Abstract

In the last decades, towards the Nearly Zero Energy Building (NZEB) standard, increasing attention has been given to the development of strategies and innovative technology solutions of building components and HVAC systems.

The human dimension, instead, especially regarding the operating modes of the building-HVAC system by occupants, is often neglected. In most cases, this causes a significant discrepancy between the expected and the real total energy use in buildings.

Nowadays the understanding of occupant behavior is inappropriate and overly simplified. A common approach to model occupant behavior consists of assumptions based on fixed schedules. In contrast to the deterministic methods, the stochastic and above all agent-based models are the most powerful and suitable methods for modeling a system as complex as the human behavior.

Furthermore, the integration of Building Energy Management Systems (BEMS) may provide significant energy savings, going not only to remedy an incorrect or inadequate management by occupants, but also to optimize the activation timing and management methods.

The objective of this research is to design "adaptive" Building Energy Management Systems (BEMS), able to maintain energy performance despite different operating conditions by occupants, by implementing an agent-based model to simulate occupant behavior and by optimizing the building components.

DICATECh 2017 Alessandro Rinaldi

Building Energy Management Systems (BEMS) optimization, by modeling occupants' behavior towards an agent-based approach

11

D.R.R.S

PhD in Risk and Environmental, Territorial and Building Development

Coordinator: Prof. Michele Mossa

XXIX CYCLE
Curriculum: Built Environment

DICATECh

Department of Civil, Environmental, Building Engineering and Chemistry

POLITECNICO DI BARI

11

2017

Alessandro Rinaldi

Building Energy Management Systems (BEMS) optimization, by modeling occupants' behavior towards an agent-based approach

Supervisor: Prof. Francesco Iannone
Department of Civil, Environmental, Building Engineering, and Chemistry, Politecnico di Bari, Italy
Advisor: Dr. Marcel Schweiker
Institute of Building Design and Technology, Karlsruhe Institute of Technology (KIT), Germany

D.R.R.S

PhD in Risk and Environmental, Territorial and Building Development

Coordinator: Prof. Michele Mossa

XXIX CYCLE
Curriculum: Built Environment

DICATECh

Department of Civil, Environmental, Building Engineering and Chemistry

POLITECNICO DI BARI

11

2017

Building Energy Management Systems (BEMS) optimization, by modeling occupants' behavior towards an agent-based approach

Supervisor:
Prof. Francesco Iannone
Department of Civil, Environmental, Building Engineering, and Chemistry, Politecnico di Bari, Italy

Advisor:
Dr. Marcel Schweiker
Institute of Building Design and Technology, Karlsruhe Institute of Technology (KIT), Germany

PhD Candidate:
Alessandro Rinaldi

POLITECNICO DI BARI

D.R.R.S

11

2017

Dottorato di Ricerca in Rischio e Sviluppo Ambientale, Territoriale ed Edilizio

Coordinatore: Prof. Michele Mossa

XXIX CICLO
Curriculum: Ambiente Costruito

DICATECh
Dipartimento di Ingegneria Civile, Ambientale, del Territorio, Edile e di Chimica

Ottimizzazione dei Sistemi di Gestione Energetica degli Edifici, modellando il comportamento degli occupanti verso un approccio agent-based

Supervisore:
Prof. Francesco Iannone
Dipartimento di Ingegneria Civile, Ambientale, del Territorio, Edile e di Chimica, Politecnico di Bari, Italia

Consulente:
Dr. Marcel Schweiker
Institute of Building Design and Technology, Karlsruhe Institute of Technology (KIT), Germany

Dottorando:
Alessandro Rinaldi

CONTENTS

LIST OF FIGURES

LIST OF TABLES

Abstract

In the last decades, in response to the high impact of buildings on global energy consumption and on the greenhouse gases emission, recent international directives have introduced the standard of "**Nearly Zero Energy Building (NZEB)**" to be realized from 2021.

Despite the increasing attention to the development of strategies and innovative technology solutions for the energy efficiency of building components and HVAC systems, **the human dimension**, especially regarding the **operating modes of the building-HVAC system by occupants,** is often neglected. In most cases, this causes a significant discrepancy between the designed and the real total energy use in buildings. Indeed, monitoring studies for identical dwellings having the same type of installations have shown great variation in energy use.

Occupants constitute one of the major source of microclimate alteration in built environment, both as "**passive agents**" (for sensible and latent energy emissions, and

emissions of pollutants), both as "**active agents**" as result of interaction with the buildings in order to achieve the desired comfort level (by acting on thermostats, by changing the state of opening or closing of windows and /or shading, by activating artificial lighting, etc.)

Above all in the buildings characterized by higher levels of the insulation and air tightness, the occupants behavior may have a great influence on the energy consumptions and on indoor environment conditions. If the occupants have the possibility to manipulate the set-points temperature, the ventilation rates etc., the performance of the building will be affected by the behavior of the occupants. As consequence, even the most efficient building, may give rise to waste in case of incorrect use by occupants.

Nowadays the understanding of occupant behavior results inappropriate, overly simplified, leading to inaccurate expectations of building energy performance. A common approach to model occupant behavior consists of assumptions based on scientists' thoughts or literature reviews. Typically human actions (operation of lights, blinds, and windows) are modeled based on **predefined fixed schedules** or **predefined rules**. In contrast to the deterministic methods, **stochastic** and **above all agent-based models (ABM)** are the most powerful and suitable methods for modeling a system as complex as the human behavior.

Especially in residential buildings, where the interaction of the occupants on the building-HVAC system is significant and hence the occupant behaviors may affect highly on building performance, the integration of Building Energy Management Systems (BEMS) may provide significant energy savings, going not only to remedy an incorrect or inadequate management by occupants, but also optimizing the activation timing and management methods.

Strictly connected with the "**resilience**" concept, the object of this research is to design "***adaptive*" Building Energy Management Systems (BEMS),** able to maintain energy performance at the desired level despite the diverse operating conditions by occupants, by optimizing building components.

In detail, several control logics for BEMS are analyzed in the residential buildings, by **optimizing** the **thermal** and **visual comfort** and by modeling the **occupant behaviors** by means of an **agent based oriented approach**. In this thesis the optimization goals are based on the adaptive thermal comfort according to EN 15251.

The thesis is structured in five chapters.

In the introduction chapter (chapter 1) the main factors influencing the building performance towards the design of the NZEB are presented.

Then, literature review regarding different studies that have analyzed the impact of occupant behaviors and the interaction with building-HVAC system (chapter 2) are reported.

The results of a questionnaire survey conducted on occupant behaviors in residential buildings are described in the chapter 3. Large differences in the behavior patterns of occupants are found between dwellings. Indeed, for the oldest buildings, where the thermal discomfort conditions are the highest, the occupants usually turn on active system, by causing more energy waste. Furthermore, it is resulted that while in winter occupants act less on the building components to improve their thermal comfort conditions, (indeed the main actions are wearing heavy clothes and turning on heating system), in summer season the occupants mostly interact with the building components, by changing the window and shading status or by adjusting set-point thermostat.

Because the actions on window and blind status are impactful on building performance, with the aim of reduce the thermal discomfort conditions and hence the variability tied to the occupant behaviors, **control logics of natural ventilation** and of **the solar shading system** for passive cooling are designed. Indeed by reducing the thermal discomfort conditions, also the actions and the interactions of occupant with building components may be less.

In detail, in an Italian dwelling with technological/typological features of sixties buildings, several studies are conducted with the aim to design BEMS for passive cooling that minimize the thermal discomfort situations, by means of Particle Swarm Optimization (PSO) method. The results of these studies are reported in the chapter 4.

In the second part of the work, in order to have BEMS adaptable to the actions and preferences of occupants, a further study is conducted (Chapter 5), where occupant behaviors are simulated in more detail, by means of an agent-based approach. In detail, actions like opening/closing windows and shielding and cooling system activation are implemented in the energy software simulation (TRNSYS), using algorithms deduced by field investigations in real buildings.

The same control logics of the BEMS (reported in the Chapter 4) are then revalued in this different occupant behavior modeling and the comparison between the models where the occupant behavior is assumed in deterministic way and then though a probabilistic and agent-based approach, allowed to assess the impact of human behavior and the designed BEMS on building performance.

This work highlighted how the BEMS may ensure high levels of comfort and energy efficiency, through the dynamic control of some components based on external and internal environmental parameters and on the occupancy conditions.

The implementation of different occupant behaviors into energy simulation software, simulated by means of an ABM method and the coupling of optimization goal for BEMS represent an innovative contribution of the work. A co-simulation architecture is created between **TRNSYS** (for building-HVAC model), **TRNFLOW** (for building air flow network), **MATLAB** (for PSO optimization) and **DAYSIM** (for visive analysis).

Keywords
Occupant behaviors; Agent-based model; Building Energy Management Systems (BEMS); Questionnaire survey; Passive cooling; Particle Swarm Optimization (PSO).

Abstract

Negli ultimi decenni, in risposta all'elevato impatto degli edifici sui consumi energetici globali e sull'emissione di gas serra, le recenti direttive internazionali hanno introdotto lo standard di "**edificio a energia quasi zero**" da realizzarsi a partire dal 2021.

Nonostante la crescente attenzione rivolta allo sviluppo di strategie e soluzioni tecnologiche innovative per l'efficienza energetica dei componenti edili ed impiantistici, la "***dimensione umana"***, specialmente riguardante le modalità operative del sistema edificio-impianto da parte degli occupanti, è spesso trascurata. Nella maggior parte dei casi, questo determina una significativa differenza tra i consumi energetici prevedibili e quelli reali durante la fase di esercizio. Infatti, studi di monitoraggio su edifici identici, con le stesse caratteristiche costruttive e impiantistiche, hanno evidenziato notevoli differenze dei consumi energetici dovuti alle varie esigenze degli occupanti (riscaldamento, raffrescamento, illuminazione etc.).

Gli occupanti costituiscono una delle principali cause dell'alterazione delle caratteristiche microclimatiche negli ambienti costruiti, sia come "**agenti passivi**" (per l'emissione di calore sensibile e latente e di inquinanti), sia in veste di "**agenti attivi**",

come risultato dell'interazione con gli edifici per il raggiungimento del livello di comfort desiderato (agendo sui termostati di attivazione degli impianti, cambiando lo stato di apertura o chiusura degli infissi e/o schermatura, attivando l'illuminazione artificiale etc.).

Soprattutto negli edifici caratterizzati da alti livelli di isolamento termico e tenuta all'aria, il comportamento degli occupanti può avere una notevole influenza sui consumi energetici e sulle condizioni ambientali interne. Se gli occupanti hanno la possibilità di manipolare le temperature di set-point, I tassi di ventilazione etc., le performance reali dell'edificio potranno variare in misura significativa rispetto alle previsioni teoriche. Di conseguenza, anche gli edifici più efficienti, potrebbero determinare sprechi ed emissioni climalteranti in caso di uso non corretto da parte degli occupanti.

Attualmente, la valutazione dei comportamenti degli utenti risulta inappropriata e semplificata, determinando inaccurate previsioni delle performance edilizie previste in fase di progettazione. Infatti, un approccio comune nella modellazione dei comportamenti degli occupanti consiste nell'assunzione di determinate azioni basate su "literature reviews". Tipicamente tali comportamenti sono modellati mediante predefinite e fisse "schedule". In contrasto con i metodi deterministici, quelli **stocastici** e soprattutto **i modelli ad agenti** sono i metodi più appropriati per la modellazione di sistemi complessi quali quelli relativi ai comportamenti umani.

Solo studi recenti si sono focalizzati sull'analisi dei comportamenti umani all'interno degli edifici, con l'obiettivo di valutare il rapporto causa-effetto tra condizioni ambientali e comportamento degli occupanti. Soprattutto nel contesto degli **edifici residenziali**, dove l'interazione degli occupanti con il sistema edificio-impianto è rilevante, tali comportamenti potrebbero determinare significativi impatti sulle performance edilizie. In tale contesto, l'integrazione di sistemi di gestione energetica degli edifici (BEMS) potrebbe determinare significativi risparmi energetici, andando non solo a porre rimedio ad una non corretta o inadeguata gestione, ma anche ottimizzando l'attivazione dei componenti edili e impiantistici.

Connesso con il tema della "**resilienza**", l'idea principale del lavoro di tesi ha riguardato la progettazione di **sistemi "adattivi" per la gestione energetica degli edi-**

fici (**BEMS)**, in grado di mantenere le prestazione energetiche degli edifici al livello desiderato, **nonostante le diverse condizioni operative degli occupanti,** ottimizzando il funzionamento dei componenti edili e impiantistici.

In dettaglio, differenti logiche di controllo per BEMS sono state analizzate su un edificio residenziale, ottimizzando il comfort termico e visivo e modellando il comportamento degli occupanti per mezzo di un approccio agent-based. Trattandosi di sistemi di controllo passivo del benessere, l'ottimizzazione è stata applicata alle prestazioni di comfort valutate secondo la teoria del comfort termico adattivo in conformità alla EN 15251.

Il lavoro di tesi è articolato in cinque capitoli.

Il capitolo introduttivo (Capitolo 1) descrive i fattori principali che influenzano le performance edilizie verso la progettazione di NZEB.

Il capitolo 2 presenta diversi studi in letteratura che hanno analizzato l'impatto dei comportamenti degli occupanti e l'interazione col sistema edifico-impianto specie mediante analisi di monitoraggio.

I risultati di un questionario condotto sui comportamenti degli occupanti in edifici residenziali, sono descritti nel capitolo 3. In particolare, differenze nei modelli comportamentali si sono evidenziate in relazione al periodo di costruzione dell'edificio. In inverno, per migliorare le condizioni di comfort termico è risultato che gli utenti agiscono di meno sui componenti edili, ma soprattutto sullo stato di abbigliamento e sull'attivazione dell'impianto di riscaldamento. Nella stagione estiva, invece, gli utenti interagiscono maggiormente con l'ambiente costruito, cambiando lo stato di apertura/chiusura delle schermature e/o finestre o agendo sull'attivazione dell'impianto.

Poiché tali azioni sono notevolmente impattanti sulle performance edilizie, con l'obiettivo di ridurre le condizioni di discomfort termico e conseguentemente la variabilità legata al comportamento umano, un secondo studio (Capitolo 4) è stato condotto sull'analisi di differenti logiche di controllo della ventilazione naturale e delle schermature solari per il raffrescamento passivo degli edifici. Con particolare riferimento ad un edificio residenziale degli anni 60', simulando il comportamento degli occupanti in maniera deterministica mediante schedule fisse, diverse logiche di controllo per BEMS sono state analizzate, mediante algoritmi di ottimizzazione (PSO).

In seguito, con l'obiettivo di progettare BEMS, che si adattassero alle azioni e preferenze degli occupanti, un ulteriore studio è stato condotto (Capitolo 5) in cui i comportamenti degli utenti sono stati simulati con maggior dettaglio, per mezzo di un approccio agent-based. In dettaglio, azioni quali apertura/chiusura infissi e schermature ed attivazione impianto di raffrescamento sono stati implementati nel software di simulazione (TRNSYS), utilizzando algoritmi presenti in letteratura che simulano i diversi comportamenti. Le logiche di controllo progettate sono state nuovamente valutate in questa diversa modellazione del comportamento degli occupanti e il confronto tra i metodi deterministici e quelli verso un approccio agent-based, hanno consentito di valutare gli impatti dell'utente e delle logiche di controllo progettate per BEMS sulle performance edilizie.

Questa tesi ha evidenziato come le tecnologie BEMS possano assicurare alti livelli di comfort ed efficienza energetica, mediante un controllo dinamico dei componenti basato sulle condizioni ambientali interne ed esterne e sulle condizioni di occupazione.

L'implementazione dei differenti comportamenti umani nei software di simulazione energetica, simulati per mezzo di un approccio ad agenti, uniti agli obiettivi di ottimizzazione delle logiche BEMS rappresentano un contributo innovativo del lavoro. Una co-simulazione è stata creata tra **TRNSYS** (per la modellazione del sistema edificio-impianto-occupante), **TRNFLOW** (per la modellazione delle reti di flusso), **MATLAB** (per l'ottimizzazione tramite PSO) e **DAYSIM**(per analisi di comfort visivo).

Keywords

Comportamento degli occupanti; Modelli Agent-based; Gestione energetica degli edifici (BEMS); Raffrescamento passivo; Questionnaire survey; Particle Swarm Optimization (PSO).

Chapter 1

Introduction: Towards Nearly Zero Energy Buildings (NZEB)

In the context of the European Union efforts to reduce the growing energy expenditure, it is widely recognized that the building sector has an important role, accounting 40% of the total energy consumption in the European Union and 36 % of the EU's CO_2 emissions (BPIE, 2010).

In this panorama the Directive on the Energy Performance of Building (EPBD) (EPBD, 2010) is lied with the objective of promoting "*the improvement of the energy performance of buildings, taking into account the outdoor climatic and local conditions, as well as the effectiveness of technological solution in terms of cost-efficiency*". The goal is to obtain a rational use of energy, reducing the consumption of non-renewable resources and the environmental impact of energy systems in the buildings. As ultimate goal, the standard of "**nearly Zero Energy Building** (NZEB) by 2020 was introduced.

The design of NZEB is strictly related to the **climatic and local data**, **technologies and materials**, **building envelope and HVAC system**, and **occupant behavior**.

User behavior is one of the most important input parameters influencing the building performance. It has a much larger influence on the energy performance of a building than the thermal process within the building façade (Hoes, et al., 2009). In particular, human/behavioral influence seems to be a prerequisite for passive control systems, and also is important in decision-making for fully sealed, mechanically controlled buildings (Hoes, et al., 2009), (Degelman, 1999).

In energy simulation models of buildings, it is now clear how the application of user behavior models with higher resolution and higher complexity improve the understanding of the relationship between building, user and building performance (Rijal, et al., 2007).

The effort in increasing the prediction accuracy of building load is analogous to increasing the accuracy of building energy simulation (henceforth, building simulation) capabilities.

Among different strategies for constructing efficient buildings, this thesis focuses on occupant behavior impact so that energy-saving features can be implemented accordingly – e.g. optimally sized shading devices, ventilation strategy, etc.

The work focuses on the impact of occupant behavior and behavioral feedback on bridging the gap between the simulated and actual energy consumption.

This thesis tries to design Building Energy Management Systems adaptive to occupant behaviors, by implement an agent based model to incorporate occupant behavior into the simulation process.

1.1. On Energy Risk and Sustainable Development of the Building Sector

National and regional authorities worldwide have passed legislation in order to mitigate climate change. For example, the “20-20-20” targets of the European Commission include a 20% improvement in energy efficiency by 2020 relative to 1990 levels. One pathway for this objective to be achieved is via improved operational and retrofitting practices in existing buildings. Renovation of the existing building stock is therefore key to meeting long term energy and climate goals.

Buildings are responsible for a relevant portion of total yearly energy consumptions and greenhouse gas emissions, ranging from 40% to 50% depending of the sources. Of those consumptions, nearly 40% is directly attributable to the heating, venting, and air conditioning of the premises, as shown in Fig. 1.1.

The greatest energy saving potential is found in buildings, as stated by the European Commission in the “Energy Efficiency Plan 2011”. A minimum energy savings in buildings could potentially generate a reduction of 60-80 Mtoe/year in final energy consumption, as stated by BPIE (Buildings Performance Institute Europe, 2011), making a considerable contribution to the reduction of GHG emission and to the achievement of prefixed goals. After the coming into force of the European Directive EPBD on energy performance of building (European Commission, 2010), low energy consumption of buildings has become an important target to achieve and nearly zero energy buildings (nZEB) as well as comfort conditions are becoming essential requirements for the new generation buildings.

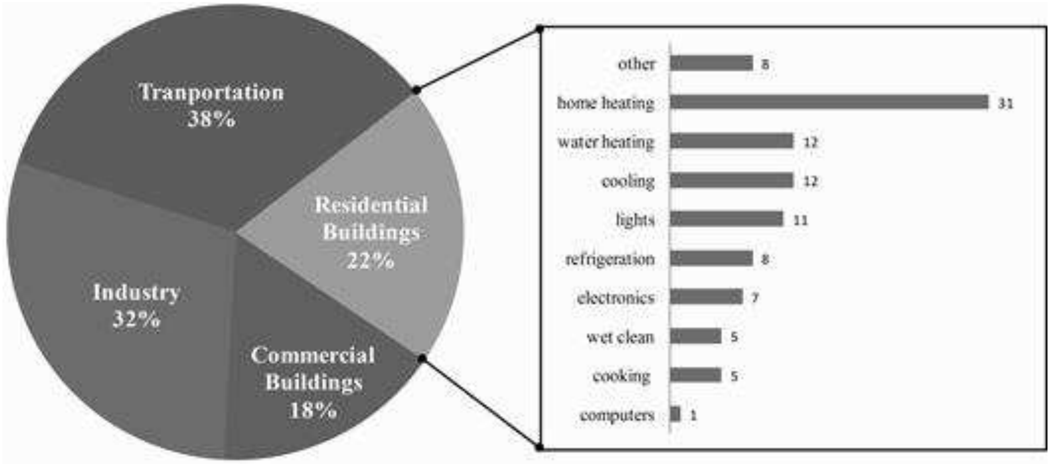

Fig. 1.1 Energy Usage by Sector (Perez-Lombard, et al., 2008)

In an important step toward energy independence the EPBD recast introduces the concept of nearly zero energy buildings forcing all new buildings to adopt this standard by the end of 2020. To serve as an example, all new public buildings are required to be nearly zero energy starting from 2018. However the challenge of refurbishment of the existing building stock should also be addressed in order to reach the objective of reducing the greenhouse gas emissions in the building sector by 90% by 2050.

The recast defines "nearly zero energy buildings" as "*a building that has a very high energy performance, where the nearly zero or very low amount of energy required should be covered to a very significant extent by energy from renewable sources, including energy from renewable sources produced on-site or nearby*".

To the EU member states is also required to prepare national plans in order to increase the number of nearly zero energy buildings also considering possible differentiations according to building categories. Each member state is also requested to introduce a national definition of the "nearly Zero Energy Buildings" according to EU guidelines. By this date each state is also asked to detail information on policies, incentives and other measures adopted for the promotion of nearly Zero Energy Buildings, including details on the use of renewable sources in new buildings and existing buildings undergoing major renovation.

The revision of Directive 30/2010 as well as the actions planned on Ecodesign and Directive 27/2012 are targeted to radically rethink the role of energy efficiency for achieving the 2030 indicative objective (ENEA, 2016). The energy efficiency potential is huge: only a small proportion of buildings is subject to major renovation and it is expected that more than two-thirds of the total will still be in use in 2050. Thanks to the adoption of the so-called Minimum Requirements Decree (Interministerial Decree 26 June 2015), Italy has focused more attention on the energy performance of buildings. Nevertheless, there are still barriers, many of which are outside the regulatory framework and as in other sectors, prevent the energy efficient potential to be fully exploited.

The framework, knowledge, materials and systems to achieve high levels of energy efficiency in buildings and strongly reduce energy consumptions, ensuring at the same time high levels of health and comfort, are readily available and can make a positive impact but they need to be properly implemented from design to construction and operation of buildings. The high energy efficient buildings bring together a vast array of practices, techniques, and skills to reduce and ultimately eliminate the impacts of buildings on the environment and human health. While the practices or technologies employed in high energy efficiency buildings are constantly evolving, fundamental principles persist: siting and structure design efficiency, indoor environmental quality enhancement, operations and maintenance optimization, etc. The essence of green building is an optimization of one or will more of these features.

1.2. Main factors influencing the building performance

In order to reduce the energy consumptions in buildings, more and more energy efficient technologies for the building-HVAC system (e.g. phase change material-PCM, solar cooling, mechanically controlled ventilation-VMC, etc.) have been developed in the last decades.

In particular, the energy consumptions of buildings depend on a complex system of factors that cause significant differences on building performance. These factors are (Fig. 1.2):

- *the climate;*
- *the building envelope characteristic;*
- *the HVAC typologies;*
- *the management of "building-HVAC" system;*
- *the occupant behavior.*

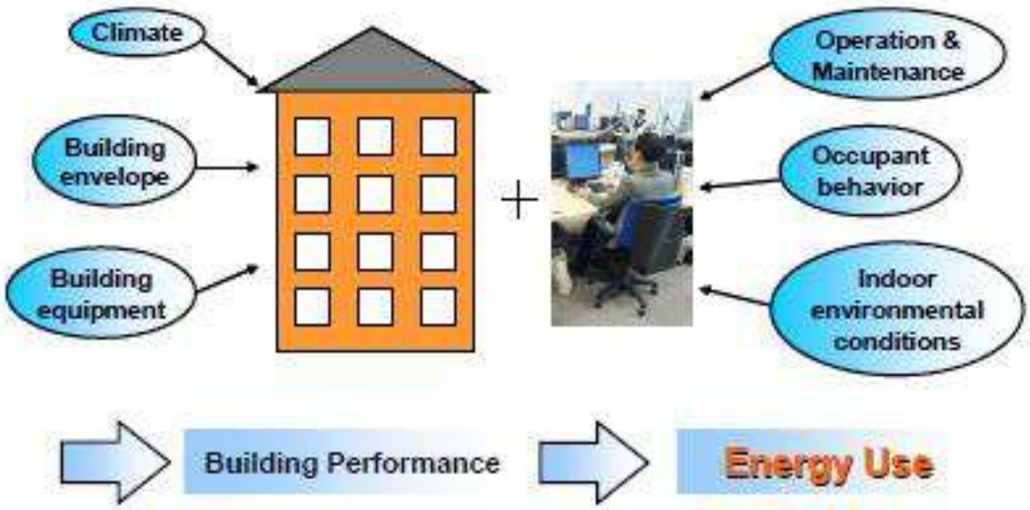

Fig. 1.2. Factors influencing energy consumptions in buildings (Final report Annex 53, 2013).

Disproportionate amounts of attention have been directed towards system or technological efficiency improvements, while ignoring the human dimension. Indeed, most researchers have focused on the physical aspects of buildings, such as the building envelope and the management of Heating, Ventilation and Air Conditioning (HVAC) systems (Alaidroos & Krarti, 2015), (Shaikh, et al., 2013), (Palonen, et al., 2009). The cognition of influences of occupant behavior is quite insufficient both in building systems design and energy retrofit.

The limited understanding of occupant behavior results inappropriate, overly simplified, assumptions which lead to inaccurate expectations of building energy performance and large discrepancies in building design optimization, energy diagnosis, and building energy simulations. This often causes a significant discrepancy between the designed and the real total energy use in buildings. Indeed, monitoring studies for identical dwellings having the same type of installations have shown great variation in energy use (Peng, et al., 2012), (Bourgeois, et al., 2006), (Juodis, et al., 2009).

Between several reasons, the main cause of these differences derives from the common practice of not deepen in the same way: the common practice design approach is often focused only on the first three factors, defined by Schweiker the "*hardware building*," while the remaining ones, named by Schweiker the "*building software*", they have been the subject only of recent global projects (IEA, 2013), (IEA & EBC, 2014). Hence, for the thesis purposes, it is interesting evaluating the influence of occupant behavior on building performance and design building automation system calibrated on the occupant preferences and behavior able to predict and reduce the variability of occupants. The goal is to predict the occupant behavior in order to adjust and optimize the building automation system.

1.3. The concept of “Active Building” and the Building Energy Management System (BEMS)

The standard NZEB requires a more sophisticated dynamic control of the entire building-HVAC system. Also the building more efficient from the point of view of construction and HVAC, it gives rise to wastage if handled incorrectly.

Despite the increasing attention to the development of strategies and innovative technology solutions for the energy efficiency of building components and systems, not much has been analyzed on the optimal management of the building-HVAC system.

Towards this direction, the role of the **Building Energy Management Systems (BEMS)** is known and significant, since these systems can contribute to the energy management and therefore to the achievement of the possible energy and cost savings (Doukas, et al., 2007). The BEMS are generally applied to the control of active systems, i.e. heating, ventilation, and air-conditioning (HVAC) systems, while also determining their operating times. In the above efforts, the performance of the BEMS is directly related to the amount of energy consumed in the buildings and the comfort of the buildings’ occupants.

In recent years, Building Automation Systems (BASs) associated with control and optimization techniques have been widely used to reduce building energy consumption and to improve indoor comfort (Kastner, et al., 2005). By means of BASs the active building systems, such as Heating Ventilating and Air-Conditioning (HVAC) systems, lighting systems etc. can be monitored and controlled in order to manage their consumption by respecting the comfort for users.

Many researches deal with the control of active systems, others both on active and passive systems, and only few researches focus on BASs for passive components. For instance, in (Wang & Wang, 2013) an intelligent controller was designed to determine the optimal ventilation rate in active systems, by maintaining the indoor CO_2 concentration in the comfort zone and by reducing energy consumption. Moreover, due to the non-linearity of the proposed model, Particle Swarm Optimization (PSO) was adopted to obtain the optimal ventilation rate: the relationship between the ventilation rate and the corresponding power consumption is described by fuzzy logic. The authors used for the control of the natural ventilation an energy management algorithm implemented in the Energy Plus simulation. In particular, the algorithm consisted of the following three components: rules on indoor air quality based on CO_2 sensors, rules on thermal comfort to prevent the overcooling, rules to reduce the risk of air draft.

Castilla et al. (Castilla, et al., 2013) proposed a multivariable nonlinear model predictive control system to maintain thermal comfort and IAQ by means of Heating Ventilation and Air Conditioning (HVAC) systems and natural ventilation. The main control objective was to maintain users' thermal comfort and IAQ inside a comfort zone defined by the Predicted Mean Vote (PMV) and the IAQ indices, respectively, minimizing, at the same time, the energy consumption necessary to achieve this comfort.

In addition, Sun et al. (Sun, et al., 2013) proposed an integrated control of active and passive heating, cooling, lighting, shading and ventilating system with the aim of minimizing total energy costs. To solve the optimization problem with the coupling HVAC capacity constraints, Lagrangian relaxation was used to obtain a near-optimal solution.

A number of modern techniques and methods have been proposed in literature for improving specific systems' controls: techniques for HVAC control, optimal regulator and adaptive control for window and solar shading control, etc.

More computerized methods, such as genetic algorithms and neural networks have been proposed for the control optimization of specific HVAC systems, too. Other methods for optimized building's systems control have, also, been proposed including empirical models, weighted linguistic fuzzy rules, simulation optimization and online adaptive control (Dias, et al., 2011), (Mendes, et al., 2001), (Le, et al., 2014).

In addition, BEMS are currently being developed to be applied in buildings, namely the ''**intelligent buildings**'' and a number of studies (Wong, et al., 2005), (Kua & Lee, 2002) have been presented for modern intelligent buildings and control systems, revealing the ongoing interest of the scientific community on this topic. Indeed, one of the research areas on building automation, in rapid development, concerns the harmonization between the concept of intelligent building and of bioclimatic one. This comes from the integration of active features, automation systems that make the building able to adapt to internal and external changes, and passive design: these represent, essentially, building strategies that promote the ability to accumulate heat and reduce heat loss, in winter conditions, and to protect from overheating in summer, limiting the use of air conditioning systems.

From this point of view, some studies (Ghiaus & Inard, 2004), (Brager & Dear, 1998), (Rowe, 1996) have shown, for example, that it is possible to achieve a significant reduction of energy consumption through the adoption of natural ventilation strategies as an alternative to air conditioning systems.

Further researches have explored the contribution resulting from the combination of active and passive management strategies applied to building systems and subsystems. In a study (Ochoa & Capeluto, 2008) developed on a building located in Haifa, Israel, the energy savings related to the implementation of three different scenarios were compared, these are:

- active features: use of reflective shielding for radiation and glare control, low-emissivity glasses and night ventilation managed according to the temperature set-point;
- intelligent passive design strategies, with overhangs shielding, lighting control, low-emissivity glasses and natural ventilation;
- the combination of the two previous scenarios, modulating the operation of the passive strategies in relation to the orientation and the depth of the projection.

Following the above studies, an integrated ‘‘**decision support model**’’ (see Fig. 1.3) for the management of the daily energy operations of a typical building is necessary, which can incorporate the following requirements in the best possible way: (a) the guarantee of the desirable levels of living quality in all building’s rooms and (b) the necessity for energy savings. In a broader sense, the capacity of building to manage, in an autonomous and adaptive way, its systems and sub-systems attracts potentialities associated not only with an efficient management of the indoor environment but also with the surrounding urban context.

Especially in existing residential buildings, the integration of building automation systems is not much present, but it reserves potential of great interest. Building automation can provide significant energy savings, going not only to remedy an incorrect or inadequate management systems, but also optimizing the activation timing and management methods. For example, only with a minimum expense, by the installation of mechanical arms controlled by electric motors and sensors it would be possible to automate the opening or closing of the windows/shielding.

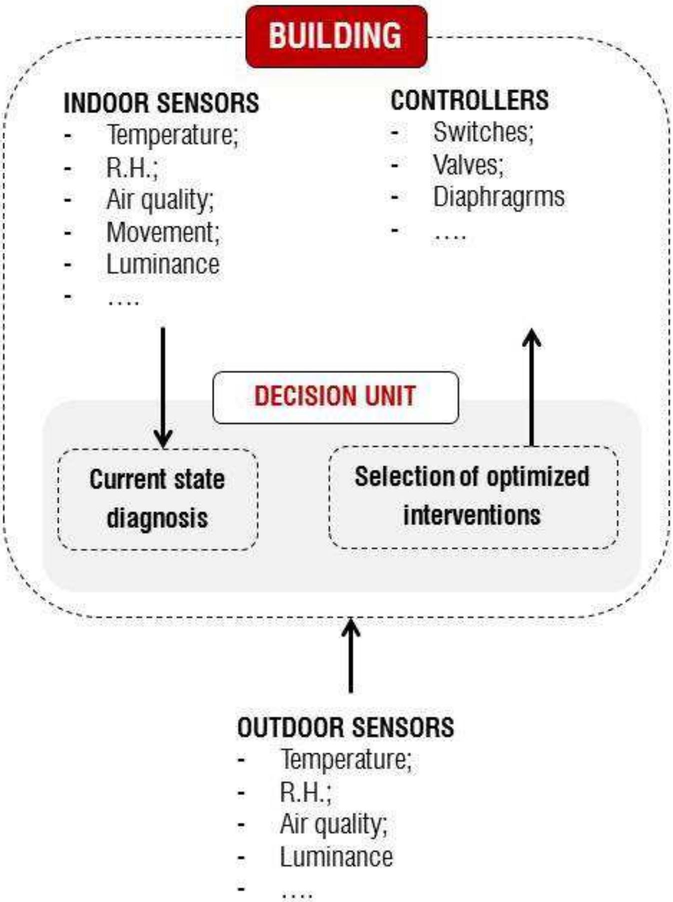

Fig. 1.3. The Decision Support Model

In this context, this PhD thesis, more than on the concept of passive building, is focused on the **active building** concept, capable of adjusting, based on external and internal conditions, the overall comfort of the users with the best feasible energy efficiency at that time. The concept of adaptive building becomes representative, therefore, of complex systems that change their behavior, and the relative performance, in response to environmental conditions or to the needs of users, contributing to the reduction of fuel consumption and emissions, thanks to the energy savings achievable through passive solutions.

1.4. The occupant behavior role

A common knowledge towards lower buildings' energy consumptions, is to use passive design strategies. Among others, it is recommended the use of super-insulation, thermal mass, solar shading, natural ventilation, etc. However, despite the use of these sustainable technologies in the recent years, energy demand has not decreased in the expected way (Schweiker, 2010).

One of the most significant barriers for achieving the desired reductions in building energy consumption is the lack of knowledge about the real functioning of a building once it is built, that cause persistent and significant discrepancy between the predicted and the real total energy use in buildings.

As explained in the previous paragraph, the **operation of the building systems by occupants** is one of the major factors influencing the buildings' actual energy performances. In fact, a lot of passive design strategies are very dependent on occupants' control, and the occupants often use it differently by how the designers have intended to employ it in the design phase (Schakib-Ekbatan, et al., 2015). Indeed, in reality occupants often act in order to maximize their comfort, adapting to the changing condition of the environment.

Research shows that if occupants don't act in a way that supports design intent, performance standards can be compromised. For modern dwellings with increased air tightness, the occupant behavior can have a larger effect on the air change rate and consequently the energy consumption of the dwelling.

Other studies (Karjalainen, 2016), (Degelman, 1999), (Schweiker & Shukuya, 2010) noted that occupant behavior has a much larger influence on the energy performance of a building than the thermal process within the building facade. Occupants may influence the indoor environment by his presence in the building, but above all by the actions that occupants take (or not). Degelman stated that building simulation is only capable of accurate predictions if the use of a building is predictable.

Although occupants are critical to the success of a high-performing building, the understanding of occupant behavior results inappropriate and oversimplified, leading to inaccurate expectations of building energy performance and large discrepancies in building design optimization, energy diagnosis, and building energy simulations.

Rijal et al. (Rijal, et al., 2007) stated that the application of occupant behavior models with higher resolution and higher complexity will improve the understanding of the relation between building, occupant and building performance.

Since realistic behavioral models are available, designers can handle occupant-related matters, while maintaining the highest degree of user's freedom. Indeed, with proper design solutions, the building would be able to maintain its energy performance at the desired level despite the diverse operating conditions. This is the founding principle of the concept of **robustness** (Palme, et al., 2006), which, applied to buildings, has been defined by Hoes et al. (Hoes, et al., 2009) as the sensitivity of identified performance indicators of a building design for errors in the design assumptions.Taking into account a more realistic behavioral models, the building would be able to maintain its energy performance at the desired level despite the diverse operating conditions.

Strictly connected to the sustainable building and the NZEB standard is the **resilience** concept, that is the adaptability capacity to the different operational conditions by occupants, climate and local conditions etc.

Today traditional energy dynamic simulation tools are based on deterministic and predefined user's behavior patterns and therefore they may be unsuitable for predicting the actual behavior of occupants that is by nature subjective, variable and stochastic.

Current practices in modeling the presence and actions of people in buildings do not display the necessary level of sophistication to reflect the complexity of people's passive and active impact on building performance. More reliable people action models require extensive observational data based on empirical studies of control oriented user behavior (as related to buildings' environmental systems) in a representative number of buildings. Thereby, possible relationships between control actions and environmental conditions inside and outside buildings can provide the underlying basis for predictive functions of user behavior for incorporation in building simulation applications.

In order to uncover salient occupant behaviors in buildings, and thus their implications for energy performance or efficiency, it is important to focus on the occupants role in the pursuit of energy conservation, which is a departure from the commonly aimed efforts for system oriented optimization for energy efficiency and then analyses the relationship between occupant behavior and energy performance. Understanding the occupant behavior is a key issue for building design optimization, energy diagnosis, performance evaluation, and building energy simulation. In order to fulfill the high expectations for energy savings in buildings in the future, better understanding of how energy-related occupant behavior influences building energy consumption is required.

Among the global project present in literature focusing on the occupant behavior interaction with the built environment, at first, Annex 53 project (IEA, 2013) and then the **Annex 66 project** (IEA & EBC, 2014) addresses these challenges by focusing on accurately capturing and/or quantifying the impacts occupant behavior has on building energy performance. The broader aim is to identify and eliminate current inconsistencies in building energy simulation. One top priority of this Annex is to foster international collaboration to establish a robust, universal, research framework. This project focuses on four key areas: (1) experimental design and data collection, (2) model development and validation, (3) database of behavioral data, and (4) knowledge exchange and sharing.

In this context, the effects of occupant behavior on energy use and the sensitivity to occupant behavior illustrate the importance of acquiring more knowledge on energy-related occupant behavior for understanding and realistically predicting the total energy use in present and future residential buildings and for adapting future building technology to occupant behavior.

1.5. Objective of this work and Thesis outline

In this PhD thesis, occupant behavior is considered a key issue for **building energy simulation, performance evaluation** and **building design optimization**. Starting from the literature review, the cognition of influences of occupant behavior is quite insufficient both in building systems design and energy retrofit, leading to limited understanding and inappropriate over-simplification. Existing studies on occupant behavior lack in-depth quantitative analysis.

Although there are many group worldwide studying occupant behavior individually, to date the behavior models created so far have often been inconsistent, with a lack of consensus in common language, in good experimental design and in modelling methodologies (IEA & EBC, 2014).

Occupants have many possibilities of interacting with the indoor environment: they can operate directly aiming at controlling the indoor environment (i.e. using thermostat, operating on windows or shadings), they can affect it unintentionally, (i.e. by appliances and equipment usage), and finally they can adjust themselves to the existing environmental conditions. This process triggers a short-term effect on occupant behavior through psychological, physiological and economic factors and also some long-term factors, such as comfort, culture and economy situation. Without taking into account the occupants' impact on building performance, even the most well designed building can fail to measure up to its high-performance potential.

This thesis sets up a simulation methodology to model behavior in buildings, and understand the influence of behavior on building energy use and the indoor environment. In detail the objectives are to:

- identify quantitative descriptions and classifications of occupant behavior,
- develop calculation methodologies of occupant behavior,
- implement occupant behavior models with building energy simulation tools,
- value the effects of occupant behaviors to design suitable control logics for BEMS.

Since during the buildings' design phase the assumptions regarding occupants' behavior are among the most erroneous, the main idea of this research is to design an “adaptive building” able to maintain its energy performance at the desired level despite the diverse operating conditions by occupants, taking into account a more realistic behavioral models. To achieve this control strategies and automation of building components and HVAC system for energy savings are defined, where the **occupants** are considered as a "*dynamic part*" for the design phase.

In the thesis work building automation systems for the energy management of the residential buildings are defined, by **optimizing** the **thermal** and **visual comfort** and modeling the **occupant behaviors** by means of an **agent based oriented approach**. In particular the thesis focuses on **residential buildings**, where the occupant generally has more degrees of freedom in the management of the building-HVAC system, and consequently the occupants behavior can greatly affect the energy performance of the building. Unlike by the commercial/office context where the building-occupant interaction is less, in the residential buildings the logics of building automation systems with the aim of the reduction of energy needs and where the human dimension is neglected might not produce beneficial, since the human behaviors are usually not driven only by the energy needs.

More in detail the main phases of the work are:

1. **identification of the main adaptive behaviors of occupants** in relation to the building, from the results of the questionnaire (see chapter 4);
2. defining the **control logics of building automation system**, and then define optimal threshold by **optimization method** (Particle Swarm Optimization - PSO);
3. **implementation of existing algorithms of occupant behaviors** relative to opening/closing window and blind and turning on the air conditioning into energetic software simulation (TRNSYS);
4. **assessment of occupant behaviors impact and the building automation effects on** building performance for the energy management of building.

Chapter 2

Occupant Behaviors in Buildings

In the past decades a large number of studies have been conducted to understand how building occupants interact with buildings environmental control systems such as windows, blinds, and HVAC systems. Most of these studies have the common goal to find a link between user control actions and the indoor or outdoor environmental conditions. Nevertheless, some building designers oversimplify the human behaviors, assuming behavior to be synonymous with presence (Hong, et al., 2016).

2.1. The occupant's behavior effects on energy consumption

The development of codes for whole building simulation has previously focused on the physical aspects of energy use such as heat loss through the facade, solar gain through windows etc. The current standard of most codes are very efficient at predicting the energy consumption of a building with specified occupant behavior.

However, energy consumption in buildings is closely related to the characteristics of their operational and space utilization, and to the behaviors of their occupants (Hoes, et al., 2009). Significant variations in energy use among apartments of the same type with identical appliances were due to the differences in occupants' behaviors.

Bishop and Frey (Bishop & Frey, 1985) compared the energy consumption of two passive solar townhouses in Pittsburgh and Pennsylvania with their design energy use. They found the measured energy consumption to be more than twice as high as the predicted consumption. This discrepancy was a result of differences in the real occupant behavior from the behavior used in the predictions.

Peng (Peng, et al., 2012) gave a quantitative description of human behavior in residential buildings, evaluating how the human behavior influences the energy use directly and indirectly by changing window openings, air-conditioner usage, lighting, etc. The method was then applied to describe a Beijing household with comparison to on-site observations of the resident' s behavior and measurements of energy use to validate the method.

Bourgeois (Bourgeois, et al., 2006), Lindelöf (Lindelöf & Morel, 2006) pointed that energy savings in excess of 40 % in buildings can result from changes in occupants' behaviors.

Sonderegger (Sonderegger, 1978) measured gas consumption for heating in 205 town houses located in the same group of houses. He found that 54 % of the variance in gas consumption was due to design features of the houses (i.e. number of rooms, area of windows etc). By comparing changes in gas consumption for heating between two different occupant behavioral, they concluded that 71 % of the unexplained variance was due to occupant behaviors.

Gartland (Gartland, et al., 1993) monitored energy consumption in four houses of identical layout in Washington. Data from the five heating seasons (1987-92) were analyzed to find correlations between energy usage and outdoor temperature for each house and heating season. This relationship was separated into two parts, the dependence of energy usage on building envelope temperature difference, and the dependence of this temperature difference on the outdoor temperature. This separation allowed insight into each building's thermal characteristics as well as into the behavioral characteristics of each building's occupants. They found that changes in heating set-point patterns accounted for as much as 27 % of the total energy used for heating, while variations in the door and window opening behavior accounted for up to 17 %. In addition they noticed how a lower infiltration rate would conserve energy but increase the impact of occupant behavior on the energy consumption. Indeed the passive buildings with a high level of thermal insulation and air tightness, are subjected to a more active role of occupant behavior (Hoes, et al., 2009).

Andersen (Andersen, et al., 2011) found that the energy consumptions of 290 Danish dwellings varied by up to a factor of 20 (from 10 to 200 kWh/m^2). Measurements of window opening and heating set-point behavior along with indoor and outdoor environmental variables were conducted in 15 dwellings in the vicinity of Copenhagen, Denmark, during the period from January to August. Measurements were carried out in 10 rented apartments and 5 privately owned single family houses. Half of the apartments were naturally ventilated while the other half were equipped with constantly running exhaust ventilation in the kitchen and bathroom.

Maier (Maier, et al., 2009) analyzed energy consumption in 22 identical houses with 4 various ventilation systems in Germany over a two year period. The house with the lowest consumption of energy had the lowest average temperature implying that the occupants conserved energy by having a lower heating set-point in the heating season.

Juodis (Juodis, et al., 2009) compared energy consumption for heating and domestic hot water of 2280 similar apartments in Lithuania. Special attention was given to compare heat consumption in identical buildings. The comparison was made on a building level. The authors concluded that the observed differences originate from differences in initial design and construction uncertainties and they did not discuss differences in occupant behavior patterns. While the diversity of the apartments construction may have effects on the different energy performances of the buildings, it seemed evident that the occupants' different behaviors significantly affect the consumptions. As a consequence, it would be worth to take the occupants' behaviors into account in the analysis.

While some scientists used energy consumption comparison to infer the effects of occupant behavior on energy consumptions, others have used questionnaire surveys to investigate the determinant for energy consumptions.

Sardianou (Sardianou, 2008) investigated the determinants of households' residential consumption for space heating in Greece employing cross-section data for 2003. It resulted that demographic and economic variables such as age of the respondent, family size and households' annual income were suitable to explain differences towards oil consumption for space heating. In addition, the results suggested that dwelling's size and rate of occupancy are positively associated with the amount of oil that Greek households consumed in order to achieve a significant level of heat comfort for their house. This indicated that the socioeconomic status had an impact on the behavior patterns of occupants.

These studies showed that occupant behavior have a very large effect on the energy performance of buildings. Understanding the importance of occupants' energy behaviors is crucial to bridge the gap between predicted and actual energy use in buildings.

2.2. The occupant actions in the built environment and their impact on building performance

The occupant behaviors can influence the microclimate of individual spaces, which are all closely connected to the overall energy performance of the building.

For the purposes of this thesis, the "*behavior*" term refers to any direct or indirect action that a building occupant takes to manage their surrounding environment. While this definition of occupant behavior pervades much of the existing literature, it is noted that several previous studies consider behavior to be a matter of presence - i.e., an occupant behaves by simply existing in the space as an added internal heat gain. Thus, this section frames behavior as a phenomenon of adaptation, and not one of presence. Behavioral adaptations may relate to a wide range of environmental conditions (i.e., temperature, air quality, light intensity, smell, sound, etc.), though existing studies tend to focus upon either temperature or lighting.

Hoes et al. (Hoes, et al., 2009) conducted a study on the effects of occupant behavior on the simulated energy performance of buildings and concluded that the simple approach used nowadays for design assessments applying numerical tools are inadequate for buildings that have close interactions with the occupants.

Recent studies (Bourgeois, et al., 2006), (Reinhart, 2004)of user-system interactions are conducted for individual building systems (lighting, shading, etc.). In the challenge of reducing the environmental impact, it is important to understand the occupant interactions with the indoor environment in order to provide comfortable conditions in the most efficient ways.

Occupants have many possibilities of interacting with the indoor environment: they can operate directly aiming at controlling the indoor environment (i.e. using thermostat, operating on windows or shadings), they can affect it unintentionally, (i.e. by appliances and equipment usage), and finally they can adjust themselves to the existing environmental conditions. This process triggers a short-term effect on occupant behavior through psychological, physiological and economic factors and also some long-term factors, such as comfort, culture and economy situation.

The following lineup of adaptations is frequently surveyed in following works:

- opening/closing windows or doors;
- adjusting blinds;
- turning on/off or dimming lights;
- changing thermostat settings;
- turning on/off personal heaters and fans;
- putting on/taking off clothing layers.

Each of these adaptive actions has a direct effect on thermal comfort.

In (Bourgeois, et al., 2006) by means of a self-contained simulation module called SHOCC (Sub-Hourly Occupancy Control), integrated in ESP-r application, it tried to bridge the gap between energy simulation and empirically-based information on occupant behavior.

As regarding the user behaviors in reference to the **illuminance conditions**, in Hunt (Hunt, 1979) a function was developed to simulate the probability that the occupants would switch on the lights upon their arrival in the office. According to this function, only illuminance levels less than 100 lx lead to a significant increase of the switching on probability. Similar functions were studied by Reinhart (Reinhart, 2004), Lindelof et al. (Lindelöf & Morel, 2006), where they noticed that the switching on actions were more common at lower than at higher illuminance values. Other studies (Eilers, et al., 1996) put in relationship the propensity of switching the lights off and the length of absence from the room, stating that people are more likely to switch off the light when leaving the office for longer periods.

Other studies regarded the **blind operation** actions by users in different contexts. For blinds that are manually controlled, there are only a few manual window blind control models that have been published in journal articles.

In Rubin at al. (Rubin, et al., 1978), Lindsay at al. (Lindsay & Littlefair, 1992) a strong correlation was found between the operation of Venetian blinds and the solar radiation intensity and the building orientation. Moreover, blinds were operated more frequently on the south facade Rubin (Rubin, et al., 1978) deduced that occupants operated shades mainly to avoid direct sunlight and overheating.

Newsham (Newsham, 1994) developed a blind operation model based on the thermal comfort model assumption that, if sunlight on window with intensity greater than 233 W/m^2 fell on the occupants, the blinds would be closed. The value of 233 W/m^2 was chosen to reflect the 20% PPD thermal comfort criterion.

Foster (Foster & Oreszczyn, 2001) chose the solar radiation threshold value of 300 W/m^2 to represent the threshold that occupants would start to use the window blinds.

In Reinhart's (Reinhart & Walkenhorst, 2001) a blind operation algorithm was developed that incorporates time of day, space occupancy and solar radiation as the major factors in blind opening or closing functions. However, the model also ignored any thermally driven mechanisms, which might further encourage the closing of blinds to avoid overheating during the summer or opening of blinds for increasing personal warmth during winter.

In Reinhart (Reinhart, 2004) the relation between blind operation and incident illumination on the facade was analyzed. In particular above a certain threshold of vertical solar irradiance on a facade (50 W/m^2) the level of shades was proportional to the solar penetration into a room. Once closed, shades seemed to remain deployed until the end of the working day or when visual conditions become intolerable. Reinhart developed LIGHTSWITCH 2002 using a dynamic stochastic algorithm. Based on an occupancy model and a dynamic daylight simulation application, predicted manual lighting and blind control actions provided the basis for the calculation of annual energy demand for electrical lighting.

As regarding the **window operation**, the window control by the users is the most frequent interaction between the user and built environment is (Fabi, et al., 2012), (D'Oca & Hong, 2014).

The probability of opening the window may be defined in function of temperature, occupant movement or CO_2 concentration etc. Indoor and outdoor temperatures are some of the most relevant parameters affecting window opening and closing behavior (Rijal, et al., 2007), (Haldi & Robinson, 2009). Opening a window produces a mixing of indoor and outdoor air and (when outdoor temperature is low) a drop in indoor temperature. The length of time the window is open is therefore governed by how long it takes for the room to cool sufficiently for the occupants to feel cold discomfort. If the room is not cooled enough to cause discomfort the window is likely to remain open. Andersen et al. (Andersen, et al., 2011) also suggested that indoor stuffiness, monitored by the carbon dioxide (CO_2) concentration levels, was an important driver for window opening behavior.

In (Herkel, et al., 2008) in 21 south-facing single offices in Freiburg, Germany, parameters such as window status, occupancy, indoor and outdoor temperatures, as well as solar radiation were regularly recorded. It resulted a strong seasonal pattern behind the window operation: in summer, 60 to 80 % of the surface of windows were open, in contrast to 10 % in winter. A strong correlation was found between the percentage of open windows and the outdoor temperature. Above 20 C , 80% of the windows were completely opened. The windows were opened and closed more frequently in the morning (9:00) and in the afternoon (15:00). Moreover, window operation occurred mostly when occupants arrived in or left their workplaces. At the end of the working day, most open windows were closed.

In Nicol (Nicol & Humphreys, 2002) a stochastic simulation approach was used to examine correlations between outdoor temperature and the use of windows, heating, and blinds. The study suggested that the solar radiation intensity would be necessary to establish correlations pertaining to light and blind usage.

In Rijal (Rijal, et al., 2007) after a field survey on window opening behavior in naturally ventilated buildings, the "adaptive algorithm" (Humphreys & Nicol, 1998) was implemented in ESP-r to quantify the effect of building design on window opening behavior, occupant comfort and building energy use.

Machintosh and Steemers (Macintosh & Steemers, 2005) conducted a post-occupancy evaluation case study in an urban housing scheme in London. The apartments were equipped with operable windows and a mechanical ventilation system with heat recovery. Based on the results from the evaluation and observations of window opening behavior, they derived a linear relationship between the outdoor temperature and the proportion of open windows. The result was that the actual use of windows and mechanical ventilation system bore no resemblance to the theoretical model. In fact, the actual energy consumption resulted in a CO_2 emission of roughly 1.5 times that of the theoretical model. In this case the designers simply assumed that the occupants would use the windows in an optimal way.

The above studies and other similar ones have provided a number of valuable insights into the circumstances and potential triggers of occupancy control actions in buildings. However, given the complexity of domain, additional long-term and monitoring studies are necessary to determine models of control-oriented user actions in buildings.

2.3. Understanding the occupant's behavior: a complex process

Human behavior can be expressed throughout the combination of many factors crossing different disciplines, from the social to natural sciences (Fabi, et al., 2012). Concerning the building science area, occupant behavior has traditionally been connected above all to indoor and outdoor thermal conditions. In particular, the occupant behavior is related to observable actions or reactions in response to external or internal stimuli, or respectively actions or reactions to adapt to ambient environmental conditions, household and other activities. These actions and activities are driven by various factors (see Fig. 2.1.)

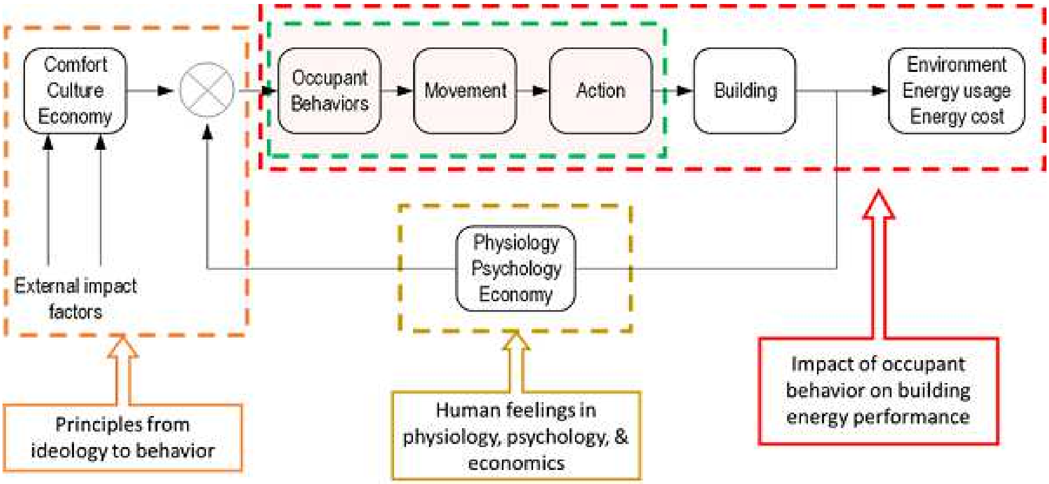

Fig. 2.1. The relationship between occupant and buildings (IEA & EBC, 2014)

In particular, occupant behavior is influenced by quite a large number of causes as proposed by Schweiker (Schweiker, 2010):

- **external** to the occupant itself (e.g., air temperature, wind speed, building properties);
- **internal or individual** (e.g., personal background, attitudes, preferences).

According to the adaptive approach, if an individual is in a state of discomfort, then she/he will take actions that would restore its state of comfort. The Fig. 2.2 shows this decision making process by user.

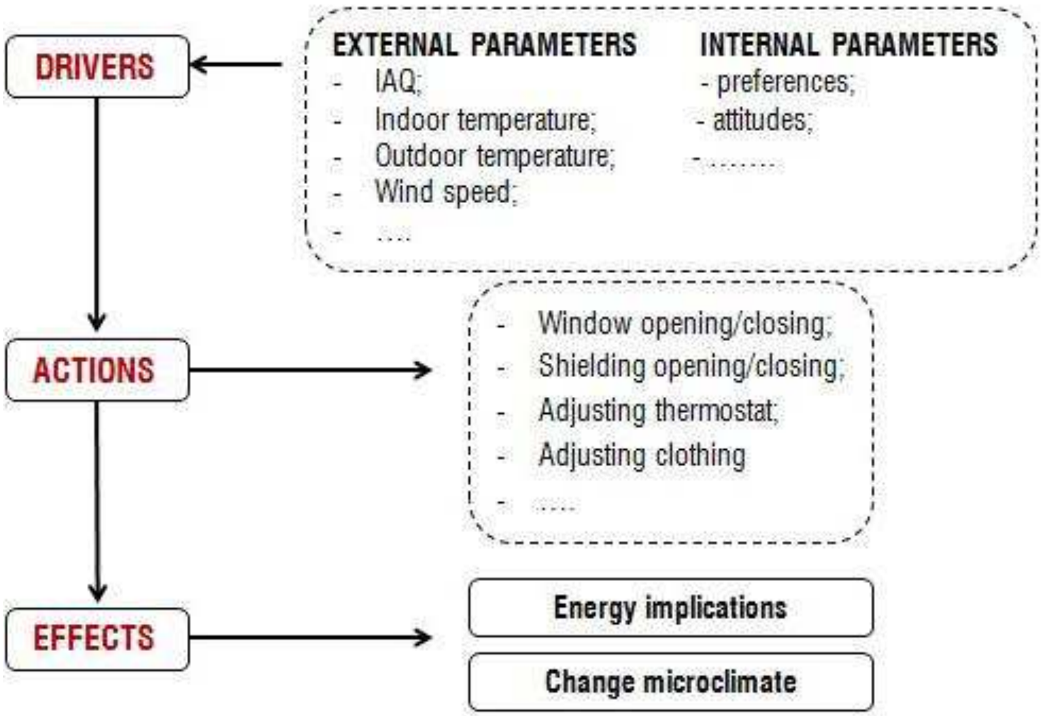

Fig. 2.2. The decision making process of occupants

The adaptive approach is based on the notion that the occupants level of adaptation and expectation is strongly related to outdoor climatic conditions. In general, research has demonstrated that occupants are more comfortable when they have a high degree of control opportunities and a freedom of choice to adapt their conditions in a clear and intuitive way (Toftum, 2010). As consequence, the behavior of the occupants becomes increasingly important and the consideration of occupants behavior in the design process becomes a necessity.

2.3.1. Internal Driving Forces

The internal driven forces (Polinder, et al., 2013) concern the **biological**, **psychological** and **social factors** as shown in the left side of the Fig. 2.3 These are being investigated in the domain of social sciences, economics, and biology. Strict differentiation between these driving forces is difficult to handle.

Examples of **biological driving forces** are age, gender, health condition, activity level, hunger, and thirst.

Psychological driving forces regard the occupants necessity to satisfy their needs concerning thermal, visual, and acoustic comfort requirements.

Furthermore, occupants may have certain expectations, e.g. the indoor environmental quality (such as temperature). Other examples of psychological driving forces are awareness (e.g. financial and environmental concerns), cognitive resources (e.g. knowledge), habits, lifestyle, perceptions, emotions, and self-efficacy (e.g. environmental control).

Apart from autonomous biological processes, there is a variety of deliberate regulation options:

- clothing: relevant in hot as well as in cold climate conditions, adequate clothing fosters reducing convection;
- thirst as the deliberate regulation of hydration;
- use of external sources for convection;
- looking for places which, which are more convenient, e.g. shade, areas with more or less natural convection;
- sleep (siesta) as an option to reduce metabolic heat production;
- acclimatization: the process by which an individual adjust the temperature of the environment. This is of importance regarding the degree by which the individual tolerates actual sensitized temperatures especially when it comes to extreme and unfamiliar climates.

Social driving forces refer to the interaction between humans. For example for residential buildings, this depends on household composition which is linked to the primary decision maker in the household, i.e. which household member determines the thermostat set point or the opening/closing of windows.

2.3.2 External Driving Forces

The external driving forces are shown at the right side of the Fig. 2.3. They regard the 'building and HVAC system' information and the physical environmental parameters.

Examples of building and building equipment properties are the insulation level of buildings, orientation of facades, heating system type, and thermostat type (e.g. manual or programmable).

Examples of physical environment aspects that drive energy-related occupant behavior are temperature, humidity, air velocity, noise, illumination, and indoor air quality.

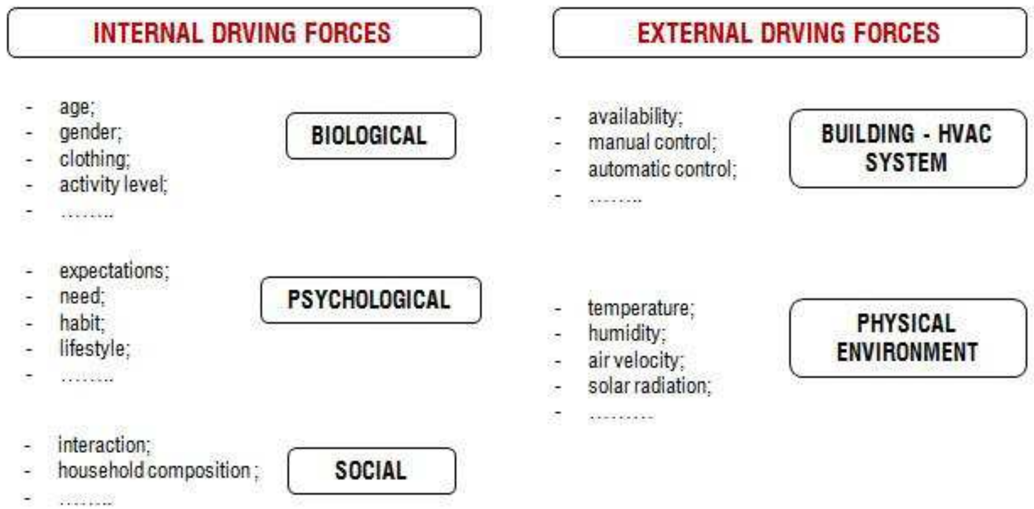

Fig. 2.3. The driven forces

2.3.3 Behavior and Comfort

As concerning the thermal comfort theory in buildings, in (Fanger, 1973) occupant behavior (e.g. changes in clothing level or the activity level) plays a key role for the Predicted Mean Vote (PMV).

The calculation of PMV consists of several variables relative tol :

- clothing level;
- metabolic rate;
- air temperature;
- mean radiant temperature;
- air velocity;
- relative humidity;
- water vapor pressure.

As examined in (Langevin, 2014), (Schiavon & Lee, 2013) some of these parameters are directly linked to the adaptive behaviors (clothing level and metabolic rate). In the most studies these inputs are assumed to be fixed, with metabolic rate constant across the year and clothing levels taking one typical value for each of the winter and summer seasons. The other parameters reflect the effects of behavior (as when, for example, opening a window increases air velocity in the space).

However, these potential effects are typically oversimplified during the design process of buildings. Indeed, by fixing the behavioral factors, a focus is often placed on optimizing interior temperature and humidity. Indeed, field studies of thermal comfort for not air-conditioned buildings have demonstrated the inadequacy of the PMV model in predicting human thermal comfort, particularly in the case of warmer climates. As underlined by Brager and de Dear (Brager & Dear, 1998), the PMV underestimates the range of optimal temperatures considered by the occupants of the buildings. Furthermore, the inaccuracies result from the failure to include behavioral adjustments in the PMV calculation.

De Dear asserts that:

> *"Fanger equation is basically valid, except that, in its application, the occupants ability to adjust to his/her thermal surroundings is ignored. In fact, occupants of a real buildings...often have considerable flexibility to change both the personal and environmental variables of Fanger equation in order to improve their comfort. Such adjustments enable occupants to maintain thermal comfort in environments outside the range that would predicted as comfortable by Fanger equations, if the ability of occupants to make adjustments is ignored".*

Specifically, an occupant in function of the surrounding thermal environment moderates his or her tolerance for a given range of thermal sensations (Langevin, et al., 2015), (Langevin, et al., 2013), (Leaman & Bordass, 2007), (Brager, et al., 2004). Several surveys in different case studies (McCartney & Nicol, 2002) showed that users have natural tendency to adapt to the mutable conditions of the their external environment. The theoretical basis of the previous analysis is the so called 'adaptive approach', which states that 'if a change occurs such as to produce discomfort, people react in ways which tend to restore their comfort' (Nicol & Humphreys, 2002). McCartney and Nicol developed an adaptive control algorithm (ACA) as an alternative to fixed temperature set-point controls within buildings. The results showed that use of the ACA had potential for energy savings in the climate-control services of a building with no reduction in the perceived thermal comfort levels of that building occupants.

2.4. Modeling of Occupant's Behavior

The occupant behavior modeling methodologies can be categorized into three areas (Polinder, et al., 2013) based on their research goals:

- schedules or deterministic profiles;
- stochastic models;
- agent based models.

2.4.1 Deterministic Models

A common approach to model occupant behavior consists of assumptions based on scientists' thoughts or literature reviews. Typically human actions (operation of lights, blinds, and windows) are modeled based on **predefined fixed schedules** or **predefined rules** (e.g. the window is always open if the indoor temperature exceeds a certain limit). These tools often reproduce building dynamics using numerical approximations of equations modeling only deterministic behaviors. In such a way, an "*occupant behavior simulation*" could refer to a computer simulation generating "fixed occupant schedules", representing a fictional behavior of a building occupant over the course of a single day (Glicksman & Taub, 1997). Often, the occupant behavior is not specifically addressed in the simulation programs, but only modeled by means of its effect e.g. the ventilation rate may be modeled as a fixed value that does not vary over time, with the assumption that occupants will manipulate windows in order to reach this ventilation rate. Moreover, in a design stage some "design conditions" are simulated, meaning that when the building is realized, the occupants' interactions with the indoor environment will exactly coincide with the design values during the entire operational time.

Deterministic models offer a simple way to represent the building occupant and they agrees well with currently energy simulation tools (Langevin, 2014). Use of the deterministic approach can provide quick, rough estimates of the possible effects that the building occupant can have on key simulated outcomes. Nevertheless, these estimates are subject to large uncertainties due to the fact that they rely on single point estimates to describe the full range of behavioral influences, and these estimates are often quite conjectural. Moreover, behavioral variation is addressed at the group level and does not reflect the behavioral differences between individual occupants.

2.4.2 Probabilistic Models

One recent alternative to using pre-defined point estimates of behavior is to consider behavior as a stochastic phenomenon that has a certain probability of occurring given a certain set of conditions. Here, statistical tools are used to identify the environmental, situational, or personal variables that are the strongest predictors of behavior in field data and functions are developed to describe the probability of a behavioral outcome in terms of those key variables. This approach has been used to model both occupancy and the direct adaptive behaviors of occupants.

In this way, the evaluation of the occupant behavior will be not only based on fixed action typologies, but also on coupling these repeatable interactions with the building control systems, with a probability of performing an action.

In order to overcome these barriers, different suitable user behavioral patterns (models) were defined by means of statistical analysis (logistic regression, Markov chains, etc.) and can now be implemented in many of the actual simulation tools (such as Esp-r, IDA Ice).

The procedure to simulate realistically the human behavior is based on a probabilistic approach for the evaluation of both input and output parameters. This probabilistic approach is related to variability and unpredictability during whole building operation in many of the actual simulation tools.

A study by Haldi and Robinson (Haldi & Robinson, 2010) was one of the earlier examples of using the statistical method. That research asked all the volunteer participants to complete an electronic survey with several questions about their activity level, thermal sensation, and adaptive opportunities exercised. At the same time, indoor and outdoor temperatures were recorded by sensors or from the local department (Swiss Federal Office of the Environment). Logistic regression was then applied to analyze the influence of thermal stimuli on occupants' behavior to open/close windows, blinds, fans, and doors. Also personal behavior like consuming drinks and adaptations on clothing was also included in the study. The authors found that internal temperature played a more important role than the external temperature on predicting the probability of occupant behaviors, with different impacts for each action.

Only concerning the **window opening behavior,** Lee et al. (Lee, et al., 2014) collected ambient data of six factors including indoor/outdoor temperature, indoor/outdoor humidity, indoor CO_2 concentration and outdoor wind speed. In this research, they used multi-factor variance analysis to find the statistical significance of the six factors to window opening activity. The study concluded that outdoor temperature is the most influencing factor. Base on the results, a logistic regression, was performed to obtain the mathematical relationship between the probability of window opening and outdoor temperature. A second comparative method namely Monte Carlo simulation was also performed to get the probability distribution of window opening activity.

Dong et al (Dong, et al., 2010) developed a statistical model that could accurately estimate the true number of occupants in a Pittsburgh office zone about 73% of the time based on real-time wireless sensor measurements of CO_2 and acoustics. The model assumed that occupant presence follows a stochastic Markov process, whereby the probability of future states of occupancy were only dependent on the current occupancy state and held independence from past states. The occupancy number was assigned as a hidden model parameter that could be determined from information about observed parameters (in this case, the environmental sensor measurements). The predictive capabilities of this “Hidden Markov” model were shown to be comparatively better on a daily and weekly basis than alternative Support Vector Machine and Artificial Neural Network methods tested.

The primary benefit of stochastic behavior models is their ability to generate detailed distributions of group-level behavioral outcomes using only a few easily measured inputs such as outdoor or indoor temperature. These distributions can then be included as inputs to energy models, which when run repeatedly can provide designers with empirically derived, quantitative estimates of the variation in key simulation outputs due to behavioral variations for each thermal zone of the building.

However, the wider applicability of these stochastic behavior models is generally limited by the quality and scope of the data that the models are derived from. In most cases, model data is constrained to one climate type and/or conditioning strategy; accordingly, the validity of regression coefficient estimates is limited to that particular situation. The same goes for personal characteristics, such as gender/age, thermal preferences, and beliefs; since the stochastic models yield a group-level or "average" behavior outcome, they do not directly account for inter-individual variability in behavior, potentially reducing their accuracy and generality.

2.4.3 Agent Based Models

Agent-based Modeling (ABM) is a computational model for simulation of occupant interaction with each other and the external environment.

In an agent-based model, individual building occupants and their interactions can be flexibly modeled in as great detail and heterogeneity as is necessary to fully represent the internal and social structures that are most relevant to the description of human behavior. In contrast to the deterministic and stochastic methods, agent-based methods describe larger behavioral trends as the aggregate results of bottom-up processes, capturing emergent and unexpected phenomena as the whole of the system becomes greater than just the sum of its constituent parts.

Though currently under-developed in the occupant behavior literature, agent-based models offer the most powerful and appropriate method for modeling a system as complex as the behavior of human building inhabitants.

The ABM approach requires a database that should include information concerning the driving forces of energy-related occupant behavior including social, psychological and biological driving forces, as well as driving forces related to the physical environment, building/installation properties, and time. This data could be gathered with questionnaires to be filled in by occupants and could possibly be obtained by means of measurements.

An **agent** can be defined as a system that acts and thinks like a human, which 'operates under autonomous control, perceive its environment, adapts to changes, and is capable of taking on specific goals' (Lee & Malkawi, 2014). This autonomous control can simply be a reactive 'if-then' rule, an ability to learn and change its behaviors in response to its experiences (Macal & North, 2010). In particular the agent has certain characteristics (Fig. 2.4):

- an agent is a discrete individual with a set of characteristics and rules governing its behaviors and decision-making capability;
- agents are self-directed, it can function independently in its environment and in its dealings with other agents.
- an agent is situated, living in an environment with which it interacts along with other agents. Agents have protocols for interaction with other agents, such as for communication, and the capability to respond to the environment;
- an agent may be goal-directed, having goals to achieve with respect to its behaviors;
- an agent is flexible, having the ability to learn and adapt its behaviors based on experience. This requires some form of memory;
- an agent may have rules that modify its rules of behavior.

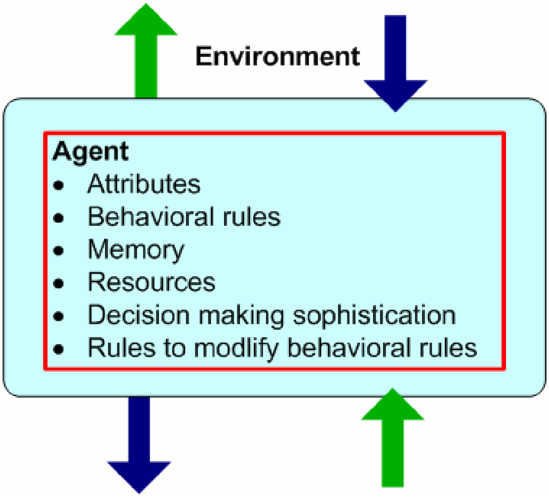

Fig. 2.4. Agent characteristics (Macal &North, 2014)

The general steps in building an agent model are as follows (Macal & North, 2010):

1. **Agents:** Identify the agent types and other objects (classes) along with their attributes.

2. **Environment:** Define the environment the agents will live in and interact with.

3. **Agent Methods:** Specify the methods by which agent attributes are updated in response to either agent-to-agent interactions or agent interactions with the environment.

4. **Agent Interactions:** Add the methods that control which agents interact, when they interact, and how they interact during the simulation.

5. **Implementation**: Implement the agent model in computational software.

As noted in Macal and North, an agent is any independent, self-directed entity that operates based on a given set of personal attributes, behavioral rules, memory/resources, decision-making sophistication, and rules to modify behavioral rules. Building inhabitants may accordingly be conceived as autonomous agents that actively interact with other agents and their environment in a manner ranging from purely reactive (automatic response to stimuli) to intelligently adaptive (based on goal setting and learning). As in the case of stochastic behavioral models, agent-based models have been used to simulate both building occupancy and occupant environmental adaptations.

Lee and Malkawi (Lee & Malkawi, 2014) presented a simulation method using an ABM approach that tried to mimic occupant behaviors in commercial buildings. The agent-based model tried to identify six common behaviors that are related to thermal comfort, and then adopted Fanger' s PMV model to identify behavior triggers. The decision making process was based on "*observe, orient, decide ,act* (OODA)" (see Fig. 2.5). The outside simulator provided environmental parameters and calculate the PMV comfort level, and then cost function was used to figure out the ranking of behaviors (orient and decide). Impact of actions was send back to outside simulators; in the process, the agent learned by upgrading the behavioral belief. Simulation coupling was also included. ABM was programmed in MATLAB and linked with Energy Plus with the help of *Building Controls Virtual Test Bed (*BCVTB) architecture, to exchange parameters in a whole loop. The results explored how different behaviors affect building energy use and occupant comfort level by adjusting relevant parameters to get different kinds of results.

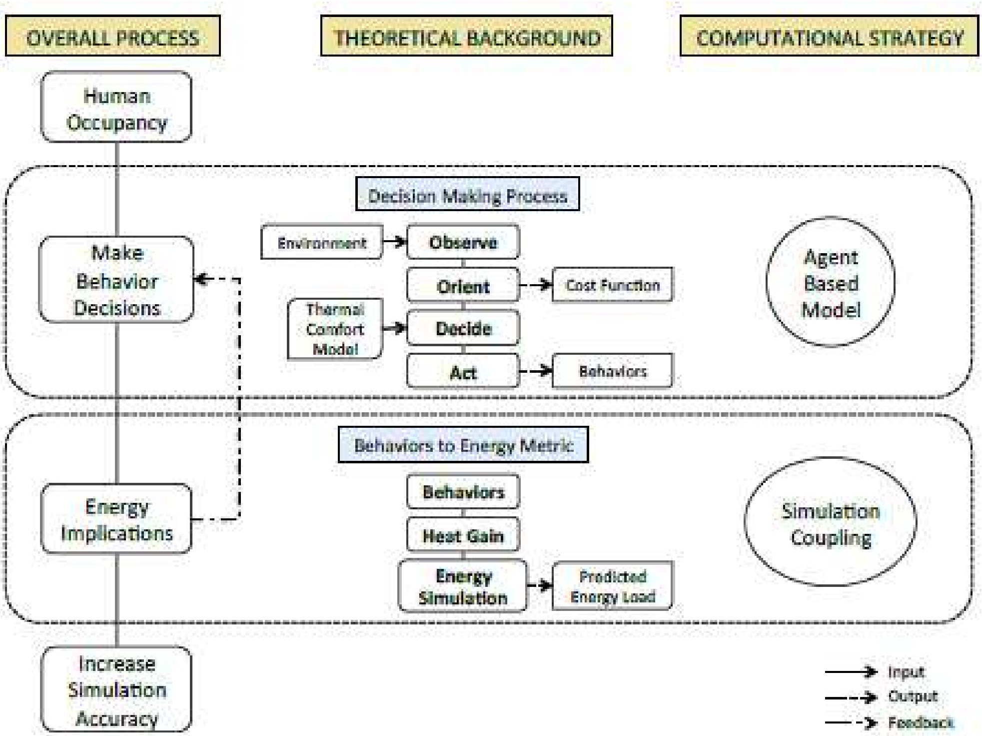

Fig. 2.5. The Decision Making Process (Lee & Malkawi, 2014)

Alfakara and Croxford (Alfakara & Croxford, 2014) used agent-based modeling to explore the interaction between occupants in residential houses and room systems for turning HVAC on/off as well as opening/closing windows. They built the ABM by dividing the objects into two classes: person and room. At the simulation stage, iterations were conducted combining the model and temperature input. Two cases were considered: a baseline and improved case, in which the improved case increased the temperature threshold of occupants. The results showed a reduction in HVAC used hours and an increase in window opening rate. Also, the cooling load was reduced by 30%.

Langevin et al. (Langevin, 2014) presented a detailed ABM using thermal comfort and behavior data from a field study in an office building. This model assigned building occupant agents dynamics for clothing, metabolic rate, thermal acceptability and behavior choice hierarchy. The rules of agent behavior conformed to Perceptual Control Theory to maintain thermal sensation. The performance of prediction was compared to other modeling options for validation. Although the study was limited to an office building, this approach provided a platform for more flexible simulations based on the interactions between occupants and surrounding built environments.

There are some drawbacks to agent-based modeling. In specifying behavioral attributes at an individual level, agent-based models are susceptible over-parameterization and high degrees of freedom, which can potentially diminish the robustness of simulated results. Moreover, model robustness must be determined by executing multiple runs while varying input parameters, which, when running through very large and intricate systems may become very computationally intensive. While advances in computational power have reduced this problem, care must be taken to specify only the most descriptive of agent attributes to ensure more efficient simulation runs. On the whole, however, the potential benefits of modeling building occupant behavior as an agent-based system far outweigh these concerns about model performance.

Chapter 3

Extracting Influencing Factors of Occupant Behavior by Means of a Questionnaire Survey

Due to the complexity and uncertainty of occupant behaviors, influenced by physical, physiological, psychological and other factors, is difficult to simulate and evaluate its impact on energy consumptions (Yan, et al., 2015).

Currently the modeling of occupant behavior in building simulation is often simplified and it is not still sophisticated enough to quantify occupants' impact on building performance and vice versa.

To measure and to value occupant behavior, new approaches are developed in order to integrate into design stage building simulations the models of users behavior. The researchers commonly follow the technical approach illustrated in the Fig. 3.1. In detail, data about occupant behaviors and environmental conditions are collected and then used for quantitative analysis to obtain correlations between indoor and outdoor environmental conditions and/or events and behaviors within a set of contextual factors. Finally, the behavior models are implemented and integrated within simulation tools for designers and researchers to use.

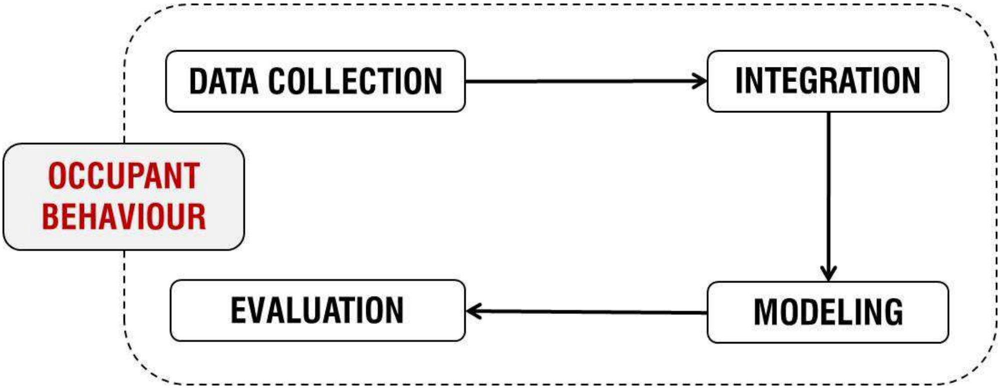

Fig. 3.1. The methodology for occupant behavior integration.

In this chapter, at first, the main methods present in literature to study the occupant behavior and its relationship with the built environment are described.

In the second section focuses on a questionnaire survey (cross sectional study) in order to extract the influencing factors of occupant behaviors in residential buildings conducted in the project ECOURB (Borri, 2011).

3.1. Behavior Data Collection

This section describes the main data collection approaches to study the human behavior, divided in three main categories:

- **cross sectional studies;**
- **longitudinal studies;**
- **observational studies.**

3.1.1 The Cross Sectional Studies

Cross sectional survey is a type of observational study that involves the analysis of data collected from a population, or a representative subset, at one specific point in time.

The survey records certain variables of interest for the respondent sample, and can be used to infer associations between these variables and identify prevalent population characteristics. This means that researchers record information about their subjects without manipulating the study environment.

The cross sectional survey can consist in a number of ways including telephone interviews, face-to-face interviews, and mail or online questionnaires.

The benefit of a cross-sectional study design is that it allows researchers to compare many different variables at the same time. We could, for example, look at age, gender, income and educational level in relation to typical occupant behaviors into buildings. In addition, cross sectional surveys are relatively quick and inexpensive to implement; by result, they tend to engage the larger number of subjects necessary to avoid problems with sampling bias.

With respect to occupant behavior research, however, the short time period in which these surveys are conducted limits the amount of environmental variation and related behaviors that can be observed amongst subjects. Moreover, findings may be subject to cohort effects: for example, it may be observed that those with higher perceived control satisfaction report higher thermal comfort scores, suggesting a possible relationship between comfort and this psychological variable. More generally, while cross sectional surveys may identify associations between variables, they cannot establish which variable is causing the other, as no information is collected on the time order of effects. This is because such studies offer a snapshot of a single moment in time; they do not consider what happens before or after the snapshot is taken.

Within the context of occupant behavior research, the ASHRAE Research Project 884 (Dear, et al., 1997) combined a large database of field observations on comfort and environmental conditions. About 21000 sets of raw thermal comfort data were collected from research group around the world. In particular, part of the survey included a section on personal control over the thermal environment, which gaged occupant satisfaction with perceived control as well as the general frequency with which occupants engaged in a series of thermal adaptations (windows; doors; thermostats; blinds; heaters; fans). Clothing and metabolic activity levels were also recorded through the survey, and simultaneous measurements of room temperature, globe temperature (accounting for radiant transfer), air velocity, and relative humidity were made at three heights. The database has been put in public domain and has had numerous application extending well beyond the initial scope of adaptive thermal comfort modeling, including empirical thermal index development and field validation of laboratory-based comfort models and standards.

In Rijal et al. (Rijal, et al., 2007) a cross sectional study was conducted on thermal comfort and control of 890 office occupants in 15 office buildings in the UK (10 air-conditioned, 5 naturally ventilated) between March 1996 and September 1997, by taking environmental measurements including measurements of outdoor air and indoor globe temperature. The surveys were administered verbally to each participant on 1 day per month, and included questions about thermal comfort at the time of visit, as well as current clothing and activity levels and use of controls. The survey recorded information about the subjects and their attitudes towards experience of the building, and also included a question about how frequently the subject uses available operable windows, which the authors used to distinguish between active and passive occupants.

3.1.2 The Longitudinal Studies

A **longitudinal study** is a correlational research study, where repeated observations of the same variables over long periods of time are conducted. The benefit of a longitudinal study is that researchers are able to better understanding of the causal relationships between response variables.

Longitudinal studies are often used to study developmental trends and human behavior pattern. The reason for this is that unlike cross-sectional studies, in which different individuals with the same characteristics are compared, longitudinal studies track the same people and so the differences observed in those people are less likely to be the result of cultural differences across generations. Indeed, usually researchers might start with a cross-sectional study to first establish whether there are links or associations between certain variables and then set up a longitudinal study to study cause and effect.

The frequency of survey follow ups can vary from once every few hours to once every several years, and the total number of survey administrations may similarly vary from as few as one to as many as hundreds of measurements collected.

Some of the disadvantages of longitudinal study include the fact that they take a lot of time and are very expensive.

Rijal (Rijal, et al., 2007) administered longitudinal surveys on window opening behavior in naturally ventilated buildings in the UK between March of 1996 and September of 1997. Occupants were asked to briefly record their thermal satisfaction, clothing and activity levels, and use of building controls four times a day (early morning; late morning; early afternoon; late afternoon). The authors found that a multiple logistic regression on the longitudinal data explained a greater proportion of the variance in proportion of windows open than did a regression on the cross sectional data, and adopted the equation from the longitudinal survey for their Humphreys algorithm for window opening, citing the much larger sample size and wider range of data points.

Newsham and Tiller (Newsham & Tiller, 1997) developed a computer survey software called ScreenSurvey and used it to collect thermal comfort data from 55 employees of 4 different office buildings (all air-conditioned) over the course of 10 weeks between October 1994 and January of 1995. Survey questions were administered twice a day for the full study period. The repeated surveys consisted of 5 questions on thermal sensation and preference, clothing levels, clothing change over the past hour, and position of window blinds. Concurrent data on mean outdoor air temperature, relative humidity, and solar radiation were collected from a nearby weather station for the study duration, and indoor air temperature and relative humidity was also measured concurrently at a location close to each participant.

Other studies, e.g. Haldi and Robinson (Haldi & Robinson, 2009), used similar types of computer surveys to collect longitudinal data more efficiently

3.1.3 Field Monitoring Studies

In **observational studies and laboratory studies** (Schweiker & Wagner, 2016), (Schweiker, et al., 2016) the occupants' behavior and presence and indoor environmental variables are passively monitored.

Several sensors, i.e. thermometers, anemometers, globe thermostats, CO_2 sensors, lux meters etc, are used to measure parameters like outdoor temperature, relative humidity, wind speed, solar radiation etc.

Data collection techniques include motion detectors (e.g., passive infrared and ultrasonic), carbon dioxide sensors, video cameras with computer vision, wearable sensors, security-based systems. Motion detectors are adopted as occupancy sensors (Lam, et al., 2009), but they are unable to detect nearly motionless occupants.

A few researchers (Hailemariam, et al., 2011) demonstrated that coupling motion detectors and carbon dioxide could improve occupancy detection accuracy, though there is a significant delay between occupancy and CO_2 increase. Cameras have been used by researchers to attempt to both identify occupancy and count the number of occupants. In particular the number of occupant is important because it influence the building performance (Haldi & Robinson, 2010).

Several recent reviews explored the potential to use wearable sensors, mobile devices, and security systems to detect occupancy, identify occupants (Atallah, et al., 2007).

Major behaviors of interest include light-switching, window blind-adjusting, window-opening, thermostat-adjusting, clothing level-choice and adjustment and fan use.

Window opening and closing behaviors were monitored by similar photographic approaches as for window blinds, using contact sensors, and by survey (Haldi & Robinson, 2009). The majority of the literature focused on window openings as a binary state; thus there is less knowledge on how occupants adjust partially open or close windows. This is likely because researchers have predominantly used contact sensors which cannot distinguish position when a window is open (Herkel, et al., 2008).

Monitoring partial opening/closing blinds is critical because daylight adequacy in not linearly related to blind position (e.g., a blind that is just partly open may still provide ample daylight). The dominant monitored daylight-related quantity to predict light and blind use is workplane illuminance (O'Brien, et al., 2013). Measurement of daylight with interior sensors is highly preferable because this greatly reduces the extensibility of results by reducing the effect of window geometry and type. Numerous daylight glare metrics have been developed based on laboratory experiments. Measurement of glare using a high dynamic range (HDR) camera has been focused on short-term studies (Konis, 2013) and further research is needed to demonstrate whether this method would be worth the additional cost, effort, and complexity.

Thermostat adjustments are best measured directly through integrated sensors or set-point logs (Gunay, et al., 2014), as air temperature alone is influenced by many factors (e.g., solar gains and window openings). The majority of research on thermostat is survey based.

Fan use is a dominant method for cooling in many buildings, particularly those which are warm but where air conditioning is a luxury. It has been studied by several researchers using surveys (Haldi & Robinson, 2008).

Clothing level does not directly impact energy use, but affects occupant comfort, which in turn influences occupants' other adaptive behaviors.

As regarding the environmental conditions, the weather data is typically an input for most models dealing with occupant interaction with facades and clothing.

The literature indicates that data sources include local weather stations, weather stations on the subject building, and even using spot measurements or descriptors. Furthermore, if solar radiation on the facade is desirable, it should be measured using a pyrometer mounted on the facade. Rain and wind speed/direction, which also vary spatially, are ideally measured on-site if they are to be used as model inputs. Indoor temperature and relative humidity (RH) are important parameters for predicting window and door opening, thermostat adjustments, and clothing levels. These quantities can be measured using deployed sensors; but care must be taken to place them away from heat, moisture, and contaminant sources (equipment, people, and solar radiation) so that their readings are representative.

3.2. Case Study: Questionnaire Survey

3.2.1 Materials and Methodology

The case study is based on data of an online questionnaire conducted between 2012 and 2015 by the “Department of Architecture and Urban Planning” of the Politecnico di Bari (Italy) inside the Strategic Plan (PS_047) "ECOURB: Analysis and Models of Air Pollution and Thermal Systems for Urban Ecolabelling" financed by Apulia Region, coordinator Prof. D. Borri (Borri, et al., 2013), (Borri, 2011), (Iannone, et al., 2012). In detail, this project was aimed at building up hybrid scenarios for the management of urban microclimates in the area of Bari, Italy, trying to work out how users with different roles and behaviors could affect urban microclimate while performing their single and/or collective activities.

The data derive from an Internet-based investigations, announced by electronic mail to the students of the teaching course of “Building services design” of Politecnico di Bari since 2012 to 2015. The compilers were 495, but only 450 completed the whole questionnaire. The questions to the participants were made only once and the answers of the participants were written once into a database and the incomplete answers were partly used for the analysis. Each participant followed an online guide that was designed to engage the respondents for 22 questions in discussions about key comfort, behavior, and energy use issues. It should be stated that users' answers were not personal but referred to the common attitudes and behaviors of the whole family.

The survey recorded certain variables of interest (information on buildings, on family behavior and attitudes, fuel consumptions) for the respondent sample, and they are used to infer associations between these variables.

In particular, part of the survey included a section on personal control over the thermal environment, which gaged occupant satisfaction with perceived control as well as the general frequency with which occupants engaged in a series of thermal adaptations (windows, blind, thermostats, etc).

Among the several data present in the whole questionnaire, only building-HVAC system and occupants data affecting the energy consumptions and thermal comfort are extrapolated by the questionnaire and used for the statistical analysis.

All buildings are located in the Mediterranean climatic context of south Italy (Puglia region), characterized by heating degree days (h.d.d.) between 901 and 2100.

The survey included different areas of questioning with supporting prompts (see Tab. 3.1):

- **Background Information of Buildings**: included questions about what type of building the resident lived, which were the characteristics of the building (e.g. window, heat source, area). In particular, the "construction year" variable enclosed all characteristics and technological solutions of the "building-HVAC" system, typical of that certain period.

- **Family General Information**: included general questions regarding the occupants.

- **Behaviors & Preferences**: included questions about when they used heating and cooling system in the house, what meant residents use to adapt interior conditions to their own preferences.

- **Fuel Consumptions**: included questions about the total fuel consumption for domestic hot water, heating and cooking. The total fuel consumptions (m^3) of the buildings was normalized, by dividing for the dwelling size, in order to have an index (m^3/m^2) approximatively independent from the building size and the number of family member.

Hence, the questionnaire combined the building-HVAC system and the occupants: data regarding the building (i.e. building typology, construction period, glazing typology, etc.) and HVAC system (i.e. heat source kind, management of active system, etc) compared with the data of the attitudes, preferences and the daily common behaviors.

In order to value and to identify the main characteristics of the examined buildings and the main attitudes and behaviors of the users, statistical analysis are conducted by the R software (Team, 2012). First, frequency and density estimation analyses are performed. In the second section, multivariate linear regressions are conducted taking into account the effects of all variables on the responses of interest. In this way it is possible to understand the relationships between variables and their relevance to the actual dependent variable (DV) under investigation. As DV the fuel consumptions and the set-point temperature for heating system adopted by the user are analyzed.

The Tab. 3.1 reports the questions above described used for this work.

3.2.2. Multivariate Regression Analysis

Multiple regression analysis are performed in order to determine the function that best expresses the relationship between the independent variables $\mathrm{X}_1, \mathrm{X}_2, \ldots \mathrm{X}_k$ and the dependent variable Y.

$$Y = b_0 + b_1 X_1 + b_2 X_2 + \cdots + b_k X_k \tag{3.1}$$

where:

- Y is the dependent variable;
- b_0 is the intercept;
- $\mathrm{b}_1, \mathrm{b}_2, \mathrm{b}_k$ are the regression coefficient;
- $\mathrm{X}_1, \mathrm{X}_2, \mathrm{X}_k$ are the independent variables.

BUILDING-HVAC SYSTEM

Background Information

1. Construction year of the building.
2. Building typology:
   - ☐ multifamily building
   - ☐ detached house
   - ☐ terraced house
3. Apartment size (m^2).
4. Heat source type:
   - ☐ biomass boiler
   - ☐ condensing boiler
   - ☐ high efficiency boiler
   - ☐ traditional boiler
5. Cooling system presence:
   - ☐ yes
   - ☐ not
6. Window glazing type:
   - ☐ double glazed (low e-coating)
   - ☐ double glazed (no low e-coating)
   - ☐ single glazed
7. Heating (cooling) system management:
   - ☐ on/off
   - ☐ climatic thermoregulation
   - ☐ chronotermostat
8. Refurbishment actions on building-HVAC system:
   - ☐ yes
   - ☐ not

Fuel consumptions

9. Annual fuel consumption (m^3/ m^2)

OCCUPANT

Family General Information

10. Number of family members.
11. Number of occupants in the dwelling:
    - from 8 a.m. to 1 p.m.
    - from 1 p.m. to 3 p.m.
    - from 3 p.m. to 8 p.m.
    - from 8 p.m. to 11 p.m.
    - from 11 p.m. to 8 a.m.
12. Family monthly income (€).

Behaviors & Attitudes

13. Daily hours of heating (cooling) system activation:
    - ☐ less than 2 hours
    - ☐ from 2 to 4 hours
    - ☐ from 4 to 8 hours
    - ☐ more than 8 hours
14. Daily time slot of heating system activation:
    - ☐ from 6 p.m. to 12 a.m.
    - ☐ from 6 a.m. to 9 a.m. and from 6 p.m. to 12 a.m.
    - ☐ from 12 a.m. to 9 a.m.
    - ☐ from 12 a.m. to 6 a.m. and from 8 p.m. to 12 a.m.
    - ☐ whole day
15. Set point temperature for heating (cooling) system.
16. User behaviors during situations of thermal discomfort in winter:
    - ☐ drinking hot drink
    - ☐ reducing opening windows
    - ☐ wearing heavy clothes
    - ☐ closing shielding system nighttime
    - ☐ turning on heating system
17. User behaviors during situations of thermal discomfort in summer:
    - ☐ drinking cold drink
    - ☐ opening windows
    - ☐ wearing light clothes
    - ☐ closing shielding systems
    - ☐ turning on cooling system
18. User preferences:

I prefer coming into a too-heated (cooled) room when outside it's cold (hot):
- ☐ agree
- ☐ indifferent
- ☐ not agree

Tab. 3.1. Questionnaire Structure

The sign and the values of the regression coefficient represent the partial effect of each variable $(e.g.\ X_1)$ on the variable Y, keeping constant the other variables $(X_2, \dots X_k)$. That is if the sign of the independent variable is positive, it leads to an increase of the dependent variable.

For the models analyzed, the coefficient of linear regression, the p-value, the adjusted R^2, and the β standardized values are calculated.

Regarding the p-value it is possible to determine if an independent variable has a statistically significant effect on the dependent variable. For this study, the significance level was set to 0.05, as conventionally defined in statistical analysis. In case the p-value is lower than this limit, the variable is significant and it can't be excluded. In order to analyze, which variables affected the dependent variable most, the comparison between the regression coefficient is only possible when they have the same measurement units. In order to realize this, partial regression coefficients are exploited, which are pure numbers and were obtained from a multiple regression equation in terms of standardized variables (β values).

3.2.3. Results

3.2.3.1. Frequency and Density estimation

Background Information

As mentioned previously, the data regarded 495 residential buildings located in the Mediterranean climatic context of southern Italy (Puglia).

With respect to the building typology and applying typical Italian typologies, the residential buildings are categorized as:

- multi-family building;
- detached house;
- terraced house.

Fig. 3.2 and Fig. 3.3 show the density of the **building typology** in function of the size of the dwelling and of the construction period of the building. Multi-family buildings are the most widespread typology in the data followed by detached houses and then terraced houses.

Regarding the **building size**, which is also related to the number of family members, the dwelling area ranged between 50 m^2 and 200 m^2, with a peak around 100 m^2 for all building typologies. This corresponds to a 4-5 member family, obtained by combining data regarding the apartment size and the number of family members.

Furthermore, the examined buildings were built after the 60s and most of them were constructed between 1980 and 2005 (Fig. 2). This range of construction periods represents only a limited slice of the entire Italian building heritage. This result can be explained by the fact that the questionnaire was subjected to university students, whereby most of the families are young and they do not live in the most ancient buildings.

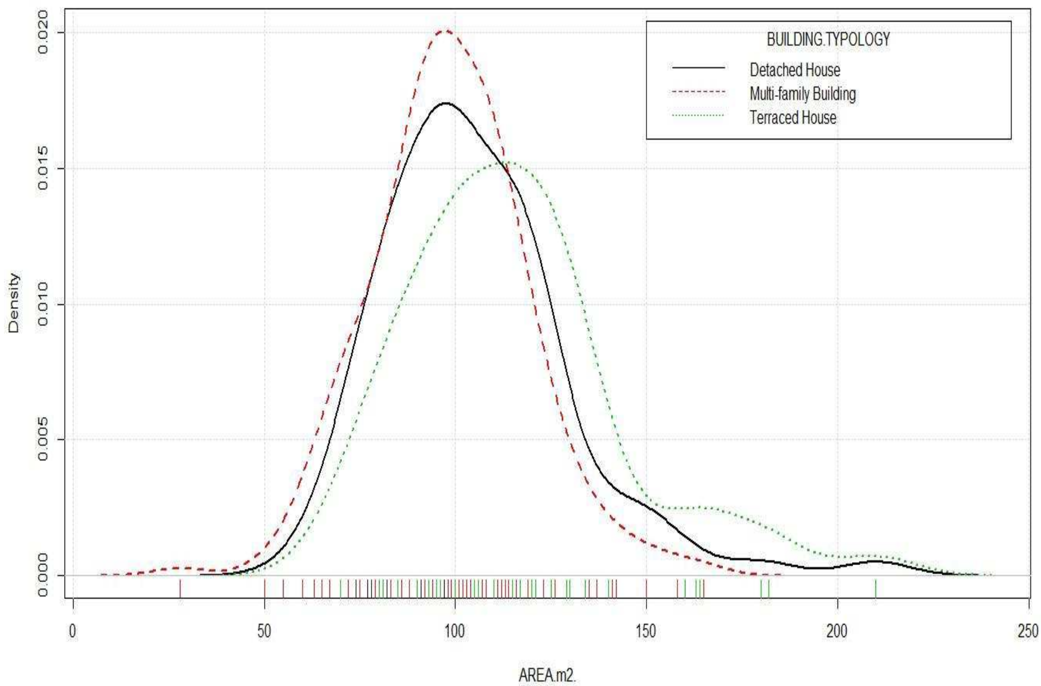

Fig. 3.2. Density of building size of the several building typology.

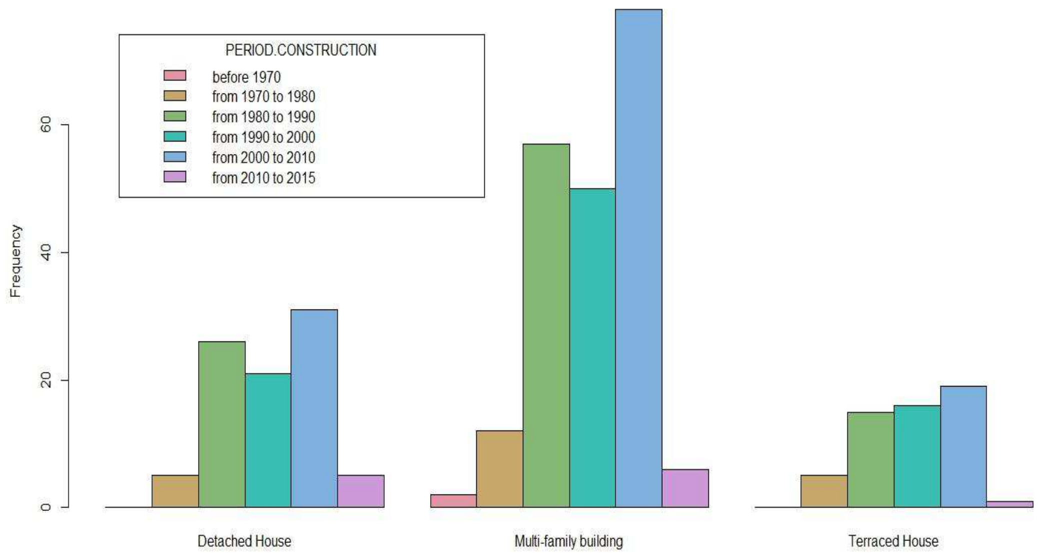

Fig. 3.3. Building typology in function of the construction period.

Fig. 3.4 and Fig. 3.5 show the variation of **window glazing type** and type of **heat source** as a function of the building construction year. As expected, both the variation of the glazing type and heat source follow the Italian regulations, which implied ever more restrictions for energy efficiency during the years (law n.373/1976, law n.10/1990 and legislative decree n.192/2005).

Regarding the glazing type, single glazed windows are typical of the most ancient buildings until 90s. Subsequently, since the late 90s the single glazed windows have been substituted by double glazed and then by more efficient glazing types such as the double glazing with low-e coating. Also the type of heat source changed from traditional boilers, typical of 80s and 90s, to high efficiency boilers and then to condensing boilers. In most of the cases (almost 85%) the heat generation systems are independent and not centralized.

Regardless of the **heating and cooling source** of the system, as concerning the management system, in 93% of cases the occupants controlled the activation of the heating and cooling system through ON/OFF systems and by setting the set-point temperature desired; in other cases a climatic thermoregulation was used for indoor

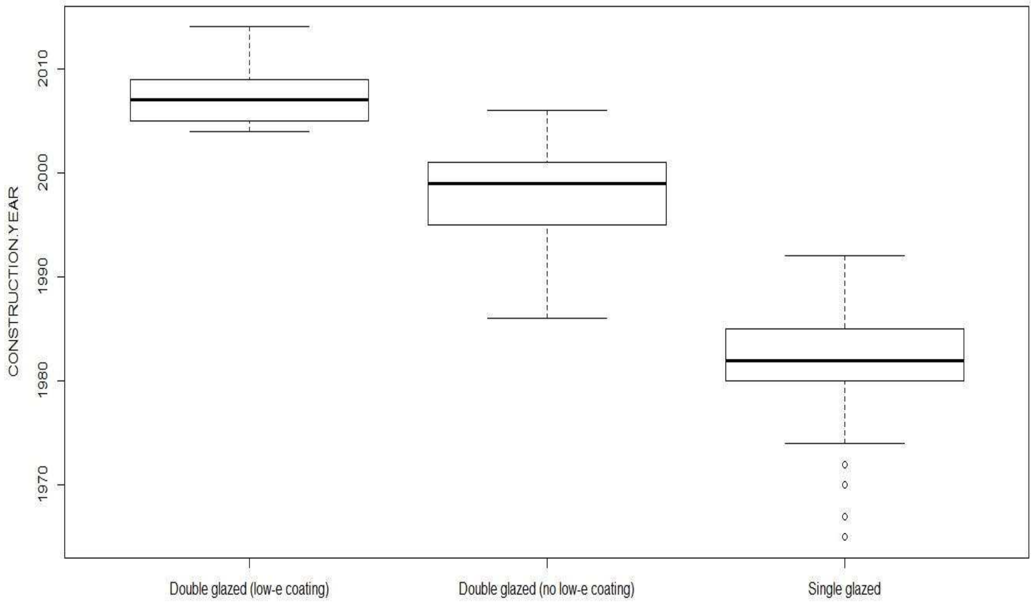

Fig. 3.4. Window glazing type in function of the construction year.

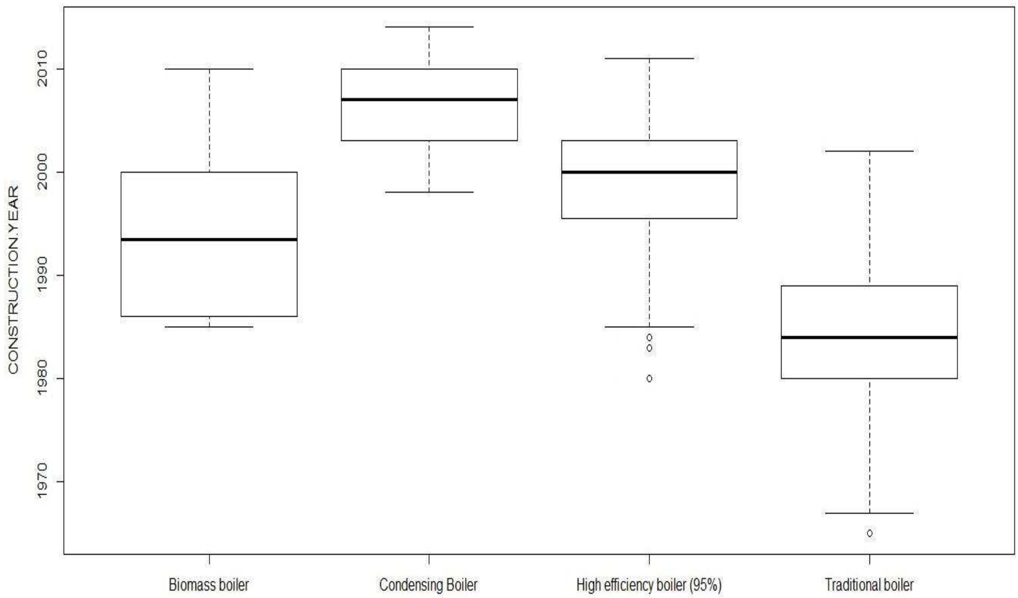

Fig. 3.5. Heat source type in relation to the construction year.

climate control. These results underline that in the residential context, the occupants generally have more degrees of freedom with respect to the building-system management. Unlike in commercial or offices buildings where either the user interaction with the building is lower and the building automation systems (BAS) are more widespread, in the residential sector the “occupant” can greatly affect the energy performance of the building and the possible activation logics of BAS.

User Preferences

Fig. 3.6 shows the **daily occupation** schedule in the dwellings, in relation to the occupancy ratio for each family. In order to homogenize the data and to obtain the occupation ratio, the number of occupants present in the dwelling during daytime are divided by the total number of family members. The occupancy ratio is the highest during nighttime and during early morning (from 11 p.m. to 8 a.m.) that correspond to the hours of sleeping. At dinner (from 8 p.m. to 11 p.m.) the number of occupant of each family present in the apartment is higher than at lunch time (from 1 p.m. to 3 p.m.). In the morning the occupancy ratio is minimal, due to the fact that almost all the members of the family are at work or school.

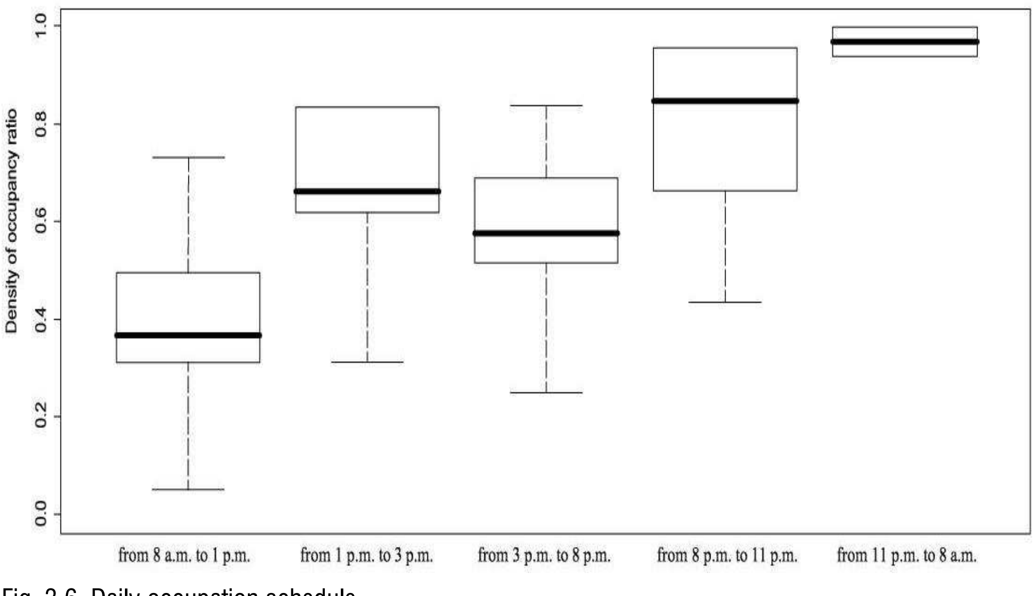

Fig. 3.6. Daily occupation schedule

Fig. 3.7 shows the **daily hours of heating system activation** in relation to the construction year of the building. In most cases it results that the daily total hours of heating system activation are between 4 hours and 8 hours. Furthermore, it is evident that the most ancient buildings (before 1985) require longer periods of heating system activation (more than 8 hours), while recent buildings (after 2005) require only few activation hours (less than 4 hours). Hence, the best thermal comfort conditions of the recent buildings, justified by the high insulation levels of the envelope, the high efficiency of HVAC systems and a sustainable design, influence also the occupant behavior related to the length of heating system activation. Improving the thermal indoor environment allows the occupant to activate the active systems less.

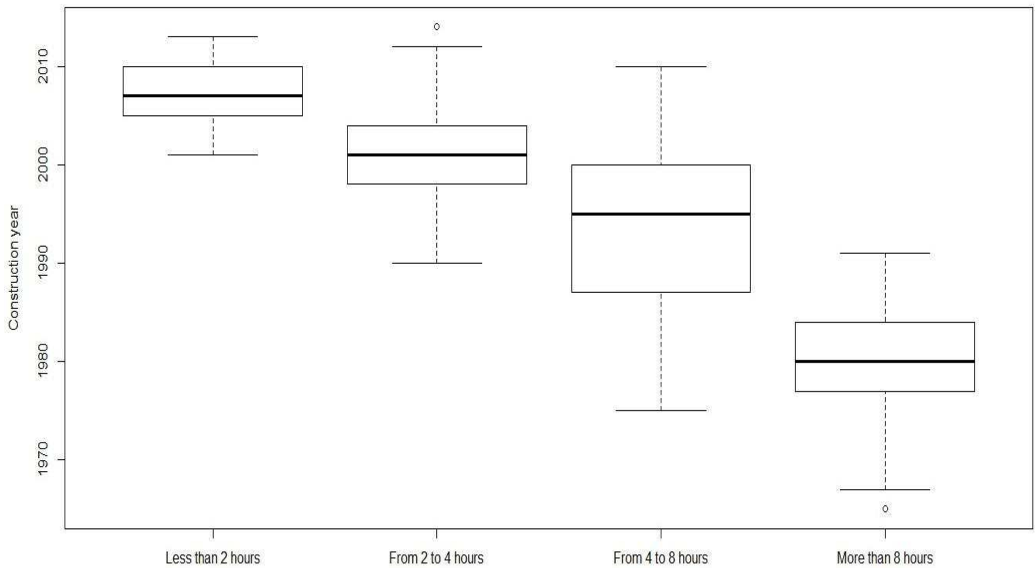

Fig. 3.7. Daily hours of heating system utilization in relation to the construction year.

Regarding the **time slots of heating system activation** indicated by the occupants, as shown in Fig. 3.8 the participants usually turn on heating system from 6 p.m. to 12 a.m. (40 %) Only a minimum percentage left the plant on during the whole day. By adding the frequency of the most common time slots, it is possible to define a widespread daily heating activation from 6 p.m. to 12 a.m.

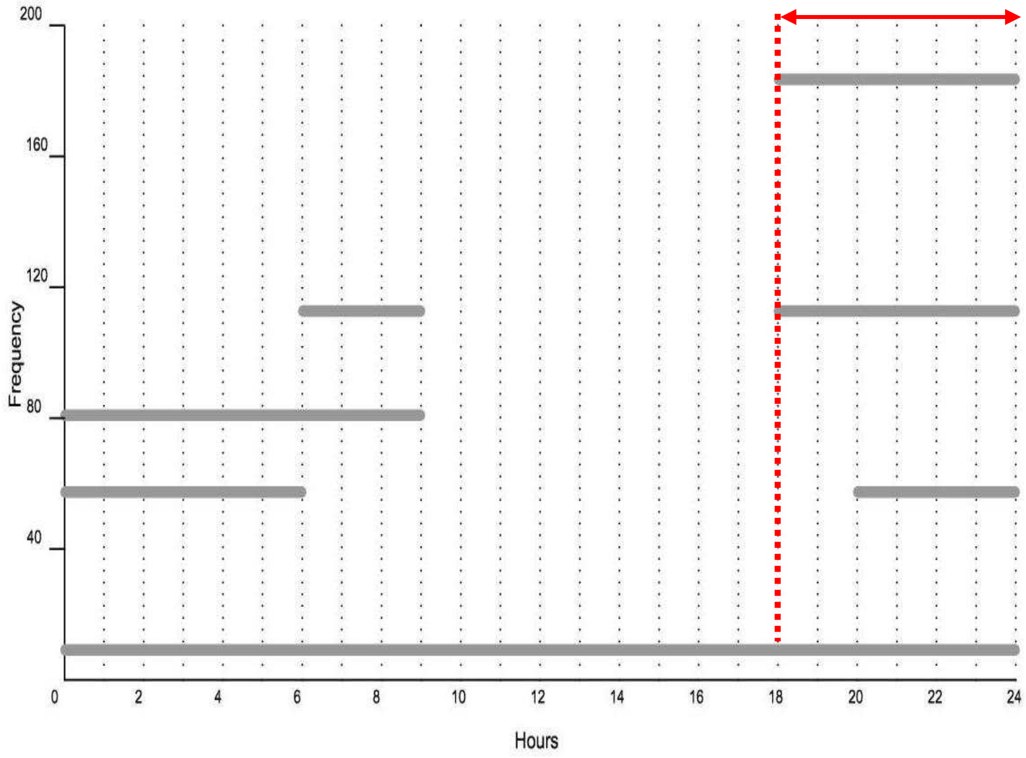

Fig. 3.8. Frequency of time slots of daily heating system activation

In accordance with above said, also the **set-point temperature of heating system** depends on the construction year of the buildings (Fig. 3.9). The occupants adopt lower set-point temperatures (< 20°C) in the most recent buildings (after the 2005). In contrast, in order to realize thermally comfortable conditions, the occupants in ancient buildings use higher set-point temperatures (> 20°C). This can be explained with notably higher heat losses due to the poor energy efficiency of the building envelope. This underlines that considering a fixed set-point temperature of 20°C, which is the common practice when estimating the energy consumptions for heating in energy simulations, may cause differences between simulated and real consumptions due to a more efficient occupant behaviors. At the same time, it could lead to an underestimation of the real energy consumptions for the most ancient buildings.

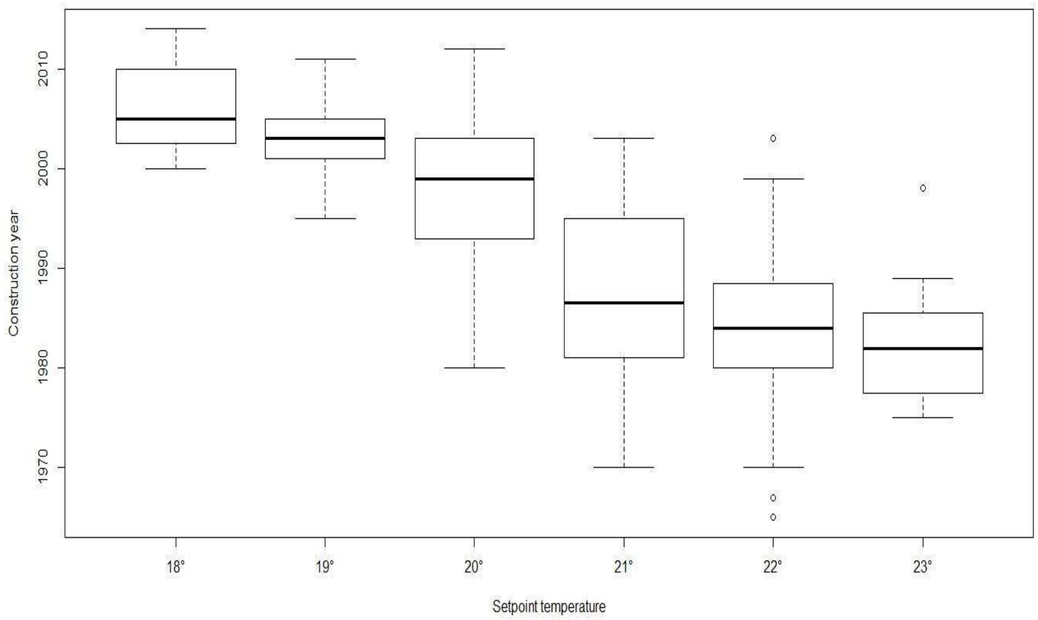

Fig. 3.9. Set-point temperature of heating system in relation to the construction year

<u>Adaptive Behaviors in Winter and Summer</u>

During **winter**, in order to reduce thermally discomfortable situations, occupants can usually choose one of the following **adaptive behaviors**:

- turning on heating system;
- drinking hot drink;
- wearing heavy clothes;
- reducing opening windows;
- closing shielding system nighttime.

As shown in Fig. 3.10 the most frequent action during thermal discomfort situations is wearing heavy clothes. The closing of shielding system is not performed by the respondents, considering that in winter season this action could reduce the incoming solar radiation.

Comparing the occupants' answers with the construction year of the buildings, it results that in the ancient buildings, the occupants usually turned on the heating system to satisfy their thermal comfort requirements. Hence in the dwellings with low energy efficiency, severe thermally discomfortable situations could be reduced only by adopting active systems. For this reason, in these buildings the energy consumptions may be consequently higher.

On the contrary, in recent buildings, the adaptive behaviors are the first actions that the users performed in order to reduce thermal discomfort. Actions like wearing heavy clothes, drinking hot drink or reducing the opening windows, reduce the usage of the active system and hence the energy consumptions for heating.

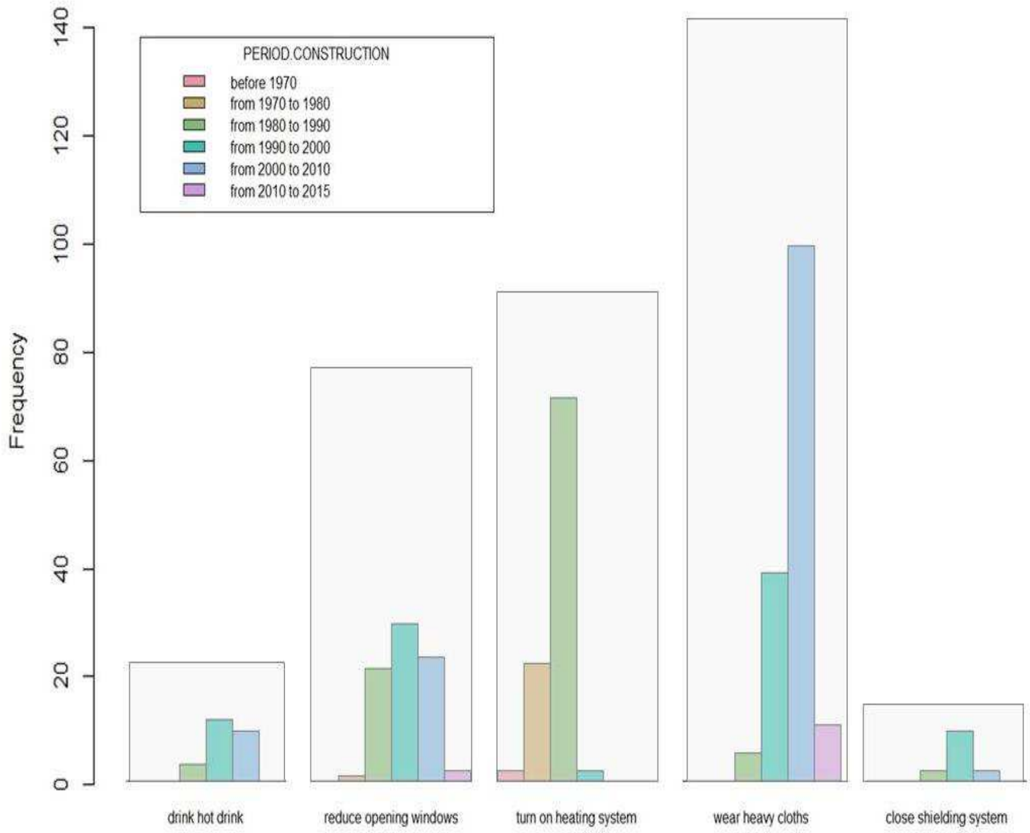

Fig. 3.10. Frequency of occupant behaviors for thermal discomfort in winter in function of the construction year.

During **summer**, in order to reduce thermally discomfortable situations, occupants can usually choose one of the following **adaptive behaviors**:

- turning on cooling system;
- drinking cold drink;
- wearing light clothes;
- opening windows;
- closing shielding system.

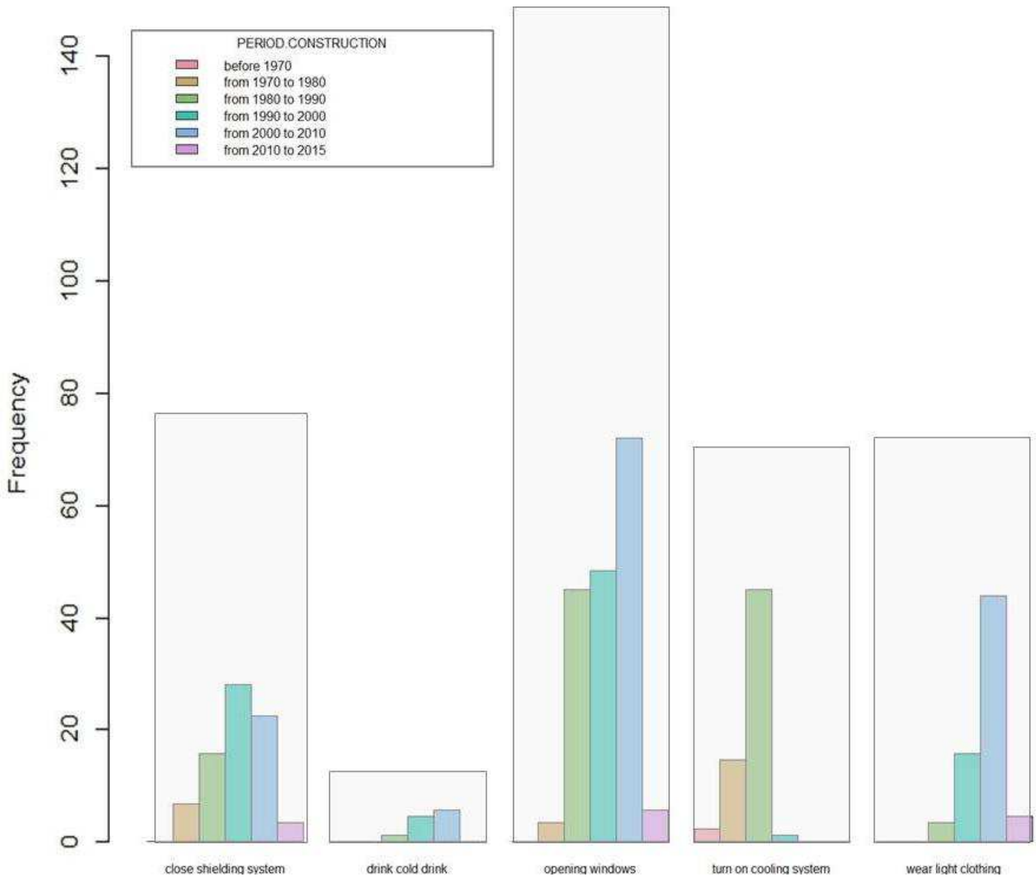

Fig. 3.11. Frequency of occupant behaviors for thermal discomfort in summer in function of the construction year.

As shown in the Fig. 3.11 the most frequent action is opening windows. Setting these answers in relation to the construction year of the buildings, it results that in the ancient buildings, the occupants turn on the cooling system to satisfy own thermal comfort more often. Hence in these dwellings with low energy efficiency, thermally discomfortable situations could be reduced only by adopting active systems.

On the contrary, in the recent buildings, the adaptive behaviors first adopted were wearing light clothes, drinking cold drink or increasing opening windows. These action reduced the usage of the active system and hence the energy consumptions for cooling.

In summary, it is important to consider the tie between the type of occupant behavior and the construction year (Fig. 3.10, Fig. 3.11), in order to reduce the usage of active components.

Occupant Behavior Impact on Fuel Consumption

As outlined on the introduction, several studies have shown that the occupants, and in particular their attitudes, their preferences, and their interactions with the building-HVAC system, has a significant impact on energy performance of buildings.

The following figures show the relationship between the **fuel consumption** and:

- the construction year of the building;
- the total daily hours of heating system utilization by the family;
- the set-point temperature of heating system;
- the adaptive behaviors during thermal discomfort situation in winter.

Fig. 3.12 shows that the fuel consumption almost linearly depended on the construction year of the building. (R2 = 0.85). The most recent buildings have the lowest fuel consumption (< $5m^3/m^2$), while the most ancient buildings have a much higher fuel consumption (> 20 m^3/m^2). This result is justified because the construction year is an inclusive index of the characteristics of the building envelope and of the plant system in a certain period of construction, and hence the most ancient buildings are more energivorous than the recent ones. Indeed, in order to reach thermal comfort situation, the users use the heating system for more hours (more than 8 hours) in the most ancient buildings as presented above. As a consequence, the fuel consumptions increase.

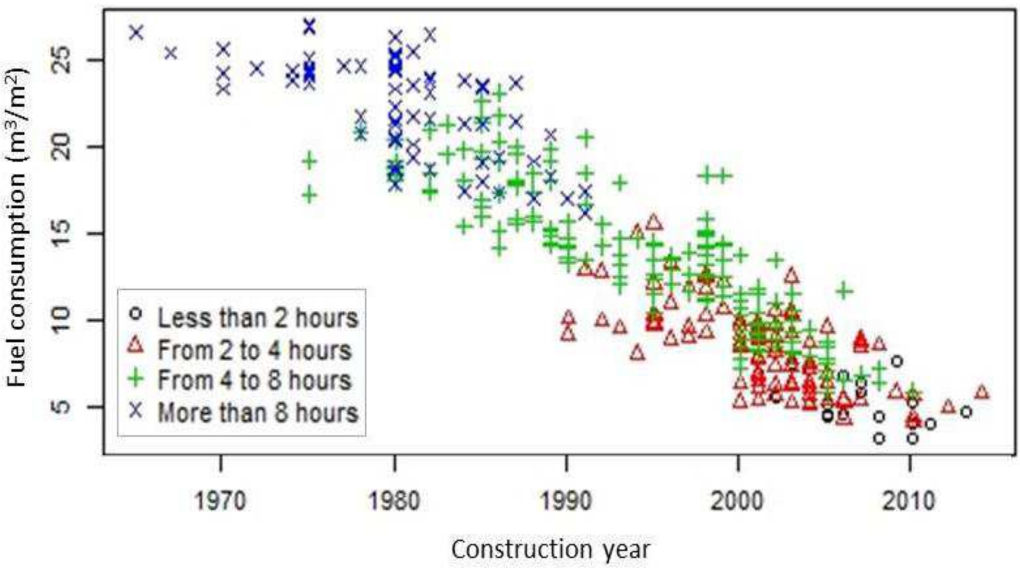

Fig. 3.12. Fuel consumption in relation to the construction year and the daily total hours of heating system utilization.

In the Fig. 3.13, as expected it is possible to notice that also the set-point temperature of the heating system adopted by the occupant influenced the fuel consumption. High values of the set-point temperature (22°C, 23°C) are necessary to offset the local discomfort conditions due to cold air flow on floor, higher air layering and infiltrations of cold air flow.

In addition, in the most ancient building the users usually use the heating system for more hours and with higher set-point temperature values. Hence, in the building with the lowest levels of energy efficiency, the user is brought to use for more hours and with higher set-point temperature the heating system, causing significant energy consumptions.

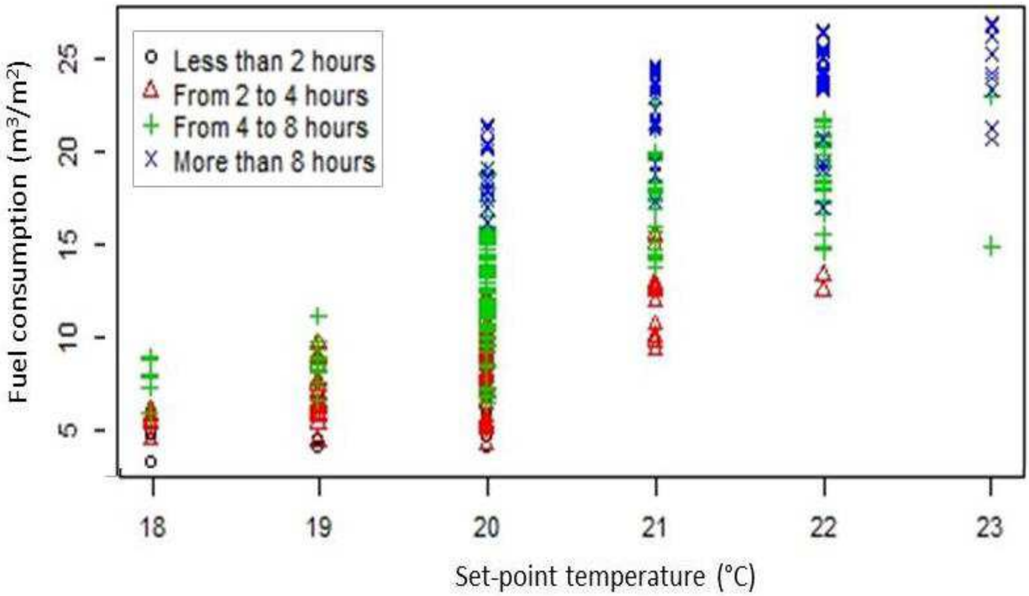

Fig. 3.13. Fuel consumption in relation to the set-point temperature and the daily total hours of heating system utilization.

Fig. 3.14 shows the main adaptive behaviors in relation to the construction year and the fuel consumption. Especially the action of turning on the heating system during thermally discomfortable situations is typical for the most ancient buildings, while in the recent buildings actions like wearing heavy clothes or closing windows are more frequent. As a consequence, the occupants satisfy their thermal comfort requirements with the use of active systems and thereby increased the fuel consumptions.

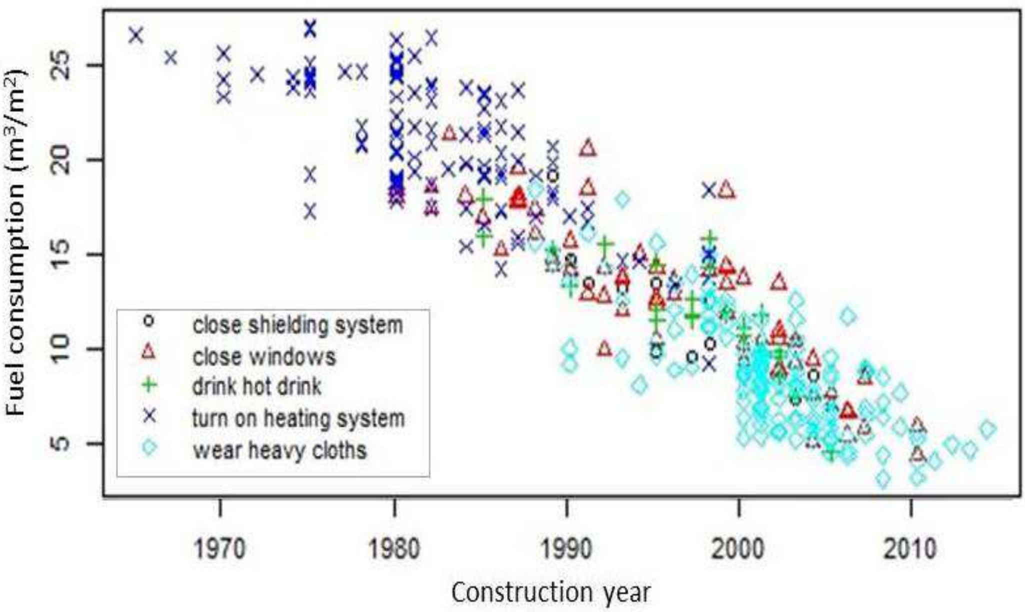

Fig. 3.14. Fuel consumption in relation to the construction year and the adaptive behavior of users.

3.2.3.2. Multivariate Regression Analysis

As shown above, the variables investigated are showing close links and a complex network of relationships. Therefore, the application of multiple regression analysis is meaningful in order to analyze the effect of individual variables on a dependent variable.

Results of multivariate regression analysis related to the fuel consumption

At first, multivariate linear regression is conducted to determine the most significant variables for the fuel consumption (Y). As independent variables $(X_1, X_2, \dots X_k)$, the following variables included in the questionnaire are selected based on introductory literature review and the findings presented in the previous section:

- *the construction period of the building;*
- *the set-point temperature of heating system;*

- *the family monthly income;*
- *the total daily total hours of heating system utilization;*
- *the user behavior in thermal discomfort situations.*

The main results of the linear regression are reported in the Tab. 3.2.

The first column reports the independent variables, the second the estimated values of regression coefficient, the third the p-values and the last column the significance of the independent variables on the dependent variable.

As can be deduced from Tab. 3.2, the main variables affecting the fuel consumption were the set-point temperature, the total daily hours of heating system utilization, the family monthly income and the construction period of the building. In particular:

- by increasing the set-point temperature and the total hours of heating system utilization, the fuel consumption increases. This is justified by the fact that the occupants that adopt higher values of set-point temperature or for more hours, cause more energy consumptions for heating in consequence of the high thermal load requested;
- as regarding the family monthly income, the wealthier families usually have higher energy consumption, as a consequence of a minor tendency to adapt to the environmental conditions but to use active conditioning system.
- as regarding the construction period of the building, the buildings built after the 2000s have a negative coefficient and hence the most recent buildings have minor consumptions;
- among the adaptive behaviors, only turning on the heating system is significant for the fuel consumption and lead to an increase of the consumptions.

		Estimate	Pr (>|t|)	Signif.code
Set-point temperature	19°C	0.832	0.033	*
	20°C	2.013	1.01 e^{-7}	***
	21°C	3.738	1.59 e^{-15}	***
	22°C	4.831	< 2 e^{-16}	***
	23°C	5.489	< 2 e^{-16}	***
Family monthly income	less than 1000 €	-1.163	0.001	**
	from 1500 € to 2000 €	1.189	2.04 e^{-5}	***
	from 2000 € to 2500 €	2.053	2.38 e^{-8}	***
	more than 2500 €	3.233	7.29 e^{-11}	***
Hours of heating system utilization	from 2 to 4 hours	0.993	0.008	*
	from 4 to 8 hours	2.682	1.26 e^{-10}	***
	more than 8 hours	5.779	< 2 e^{-16}	***
Construction period	from 1970 to 1980	-1.190	0.260	
	from 1980 to 1990	-2.216	0.035	*
	from 1990 to 2000	-5.184	2.91 e^{-6}	***
	from 2000 to 2010	-7.085	6.35 e^{-10}	***
	from 2010 to 2015	-7.940	3.09 e^{-10}	***
Adaptive behaviour	reducing opening windows	0.192	0.582	
	turning on heating system	0.668	0.004	*
	wearing heavy clothes	-0.087	0.796	
	closing shielding system	0.063	0.905	
Adjusted R^2		**0.948**		

Tab. 3.2. Multivariate analysis results on the fuel consumption.

By analyzing the model, the determination coefficient **Adjusted R2** for the goodness of the model is equal to **0.948**: almost the 95% of the data is explained by the considered variables.

In order to compare the influence of the independent variables on the fuel consumption, the β standardized values are compared. This shows that the explicative variables mostly influencing the fuel consumption are the construction period of the building, the set-point temperature adopted by the occupants and the total hours of heating system utilization (see Fig. 3.15). This proves that the occupant behavior significantly affects the building performance and so the energy consumption. For these reasons it is important to investigate further the factors influencing the user behavior.

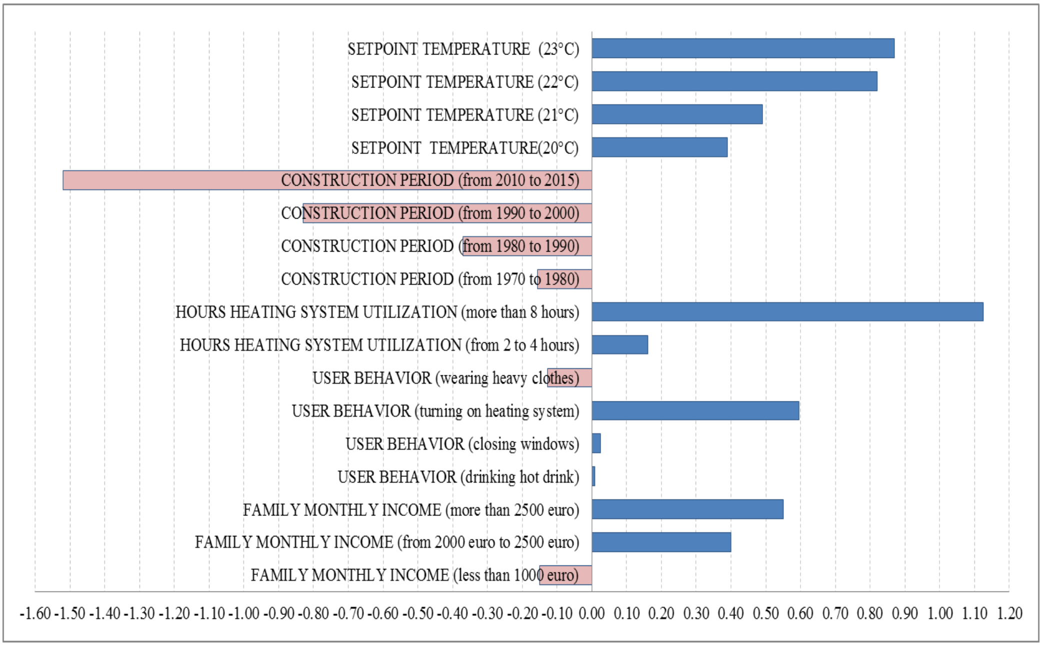

Fig. 3.15. The β standardized values of the fuel consumption.

Results of multivariate regression analysis related to the set-point temperature

The second multivariate linear regression analysis is conducted in order to determine the most significant variables influencing the set-point temperature of the heating system (Y).

The following data points provided by the questionnaire are considered as independent variables $(X_1, X_2, \dots X_k)$:

- *the construction period of the building;*
- *the monthly family income;*

- *the daily total hours of heating system utilization;*
- *the adaptive behavior in thermally discomfortable situations.*

The main results of the linear regression are reported in Tab. 3.3. They show that the main variables affecting the set-point temperature are the monthly family income and the construction period of the building. In particular:

- by increasing the total hours of heating system utilization, the set-point temperature increases. This is justified by the fact that the users that adopt the heating system for more hours also use higher set-point temperatures as a consequence of the low energy efficiency of the buildings (see also previous section).
  Furthermore, considering the regression coefficients of the construction periods of the building, the buildings built after the 2000s have a negative coefficient, i.e. the set-point temperature is lower, and hence the most recent buildings have minor consumptions due to being more efficient and their occupants being free to use less heating with a lower set-point while still being comfortable;

- the wealthier families usually adopt higher set-point temperature as a consequence of the tendency to use less adaptive behaviors and to prefer using active conditioning systems;

- between the adaptive behaviors, only turning on the heating system had a significant influence on the set-point temperature. In particular it can be seen that the occupants who first used the action turning on the heating system, also adopted high set-point temperatures.
  As explained in relation to Fig. 3.9 these behaviors are most likely within the oldest buildings, where the main action for thermal discomfort situations is turning on the active system and using high values of set-point temperature.

		Estimate	Pr (>|t|)	Signif.code
Family monthly income	less than 1000 €	-0.117	0.519	
	from 1500 € to 2000 €	0.218	0.015	*
	from 2000 € to 2500 €	0.456	0.239	
	more than 2500 €	1.00	2.35 e^{-5}	***
Hours of heating system utilization	from 2 to 4 hours	-0.467	0.065	
	from 4 to 8 hours	-0.196	0.321	
	more than 8 hours	0.009	0.956	
Construction period	from 1970 to 1980	-0.025	0.962	
	from 1980 to 1990	-0.044	0.931	
	from 1990 to 2000	-0.207	0.695	
	from 2000 to 2010	-0.607	0.249	
	from 2010 to 2015	-1.554	0.008	**
Adaptive behaviour	reducing opening windows	0.042	0.860	
	turning on heating system	0.579	0.024	*
	wearing heavy clothes	-0.185	0.412	
	drinking hot drink	0.022	0.929	
Adjusted R^2		**0.684**		

Tab. 3.3. Multivariate analysis results on the set-point temperature.

The determination coefficient Adjusted R2 of the model is equal to 0.684: more than 68% of the data was explained by the considered variables.

Comparing the β standardized values, it results that the explicative variables mostly influencing the set-point temperature were the construction period of the building and the family monthly income (see Fig. 3.16). It proves how the user behavior can significantly affect the building performance and so the energy consumptions.

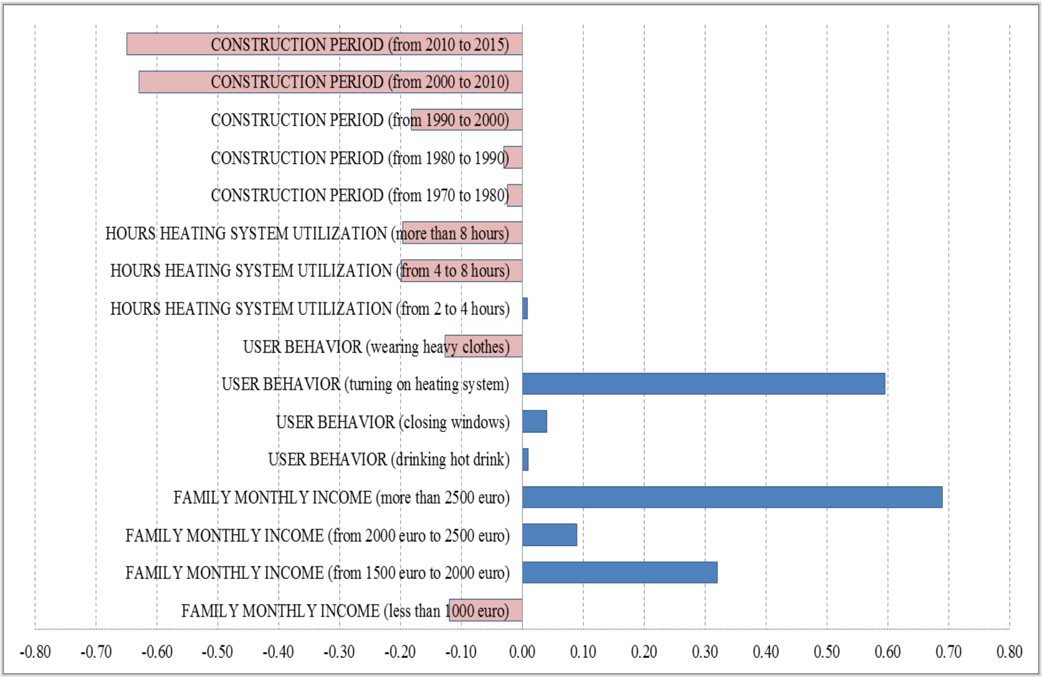

Fig. 3.16 The **β** standardized values of the set-point temperature.

3.2.4. Discussion

While most of the studies, that have investigated the influence of occupant behavior on the energy performance of buildings, have compared energy consumptions of identical buildings (Socolow, 1978), (Sonderegger, 1978), (Seligman, et al., 1978), (Gartland, et al., 1993), (Juodis, et al., 2009), this work has tried to define the tie between different residential buildings and occupant actions by means of questionnaire survey.

In particular an overall view of both the performance of buildings and the subjective indication given by occupants were compared.

In detail the key findings from this work can be compared to existing literature as follows:

- the relationship between occupant behavior and building environment reflects the difficulty of adapting to discomfortable conditions especially in the most ancient building with worst conditions;
- with respect to the order of adaptive behaviors, Langevin (Langevin, et al., 2013) found that clothing adjustment was the first action both in winter and summer. In this work only in winter season, clothing is adjusted first, followed by other adjustments. Clothing is not as frequently adjusted when people are feeling warm because people dress in as few layers as possible in summer in expectation of warm conditions;
- as already shown in Langevin (Langevin, et al., 2013), this study supports the findings that the socioeconomic status (family size, monthly income) has an impact on the behavioral patterns of occupants;
- in contrast to Langevin's results, where windows were not used in the heat of the summer because they could make conditions worse, in this study in summer during discomfort conditions the first action performed by the occupant was opening windows. The difference between these results may be explained by the difference in outdoor climatic conditions between the two questionnaire studies.

In addition, this study allows a more precise quantification of important trends, such as the tie between the building performance and the occupant behaviors, the relationship between the effectiveness of adaptive actions and the hierarchy of adaptive actions.

Differently by (Andersen, et al., 2009) where field monitoring campaign and repeated surveys of occupant control of the indoor environment were carried out, this cross sectional survey may identify associations between variables but they cannot establish the cause-and-effect relationships. This is because such studies offer a snapshot of a single moment in time; they do not consider what happens before or after the snapshot is taken.

Another limitation of this work is identified in the limited slice of the entire building heritage having been analyzed as result of the young families that had been subject to this questionnaire. In particular most of buildings analyzed were constructed after the 1980. To be able to represent more the relationship between the building-HVAC system and the occupants, more data on the most ancient buildings should be added.

Furthermore, it is worth noting that in order to have a more accurate prediction of the fuel consumption for heating, the fuel consumption for domestic hot water (DHW) and for cooking have to be curtailed through a more accurate evaluation. Indeed while the consumptions for heating depend by the building-HVAC characteristics and occupant behavior, the consumptions for DHW and cooking depend above all by the number of the family members and they don't reflect the building performance and the occupant behaviors.

Chapter 4

Building Energy Management Systems (BEMS) for passive cooling

Starting from the results of the questionnaire survey, general control-related behavioral trends and patterns for groups of building occupants were extracted by the cross sectional study described in the chapter 3.

In detail, based on questionnaire results, the interaction between occupant and building-HVAC system was maximum during the cooling season and hence the impacts of occupant behavior are higher than in winter season. Indeed, it resulted that in summer season to improve thermal comfort conditions, the occupants might change the window or shading status, or turn on the cooling plant. These actions have great influence on energy consumptions and building performance. Instead, in winter season, occupants acted mainly by changing the clothes status, wearing heavy clothes and less on the building components to improve their thermal comfort conditions

Known that the actions on window and blind status are mostly impactful on building performance, with the goal to design optimal BEMS as retrofit solutions for the energy renovation, this second study focused on the analysis of different **control logics of natural ventilation** and of the **solar shading system** for passive cooling.

On the other hand, passive techniques such as natural ventilation and solar shading may be introduced to satisfy the indoor comfort while minimizing the use of electrical systems in buildings (Sarker, et al., 2014), (Yang, et al., 2011). The adoption of passive solutions enhances the emerging trend of nearly Zero-Energy Buildings, that are buildings with a very high energy performance, according to the 31/2010 European directive on energy performance of buildings (EPBD, 2010). Natural ventilation could significantly reduce building energy consumption for cooling and improve thermal comfort with the indoor environment (Borgeson & Brager, 2011).

In residential buildings the ventilation is generally manual and not always aimed at cooling needs. Building automation systems and suitable control logics based on the building profiles of use and on the comfort performance are required.

Hence, with particular reference to the summer season, the aim of the work is to design BEMS for comfort and energy savings in residential buildings, by defining optimal control logics **of natural ventilation** (by means of windows opening/closing) and of the **solar** shading system.

In this chapter several studies are conducted with the aim to define control logics of building automation systems for passive cooling minimizing energy consumptions and thermal comfort, by simulating the **occupant behavior in deterministic way through defined schedules**.

Part of the research shows the results of investigations carried out within the project *RES NOVAE - Reti, Edifici, Strade, Nuovi Obiettivi Virtuosi per l'Ambiente e l'Energia*, financed by the Ministry of Education, MIUR (National Operational Program Research and Competitiveness 2007-2013 for the development of Smart City) the involved partners (Enel Distribution, IBM, General Electric Transportation Systems, Elettronika Group, Asperience, Polytechnic University of Bari, University of Calabria, CNR, ENEA) aim to research, model and test, on a demonstration scale, an advanced management system of energy flows at the municipal level, based on the integration of technologies for monitoring, control and optimized management of energy flows toward the buildings and the implementation of "active demand" strategies.

In particular, in an Italian dwelling with technological/typological features of ‘60s, different partialization strategies of existing shading systems and natural ventilation control strategies are simulated.in relation to the orientation, to the external climatic conditions, to the occupation and to the minimum illuminance levels required for the rooms.

Regarding **thermal comfort optimization**, most researchers refer exclusively to the Fanger’s model (Fanger, 1973) that assesses thermal comfort conditions by means of two correlated indices: the Predicted mean vote (PMV) and the Predicted percentage of dissatisfied (PPD). In this thesis the optimization goals are based on the **adaptive thermal comfort** (EN15251, 2007). Thermal comfort analysis, according to the adaptive thermal comfort theory and the energy analysis in dynamic regime are conducted in order to evaluate the benefits of such control logics.

A co-simulation architecture is created between **TRNSYS** (building-HVAC model), **TRNFLOW** (building air flow network) and **MATLAB** (PSO optimization).

The several studies described in this chapter were object of different publications whose details are reported in the (Dell’Osso, et al., 2015), (Rinaldi & Iannone, 2016), (Fanti, et al., 2016), (Rinaldi, et al., 2016).

4.1. Building description

The case study is representative of building typology of south Italy built on the postwar period, characterized by poor building performance. In addition the dwelling presents also a bad orientation regarding the sun control. For these buildings, the PhD thesis is focused on analyze how the BEMS may contribute to the energy efficiency with low cost investments and with not invasive interventions on building components.

In detail the case study is a four-floor residential building of the ’60s located in the South Italy (Bari - Italy, 41° 07’31" N, 16° 52’00" E, 5 m asl). The considered apartment is situated at the intermediate floor and has a net floor area of about 100 m^2. It is characterized by (see Fig. 4.1):

- windowed sides faced to North-West and South-East with two overhangs as shown in the Fig. 4.2;
- compactness index (ratio between enveloping surface and heated volume) equal to 0.65, as result of the building type;
- bedroom1, kitchen and bathroom faces to North-West and living room, bedroom2 and study room faces to South-East.

As regarding the building envelope, the following building technologies are present, typical of a residential building of ’60s:

- external wall: double-brick mansonry (12-12 cm) with interposed uninsulated air cavity of 6 cm;
- partition wall: brick mansonry (25 cm);
- ceiling- floor: concrete-brick flat (30 cm) and cement floor screed with flooring (10 cm);
- windows: wood frame (7 cm) and single glass of 6 mm of tilt-turn type.

In the Tab. 4.1 the main parameters of the modeled envelope (transmittance, internal heat capacity and the solar factor) are reported.

Tab. 4.1. Thermal characteristics of building envelope.

Items	**U-value (W/m^2 K)**	**Internal heat capacity (kJ/m^2K)**	**g-value**
External wall	1,10	56.2	-
Partition wall	1,54	59.4	-
Ceiling-floor	0,83	88.2	-
Window	5,6	-	0.8

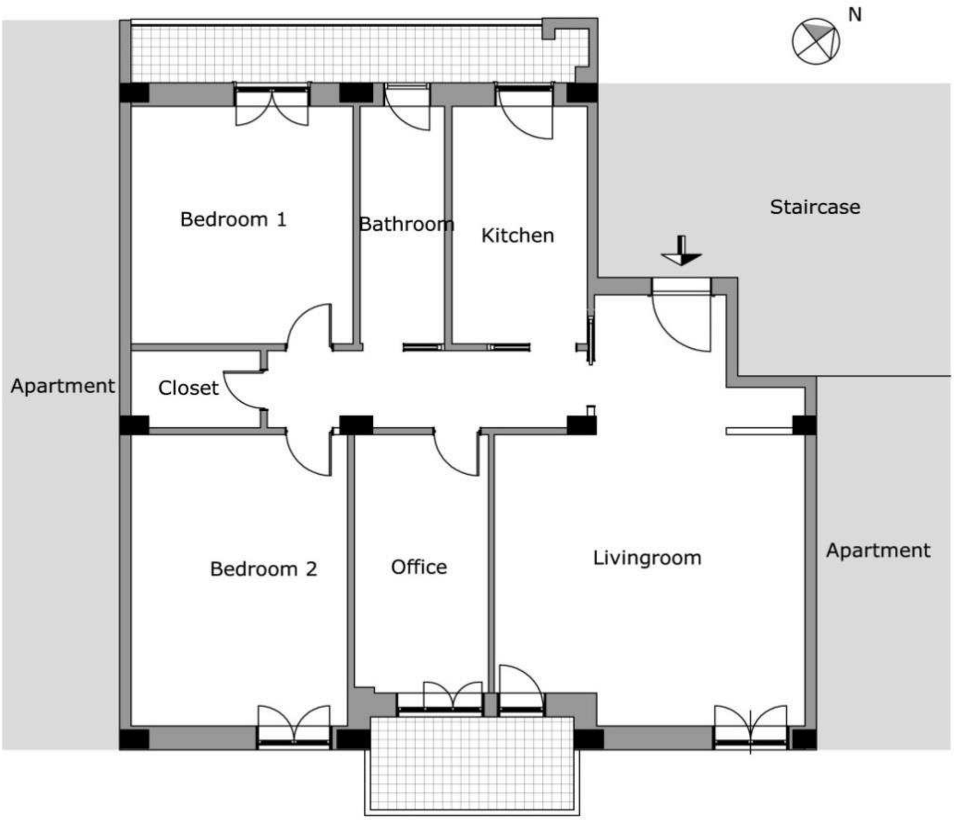

Fig. 4.1. Apartment plant

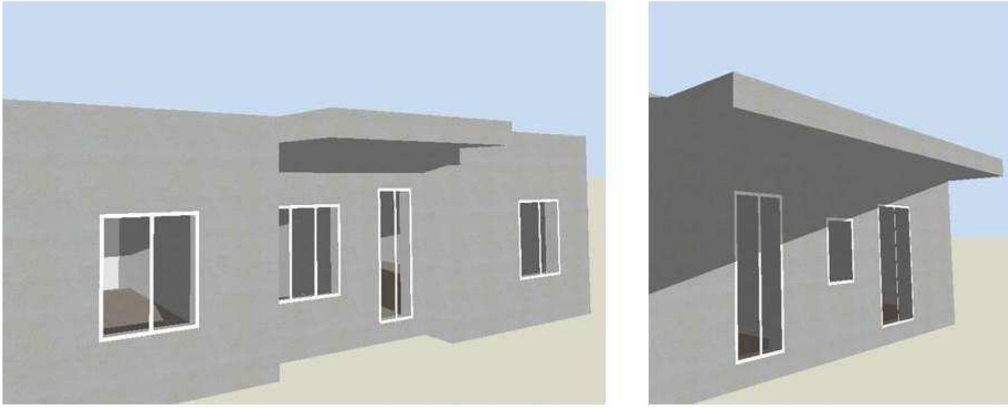

Fig. 4.2. The 3d model of the apartment. South-East and North-West view

In reference to this specific case study, the energy hourly variations for occupancy, lighting and domestic appliances are implemented using typical fixed schedules. The Tab. 4.2 shows the scheduled daily occupancy of each room., that is differentiated for each rooms, evaluating the occupancy ratio in relation to the number of present occupants.

Tab. 4.2. Scheduled daily occupancy for each room.

Room	**Occupancy daily time slots**
Bedroom2	6 p.m. - 8 a.m.
Kitchen	7 a.m. - 9 a.m.; 12 p.m. - 2 p.m.; 8 p.m. - 10 p.m.
Bedroom1	10 p.m. - 8 a.m.
Office	9 a.m. - 12 p.m.; 3 p.m. - 7 p.m.
Living room	8 a.m. - 9 a.m.; 4 p.m. - 12 a.m.

The type of windows is tilt-turn window, with possible automated bottom-hinged opening (corresponding to the 50% of the opening for windows with two shutters). In detail, because of the automation of window regard only the “hopper windows opening”, the opening factor of window has to be multiplied for a factor (Ck) depending on the maximum window tilt according to the EN 15242 – 2008 (see Tab. 4.3).

Tab. 4.3. Opening window parameters.

Item	Maximum window tilt	Opening Coefficient Ck
Window_(h=2,2 mt)	13°	0,22
Window_(h=1,2 mt)	25°	0,39

The air permeability characteristics, used in the various simulations that describe a low air tightness of the building envelope, are shown in the Tab. 4.4.

Tab. 4.4. Air permeability characteristic of building envelope

Item	Air Mass Flow Coefficient Cs (Kg/sPa) crack (Kg/s m Pa) large opening	Air Flow Exponent n	Discharge Coefficient Cd
Crack _External Wall	0,00002	0,85	-
Large Opening _Window	0,0003	0,6	0,6
Large Opening _Door	0,0015	0,6	0,6

The weather data (.epw file format) for the city of Bari are extrapolated by “Gianni De Giorgio database” and the wind speed profile is modified by terrain roughness parameters for suburbs area.

To ensure conditions of Indoor Air Quality (IAQ), a schedule opening-windows is assumed at certain hours (8 a.m. - 10 a.m.; 1 p.m.- 2 p.m.; 8 p.m. - 9 p.m.). These periods correspond to the activities of preparing and cooking foods and of household cleaning. During these hours a bottom hinged opening is hypothesized. The window opening for IAQ during these hours is the same in all the cases simulated, managed directly by the user and independent by automation systems. During the others hours, the control logics open the windows on the basis of the strategies (4.1) and (4.2) in order to reduce discomfort conditions and hence energy consumptions.

4.2. The Co-Simulation Architecture

In this section the co-simulation architecture is presented to combine the building-HVAC system simulation and optimization goal for control logic of BEMS. The co-simulation architecture is shown in Fig. 4.3.

In particular, the **building thermal behavior** is performed by TRNSYS software v.17. (TRNSYS, 2009). It recognizes a system description language in which the user specifies the components that constitute the system and the manner in which they are connected. Moreover, the thermal building module of TRNSYS (Type 56) is integrated with TRNFLOW that models the air flows between airnodes (coupling), from outside into the building (infiltration) and from the ventilation system (ventilation). In the analyzed case studies present in this chapter the occupant is simulated in deterministic way with fixed schedules inserted in Type 56, without taking into account his behaviors in buildings.

The **optimization algorithms** to solve the objective functions described in the following paragraphs for the minimization of thermal discomfort hours for overheating and undercooling, are implemented in MATLAB and then coupled with the TRNSYS energy simulator. More precisely, in the MATLAB program is implemented the Particle Swarm Optimization (PSO) algorithm, described in the following paragraph 4.2.2.

Iteratively, the PSO algorithm values of variables to be optimized in order to minimize the thermal discomfort, and exchanges these values with TRNSYS through the BEMS calculator to command the building automation system.

4.2.1. TRNSYS and TRNFLOW

The building thermal behavior is modeled by TRNSYS v.17 software, a complete and extensible simulation environment for the transient simulation of systems, including multi-zone buildings.

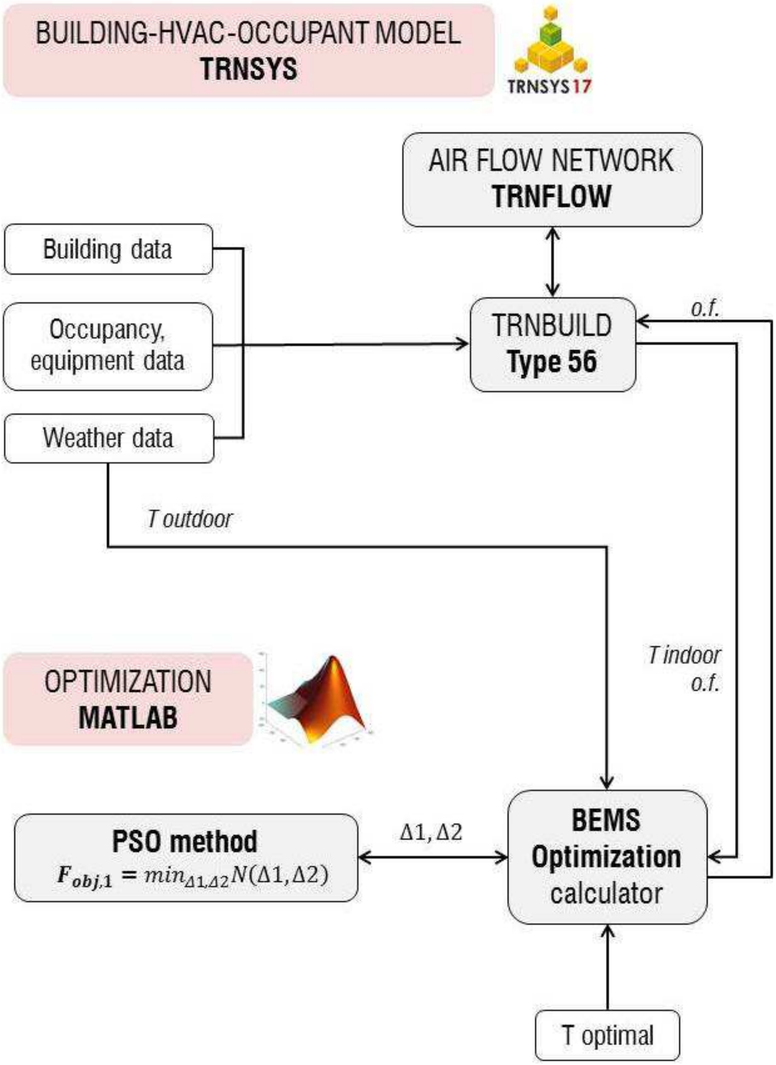

Fig. 4.3. The co-simulation architecture with occupant behavior modeling in deterministic way

One of the key factors in TRNSYS is its modular and flexible architecture based on Dynamic-Link Library (DLL) concept, which facilitates the addition to the program of new component models, not included in the standard TRNSYS library.

In particular, TRNSYS is made up of two parts. The first part is an engine (the kernel) that reads and processes the input file, iteratively solves the system, determines convergence, and plots system variables. The kernel also provides utilities that determine thermophysical properties, invert matrices, perform linear regressions, and interpolate external data files. The second part of TRNSYS is an extensive library of components, each of which models the performance of one part of the system. The TRNSYS library includes many of the components commonly found in thermal and electrical energy systems, as well as component routines to handle input of weather data or other time-dependent forcing functions and output of simulation results.

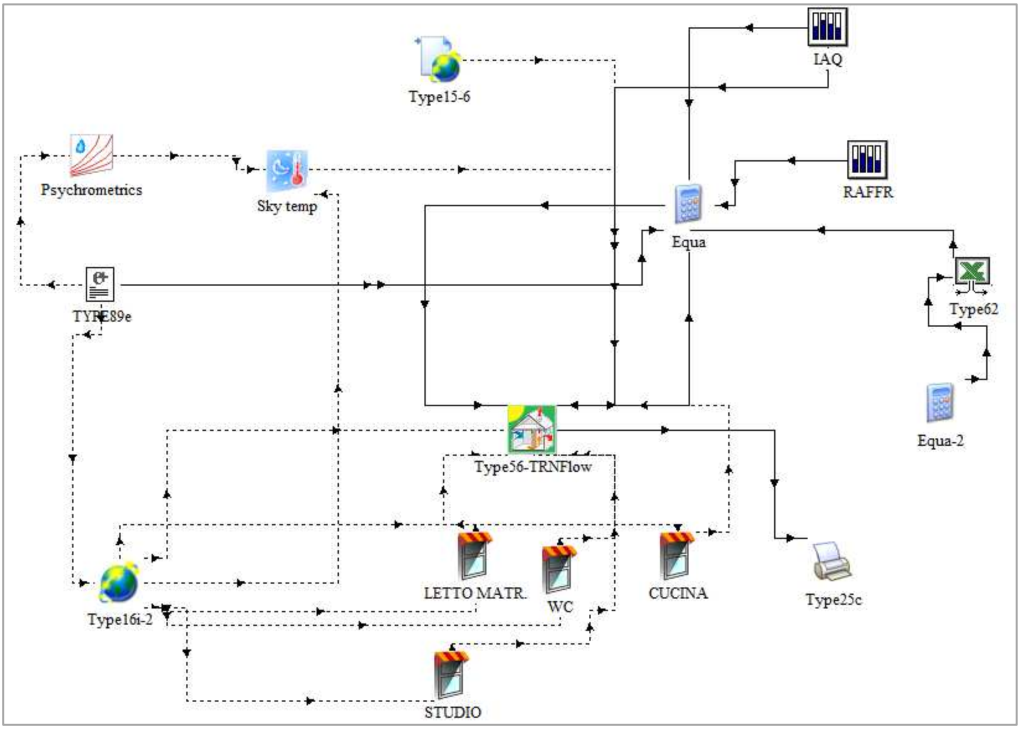

Fig. 4.4. Building-HVAC model in Simulation Studio

The interface platform is Simulation Studio, where the total model is visible, obtained by assembling the building envelope and HVAC components, linked through logical-mathematical correlation. Fig. 4.4 shows an example of a system model built by TRNSYS and Simulation Studio.

Moreover, in this study the thermal building module (Type 56) is integrated by TRNFLOW software that models the air flows between outdoor and indoor air nodes. In particular, this multizone airflow model schematizes the building as a network of nodes and airflow links. The nodes represent the rooms and the building surrounding and the links depict openings, doors, cracks, window joints and shafts, as well as ventilation components like air inlets, outlets, ducts and fans (see Fig. 4.5). The boundary conditions are the wind pressures on the facade and the indoor and outdoor air temperatures.

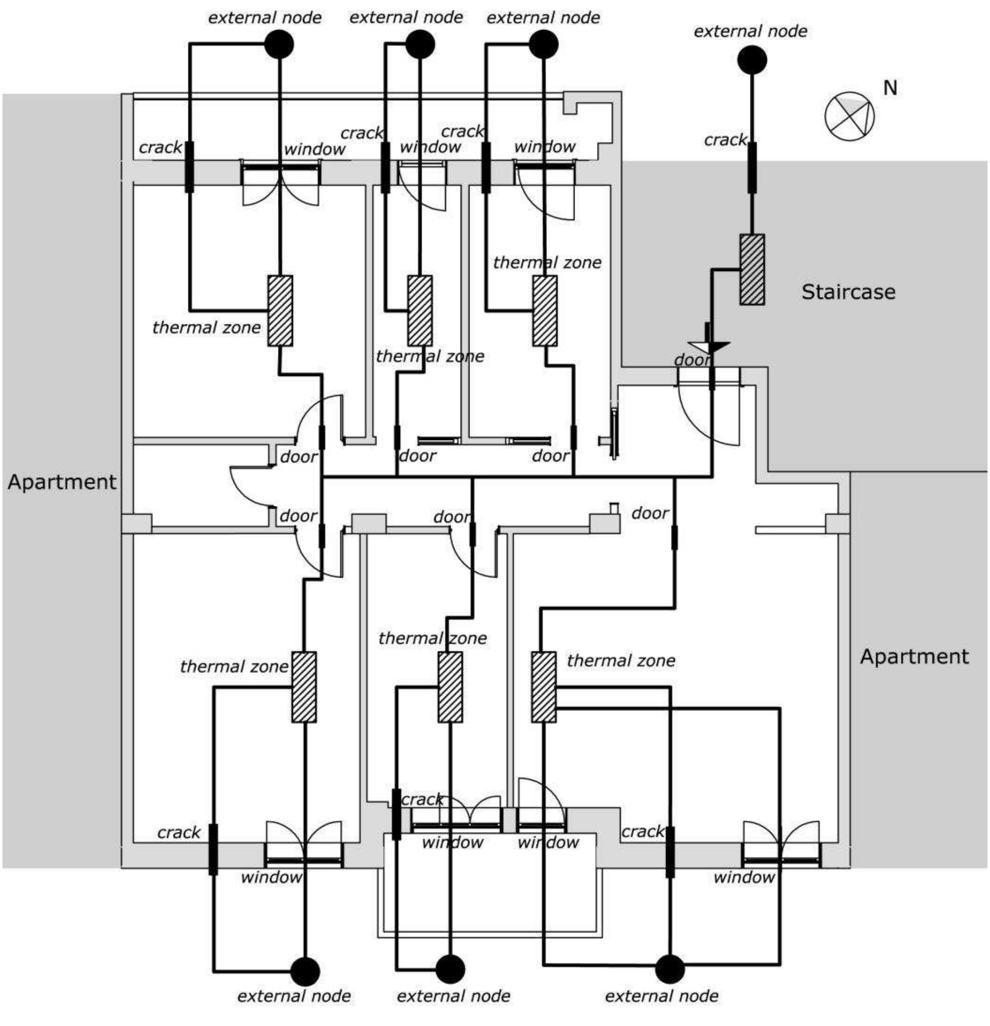

Fig. 4.5. Air-flow network in TRNFLOW

4.2.2. The Particle Swarm Optimization (PSO) in MATLAB

In this work, Particle Swarm Optimization (PSO) algorithm is used for its strength and effectiveness in converge towards the global minimum of the utility function.

PSO (Kennedy & Eberhart, 1995) is a computational method that a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. It is a stochastic optimization algorithm developed by computer scientists to solve difficult problems, i.e. problems that cannot be easily solved by simpler optimization algorithms like Newton's Method, simplex methods, gradient descent, and/or Least Mean Squares (Becker, 2013).

PSO is a minimization algorithm meaning that it searches for solutions that minimize an objective function. It solves a problem by having a population of candidate solutions, here dubbed particles, and moving these particles around in the search-space according to simple mathematical formulae over the particle's position and velocity (Fig. 4.6.). Each particle's movement is influenced by its local best known position, but is also guided toward the best known positions in the search-space, which are updated as better positions are found by other particles. This is expected to move the swarm toward the best solutions.

In particular, each particle of the swarm is composed of three *D*-dimensional vectors, where *D* is the dimension of the search space: the current position x_i, the previous its best position p_i, and the velocity v_i. The movements of the particles are guided by their own best known position in the search-space as well as the entire swarm's best known position. When improved positions are being discovered these will then come to guide the movements of the swarm. The process is repeated and by doing so it is hoped, but not guaranteed, that a satisfactory solution will eventually be discovered.

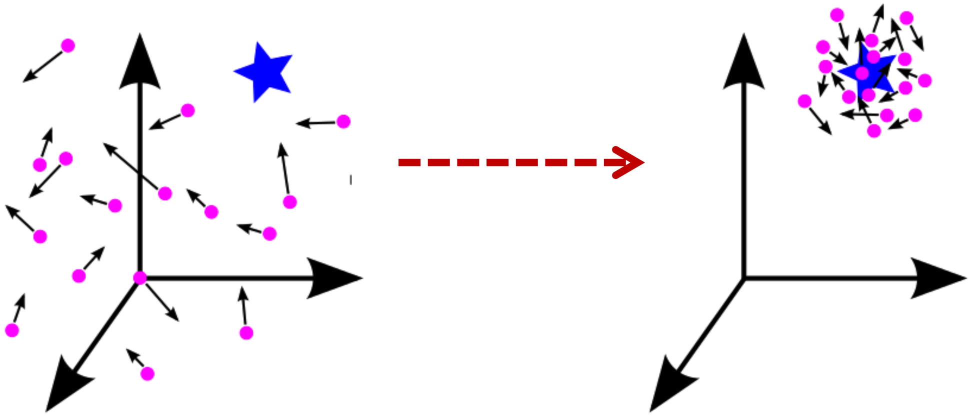

Fig. 4.6. Conceptual diagram of PSO (Becker, 2013)

An important aspect of the algorithm is the fact that all particles keep track of their positions and fitness values throughout the optimization process. The swarm of particles is randomly initialized and the algorithm searches for optimal by updating particles at each generation. The particles are placed in the search space of some problem or function, and each of them evaluates the objective function at its current location. Each particle then determines its movement through the search space by combining some aspect of the history of its own current and best (best-fitness) locations with those of one or more members of the swarm, with some random perturbations. The next iteration takes place after all particles have been moved (Poli, et al., 2007). In detail, the current position x_i can be considered as a set of coordinates describing a point in the space and is evaluated as a possible problem solution. If such position results to be better than the previous ones, then its coordinates are stored in the vector p_i. The value of the resulted best function is stored in a variable called previous best $pbest_i$, for comparison on the later iterations. The objective of each particle is to find better positions and update p_i and $pbest_i$ vectors. For this reason, the algorithm iteratively updates the velocity vector v_i of each particle and calculates new positions x_i, also considering the best location of all particles (*gbest*), in accordance with the following two-update equations:

$$v_i(k+1) = w \cdot v_i(k) + c_1 \cdot r_1^{(k)} \cdot [pbest_i(k) - x_i(k)] +$$
$$\dots + c_2 \cdot r_2^{(k)} \cdot [gbest(k) - x_i(k)] \tag{4.9}$$
$$x_i(k+1) = x_i(k) + v_i(k+1) \tag{4.10}$$

where

- w is the inertia weight;
- k is the iteration number;
- c_1.and c_2 are respectively the cognitive and social weight;
- r_1 and r_2 are vectors of random numbers sampled from a uniform distribution in the range [0,1].

Since the aim is minimize the objective function the current position $\mathrm{x_i(k)}$ is a vector of the values that variables to be optimized assume at the iteration k.

In addition, the parameters w, c_1, c_2 and the particle numbers have to be fixed equal to (Poli, et al., 2007):

- $\mathrm{w} = 0.7298$;
- $\mathrm{c}_1 = \mathrm{c}_2 = 1.49618$;
- size of the population equal to 10 particles.

Finally, the optimization process is completed if the best location gbest does not change for a fixed number M of consecutive iterations. The corresponding value $\mathrm{F_{obj}}$ is the optimal value of the objective function determined by the PSO. More in detail the Fobj implemented in the simulations and the variables to optimize are described in the paragraph 4.3.2.

4.3. Building Energy Management System for Ventilative Cooling

Known that the natural ventilation control by window opening/closing is one of the main actions performed by occupants (as resulted by the chapter 3) and that it may influence the building performance especially in summer season, several studies are conducted, focusing on the potential of **BEMS for the control of ventilation and solar shading for passive cooling** as retrofit solutions to improve thermal comfort in existing residential building located in a suburban zone of the Bari's city (Italy).

In detail the several studies conducted for BEMS focused on:

- natural ventilation control strategies with if/then rule based on indoor and outdoor temperature and R.H.;
- optimization of the above control logics for natural ventilation with objective function for the minimization of thermal discomfort conditions;
- sensitive analysis in different climate conditions and orientations and optimization of the natural ventilation control logics;
- coupling of natural ventilation strategies with solar shading systems for passive cooling.

Adaptive thermal comfort simulations are performed in order to value the effectiveness of window opening control logic in the different contexts. According to the European standard UNI EN 15251, three comfort categories limited by three temperatures ranges are defined. Thermal comfort is evaluated on the difference between the optimal operative temperature and the simulated operative temperatures. The operative temperatures outputs during the occupation hours are compared with the Upper Temperature limit and Lower Temperature limit.

4.3.1. Natural ventilation control strategies and automation systems

In a first study (Dell'Osso, et al., 2015), several control strategies of natural ventilation are analyzed to reduce energy consumptions for cooling and ensure adequate levels of indoor comfort. Energy efficiency solutions involve the installation of a network of sensors (wireless low-power) and actuators for the implementation of natural ventilation strategies. Opening actuators can be applied to existing windows, controlled by temperatures and humidity sensors

Six cases are simulated: the Case 0 (the base case) is without natural ventilation control strategies and with opening windows only for IAQ and no cooling system; the Case 5 is the base case with active cooling, and in the other four cases, in order to keep a comfortable temperature and humidity, different control strategies of natural ventilation are simulated. In detail, during the hours not included for IAQ, the windows in each room are opened if:

1) *Case 1 (actuators operated by temperature sensors)*

   - T indoor > T optimal (valuated according UNI EN 15251);
   - T indoor – 3°C < T outdoor < T indoor (in order to avoid undercooling discomfort).

2) *Case 2 (actuators operated by temperature or humidity sensors)*

   - T indoor > T optimal;
   - T indoor – 3°C < T outdoor < T indoor.
     Or if:
   - R.H. indoor (relative indoor humidity) > 70%;
   - absolute indoor humidity > absolute outdoor humidity.

3) *Case 3 (actuators operated by temperature and humidity sensors)*

   - T indoor > T optimal;
   - T indoor – 3°C < T outdoor < T indoor.
     Or if:
   - R.H. indoor (relative indoor humidity) > 70%;
   - absolute indoor humidity > absolute outdoor humidity.
   - T indoor > T optimal;

4) *Case 4 (hybrid system with cooling system)*

   - T indoor > 26°C;

- T indoor – 3°C < T outdoor < 26°C.

The operation of air to air heat pump for cooling, during the hours of occupation, if:

- T indoor > 26°C;
- T outdoor > 26°C.

The T optimal (and not the overheating temperature) is chosen as the threshold for the window opening in order to exploit mostly the benefits of natural ventilation before indoor temperature increases.

After setting up the building's thermal model and the multi-zone airflow network model within the TRNFLOW–TRNSYS software, different ventilation strategies are compared through:

- thermal comfort analysis, according to the standard (EN15251, 2007), assuming the category n. II (relative to new construction and existing buildings subject to refurbishment)
- energetic analysis in dynamic regime.

Simulations are performed during the cooling season (1 June – 30 September) to analyze the passive behavior of the building. In particular, relatively to the occupation hours, the discomfort due to overheating and undercooling has been calculated, in reference to the upper and lower temperature limit.

In relation to internal and external temperature and humidity (relative and absolute), four design solutions have been simulated in order to choose the optimal control of ventilation. Four cases are performed without any active cooling system (Case 0, Case 1, Case 2, Case 3). In a case (Case 4) the combination of a natural ventilation system with an air to air heat pump has been simulated to evaluate the reduction of cooling energy consumptions.

Results

The four cases without active cooling are compared in terms of adaptive thermal comfort and relative humidity conditions. The percentage discomfort is evaluated by adding the total discomfort hours during the occupation hours and then dividing for the summer simulation period.

Simulation results show the efficacy of the proposed ventilative cooling strategies. A natural ventilation system, calibrated on a variable set-point based on the optimal temperatures (according to the theory of adaptive comfort) determines a significant reduction of overheating during the occupation hours.

The Bedroom2 presents the more situations of discomfort for overheating. The orientation non-optimal and the absence of any shielding system, the night- ventilation lack and the high internal gains are the main causes. The Tab. 4.5 reports the thermal discomfort percentages for overheating (OH) and undercooling (UC) for each room.

Tab. 4.5. Thermal discomfort results.

Room	**CASE 0**		**CASE 1**		**CASE 2**		**CASE 3**	
	(OH)	(UC)	(OH)	(UC)	(OH)	(UC)	(OH)	(UC)
Bedroom1	2,3 %	3,7%	0,0 %	3,9%	0.0 %	9,3%	0,0 %	4,4%
Bedroom2	10,7%	0,9%	2,5%	0,9%	4,7%	5,4%	2,3%	1,6%
Study room	9,7%	1,6%	3,5%	1,6%	5,4%	5,1%	3,4%	2,0%
Living room	10,7%	1,2%	2,9%	1,3%	5,0%	4,7%	2,9%	1,8%

Furthermore the simulations show high levels of relative humidity (>70%) in the bedrooms.

In order to reduce the high level of relative indoor humidity (>70 %), a natural ventilation strategy controlled by humidity sensor is necessary. In fact as showed in the Tab. 4.6, in the Case 2, when the control of relative humidity is independent by indoor temperature, the discomfort situations for high levels of relative humidity have halved, although some undercooling occurs due to the opening of the windows when the control on the temperature is set off. In the other cases relative humidity discomfort percentages are almost the same.

Activation system controlled by humidity and temperatures sensors with logics above described (Case 3) allow significant overheating discomfort reductions. The Fig. 4.7 shows the indoor temperature of the Bedroom2 in the Case 0 and Case 3 in relation to optimal, overheating and undercooling temperatures.

Tab. 4.6. Relative Humidity discomfort percentages (R.H.>70%)

Room	**Case 0**	**Case 1**	**Case 2**	**Case 3**
Bedroom1	50,3 %	51,3%	23,3%	50,4%
Bedroom2	**37,1%**	**38,6%**	**17,2%**	**37,9%**
Study room	10,0%	11,7%	4,6%	10,7%
Living room	15,6	18,9%	3,8%	17,7%

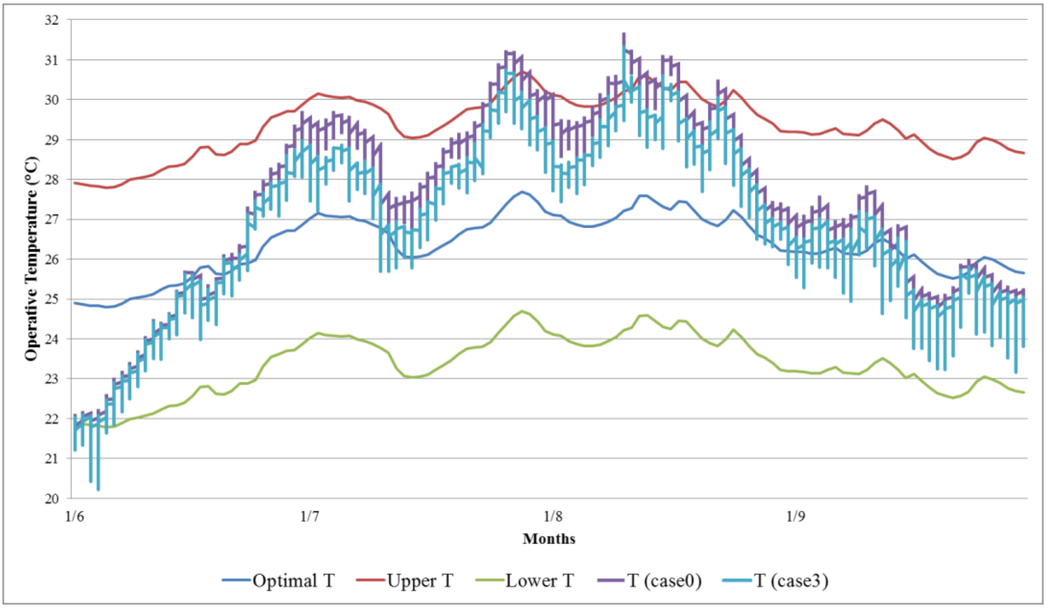

Fig. 4.7. Thermal comfort simulation results – Bedroom2 (Case 0 – Case 3)

The other two cases (Case 4 and Case 5) energy needs for cooling are evaluated. The simulation results show that the control strategies of ventilation for passive cooling enable a 50% reduction of energy consumption, from 905 kWh to 445 kWh, in similar comfort conditions.

This first study have underlined that ventilation strategies for passive cooling, can contribute even more effectively to the improvement of the behavior of the building envelope, integrating or replacing the conventional efficiency strategies, if properly integrated with adequate control systems.

With low investment costs the natural ventilation could reduce the high energy consumptions of cooling systems

4.3.2. Optimizing natural ventilation control strategies by minimizing thermal discomfort

Starting from the results presented in (Dell'Osso, et al., 2015), a second study is conducted in (Fanti, et al., 2016) where an optimized control strategy of window opening is developed to minimize thermal discomfort conditions. In particular, the control of ventilation is calibrated on dynamic set-point based on optimal temperatures according to the adaptive thermal comfort theory (EN15251, 2007).

The objective of this second study is to optimize the thresholds to open and close the windows in order to realize the natural ventilation flows for indoor thermal comfort, by means of a BEMS. To this aim, the prediction of the natural ventilation effects is evaluated by a co-simulation strategy where TRNSYS and TRNFLOW software are used to simulate thermal building behavior and ventilation dynamics, respectively. Moreover, the PSO is adopted to choose the optimal set point temperature for window opening, by minimizing the thermal discomfort.

The designed energy efficiency solutions consist in an on-off control strategy of natural ventilation, by opening and closing windows at suitable time intervals.

The control of ventilation is calibrated on the basis of a dynamic set-point figure, denoted by $T_{optimal}(t)$ and determined on the basis of running mean outdoor temperature. Note that $t \in \mathcal{T}$ is a natural number denoting the actuating time interval and

$\mathcal{T}$ is a time period of the year. Moreover, $T_{optimal}(t)$ is calculated according to the standard EN 15251, assuming the category n. II (relative to new construction and existing buildings subject to refurbishment). In particular, the optimal comfort range is $[T_{optimal}(t) - 3°C,\, T_{optimal}(t) + 3°C]$.

Moreover, denoting respectively by $\mathrm{T_{indoor}(t)}$ and $\mathrm{T_{outdoor}(t)}$ with $\mathrm{t} \in \mathcal{T}$ the apartment and external temperature, the ventilation control logic is applied by defining an on-off control condition. Let $\mathrm{y(t)} \in \{0,1\}$ be the control variable where $\mathrm{y(t)} = 1$ ($\mathrm{y(t)} = 0$) means that the windows are opened (closed) at time $\mathrm{t} \in \mathcal{T}$.
More precisely, the control logics is defined as follows:

$$\mathrm{y(t)} = 1 \qquad \text{if } \mathrm{T_{indoor}(t)} > \mathrm{T_{optimal}(t)} + \Delta 1 \tag{4.1}$$

and

$$\text{if } \mathrm{T_{indoor}(t)} + \Delta 2 < \mathrm{T_{outdoor}(t)} < \mathrm{T_{indoor}(t)} \tag{4.2}$$

$$\mathrm{y(t)} = 0 \qquad \text{otherwise}$$

with
$\Delta 1 \in \mathbb{R}$ and $\Delta 1 \in$[-6°C, 6°C]
$\Delta 2 \in \mathbb{R}$ and $\Delta 2 \in$[-6°C, 0°C].

Equations (4.1) and (4.2) allow the windows opening when the outdoor temperature is favorable to the reduction of overheating thermal discomfort. In addition, in equation (4.2) Δ2 is introduced to close the windows if the outdoor temperature is too low in comparison with the indoor temperature in order to limit the undercooling discomfort conditions.

The values of Δ1 and Δ2 are determined through the PSO optimization strategy with the aim of minimizing the thermal discomfort, i.e., the total discomfort hours $\mathrm{N}(\Delta 1, \Delta 2)$ for overheating ($\mathrm{N_{heat}}$) and undercooling ($\mathrm{N_{cool}}$), just counting the number of hours, or the percentage of hours, when indoor conditions exceed a given fixed set-point temperature:

$$F_{obj} = \min_{\Delta 1, \Delta 2}[N_{heat}(\Delta 1, \Delta 2) + N_{cool}(\Delta 1, \Delta 2)] \quad (4.3)$$

Hence the **thermal discomfort** is obtained calculating the number of occupied hours when uncomfortable conditions are recorded. The numbers of discomfort hours for overheating and undercooling are determined according to the adaptive thermal comfort theory EN 15251 as follows:

- N_{cool} is the number of hours in which $T_{indoor}(t) < T_{optimal}(t) - 3°C$
- N_{heat} is the number of hours in which $T_{indoor}(t) > T_{optimal}(t) + 3°C$.

Results

Considering the same case study, in this section the analysis focuses on the Bedroom 2, that as reported in the previous study, it resulted the most uncomfortable room.

The simulations are performed considering a period of 62 days (July-August) and two operative cases:

- Case 1: the control rules (4.1) and (4.2) are applied with $\Delta 1 = 0°C$, $\Delta 2$=3°C;
- Case 2: the control rules (4.1) and (4.2) are applied with $\Delta 1$ and $\Delta 2$ determined by the PSO.

More precisely, Case 1 uses the values of $\Delta 1$ and $\Delta 2$ of the simulation performed in (Dell'Osso, et al., 2015), that resulted the best solution of natural ventilation activation to reduce the thermal discomfort.

Furthermore, regarding the simulation period, a restricted period is considered respect to the studies described in the paragraph 4.3.1, both because for the analyzed climate context, the analysis only on July-August (the warmest months) does not modify the methodological approach and the results, and both to reduce computational times. Case 2 uses the optimal values obtained by the proposed co-simulation and optimization strategy obtained with the minimal objective function $N = 209$ with $\Delta 1 = -3.8$ °C and $\Delta 2 = -5.0°C$, i.e.:

$y(t) = 1$ if $T_{indoor}(t) > T_{optimal}(t) - 3.8°C$ (4.4)

and

if $T_{indoor}(t) - 5.0\ °C < T_{outdoor}(t) < T_{indoor}(t)$ (4.5)

$y(t) = 0$ otherwise

Comparing Case 1 and Case 2, it is apparent that there is a significant reduction of the total discomfort hours. In particular, the discomfort hours for the overheating between the two cases decrease by 31.8%, while those for undercooling are almost the same (see Tab. 4.7). Taking into account only the hours with users presence in Bedroom 2 (6 p.m. to 8 a.m.), the percentage of thermal discomfort reduction between the two cases is lower. In particular, there is a reduction by 20% of discomfort hours for overheating, while thermal discomfort hours for undercooling are almost the same. In detail the percentage of time when the windows is opening in the Case 2 is higher than 35% than in the Case 1.

Tab. 4.7. Thermal Discomfort Results

Case	**Thermal discomfort** (without considering user presence)					
	For overheating		**For undercooling**		**Total**	
	Hours	**%**	**Hours**	**%**	**Hours**	**%**
Case1	606	40.6 %	48	3.2	654	43.8
Case2	159	8.8 %	50	3.3	209	14.0
Case	**Thermal discomfort** (considering user presence)					
	For overheating		**For undercooling**		**Total**	
	Hours	**%**	**Hours**	**%**	**Hours**	**%**
Case1	378	25.5	26	1.7	414	27.2
Case2	82	5.5	38	2.5	120	8.0

It can be noted how the discomfort percentage of the Case 1 are higher than those of the same case view in the previous study. This difference is due to the different period of simulation taken into account: indeed, in the previous study the considered period of simulation (1 June - 30 September), i.e. 2928 hours, is longer than in this study (July-August), i.e. 1488 hours. Hence because of the thermal discomfort hours are mainly in July and August, in the previous study, where the discomfort hours are divided for the whole summer period, the discomfort percentages are lower.

Moreover, Fig. 4.8 shows the internal temperature profiles obtained in the two operative cases and the lower and upper temperatures according to EN 15251. It results that the control logic of optimized ventilation activation of Case 2 determines an internal temperature lower than the Case 1. More in detail, the temperature profile of the optimized case is almost contained in the optimal range of temperature defined by the adaptive thermal comfort theory, justifying the reduction of overheating discomfort.

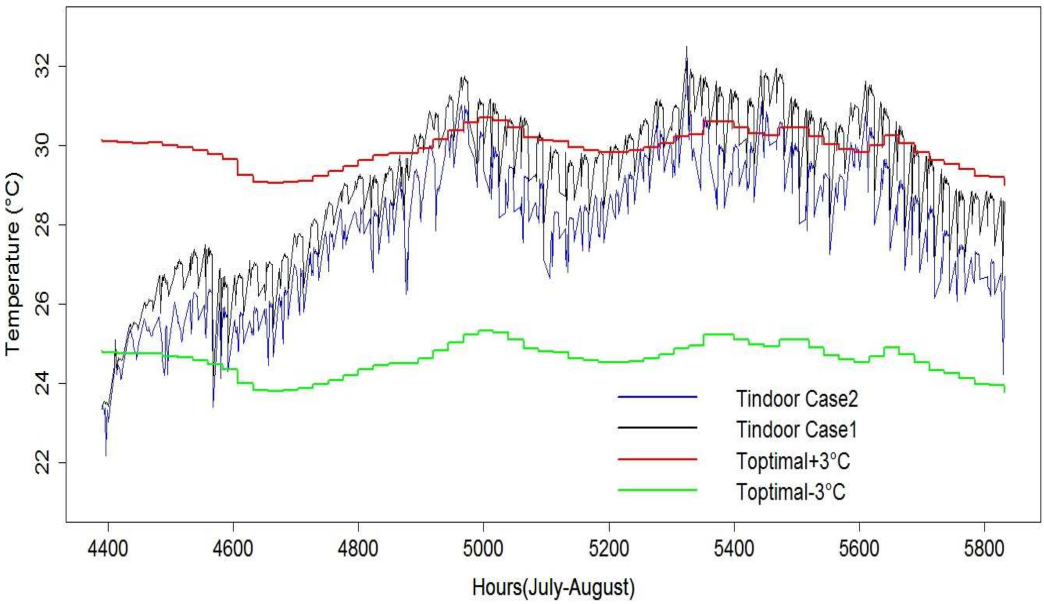

Fig. 4.8. Indoor and optimal range temperature

In this second study a control strategy is defined, based on: i) the thermal comfort analysis according to the adaptive thermal comfort theory (EN15251, 2007); ii) an on-off control strategy for natural ventilation to determine a significant reduction of overheating discomfort. The optimization strategy, determining the optimal ranges of time to close and open the windows, showed how the integration of suitable control logics increases the potentialities of natural ventilation strategies to the improvement of energy and thermal performance of buildings.

4.3.3. Sensitivity of the natural ventilation control strategies to different weather conditions

In a third study (Rinaldi & Iannone, 2016), the optimized control strategy of windows opening described previously have involved different scenarios. In particular, according to **different climate conditions and orientations** of the case study, the objective of the study is to value how the optimized thresholds to open and close the windows vary to realize a natural ventilation flows for indoor thermal comfort.

The case-study building is located in four Italian cities (Bolzano, Gioia del Colle, Bari and Palermo), characterized by different summer conditions and cooling degree days (c.d.d.). The c.d.d. are calculated only by adding the positive differences between the hourly outdoor temperature and the conventional indoor temperature of 26°C during the period of July and August: Bolzano (BZ) (c.d.d.=765), Gioia del Colle (GDC) (c.d.d.=982), Bari (BA) (c.d.d.=1180), and Palermo (PA) (c.d.d.=1497). For each case, two orientations of the building were considered, i.e. windowed sides facing to North-West and South-East and then to North-East and South-West. In detail, in the first sets of simulations the windowed sided facing to N-W and S-E, as shown in the Fig. 4.1, then it is hypothesized to turn the building of 90° clockwise, with the windowed sides facing to N-E and S-W.

For these eight cases, the designed energy efficiency solutions consist in an on-off control strategy of natural ventilation, by opening and closing windows at suitable time intervals according to (4.1) and (4.2) where the values of Δ1 and Δ2 are determined through the PSO optimization strategy with the aim of minimizing the thermal discomfort according to (4.3).

Results

Adaptive thermal comfort simulations are performed in order to value the effectiveness of window opening control logic in the different contexts.

In particular, the analysis are referred to the Bedroom2, that as reported in the previous studies, is resulted the most uncomfortable room in every case. For this reason the indoor temperature of Bedroom2 is considered in (4.1) and (4.2) to control the window openings of all the windows of the dwelling. Furthermore, the adaptive thermal comfort results refer to this room.

In this study, differently by the previous study, the variation ranges of $\Delta 1$ and $\Delta 2$ are increased in order to exploit more the benefits for summer cooling of entrance of cooler air flow from outdoor:

- $\Delta 1 \in \mathbb{R}$ and $\Delta 1 \in$[-6°C, 6°C]
- $\Delta 2 \in \mathbb{R}$ and $\Delta 2 \in$[-10°C, 0°C].

The period taken into account for the simulation is July-August (62 days). It should be stated that in the thermal comfort simulations, only the hours with users presence in Bedroom2 (6 p.m. to 8 a.m.) are taken into account, i.e. 868 total occupation hours.

For the eight cases (four different locations and two orientations of the building), two control strategies (named Case1 and Case2) are compared, for a total of 16 simulations:

- **Case 1**: the control rules (4.1) and (4.2) are applied with $\Delta 1 = 0°\text{C}$, $\Delta 2$=-3°C (the strategy adopted in (Fanti, et al., 2016);

- **Case 2**: the control rules (4.1) and (4.2) are applied with $\Delta 1$ and $\Delta 2$ determined by the PSO, after $\text{M} = 10$ consecutive iterations exhibiting the same values of the objective function or however at the end of optimization running iterations.

The Tab. 4.8 reports the thermal discomfort results for the different cities and the different exposure of the Bedroom2.

In this work, the thermal discomfort percentage are evaluated in relation to the occupation hours of the Bedroom2 during the July-August period (868 hours).

Comparing Case 1 and Case 2 of the eight cases, it is apparent that there is a significant reduction of the total discomfort hours. In particular, in function of cooling degree days, the window opening control logics allow even more improvement of thermal comfort conditions.

In the building located in Palermo, regardless the windows sides orientation, there is the maximum reduction of thermal discomfort hours for overheating (about 68%). In the case study located in Bolzano, Gioia del Colle and Bari the maximum reduction percentages of thermal discomfort for overheating are respectively 29% and 65% and 66%. It demonstrates how in the warmest climate the passive cooling strategy can significantly improve the indoor thermal conditions and consequently reduces the energy consumptions for cooling.

In each simulations, the optimization logics of Case2 don't determine variations of thermal discomfort for undercooling. As expected, the building located in Bolzano, the coldest climate between the examined cases, presents the most discomfort conditions for undercooling.

As regarding the windowed sides orientation of the Bedroom2, because the occupation hours of this room starts from afternoon to early morning (6 p.m. to 8 a.m.) and the orientation without solar shading is not optimal, in all the cases facing to S-W it results an increase of thermal discomfort conditions for overheating compared to S-E exposure. Because of the exposure S-W, regardless the location variations, by increasing the indoor temperatures, the gap between the values of indoor temperature lower than optimal temperature decreases.

Hence, the control logic of (4.1) can start with lower values (in absolute values) of $\Delta 1$ as resulted in the Tab. 4.8. On the contrary, ever more high $\Delta 2$ values in (4.2) are necessary to reduce the thermal discomfort hours.

Tab. 4.8. Thermal discomfort results for different cities and orientations

City	Exposure	Case	$\Delta 1$	$\Delta 2$	Overheating (Nh)		Undercooling (Nc)		Total (N)	
					Hours	%	Hours	%	Hours	%
BZ	S-E	Case1	0.00	-3.00	98	11.2	87	10.0	185	21.3
		Case2	-2.55	-5.20	43	3.8	89	10.1	132	15.1
	S-W	Case1	0.00	-3.00	127	14.6	75	8.6	202	23.3
		Case2	-1.70	-5.50	88	10.1	77	8.8	165	19.0
GDC	S-E	Case1	0.00	-3.00	402	46.3	43	4.9	445	51.2
		Case2	-1.42	-5.50	101	11.6	65	7.4	166	19.1
	S-W	Case1	0.00	-3.00	424	48.8	37	4.2	461	53.1
		Case2	-1.35	-6.15	99	11.4	60	6.9	159	18.3
BA	S-E	Case1	0.00	-3.00	378	43.5	26	2.9	404	46.5
		Case2	-1.65	-7.50	132	15.2	28	3.2	160	18.4
	S-W	Case1	0.00	-3.00	401	46.2	18	2.0	419	48.2
		Case2	-1.59	-7.93	111	12. 7	31	3.5	142	16.4
PA	S-E	Case1	0.00	-3.00	658	75.8	16	1.8	674	77.6
		Case2	-0.93	-8.50	275	31.6	16	1.8	291	33.5
	S-W	Case1	0.00	-3.00	673	77.5	14	1.6	687	79.1
		Case2	-0.58	-8.91	186	21.4	35	4.0	221	25.4

The Fig. 4.9 and Fig. 4.10 put in relations the optimal values of Δ1 and Δ2 with the cooling degree days of the four climate conditions, respectively for S-E orientation and the S-W orientation. In particular, regardless of orientation, in function of c.d.d. there is almost a linear increase ($R^2=0.91$ for the S-E orientation; $R^2=0.94$ for the S-W orientation) of Δ2 values and a linear reduction ($R^2=0.79$ for the S-E orientation; $R^2=0.74$ for the S-W orientation) of Δ1 values.

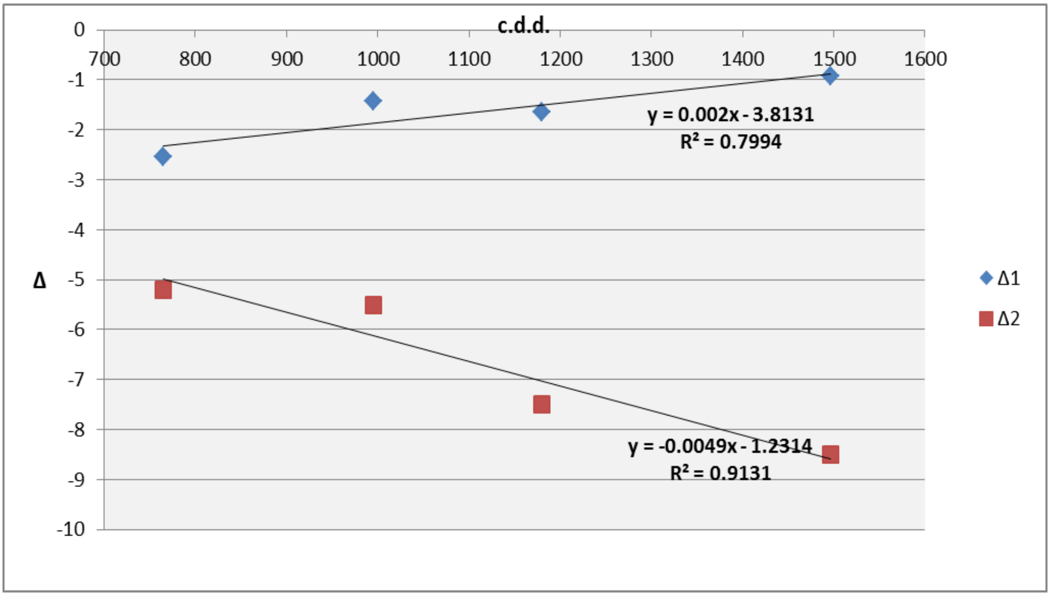

Fig. 4.9. Relation between Δ1 and Δ2 values and the cooling degree days for the S-E orientation.

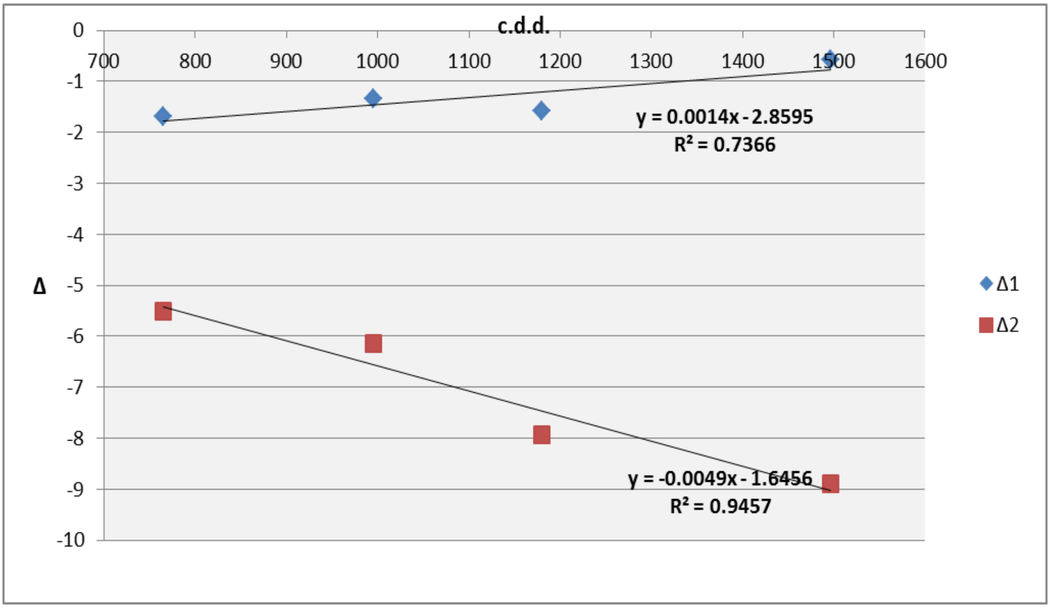

Fig. 4.10. Relation between Δ1 and Δ2 values and the cooling degree days for the S-W orientation.

More in detail, to justify this trend, by analyzing the indoor, outdoor and optimal temperatures for the coldest and warmest climate conditions corresponding to Bolzano and Palermo (Fig. 4.11) it results how:

- except the first two weeks of July, the indoor temperature of Case1 is higher than the optimal temperature (blue line). Hence the condition (4.1) for window opening is usually verified and $\Delta 1$ values different from zero are necessary only to reduce the thermal discomfort conditions for the first weeks of July. It justifies how, for the case studies located in Palermo, the $\Delta 1$ values of the Case2 (Tab. 4.8) are the lowest between the four cases (<1°C) because the optimal temperature is higher than indoor temperature at most of 1°C.

- the outdoor temperature is usually lower than the indoor temperature (red line). In particular, this difference is maximum (in absolute value) for Bolzano. But since the difference Tind-Topt (blue line) is minimum for Bolzano, for the control logic (4.2) high values of $\Delta 2$ are not allowed to not increase the discomfort conditions for undercooling. Instead for Palermo, where the difference Tind-Topt (blue line) is higher, the undercooling risk is minimum and hence higher values of $\Delta 2$ are allowed.

This work shows the benefits of the optimized natural ventilation control logics for the improvement of thermal performance of buildings, especially in the warmest climate.

The designed control logics, adaptive to different climate conditions, allow the reduction of thermal discomfort hours for overheating of about 60 %, by changing the set-point temperatures for the control logics of window opening in relation to the c.d.d. values. In particular for the warmest climate, in order to improve the thermal comfort conditions, it is necessary allowing the window opening more frequently (i.e. with higher values of $\Delta 1$ and $\Delta 2$) in order to exploit the positive effect of natural ventilation for passive cooling.

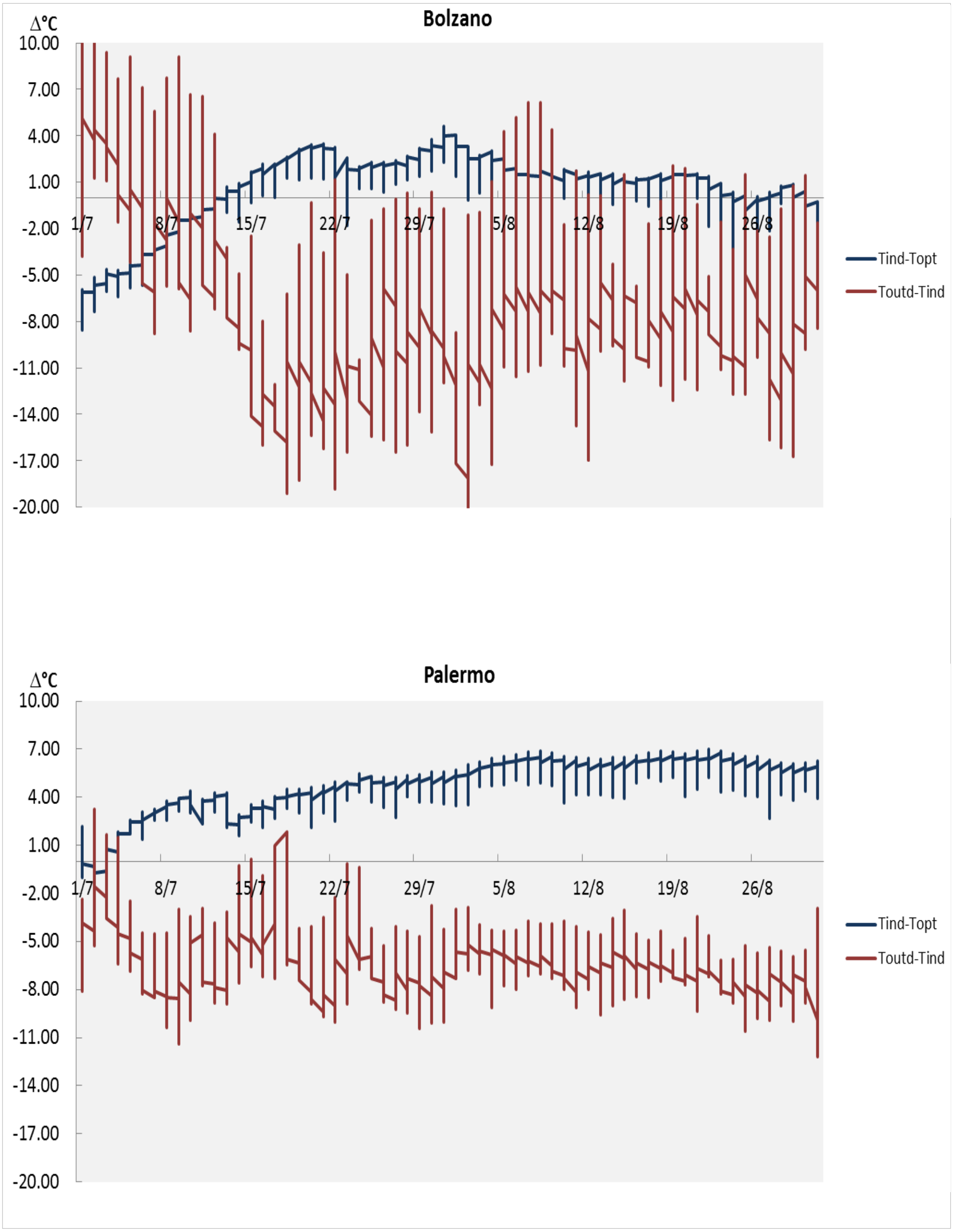

Fig. 4.11. Indoor, outdoor and optimal temperatures for Bolzano and Palermo (Case1, S-E orientation).

4.3.4. Implementing solar shading system and optimizing the natural ventilation control strategies for passive cooling

While in the previous studies none solar shading system are considered, in Rinaldi et al. (Rinaldi, et al., 2016) **solar shading system** are introduced to evaluate the impact on the proposed BA strategy for natural ventilation.

In particular, rolling window shutters are considered and ruled on the basis of the shading factor (s.f.) that represents the percentage of opaque area due to the shading respect to the glazing surface of the window. Regarding the shading system, the rolling window shutters are typical of local buildings especially for the construction postwar period of the examined case study. Then, the airflow opening areas are modified according to the specified shading percentages.

In detail, two operative conditions that consider the presence or absence of users are studied:

- s.f. = 0.25 (presence of users)
- s.f. = 0.75 (absence of users).

This assumption simulates in deterministic way the occupant behaviors, who close rolling window shutters by obtaining a shading percentage of the windows equal to 75 % (s.f.= 0.75) in unoccupied rooms, and a shading percentage equal to 25 % (s.f.= 0.25) to avoid dark rooms when users are present. Then, the airflow opening areas are modified according to the specified percentages.

In this new configuration the control logics of window opening are optimized to minimize the thermal discomfort. Moreover, an active cooling system is introduced to assess the effects of the proposed control logics on the energy consumption.

Results

As in the previous works, the adaptive thermal comfort simulations and results refer to Bedroom2, the most uncomfortable room. Then, the indoor temperature T_{indoor} of Bedroom2 is considered to control the openings of all the dwelling windows.

The considered period for the simulations is July-August hence the simulation runs are of $\mathcal{T}$ =1488 hours with hourly time step t. The simulation results take into account only the hours with users presence in Bedroom2 for a total of $\mathcal{T}$o= 868 hours.

The simulations are executed considering three cases:

- **Case 0**: natural ventilation only for IAQ at fixed hours;
- **Case 1**: ventilative cooling under control rules (4.1) and (4.2) with Δ1= 0°C, Δ2= -3°C;
- **Case 2**: ventilative cooling under control rules (4.1) and (4.2) with optimal values of Δ1 and Δ2.

More precisely, in Case 0 the windows are opened only at certain hours (8 a.m. - 10 a.m.; 1 p.m.- 2 p.m.; 8 p.m. - 9 p.m.) during the activities of preparing and cooking foods and of household cleaning.

Moreover, in Case 1, in addition to the natural ventilation for IAQ of the Case 0, during the other daily hours ventilative cooling is granted under control rules (4.1) and (4.2), where the values of Δ1 and Δ2, as previously specified, are fixed a priori on the basis of the what-if analysis results obtained in the first study (Dell'Osso, et al., 2015).

Furthermore, Case 2 uses the optimal values obtained by the proposed co-simulation and optimization strategy: the optimal objective function values are obtained with Δ1= -1.07 °C and Δ2= -7.51°C corresponding to the 16th PSO iteration (as it is highlighted in Fig. 4.12 and Fig. 4.13).

In particular, Fig. 4.12 shows the optimization running: the iterative optimization procedure starts assigning random values to Δ1 and Δ2. According to the values of Δ1 and Δ2, the set-point temperature for the window opening activation in (4.1) and (4.2) varies.

In Fig. 4.13 it is possible to notice how the discomfort conditions vary from a maximum of about 700 hours to a minimum of about 80 hours.

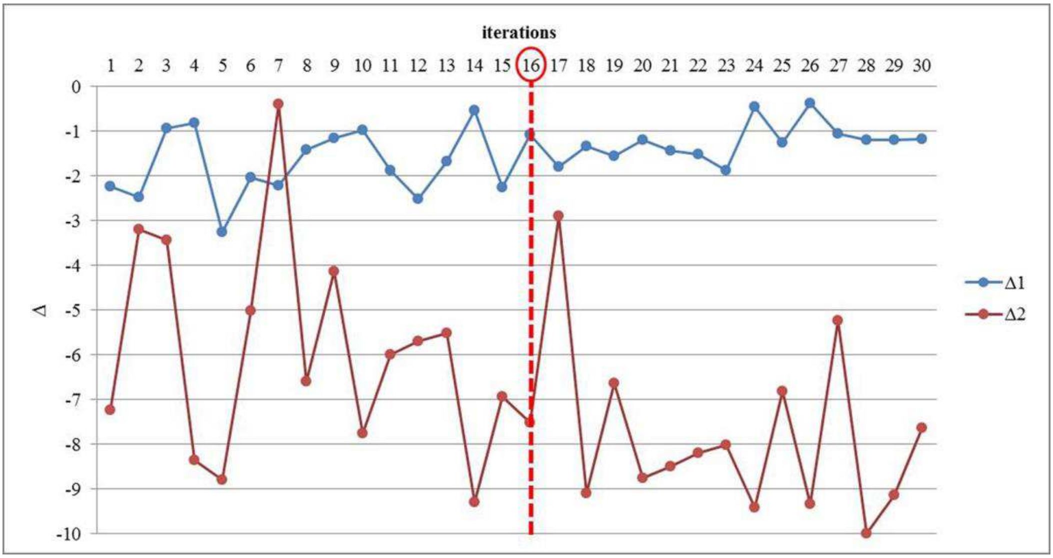

Fig. 4.12. The optimization running

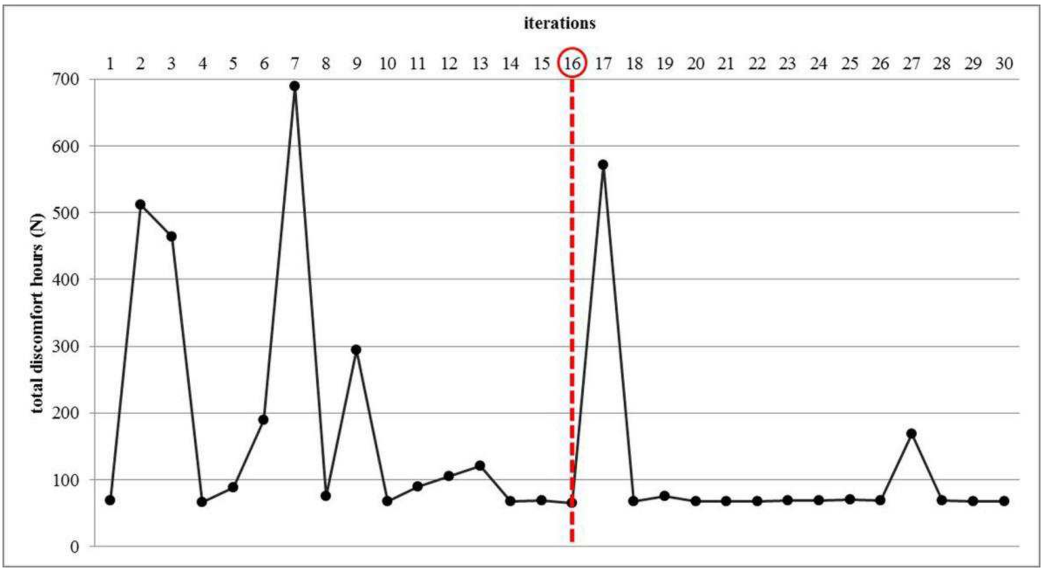

Fig. 4.13. The total number N of discomfort hours in function of Δ1 and Δ2.

Furthermore, Fig. 4.12 and Fig. 4.13 highlight how function $N(\Delta 1, \Delta 2)$ is more sensitive to the variations of Δ2 with respect to the variations of Δ1. This result is due to the effects of Δ2 in (4.2): increasing the absolute value of Δ2 allows ventilation also in the case of lower outdoor temperatures and consequently it enhances passive cooling.

The results of the simulations are compared by computing the following performance indices:

- $\mathrm{N_{heat}}$, number of discomfort hours for overheating in $\mathcal{T}$o
- $\mathrm{N_{cool}}$, number of discomfort hours for undercooling in $\mathcal{T}$o
- N, total number of discomfort hours in $\mathcal{T}$o
- $\mathrm{N_{heat}}/\mathcal{T}$o·100, percentage of discomfort hours for overheating
- $\mathrm{N_{cool}}/\mathcal{T}$o ·100, percentage of discomfort hours for undercooling
- N / $\mathcal{T}$o·100, percentage of discomfort hours.

The computed performance indices are reported in Tab. 4.9.

Comparing Case 1 and Case 2 with respect to Case 0, Fig. 4.14 and Tab. 4.9. show that the natural ventilation control logics allow significant reductions of the total thermal discomfort hours. The total thermal discomfort percentage moves from 32.9 % (Case 0) to 13.3 % (Case 1) and to 8.7 % (Case 2).

In particular the reduction of total discomfort hours depends from the overheating discomfort conditions that decreases about 65 % in Case 1 and about 81 % in Case 2 with respect to Case 0. On the other hand, the natural ventilation control logics do not determine variations of thermal discomfort for undercooling.

In order to value the effectiveness of window opening control logic on the energy consumptions, the three cases previously examined are performed by adding an active cooling system. The cooling system is switched-on in each room when $T_{indoor}(t)>26°$ according to the scheduled occupancy shown in Tab. 4.2. Hence, the energy E needed for cooling referred to Bedroom2 is reported in Tab. 4.9 and Fig. 4.14 for the three cases.

Tab. 4.9. Thermal comfort and energy needs for cooling results.

Case	Thermal discomfort (no active system)						Energy needs for cooling (with active system on)	
	Overheating		Undercooling		Total			
	N_{heat}	%	N_{cool}	%	N_{tot}	%	*E* (kWh)	Δ%
Case 0	262	30.2	24	2.7	286	32.9	178	-
Case 1	91	10.4	25	2.8	116	13.3	134	-24.5
Case 2	49	5.6	27	3.1	76	8.7	121	-32.1

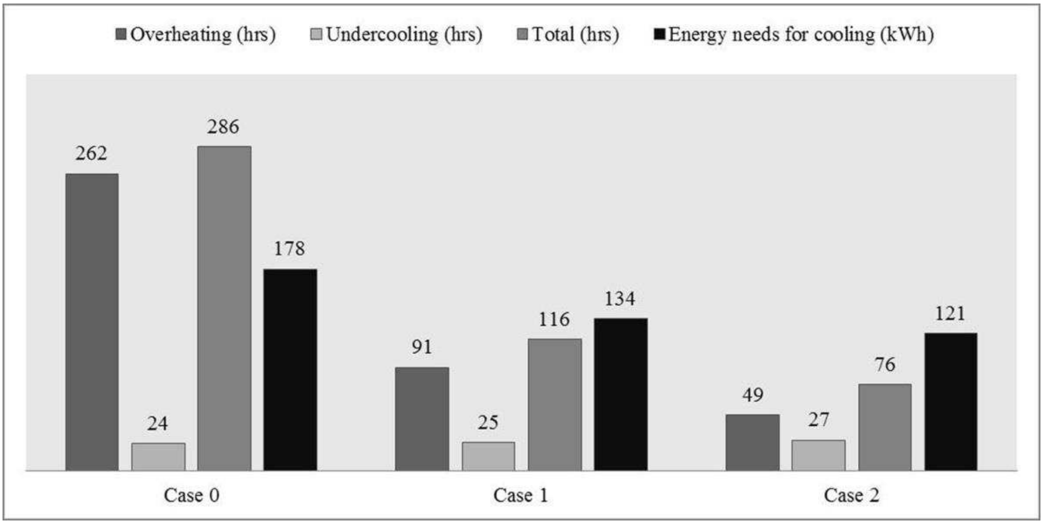

Fig. 4.14. Adaptive thermal comfort and energy results.

The results show how the proposed passive strategy for window opening allows reducing of the energy needs, that in Case 1 are reduced of 24.5% and in Case 2 of 32.1 % respect to Case 0.

Regarding the set-point temperature for activation of cooling system, a fix 26°C is chosen as the standard approach in literature. However in the following the chapter, in order to better taking into account the occupant behavior, the threshold of cooling activation is set according to adaptive thermal comfort theory.

Chapter 5

Optimizing BEMS for passive cooling, modeling the occupant behaviors towards an agent-based oriented approach

The examined case studies of the Chapter 4, simulating the occupant behavior in deterministic way through defined schedules, showed the benefits in terms of thermal comfort and energy needs reduction of the designed control logics of window opening.

In addition, while in the previous chapter the thermal comfort analysis and the energy needs for cooling are referred to the most discomfortable room, in this chapter in order to value the thermal comfort situations and the energy needs for cooling for the whole apartment, the optimization adopts the Long-term percentage of dissatisfied (LPD) index. This **long-term thermal discomfort index** quantifies predicted thermal discomfort over a calculation period, by a weighted average of discomfort over the thermal zones of a given building and over the time in a given calculation period.

Furthermore, with the aim of designing **BEMS, adaptable to occupant's actions and satisfaction**, the occupant behaviors is modeled with more detail. In this manner there are two positive aspects: there is an improvement of building performance and, by limiting the thermal discomfort situations, there is a reduction of the impact of occupant behavior, because the occupants actions will be less.

In this work the **indoor temperature** is one of the main parameter both to control the BEMS and both to simulate the occupant behaviors. In detail the designed BEMS to control window opening and solar shading aims to reduce the indoor temperature in order to reduce the usage of active system by occupant. Indeed, in accordance to the results of the questionnaire survey described in the Chapter 3 (see Fig. 3.11), in summer in the most ancient buildings, where the indoor temperature values are high due to low energy efficiency of buildings, the energy consumptions are higher because occupants more often turn on the cooling system to satisfy own thermal comfort.

In this chapter, referring on the same Italian dwelling with technological/typological features of sixties buildings, and whose methods and control logics are defined in the previous chapter, several studies are presented, where the occupant interactions with the building system (in particular regarding the window and solar shading opening/closing, turning on the air conditioner) are modeled in **a probabilistic and multi-agent approach.**

The comparison between the models where the occupant behavior is assumed in deterministic way and in a probabilistic and multi-agent approach, it allowed to assess the impact of human behavior on building performance. Then, the optimization of BEMS for window opening and shading closing enabled to minimize the thermal discomfort situations and the energy needs for cooling.

The ABM of occupant behaviors is implemented in the energy software simulation (TRNSYS), based on algorithms deduced by field investigations in real buildings. A co-simulation architecture is created between **TRNSYS** (building-HVAC model), **TRN-**

FLOW (building air flow network), **MATLAB** (PSO optimization) and **DAYSIM** (visive analysis).

5.1. Modeling the Occupant Behaviors by means of stochastic and towards an Agent-Based Oriented Approach

In this section in order to design BEMS that respond to occupant's actions and preferences, a more realistic occupant behavior is simulated. In particular the thesis focused on the **adaptive behaviors** of residential occupants during the warm season. Indeed, several studies in literature (Nicol, 2001), (Nicol & Humphreys, 2004), (Rijal, et al., 2007) found that occupants have a natural ability to adapt to the environmental climatic conditions by changing the clothes, by increasing the ventilation, by activating shading system, etc. In particular, after field monitoring studies, they defined probabilistic models for actions where the occupant controls depended on the outdoor and indoor temperature.

In this thesis, towards a multi agent-based model, the modeling of occupant behaviors is considered in a simplified **agent-based approach**. In particular, assuming only the thermal stimuli as driven forces for occupant actions, one autonomous agent (i.e. one occupant) is only considered and hence there is not interaction with other occupants but only with the built environments. The agent is in a specific state at a specific time during the simulation according to fixed schedule of daily occupation. Concerning the daily occupation, it is assumed a "fixed schedule" and different for each room in function of plausible occupations by users.

Fig. 5.1 shows the decision making process of occupant. The OODA (observe, orient, decide, and act) loop is used to explain the concept of the ABM decision making process. In detail, the agent (i.e. the occupant) make several actions:

1. **observe**: the agent understands its surrounding, e.g. climatic conditions and given space.

2. **orient:** then agent evaluates its agent parameters and evaluates behavior options.

3. **decide**: based on its level of thermal comfort, the agent makes behavior decisions to address comfort dissatisfaction.

4. **act**: the agent communicates with an external simulator to calculate the behavior impact on energy use and comfort level.

In detail, with object of minimize thermal discomfort hours according to EN15251 (EN15251, 2007), in reference to occupied hours, in each room the internal temperature is calculated and compared with the adaptive comfort temperature to value thermal discomfort conditions. If the $\mathrm{T_{indoor}} > \mathrm{T_{comfort}} + 3\mathrm{K}$ then the state is ''hot'', if $\mathrm{T_{indoor}} < \mathrm{T_{comfort}} - 3\mathrm{K}$ then the state is ''cold''. In the other cases there are thermal comfort conditions. In order to reach thermal comfort situations, the agent may make several adaptive actions (see Tab. 5.1), that in this thesis are restricted to:

- *window opening/closing;*
- *shading system closing;*
- *air conditioning (AC)activation.*

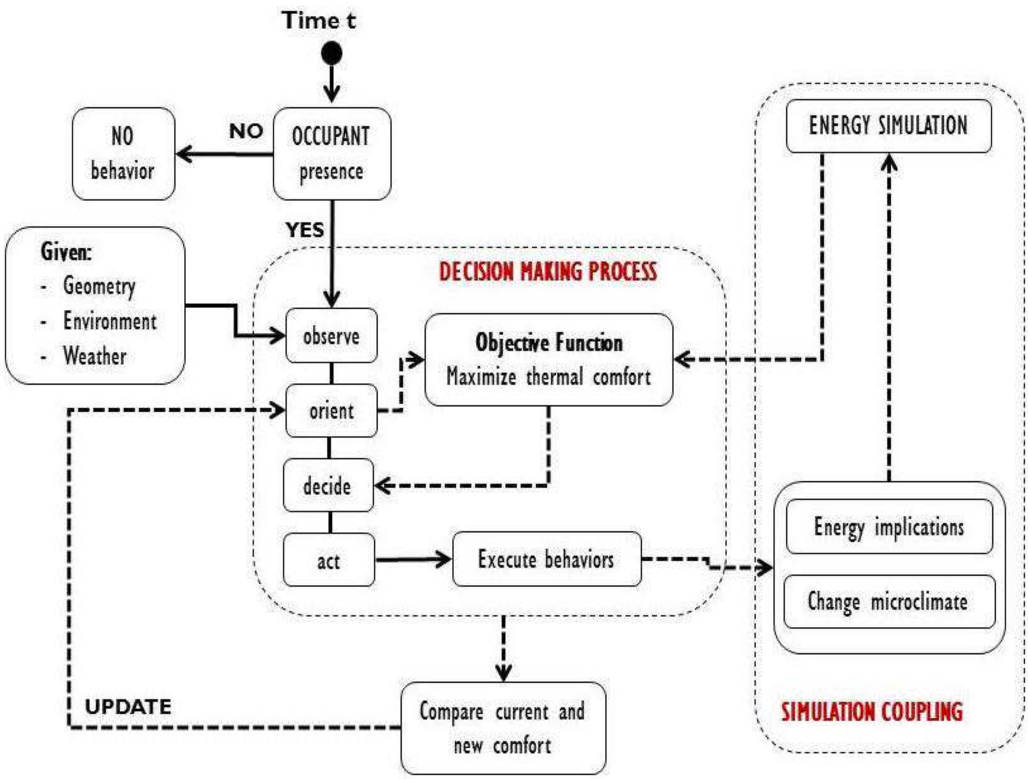

Fig. 5.1. Decision Making Process by occupants.

Tab. 5.1. Adaptive behavior action.

Condition	**Status**
$T_{indoor} > T_{comfort} + 3K$	Adaptive probability to open window Adaptive probability to close blinds Adaptive probability to turn on AC
$T_{indoor} < T_{comfort} - 3K$	Adaptive probability to close window Adaptive probability to open blinds Adaptive probability to turn off AC
$T_{comfort} - 3K < T_{indoor} < T_{comfort} + 3K$	No action

Furthermore, based on stochastic algorithms in literature, the probability of make the several considered adaptive actions is calculated (see following paragraphs). There is not a hierarchy of actions, but it depends on stochastic algorithm described in the following paragraphs for the several occupant behaviors. To decide whether an action will occur, the calculated probability of opening windows, closing blinds and turn on AC, are compared to a random number (p_{random}) between 0 and 1 to represent a single throw binomial function.

In particular if the indoor temperature is “hot” (see Tab. 5.1):

- *the window will be open if the random number is less than the probability of the window being open;*
- *the blind will be closed if the random number is less than the probability of the blind being closed;*
- *the AC will be on if the random number is less than the probability of the AC being on;*
- *no action will be taken if the window is just open, the blind is closed and the AC is on.*

If the indoor temperature is “cold”:

- *the window will be closed if the random number is greater than the probability of the window being open;*
- *the blind will be open if the random number is greater than the probability of the blind being closed;*
- *the AC will be off if the random number is greater than the probability of the AC being on;*
- *no action will be taken if the window is just closed, the blind is open and the AC is off.*

When the occupant is ‘‘comfortable’’ (neither ‘‘hot’’ nor ‘‘cold’’), then no action is taken.

The stochastic algorithm and the condition reported in the Tab. 5.2 are implemented in TRNSYS to allow control of windows, blind and AC. Daily values for running mean outdoor temperature and the comfort temperature are calculated as the standard EN15251 (Olesen, 2007).

In detail the control system manages the window opening factor (o.f.), the shading factor (s.f.) and AC activation which, in the model, have been set respectively to 0 or 1 with the hypothesis of a fully closed/open window, to 0 or 0.7 for a fully open/partial closed shading, and to 0 or 1 for regarding the off/on AC activation. In particular, regarding the shading system, when the conditions for the closing of the blind are satisfied (s.f. =0.7), the visual comfort in each room is verified by checking that the average illuminance in the center of the room is greater than 200 lux, by TRNSYS-DAYSIM co-simulation. Otherwise the blind are fully open (s.f.=0).

Furthermore, while opening window and closing blind is a possible action of the occupant in function of the control rules above cited, if there is the activation of the air conditioning system, it is hypothesized that the occupant closes the window to avoid the warm air inlet.

Tab. 5.2. Adaptive behavior by occupant.

Condition		**Action**
$T_{indoor} > T_{comfort} + 3K$	$p_{window} > p_{random}$	open window (opening factor changes from 0 to 1)
	$p_{blind} > p_{random}$	Close blind (shading factor changes from 0 to 0.7)
	$p_{AC} > p_{random}$	Turn on AC (activation changes from 0 to 1)
$T_{indoor} < T_{comfort} - 3K$	$p_{window} < p_{random}$	close window (opening factor changes from 1 to 0)
	$p_{blind} < p_{random}$	Open blind (shading factor changes from 0.7 to 0)
	$p_{AC} < p_{random}$	Turn off AC (activation changes from 1 to 0)

5.1.1. Opening the window

In this study, the occupant action of window control (opening and closing the window in the apartment) is simulated based on Rijal model (Rijal, et al., 2007), where the prediction of the probability of opening or closing is described as a function of **indoor** and **outdoor temperature**.

Although in literature other studies (Andersen, et al., 2011), (Hong, et al., 2016) have suggested that indoor stuffiness, monitored by the carbon dioxide (CO_2) concentration levels, or wind speed and direction, relative humidity and rainfall (Haldi & Robinson, 2009) are important driver for window opening behavior, due to limitations for running simulations, only these parameters (indoor and outdoor temperature) are considered, reserving for future developments the use of more detailed algorithms.

It is assumed that the window opening behavior was largely governed by the quest for comfort. The behavioral actions include: opening the window when the occupant feels hot or closing the window when feeling cold.

In particular, in Rijal (Rijal, et al., 2007) the data about window opening are based on a logistic regression governed by the logit relationship:

$$logit(p) = \log\left(\frac{p}{1-p}\right) = bT + c \tag{5.1}$$

whence

$$p(T) = \frac{e^{(bT+c)}}{1+e^{(bT+c)}} \tag{5.2}$$

- p is the probability that the window is open;
- T the temperature (indoor or outdoor);
- b the regression coefficient for T and c is the constant in the regression equation.

According to Rijal investigation results, the probability of the window being open p is calculated from the operative temperature ($\mathrm{T_{op}}$) and the outdoor temperature ($\mathrm{T_{out}}$) using the logit function derived from the survey data (5.3).

$$logit(p) = 0.171 \times T_{op} + 0.166 \times T_{out} - 6.4\,K \tag{5.3}$$

In this work the operative temperature $(\mathrm{T_{op}})$ is substituted by the indoor temperature $(\mathrm{T_{indoor}})$.

5.1.2. Closing the blind

Regarding the closing of the blinds by occupants, this thesis focuses only on the influence of **thermal stimuli**, i.e. both internal and external temperature, as driven force for the occupant action. In particular, the **visual comfort** is not considered as "driven force" for the occupant behaviors, because in the residential buildings the risk of glare and illuminance issues may be less significant than in the offices. Indeed, in the housings the occupants do not have a “fixed place” in each room where they spend most of the day, as instead happens in the offices where the occupant usually stayed in a fixed place, i.e. the workplane. Hence the visual comfort issue in the offices (especially evaluated at the workplane where the employees work) is more significant than the residential building where the visual comfort is usually evaluated through the average illuminance of each room. In this work, however a check of the average illuminance of each rooms is calculated in order to verify the minimum required limits of illuminance.

Hence, in order to simulate the closing blind action by occupant due to overheating discomfort, the probability function obtained in Haldi (Haldi & Robinson, 2008) is used, where a multiple logistic regression was used to obtain probability distributions depending jointly on indoor and outdoor temperature derived from the survey data:

$$p\,(T_{in}, T_{out}) = \frac{e^{(a_{in}T_{in} + a_{out}T_{out} + b)}}{1+e^{(a_{in}T_{in} + a_{out}T_{out} + b)}} \tag{5.4}$$

where:

- p is the probability that the blind is closed;
- T_{in}, T_{out} are the indoor and outdoor temperature;

- a_{in}, a_{out} are the regression coefficients for T_{in}, T_{out} and b is the constant in the regression equation.

In detail, according to Haldi (Haldi & Robinson, 2008), from the multiple logistic regression, it resulted that the regression coefficient and the constant of the regression are equal to:

- $a_{in} = 0.407;$
- $a_{out} = 0.010;$
- $b = \ -11.15.$

5.1.3. Turn on the air conditioner

Concerning the occupant action of **turning on the air conditioner** (AC) when feeling hot, a stochastic model was used to describe the probability of turning on AC as a function of indoor air temperature. In detail, this thesis implement the stochastic function obtained in Ren (Ren, et al., 2014) and Hong (Hong, et al., 2015) where by means of data from field study, a probabilistic model was found to set up the AC usage for residential buildings. The stochastic model was an action-based model that included multiple factors with the ability to explain the effect of different behavioral patterns. In particular the probability of turning the AC on when occupied increasing as the indoor temperature increases. In detail by means of a Weibull distribution, Ren found that:

$$p\ (T_{in}) = \begin{cases} 1 - \ e^{-\left(\frac{Tin-U}{L}\right)^{k}\ \Delta t}, & T_{in} > U \\ 0 & T_{in} < U \end{cases} \tag{5.5}$$

where:

- $p\ (\mathrm{T_{in}})$ is the probability to turn on the AC by occupant;
- $\mathrm{T_{in}}$ is the indoor temperature;
- U is the threshold minimum temperature;

- k is a constant representing the slope of the probability curve;
- Δt is the time interval;
- L represents the difference between the maximum and minimum comfort range.

In particular, the coefficients have been determined by Ren, and respectively:

- U has been assumed equal to the overheating temperature according to EN15251, i.e. $\mathrm{T_{comfort}} + 3\mathrm{K}$;
- k equal to 8;
- Δt equal to 60 minutes;
- L equal to 6, obtained considering the comfort range according adaptive thermal comfort theory, i.e. $\mathrm{T_{comfort}} - 3\mathrm{K} < \mathrm{T_{indoor}} < \mathrm{T_{comfort}} + 3\mathrm{K}$.

5.2. Optimizing natural ventilation and solar shading control strategies by minimizing thermal discomfort

In this section, in order to value the thermal comfort situations and the energy needs for cooling for the whole apartment (and not more only limited to the most discomfortable room), the optimization adopts the Long-term percentage of dissatisfied (LPD) index defined in Carlucci (Carlucci, 2013), (Carlucci, et al., 2015). This long-term thermal discomfort index quantifies predicted thermal discomfort over a calculation period, by a weighted average of discomfort over the thermal zones of a given building and over the time in a given calculation period:

$$\mathrm{LPD} = \frac{\sum_{t=1}^{T}\sum_{z=1}^{Z}(p_{z,t} \times LD_{z,t})}{\sum_{t=1}^{T}\sum_{z=1}^{Z}(p_{z,t})} \qquad (5.6)$$

where

- t is the counter for the time step of the calculation period;
- T is the last progressive time step of the calculation period;
- z is the counter for the zones of a building;
- Z is the total number of the zones;
- $p_{z,t}$ is the zone occupation rate at a certain time step;
- $LD_{z,t}$ is the Likelihood of dissatisfied inside a certain zone at a certain time step (one hour).

The Likelihood of dissatisfied (LD) is an analytical function that estimates "*the severity of the deviations from a theoretical thermal comfort objective, given certain outdoor and indoor conditions at specified time and space location*" (Carlucci, 2013). Since the theoretical thermal comfort objective depends on the reference comfort model, the formulations of LD for the ASHRAE adaptive thermal comfort model developed by Carlucci:

$$\mathrm{LD} = \frac{e^{0.008\times\Delta\theta_{op}^2+0.406\times\Delta\theta_{op}-3.050}}{1+e^{0.008\times\Delta\theta_{op}^2+0.406\times\Delta\theta_{op}-3.050}} \tag{5.7}$$

where $\Delta\theta_{op}$ is the absolute value of the difference between the indoor operative temperature and the optimal comfort temperature calculated accordingly to the ASHRAE adaptive model.

Now the objective of the research is to optimize the thresholds to open and close the windows and the blinds in order to minimize the (LPD). Moreover, assuming the same control logics (5.1), (5.2), the PSO was adopted to choose the optimal threshold temperature for window opening and closing blinds, by minimizing the thermal discomfort.

Moreover, denoting respectively by $\mathrm{T_{indoor}}(t)$ and $\mathrm{T_{outdoor}}(t)$ with $t \in \mathcal{T}$ the room and external temperature, the designed control logic is applied by defining an on-off control condition, by opening and closing windows and blinds at suitable time intervals (Tab. 5.3). More precisely, the control logics is defined as follows:

Tab. 5.3. Control logics of window and blind by BEMS.

<table>
<tr><th colspan="2">Status</th><th>Condition</th></tr>
<tr><td rowspan="2">window</td><td>Opening factor = 0.22 or 0.39</td><td>$\mathrm{T_{indoor}}(t) > \mathrm{T_{optimal}}(t) + \Delta 1$
$\mathrm{T_{indoor}}(t) + \Delta 2 < \mathrm{T_{outdoor}}(t) < \mathrm{T_{indoor}}(t)$
Opening factor = 0</td></tr>
<tr><td>Opening factor = 0</td><td>otherwise</td></tr>
<tr><td rowspan="2">blind</td><td>shading factor = β</td><td>$\mathrm{T_{indoor}}(t) > \mathrm{T_{optimal}}(t) + \Delta 1$
$\mathrm{T_{indoor}}(t) + \Delta 2 < \mathrm{T_{outdoor}}(t) < \mathrm{T_{indoor}}(t)$
Shading factor =0</td></tr>
<tr><td>shading factor = 0.0</td><td>otherwise</td></tr>
</table>

with:

- $\Delta 1 \in \mathbb{R}$ and $\Delta 1 \in$[-10°C, 10°C];
- $\Delta 2 \in \mathbb{R}$ and $\Delta 2 \in$[-10°C, 0°C];
- $\beta \in \mathbb{R}$ and $\beta \in$[0, 1].

The goal of the designed control logic of BEMS is to have automation systems that by adapting to the occupant preferences and not by obstructing the free action and interaction of the occupation on the built environment, they may improve the thermal comfort conditions and prevent the occupant actions. Indeed, differently by the occupant behavior logics (see Tab. 5.2 **Tab. 5.2**) where the occupant action is possible only when there are discomfort conditions for overheating, i.e. $\mathrm{T_{indoor}} < \mathrm{T_{comfort}} - 3\mathrm{K}$, or undercooling, i.e. $\mathrm{T_{indoor}} < \mathrm{T_{comfort}} - 3\mathrm{K}$, the BEMS control logics are active first, i.e. $\mathrm{T_{indoor}}(\mathrm{t}) > \mathrm{T_{optimal}}(\mathrm{t}) + \Delta 1$, before the indoor temperature reaches the thermal discomfort situations (Tab. 5.3.)

Furthermore, the control logics of opening window and closing blind are active only when there is none action of the occupant, i.e. when the opening factor due to the actions of occupant is equal to 0 (window closed) or the shading factor is 0 (shading open).

The values of Δ1, Δ2 and β are determined through the PSO optimization strategy with the aim of minimizing the thermal discomfort (LPD) during the occupation hours of each room:

$$\mathrm{F_{obj}} = \min_{\Delta 1, \Delta 2, \beta}[\mathrm{LPD}] \tag{5.8}$$

Regarding the β values, in order to avoid an excessive partialization of the shading and to reduce the computational timing, five optimal shading configurations are considered for BEMS: $\beta = 0$ (no shading); 0.25; 0.5; 0.75; 1 (total shading).

The optimization running determined the optimal value of shading system (β) in order to reduce the thermal discomfort situations for overheating. Moreover, for each shading configuration the illuminance values have been calculated through the DAYSIM software in order to verify that these values are greater than 200 lux. Otherwise the shading status is reduced of 0.25.

5.3. The Co-Simulation Architecture

In this section the co-simulation architecture is presented to combine the human behaviors simulation with building-HVAC system simulation and optimization goal for control logic of BEMS.

In particular, in addition to what stated in the paragraph 4.2. regarding the description of TRNSYS software and PSO method, here the **ABM** for occupant behavior is implemented in TRNSYS software v.17. While in the studies reported in the previous chapter the occupant is simulated in deterministic way with fixed schedules, in this section the implementation of the occupant behaviors logics, described in the previous paragraphs, is obtained in TRNSYS by a calculator where the several equations (5.3), (5.4), (5.5), regarding the window opening, the blind closing and the turning on the AC, and the logics of occupant behaviors of are inserted (see Fig. 5.2.). The exchanged data as input/output between the several types in TRNSYS, according to the several equations subject to Tab. 5.3, are the:

- opening factor (o.f.);
- shading factor (s.f.);
- AC status;
- indoor temperature (tind);
- outdoor temperature (tout).

The DAYSIM software is used to perform **daylight simulations** in order to check that the shading factor (s.f.) obtained by TRNSYS calculator does not cause illuminance values less than 200 lux.

The **optimization algorithms** to solve (5.8) for the minimization of the long-term thermal discomfort index (LPD) are implemented in MATLAB and then coupled with the TRNSYS energy simulator. In this section MATLAB, implementing the PSO algorithm, exchanges iteratively with TRNSYS the values of $\Delta 1, \Delta 2$ and β to minimize (5.8). Such values are transmitted to TRNSYS-BEMS calculator (Fig. 5.2.) that implements the control strategy of Tab. 5.3 to command the window opening and the blind closing. Iteratively, the PSO algorithm evaluates the optimal values of the three decision variables $\Delta 1$, $\Delta 2$ and β in order to minimize the long-term thermal discomfort index (LPD).

5.3.1. RADIANCE and DAYSIM

RADIANCE (G. Ward, 1989) is a software developed by Greg Ward at Lawrence Berkeley National Laboratory. It is able to predict internal illuminance and luminance distributions in complex buildings under arbitrary sky conditions.

Radiance uses the back ray tracing approach that consist in following the light path (specular reflected, transmitted and refracted) from the reception point (eyes or sensors) into the scene to the light source. The latter "blends deterministic and stochastic ray-tracing techniques" to reduce the number of traced rays. To further reduce the raytracing effort, the program incorporates interpolation and extrapolation schemes which allow to estimate the luminances at point of interest from the luminances of nearby points. In the practice it is considered the best and more flexible software for lighting simulation; in fact is used as calculation engine in the most lighting design software available.

DAYSIM (DAYSIM, 2010) is a simulation tool that efficiently calculates annual illuminance/luminance profiles. DAYSIM is a RADIANCE-based daylighting analysis tool that has been developed at the National Research Council Canada and the Fraunhofer Institute for Solar Energy Systems in Germany. While RADIANCE has been primarily developed to simulate luminances and illuminances under selected sky conditions, DAYSIM uses the RADIANCE simulation algorithms to efficiently calculate illuminance distributions under all appearing sky conditions in a year. In order to calculate annual illuminance profiles, one could in principle also use the standard Radiance programs and start thousands of individual raytracing runs for all sky conditions of the year. This approach is not practical as a Radiance simulation for a single sky condition can take hours so that an hourly annual simulation would literally require years of calculation time. To keep simulation times short, Daysim uses the Radiance algorithm coupled with a daylight coefficient approach.

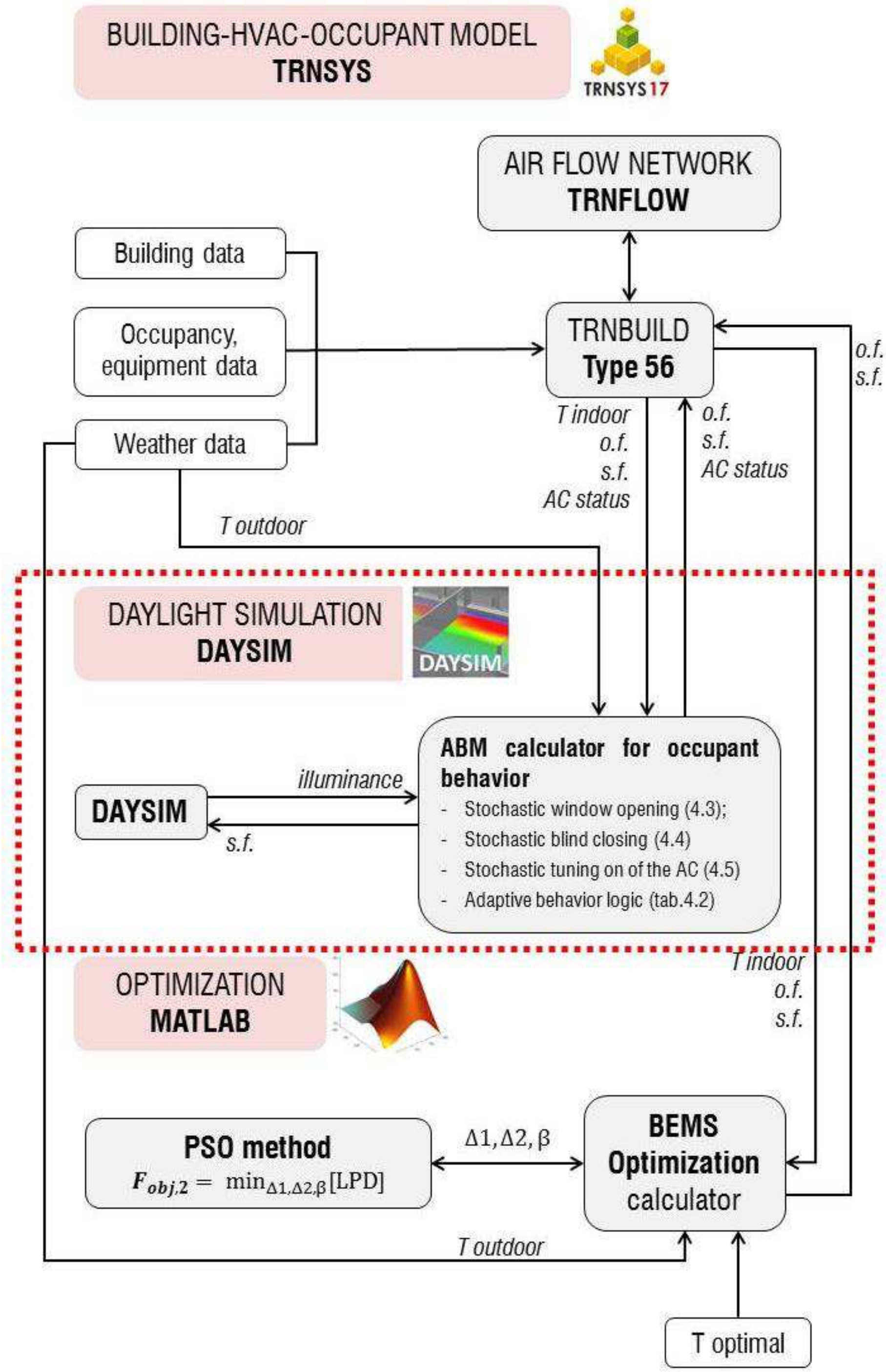

Fig. 5.2. The co-simulation architecture with occupant behaviors modeling and daylight simulations.

5.4. Occupant behavior impact on building performance, comparing the deterministic and stochastic-ABM approach

In order to value both the impact of the adaptive occupant behaviors on the thermal comfort and on the energy consumptions for cooling, and the benefits of BEMS for natural ventilation control and solar shading, four cases are simulated (Tab. 5.4.). The period taken into account for the simulation is July-August (62 days).

In particular, in the four cases it is hypothesized a free running mode for the cooling system and hence the case studies are compared in terms of the long term percentage of dissatisfied index (LPD). Then, in the same cases, the active cooling is introduced and the several cases are compared in relation to the energy consumptions for cooling. In detail, in the Case 1.0 and Case 1.1. the occupant behaviors, referring to the window opening and blind closing, are considered in deterministic way, with fixed schedules. In the other two cases (Case 2.0 and Case 2.1) the occupant actions are simulated by means of a stochastic and agent-based model as described in the paragraph 5.1. Regarding the BEMS to control the window and shading status, while in the Case 1.0 and Case 1.2 there are not automation systems, in the other two cases optimized control logics are found with optimal values of $\Delta 1$, $\Delta 2$ (for the Case 1.1) and $\Delta 1$, $\Delta 2$ and β (for the Case 2.1) with the objective function (5.8) of minimize the long term percentage of dissatisfied index (LPD).

Tab. 5.4. Simulated cases.

Case	**Occupant behaviors**			**BEMS control logics**
	Approach	**Window status**	**Shading status**	
Case 1.0	**Deterministic**	Opening only for IAQ	- s.f. = 0.25 (presence of users) - s.f. = 0.75 (absence of users).	Not present
Case 1.1				ventilative cooling under control rules (4.1) and (4.2) with optimal values of Δ1 and Δ2
Case 2.0	**Stochastic-ABM**	ABM according to Tab. 5.2		Not present
Case 2.1				BEMS according to Tab. 5.3

Results

Comparing Case 1.0 and Case 2.0 (Tab. 5.5), where the occupant is simulated respectively with deterministic and ABM approach, **there is a significant increasing of the total discomfort conditions** evaluated with the LPD index.

In particular, the evaluation of the **occupant behaviors by means of a stochastic-ABM approach has a significant impact on building performance**, leading to increase by 35 % of the discomfort situations for the overheating between the two cases. This is due to the occupant behaviors modeling assumed in the Case 2.0, regarding the window and shading status.

Tab. 5.5. Thermal discomfort and energy needs for cooling.

Case	**Long term percentage of dissatisfied index (LPD) (no active system)** **%**	**Energy needs for cooling (with active system)** ***E* (kWh/m^2)**
Case 1.0	36	90
Case 2.0	52	110
Case 1.1	22	61
Case 2.1	32	77

In detail, in the Case 2.0, the probability of **window opening** by occupant is in relation to the outdoor and indoor temperature according to (5.3) (see Fig. 5.3.), by assuming that the occupant has a natural tendency to open the windows with higher values of both outdoor and indoor temperature in order to exploit the positive effects of the natural ventilation. However, the entrance of warm air by outside may cause worsening conditions of thermal discomfort situation for overheating and hence the LPD index is increased.

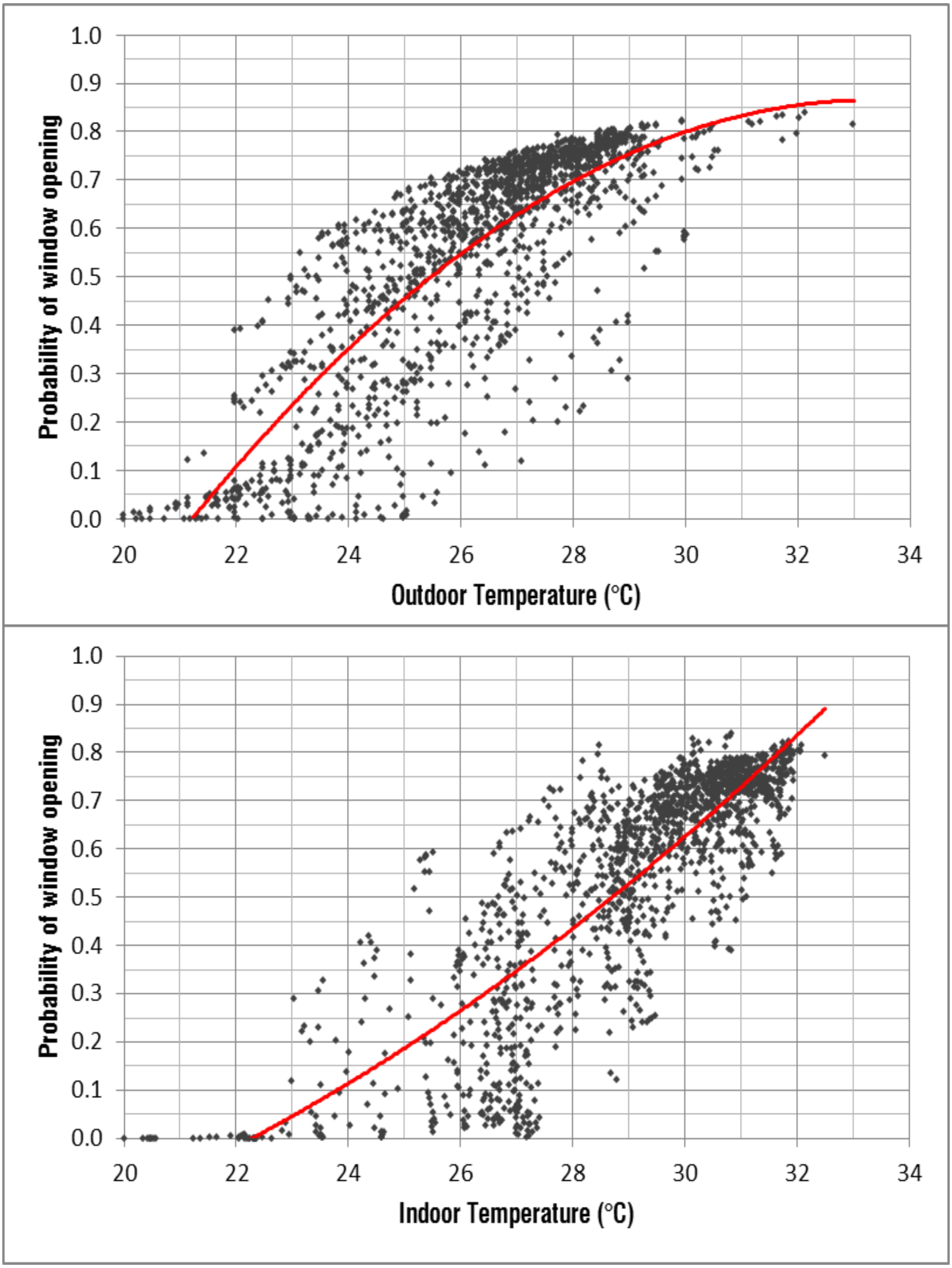

Fig. 5.3. Cumulative distribuction probability of window opening in relation to outdoor and indoor temperature.

Regarding the probability of **blind closing** by occupants (taken in the Case 2.0), subject to (5.4) discussed in the paragraph 5.1.2, the indoor temperature is the main factor that influences the action by occupant (Fig. 5.4). In particular, this probability increases with the increasing of the indoor temperatures, i.e. the occupant tends to close the shading during thermal discomfort situation for overheating in order to limit the entrance of external solar radiations, while there is no correlation between the probability of blind closing and the outdoor temperature. This action, if on the one hand it leads to a reduction of solar radiation, on the other hand may lead to limit the effect of natural ventilation due to opening window.

Furthermore, regarding the **BEMS** to control the window and shading status, the control logic of optimized ventilation activation of Case 1.1 and of Case 2.1 determines significant reduction of LPD index. More in detail, the temperature profile of the optimized case is almost contained in the optimal range of temperature defined by the adaptive thermal comfort theory, justifying the reduction of overheating discomfort. In detail the optimal objective function values for the Case 1.1 and the Case 2.1. are obtained with:

- $\Delta 1 = -1.25$ °C and $\Delta 2 = -6.70$°C corresponding to the 27th PSO iteration (for the Case 1.1.);
- $\Delta 1 = -1.15$ °C and $\Delta 2 = -7.30$°C, $\beta = 0.5$ corresponding to the 25th PSO iteration (for the Case 2.1.).

In particular, Fig. 5.5 shows the optimization running. According to the PSO method, several values of $\Delta 1$, $\Delta 2$ and β are determined to control the window opening and the closing blind (according to Tab. 5.5). In function of these values, the long term percentage of dissatisfied index (LPD) of the Case 1.1. varies from a maximum of about 75 % to a minimum of about 22%, the LPD of the Case 2.1. from a maximum of 85% to a minimum of 32%.

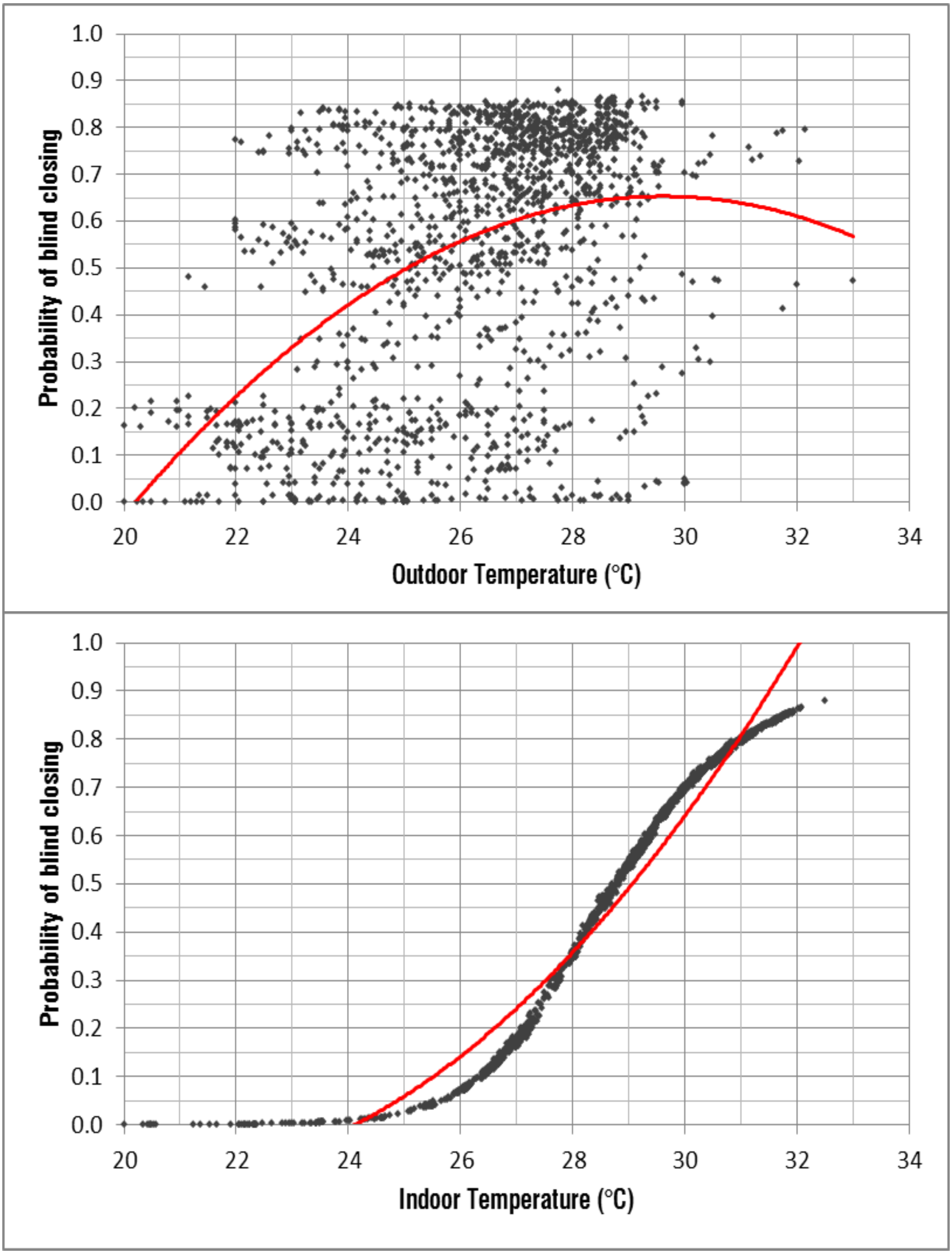

Fig. 5.4. Cumulative distribuction probability of blind closing in relation to outdoor and indoor temperature.

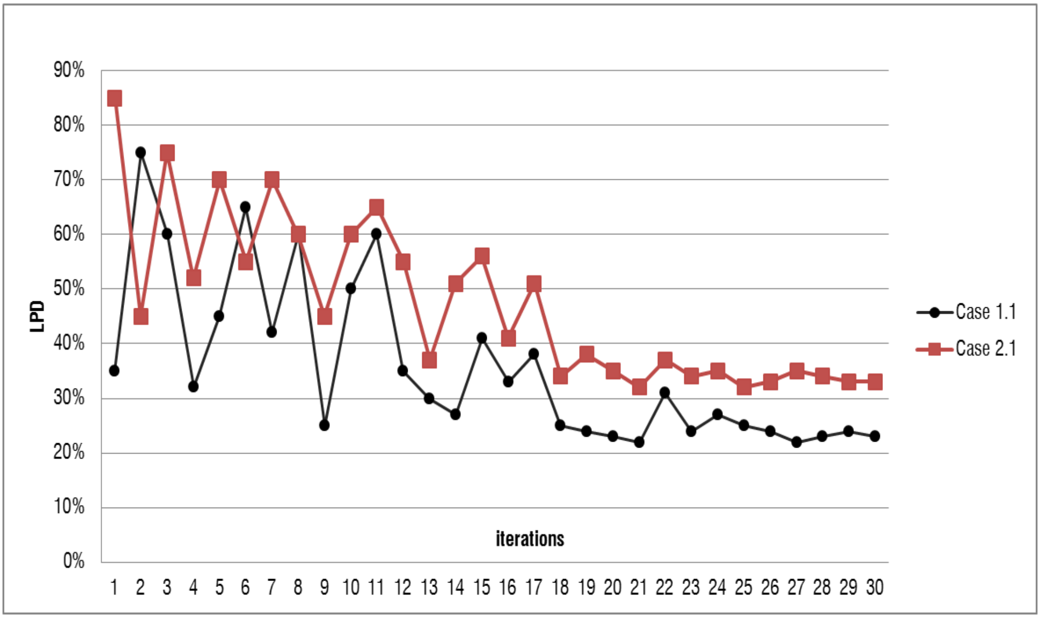

Fig. 5.5. Optimization running for Case 1.1 and Case 2.1

In order to value the impact of occupant behaviors on building performance and the benefits of the designed BEMS control logics on the energy consumptions, the four cases previously examined are performed by adding an active cooling system.

In detail, in the cases where the occupant behaviors are considered in deterministic way (i.e. Case 1.0, Case 1.1.), the cooling system is switched on in each room when $T_{indoor}(t) > 26°$ according to the scheduled occupancy shown in Tab. 4.2. In the other cases, where the occupant behaviors are considered in stochastic-ABM approach (i.e. Case 2.0, Case 2.1.), the cooling system is switched-on in each room according to Tab. 5.2 when there is occupancy.

In particular the **probability of turning on the AC** by occupant, assumed in the Case 2.0 and case 2.1, is in relation to the indoor temperature (Fig. 5.6). This probability increases for higher values of the indoor temperature. Differently by the occupant behaviors (i.e. window opening and blind closing), where the probability to make these actions started for indoor temperature threshold higher than 20°C, the probability of turning on the AC starts for indoor temperature by 26°C. These assumptions are in accordance to the results of the questionnaire survey described in the Chapter 3 (see Fig. 3.11), where in the most ancient buildings, with supposedly high indoor temperature values in summer due to low energy efficiency of buildings, the occupants more often turn on the cooling system to satisfy own thermal comfort with consequently higher energy consumptions.

The energy E needed for cooling referred to whole dwelling is reported in Tab. 5.5 for the four cases.

In accordance to thermal comfort analysis, the assumptions of the ABM approach to simulate occupant behaviors cause an increasing of energy needs for cooling, while the designed BEMS control logics allow **a significant decreasing of the energy needs for cooling**, especially when the discomfort conditions are higher (Case 2.0). In detail:

- comparing Case 1.0 (deterministic occupant behavior) and Case 2.0 (ABM approach), also the energy consumptions for cooling increases in the Case 2.0.

  Hence the **different assumptions of occupant behavior has a negative impact on building performance**, causing an increase of 22 % of energy needs. This is a consequence of the worsening of thermal discomfort conditions;

- the proposed passive strategy for window opening and solar shading (Case 1.1 - with deterministic occupant behavior and BEMS, and Case 2.1 - with ABM approach and BEMS), allows reducing of the energy needs, that are reduced of 30% and of 34 % respect respectively to Case 1.0 and Case 2.0.

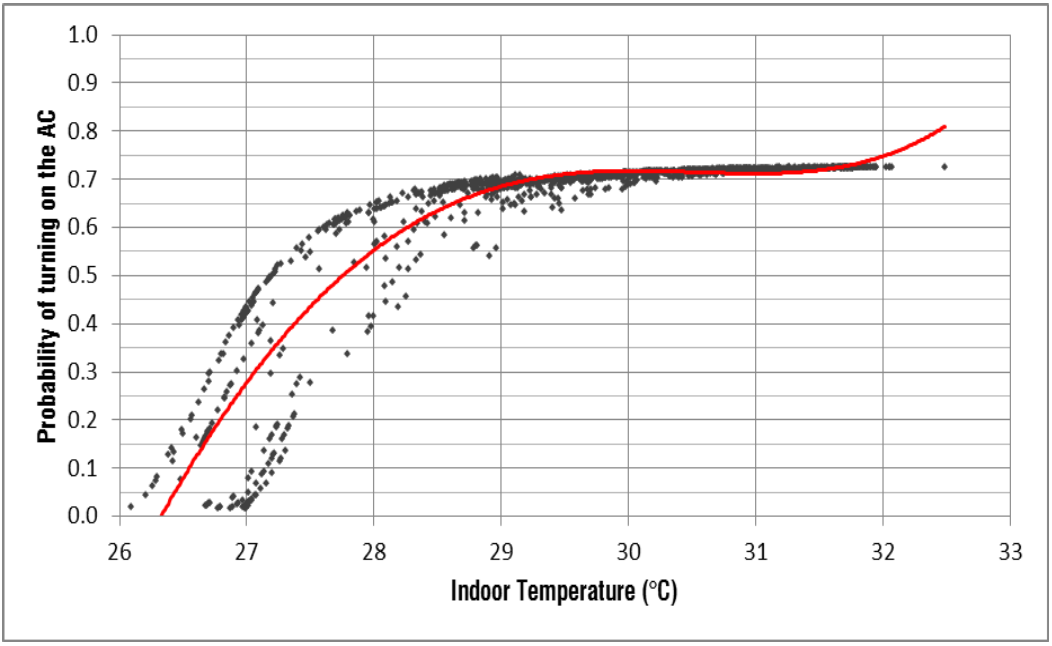

Fig. 5.6. Cumulative distribuction probability of turning on the AC in relation to indoor temperature.

5.5. Occupant behavior influence in high performing building and BEMS adaptive to occupant actions

In order to reach the NZEB target, the impact of occupant behaviors on building performance have to be investigated also during the operation phase, because as discussed in the Chapter 1, design building as NZEB does not meant that it will be NZEB in practice.

Understanding the occupant behavior is a key issue for building design optimization, energy diagnosis, performance evaluation, and building energy simulation.

In particular, strictly connected to ***resilience*** concept of buildings, that in this study is limited to the adaptability capacity to the different operational conditions by occupants, in this section different profiles of occupant behavior and the BEMS response to the different occupant behaviors are analyzed in high performing building.

The case study regards the same reference building (typology, orientation, area) described in the paragraph 4.1, but with high performance of the building envelope. In the Tab. 5.6 and the Tab. 5.7 the main parameters of the modeled envelope (transmittance, internal heat capacity and the solar factor) are reported.

Tab. 5.6. Thermal characteristics of building opaque envelope

	U-values ($W/m^2 K$)	**Surface Mass (kg/m^2)**	**Decrement Factor (-)**	**Thermal Lag (hr)**	**Periodic Therm. Transm. (W/ m^2K)**	**Areic Heat Capacity (KJ/m^2K)**
Ceiling-floor	0,47	382	0,1	12	0,033	368
External Wall	0,31	296	0,08	16	0,026	263
Partition wall	0,51	311	0,1	13	0,034	221

Tab. 5.7. Thermal and optical properties of windows.

Glass Type	**U-value (W/ m^2K)**	**SHGC (-)**	**VT (%)**
WIN (insul.glass low -Ar)	1,7	0,62	0,75

In particular, in order to evaluate the impacts of “*extreme cases*” related to occupants behaviors, that an occupant may perform differently by the stochastic logics, three different occupant profiles are analyzed, by assuming different stochastic algorithms for the three occupant behaviors (window opening, closing blind and turning on the AC) described in the previous sections.

In detail the three occupant profiles (i.e. the extreme cases) are introduced to simulate an **active, standard** and **passive** occupant.

The **active** occupant uses the air conditioning more frequently than the others, and less frequently changes the window and shading status. In order to consider this different sensitivity of the occupant, the probability of window opening (5.3) and of blind closing (5.4) are reduced by a factor assumed equal to 0.7, while the probability of turning on the AC is increased, multiplying (5.5) for a factor equal to 1.3.

Instead, the **passive** occupant interacts more frequently by opening the window and closing blind, by reducing the a.c. usage. In these cases, the probability (5.3) and (5.4) are increased by 1.3, while the probability (5.5) is decreased by 0.7.

It shall be noted that these numeric factors and these cases are artificial, and the goal is only simulate the extreme cases of occupant actions, by assuming occupant purely active or passive, without taking into account the several possible cases of occupant behavior that e.g. may be active both for cooling system and window opening etc.

In detail six cases are analyzed, by assuming the three different occupant profiles and with or without the BEMS control logics (see Tab. 5.8.). In particular, regarding the BEMS to control the window and shading status, while in the Case 1 there are not automation systems, in the other three cases optimized control logics are found with optimal values of $\Delta 1$, $\Delta 2$ and β (for the Case 2) with the objective function (5.8) of minimize the long term percentage of dissatisfied index (LPD).

Tab. 5.8. Simulated cases for different occupant profiles.

Case	Occupant behaviors				BEMS control logics
	Occupant type	**Window status**	**Shading status**	**AC status**	
Case 1	Passive	ABM according to Tab. 5.2			-
	Standard	ABM according to Tab. 5.2			
	Active	ABM according to Tab. 5.2			
Case 2	Passive	ABM according to Tab. 5.2			BEMS according to Tab. 5.3
	Standard	ABM according to Tab. 5.2			
	Active	ABM according to Tab. 5.2			

The energy E needed for cooling are calculated for the different occupant profiles and BEMS activation. In detail the optimal objective function values for the Case 2 for different occupant type are obtained with:

- $\Delta1 = -1.75$ °C and $\Delta2 = -4.30$°C, $\beta = 0.5$ (for passive occupant.);
- $\Delta1 = -1.95$ °C and $\Delta2 = -3.55$°C, $\beta = 0.5$ (for standard occupant);
- $\Delta1 = -1.97$ °C and $\Delta2 = -3.20$°C, $\beta = 0.5$ (for active occupant).

In particular, the different values obtained may be justified by the fact that by increasing the indoor temperatures (due to the negative impact of occupant action especially for the passive occupant described in the previous paragraph), the gap between the values of indoor temperature lower than optimal temperature decreases. Hence, the control logic of (4.1) can start with lower values (in absolute values) of $\Delta1$. On the contrary, ever more high $\Delta2$ values in (4.2) are necessary to reduce the thermal discomfort hours. This underlines the necessity to design BEMS adaptable to the occupant behaviors in order to satisfy its thermal comfort.

The energy needs for cooling due to the impact of occupant behaviors are reported in Fig. 5.7. It results that:

- comparing the cases without BEMS activation (Case 1.0) for the three occupant type, the energy consumptions for cooling increases with a maximum variation between passive and active type about 41 %. **Hence the occupant behavior has a significant impact on building performance**;
- comparing the cases with BEMS activation (Case 2.0) for the three occupant type, it is possible to notice how the control logics of window opening and solar shading have the maximum benefits for the case with worsening thermal discomfort conditions, i.e. for the case with passive occupant, allowing a reduction of energy needs about 32 %. In this manner an optimized BEMS may reduce the negative effects of incorrect occupant behaviors, by reducing the thermal discomfort situations and hence the energy needs for cooling.

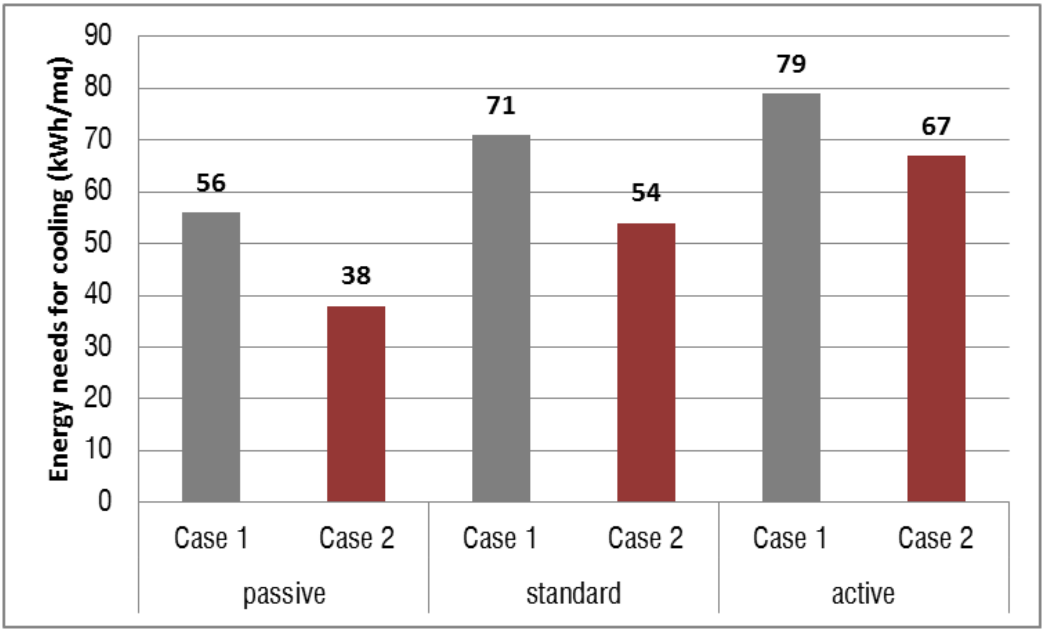

Fig. 5.7. Energy needs for cooling for different occupant profile and BEMS activation.

General Discussion and Conclusions

Towards the design of NZEB, with low energy consumptions during the operating phase, the dissertation underscored the importance of **occupant behaviors** and of the design of **Building Energy Management Systems (BEMS),** able to maintain its energy performance despite the diverse operating conditions by occupants. Particular attention was devoted to management of building components, by designing control logics based on the adaptive thermal comfort theory (EN15251, 2007).

In detail, the PhD thesis focused on the development of BEMS in the residential buildings, by **optimizing thermal** and **visual comfort** and by modeling the **occupant behaviors** by means of an **agent based oriented approach**.

Indeed, because current simulation capabilities do not account for realistic occupant behaviors, by underestimating the actual energy consumption observed in buildings, a secondary effort of the thesis was to define a new methodology to increase the accuracy of building energy simulation results.

At first, **a questionnaire survey** (Chapter 3) was conducted to quantify the relationships between environmental physical and occupant behavior in dwellings and to investigate driving forces for the behavior of the occupants.

Differently by other studies present in literature where the occupant impact on energy consumption was analyzed for identical buildings (Socolow, 1978), (Sonderegger, 1978), (Seligman, et al., 1978), (Gartland, et al., 1993), (Juodis, et al., 2009), the questionnaire tried to define the tie between different residential buildings and occupant actions by means of questionnaire survey.

In detail large differences in the behavior patterns of occupants were found between dwellings. In particular, the relationship between occupant behavior and building environment reflected the difficulty of adapting to discomfortable conditions especially in the most ancient building with worst conditions.

In addition, this study allowed a more precise quantification of important trends, such as the tie between the building performance and the occupant behaviors, the relationship between the effectiveness of adaptive actions and the hierarchy of adaptive actions.

Based on questionnaire survey, while in winter it resulted that the occupants act less on the building components to improve their thermal comfort conditions, (indeed the main actions were wearing heavy clothes and turning on heating system), in summer season the occupants mostly interacted with the building components, by changing the window and shading status or by adjusting set-point thermostat.

Furthermore, known that the actions on window and blind status have significant impact on building performance, with the final goal of simulating more in detail these occupant actions, by means of ABM approach, and to design optimal BEMS as retrofit solutions for the energy renovation, the second part of study (Chapter 4) focused on the analysis of different **control logics of natural ventilation** and of **the solar shading system** for passive cooling.

In this section, optimization goals were direct towards objective function for the minimization of thermal discomfort conditions, by simulating the occupant behavior in deterministic way through defined schedules.

Many researches dealt with the control of active systems, others both on active and passive systems, and only few researches focused on BASs for passive components.

Concerning the related literature, it is apparent that the contributions focusing on passive systems base the choices on heuristic approaches, while optimization strategies are mainly used for active system operations.

Furthermore, while in Wang (Wang & Wang, 2013), Castilla (Castilla, et al., 2013) and Sun (Sun, et al., 2013) an integrated control of active and passive system were analyzed with the aim of minimizing total energy costs, in this study the effects of passive strategies were studied with the goal to reduce thermal discomfort conditions according to adaptive thermal comfort theory (EN15251, 2007).

With this purpose, simulation studies on the effects of BEMS control logics for windows and shading system on thermal comfort and energy demands were conducted in a typical Italian dwelling of 60s.

A control strategy was defined, based on: i) the thermal comfort analysis according to the adaptive thermal comfort theory (EN15251, 2007); ii) an on-off control strategy for natural ventilation to determine a significant reduction of overheating discomfort.

The optimization strategy, determining the optimal ranges of time to close and open the windows, showed how the integration of suitable control logics increased the potentialities of natural ventilation strategies to the improvement of energy and thermal performance of buildings.

The designed control logics, adaptive to different climate conditions, allowed significant reduction of thermal discomfort hours for overheating. In particular for the warmest climate, in order to improve the thermal comfort conditions, it was necessary allowing the window opening more frequently in order to exploit the positive effect of natural ventilation for passive cooling.

The ventilation strategies for passive cooling, could contribute even more effectively to the improvement of the behavior of the building envelope, integrating or replacing the conventional efficiency strategies, if properly integrated with adequate control systems. With low investment costs the natural ventilation could reduce the high energy consumptions of cooling systems.

Then, in the last study (Chapter 5) with the aim of designing **BEMS, adaptable to occupant's actions and satisfaction**, the occupant behaviors were modeled with more detail, by means of an **ABM approach**.

In mostly studies present in literature, in the design of BEMS the occupant behaviors and preferences are seldom taken into account. Almost always the logics of BEMS aims to minimize the energy needs and they are less adaptive to occupant behavior.

Furthermore, even though the occupants' control of the various systems in the building has a significant impact on the energy consumption and the indoor environment, only recent studies have focused on the behavior of their occupant by simulating the actions by means of an ABM approach.

Indeed most studies present in literature (Andersen, et al., 2011), (Rijal, et al., 2007), (Haldi & Robinson, 2009) have analyzed only an individual occupant behavior by means of statistical analysis, by analyzing data of longitudinal studies, cross sectional studies and monitoring campaign for several years.

In recent studies (Langevin, 2014), (Lee & Malkawi, 2014) the modeling of occupant behaviors are performed in a more realistic way, by means of an agent-based approach, where the occupant actions are ruled by PMV analysis.

In this thesis, the occupant interactions with the building system (in particular regarding the window and solar shading opening/closing, set-point adjustment for the air conditioner) were implemented in the energy software simulation, based on algorithms deduced by field investigations in real buildings.

The comparison between the models where the occupant behavior was assumed in deterministic way and in a probabilistic and multi-agent approach, it allowed to assess the significant impact of human behavior on building performance. In detail, comparing the cases, where the occupant was simulated with deterministic and ABM approach, there was a significant increasing of the total discomfort conditions in the second case.

In accordance to thermal comfort analysis, the assumptions of the ABM approach to simulate occupant behaviors caused an increasing of energy needs for cooling,

Then, the optimization of BEMS for window opening and shading closing enabled to minimize the thermal discomfort situations and the energy needs for cooling. It was possible to notice how the control logics of window opening and solar shading had the maximum benefits for the case with worsening thermal discomfort conditions.

Finally, similar to the study reported in Fabi (Fabi, et al., 2013), **three different occupant profiles** in a high performing building were analyzed. It resulted how for the "active" occupant, there was significant increase of energy needs for cooling, As reported.

In conclusions, this work highlighted how the designed BEMS may ensure high levels of comfort and energy efficiency, through the dynamic control of some components based on external and internal environmental parameters and on the occupancy conditions.

Especially in existing residential buildings, where the interaction of occupant behavior on building-HVAC system is maximum, the integration of Building Energy Management Systems (BEMS) may provide significant energy savings, going not only to remedy an incorrect or inadequate management systems, but also optimizing the activation timing and management methods.

An intelligent decision support model, that could control how the building operational data deviates from the settings as well as carry out diagnosis of internal conditions and optimize building's energy operation, is the goal for the future BEMS. Indeed, latest trends in the design of BEMS integrate "human-machine" interface that may store user preferences and adapt accordingly control strategy.

The implementation of different occupant behaviors into energy simulation software, simulated by means of an ABM method and the coupling of optimization goal for BEMS is an innovative approach.

Next phase may regard the modeling of several occupant behaviors, by means of more complex agent-based oriented approach, by assuming different stimuli as driven forces for occupant actions (not only the thermal stimuli), more autonomous agents and by considering the interaction with other occupants. Furthermore, different algorithms will be implemented in order to simulate the occupant actions, based on literature studies or deduced by field monitoring.

As further development, these information regarding the occupants behaviors patterns may be implemented in **Building Information Modeling (BIM) platform**. In this manner, BIM as well as involving the generation and management of digital representations of the physical characteristics of buildings (envelope, technologies, HVAC system etc.) may contain all the data regarding the occupant, whose actions may affect the building performance during the life cycle of building. These data may allow and support information exchange and networking among different stakeholders who plan, design, construct, operate and maintain buildings.

Acknowledgements

This PhD thesis is the result of the work during these three years, to which I have devoted energies, ideas and above all enthusiasm.

It seems only right, therefore, to sincerely thank the people who helped and supported me.

I am sincerely grateful to my supervisor, Professor Francesco Iannone, for all his support and his advices, without which this work would not have been as it is. He has been my guide and reference point, with his support and for having addressed me during this work.

Further thanks are devoted to Doctor Marcel Schweiker and to the Institute of Building Design and Technology, at Karlsruhe Institute of Technology (Germany) for having hosted me for four months in their department and to having helped me to the study of occupant behavior and to the multi agent modelling.

I would also to thank the Professor Maria Pia Fanti, the Doctor Agostino Marcello Mangini and Doctor Michele Roccotelli of the Department of Electrical and Information Engineering of the Polytechnic of Bari (Italy) for their collaboration regarding the optimization issues and the creation of co-simulation architecture between different software.

Further thanks to Professor Guido Dell'Osso of the Department of Civil, Environmental, Building Engineering, and Chemistry of the Polytechnic of Bari (Italy) for the contribution regarding the designed natural ventilation control logics presented in the thesis and for making me participant to the research group of "RES NOVAE-Networks, Buildings, Roads - New Virtuosos Objectives for the Environment and Energy".

I wish to acknowledge my thank to my friends and colleagues, especially to Antonello, my office mate during these three years, who has shared with me this PhD experience, with whom I have spent much of the daily time and he has been a constant reference point for me.

A special thanks goes to my family, for all the values that have been able to give me and that with great support they have allowed me to achieve this important goal.

Last but not least, I would like to thank you, Giovanna, my life, who has been always by my side, especially during difficult times and for all the love that is giving me every day.

Thanks, finally, to those who stood by me, with sincere affection, sharing the stages of this path.

References

Alaidroos, A. & Krarti, M., 2015. *Impact of Passive Cooling Strategies on Energy Consumption Reduction of Residential Buildings in the Kingdom of Saudi Arabia.* American Society of Mechanical Engineers.

Alfakara, A. & Croxford, B., 2014. *Understanding occupants' behaviours using detailed agent- based modelling.* London, UK, Building Simulation and Optimization.

Andersen, R. V., Olesen, B. W. & Toftum, J., 2011. *Modelling window opening behaviour in Danish dwellings*.

Andersen, R. V., Toftum, J., Andersen, K. K. & Olesen, B. W., 2009. Survey of occupant behaviour and control of indoor environment in Danish dwellings. *Energy and Buildings 41.1,* pp. 11-16.

Atallah, L. et al., 2007. *Behaviour profiling with ambient and wearable sensing.* s.l., In 4th International Workshop on Wearable and Implantable Body Sensor Networks (BSN 2007).

Becker, J., 2013. *An Introduction to Particle Swarm Optimization (PSO) with Applications to Antenna Optimization Problems*.

Bishop, R. C. & Frey, D. J., 1985. *Occupant effects on energy performance of monitored houses.* s.l., Proceedings of the 10th national passive solar conference.

Borgeson, S. & Brager, G., 2011. Comfort standards and variations in exceedance for mixed-mode buildings. *Building Research & Information 39.2 ,* pp. 118-133.

Borri, D., 2011. *ECOURB: Analysis and Models of Air Pollution and Thermal Systems for Urban Ecolabelling (PS_047)*: Puglia Region.

Borri, D., Camarda, D. & Pluchinotta, I., 2013. *Planning urban microclimate through multiagent modelling: A cognitive mapping approach.* Springer Berlin Heidelberg.

Bourgeois, D., Reinhart, C. & Macdonald, I., 2006. Adding advanced behavioural models in whole building energy simulation: a study on the total energy impact of manual and automated lighting control. *Energy and buildings, 38 (7),* pp. 814-823.

BPIE, 2010. *Cost Optimality. Discussing methodology and challenges within the recast Energy Perfomance of Building Directiv*.:Building Performance Institute Europe.

Brager, G., Paliaga, G. & Dear, R. D., 2004. *Operable windows, personal control and occupant comfort*:Center for Building Environment.

Brager, G. S. & Dear, R. J. d., 1998. Thermal adaptation in the built environment: a literature review. *Energy and buildings, 27 (1),* pp. 83-96.

Buso, T., Fabi, V., Andersen, R. K. & Corgnati, S. P., 2015. Occupant behaviour and robustness of building design. *Building and Environment 94,* pp. 694-703.

Carlucci, S., 2013. *Thermal Comfort Assessment of Buildings.* London, Springer.

Carlucci, S., Cattarin, G., Causone, F. & Pagliano, L., 2015. Multi-objective optimization of a nearly zero-energy building based on thermal and visual discomfort minimization using a non-dominated sorting genetic algorithm (NSGA-II). *Energy and Buildings,* Volume 104, pp. 378-394.

Castilla, M. d. M. et al., 2013. *A multivariable nonlinear MPC control strategy for thermal comfort and indoor-air quality*, 39th Annual Conference of the IEEE Industrial Electronics Society, IECON .

DAYSIM, 2010. *DAYSIM – Dynamic Daylight Simulations.* [Online] Available at: http://www.daysim.com

Dear, R. D., Brager, G. & Cooper, D., 1997. *Final reportashrae project rp-884: developing an adaptive model of thermal comfort and preference,* Atlanta,GA: ASHRAE .

Degelman, L. O., 1999. *A model for simulation of daylighting and occupancy sensors as an energy control strategy for office buildings*.

Dell'Osso, G. R., Iannone, F., Pierucci, A. & Rinaldi, A., 2015. *Control Strategies of the Natural Ventilation for Passive Cooling for an Existing Residential Building in Mediterranean Climate.* s.l., In Proceedings of the 36th AIVC-5th Tight.

Deuble, M. P. & De Dear, R. J., 2012. Green occupants for green buildings: the missing link?. *Building and Environment 56,* pp. 21-27.

Dias, M., Bernardo, H., Ramos, J. & Egido, M., 2011. *Indoor environment and energy efficiency in education buildings - part 2: Energy simulation.* Leiria, Energetics (IYCE), Proceedings of the 2011 3rd International Youth Conference .

D'Oca, S. & Hong, T., 2014. A data-mining approach to discover patterns of window opening and closing behavior in offices. *Building and Environment 82,* pp. 726-739.

Dong, B. et al., 2010. An information technology enabled sustainability test-bed (ITEST) for occupancy detection through an environmental sensing network. *Energy and Buildings 42.7,* pp. 1038-1046.

Doukas, H., Patlitzianas, K. D., Iatropoulos, K. & Psarras, J., 2007. Intelligent building energy management system using rule sets. *Building and environment 42.10,* pp. 3562-3569.

Dounis, A. I. & Caraiscos, C., 2009. Advanced control systems engineering for energy and comfort management in a building environment. A review. *Renewable and Sustainable Energy Reviews,* pp. 1246-1261.

Eilers, M., Reed, J. & Works, T., 1996. *Behavioral aspects of lighting and occupancy sensors in private offices: a case study of a university office building.* s.l., ACEEE 1996 Summer Study on Energy Efficiency in Buildings.

EN15251, 2007. *Indoor environmental input parameters for design and assessment of energy performance of buildings addressing indoor air quality, thermal environment, lighting and acoustics*.

ENEA, 2016. *Italy's Energy Efficiency Annual Report*.

EPBD, 2010. Directive 2010/31/UE of the European Parliament and of Counvil of 19 May 2010 on the energy performance of buildings. *Official Journal of the European Union,* pp. 13-25.

Fabi, V., Andersen, R. V., Corgnati, S. & Olesen, B. W., 2012. Occupants' window opening behaviour: A literature review of factors influencing occupant behaviour and models. *Building and Environment, 58,* pp. 188-198.

Fabi, V. et al., 2013. *Robustness of building design with respect to energy related occupant behaviour*.

Fabi, V., D'Oca, S., Buso, T. & Corgnati, S. P., 2013. *The influence of occupant's behaviour in a high performing building*.

Fanger, P., 1973. *Thermal comfort.* s.l.:McGraw-Hill.

Fanti, M. P. et al., 2016. *A Natural Ventilation Control in Buildings Based on Co-Simulation.* Budapest, Hungary, IEEE International Conference on Systems, Man, and Cybernetics (SMC 2016).

Foster, M. & Oreszczyn, T., 2001. Occupant control of passive systems: the use of Venetian Blinds. *Building and Environment, 36,* pp. 149-155.

G. Ward, J., 1989. *The RADIANCE Lighting Simulation and Rendering System.* s.l., 21st Annual Conference Computer Graphics & Interactive Techniques.

Gartland, L. M., Emery, A. F., Sun, Y. S. & Kippenhan, C. J., 1993. Residential energy usage and the influence of occupant behavior. *ASME.*

Ghiaus, C. & Inard, C., 2004. *Energy and environmental issues of smart buildings, A Handbook for Intelligent Building,* 26-51.

Glicksman, L. R. & Taub, S., 1997. Thermal and behavioral modeling of occupant-controlled heating, ventilating and air conditioning systems. *Energy and Buildings 25.3 ,* pp. 243-249.

Gunay, H. B., O'Brien, W., Beausoleil-Morrison, I. & Perna, A., 2014. On the behavioral effects of residential electricity submetering in a heating season.. *Building and Environment, 81,* pp. 396-403.

Hailemariam, E., Goldstein, R., Attar, R. & Khan, A., 2011. *Real-time occupancy detection using decision trees with multiple sensor types.* s.l., In Proceedings of the 2011 Symposium on Simulation for Architecture and Urban Design. Society for Computer Simulation International.

Haldi, F. & Robinson, D., 2008. On the behaviour and adaptation of office occupants. *Building and environment, 43 (12),* pp. 2163-2177.

Haldi, F. & Robinson, D., 2009. Interactions with window openings by office occupants. *Building and Environment, 44 (12),* pp. 2378-2395.

Haldi, F. & Robinson, D., 2010. Adaptive actions on shading devices in response to local visual stimuli. *Journal of Building Performance Simulation, 3 (2),* pp. 135-153.

Herkel, S., Knapp, U. & Pfafferott, J., 2008. Towards a model of user behaviour regarding the manual control of windows in office buildings. *Building and Environment, 43 (4),* pp. 588-600.

Hoes, P. et al., 2009. User behavior in whole building simulation. *Energy and Buildings, 41(3),* pp. 295-302.

Hong, T. et al., 2015. An ontology to represent energy-related occupant behavior in buildings. Part II: Implementation of the DNAS framework using an XML schema. *Building and Environment 94,* pp. 196-205.

Hong, T. et al., 2016. An occupant behavior modeling tool for co-simulation. *Energy and Buildings,117,* pp. 272-281.

Hong, T. et al., 2016. An occupant behavior modeling tool for co-simulation. *Energy and Buildings 117,* pp. 272-281.

Hong, T. et al., 2016. Advances in research and applications of energy-related occupant behavior in buildings. *Energy and Buildings 116,* pp. 694-702.

Humphreys, M. A. & Nicol, J. F., 1998. *Understanding the adaptive approach to thermal comfort.* s.l., ASHRAE transactions, 104.

Hunt, D., 1979. The use of artificial lighting in relation to daylight levels and occupancy. *Building and Environment, 14 (1),* pp. 21-33.

Iannone, F., Borri, D., Camarda, D. & Pluchinotta, I., 2012. *The management of indoor spaces in urban microclimate: a multi-agent approach.*

IEA, 2013. *Annex 53. Total energy use in buildings. Analysis and evaluation method.* s.l., Final Report Annex 53.

IEA & EBC, 2014. *IEA - EBC Annex 66. Definition and simulation of occupant behavior in buildings.* [Online]
Available at: http://www.annex66.org/

Juodis, E., Jaraminiene, E. & Dudkiewicz, E., 2009. Inherent variability of heat consumption in residential buildings. *Energy and Buildings, 41 (11),* pp. 1188-1194.

Karjalainen, S., 2016. Should we design buildings that are less sensitive to occupant behaviour? A simulation study of effects of behaviour and design on office energy consumption. *Energy Efficiency,* pp. 1-14.

Kastner, W., Neugschwandtner, G., Soucek, S. & Newmann, H. M., 2005. *Communication Systems for Building Automation and Control.* s.l., Proceedings of the IEEE, vol. 93, no. 6, pp. 1178-1203..

Kennedy, J. & Eberhart, R., 1995. *Particle swarm optimization.* s.l., IEEE International Conference on Neural Networks.

Konis, A. K., 2013. *The influence of occupant behavior on facade solar transmission: discrepancies between observed shade control behavior and simulation-based shade control models.* Phd thesis.

Kua, H. W. & Lee, S. E., 2002. Demonstration intelligent building—a methodology for the promotion of total sustainability in the built environment. *Building and Environment 37.3 ,* pp. 231-240.

Lam, K. P. et al., 2009. *Occupancy detection through an extensive environmental sensor network in an open-plan office building.* s.l., IBPSA Building Simulation, 145: 1452–1459.

Langevin, J., 2014. *Environmental Adaptation, Personal Comfort, & Energy Use in the Built Environment.* s.l.:PhD thesis.

Langevin, J., Gurian, P. L. & & Wen, J., 2013. Reducing energy consumption in low income public housing: Interviewing residents about energy behaviors. *Applied Energy 102,* pp. 1358-1370.

Langevin, J., Wen, J. & Gurian, P. L., 2015. Simulating the human-building interaction: Development and validation of an agent-based model of office occupant behaviors. *Building and Environment, 88,* pp. 27-45.

Leaman, A. & Bordass, B., 2007. Are users more tolerant of "green" buildings?. *Building Research & Information, 35 (6),* pp. 662-673.

Lee, C., Tong, J. & Cheng, V., 2014. *Occupant Behavior in Building Design and Operation.* Hong Kong, HK Joint Symposium 2014.

Lee, Y. S. & Malkawi, A. M., 2014. Simulating multiple occupant behaviors in buildings: An agent-based modeling approach. *Energy and Buildings 69,* pp. 407-416.

Le, K., Bourdais, R. & Gueguen, H., 2014. *Optimal control of shading system using Hybrid Model Predictive control.* Strasbourg, European Control Conference (ECC).

Lindelöf, D. & Morel, N., 2006. A field investigation of the intermediate light switching by users. *Energy and Buildings, 38 (7),* pp. 790-801.

Lindsay, C. & Littlefair, P., 1992. *Occupant use of venetian blinds in offices.* s.l., Building research establishment.

Macal, C. M. & North, M. J., 2010. Tutorial on agent-based modeling and simulation. *Journal of simulation 4.3,* pp. 151-162.

Macintosh, A. & Steemers, K., 2005. Ventilation strategies for urban housing: lessons from a PoE case study. *Building Research & Information 33.1,* pp. 17-31.

Maier, T., Krzaczek, M. & Tejchman, J., 2009. Comparison of physical performances of the ventilation systems in low-energy residential houses. *Energy and buildings, 41 (3),* pp. 337-353.

McCartney, K. J. & Nicol, J. F., 2002. Developing an adaptive control algorithm for europe. *Energy and buildings, 34 (6),* pp. 623-635.

Mendes, N., Oliveira, G. H. & Araújo, H. X. D., 2001. *Building thermal performance analysis by using matlab/simulink.* Rio de Janeiro, Brazil, In Seventh International IBPSA Conference..

Newsham, G., 1994. Manual control of window blinds and electric lighting: Implication for comfort and energy consumption. *Indoor Environment, 3 (3),* pp. 135-144.

Newsham, G. R. & Tiller, D. K., 1997. *Method and system for polling and data collection.* s.l., US Patent 5,615,134.

Nicol, J., 2001. *Characterising occupant behaviour in buildings: towards a stochastic model of occupant use of windows, lights, blinds, heaters and fans.* s.l., In: Proceedings of seventh international IBPSA conference.

Nicol, J. F. & Humphreys, M. A., 2002. Adaptive thermal comfort and sustainable thermal standards for buildings. *Energy and Buildings, 34 (6),* pp. 563-572.

Nicol, J. & Humphreys, M., 2004. A stochastic approach to thermal comfort—occupant behaviour and energy use in buildings. *ASHRAE Transactions;110(2),* pp. 554-568.

O'Brien, W., Kapsis, K. & Athienitis, A. K., 2013. Manually-operated window shade patterns in office buildings: A critical review.. *Building and Environment, 60,* pp. 319-338.

Ochoa, C. E. & Capeluto, I. G., 2008. Strategic decision-making for intelligent buildings: Comparative impact of passive design strategies and active features in a hot climate. *Building and Environment 43.11,* pp. 1829-1839.

Olesen, B. W., 2007. The philosophy behind EN15251: Indoor environmental criteria for design and calculation of energy performance of buildings.. *Energy and Buildings 39.7,* pp. 740-749.

Palme, M., Isalgue, A., Coch, H. & Serra, R., 2006. *Robust design: A way to control energy use from human behavior in architectural spaces.* s.l., Proceedings of the PLEA Conference.

Palonen, M., Hasan, A. & Siren, K., 2009. *A genetic algorithm for optimization of building envelope and HVAC system parameters.* Glasgow, Scotland.

Parliament, E., 2010. *Directive 31/2010/UE on the energy performance of buildings*.

Peng, C. et al., 2012. Quantitative description and simulation of human behavior in residential buildings. *C. Peng, D. Yan, R. Wu, C. Wang, X. Zhou, and Y. Jiang. Quantitative description and simulatioBuilding simulation,* Volume 5, pp. 85-94.

Perez-Lombard, L., Ortiz, J. & Pout, C., 2008. A review on buildings energy consumption information. *Energy and Building 40(3),* pp. 394-398.

Polinder, H. et al., 2013. *Occupant behavior and modeling,* s.l.: Total energy use in buildings, analysis and evaluation methods. Final Report Annex 53.

Poli, R., Kennedy, J. & Blackwell, T., 2007. Particle Swarm Optimization, an Overview. *Swarm Intelligence,* Volume 1, pp. 33-57.

Poli, R., Kennedy, J. & Blackwell, T., 2007. Particle Swarm Optimization, an Overview. *Swarm Intelligence,* Volume 1, pp. 33-57.

Reinhart, C. F., 2004. Lightswitch-2002: a model for manual and automated control of electric lighting and blinds. *Solar Energy, 77 (1),* pp. 15-28.

Reinhart, C. F. & Walkenhorst, O., 2001. Dynamic RADIANCE-based daylight simulations for a full-scale test office with outer venetian blinds. *Energy & Buildings, 33:7 ,* pp. 683-697.

Ren, X., Yan, D. & Wang, C., 2014. Air-conditioning usage conditional probability model for residential buildings. *Building and Environment 81,* pp. 172-182.

Rijal, H. B. et al., 2007. Using results from field surveys to predict the effect of open windows on thermal comfort and energy use in buildings. *Energy and Buildings, 39 (7),* pp. 823-836.

Rinaldi, A. & Iannone, F., 2016. *Control logics of natural ventilation for energy efficiency and thermal comfort.* Algarve, Portugal, 41st IAHS WORLD CONGRESS- Sustainability and Innovation for the Future.

Rinaldi, A. et al., 2016. *Natural Ventilation for Passive Cooling by Means of Optimized Control Logics.* s.l., International High- Performance Built Environment Conference – A Sustainable Built Environment Conference 2016 Series (SBE16), iHBE 2016.

Rowe, D., 1996. Mxed mode climate control: some hands-on experience.. *AIRAH Journal, 50 (12),* pp. 19-23.

Rubin, A. I., Collins, B. L. & Tibbott, R. L., 1978. *Window blinds as a potential energy saver: A case study.* US Department of Commerce, National Bureau of Standards.

Santin, O. G., 2011. Behavioural patterns and user profiles related to energy consumption for heating. *Energy and Buildings 43.10,* pp. 2662-2672.

Sardianou, E., 2008. Estimating space heating determinants: An analysis of Greek households. *Energy and Buildings 40.6,* pp. 1084-1093.

Sarker, M., Rabbi, M. F., Assad-Uz-Zaman, M. & Mashud, M., 2014. *A solar passive cooling system of buildings in summer season.* s.l., Strategic Technology (IFOST), 9th International Forum on, Cox's Bazar, pp. 347-350.

Schakib-Ekbatan, K., Çakıcı, F. Z., Schweiker, M. & Wagner, A., 2015. Does the occupant behavior match the energy concept of the building?–Analysis of a German naturally ventilated office building. *Building and Environment, 84,* pp. 142-150.

Schiavon, S. & Lee, K., 2013. Dynamic predictive clothing insulation models based on outdoor air and indoor operative temperatures. *Building and Environment, 59,* pp. 250-260.

Schweiker, M., 2010. *Occupant behaviour and the related reference levels for heating and cooling: analysis of the factors causing individual differences together with the evaluation of their effect on the exergy consumption within the residential built environment.* Tokyo City University, Yokohama, Japan: PhD thesis.

Schweiker, M., Haldi, F., Shukuya, M. & Robinson, D., 2012. Verification of stochastic models of window opening behaviour for residential buildings. *Journal of Building Performance Simulation 5.1,* pp. 55-74.

Schweiker, M., Hawighorst, M. & Wagner, A., 2016. The influence of personality traits on occupant behavioural patterns. *Energy and Buildings 131,* pp. 63-75.

Schweiker, M. & Shukuya, M., 2010. Comparative effects of building envelope improvements and occupant behavioural changes on the exergy consumption for heating and cooling. *Energy Policy, 38(6),* pp. 2976-2986..

Schweiker, M. & Wagner, A., 2016. The effect of occupancy on perceived control, neutral temperature, and behavioral patterns. *Energy and Buildings 117,* pp. 246-259.

Seligman, C., Darley, J. M. & & Becker, L. J., 1978. Behavioral approaches to residential energy conservation. *Energy and buildings 1.3,* pp. 325-337.

Shaikh, P. H. et al., 2014. A review on optimized control systems for building energy and comfort management of smart sustainable buildings. *Renewable and Sustainable Energy Reviews 34,* pp. 409-429.

Shaikh, P. H., Nor, N. M., Nallagownden, P. & Elamvazuthi, I., 2013. Intelligent optimized control system for energy and comfort management in efficient and sustainable buildings. *Procedia Technology 11,* pp. 99-106.

Socolow, R. H., 1978. The Twin Rivers program on energy conservation in housing: Highlights and conclusions. *Energy and Buildings 1.3,* pp. 207-242.

Sonderegger, R. C., 1978. Movers and stayers: the resident's contribution to variation across houses in energy consumption for space heating. *Energy and Buildings, 1 (3),* pp. 313-324.

Sun, B. et al., 2013. *Building Energy Management: Integrated Control of Active and Passive Heating, Cooling, Lighting, Shading, and Ventilation Systems.* s.l., IEEE Transactions on Automation Science and Engineering.

Team, R. D. C., 2012. *R: A language and Environment for statistical computing.* Vienna, Austria: R Foundation for Statistical Computing.

Toftum, J., 2010. Central automatic control or distributed occupant control for better indoor environment quality in the future. *Building and Environment,45,* pp. 23-28.

TRNSYS, 2009. [Online] Available at: http: // www. trnsys. com/

Wang, Z. & Wang, L., 2013. *Intelligent Control of Ventilation System for Energy-Efficient Buildings With CO2 Predictive Model.* s.l., IEEE Transactions on Smart Grid, 4.2, 686-693..

Wong, J. K., Li, H. & Wang, S. W., 2005. Intelligent building research: a review. *Automation in construction 14.1,* pp. 143-159.

Yan, D. et al., 2015. Occupant behavior modeling for building performance simulation: Current state and future challenges. *Energy and Buildings 107,* pp. 264-278.

Yang, R., Wang, Z. & Wang, L., 2011. *A GUI-based simulation platform for energy and comfort management in Zero-Energy Buildings.* Boston, MA, North American Power Symposium (NAPS), pp. 1-7..

Yan, L. & Xiaofeng, L., 2014. Natural ventilation potential of high.rise residential buildings in northern China using coupling thermal and airflow simulations. *Building Simulation. vol.2, issue 1,* pp. 51-64.

Zavala, V. M., 2012. Real-Time Optimization Strategies for Building Systems. *Industrial & Engineering Chemistry Research 52.9,* pp. 3137-3150.

Zhao, R. & Xia, Y., 1998. *Effective non-isothermal and intermittent air movement on human thermal responses.* Stockholm, Sweden, In: Proceedings of 6th International Conference on Air Distribution in Rooms, pp.351-357.

Curriculum Vitae and Publication List

EDUCATION

2014-2017
Department of Civil, Environmental, Building Engineering, and Chemistry, Politecnico di Bari, Italy
PhD-candidate

2007 - 2012
Politecnico di Bari, Bari (Italy)
Master Degree in Ingegneria Edile-Architettura
Dissertation title:
Design of Nearly Zero Energy Buildings (NZEB). Optimization of building-HVAC system in a residential building located in Mediterranean climate.

RESEARCH EXPERIENCE

2015
Inserted in the research group of PON "RES NOVAE-Networks, Buildings, Roads - New Virtuosos Objectives for the Environment and Energy"- Ministry of Education and Research (MIUR) "Smart cities and Communities and Social Innovation" - axis II of the National Operational Program "Research and Competitiveness, 2007/2013". Politecnico di Bari with the National Research Council (CNR), ENEL, ENEA, Data management S.p.A., University of Calabria, IBM studies, General Electric, Elettronika srl.

PUBLICATION LIST

[10] **RINALDI A**., Schweiker M., F. Iannone (2016). Towards Nearly Zero Energy Buildings: Extracting influencing Factors of Occupant Behaviour by Means of a Questionnaire Survey. Article in Press. Energy and Buildings.

[9] **RINALDI A.,** Roccotelli M., A.M. Mangini, F. Iannone (2016). Natural ventilation for passive cooling by means of optimized control logics. International High-Performance Built Environment Conference – A Sustainable Built Environment Conference 2016 Series (SBE16), iHBE 2016, 17-18th November 2016 Sydney

(Australia).

[8] M. P. Fanti., A.M. Mangini, M. Roccotelli, **A. RINALDI**, F. Iannone (2016). A Natural Ventilation Control in Buildings Based on Co-Simulation. IEEE International Conference on Systems, Man, and Cybernetics (SMC 2016). Budapest, Hungary.

[7] G.R. Dell'Osso, F. Iannone, A. Pierucci, **A. RINALDI** (2015). The Management of Summer Thermal Loads through Building Automation System. In: Environmental Sustainability Circular Economy and Building Production. Politecnico di Milano, 24- 25 September 2015, RIMINI: Maggioli Editore, pp. 367-386, ISBN 978-88-916-1222-9.

[6] G.R. Dell'Osso, F. Iannone, A. Pierucci, **A. RINALDI** (2015). Control Strategies of the Natural Ventilation for Passive Cooling for an Existing Residential Building in Mediterranean Climate. In 36th AIVC Conference, 23-24 September 2015, Madrid, Spain pp. 406-415, ISBN : 2-930471-45-X EAN: 9782930471457.

[5] G. Addante, F. Iannone, **A. RINALDI** (2015). Evaporative Cooling and Ventilation Control Strategies for a Kindergarten in Mediterranean Climate. In 36th AIVC Conference, 23-24 September 2015, Madrid, Spain pp. 416-425, ISBN : 2-930471-45-X EAN: 9782930471457.

[4] RINALDI A. (2015). Strategies and technology solutions for the optimal management of building-HVAC system. In: ARTEC 2014 – Incontro COLLOQUI.ATE. VICO EQUENSE (NA), 20-21 NOVEMBRE 2014, vol. 1

[3] Decarolis D, **RINALDI A**., Iannone F (2014). Soluzioni bioclimatiche e di building automation per la riqualificazione energetica di un edificio residenziale in clima Mediterraneo. In: Energia, sostenibilità e dematerializzazione operativa. Politecnico di Bari, 10 - 11 luglio 2014, RIMINI: Maggioli Editore, p. 383-402, ISBN/ISSN: 9788891604361.

[2] De Tommasi G, Di Marzo M, Moschini F, Conte E, Fatiguso F, Dell'Osso G, Iannone F, De Fino M, Pierucci A, Scioti A, Colapietro D, Martino A, **RINALDI A**., Maggiore F, Pietropaolo L (2014). Research group "Building Technology, Building Construction, History of Architecture". In: 1st State of the art and Challenges

of Research Efforts (S.C.O.R.E.), 3 - 5 dicembre 2014.

[1] Iannone F, **RINALDI A**. (2013). Design and Economic Optimization of Near Zero Energy Residential Buildings in Mediterranean Climate. In: Changing Needs, Adaptive Buildings, Smart Cities. Politecnico di Milano, Italy, September 17-20,2013, MILANO: Poliscript - Politecnico di Milano, vol. 2, p. 171-177, ISBN/ISSN: 9788864930206.

TEACHING

2014-2017 **Didactic support** for "Servizi tecnologici e da fonti rinnovabili", Master degree in Sistemi edilizi, Politecnico di Bari.

2015 **Teaching activity** for project called " Percorsi di formazione assetto del territorio-orizzonte Tavoliere" of Scope 2 (sustainable living) financed by the Apulia region-Forpuglia.

SKILLS

Windows, Office, Google Sketchup, Autocad, Archicad, Artlantis, Trnsys, Termus, Mc11300, T-Sol, Pv-Sol, Solarius Pv, Ecotect, Pv-System, R Computing, Spss, Matlab, Latex