived if more severe climates, either hot and humid or colder, were considered.

Chapter 2
Indoor Environmental Quality

Abstract This chapter starts by explaining the notion of indoor environmental quality. Afterwards a complete description of thermal comfort and indoor air quality is provided. The thermal comfort concept, the factors that most influence it and the criteria for thermal comfort assessment, including the adaptive models, are described in detail. Regarding the indoor air quality, the most important pollutants are presented, including their concentration limits currently in force in Portugal.

Keywords Indoor environmental quality · Thermal comfort · Indoor air quality

2.1 Introduction

The search for a safe and comfortable environment has always been a major concern for humanity. In ancient times people used the experience acquired over the years to achieve adequate living conditions, making the best use of the available resources. The Greek writer Xenophon, in his memoirs, shares some of the teachings of the Greek philosopher Socrates (470–399 BC) about proper orientation of buildings, in order to have cool houses in summer and warm in winter. In the 1st century BC, Romans conceived a technique for central heating based on the use of double floors with a cavity where warm air from a fireplace flows (Florides et al. 2002). Also in the same period, Romans started using materials such as mica or glass for windows, both admitting the entry of light into the house and protecting it from the wind and rain. In Persia, on the other hand, a first effort for night ventilation was tested. Predominant wind was used as cool air during the night, providing a cooler environment during the day (Kreider and Rabl 1994).

In recent decades the occupancy levels of the buildings, the construction practices (lower air permeability of the envelope and the generalized use of heating, ventilation and air conditioning (HVAC) systems) and the users' expectations have dramatically changed, leading to a growing interest in the theme of the indoor environment quality. In fact, nowadays the indoor environment quality is an important factor for the health, comfort and performance of populations, since in developed areas of the

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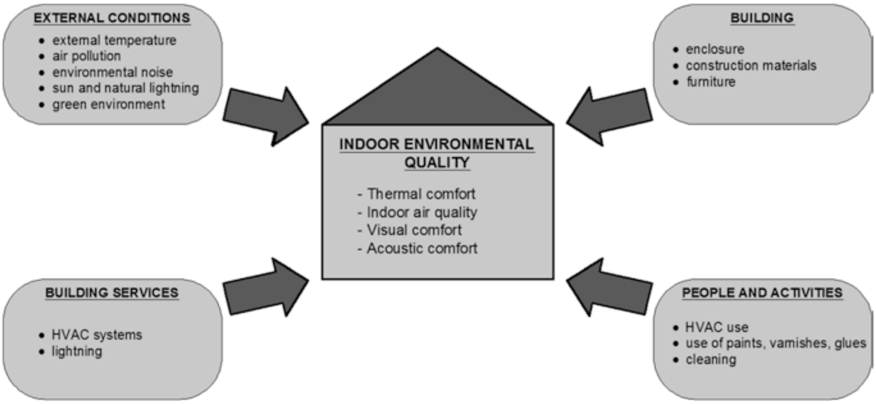

Fig. 2.1 Indoor environmental quality (adapted from REHVA 2010)

planet people spend most of their time inside buildings (Wargocki 2009). In addition, indoor environmental factors significantly affect the energy consumption of a building and, therefore, their evaluation and quantification during the design process has been widely debated (Santamouris et al. 2008; Alfano et al. 2010).

The concept of indoor environmental quality is very broad and depends on many variables such as temperature, relative humidity, air velocity, air flow, occupancy, concentration of pollutants, noise, lighting… These can be grouped into four major areas that define the quality of the environment inside a space, namely (Franchimon et al. 2009; Alfano et al. 2010):

- Thermal comfort;
- Indoor air quality;
- Visual comfort;
- Acoustic comfort.

Indoor environmental quality evaluation depends on numerous factors that can be subdivided into four categories: external conditions, building, building services and human activities (REHVA 2010). Figure 2.1 schematically presents those variables and factors. Within this book objectives only thermal comfort and air quality are discussed and detailed in the following sections.

2.2 Thermal Comfort

2.2.1 Introduction

The classic definition of thermal comfort is the one presented by Fanger (1970) describing it as “the state of mind in which a person expresses satisfaction with the thermal environment”. Afterwards several authors defended that satisfaction with the thermal environment depends, in addition to the physical factors that determine

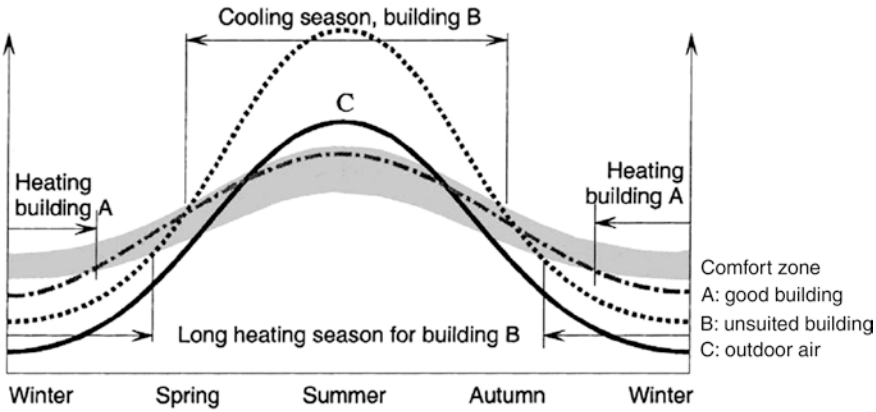

Fig. 2.2 Annual temperature fluctuation on a free floating building (adapted from Roulet 2001)

the heat exchange between the human body and the environment in which he is located (thermal balance), of other factors such as social, cultural and psychological, which justify the different perceptions and responses for the same sensory stimuli. Therefore, users' past experiences and expectations play a key role.

Several researchers had addressed their attention to the evaluation and quantification of thermal comfort in indoor environments. The main idea is to better understand which variables are involved, how it can be achieved, its impact in terms of occupants' health and productivity and how it can be quantified.

According to Chatelet et al. (1998) in a passive building without heating or cooling systems, the indoor environment should be at least as comfortable as the outside environment. This idea is reflected in Fig. 2.2, applicable to residential buildings. The comfort zone is wider in summer than in winter, since people' needs and requirements vary due to changes in their clothing.

An ill-conceived building design will only ensure comfort condition through high energy consumption since HVAC systems must be used for heating in winter and cooling in summer (De Dear and Bragger 1998).

2.2.2 *Thermal Exchanges, Thermoregulation Mechanisms and Heat Balance*

Man is a homoeothermic organism since maintains a relatively constant and warm body temperature independent of environmental temperature. To guarantee this condition body uses oxygen for the process of metabolism, producing internal heat. This energy must be dissipated to guarantee equilibrium. For a person to be comfortable it is necessary that at least his body is in thermal equilibrium, that is, the energy produced must be equal to the losses.

When no equilibrium is achieved, body temperature, which is around 36 ± 1 °C, tends to increase or decrease and might cause health problems and, in extreme cases, even death. For this reason human body has mechanisms to maintain internal temperature approximately constant, which are activated when the external environment conditions exceed certain limits.

The center control organ for human body temperature is the hypothalamus, located in the brain, which has a function similar to a thermostat. The internal temperature may vary slightly depending on the physiological conditions and on the signals that the hypothalamus receives from the nervous system. Thus, in cold environments internal temperature can drop and, consequently, heat losses diminish. Heat is conserved by vasoconstriction (skin blood flow is reduced). Moreover, in warm environments the internal temperature can rise, with increased heat losses. Internal heat is transferred for the skin through vasodilation (skin blood flow is increased) facilitating its transfer to the environment (Astrand and Rodahl 1986).

The thermal exchanges between the human body and the surrounding environment occur through heat transfer from the warmer to the colder element until equal temperatures are established. This corresponds to a heat transfer situation between two systems, enhanced by the temperature difference between them. It can occur in the following ways:

- Conduction: is the transfer of internal energy by direct contact between parts of the body and the surrounding environment due to a temperature gradient;
- Convection: is the transfer of energy between an object and its environment, due to fluid motion (air movement around the human body);
- Radiation: is the transfer of energy by electromagnetic waves between human skin and the surrounding environment due to a temperature gradient;
- Respiration: is the transfer of energy due to a temperature gradient between air breathe in and out;
- Evaporation: is the transfer of energy for the surrounding environment due moisture evaporation from the skin.

A resting adult produces approximately 100 W of heat. If the clothing and the environmental conditions are suitable, the heat losses are equivalent and, therefore, the heat balance is null and the person feels thermally neutral.

With increasing environmental temperature heat exchanges by conduction, convection and radiation decrease and evaporation should compensate to ensure thermal equilibrium. However, evaporation due to sweat is associated with an increase in temperature and might cause a discomfort feeling.

With decreasing environmental temperature heat exchanges by conduction, convection and radiation increase and the total energy losses are higher than the equilibrium value. The physiological response to this condition is to reduce the blood flow, decreasing the temperature gradient. In this situation a cold feeling appears and cloth changing can be the response.

Therefore, to ensure thermal comfort heat exchanges must remain within a relatively narrow range (Nilsson 2004).

As mentioned human thermoregulation mechanisms maintain body temperature approximately constant, forcing for an equilibrium between the internal generated heat and transfers for the surrounding environment (Fig. 2.3).

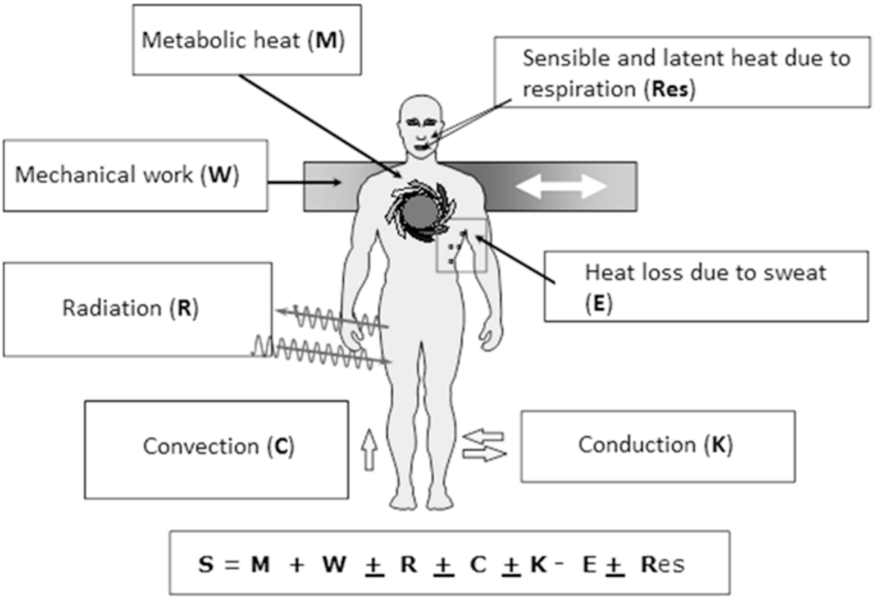

Fig. 2.3 Heat balance of the human body (adapted from Silva 2006)

This balance is described in the following equation where thermal equilibrium corresponds to a null S value:

$$S = M \pm W \pm R \pm C \pm K - E \pm Res \tag{2.1}$$

2.2.3 Factors Influencing Thermal Comfort

According to Fanger (1970) thermal comfort depends on six factors, two individual and four environmental:

- Individual factors: metabolic rate, M [met]; and clothing insulation, I_{CL} [clo];
- Environmental factors: air temperature, T_a [ºC]; mean radiant temperature, T_{mr} [ºC], air velocity, v_{ar} [m/s]; and water vapor pressure, p_a [Pa].

These factors are decisive for equilibrium in steady state conditions. However, besides these, other more subjective (psychosocial parameters) are also important for thermal comfort perception in a given environment (Matias 2010).

Metabolic rate is related to the physiological process by which human beings produce energy from organic substances (metabolic process). The greater the physical activity, greater metabolic production and, consequently, internal heat generation. Metabolic rate is commonly express as generated energy per unit DuBois area. The unit is *met*, defined as the metabolic rate of a sedentary person (seated, quiet): 1 met = 58.2 W/m^2. This value is based on an average male adult (A_D = 1.8 m^2)

(ASHRAE 2009). Metabolic rate depends varies depending on the activity and typical values can be found in ISO 7730 (ISO 2005) and ASHRAE 55 (ASHRAE 2010).

Body exchanges heat with the clothing, which in turn exchanges it with the surrounding environment. These exchanges depend on clothing insulation. Additionally, garment also has the effect of reducing the body's sensitivity to air velocity and temperature variations. Clothing insulation depends on several factors such as type of fabric, fiber and body fit, and it can be expressed in *clo* units: 1 clo = 0.155 (m^2 K)/W. Typical values for clothing insulation can be found in ISO 7730 (ISO 2005) and ASHRAE 55 (ASHRAE 2010).

Air temperature is the most important variable for thermal comfort quantification, since the sense of comfort in based on heat exchanges between body and environment and, therefore, enhanced by the temperature gradient between them (Lamberts 2005). Sometimes, only air temperature is used to establish comfort conditions. Portuguese regulation defines comfort based on air temperature: 20 ºC in winter and 25 ºC in summer.

Mean radiant temperature is defined as the uniform surface temperature of an imaginary enclosure in which an occupant transfers the same amount of radiant heat as in the actual non-uniform enclosure (ASHRAE 2010). It is the weighted average of the surrounding surfaces temperature of the enclosure, including the effect of solar radiation. Mathematically the exact calculation of this parameter is not simple since besides being required temperature, emissivity and area of all surfaces, it is also necessary to quantify angle factors between the person and each surface. Furthermore, when direct exposure to solar radiation is present, complexity significantly increases (Matias 2010). Thus, in practice an estimation of mean radiant temperature is used, based on measurements through a globe thermometer.

Air velocity is defines as the magnitude of the air flow velocity vector at the measuring point. It is important to include its effect in indoor environments due to its direct involvement in heat exchanges by convection and evaporation. In indoor environments air velocity is independent of wind and typically ranges below 1 m/s. Air movement occurs due to a temperature gradient, where hot air rises and cold air sinks (natural convection). When air movement is forced, by a fan for instance, convection coefficient rises, increasing heat losses (forced convection). Air velocity also has an effect on heat losses due to evaporation by removing moisture from the skin surface more efficiently, reducing the feeling of warm (Lamberts 2005).

Water vapor pressure is directly related to relative humidity. Corresponds to the pressure which water vapor would exert if it occupies the entire volume occupied by the moist air at the same temperature. It is formed by water evaporation. At a given temperature air can only contain a certain amount of water (saturated air), and above this value the condensation phenomenon occurs, increasing the surface temperature where it occurs. This process enhances the heat transfer between one body losing heat by evaporation, which is transferred to another where condensation occurs.

Water vapor pressure and air velocity are involved in heat exchanges by evaporation. Since approximately 25 % of generated body energy is eliminated as latent heat, it is important to guarantee environmental conditions which enhances these losses. As air temperature increases, convection and radiation losses decrease and body have to compensate by increasing evaporation. The higher the relative humidity, the lower the evaporation efficiency, and, therefore, suitable ventilation is required to control the amount of water vapor in the air.

2.2.4 Criteria for Thermal Comfort

For many years, the correct combination of environmental factors that leads to comfort conditions has been pursued by numerous researchers. Thus, several attempts have been proposed to quantify an indoor environment on a single hygro-thermal index. The idea is to use it to establish admissible comfort limits for that environment. Typically, environmental parameters are combined for constant values of metabolic rate and clothing insulation—charts and nomographs.

In the 70's, based on Fanger's studies, ASHRAE presented a seven-level scale for thermal comfort assessment (Table 2.1). This scale became dominant in thermal comfort studies, being adopted in ISO 7730 (ISO 2005) and ASHRAE 55 (ASHRAE 2010) standards.

Fanger (1970) derived a general equation of comfort that attempts to include the effect of individual and environmental factors. This index estimates the average vote for a group of persons of different nationalities, ages and sexes, according to the previous mentioned scale (Table 2.1) and was designated as *Predicted Mean Vote* (PMV). The PMV equation was derived from a statistical analysis of the results obtained in numerous experiments (more than 1300) carried out under controlled environmental conditions where people were asked to quantify the environment. PMV can be used both for thermal comfort verification and to establish minimum acceptable limits for a specific comfort level. Although it was derived for steady-state conditions, it can be used as a good approximation when one or two input parameters have small variations. Fanger also suggested that the percentage of people who considered the environment as uncomfortable (feeling hot or cold) is related to their average vote, defining a second index called the *Predicted Percentage Dissatisfied* (PPD). The relationship between the two indices is as follows:

$$PPD = 100 - 95 \times e^{\left(-0.03353 \times PMV^4 - 0.2179 \times PMV^2\right)} \tag{2.2}$$

According to this model it is impossible that all people feel comfortable in a given space for a given time. Even for a thermal comfort condition in which the average vote corresponds to a sense of neutral/comfortable, which corresponds to a PMV = 0, there are still 5 % of people uncomfortable.

Table 2.1 Thermal comfort scale (adapted from ISO 2005 and ASHRAE 2010)

+3	Hot	*Uncomfortable*
+2	Warm	
+1	Slightly warm	*Comfortable*
0	Neutral	
−1	Slightly cool	
−2	Cool	*Uncomfortable*
−3	Cold	

Table 2.2 Thermal environment categories (adapted from ISO 2005)

Category	Thermal state of the body as whole	
	PPD [%]	PMV
A	<6	$-0.2 < \text{PMV} < +0.2$
B	<10	$-0.5 < \text{PMV} < +0.5$
C	<15	$-0.7 < \text{PMV} < +0.7$

PMV and PPD are commonly used as reference values in international standards to establish comfort conditions. ASHRAE Standard 55 (ASHRAE 2010) states that the condition to be met is:

$$-0.5 < \text{PMV} < +0.5 \text{ or } PPD < 10\,\%$$

This condition also appears in standard ISO 7730 (ISO 2005), corresponding to category B. This standard proposes three categories (A, B and C) to classify buildings thermal environment. This approach considers that comfort limits do not have to be the same in all spaces, since local or technical conditions may suggest different targets. The limits proposed by the standard are presented in Table 2.2.

A simplified graphical method (Fig. 2.4) to evaluate thermal comfort is also proposed by ASHRAE Standard 55 (ASHRAE 2010). This method is applicable to environments with air velocity below 0.2 m/s, where the occupants' activities are sedentary (ranging between 1.0 and 1.3 met) and clothing insulation varies from 0.5 to 1.0 clo.

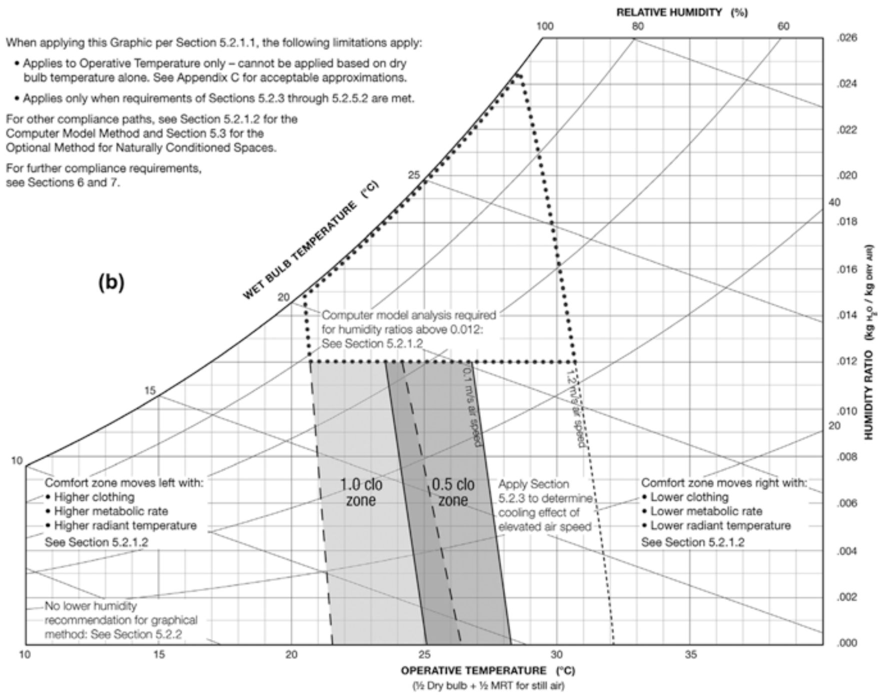

Fig. 2.4 Graphic comfort zone method (ASHRAE 2010)

The comfort zone is for 80 % occupant acceptability, resulting from the combined effect of 10 % dissatisfied due to discomfort related to the whole body and 10 % that may occur from local thermal discomfort.

2.2.5 Adaptive Models

There are two ways of tackling thermal comfort issues. The first, previously described, corresponds to an analytical approach, based on experimental results in climatic chambers and using the heat balance equation considering a steady state regime. The second approach, called adaptive model, assumes a dynamic regime in which an individual can interact physically and psychologically with the environment that surrounds him. This alternative method to the conventional theory of thermal comfort believes that an individual has a fundamental role in the creation of his own thermal environment, through the way he interacts with the environment, modifying behaviors and habits or gradually adapting his expectations (Brager and de Dear 1998).

The interest in adaptive thermal comfort models began in the 70's in response to the energy crisis experienced at the time and, in recent years, regained interest from the scientific community due to climate changes. Allowing people to control the indoor environment, letting the interior air temperature to be closer to the exterior, may correspond to an important improvement in both comfort conditions and energy consumption (Milne 1995).

Adaptive models usually considered three forms of adaptation to the environment (De Dear et al. 1997):

- Behavioral: all actions consciously or unconsciously taken to ensure thermal equilibrium;
- Physiological: changes performed by the thermoregulation mechanisms, during a certain period of time, to adjust the body response to the environmental conditions;
- Psychological: effects of cognitive and cultural variables, and describes the extent to which habituation and expectation alter thermal perceptions.

Adaptive models are also present in international standards such as ASHRAE 55 (ASHRAE 2010), which includes a graphical method for indoor thermal comfort evaluation (Fig. 2.5).

This method can be applied to spaces where the occupants are engaged in near-sedentary physical activities, with metabolic rates ranging from 1.0 to 1.3 met. The base equation of the model was proposed by Brager et al. (2004), which establishes the indoor operative temperature, T_{oc}:

$$T_{oc} = 17.8 + 0.31 \cdot T_m \tag{2.3}$$

in which

T_{oc} [ºC] Indoor operative temperature
T_m [ºC] Mean monthly outdoor air temperature

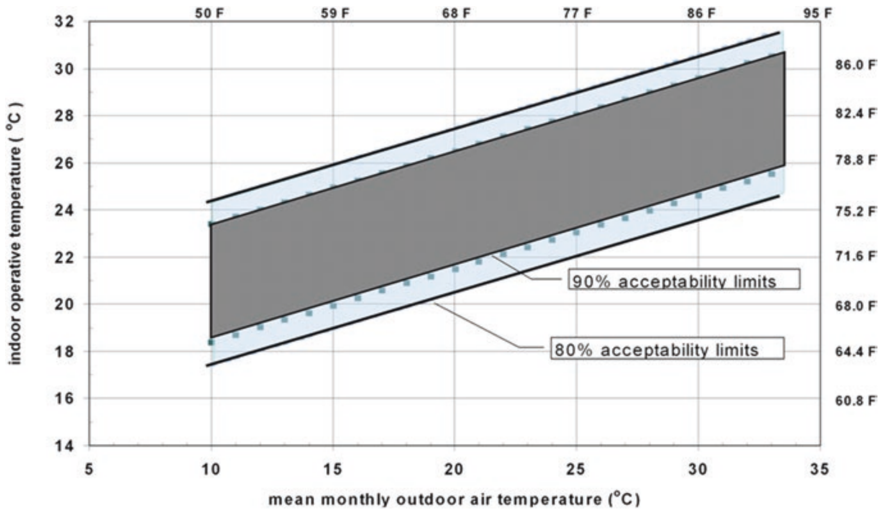

Fig. 2.5 ASHRAE adaptive model (ASHRAE 2010)

The 80 % acceptability limits are for typical applications and accepts ±3.5 ºC around the comfort temperature; the 90 % acceptability limits should be used when a higher standard of thermal comfort is desired and accepts ±2.5 ºC around the comfort temperature.

2.3 Indoor Air Quality

2.3.1 Introduction

Acceptable indoor air quality is defined in ASHRAE standard 62.1 (ASHRAE 2004) as air where there are no known contaminants in hazardous concentrations, determined according with the recognized authorities recommendations, and where a majority (at least 80 %) of the exposed occupants do not express dissatisfaction.

Over the past years, efforts were made in the building industry to increase indoor thermal comfort. In the 70's, the oil crises emphasized the need for energy conservation and building airtightness was improved, minimizing heat losses. However, inside buildings pollutants are also produced. In fact, indoor air quality can affected by various contaminants, not only from external sources but also internal ones. The outside air enters the building through ventilation and, additionally, furniture, construction materials, people and poor maintenance of HVAC systems can be a source of indoor pollution (REHVA 2010).

In 1984, a World Health Organization (WHO) report (1984) indicated that 30 % of buildings, new or rehabilitated, revealed excessive levels of air pollutants. This

Table 2.3 Pollutants concentration limits

Pollutants	Concentration limit
Particulate matter, PM_{10}	50 $\mu g/m^3$
Particulate matter, $PM_{2.5}$	25 $\mu g/m^3$
Volatile organic compounds, VOCs	600 $\mu g/m^3$
Carbon monoxide, CO	10 mg/m^3/9 ppm
Formaldehyde, CH_2O	100 $\mu g/m^3$/0.08 ppm
Carbon dioxide, CO_2	2250 mg/ m^3/1250 ppm
Radon, Rn	400 Bq/m^3

problem led to the "Sick Building Syndrome", used to describe situations in which building occupants suffer from health problems related to the time they spend inside the building and no specific cause can be detected.

2.3.2 Indoor Air Pollutants

Indoor air quality must on the one hand prevent pollutants from reaching concentrations that may endanger occupants' health and on the other maintain a pleasant environment (Viegas 2000).

In Portugal, indoor air quality is regulated in a national standard, which defines concentration limits for the most common indoor pollutants (see Table 2.3).

When one analyses indoor air quality in educational buildings, carbon dioxide arises as the most important indicator since it is a product of human respiration and typically these buildings present high occupancy levels. Therefore, in several international standards, is common to find carbon dioxide maximum concentration as the air quality criterion for classrooms.

Carbon dioxide is an odorless, tasteless and colorless non-flammable gas, which is present in exterior air with concentrations around 380 ppm (680 mg/m^3) (in unpolluted regions).

Usually, CO_2 concentration in buildings is very low and, therefore, harmless. However, in very high concentrations, which can occur in classrooms due to their high occupancy and low levels of ventilation, CO_2 can cause breathing problems, difficulty in concentration and headaches.

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Chapter 3
Optimization and Approximation Methods

Abstract This chapter describes the basic mathematical formulation of the Artificial Neural Networks and the multi-objective optimization methods. The concept of Artificial Neural Network is presented and its potential for engineering applications is highlighted. The multi-objective optimization problem is described and formulated and the evolutionary algorithms are described as very promising tools for solving this kind of problems.

Keywords Artificial neural networks · Optimization · Evolutionary algorithms

3.1 Introduction

One goal of this book is to present an optimization methodology that can be used to selecting the most adequate constructive solutions in rehabilitation of school buildings. The objectives used in the optimization are buildings energy efficiency and indoor environmental quality and the life cycle cost of the solutions. Therefore, it is a multi-objective optimization procedure: maximization of IEQ and comfort while minimizing energy consumption and cost.

To properly evaluate the effect of a certain constructive solution in buildings thermal and energy performances, the use of simulation software, such as EnergyPlus, is required. However, when one intends to simulate complex models, for long periods of time (annual simulations), the procedure becomes very time-consuming and computationally demanding. Since multi-objective optimization algorithms require many iterations it becomes practically impossible to use them directly with the simulation software.

In order to overcome this problem Artificial Neural Networks (ANN) were trained to approximate the results of computational simulation and in this way

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significantly decreasing the time required for the optimization. After ANN validation, two optimization approaches were tested:

- Weight method: each objective function was affected by a certain weight that reflects its importance for the decision-maker; afterwards they are all combined in one single function that is optimized;
- Multi-objective optimization: a complete multi-objective optimization is performed and the Pareto front of optimum solutions is obtained.

3.2 Artificial Neural Networks

The use of ANN started in the 40's with a research by McCulloch and Pitts (1943), who showed that, in theory, an ANN can approximate the value of any arithmetic or logical function. They can learn from examples and are able to deal with non-linear problems.

The first practical application of an ANN appeared in the late 50's by Rosenblatt (1958) in the field of pattern recognition. Afterwards the research on ANN had great advances in the 80's. Two reasons help to explain it. Computers become more powerful and affordable, and two new fundamental ideas emerged: the use of statistical methods to explain the behaviour of some types of neurons and the introduction of the backpropagation algorithm for networks with multiple neuronal layers (Hagan et al. 1996).

The structure of ANN is based on the human brain central nervous system. It comprises a network of interconnected neurons that, when properly trained, are capable of self-learning, and thereafter may respond to stimuli (Patterson 1996). In such a system, excitation is applied to the input of the network. Following some suitable operation, it results in a desired output. At the synapses, there is an accumulation of some potential, which in the case of artificial neurons, is modelled as a connection weight. These weights are continuously modified, based on suitable learning rules (Kalogirou 1999). Thus, it is a mathematical model defined by three parameters: neurons, network architecture and learning algorithm.

Figure 3.1 shows a typical ANN structure with 2 inputs, 2 layers of 3 neurons and 1 output.

ANN operate like "black box" models, requiring no detailed information about the system. Instead, they learn the relationship between the input parameters and the controlled and uncontrolled variables by studying previously recorded data (Kalogirou 1999).

Each single node of an ANN is a processing unit (neuron). It receives a signal, x_i, from the input or from preceding neurons, and applies a specific weight, w_i, on this signal. First, these are added, and possibly affected by a bias, b, and the result is then passed through an activation function, f, which generates the neuron's output, Y. Figure 3.2 illustrates the procedure.

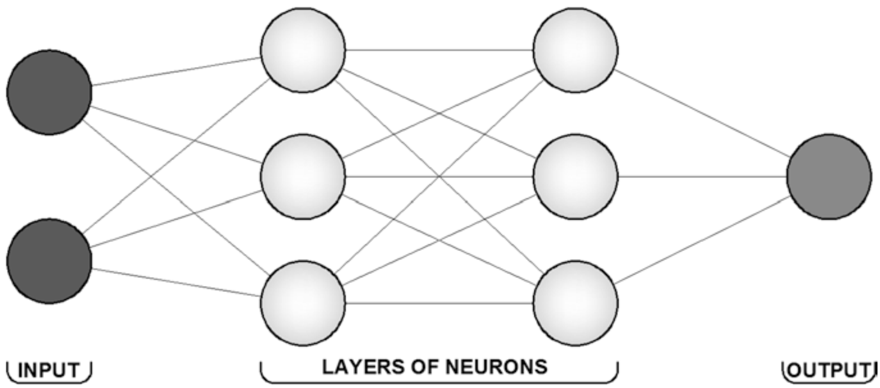


Fig. 3.1 ANN architecture

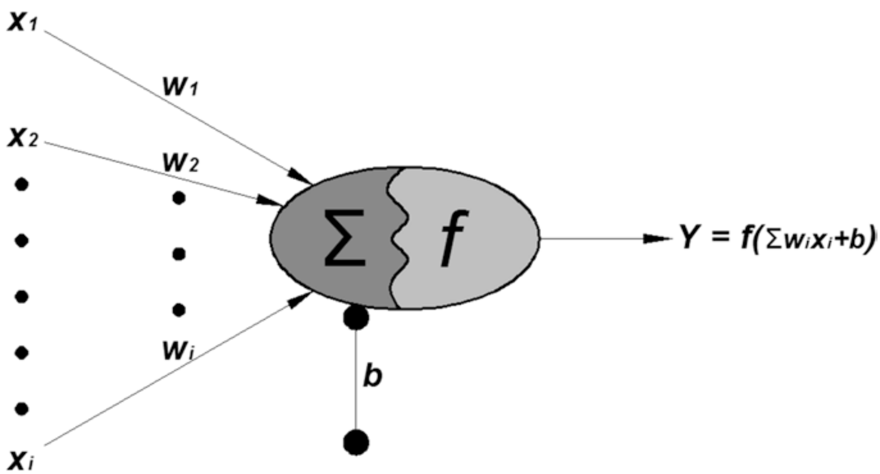


Fig. 3.2 Neural network processing unit (neuron)

There are several activation functions which can be selected. However, only three are commonly used (Fig. 3.3): *hard-limit* function, *linear* function and *log-sigmoid* function.

There are no theoretical limit for the number of inputs, outputs and neurons of an ANN. Yet, increasing complexity of the network, especially large number of neurons on the intermediate layers, leads to increasing processing time. The number of neurons is also crucial for the accuracy of the ANN. According to MatLab (2006), an ANN with 2 layers of neurons, which uses a log-sigmoid activation function on the former and a linear function on the latter, should be able to approximate any function with a finite number of discontinuities.

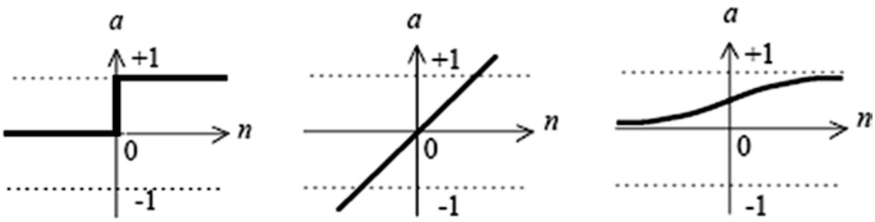


Fig. 3.3 Activation functions (Hagan et al. 1996)

The underlying concept of an ANN is learning. From the moment that the number of layers, the number of neurons and the activation functions are selected, the ANN starts an iterative learning process where each neuron weights, w_i, are modified to approximate a pre-established objective. This procedure is called training and requires a set of data containing inputs and respective outputs.

This set of data must be accurate (typically results from experiments or computer simulation), in sufficient quantity and must represent the all space of the system that the ANN is supposed to estimate. The training set has to be a representative collection of input-output examples. After training, the ANN should be tested and validated using a new set of data different from the initial. The ANN processes these new data and the results are compared. An error of 5 % is usually considered as acceptable (Magnier and Haghighat 2010).

The most popular algorithms are the back-propagation and its variations. The back-propagation algorithm is one of the most powerful learning algorithms in neural networks. Back-propagation training is a gradient descent algorithm, which tries to improve the ANN performance by reducing the total error by changing the weights along its gradient.

3.3 Optimization and Evolutionary Algorithms

Optimization is the continuous process of finding and comparing solutions of a given problem until no better solution can be found (Deb 2001).

Multi-objective optimization is a decision problem where two or more, usually conflicting, objectives are present. The main difference from single-objective optimization is that a multi-objective optimization problem has more than one optimal solution, each representing a compromise between objectives.

Solving multi-objective optimization problems is a mathematically complex task and in most situations results in a very time consuming procedure. One simply way to avoid this complexity is to group all the objectives in one single function and then calculating a single fitness value. In this method each objective is affected by a weight that reflects its importance for the decision-maker. The problem of this method is to be very subjective as it leaves the decision maker in charge of defining the weights, assuming that he has a prior knowledge of their relative importance.

3.3.1 Mathematical Formulation and Main Concepts

A multi-objective optimization problem includes several objective functions to be optimized (maximize or minimize) by the solution X. These functions may be constrained. Thus, a multi-objective optimization problem can be formulated as follows (Deb 2001):

$$\begin{array}{lll} \text{Minimize/Maximize} & f_m(X), & \mathrm{m} = 1, 2, \ldots, \mathrm{M}; \\ \text{Subject to} & g_j(X) \geq 0, & \mathrm{j} = 1, 2, \ldots, \mathrm{J}; \\ & h_k(X) = 0, & \mathrm{k} = 1, 2, \ldots, \mathrm{K}; \\ & x_i^{(\mathrm{inf})} \leq x_i \leq x_i^{(\mathrm{sup})}, & \mathrm{i} = 1, 2, \ldots, \mathrm{n}. \end{array} \tag{3.1}$$

One solution of the problem corresponds to a vector X, n-dimensional corresponding to the decision variables: $X = (x_1, x_2, \ldots, x_n)^{\mathrm{T}}$.

The latter set of restrictions defines the upper and lower bounds, $x_i^{(inf)}$ and $x_i^{(sup)}$, defined for each decision variable. These limits constitute the decision variable space or simply the decision space, D.

The problem is constrained by J inequality and K equality constraints (Eq. 3.1). Every solution that simultaneously satisfies all the imposed limits and constrains is considered as feasible. The set of feasible solutions corresponds to the feasible part of the decision space, S ($S \subset D$). Therefore, not all the solutions belonging to the decision space are feasible solutions.

Typically, to simplifying procedures, all the functions are converted into minimization problems through the following equation:

$$\max(Z) = -\min(-Z) \tag{3.2}$$

Contrary to the single-objective optimization problems, in multi-objective optimization, in addition to the decision space, also the objective functions constitute a multidimensional space. This additional space is called the objective space, Z. For each solution X of the decision space there is a corresponding point in the objective space defined by $f(X) = Z = (z_1,\ z_2,\ \ldots,\ z_M)^{\mathrm{T}}$. Figure 3.4 illustrates this relation using an example case with three decision variables and two objective functions.

Passing from single to multi-objective optimization introduces a new challenge: how to compare solutions as each corresponds to a vector instead of a single value. In single-objective optimization the solution space can be organized according to the objective function as for any two solution, x_1 and x_2, $f(x_1) \leq f(x_2)$ or $f(x_2) < f(x_1)$. This is not true when more than one objective function is present as illustrated in Fig. 3.5, where four solutions (a, b, c and d) of a two objective ($f_1(x)$ and $f_2(x)$) optimization (minimization) problem are shown (Costa 2003).

Solution a is better than solution c in both objectives. On the other hand, solution b is better than solution d as, although equal in the second objective, it performs better in the first. However, when comparing solutions a and b no choice can be made as solution a is better in the second objective while solution b is better in the first.

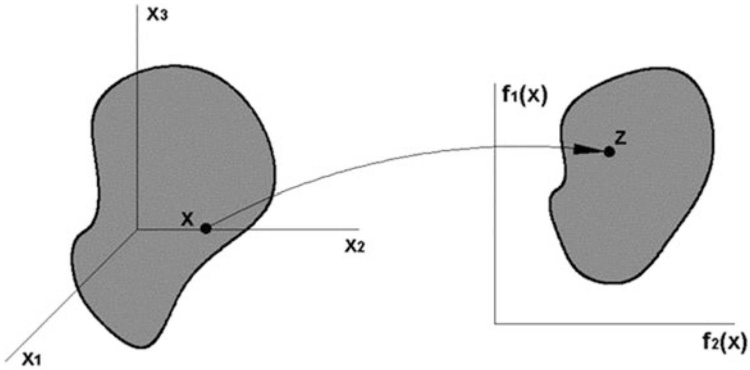
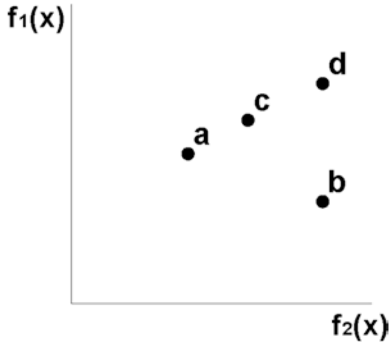


Fig. 3.4 Variable and objective spaces

Fig. 3.5 Solutions in the objective space



The concept of Pareto dominance arises as a solution for these problems as it enables comparison of the solutions. Solution x_1 dominates solution x_2 ($x_1 \prec x_2$) if the following two conditions are verified: (1) solution x_1 is no worse than solution x_2 in all objectives; (2) solution x_1 is better than solution x_2 on at least in one objective. These conditions can be mathematically formulated as follows (minimization problem):

$$f_m(x_1) \leq f_m(x_2) \forall\, m \in \{1, \ldots, M\} \wedge \exists\, i \in \{1, \ldots, M\} : f_i(x_i) < f_i(x_2) \quad (3.3)$$

Using the concept of Pareto dominance one can conclude that on multi-objective optimization a dominant solution is the best choice. Therefore, through dominance relations solutions can be classified and organized and the Pareto rank can be established. The best rank corresponds to the most dominant solutions.

The binary dominance relation has several import properties for multi-objective optimization such as transitivity (if $x \prec y$ and $y \prec z$ then $x \prec z$), asymmetry (if $x \prec y$ then $y \nprec x$) and non-reflexivity ($x \nprec x$). Yet, several other conditions exist. Table 3.1 synthesizes the most relevant, including the corresponding notation and interpretation (Justesen 2010).

Table 3.1 Dominance relations

Relation	Notation	Interpretation
Strictly dominates	$x \prec\prec y$	$f_m(x) < f_m(y) \quad \forall\, m$
Dominates	$x \prec y$	$f_m(x) \leq f_m(y) \quad \forall\, m \wedge \exists i : f_i(x) < f_i(y)$
Weakly dominates	$x \preceq y$	$f_m(x) \leq f_m(y) \quad \forall\, m$

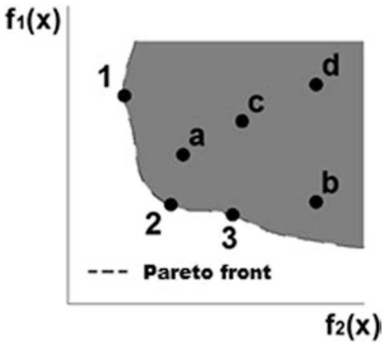


Fig. 3.6 Pareto front

The Pareto dominance can be used as criterion for comparing and selecting solutions in the context of multi-objective optimization. One solution x will be a Pareto optimal if no other solution of the feasible space dominates it. Optimal Pareto solutions are characterized by not allowing the improvement of one objective without degrading of, at least, one of the others. The set of optimal Pareto solutions is called Pareto front. The mathematical formulation of a Pareto optimal solution is the following:

$$\neg\exists y \in S : y \prec x \tag{3.4}$$

In Fig. 3.6, solutions *1*, *2* and *3* are Pareto optimal and, therefore, indifferent among as no dominance between can be found.

In this way, a multi-objective optimization procedure can be defined as the search for the Pareto optimal solutions through an efficient solution algorithm. After the determination of the Pareto front the decision maker establish his own criteria according to the importance given to each objective. This methodology is schematically represented in Fig. 3.7.

3.3.2 The Weighted Sum Approach

The Weighted Sum Method simplifies a multi-objective optimization problem to a single-objective one, using one single function aggregating all the objectives and affects each by a pre-established weight defined by the decision maker. With this simplification the mathematical procedure is much easier to implement. The weight selected for each objective should reflect the relative importance of the objective for the decision maker in the context of the optimization problem.

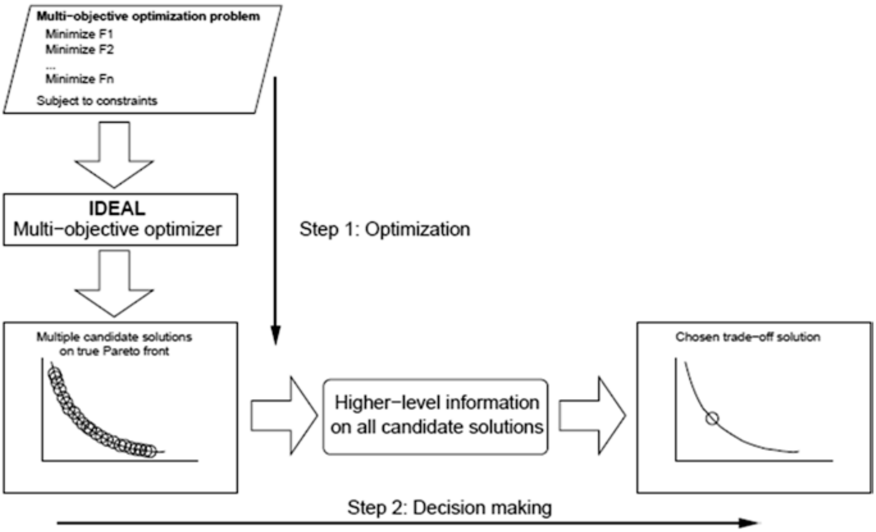


Fig. 3.7 Multi-objective optimization procedure (Justesen 2010)

Therefore, subjectivity is introduced in the process. When selecting the weights one should also take into account the magnitude of the objective functions, which can be very different. To overcome this issue, the objective functions can be normalized. The most common procedure for it is the following:

$$f_m^{trans}(x) = \frac{f_m(x) - f_m^0}{f_m^{\max} - f_m^0} \tag{3.5}$$

in which

$f_m^{trans}(x)$ [-]	Normalized function
$f_m(x)$ [-]	Original function
f_m^0 [-]	Minimum value of the original function
f_m^{max} [-]	Maximum value of the original function

Using this methodology objective functions range from 0 to 1, which guarantees the same magnitude among them.

After normalization, the single objective function is defined as a linear combination of the objectives, affected by the corresponding weights, and the new single objective optimization problem can then be formulated as follows:

$$\begin{array}{lll} \text{Minimize} & F(X) = \sum_{m=1}^{M} w_m \cdot f_m^{trans}(x), & \text{m} = 1, 2, \ldots, \text{M}; \\ \text{Subject to} & g_j(X) \geq 0, & \text{j} = 1, 2, \ldots, \text{J}; \\ & h_k(X) = 0, & \text{k} = 1, 2, \ldots, \text{K}; \\ & x_i^{(\text{inf})} \leq x_i \leq x_i^{(\text{sup})}, & \text{i} = 1, 2, \ldots, \text{n}. \end{array} \tag{3.6}$$

All the variables have the same meaning as in the multi-objective procedure and coefficient w_m corresponds to (assigned to) function m. The weights must accomplish the following conditions:

$$w_m \in [0, 1] \wedge \sum_{m=1}^{M} w_m = 1 \tag{3.7}$$

This methods assumes that the decision process is made before the minimization as the weights assigned to each objective are crucial for the final solution. The solution of this single-objective optimization process leads to one single solution, which will be a Pareto optimal, if positive weights are used. Therefore, if different weight combinations are used, a set of Pareto solutions will be found. However, the main disadvantage of this method is that it will never discover all the optimal solutions if the Pareto front is non-convex as in Fig. 3.6, where point *3* cannot be obtained. Moreover, determining multiple solutions implies running the algorithm several times, losing in this way the added value associated with the processing time.

3.3.3 Evolutionary Algorithms

One possible procedure for multi-objective optimization is through the use of evolutionary algorithms. These algorithms are based on Darwin's theory of evolution and encompass the concept of survival of the fittest. In evolutionary algorithms each solution is considered as an individual of a given population, where their strength is measured by how it resolves, better or worse, the problem under study. In the population, individuals can cross to create offspring, causing parents and children to compete with each other for inclusion in the new generation. Since only the stronger, better solutions to the problem, will survive, the population will iteratively being improved in every generation.

The great advantage of evolutionary algorithms is the use of a set of solutions (population) in each generation, rather than a single solution for improvement, becoming more efficient in searching for the Pareto optimal solutions. Moreover, a multi-objective optimization seeks to find a set of well distributed Pareto optimal solutions. Evolutionary algorithms, using mechanisms to preserve the diversity of the solutions in the population, can provide a set of solutions which represent the entire objective space.

An evolutionary algorithm is a stochastic method based on probabilistic operators. Thus, in contrast to deterministic algorithms, evolutionary algorithms, for the same problem, may produce different solutions each time they are used.

In recent decades several evolutionary algorithms have been proposed and can be divided into two groups, depending on the use or not of the concept of elitism. The use of elitism ensures that valuable solutions are not lost during the process and the quality of the solutions can only improve.

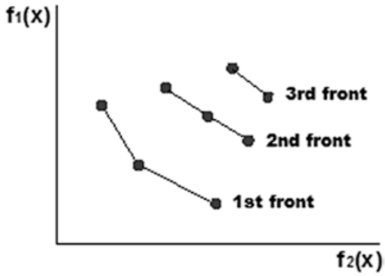


Fig. 3.8 Distribution of the solutions in fronts (adapted from Costa 2003)

The first group, which does not include elitism, contains the first evolutionary algorithms, including the *Vector Evaluated Genetic Algorithm* (VEGA) (Schaffer 1985), the *Multiple Objective Genetic Algorithm* (MOGA) (Fonseca and Fleming 1993), the *Niched Pareto Genetic Algorithm* (NPGA) (Horn et al. 1994) and the *Non-dominated Sorting Genetic Algorithm* (NSGA) (Deb et al. 2000).

The second group, which includes elitism, contains the most recent algorithms. The first was the elite evolutionary algorithm *Non-dominated Sorting Genetic Algorithm II* (NSGAII) (Deb et al. 2000), followed by the *Strength Pareto Evolutionary Algorithm* (SPEA2) (Zitzler et al. 2001).

The NSGAII algorithm was selected for our research as it is an algorithm that is properly validated and tested and it is available in a Toolbox of MatLab. This algorithm is the most efficient in terms of convergence and diversity of solutions (Zitzler et al. 2000; Jain et al. 2005). The structure is relatively simple and thus requires less computational effort, and hence less processing time, than other algorithms.

The NSGAII algorithm uses the concept of ranking among individuals in order to classify them into fronts, according to the degree of dominance. Thus, those who are in the first front are considered the best solution of that generation, while in the last front are the worst (Fig. 3.8).

Additionally the NSGAII algorithm includes a key operator, the Crowding Distance. After the individuals classification, and consequent placement in fronts, this operator will sort them according to their distance to neighbouring points in the same front. To ensure the diversity and representativeness of the solutions in the objective space, thereby spreading the Pareto front, individuals who experience a greater Crowding Distance are preferred over others.

Thus, after sorting in fronts and calculating the Crowding Distance, the selection of the next generation can procede. Using this methodology, the algorithm proceeds iteratively until it reaches the solutions which constitute the Pareto front.

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Chapter 4
Indoor Environmental Quality in Classrooms: Case Studies

Abstract This chapter presents the results of the in-situ evaluation of the hygrothermal performance of classrooms of 9 Portuguese school buildings (2 non-retrofitted and 7 recently retrofitted). Temperature, relative humidity and carbon dioxide concentration were monitored in continuum for at least 1 week in each classroom. Results are analysed and discussed.

Keywords Temperature · Relative humidity · Carbon dioxide · Classrooms

4.1 Introduction and Motivation

Excellence in education is a clear aim of any modern society. Several international studies have been conducted to evaluate student's performance and factors that most influence it, namely classrooms indoor environmental quality (Daisey et al. 2003; Bakó-Biró et al. 2012).

Environmental conditions inside classrooms, including the effect of temperature and indoor air quality, influence students' health, attitude and performance. It is well established that there are classroom environments where indoor environmental quality is poor (Daisey et al. 2003; Higgins et al. 2005; Heudorf et al. 2009; Madureira et al. 2009; Haverinen-Shaughnessy et al. 2011; Gładyszewska-Fiedoruk 2013; Ramalho et al. 2013; Michelot et al. 2013). Knowing that children spend a large amount of their time inside school buildings and that they are more susceptible than adults to the adverse effects of indoor pollutants, since their ratio of air breathed volume versus weight is greater and their tissues and organs are still growing, the rehabilitation of school buildings is assumed as an appropriate strategy, and that will have repercussions throughout the school environment, ensuring that users have the adequate conditions for carrying out their work. This issue has gained particular importance in recent years and has been studied by several researchers (Shendell et al. 2004; Mendell and Heath 2005; Wargocki and Wyon 2007; Clements-Croome et al. 2008; Bakó-Biró et al. 2012; de Giuli et al. 2012; Conceição and Lúcio 2006; Wargocki and Wyon 2013).

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Furthermore, the rehabilitation of school buildings is also an exceptional opportunity to guarantee a significant improvement in their energy efficiency, which is essential, since these buildings are responsible for a large percentage of the energy consumption in the public sector. In 2002, the Directive 2002/91/EC (EPBD 2002) of the European Parliament and Council was published, recently recast by Directive 2010/31/EU (EPBD 2010), with the main objective of "to promote an improvement in the energy performance of buildings", establishing very tough targets for the reduction of energy consumption. It sets the year 2020 as the date on which all new buildings must be "Nearly Zero Energy Buildings", and in public buildings the date is anticipated to 2018 (EPBD 2010). In relation to school buildings, in Europe there is a growing concern and awareness of the need for the use of sustainable strategies, measures and constructive solutions, both in new and renovated buildings. In a study sponsored by the International Energy Agency (IEA) in order to assess the impact of different strategies for the rehabilitation of school buildings concerning their energy consumption, it was found, by analysing actual cases, that the heating load can be reduced by up to 75 % and the electricity consumption can be reduced by 40 % (Erhorn-Kluttig et al. 2005). Yet it must be referred that this study was developed in northern European countries.

Consequently, some countries have sponsored nationwide programs for school buildings rehabilitation, whose result has been, in some cases, other than the expected. Several studies have shown that the performance of buildings after rehabilitation is substantially different from that assumed in the design stage (Mumovic et al. 2009; Guedes et al. 2009; Jenkins et al. 2009; Al-Rashidi et al. 2012). Typically, the indoor temperature is higher than the one predicted. In fact, the models used in codes of practice have proved inadequate in some situations, since the users' behaviour is impossible to predict with accuracy. Sociological and cultural aspects are sometimes crucial for the understanding of their behaviour (de Dear and Bragger 1998). Table 4.1 presents the hygrothermal requirements in several international standards.

Classrooms performance in service conditions must be evaluated and, from the results, optimized solutions should be established and carefully designed and executed to have the desired effect. This is particularly important in a time of severe economic crisis, with few available financial resources and, as such, their management and the

Table 4.1 Hygrothermal requirements in classrooms

Country [standard]	Temperature [°C]		Relative humidity [%]	
	Winter	Summer	Winter	Summer
Portugal [RECS]	20–25		–	–
United Kingdom [building bulletin 87 and 101]	18	24 ± 4[a]	–	<70[b]
Germany [DIN 4108 and DIN 4701]	20–23	<26	40–60	
Finland [National building code—Part D2]	21 ± 1	<25	–	–
USA [ASHRAE 62.1]	–	–	≤65	
Europe [EN 15251][c]	20	26	–	–

[a]This value can be exceeded during 80 h/year
[b]This value can be exceeded during 2 h in 12 h period
[c]Value for class II (normal level of expectation—new buildings and renovations)

investment decisions require great prudence from the decision maker. In southern European countries, with mild climate, these problems are under discussion and some studies are being published (Santamouris et al. 2008; Guedes et al. 2009; Conceição and Lúcio 2006; Calise 2012; Conceição et al. 2012; Katafygiotou and Serghides 2014a, b).

Recently was performed a study in France that included 489 classrooms of 108 school buildings (Ramalho et al. 2013). The most representative ventilation system was mechanical ventilation, installed in 20 % of schools, 60 % of which had mechanical extraction. Three air pollutants were measured, including CO_2, for 2 weeks and throughout a total period of one year. In the occupation period, 33 % of the schools revealed CO_2 concentration above 1700 ppm in more than 66 % of the records. Conceição and Lúcio (2006) monitored 2 unoccupied classrooms of 1 school in the south of Portugal, ventilated in accordance with the philosophy of cross ventilation, using the bottom-hung windows opening, located above the main doors and windows (sliding windows). Santamouris et al. (2008) monitored the indoor air quality in 62 classrooms of 27 naturally ventilated schools of Athens. The measurements were taken in the spring and fall seasons when window opening is the main ventilation procedure. Three situations were assessed: (a) empty rooms and windows closed, (b) during classes, with some windows opened; (c) between classes, with most of the windows opened. The average flow rates obtained were 1.5 l/s/person, 4.5 l/s/person and 7 l/s/person, respectively. During the three measurement periods, 52 % of the classrooms presented a CO_2 concentration greater than 1000 ppm with a median of 1070 ppm. At the end of the class period, there was a maximum concentration of 3000 ppm with a median of 1650 ppm. A statistically significant relationship between the window opening and difference in indoor-outdoor temperature was confirmed. Katafygiotou and Serghides (Katafygiotou and Serghides 2014a, b) conducted a field study in a secondary school building in Cyprus, to assess the indoor thermal conditions during the students' lesson hours. Air temperature and relative humidity were monitored throughout the four seasons of the year. During winter temperature ranged between 19 and 26 °C and relative humidity between 50 and 60 %, during summer temperatures varied from 27 to 35 °C and relative humidity from 40 to 46 %. de Giuli et al. (2014) evaluated the indoor environmental comfort, from March to June, in four Italian classrooms by means of spot-measuring campaigns, long-term monitoring, and surveys. The school building were not equipped with a mechanical ventilation system, therefore CO_2 concentrations were extremely high in all the classrooms, and they decreased as hot season approached since the windows were opened more frequently. Operative temperatures varied from 20 to 30 °C during the spot-monitoring campaigns and, considering the whole monitoring period, it came to light that from May indoor temperatures were unacceptable most of the time, since they often exceeded 30 °C.

4.2 Materials and Methods

The classrooms hygrothermal performance was evaluated by continuous measurement of temperature and relative humidity and the indoor air quality was assessed, during the same period, by the CO_2 concentration. Additionally, to properly

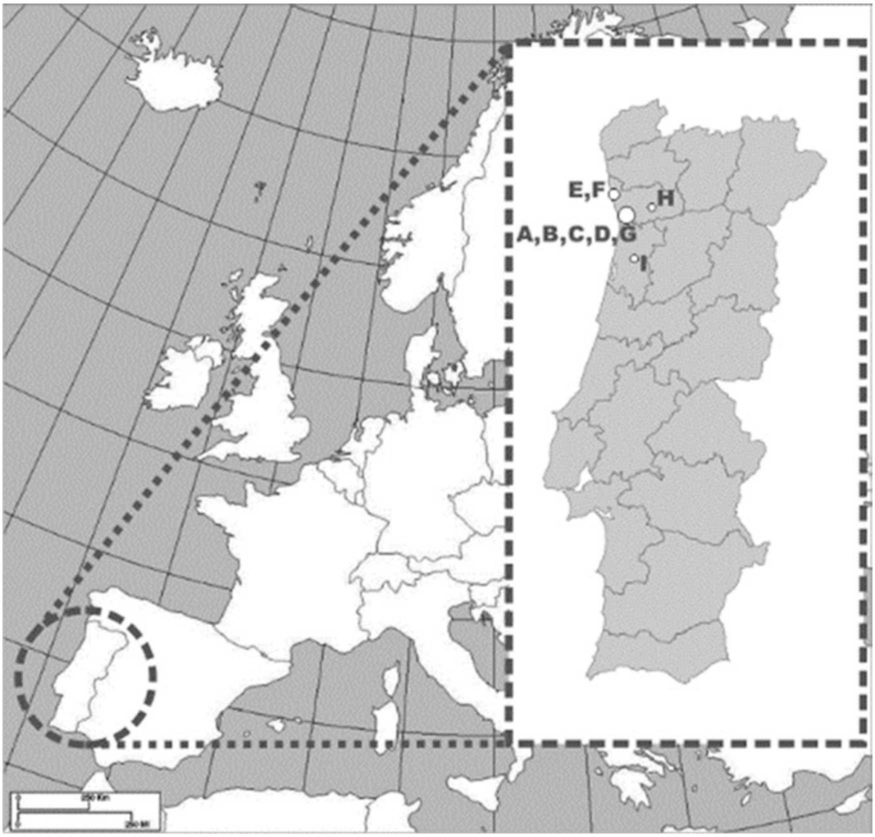

Fig. 4.1 School buildings location

evaluate the indoor air quality, the performance of classrooms ventilation systems was assessed by tracer gas measurements of ventilation rates. The experimental procedure employed was the decay technique.

Overall, a total of 24 classrooms were monitored, in 9 school buildings (2 non-retrofitted and 7 recently retrofitted) situated near the northern coast of Portugal (Fig. 4.1). Portugal has a temperate Mediterranean climate. The research was conducted over one year, with three measurement campaigns: winter, mid-season and summer conditions, each with three weeks length. The exception were the two non-retrofitted school buildings that were only monitored during the winter period. Although this limitation, some discussion and preliminary conclusions can be pointed, since the results indicate very poor indoor environmental quality in these schools.

Mean, maximum and minimum values of the outside temperature during the three monitoring periods are presented in Table 4.2.

The hygrothermal variables were recorded by means of data loggers HOBO-U12-011, with a precision of ±0.35 °C and ±2.5 % and a resolution of

Table 4.2 Outside temperature

Winter			Mid-season			Summer		
Mean	Max.	Min.	Mean	Max.	Min.	Mean	Max.	Min.
9.5 °C	14.1 °C	5.2 °C	17.1 °C	21.4 °C	13.2 °C	19.1 °C	23.4 °C	15.1 °C

0.03 °C and 0.03 %, for temperature and relative humidity, respectively. The CO_2 concentration was measured with the TelAire 7001, associated to a data logger HOBO-H08-007-02. This system has a maximum error of ±50 ppm. The sensors were located on an unoccupied student desk, approximately in the middle of the classroom, accordingly to existing international recommendations (WHO 2011; ASTM 2012). All the sensors used in this project were calibrated by an independent governmental entity and by the manufacturers. The interval of measurement was 2 min.

The ventilation rates were estimated by the tracer gas method and the decay technique. This method is based on the fact that for the typical situation inside a classroom, with temperature and wind steady (almost constant air flow), the mass balance of the tracer gas can be expressed by the following differential equation (Awbi 2003):

$$\mathrm{V} \cdot \frac{\partial C(t)}{\partial t} = G + Q \cdot C_{ex} - Q \cdot C(t) \tag{4.1}$$

in which

V [m^3] Volume of the classroom
$C(t)$ [ppm] Concentration of the tracer gas at instant t
t [s] Time
G [cm^3/s] Generation rate of the tracer gas
Q [m^3/s] Internal-external exchange rate
C_{ex} [ppm] External concentration of the tracer gas

The analytical solution of this equation is the following:

$$C(t) = C_{ex} + \frac{G}{Q} + \left(C_{in} - C_{ex} - \frac{G}{Q} \right) \cdot e^{-\frac{Q}{V} \cdot t} \tag{4.2}$$

in which

C_{in} [ppm] Initial concentration of the tracer gas

Since the tracer gas should have low concentrations in the exterior and interior air, and during the test there are no generation of the tracer gas, the exterior concentration and the generation rate can be neglected in Eq. (4.2), and the solution simplified to:

$$\frac{Q}{V} = n = \frac{\ln\left(\frac{C_{in}}{C(t)}\right)}{t} \tag{4.3}$$

in which

n [h^{-1}] Air change rate

Therefore, to calculate the ventilation rate in a space that can be considered as a single zone, it is sufficient to introduce a tracer gas to achieve a uniform initial concentration, C_{in}, afterwards, record the evolution of the concentration of this gas over time, which in a graph ln (C) versus *time*, by Eq. (4.3), is a straight line. The magnitude of the slope of this line, Q/V, is the unknown that allows the calculation of the air change rate, n. This test is regulated by ISO 12569 (ISO 2000) and ASTM E741-00 (ASTM 2011). In the present research, to perform this test was used the Inova multi-gas monitor reference 1312, based on the photoacoustic infra-red detection method (repeatability of 1 % of measured value), and the tracer gas was the sulphur hexafluoride (SF_6). The sampling point was located in the middle of the classroom. To minimize the weather conditions impact, tests were performed with calm winds (<1.0 m/s) and moderate temperatures (between 15 and 25 °C).

For the simulation of the CO_2 concentration, the method proposed by Coley and Beisteiner (Coley and Beisteiner 2002) and applied by Griffiths and Eftekhari (Griffiths and Eftekhari 2008) was used, which is based on the fact that the variation of the CO_2 concentration only depends on its concentration in the inlet air and the exhaust air and on the internal production. Consequently, Eqs. (4.1) and (4.2), reflecting their temporal variation, can be applied to this problem. According to this methodology, it is necessary to estimate the internal CO_2 production in the space that is being analysed. For that purpose, the formulation proposed by Coley and Beisteiner (2002) was used, assuming the height and weight values of the occupants suggested by Robert and Malina (2004) and a metabolic activity of 94.5 W/person for students and 126 W/person for the teacher. The CO_2 concentration in the outdoor air was considered equal to 450 ppm and the ventilation rates were the ones measured by the tracer gas method.

4.3 School Buildings and Classrooms Characterization

This study was conducted in 9 school buildings, 2 non-retrofitted (A and B) and 7 (C, D, E, F, G, H and I) recently retrofitted. A total of 24 classrooms were evaluated.

Table 4.3 summarizes the school buildings constructive characteristics, including heating and ventilation systems, with the respective design ventilation rates. Classrooms predominant orientation and location in the building are also provided. These school buildings represent different typical designs and structural periods. The sample as a whole covers the main building typologies in terms of school buildings in Portugal.

The classrooms performance in terms of IEQ is obviously linked to the ventilation system and, therefore, in the following a complete characterization of the

Table 4.3 School buildings description

School building	Year of construction	Year of renovation	Classrooms					Heating system	Ventilation	U [W/(m²K)]		
			Id.	Orientation	Floor	wfr[a]	Number of students[b]			External wall	Roof	Window
A	1997	–	A1	W	Ground	0.13	23	–	Natural	0.96	3.40	6.20
			A2	W	Top		26					
B	1993	–	B1	SW	Top	0.16	21	–	Natural	0.96	1.60	6.20
			B2	SE	Top		24					
C	1982	2008	C1	S	Ground	0.19	16	Hot water radiator	Natural/ Mechanical (400 m^3/h)	0.96	0.53	2.00
			C2	E	Top		17					
D	1932	2008	D1	E	Ground	0.11	21	Hot water radiator	Natural/ Mechanical (700 m^3/h)	0.46	0.36	2.80
			D2	E	Top		19					
E	1962	2010	E1	N	Ground	0.15	18	Heat pump	Mechanical (750 m^3/h)	0.55	0.36	2.80
			E2	S	Ground		23					
			E3	N	Top		21					
			E4	S	Top		21					
F	1955	2009	F1	NW	Top	0.14	19	Heat pump	Mechanical (750 m^3/h)	0.46	0.36	2.80
			F2	SE	Top	0.16	22					
G	1970	2009	G1	N	Ground	0.13	24	Heat pump	Mechanical (750 m^3/h)	0.44	0.44	1.60
			G2	S	Ground		22					
			G3	N	Top		22					
			G4	S	Top		19					
H	1976	2009	H1	E	Ground	0.19	17	Heat pump	Mechanical (750 m^3/h)	0.44	0.44	1.60
			H2	W	Ground	0.14	19					
			H3	E	Top	0.18	18					
			H4	W	Top	0.19	21					
I	1988	2010	I1	NW	Ground	0.11	20	Heat pump	Mechanical (940 m^3/h)	0.44	0.53	2.80
			I2	NW	Top		19					

[a]wfr—window to floor ratio
[b]average number of students during measurements

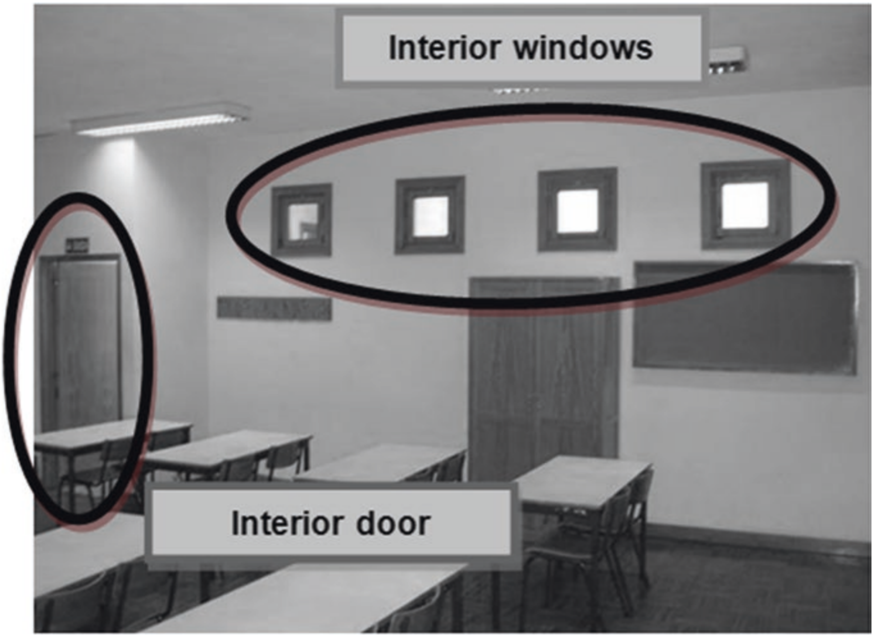

Fig. 4.2 School A classroom

classrooms ventilation systems is presented. The experimental measurements of the air change rate allowed to validate the designer information and to provide accurate information for the analysis afterwards.

In the 2 non-retrofitted schools, ventilation was natural, dependent on the window opening, and there were no heating systems. The selected school buildings are typical constructions whose design, with minimum adjustments, was repeated throughout the country. In school building A ventilation rate was estimated by tracer gas measurements. Three scenarios were assessed (Fig. 4.2): (a) door and interior windows closed; (b) door opened and interior windows closed; (c) door closed and interior windows opened. Figure 4.3 shows the concentration decay in the two testing set-ups. Ventilation rates as low as 11 m^3/h (0.12 l/s/person) were observed, in a situation that corresponds to fresh air infiltration (scenario (a)) and that is frequently observed during classes. The results indicate that the air admission is not sufficient to dilute and control the CO_2 internal production (ASHRAE 62.1 (ASHRAE 2004) recommended rate is 5.0 l/s/person), leading to a situation of poor IAQ.

In the 7 retrofitted buildings various improvements were introduced: the characteristics and properties of the external walls and roofs, accomplished by the application of thermal insulation; windows and solar protections were replaced by others of superior performance; and the heating and ventilation systems were introduced or modified. The average duration of these interventions was 2 years.

Hot water radiators were selected as the heating system in schools C and D: in school C the system could be controlled individually in each classroom and in

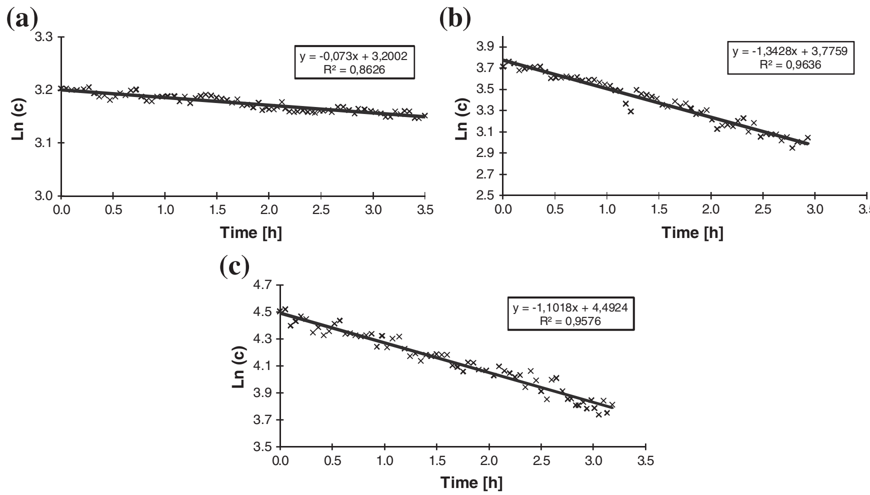

Fig. 4.3 Tracer gas decay—school A: **a** scenario (a); **b** scenario (b); **c** scenario (c)

school D temperature regulation was done by environmental probes that controlled motorized valves in the input fuel lines of the radiators in each classroom. For ventilation, classrooms were equipped with pressure-controlled louvers that guaranteed an almost constant air flow and with a variable speed mechanical system for the extraction, adjustable by the user. If the mechanical extraction system was off, ventilation would be merely natural. Admission devices were placed above windows in school C and behind hot water radiators in school D. Figure 4.4 shows the school C classrooms configuration and Fig. 4.5 contains a schematic representation of the heating and ventilation systems of schools C and D.

Design ventilation rates were evaluated in schools C and D by the tracer gas method and the decay technique. Two scenarios were assessed: (a) mechanical air extraction off and (b) mechanical air extraction on. In both scenarios door and windows were closed.

In both schools, the ventilation rates obtained in scenario (b) —mechanical air extraction on—are fairly close to the expected (Table 4.3). It is important to refer that for scenario (a)—mechanical air extraction off—an important fresh air admission portion is still provided. Figures 4.6 and 4.7 shows the concentration decay in school C and in school D, respectively, and Table 4.4 summarizes the results of all tracer gas measurements including the coefficient of determination R^2.

The other 5 retrofitted buildings (E, F, G, H and I) had HVAC systems, including heat pumps and air handling units. No air admission devices apart from windows were applied and, consequently, no natural ventilation parcel was considered at design stage. The ventilation rates presented in Table 4.3 were confirmed by external audits and, in all situations, the results were slightly above the design values. However, during the monitoring period it was observed that HVAC systems

Fig. 4.4 School building C: heating and ventilation system

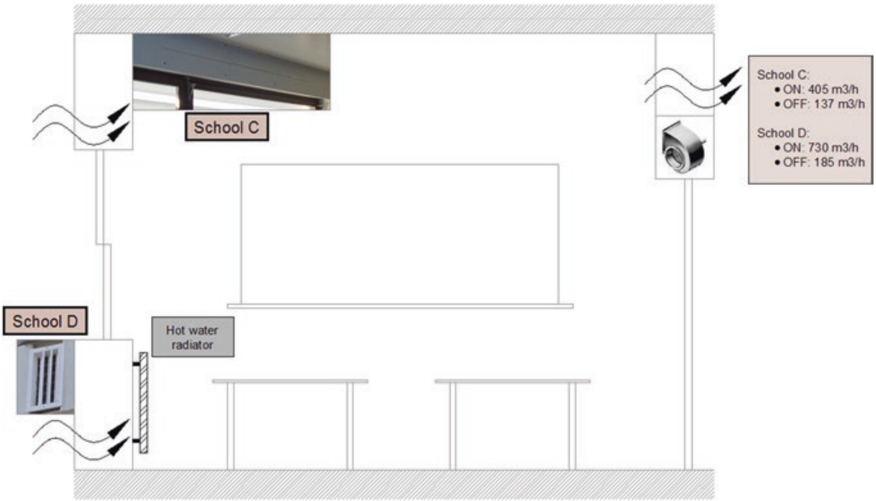

Fig. 4.5 Classrooms heating and ventilation systems—schools C and D

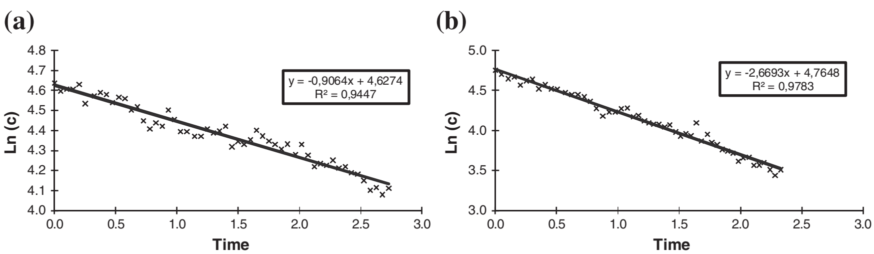

Fig. 4.6 Tracer gas decay—school C: **a** scenario (a); **b** scenario (b)

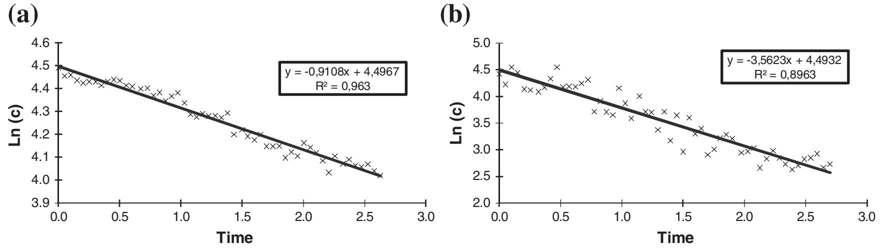

Fig. 4.7 Tracer gas decay—school D: **a** scenario (a); **b** scenario (b)

Table 4.4 Ventilation rates (tracer gas measurements)

	School A			School C		School D	
	(a)	(b)	(c)	(a)	(b)	(a)	(b)
Ventilation rate [m^3/h]	11	201	165	137	405	185	730
Ventilation rate per person[a] [l/s/person]	0.12	2.28	1.87	1.67	4.95	2.11	8.32
R^2	0.86	0.96	0.96	0.94	0.98	0.96	0.90

[a]Assuming occupancy of 2.0 m^2/person (ISO 2000)

were turned off due to economic reasons and, consequently, the indoor environmental conditions were far from what was expected.

4.4 IEQ Evaluation

As this research included a large amount of measurements, a large amount of results were also produced. In this section, the most relevant ones are presented and statistically analysed, including descriptive statistics and statistical analysis of variance. The three monitoring periods (winter, mid-season and summer) are presented in different sections. In the statistical analysis were only considered the results obtained during the theoretical period of occupied classrooms, defined as the interval between 8:30 am and 6:00 pm. This period corresponds to the typical daily schedule in Portuguese schools.

4.4.1 Winter

Figures 4.8, 4.9 and 4.10 show the temperature cumulative distribution in all the classrooms according to the nature of the ventilation system: non-retrofitted, natural/mechanical ventilation and mechanical ventilation, respectively. Table 4.5 contains the respective results of the descriptive statistics.

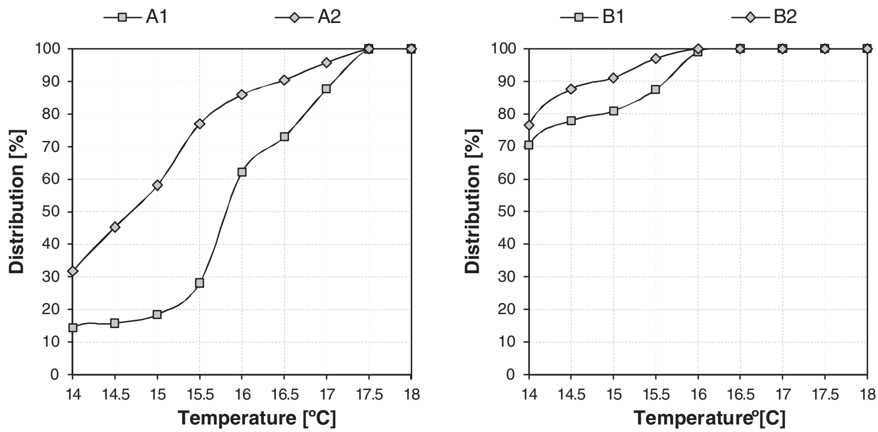

Fig. 4.8 Temperature cumulative distribution—non-retrofitted buildings (*A* and *B*)

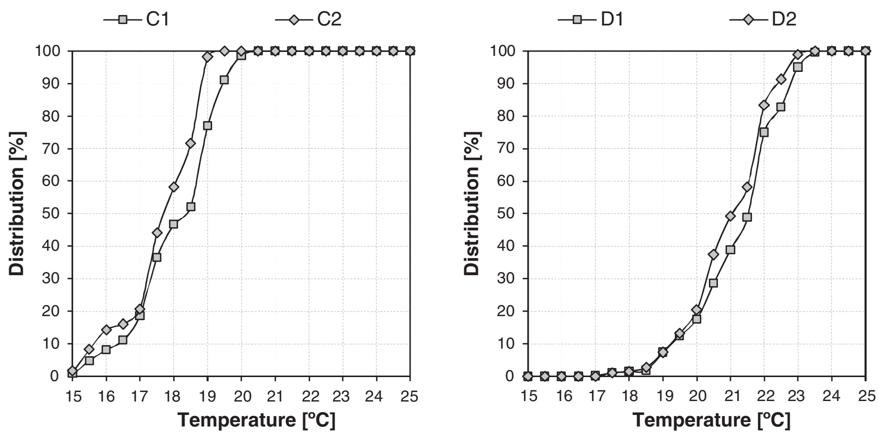

Fig. 4.9 Temperature cumulative distribution—naturally/mechanically ventilated buildings (*C* and *D*)

The results showed that temperature inside the classrooms of the non-retrofitted schools (A and B) was below the desirable and, thus, these buildings do not guarantee their users the appropriate comfort. The Portuguese building regulation recommends a target value of 20 °C in the heating season, which in these schools was never accomplished (Fig. 4.8).The average air temperature for this group was 14.9 °C. In some periods of the early morning, temperature inside these classrooms was even lower than in the exterior (maximum difference of 2 °C).

As it was expected, in retrofitted schools, air temperature fluctuation is closer to the reference value, though some differences were found.

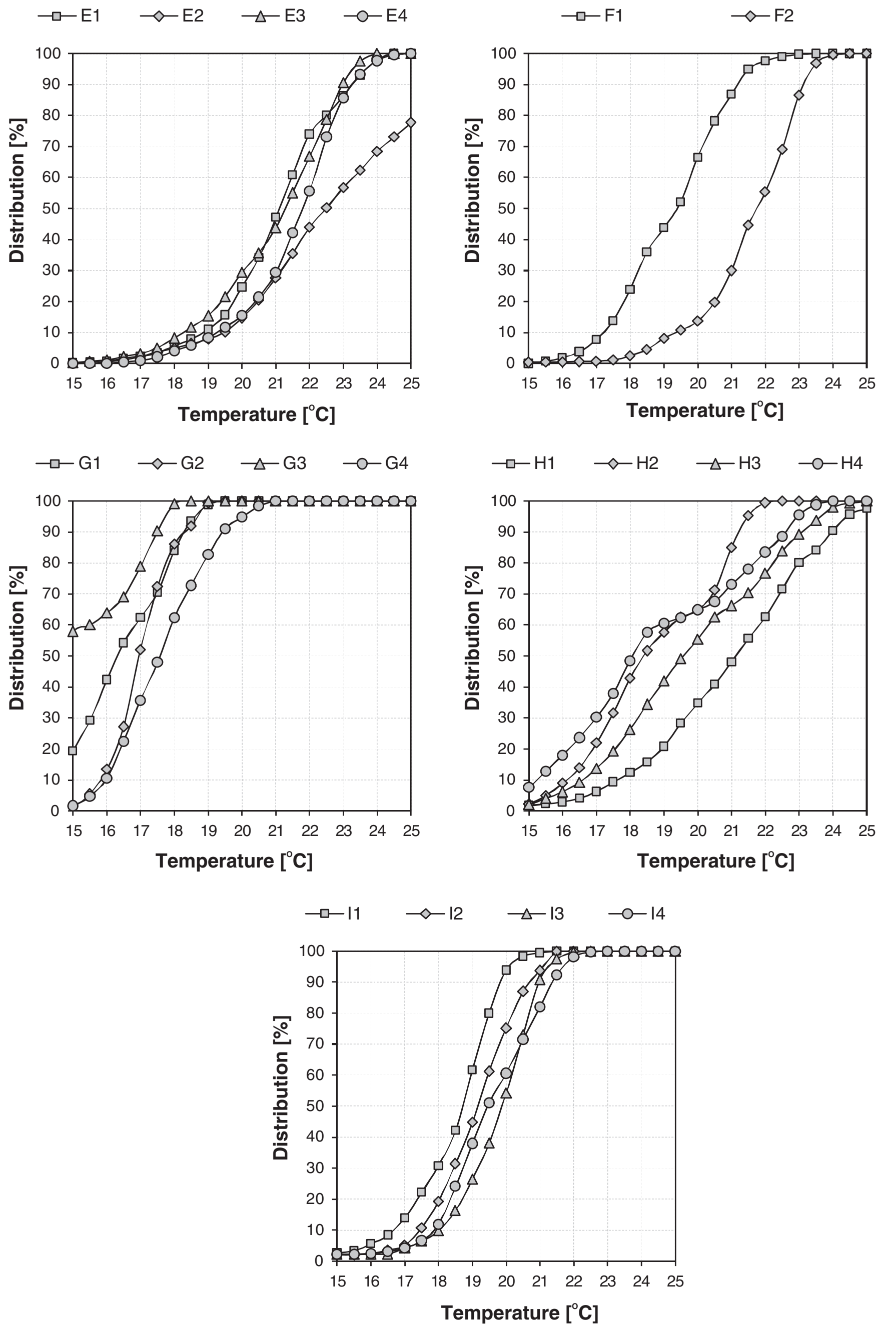

Fig. 4.10 Temperature cumulative distribution—mechanically ventilated buildings (*E*, *F*, *G*, *H* and *I*)

Table 4.5 Descriptive statistics of temperature—winter

School building	Number of classrooms	Temperature [°C]			
		Mean	Maximum	Minimum	Standard deviation
A	2	15.7	17.9	13.3	1.17
B	2	14.1	16.8	11.0	1.07
C	2	18.3	20.6	14.9	1.22
D	2	21.6	24.0	17.1	1.28
E	4	22.0	29.4	14.5	2.11
M	2	20.9	24.7	12.6	1.91
G	4	17.0	21.4	11.9	1.70
H	4	20.0	26.6	12.1	2.60
I	4	19.8	23.1	14.8	1.29

In school C occupants had the possibility to control the temperature inside the classroom by adjusting the heating system. However, the results show that most of the time temperature was below the reference value of 20 °C and, as so, it seems reasonable to conclude that users felt thermally comfortable with a temperature lower than the one indicated in the regulation. This result paves the way for a discussion on how to define regulatory limits. In fact, the imposition of a reference value for the temperature is very strict. The use of adaptive models as the ones proposed in CEN—EN 15251 (2007) and ASHRAE 55 (2010), or even probabilistic criteria, which reflect the occupants' ability to adapt to the environment they are inserted in, would certainly lead to a reduction of the costs associated with HVAC equipment. Schools C average air temperature was 18.3 °C and in school D was 21.6 °C.

The group of schools where HVAC systems were introduced, schools E to I, revealed average records (19.9 °C) very close to the design value, the exception being school G where the temperature was significantly lower, with a mean value of 17 °C. On an unexpected manner, an enormous variability in the temperature results was observed. Also noteworthy was the fact that despite the measurements were conducted in the winter period, there are records of temperature relatively high for this season (ex.: 29.4 °C). Similar situations were already reported in other studies (Mumovic et al. 2009; Guedes et al. 2009; Jenkins et al. 2009) and reinforce the idea that, in mild climates, internal gains and a thermally efficient building envelope might be enough to ensure adequate comfort conditions.

The measurement campaign showed that the relative humidity is not a problem in classrooms of both non-retrofitted and retrofitted schools. However, some differences can be pointed. In retrofitted schools E to I the variability of the relative humidity is significantly higher (standard deviation above 10 %) and very low values appear in the first hours of the day. In all these schools minimum values below 35 % were recorded, situation somewhat unexpected given the high vapour production due to occupation. The reason might be the fact that the analysis refers to the theoretical period of occupation and these values were recorded at the

Table 4.6 Descriptive statistics of relative humidity—winter

School building	Number of classrooms	Relative humidity [%]			
		Mean	Maximum	Minimum	Standard deviation
A	2	56	74	49	3.3
B	2	59	82	52	4.7
C	2	48	58	38	4.5
D	2	47	58	37	4.0
E	4	40	78	17	12.3
M	2	44	69	26	10.9
G	4	61	83	30	11.6
H	4	43	68	17	10.3
I	4	69	88	30	10.7

beginning of the day, in a period when the classroom could in fact be unoccupied or with a low occupancy rate (occupancy tends to be lower in the first hours of the day). Table 4.6 presents the descriptive statistics of the relative humidity.

When analysing the CO_2 concentration, results exposed an enormous difference between the performance of non-retrofitted and retrofitted school buildings. Nevertheless, in none of the buildings, the regulation limit for the maximum CO_2 concentration (1250 ppm in Portugal) was fulfilled. Figures 4.11, 4.12 and 4.13 show the CO_2 concentration cumulative distribution in all the classrooms according to the nature of the ventilation system: non-retrofitted, natural/mechanical ventilation and mechanical ventilation, respectively.

Table 4.7 includes information concerning the percentage of time in which the CO_2 concentration was lower than 1250 ppm, lower than 1500 ppm and higher than 2500 ppm. The median value of the data is further indicated.

The best performance was found in school D where in 93 % of the occupancy period CO_2 concentration was below 1250 ppm and the worst performance was in school I with just 12 %. In fact, despite the renovation intervention, CO_2 concentration above 2500 ppm was recorded in school I in 56 % of the occupancy period, even worse than the values observed in the non-retrofitted schools (41 % and 50 % in schools A and B, respectively). On the other hand, schools D and E never exceed this limit and in schools C and H it was a residual period.

The CO_2 concentration statistical analysis of variance exposed significant differences between schools. Schools were grouped according to their characteristics: group (1) included schools A and B and corresponds to the non-retrofitted school buildings; group (2) included schools C and D and corresponds to the retrofitted schools with natural/mechanical ventilation systems; and group (3) included schools E, F, G, H and I and corresponds to the retrofitted schools with HVAC systems. A significance level of 0.05 was used in the analysis. The resulting P-value of Levene's test for equality of variances was 0.001 and, thus, the null hypothesis of equal variances was rejected and the robust tests of equality of means were

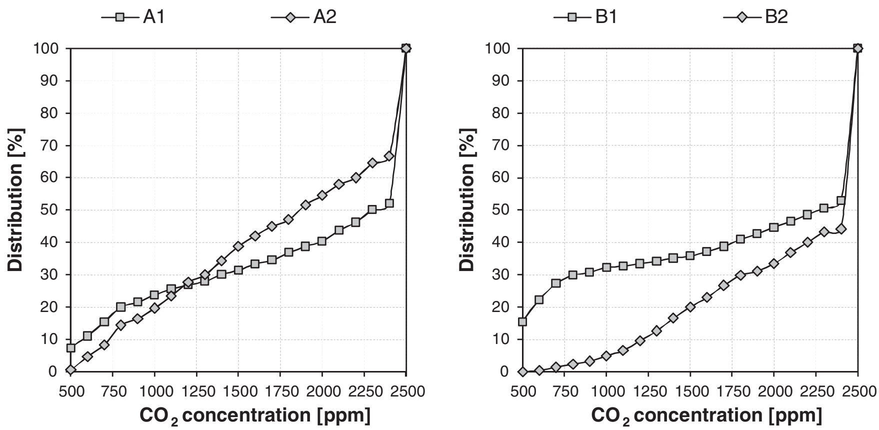

Fig. 4.11 CO_2 concentration cumulative distribution—non-retrofitted buildings (*A* and *B*)

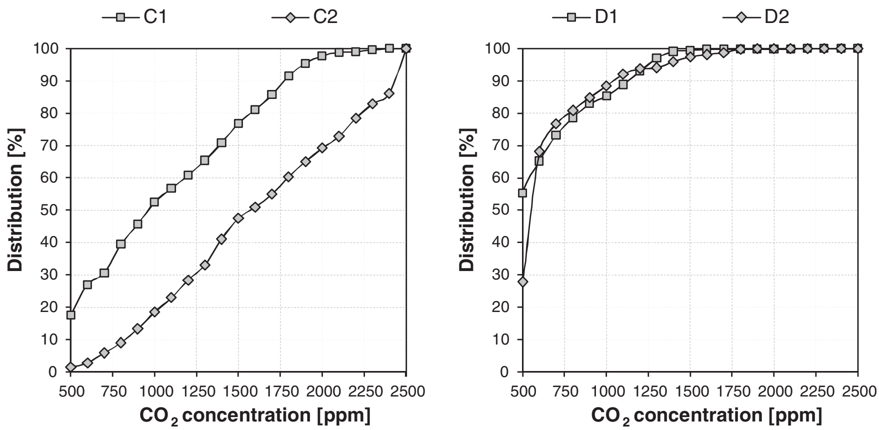

Fig. 4.12 CO_2 concentration cumulative distribution—naturally/mechanically ventilated buildings (*C* and *D*)

employed (Welch and Brown-Forsythe). Significant differences between means were found (P-value < 0.05). Scheffé's method for multiple comparison revealed that differences are significant between the three groups. Therefore, the statistical analysis confirmed that group (2) schools were the best performing with a mean CO_2 concentration of 1052 ppm. In group (3) schools the mean CO_2 concentration was 1464 ppm and in group (1) was 1905 ppm.

As stated before, in the non-retrofitted schools (group (1)) fresh air admission in the classroom is only possible, besides infiltration, through window opening, since they are not provided with any ventilation devices. However, these measurements took place during the heating season, with low outside temperatures and

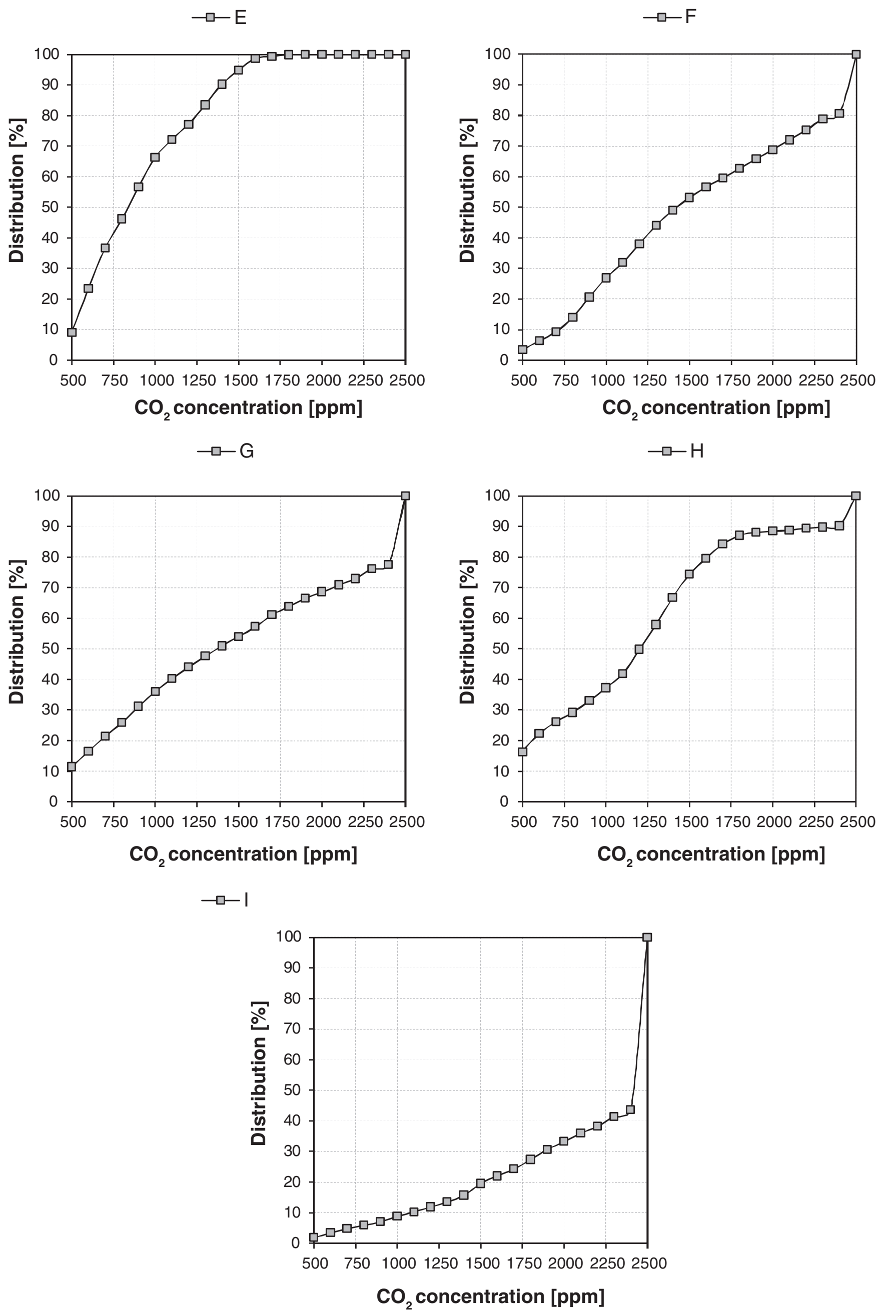

Fig. 4.13 CO_2 concentration cumulative distribution—mechanically ventilated buildings (*E*, *F*, *G*, *H* and *I*)

Table 4.7 Descriptive statistics of CO_2 concentration—winter

School building	Number of classrooms	CO_2 concentration [ppm]			
		% of time classrooms were occupied			Median
		<1250	<1500	>2500	
A	2	27.3	32.3	40.6	2261
B	2	21.5	25.9	49.8	2485
C	2	44.8	55.9	6.9	1343
D	2	92.7	97.5	0.0	659
E	1	77.2	90.2	0.0	933
F	1	38.1	49.0	19.4	1528
G	1	44.0	51.0	22.4	1484
H	1	49.8	66.8	9.9	1304
I	1	11.8	15.7	56.4	2500

rainfall in some periods. This is not compatible with window opening and might help explaining the very high values of CO_2 concentration observed. The IAQ evaluation in the retrofitted schools revealed a quite different scenario. Comparing the performance of schools C and D (group (2)), with those that received HVAC systems (E to I), significant differences were found. Finally, special references must be made to school D that, due to the natural ventilation contribution (185 m^3/h), presented a very interesting performance and to school I that, as stated before, exposed very poor IAQ conditions.

4.4.2 Mid-season

Mid-season period is the mildest one and, therefore, indoor air temperature inside the comfort range was expected. However, during the three weeks period of monitoring the outside temperature was similar to the one observed in the summer campaign and, thus, conditioned the results. Table 4.8 shows the descriptive statistics of the air temperature monitoring.

Air temperature as high as 32.7 °C was recorded in school H, indicating possible overheating problems during the warmer months. In 3 out of 7 school buildings was observed temperatures above 30 °C. However, mean values were inside the comfort range 20–25 °C. The only exception was school F with a mean value of 25.8 °C. The lowest average air temperature was recorded in classrooms of school I (22.2 °C).

Regarding relative humidity, variations were within the expected range, despite the minimum values that, however, as discussed previously, correspond to outliers recorded in the beginning of the day (Table 4.9).

Classrooms IAQ improved. CO_2 concentration levels are now significantly lower as ban be seen in Table 4.10. All the schools present a median CO_2

Table 4.8 Descriptive statistics of temperature—mid-season

School building	Number of classrooms	Temperature [°C]			
		Mean	Maximum	Minimum	Standard deviation
C	2	22.5	30.6	18.9	1.83
D	2	23.6	29.2	19.3	1.48
E	4	24.9	29.3	18.8	1.57
F	2	25.8	31.2	18.8	2.22
G	4	23.6	26.4	19.9	1.03
H	4	24.6	32.7	17.8	2.50
I	4	22.2	25.9	19.5	1.27

Table 4.9 Descriptive statistics of relative humidity—mid-season

School building	Number of classrooms	Relative humidity [%]			
		Mean	Maximum	Minimum	Standard deviation
C	2	59	71	39	9.7
D	2	57	66	43	7.7
E	4	52	78	27	9.9
F	2	49	70	28	10.7
G	4	57	80	35	9.2
H	4	49	76	20	13.2
I	4	66	79	51	6.6

Table 4.10 Descriptive statistics of CO_2 concentration—mid-season

School building	Number of classrooms	CO_2 concentration [ppm]			
		% of time classrooms were occupied			Median
		<1250	<1500	>2500	
C	2	65.8	73.2	2.4	938
D	2	98.2	98.9	0.0	621
E	1	98.1	99.9	0.0	747
F	1	93.7	99.4	0.0	957
G	1	63.2	74.6	5.6	942
H	1	62.1	77.0	7.9	1021
I	1	55.9	71.1	6.7	1108

concentration under 1250 ppm. However, the maximum level of 1250 ppm is still not completely satisfied. Some differences can be pointed between schools with HVAC systems (E, F, G, H and I) and the other two with the mixed ventilation system. If one focus on the extremes: schools D and E present CO_2 concentration below 1250 ppm in 98 % of the occupancy period; and school I only in 56 %. Results indicate that students made use of window opening for fresh air admission. This situation was confirmed during the visits.

4.4.3 Summer

The tendency observed previously was confirmed by the summer monitoring. Tables 4.11, 4.12 and 4.13 present the descriptive statistical analysis of air temperature, relative humidity and of CO_2 concentration, respectively. Globally, results reveal on the one hand high temperatures inside classrooms, suggesting an overheating problem, and, on the other hand, an improved IAQ.

In fact, results revealed overheating problems in these schools. Temperatures above 30 °C were recorded in all school buildings, reaching a maximum of 36.9 °C in school H. In this school during 9 % of the monitoring period temperature was higher than 30 °C. If one focus on the average, only schools D, E and H presented values above 25 °C (25.1 °C, 25.9 °C and 27.5 °C, respectively).

Once again, there is no special concern regarding relative humidity.

Table 4.11 Descriptive statistics of temperature—summer

School building	Number of classrooms	Temperature [°C]			
		Mean	Maximum	Minimum	Standard deviation
C	2	24.2	33.2	20.9	1.75
D	2	25.1	31.8	20.7	1.39
E	4	25.9	33.0	20.2	2.21
F	2	24.8	32.5	19.1	2.13
G	4	24.8	31.5	21.3	1.64
H	4	27.5	36.9	21.1	2.60
I	4	23.8	30.3	18.6	1.79

Table 4.12 Descriptive statistics of relative humidity—summer

School building	Number of classrooms	Relative humidity [%]			
		Mean	Maximum	Minimum	Standard deviation
C	2	54	68	38	9.0
D	2	50	65	41	8.3
E	4	54	72	27	7.9
F	2	51	66	32	7.1
G	4	59	71	37	6.4
H	4	47	67	22	7.5
I	4	65	75	45	7.9

Table 4.13 Descriptive statistics of CO_2 concentration—summer

School building	Number of classrooms	CO_2 concentration [ppm]			
		% of time classrooms were occupied			Median
		<1250	<1500	>2500	
C	2	94.7	100.0	0.0	601
D	2	99.6	100.0	0.0	588
E	1	99.1	100.0	0.0	562
F	1	92.5	98.3	0.0	591
G	1	91.5	95.8	0.0	562
H	1	73.1	81.3	3.3	688
I	1	82.5	95.4	0.2	645

In this period CO_2 concentration levels are rather low, with median values below 700 ppm in all classrooms. Clearly the IAQ improvement was obtained at the expense of thermal comfort, with results indicating that fresh air admission from window opening was the option.

4.4.4 Results and Discussion

The results confirm that the IEQ in the non-retrofitted school buildings is not adequate. Classrooms are thermally uncomfortable, with records considerably below the reference temperature specified in regulations, and the CO_2 concentration exposed a very poor IAQ. So, it is clear that a technical intervention is required in these buildings, in order to improve their performance and achieve adequate IEQ conditions, providing students with an adequate learning environment.

The retrofitted schools revealed substantial differences when compared to the non-retrofitted ones. The effect of the intervention was obvious. However, some differences from what was expected in the design stage were observed. The mechanical ventilation systems were off, with important consequences in the IEQ of the classrooms. This situation can in part be explained by the exploration and maintenance costs of these systems and the economic crisis we are experiencing, which reduced the school budgets.

A simulation of the CO_2 concentration was carried out to evaluate the ventilation performance in service conditions. Simulation results were compared with simulations and the limited use of the mechanical ventilation systems was confirmed. This procedure was possible because the classroom occupation in school building C was recorded and, therefore, the CO_2 internal production could be estimated. The method proposed by Coley and Beisteiner (Coley and Beisteiner 2002) and applied by Griffiths and Eftekhari (2008) was used, which is based on the fact that the variation of the CO_2 concentration only depends on its concentration in the inlet air and the exhaust air and on the internal production. Consequently, Eqs. (4.1) and (4.2), reflecting its temporal variation, can be applied to this problem. According to this methodology, it is necessary to estimate the internal CO_2 production in the space that is being analysed. For that purpose, the formulation proposed by Coley and Beisteiner (2002) was used, assuming the height and weight values of the occupants suggested by Robert and Malina (2004) and a metabolic activity of 94.5 W/person for students and 126 W/person for the teacher. The CO_2 concentration in the outdoor air was considered equal to 450 ppm and the ventilation rates were the ones measured by the tracer gas method (Table 4.4).

Figure 4.14 shows the simulation results for the two ventilation scenarios versus the measured CO_2 concentration. An agreement between the measured concentration and the simulation in a scenario of 403 m^3/h can be observed ($R^2 = 0.84$), which can indicate the situation of mechanical extraction off and is in line with the results previously presented.

These constraints in the use of mechanical ventilation clearly affected classrooms temperature. Although most of the time temperature was within the comfort range (20–25 °C) an overheating problem was observed in the mid-season and summer campaigns. In all schools temperature above 25 °C was recorded. In the summer campaign, the average plus standard deviation temperature was higher than 25 °C in all schools (between 25.6 °C in school I and 30.0 °C in school H). Even the average temperature was higher than 25 °C in schools D, E and H. Figure 4.15 shows the average and standard deviation values of temperature in the 7 retrofitted school buildings. The comfort range is also included in the graph. Regarding the winter period, the worst performing schools were C and G where even the average plus standard deviation temperature was below 20 °C (19.5 °C in school C and 18.7 °C in school G).

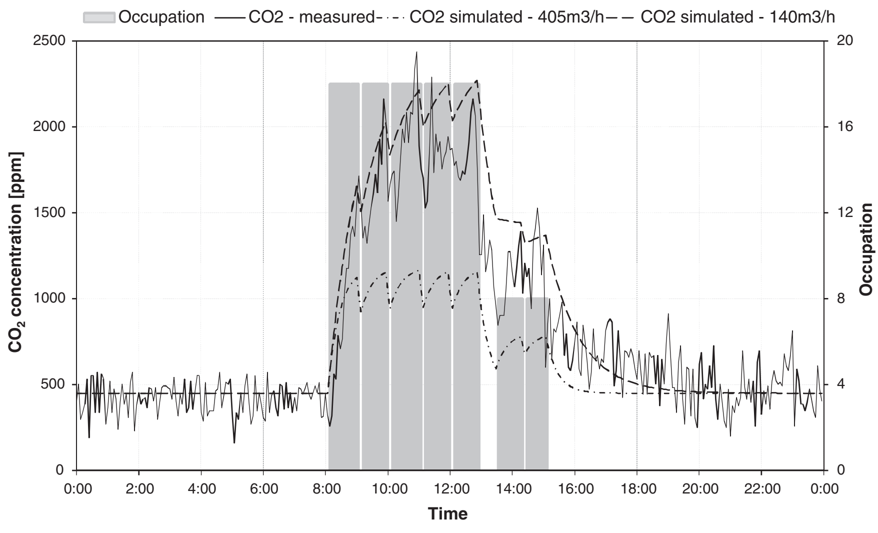

Fig. 4.14 Measurements versus simulated values for the CO_2 concentration in school C

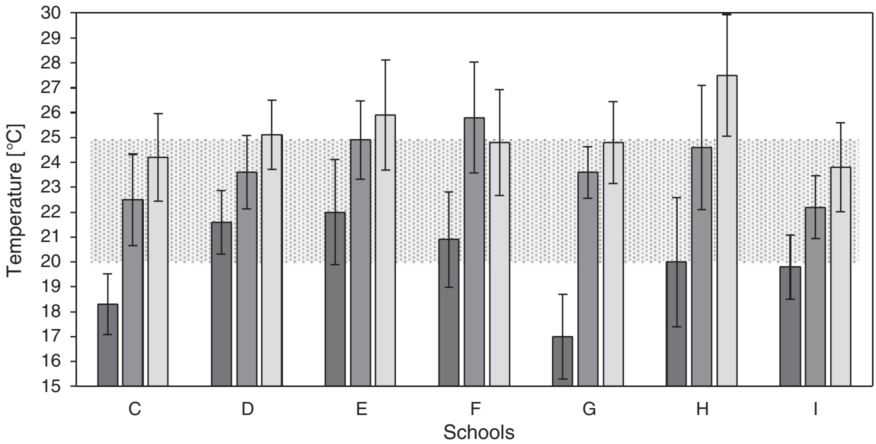

Fig. 4.15 Average temperature and standard deviation measured in all the buildings and for the three seasons

Another possibility to evaluate the comfort conditions is to use the graphic comfort zone method for typical indoor environments proposed by ASHRAE 55. This method defines a comfort zone on a psychometric chart and can be applied in spaces where the occupants have activity levels that result in metabolic rates between 1.0 and 1.3 met and where clothing is worn that provides between 0.5 and 1.0 clo of thermal insulation. This method was applied to evaluate the comfort conditions on schools C to I (Fig. 4.16) and resultant percentage of discomfort hours was computed (Table 4.14). Results reveal that school D is the most comfortable in the three seasons; the worst performance in the winter season is in school F and in the summer season is in school H.

On the other hand, CO_2 concentration decreases when temperature is higher (Fig. 4.17). Fresh air admission through window opening helps explaining this situation. During the winter campaign, with obvious limitations in the window opening, CO_2 average concentration reaches almost 2500 ppm in school I. The mean plus standard deviation CO_2 concentration was higher than 1250 ppm in all schools (between 1297 ppm in school D and 2998 ppm in school I). Regarding the summer period, all schools tended to perform well, with the mean plus standard deviation CO_2 concentration below 1000 ppm (791 ppm in school E and 943 ppm in school I), the only exception was school H where this value reached 1036 ppm. The most interesting performance was obtained in school D, probably due to the natural ventilation contribution. As stated before (Fig. 4.5; Table 4.4), these classrooms have a ventilation system that includes a significant natural ventilation contribution (185 m^3/h). Therefore, when the mechanical extraction system is off, a relevant fresh air admission is still provided. However, in school C, with a similar ventilation system, the outcome was not so successful.

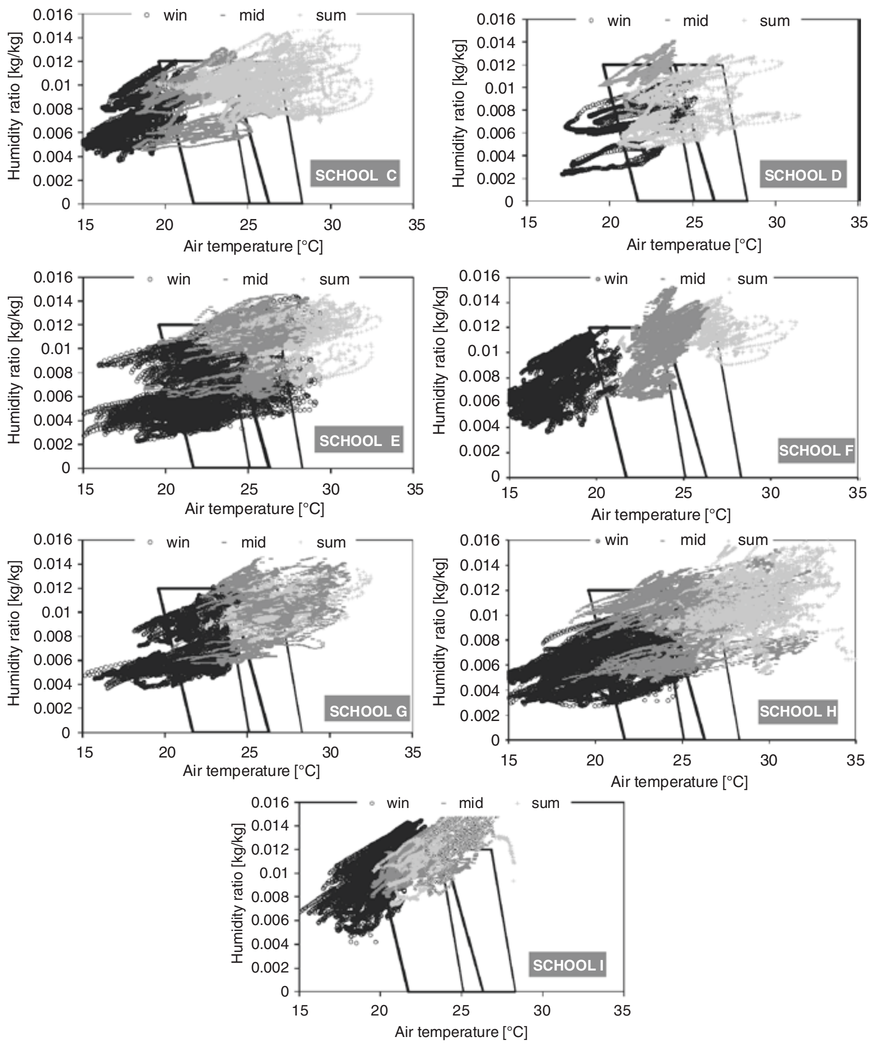

Fig. 4.16 Comfort according to ASHRAE graphical method

Table 4.14 Hours with discomfort according to ASHRAE graphical method

% of hours with discomfort							
Schools	C	D	E	F	G	H	I
Winter	74	19	21	81	31	44	72
Mid-season	18	11	22	19	38	16	36
Summer	38	15	34	51	47	77	40

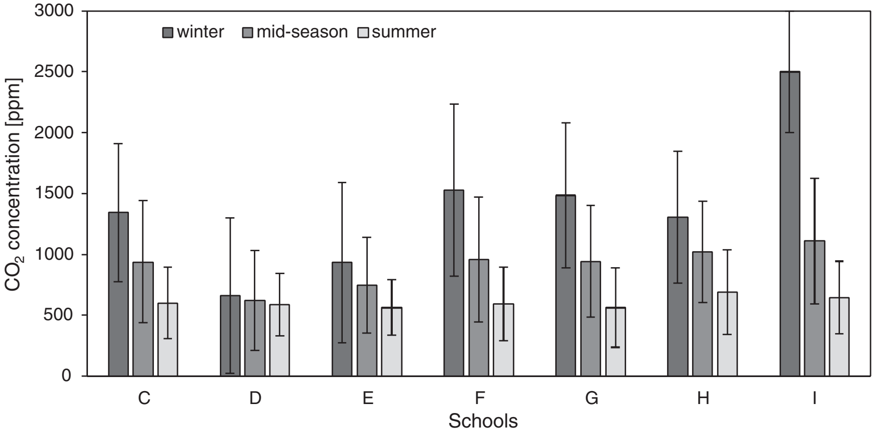

Fig. 4.17 Average CO_2 concentration and standard deviation measured in all the buildings and for the three seasons

Therefore, the conclusion is that overall the mechanical ventilation systems are not in use, with important consequences on the IAQ of these classrooms. This situation is compounded by the fact that the buildings envelope is very tight in schools E, F, G, H and I, limiting the admission of fresh air and meaning that these schools ventilation is only due to infiltration and window opening.

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Chapter 5
Enclosure Optimization

Abstract This chapter presents a methodology for the optimization of the insulation thickness of external walls and roofs. Its application in school buildings rehabilitation is tried. The methodology is presented and formulated. Objectives related to building's energy efficiency, summer comfort and life cycle cost are combined. A sensitivity analysis is presented and an example case is used to test the methodology.

Keywords Optimization · Insulation thickness · Life cycle cost

5.1 Introduction and Motivation

The energy efficiency of buildings, including public buildings, is a major concern for all European governments (EPBD 2002; EPBD 2010). In Portugal, public buildings are responsible for more than 50 % of the total energy bill of the state and school buildings play an important role in these costs. The best strategy to reverse this scenario includes efforts on the rehabilitation of these buildings, improving their energy efficiency, without sacrificing the indoor environmental quality. These interventions must be carefully prepared and the technical decisions must be scientifically supported to guarantee the economic sustainability of the buildings, often neglected during the design process. Thus, the rehabilitation of a school building should be regarded as a procedure of combining a number of variables and objectives, sometimes conflicting, including energy, indoor environmental quality and costs (initial, operational and maintenance), on a search for an "optimum solution".

The compatibility of conflicting objectives, including economic aspects, in optimization procedures is the subject of interest and attention of numerous researchers from various areas (Diakaki et al. 2008, 2010; Mateus and Oliveira 2009; Calise et al. 2011; Calise 2012; Kumbaroğlu and Madlener 2012; Ozel 2012; Hamdy et al. 2013). In building rehabilitation, it is often accomplished by the creation of a large number of construction scenarios, which establish

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the decision space. These scenarios are simulated and evaluated, resulting in a ranking of the solutions (Santamouris et al. 2007; Calise 2010; Ochoa et al. 2012). This method is relatively fast and easy to implement. However, the final solution is restricted to the scenarios that were initially defined. This limitation can be overcome by other approaches, based on more complex numerical methods, where the decision space is extended and optimization procedures, based on evolutionary algorithms, such as the genetic algorithms, are employed. These methods, when applied to problems with more than one objective, result in a set of optimal solutions, each of which represents a particular level of compromise between the objectives. To establish a criterion for the rejection of feasible solutions during the optimization process, these methods use the concept of dominance and the final set of optimum solutions is called the Pareto front. The optimal Pareto solutions are situated in a region where it is impossible to improve any of the objectives, without degrading at least one of the other objectives (Deb 2001; Konak et al. 2006).

Typically, these methods are applied in buildings energy optimization together with computer simulation software, such as EnergyPlus, TRNSYS or ESP-r, that are responsible for evaluating the effect of a particular solution (rehabilitation scenario) on each of the established objectives, that should be quantitatively described by mathematical functions.

One of the first applications of genetic algorithms in the optimization of buildings energy consumption was made by Wright et al. (2002) in the identification of the optimum pay-off characteristic between the energy cost of a building and the occupants' thermal discomfort. Magnier and Haghighat (2010) used a popular multi-objective genetic algorithm (NSGA-II) for the optimization of thermal comfort and energy consumption in a residential house. Chantrelle et al. (2011) developed a multicriteria tool for the optimization of renovation operations.

The main limitation of these methodologies is the large number of computer simulations required by the genetic algorithm, making it almost impractical when applied directly to the thermal and energy simulation of complex models over extended periods. Several researchers proposed alternatives to overcome this difficulty using statistical methods, such as time-series, Fourier series, regression models and Artificial Neural Networks (ANN) (O'Neill et al. 1991; Dhar et al. 1998; Karatasou et al. 2006; Freire et al. 2008; Catalina et al. 2008). Statistical methods are prediction models that use functions to approximate the solutions and can be used both in continuum and discrete problems. ANN models are based on the central nervous system of the human brain. It is a network of interconnected neurons, which have the capacity for self-learning, when properly trained, and can respond to stimulus (inputs). ANN are already programmed on a Matlab Toolbox, making them easy to use, and they tend to perform better than other statistical methods in this kind of problems due to their ability to model non-linear patterns (Kreider 1991; Kawashima et al. 1995; Tso and Yau 2007; Kumar et al. 2013). ANN were employed in a number of diverse applications. Ben-Nakhi and Mahmood (2004) used ANN to investigate the feasibility of this technology to optimize HVAC thermal energy storage in public and office buildings. Indoor temperature of a residential building was predicted with auto regressive with exogenous input neural networks in a research by Mechaqrane and Zouak (2004). Aydinalp et al. (2004) used an ANN method to model residential energy consumption. Boithias et al. (2012a, b) used genetic algorithms and ANN with regard to two objectives: energy consumption and indoor discomfort. Gossard et al. (2013) presented a method to optimize the equivalent thermophysical properties of external walls of a dwelling in order to improve their thermal efficiency. The methodology included the use of ANN and the genetic algorithm NSGA-II.

Another difficulty concerning the application of multi-objective optimization methodologies is related to the final choice of a single solution, since all the solutions belonging to the Pareto front are optimal and, therefore, theoretically, none is better than the other. These difficulties are described in the work of Magnier and Haghighat (2010), Suga et al. (2010) and Chantrelle et al. (2011) and a possibility to overcome them is to employ the weighted sum method. This classical approach to solve a multi-objective optimization problem consists in assigning a weight to each normalized objective function so that the problem is converted to a single objective problem with a scalar objective function (Konak et al. 2006). Despite deficiencies with respect to depicting the Pareto optimal set, the weighted sum method for multi-objective optimization continues to be used extensively not only to provide multiple solution points by varying the weights consistently, but also to provide a single solution point that reflects preferences presumably incorporated in the selection of a single set of weights (Marler and Arora 2010). However, the final solution is highly dependent on the chosen weights.

This book explores another possibility to obtain a single solution: the use of Life Cycle Cost (LCC) analysis as a final criterion for a unique solution. The use of LCC is common in buildings retrofit optimization. Gustafsson (2000) applied this method for the optimization of insulation measures in existing buildings and Hasan et al. (2008) have used LCC, combined with simulation, on the optimization of the U-values of typical Finnish constructions. Other economic approaches to the optimum thickness of insulation materials can be found in the literature (Ozel 2012, 2013).

In this book a methodology to optimize the insulation thickness of the external walls and roof is proposed using a school building refurbishment as an example case.

5.2 Methodology

5.2.1 Model

The school under study was built on the 90s and has no insulation in the exterior walls and roof, the windows have single glass, there are no heating systems and the ventilation is natural, achieved from the window opening and infiltrations. The software chosen for the simulations was EnergyPlus with the model being created with DesignBuilder. Four types of zones were considered in the model, each with specific metabolic rates, occupation density and schedule: classroom, circulation, storage and toilet.

- Classroom: 95 W/person; 0.40 person/m^2;
- Circulation: 110 W/person; 0.60 person/m^2;
- Storage: 110 W/person; 0.10 person/m^2;
- Toilet: 110 W/person; 0.60 person/m^2.

Figure 5.1 illustrates the geometry of the building and the zones considered. The simulations were performed on an annual base with hourly outputs and 10 time steps per hour. It was considered a summer holiday period of two months, July and August, and a two weeks break in Christmas.

The values considered in the simulation for the most relevant construction elements properties (U-value of external walls [U_{walls}], roof [U_{roof}] and windows [U_{window}], windows total solar transmittance [G_{window}] and the air change rate [ACR]), which are also the variables to optimize, are summarized in Table 5.1. Blinds with medium reflectivity slats were considered as shading devices, with operation by solar radiation control assuming a set point of 120 W/m^2. These values were defined after a complete survey carried out in 20 school buildings. The air change rate value results from the experimental survey described in previous chapter. The computer model was validated with in situ measurements.

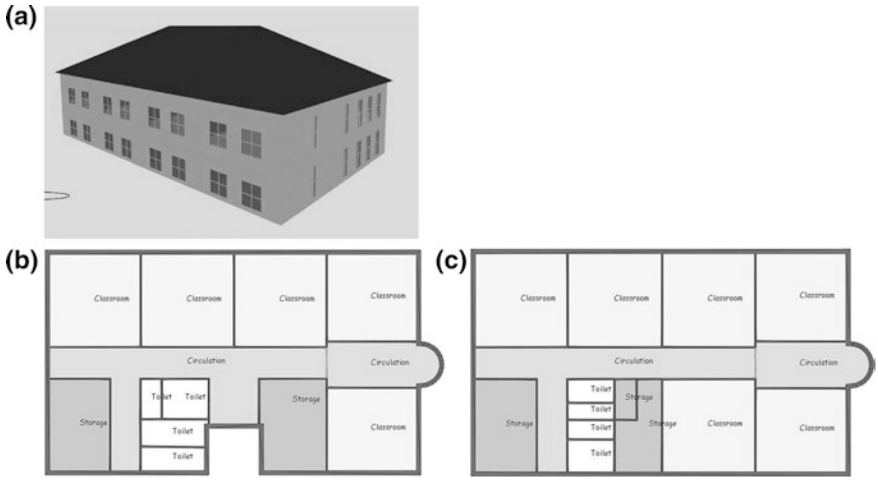

Fig. 5.1 School building model: **a** tri-dimensional overview; **b** ground floor; **c** first floor

Table 5.1 Construction elements characterization

	U_{walls} [W/(m^2.K)]	U_{roof} [W/(m^2.K)]	U_{window} [W/(m^2.K)]	G_{window} [-]	ACR [h^{-1}]
Actual	0.96	2.51	6.10	0.81	0.25

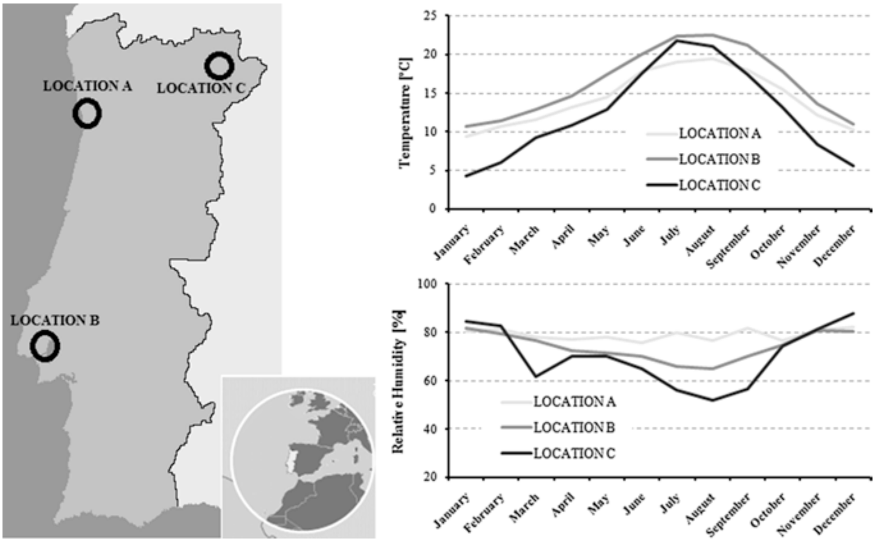

Fig. 5.2 Local climate data and location

The school building's performance was modeled and simulated in three locations, A, B and C, each with a weather that is considered characteristic of its region and that together represent the different climatic conditions in Portugal. Figure 5.2 shows the monthly average values of air temperature and relative humidity of those locations and its relative position in the country.

The effect of different building's predominant orientation was also assessed. The orientation was defined in relation to the façade where are the largest number of classrooms.

The rehabilitation proposal comprises the introduction of insulation in walls and roof, improvement of the windows properties (windows replacement) and inclusion of hot water radiators as heating systems. Since the measurements performed in these buildings revealed that, in winter conditions, temperature is below comfort limits, it is considered in this study that the introduction of heating systems is essential and, as so, even when the current performance of the building is referred, we are assuming the inclusion of the hot water radiators.

5.2.2 Variables and Performance Functions

The selected decision variables are properties of the constructive elements of the building envelope, whose performance is typically improved in a rehabilitation intervention, namely the heat transfer coefficient of external walls [U_{walls}], roof [U_{roof}] and windows [U_{window}] and the total solar energy transmittance of windows

[G_{window}]. Since building ventilation represents a major contribution for both energy performance and thermal comfort, the air change rate [ACR] was also considered as a decision variable.

Results previously presented are in line with other authors (Guedes et al. 2009) and showed that, in terms of thermal comfort, the Portuguese climate allows the use in schools of ventilation systems with a strong natural component, combined with heating systems, such as hot water radiators, which should guarantee adequate temperatures during the winter season. However, some difficulties might be found related to the indoor air quality and, during summer, overheating could be a problem in some classrooms.

Hence, two performance functions were created. The first is the annual heating load, defined as the necessary energy to guarantee a minimum temperature of 20 °C inside the classrooms and the second function intends to assess the discomfort in the classrooms due to overheating, by quantifying the time of occupancy in which temperature is above 25 °C. Both functions consider only the theoretical period of occupation (8:30–18:00). The functions are obviously dependent on the five decision variables stated before and were computed from the results of the annual simulations of the building, performed with EnergyPlus, as defined in the following equations:

$$\begin{cases} f_1\left(U_{wall}, U_{roof}, U_{window}, G_{window}, ACR\right) = \frac{\sum_{year} H.L.}{A} \\ T_{\mathrm{int}} \geq 20\ °\mathrm{C} \end{cases} \tag{5.1}$$

$$\begin{cases} f_2\left(U_{wall}, U_{roof}, U_{window}, G_{window}, ACR\right) = \frac{\sum_{year} (T_{\mathrm{int}}-25)}{A} \\ T_{\mathrm{int}} > 25\ °\mathrm{C} \end{cases} \tag{5.2}$$

in which

H.L. [kWh]	Hourly heating load
A [m^2]	Net floor area of the building
T_{int} [°C]	Hourly average interior temperature

H.L. and T_{int} are outputs of the simulation.

For the five decision variables a range of variation (variables space) was considered as presented in Table 5.2. The minimum value of the ACR, despite being far from guaranteeing adequate indoor air quality, was selected given the current conditions of the building, confirmed by the tracer gas measurements previously presented.

Table 5.2 Decision variables limits—variables space

	U_{walls} [W/(m^2.K)]	U_{roof} [W/(m^2.K)]	U_{window} [W/(m^2.K)]	G_{window} [-]	ACR [h^{-1}]
Maximum	1.80	3.00	6.10	0.90	5.00
Minimum	0.25	0.25	1.00	0.20	0.10

The maximum limits for the exterior walls, roof and windows were defined in accordance with the current characteristics of the school building (Table 5.1).

5.2.3 Artificial Neural Networks (ANN)

The calculation of the performance functions requires the results of an annual simulation of the building. Since these simulations are time consuming and the NSGA-II requires a large number of inputs, it was decided to use ANN to approximate the functions.

The main concept of ANN is learning. After the definition of the internal architecture, the ANN starts an iterative self-learning procedure of a function by adjusting the internal weights. This training process requires the definition of input data, and respective outputs, in a sufficient number to cover all the variables space, in order to achieve reliable approximations. After training, the ANN should be validated with a different set of input/output data.

The architecture of the networks employed in this research was of the multi-layer feedforward type with backpropagation, 20 neurons, 5 inputs and 1 output, as schematically described in Fig. 5.3. The training algorithm was the Levenberg-Marquardt, with Bayesian regulation. The required training sample was defined using the Latin

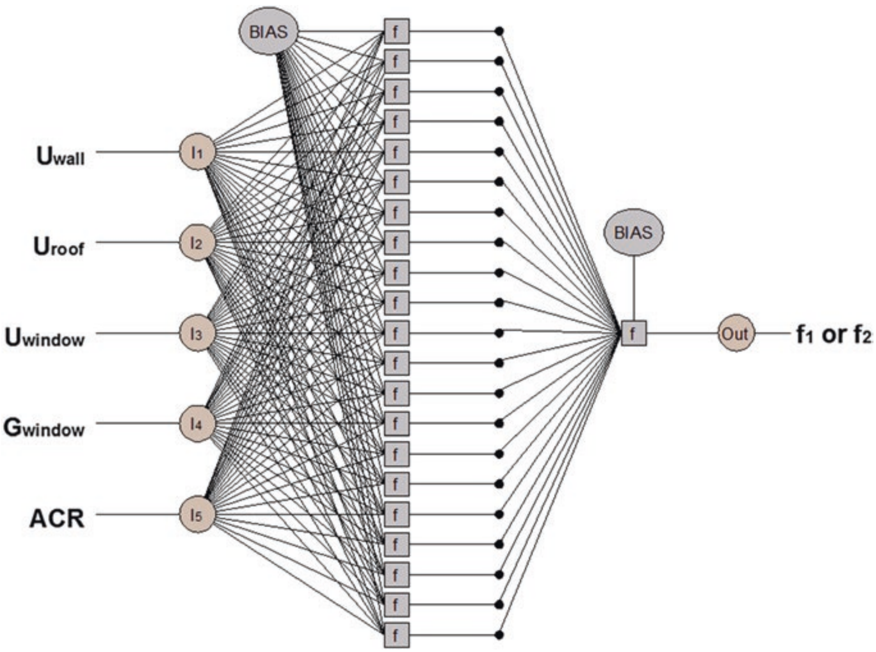

Fig. 5.3 Artificial neural networks architecture

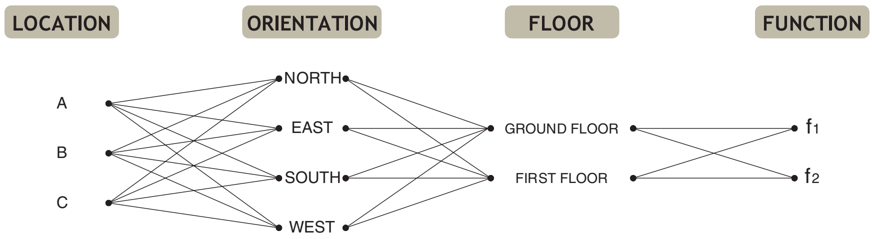

Fig. 5.4 Artificial neural networks combinations

Hypercube Sampling (LHS) method, which guarantees an effective distribution of the data over the variables space. LHS algorithm provides good convergence of parameter space with relatively few samples compared to the simple random sampling. This method is a form of stratified sampling since it divides the input into strata and then generates samples so that the value generated for each parameter comes from a different stratum (Helton and Davis 2003).

As stated above, ANN must be properly trained, in order to have an adequate performance. Thus, for each ANN, 150 cases for training and 10 cases for validation were created. As the study included 3 locations and 4 orientations, 1920 annual simulations were required, in order to obtain the necessary input/output data-set for the ANN training. A total of 48 ANN were produced, as schematically described in Fig. 5.4.

To automatize the calculation procedure of the performance functions, a Visual Basic program was developed and employed in the training and validation of the ANN.

The ANN validation accuracy was confirmed by the respective coefficient of determination (R^2), calculated as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{10} (y_i - p_i)^2}{\sum_{i=1}^{10} (y_i - y_m)^2} \tag{5.3}$$

in which

R^2 [-]	Coefficient of determination
y_i [-]	Exact value of the function computed from the annual simulation
p_i [-]	Predicted value of the function computed from the ANN
y_m [-]	Mean value of the y_i data-set

Table 5.3 shows the results obtained for R^2. An overall mean value of 0.9868 was achieved which indicates very accurate approximations.

5.2.4 *Multi-objective Optimization*

As described in detail in Sect. 3.3.3, the most common multi-objective optimization procedures are the evolutionary algorithms, inspired by Darwin's theory of natural selection. These algorithms are based on stochastic approaches and their

Table 5.3 Artificial neural networks accuracy

		Location A		Location B		Location C	
		f_1	f_2	f_1	f_2	f_1	f_2
N	GF	0.9990	0.9727	0.9989	0.9800	0.9990	0.9252
	1st F	0.9976	0.9949	0.9969	0.9832	0.9983	0.9865
E	GF	0.9990	0.9766	0.9989	0.9784	0.9990	0.9045
	1st F	0.9979	0.9840	0.9969	0.9864	0.9979	0.9899
S	GF	0.9990	0.9323	0.9988	0.9711	0.9990	0.9818
	1st F	0.9980	0.9871	0.9963	0.9865	0.9978	0.9995
W	GF	0.9990	0.9751	0.9988	0.9719	0.9989	0.9868
	1st F	0.9980	0.9886	0.9966	0.9670	0.9983	0.9962
Mean values		0.9984	0.9764	0.9978	0.9781	0.9985	0.9417
		0.9874		0.9879		0.9701	
		0.9818					

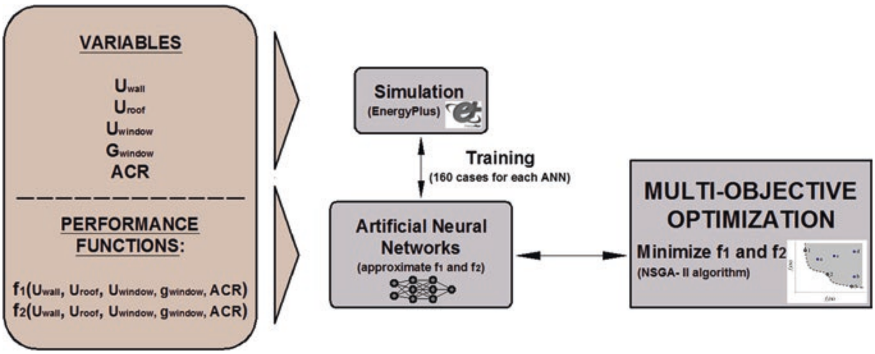

Fig. 5.5 Multi-objective optimization methodology

main advantage is that a large number of solutions (population) is used in each iteration, instead of improving one single solution. Furthermore, in these algorithms, the spreading of the solution front is ensured by internal operators, such as the Crowding Distance. The multi-objective algorithm chosen for this research was the NSGA-II, developed by Deb (2001). Figure 5.5 schematically describes the proposed multi-objective optimization methodology used in this research.

5.2.5 *Life Cycle Cost Analysis*

Life Cycle Cost (LCC) was included in this research as a key instrument to support a methodology for optimization of the insulation thickness of walls and roof in the context of school buildings refurbishment. Therefore, with this approach, criteria based on energy efficiency, occupants' thermal comfort (overheating) and economic performance are included.

LCC is the sum of the present value of investment and operating costs for the building and service systems, including those related to maintenance and replacement, over a specified life span.

In the context of this book, the absolute value of the LCC of each retrofitting solution is not required. It can be substituted by the difference *dLCCi*, between the LCC for any case *i* and the one of the reference case. With this approach, there is no need to include cost data for all building components as only the differences produced by the variation on the insulation thickness between the reference case and any other case are relevant for the problem. This methodology was proposed and applied by Hasan et al. (2008). Thus, the LCC difference, *dLCCi*, for this situation is as follows:

$$dLCC_i = (dIc)_i + (dOc)_i \tag{5.4}$$

in which

dIc [€]	Difference in the initial investment cost
dOc [€]	Difference in the operating cost

The difference in the initial investment cost of a retrofit scenario *i* can be computed from:

$$(dIc)_i = \left[C_{ins} \times \lambda_{ins} \times S \times \left(\frac{1}{U_{re}} - \frac{1}{U_{ini}}\right)\right]_i \tag{5.5}$$

in which

C_{ins} [€/m^3]	Cost of insulation
λ_{ins} [W/(m.K)]	Thermal conductivity of the insulation
U_{re} [W/(m^2.K)]	Heat transfer coefficient of the retrofitted element
U_{ini} [W/(m^2.K)]	Heat transfer coefficient of the element before retrofit

dOc is due to the difference in the annual heating load and, for each scenario *i*, must be calculated to its present value as follows:

$$(dOc)_i = \left[df \times c_e \times (HD_{re} - HD_{ini})\right]_i \tag{5.6}$$

in which

df [-]	Discount factor which takes into account the effect of inflation and variation of energy price
c_e [€/kWh]	Energy price
HD_{re} [kWh]	Annual heat demand after retrofit
HD_{ini} [kWh]	Annual heat demand before retrofit

The discount factor, *df*, is calculated as follows:

$$df = \frac{1 - (1 + r)^{-n}}{r} \tag{5.7}$$

in which

r [-]	Real interest rate
n [years]	Period of analysis

HD_{re} and HD_{ini} are the output of the first performance function (Eq. 5.1), f_1, and, therefore, can be estimated using the corresponding ANN.

5.3 Sensitivity Analysis

5.3.1 Evaluation of the School Building Performance

The first analysis was intended to evaluate the school building's actual performance, at the three locations and assuming four different predominant orientations for the building. The two performance functions were calculated and the results are depicted in Figs. 5.6 and 5.7. The functions were separately computed for the ground floor, first floor and for the all building, allowing for a more detailed analysis of the performance.

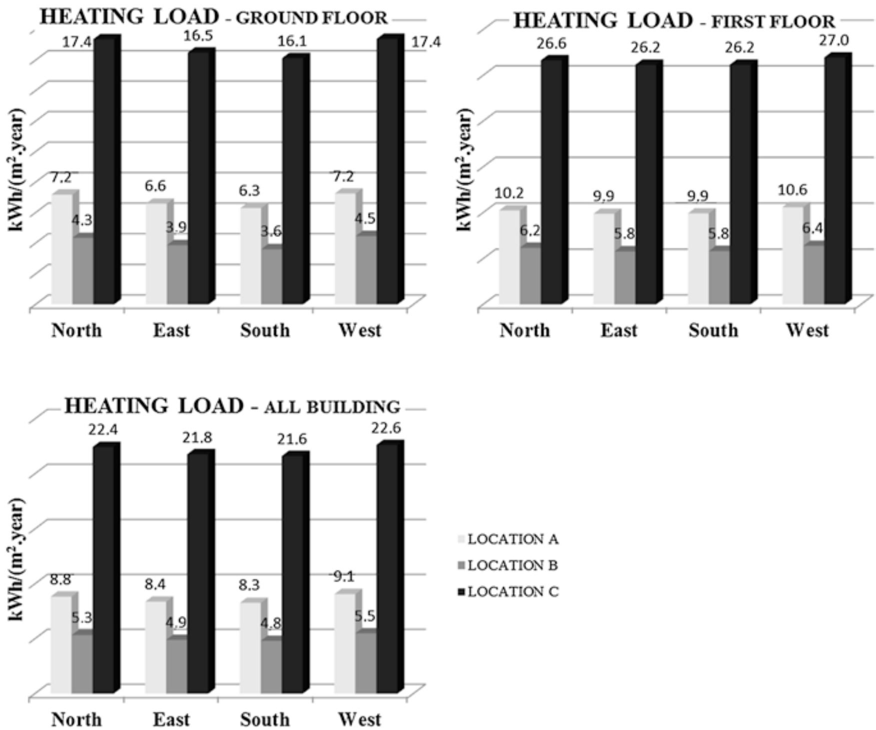

Fig. 5.6 Evaluation of the actual performance of the school building: performance function f_1

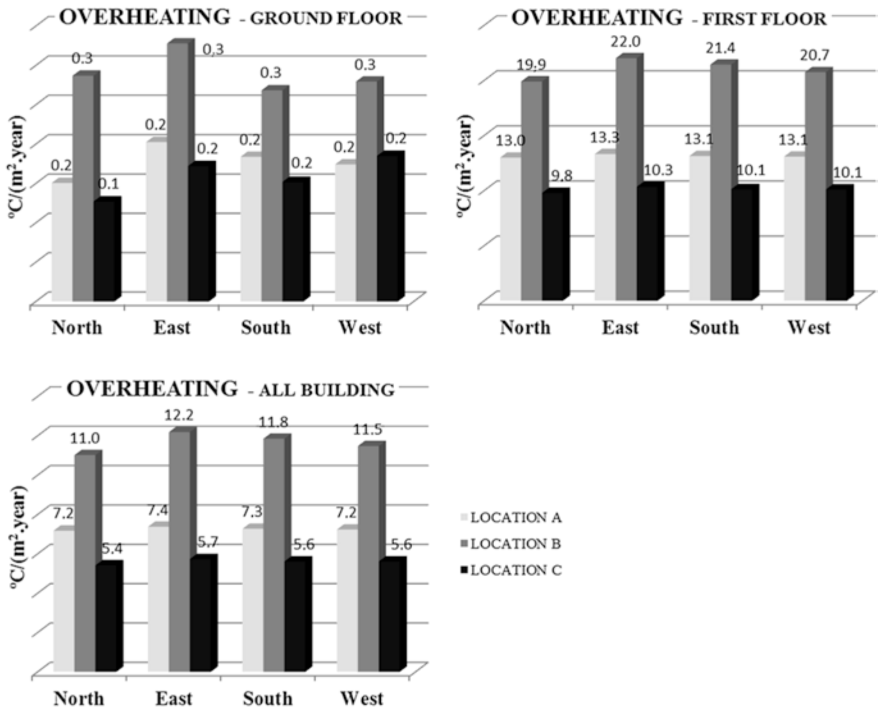

Fig. 5.7 Evaluation of the actual performance of the school building: performance function f_2

The results showed that the heating load in the first floor is higher than in the ground floor, indicating that the heat losses through the roof are rather significant. Hence, the insulation of the roof should be an effective measure to improve the building's energy efficiency. The discomfort due to the overheating revealed irrelevant on the ground floor as only the classrooms on the first floor seem to have overheating issues.

Differences in the building's performance due to changes in the predominant orientation were also identified. For the all building performance it can reach almost 10 %, as the mean difference, in the three locations, was 9.5 % for the heating load (performance function f_1) and 6.4 % for the discomfort due to the overheating (performance function f_2). As it would be expected, the situation that has less heating demand is the one with the larger number of classrooms facing south. On the other hand, for minimizing the discomfort due to the overheating the ideal predominant orientation would be north.

5.3.2 Parametric Analysis

The results of the evaluation of the school building's current performance, presented in the previous section, demonstrated that the predominant orientation of the building can be responsible for some differences in the performance functions. Even though, when performing a parametric analysis to assess the model's sensitivity to changes in the input parameters, the relative importance of the orientation should be comparable between data-sets and, consequently, similar results to the ones presented here should be obtained for the other predominant orientations. This situation was confirmed in our analysis. Therefore, in this book, the parametric results considering north as predominant orientation were selected for presentation.

The parametric analysis consisted in computing the values of the two performance functions, individually for the entire range of variation of each input variable. This approach allows evaluating the individual impact of each variable in the whole building performance. To better assess this effect it was chosen to present the results as a relative variation of the function in order to the actual value (actual performance of the building), in which positive variations correspond to an improvement on the current performance of the building. The results are presented in Figs. 5.8, 5.9, 5.10 and 5.11.

The results of the parametric analysis can be used as indicators for assessing the most effective measures to improve the building's envelope performance. For instance, it was observed that varying the insulation of the roof could decrease the heating load from 73 %, in location B, to 50 %, in location C, and that in locations A and C this change also improves the summer comfort conditions of the building.

The wall insulation could guarantee a reduction of up to 45 % in the heating load but, on the other hand, will be responsible for a decrease in the summer comfort conditions.

The results also revealed that the changes in the windows properties are the most ineffective ones, as although being possible to achieve a reduction of up to 30 % in the heating load, the consequence is amplifying the overheating issues in the classrooms.

A value of 4.0 h^{-1} in the ACR implies an increase on the heating load that goes from 310 %, in location C, to 640 %, in location B. Nevertheless, the same change would decrease the overheating problem in 48 %, in location B, and 80 %, in location A.

5.4 Multi-objective Optimization

The first multi-objective optimization procedure was the minimization of the two performance functions, f_1 (energy) and f_2 (overheating), described in Eqs. 5.1 and 5.2. As previous mentioned, the NSGA-II evolutionary (genetic) algorithm, available in a Matlab Toolbox, was employed. The parameters required by the optimization algorithm were defined as follows:

- Population: 100;
- Selection function: Tournament;

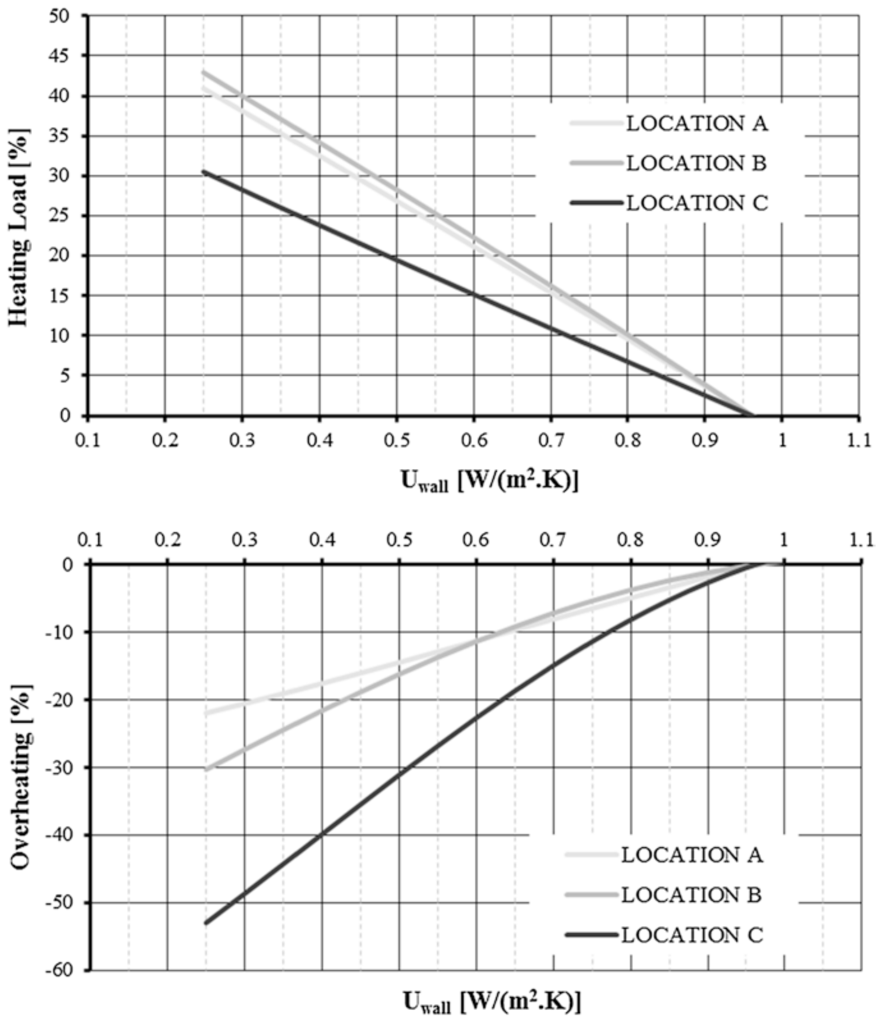

Fig. 5.8 Sensitivity analysis of the thermal coefficient of the external walls

- Reproduction: 80 % crossover and 20 % mutation;
- Crossover function: Intermediate;
- Pareto front population fraction: 1.

The optimization task included analysing the three locations and the four predominant orientations. Consequently, a large number of outputs, which correspond to the Pareto front, were produced. As an example, Fig. 5.12 shows the Pareto front obtained for the building model with east orientation and for the three locations under study. The point that represents the current performance of the building was also included.

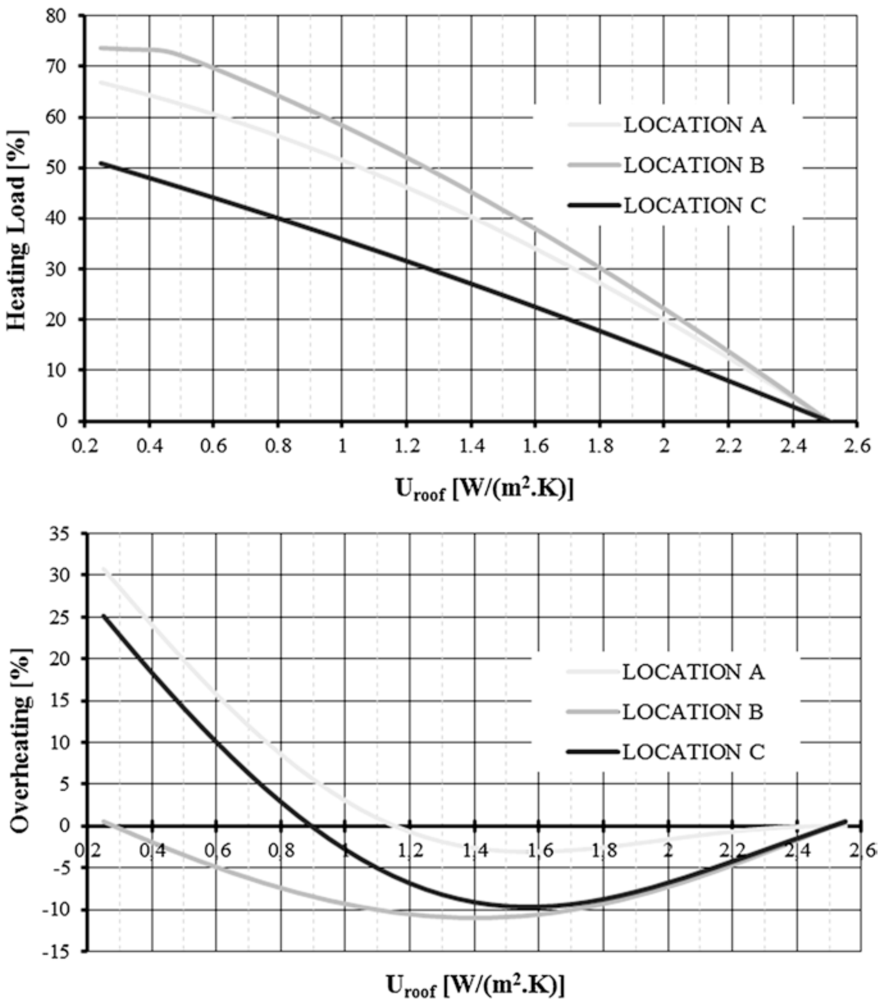

Fig. 5.9 Sensitivity analysis of the thermal coefficient of the roof

When comparing the Pareto front of optimum solutions with the building's current performance, a significant improvement potential arises. This is a common scenario for all the locations, yet some considerations regarding the exterior climate can be pointed: location B is conditioned by function f_2 as in this location summer conditions are decisive; location C is strongly conditioned by function f_1, since in this location winter conditions are more severe; and location A has the mildest climate.

However, a detailed analysis of the results revealed that the results are strongly dependent on the minimum and maximum limits imposed for the decision space. In fact, most of the optimal solutions correspond to unrealistic constructive scenarios,

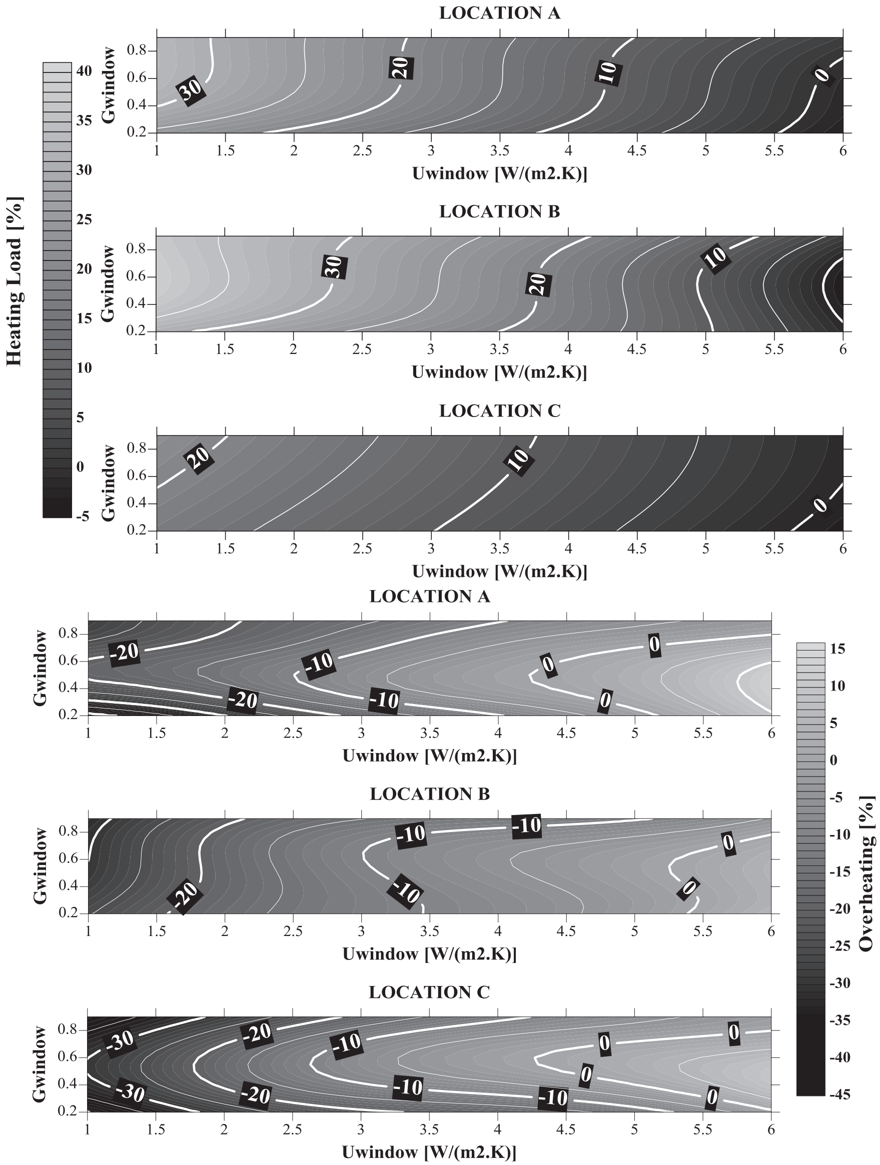

Fig. 5.10 Sensitivity analysis of the window properties: thermal coefficient and total solar energy transmittance

especially for the ACR, with very low values that cannot be considered valid, since that would lead to inadequate air quality inside classrooms. Therefore, it was decided to proceed to a new multi-objective optimization, establishing a minimum ACR of 1.5 h^{-1}, which, for typical occupation of the classroom, corresponds to

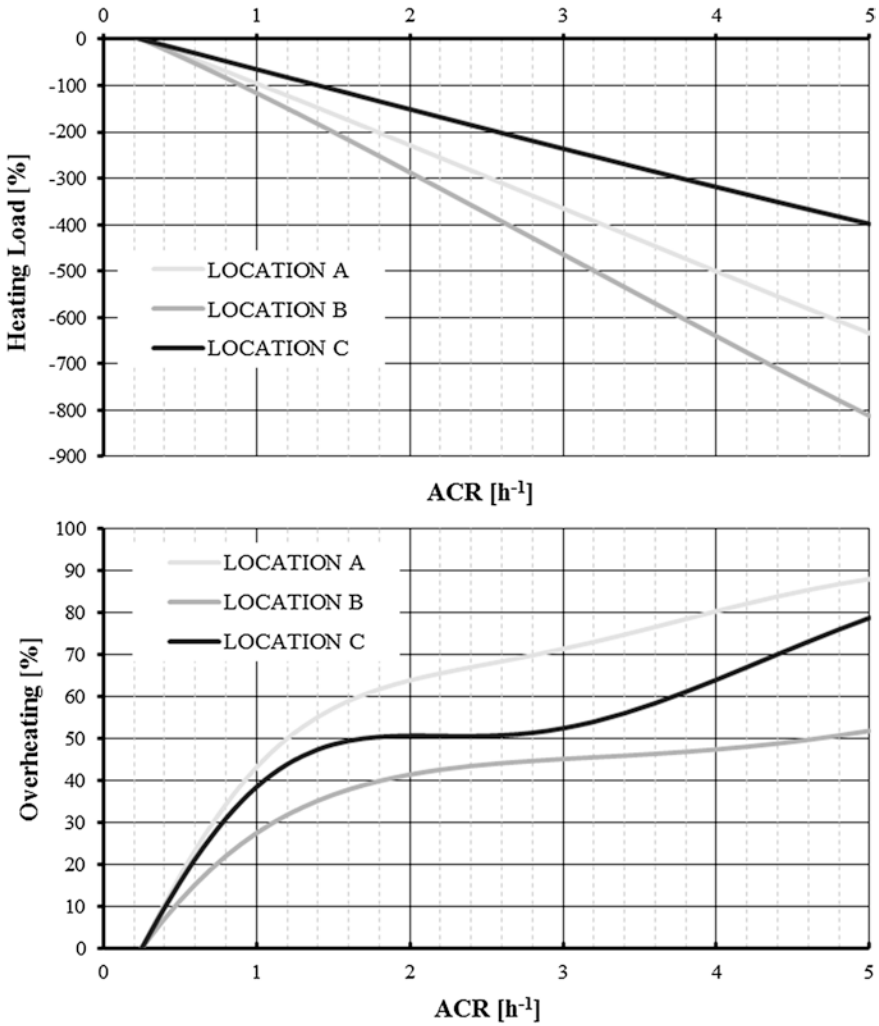

Fig. 5.11 Sensitivity analysis of the air change rate

3.125 l/(s.person). Figure 5.13 shows the results of this new optimization procedure, for the same building model.

Results are significantly different from those initially obtained, since Pareto fronts are now less dispersed. In fact, the initial variability of the optimum solutions resulted from the possibility of considering very low ACR, allowing for constructive scenarios with unrealistic heating demand.

Another important feature that arises from the imposition of a minimum ventilation rate is that the solution adopted for the rehabilitation will always lead to an increase in the annual heating load. As previous described in the book (Sect. 5.4),

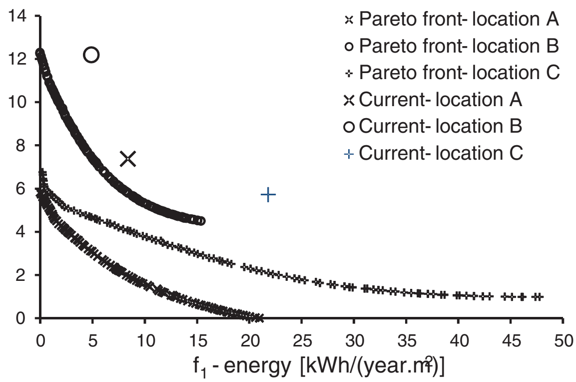

Fig. 5.12 Pareto front and current performance of the building

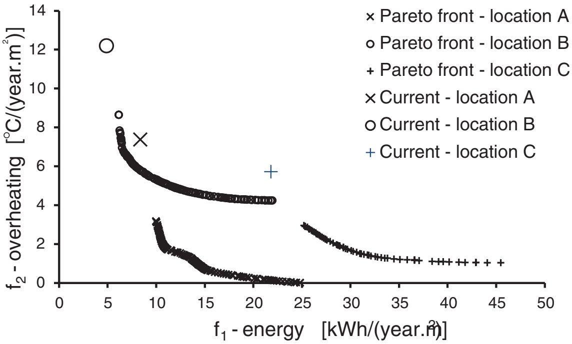

Fig. 5.13 Pareto front and current performance of the building with an higher minimum limit for the air change rate

current Portuguese school buildings do not provide their users with appropriate indoor air quality conditions, allowing, in this way, to a minimization of the heating energy demand. In short, the necessary improvement of the indoor air quality will always correspond to an increase in the operational costs of the building.

5.5 Life Cycle Cost

The methodology described in Sect. 5.2.5 was implemented and tested for the calculation of the optimum insulation thickness of walls and roofs in school buildings refurbishment. With this objective, a software tool, programmed in Excel VBA, was developed. This application allows optimizing the LCC of the insulation, after defining the economic scenario and the period of analysis.

The software computes the LCC of each rehabilitation scenario that belongs to the Pareto front and also for the reference case (do nothing alternative). Then the *dLCCi* is determined and minimized. The minimum value corresponds to the cost-optimum solution.

To make the application as comprehensive as possible, the user can define all the variables required for the complete characterization of the problem. The required input data can be gathered into three major groups: initial options, which include model type, location, orientation and air change rate; investment, which includes insulation price and its thermal conductivity; and economic analysis, which includes the period of analysis, energy price, real interest rate, inflation and the expected variation on the energy price (energy price escalation).

To help understanding the tool potential, an example case of a school building located in Porto (location A), with west orientation, was selected as an example-case (Fig. 5.14).

An air change rate of 2.0 h^{-1} was considered and Table 5.4 includes the values considered for the investment and economic input parameters. Two different economic scenario (A and B), in which a different value was considered for the expected variation of the energy price, were created to highlight the model's sensitivity to the economic parameters.

Fig. 5.14 Example case: school building in Porto (location A)

Table 5.4 Investment and economic input parameters

	A	B
Insulation price [€/cm]	2.0	2.0
Thermal conductivity [W/(K.m)]	0.037	0.037
Period [years]	25	25
Energy price [€/kWh]	0.14	0.14
Real interest rate [%]	2.0	2.0
Inflation [%]	2.0	2.0
Variation of energy price [%]	1.0	5.0

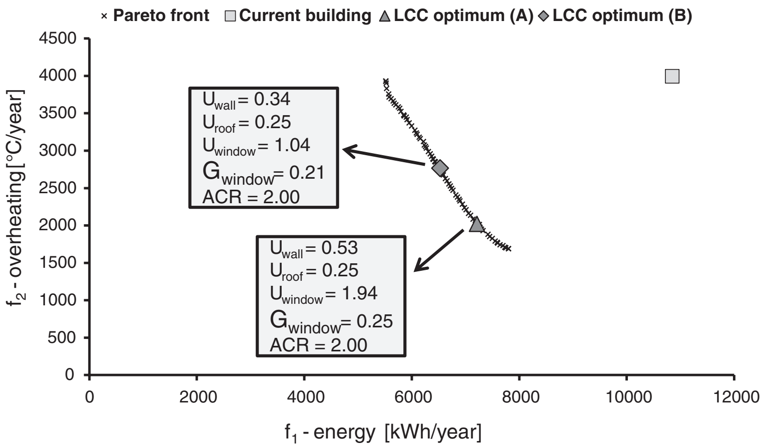

Fig. 5.15 Example case: graphical output

The software output is presented in Fig. 5.15 in which the current building performance, the Pareto front and the LCC optimum solutions are graphically represented. For the optimum solutions the corresponding decision variables value are also indicated.

It can be observed that in both scenarios the optimum solution corresponds to a situation near to maximum roof insulation ($U_{roof} = 0.28$), as according to the decision space previous defined its minimum value is 0.25.

Afterwards, using these results it is possible to calculate the optimum insulation thickness of external walls and roof. The software performs this task automatically. For this example, the optimum insulation thickness achieved by the LCC minimization for scenario A was 3.6 and 6.2 cm for walls and roof, respectively, and 5.9 and 6.2 cm for scenario B. These differences highlight the importance of the economic scenario for the final result.

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Chapter 6
Conclusions and Recommendations

Abstract This chapter presents the book's main conclusions and practical recommendations. The most relevant findings are synthesized and the some recommendations, which intend a compromise between the indoor air quality and the economic costs of the ventilation systems, are proposed. Yet, the climate dependent nature of the recommendations is stressed.

Keywords Conclusion · Recommendations · Rehabilitation

The indoor environmental quality of school buildings, particularly thermal comfort and indoor air quality, is, currently, motive of concern of both the scientific community and the society at large. Beyond the effect of environmental conditions in students' performance, the growing concerns with buildings energy efficiency gives more emphasis to this topic.

This book allows us to better understand the reality of school buildings in terms of hygrothermal performance under service conditions, both the newly refurbished ones and the non-refurbished.

The most relevant findings that arise from the monitoring campaigns are the following:

- Non-retrofitted schools do not have suitable conditions of comfort and indoor air quality (IAQ), thus it is imperative to improve it. The average air temperature for this group was very low and in some periods even lower than in the exterior. These schools do not have heating systems and the walls, roofs and windows have a high U-value, which might help to explain the results. The ventilation rates were very low and, consequently, insufficient to control the CO_2 concentration. So, the IAQ must be improved by means of higher levels of fresh air, even if this action involves an increase of the heat losses due to ventilation. The use of demand controlled ventilation systems, based on both comfort and IAQ criteria, might be an interesting solution and should be tested;
- In the retrofitted school buildings, the results showed that, during winter monitoring, temperature is within the usually considered comfort boundaries.

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Schools C and G were the exception. However, school C occupants had the possibility to control the temperature inside the classroom by adjusting the heating system and, as so, it seems reasonable to conclude that users felt thermally comfortable with a lower temperature. The use of adaptive models should be taken into account at design stage.

- In the retrofitted school buildings, classrooms temperature was clearly affected by the limited use of mechanical ventilation. Although most of the time temperature was within the comfort range (20–25 °C) an overheating problem was observed in the mid-season and summer campaigns. A maximum temperature of 36.9 °C was recorded. During summer campaign, temperatures above 30 °C were observed in all school buildings. Since mechanical ventilation systems are turned off, average CO_2 concentration decrease when temperature is high due to fresh air admission through window opening. During the winter campaign, with obvious limitations in the window opening, CO_2 average concentration reaches almost 2500 ppm in school I. The most interesting performance was obtained in school D, due to the natural ventilation contribution.

As a final conclusion it can be stated that retrofitted schools revealed substantial differences when compared to the non-retrofitted ones. The effect of the intervention was obvious. However, some differences from what was expected in the design stage were observed. The mechanical ventilation systems were off with important consequences in the indoor environmental quality of the classrooms. The contribution from natural ventilation (air inlet devices) was clearly identified in schools C and D. These schools presented the most interesting performance. Ventilation strategies based on demand controlled ventilation, including natural and mechanical contributions can be a solution to guarantee a compromise between the IAQ and economic costs of the ventilation systems. Yet, it is important to refer that this recommendation was derived considering the scenario of a mild climate country as in most southern European countries.

In the second part of this book, an insulation thickness optimization methodology for school buildings rehabilitation, combining artificial neural networks (ANN) and life cycle cost (LCC) was proposed. To this end five decision variables were defined and two mathematical functions were created to evaluate the building performance, one related to the heating energy demand and the other with the classrooms thermal discomfort due to overheating.

Since the optimization procedure is based on evolutionary algorithms, which require a large number of computer simulations, approximation methods were employed. ANN was the choice. The ANN proved to be effective and useful to approximate complex functions and, after being properly trained, can be used to replace the annual computer simulations. In this study, 48 ANN were created and validated with 10 cases. For the validation the respective R^2 was computed and the mean value obtained was $R^2 = 0.9818$. Still, it was verified that ANN require a large number of input data for their training, in order to achieve a good approximation. For each neural network, 160 cases were used, 150 for training and 10 for validation.

As expected, the optimization procedure revealed that Pareto fronts, i.e. the set of optimal solutions, are highly dependent on the minimum and maximum limits imposed for the variables space. In this particular case it was found that this is particularly important for the minimum limit of the air change rate.

The interpretation of Pareto fronts and subsequent definition of a criterion for the selection of a single solution is very complicated when dealing with problems such as the one presented. In this paper the inclusion of LCC as a decision criterion was proposed. For each solution belonging to the Pareto front the respective LCC was computed. The minimum LCC value was the decision criterion. This procedure allow the posterior calculation of the optimum insulation thickness of walls and roof. With this methodology the economic impact of the rehabilitation was implicitly introduced in the optimization. The method revealed that the LCC is a simple and appropriate instrument for this kind of problems.

The implementation was accomplished by the development of a software tool that automatizes the procedure. An example case of a typical Portuguese school building was selected to demonstrate the possibilities of the methodology.