An innovative decision-making approach for a sustainable building design

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An innovative decision-making approach for a sustainable building design

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Dedicated to my family

Abstract

Building energy simulation models play an important role in the design and optimization of buildings. For the estimation of the energy flow and the performance of building elements and their materials, simulation models are often used to compare the cost-effectiveness of energy-conservation measures in the design stage as well as assessing various performance optimization measures during the operational stage. However, there is a complexity linked to the large number of independent variables that prevent to achieve a precise picture of the real-world building operation. Therefore, by analyzing model outputs and measured data, we can reach more precise and reliable results. This connection of model output results with measured data is known as calibration. This research project presents one possible approach to analyze the measured data (outdoor and indoor space temperature of the "Solatrium House" collected thanks to several temperature loggers for one year) with a specific data mining software and to develop a calibration process with them and the thermal simulation outputs, highlighting the influence of uncertainty in the calibration process. This analysis can be useful in several ways including: monitoring of the building thermal comfort, controlling the efficiency of the HVAC equipment, estimating the energy demand by utility companies and forecasting the energy savings due to equipment retrofits or implementation of an energy conservation measure. Furthermore, this type of approach is also used as an inverse modeling tool to better understand the performance requirements of new adaptive façade materials, for example, to establish the preferred physical property ranges that lead to zero-energy building enclosures.

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Contents

1. INTRODUCTION

1.1 Energy management in smart buildings

Data science and Information Technologies are currently playing a crucial role in the context of buildings sustainability and energy efficiency. The achievements of relevant energy performances through the optimal control of building subsystems and the introduction of innovative decision support tools in the early-stages of the design are noteworthy features of contemporary smart buildings. Smart buildings are demonstrating several distinctive features that are opening new markets and establishing new innovative design solution. Not surprisingly, the design phase of new buildings has acquired primary importance for the improvement of sustainability and the reduction of the energy demand. Nowadays, buildings represent 40% of world primary energy consumption and 24% of greenhouse emissions. There is a growing interest in precisely understanding and profiling the actual building energy consumptions (e.g., when higher peaks occur and how much they are). This implies that the development of advanced energy consumption measurements, verification instruments and forecasting algorithms is an emerging need. Indeed, existing building simulation tools provide a realistic representation of building operations only when the simulated models are properly calibrated and validated. Thanks to these instruments, in this context, the objective of the present research thesis is to carry out a development of decision support tool, based on a parametric analysis, for helping designers in evaluating the choice of different building components, such as insulation foams and glazing systems and evaluating their benefits for thermal comfort and energy savings through a real building performance simulation model.

In fact, the developed tool is intended to play an important role in the early design phase, when it is well known that parametric analysis is useful for evaluating high-level benchmarking. On the other hand, the complexity related to the large number of variables affecting the building behavior prevents achieving a precise picture of the real-world building operation. To address such an issue, the proposed method enables powerful parametric studies in a reasonable time.

The main feature of the proposed tool is the integration of the definition of the building model including the calibration and validation procedures, with a sensitivity analyzer based on an automatic process. The proposed tool compares several possible alternative models of the given building, obtained by automatically combining different thermal behaviors, physical parameters and climatic zones, and using long-term comfort indices. The main goal is to estimate e the values of long-term indices for a preliminary thermal performance evaluation of the given building in different contexts and with different parameters combinations. In particular, a Matlab tested has been developed for co-simulation with the whole-building energy simulator EnergyPlus. The tool is provided with a front-end in order to facilitate the configuration process in defining the building model and listing the associated building parameters needed for the co-simulation. Moreover, the front-end allows the selection of desired performance indices: for instance, the Predicted Mean Vote (PMV) and the Predicted Percentage of Dissatisfied (PPD) indices are implemented and standardized in accordance with the ASHRAE 55 Thermal Comfort Code. Finally, the tool is provided with a data analysis module: after co-simulation runs, the output data from EnergyPlus are aggregated, analyzed and visualized in Matlab both in tabular and graphical views.

As a result, this analysis can be useful in several ways including: monitoring of the building thermal comfort, controlling the efficiency of the HVAC equipment, estimating the energy demand by utility companies and forecasting the energy savings due to equipment retrofits or implementation of an energy conservation measure. Furthermore, this type of approach is also used as an inverse modeling tool to better understand the performance requirements of materials, for example, to establish the preferred physical property ranges that lead to zero-energy building enclosures.

The first part of the thesis focuses on a literature review and the state-of-art of the building performance simulation, calibration and validation approaches and optimization techniques for buildings' thermal comfort and energy savings.

While, the second part of the thesis focuses on a real case study (Solatrium House), where is applied a novel calibration and validation approach and the description of the conducted parametric analysis for evaluating the benefits of different design choices on a building's performance.

1.2 Thesis Outlines

This thesis presents the results of a research conducted on a real case study developed by the Worcester Polytechnic Institute: the "Solatrium House". The thesis is structured in two main parts -anticipated by the present Introduction- as described in the sequel.

The first part focuses on building performance simulation, calibration and validation approaches and optimization techniques for energy savings and thermal comfort benefit and it is structured as follows.

In Chapter 2 a literature overview on building performance simulation is presented. Researchers have recently made significant efforts in order to develop robust simulation models adapted to reach different goals, such as energy services activities, energy forecast, inspection and audit, evaluation of on-going energy performance diagnosis. In particular, the chapter focuses on several simulation tools for improving building energy predictions.

In Chapter 3 a literature overview on calibration and validation approach of Dynamic Building Simulation Model is presented. The chapter is focused on the explanation of most common methodologies for calibration, emphasizing criticalities and gaps that can be faced. In particular, the main issues to be addressed, when carrying out calibrated simulation, are discussed. The standard statistical criteria for considering the building models calibrated and for evaluating their goodness-of-fit are also explained. for new studies are finally provided.

In Chapter 4-5 a literature overview on optimization techniques used by building performance simulation model is presented. In fact, building energy efficiency and thermal comfort have turned out to be a multi-faceted problem, when provided with the limitation for the satisfaction of the indoor comfort index. However, the comfort level for occupants and their behavior have a significant effect on the energy consumption pattern. Researchers and investigators have been working with this issue for over a decade; yet it remains a challenge. This chapter presents a comprehensive study conducted on state-of-the-art of computational optimization methods applied for decreasing building energy consumption and conducting a comfort analysis.

In Chapter 6, 7 and 8 the calibration and validation of a real building simulation model is presented. The case study consists in passive solar house designed by the Worcester

Polytechnic Institute (WPI) for the Solar Decathlon Challenge 2013, held in Datong, China. A novel calibration and validation approach based on the indoor temperature is presented. The presented methodology is coupled with an innovative optimization tool that run a specific parametric analysis for evaluating benefits and advantages of different building design solutions.

Finally, the aforementioned parts of this thesis are followed by the Conclusions that discuss the main results and the possible future developments of the presented research.

2. BUILDING PERFORMANCE SIMULATION: STATE OF THE ART AND RELATED LITERATURE

2.1 Motivation

Due to increasing populations, improving infrastructures, and declining budgets, cities are facing non-trivial long-term challenges across all their systems which are central to their operation and development.

In fact, it is expected that the percentage of world population in urban areas will grow up to 70% by 2050 [1]. At the same time, more than 80 percent of the world global Gross Domestic Product (GDP) is generated in cities. Moreover, cities are responsible for over 70% of the world's greenhouse emissions. In such a scenario, the demand for a more efficient, sustainable, livable model for cities is growing [2], [3], [4].

For this reason, the concept of smart city has been introduced as a timely and proficient answer to the needs regarding key themes such as sustainable development, business creation and employment, healthcare, education, energy and the environment, safety, and public services [5]. As an impressive goal, different programs are promoting the development of smart cities around the world [6]. Not surprisingly, the common feature is that the implementation of strategic plans to mitigate current urban problems and make cities more efficient, sustainable, and livable steps through the realization of smart governance. This aspect is widely recognized to be at the core of all the smart city initiatives [7].

In this context, the concept of "Smart Building" takes part since the energy consumption of buildings accounts for around 30% of all energy consumed in advanced countries, while also exceeding the energy consumption of the industrial and transportation sectors in the EU and US [8]. Usually those type of "intelligent" buildings are misled just with building automation, while the assistive domotic is only one of their potential benefits. In fact, the main ones are: energy savings, habitants thermal comfort, time savings, safety, expert systems and health and care [9]. For this reason, the researchers and the designers have

introduced, in past century, novel design approaches, energy efficiency methods, simulation tools and green policies, in the building sector, for decreasing the global energy use and promoting the environmental sustainability.

Additionally, some studies have shown that most of the energy consumption related to the building sector is due to existing buildings [10], [11] and, for trying to reduce this problem, many of the international organizations and governments started to provide substantial resources in the renovation process and to introduce restrictive governmental policies [12].

In these terms, the design phase of a building plays an important role for reaching the energy efficiency and decreasing the related energy demand. The cooperation of different professions, such as engineers, architects and building physicists, develops an integrated design process starting from the concept phase to the building operational phase [13] because, nowadays, during the early-stage of the project, the design teams have started to use the Building Performance Simulation (BPS) models. They are able to approximate and predict the thermal comfort and the energy consumption for the new and renovated buildings [14] and, consequently, their connection to specific application and optimization tools, aid the stakeholders to reach a final decision trough a set of possible actions to improve the energy efficiency in buildings.

2.2 Introduction

In order to increase the quality of the building design process, especially in the early stage, several research studies have developed different building performance simulation tools.

Until the 70s simplified calculations for energy use based on rules of thumbs, simple equations and simplified boundary conditions have been used by building design engineers to determinate heating and cooling loads, especially, for selecting equipment and Heating, Ventilation, and Air Conditioning (HVAC) sizes [15].

While, in the past decade, computerized and simulation tools have been coded to produce building models with actual behaviors. Specifically, Building Performance Simulation (BPS) is a novel approach based on computer models that cover performance aspects, usually, related to energy consumption and thermal comfort in buildings and

describe the complex interaction between them. Crawly [14, 16] believes that the BPS is a powerful and useful tool which reproduces, mainly, the dynamic interaction of mass, heat and light within the building to forecast its energy consumption and environmental performance as it is exposed to climate, occupant activities and HVAC systems.

After years of studies and development, the design process has introduced BPS in each phase for rapidly prototyping and providing different design concepts in order to reach feasible, but not optimal, design solutions.

In fact, the integration of design optimization, as a BPS component, is either not applied in simulation tools or it is not used because of expenditure of time and effort.

In this context, De Wilde [16] explains that BPS, as a novel approach, is able to integrate the system optimization within the model, provide significant design solutions by numbers and graphs, introduce uncertainty, support generation of design alternatives and generate informed decision making by choices between several design options. While, on the other hand, he believes that different simulation tools such as design tools, analysis tools and modeling tools exist but they are neither used to support the generation of design alternatives, nor to make informed choices between different design options.

According to Morbitzer [17], building simulation introduces the concept of performance prediction. Thanks to their help, the user can customize the model based on the inputs and parameters that have a big impact on the overall building performance for achieving predicted results close to reality as much as possible.

Due to the fact that nowadays buildings are appreciated with a low energy consumption and high thermal comfort, the BPS becomes pivotal to forecast the building performance as realistic as possible. This is obviously not possible without the use of building performance simulation as tool in the design process.

The remainder of this chapter is organized as follows. Section 2.3 provides a description about aims and issues of the building performance simulation.

In addition, Section 2.4 presents a literature overview on the main building simulation tools, positioning the research contribution with respect to the related literature and showing its advancement.

2.3 Aims and Issues of Building Performance Simulation

The building simulation offers a tool and method for evaluating the building performance but its use, in the current building design projects, is restricted. In fact, even if a large number of simulation tools is available, their application is limited to the detailed design phase.

Nowadays, most of the building performance tools are legacy software that have been developed by a monolithic structure and they are becoming very hard to maintain. The users need expert skills to build up and set up the model and perform simulation that are going to generate the right outputs from which the desired performance data can be extracted. In that context, the designer experience plays an important role because the use of simulation tools has a pivotal impact assessment on different parameters. While, the use of building simulation, without any experience, does not provide benefits requested by the users and, on the other hand, they get the risk to produce results which do not reach the domain characteristics.

Today, the decision-making process is usually supported by the building performance simulation in understanding the potential benefits and design alternatives of an individual building. Moreover, there is another use related to the BPS that lies beyond the performance of individual buildings. Literally, it is involved in developing and improving building policy settings, such as minimum standard regulation or the building performance for governments or utility companies.

Some of the most example of policy goals are:

- Estimating the performance of an existing or new building energy standard;
- Evaluating the introduction of novel technologies or systems for the new building design or existing building retrofit;
- Evaluating requirements for existing or new energy suppliers;
- Estimating the potential impact on building performance of changes linked to the environment;

- Defining the financial incentives for improved building energy performance.

In fact, as Crawley show in his studies, the BPS can determinate many aspects of the building performance, such as energy consumption and demand, thermal comfort, initial and maintain costs, renewably energy performance and CO_2 emissions that can help the stakeholders to reach the policy achievements listed above.

Moreover, there is another important issue that affects the BPS. Because, the design stages involve different fields and it is very complicated for design disciplines to recognize the impact of their solutions and choices on the works of others. For this reason, BPS should include the possibility to take into account more than one performance aspect.

Another important aspect of the BPS is the role of uncertainties. BPS is a multi-disciplinary, problem oriented, dynamic tool using numerical methods that approximate a solution of a realistic model.

There is a big difference between the traditional tools and simulation ones based on the complexity of models. Nowadays, software simulation involves a large set of variables that should have a high grade of assurance [18]. Uncertainty studies are a hot topic of several ongoing researches where they show the different approaches use embedded for either parameter screening and reduction [19], or robustness analysis [20], [21].

The building performance simulation are really affected by the explained issues and uncertainty. In fact, uncertainty for instance can generate information about reliability towards design parameters, respectively to the overall design. The uncertainty issue [22] needs that the decision making process takes into account uncertainty analysis, risk management and confidence, especially, because uncertainty is one major aspect. When the uncertainty is connected with the decision-making process, it is used to help the BPS outputs and get the designer or the building physic engineer conscious about the risk that one option could stick out in a performance aspect.

2.4 Overview of the main building simulation tools

From the literature review, a brief summary of different simulation tools for dynamic thermal building simulation is presented in this section. The tools have been selected to provide a brief overview on the basis that they claim to be of use for different design stages.

- **Building Loads Analysis and System Thermodynamics (BLAST)**

The BLAST tool forecasts energy consumption, energy system performance and building costs. It is coded based on three main components: Central Plant, Space Loads Prediction and Air System Simulation. Architects and building physic engineers can involve BLAST into the design process to determinate the energy performance of new or retrofit design options of almost any type and size [23].

- **Energy 10**

Energy 10 is a simulation tool used during the conceptual phase. Its aim is produce a whole-building tradeoff during early design phases for buildings with limited area or that can be treated as one or two-zone compartments. It performs building energy analysis for 8,760 hours/year, including dynamic thermal and day lighting calculations. The Energy 10 is developed to evaluate the energy-efficient building features at the beginning of the design process [24].

- **BSim**

Bsim is a user-friendly tool that provides hydrothermal simulations of buildings and constructions. The developers have coded this software thanks to several modules: SimView, TSBI5, SimLight, XSun, NatVent and SimDxf. Nowadays, it is commonly used in Denmark for helping the building energy design and for moisture analysis [23].

- **MIT Design Advisor**

MIT Design Advisor is an on-line design tool for architects and building engineers. It has been developed to generate preliminary estimates for the performance of building facades. In fact, double skin facades may be compared to conventional facades based on location, occupancy and depth of the perimeter space [24].

- **Designer's simulation toolkits (DeST)**

DeST provides specific analysis of building thermal process and HVAC system performance. It is coded based on different modules useful to handle several functions. It has been mostly used in China for numerous important projects such as the State Grand Theatre and the State Swimming Center [23].

- **ECOTECT**

Ecotect is an architectural design visualizer developed by Autodesk. It was used in the early design process thanks to its modeling and analysis behaviors that can process geometry of any size and complexity. It has a wide range of performance analysis functions that involve energy, shading, acoustics, thermal and cost aspects [23].

- **DOE 2.1**

DOE 2.1 performs a prediction of hourly energy use and energy cost of a building trough the hourly weather information, a building geometry and HVAC system description. The developers have coded this tool based on one subprogram for input translation and four simulation subprograms: PLANT, LOADS, SYSTEMS and ECON.

DOE 2.1 has been involved in the design process for more than twenty-five years for building design studies, analysis of retrofit options and for introducing and testing building energy standards in the US and around the world [23].

- **Building Design Advisor**

The Building Design Advisor (BDA) is a stand-alone integrated design tool. It is able to have a big impact on the initial design phase to specific system definition. The software is supposed to perform as data manager and process controller for three simulation components DCM (Day lighting Computation Module), ECM (Electric lighting Computation Module), and DOE2 (that is, an energy analysis module) [24].

- **e-Quest**

e-QUEST is an advanced, user-friendly, analysis tool, which provides energy consumption and thermal comfort results with an affordable level of effort. e-QUEST was coded to perform comparative analysis of building designs and technologies thanks to sophisticated simulation techniques that do not require a strong experience in the "art" of building performance modeling [24].

- **Ener-Win Version EC**

Ener-Win is a toll that required only three basic inputs: the building type, the building's location, and its geometrical data. It runs simulations that provide annual, monthly and hourly energy consumption in buildings, peak heating and cooling loads, solar heating and life-cycle cost analysis [24].

- **SEMPER**

SEMPER has been coded at Carnegie Mellon University and it is a multi-aspect building performance simulation system [25]. It has been developed as stand-alone design support tool. Based on it, SEMPER-II was developed which is an internet-based computational design environment handling multiple users and queuing multiple request of simulation runs [26].

- **VA114**

VA114 forms part of the uniform environment. The uniform environment is a software toolbox that allows shifting model files between several tools for different types of analysis.

VA114 is a calculation engine dedicated to assess the annual heating and cooling demand and the thermal behavior of building. The model is based on standard heat and mass transport equations.

Different climate files can be simulated. However, the most common one is the climate file for the reference year "De Bilt 64/65". Current research conducted [27] addresses the integration of climate change scenarios. Based on the existing traditional reference year "De Bilt 64/65", NEN 5060:2008 released a new norm that introduces four new climate files for different types of climate adjustments.

- **Energy Express**

Energy Express is a design tool and it has two versions: for Architects and for Engineers. The former provides graphical geometry input and editing, several reports viewing, comparison of alternative designs and results and simplified HVAC model, while the latter estimates the energy consumption as Ener-Win and generate thermal plant layouts.

It has been extensively involved in the design process for evaluating energy consumption and cost at the early-stages because it has a user-friendly interface that allows fast and accurate model creation and customization [23].

- **Energy Plus**

Energy Plus is one of the most important simulation tool. It is an engine with input and output text file. Different user-friendly software, such as Design Builder, use it as a system simulation module. It has been developed based on BLAST and DOE 2.1 capabilities. It can run simulation for sizing heating and cooling system and plant and electrical power response. Its simulations are based on a user-specified time-step (at least 15 minutes) and they generate more accurate predicted space temperature, realistic system controls, moisture problems and air flow between different zones [23].

- **ESP-r**

ESP is a tool where the users can regulate the complexity of the geometric, environmental control and operations to match the requirements of particular projects. It simulates different aspects of the building, such as thermal comfort, inter-zone air flow, HVAC systems and electrical power flow [23].

- **Hourly Analysis Program (HAP)**

HAP is suitable tool for a wide range of new design and retrofit applications and it is composed by two packages- The first one sizes commercial HVAC systems while the second one provides an hourly energy performance to calculate the total annual energy use and its relative costs.

The developers have coded HAP for helping the engineers to reach efficient results in a short-time period. In fact, HAP provides them an estimation of loads, a preliminary design of systems and a report about the energy performance [23].

- **HEED**

The main goal of HEED is to mix a single-zone simulation engine with a user-friendly interface. Usually, it is involved in the design stage at the very beginning of the process.

HEED requires four building inputs: type, location, floor area and number of stories. Thanks to those data, an advanced system uses them to design two base case buildings: scheme 1 meets California's Title 24 Energy Code, and a scheme 2 which is 30% more energy efficient. HEED automatically manages up to 9 schemes for up to 25 different projects.

One of the main HEED behaviors is the computational speed and the ability to quickly compare multiple design options [23].

- **IDA Indoor Climate and Energy (IDA ICE)**

IDA ICE is based on a general simulation platform for modular systems, i.e., the IDA simulation environment. IDA ICE offers separated but integrated user interfaces to different user categories: 1) the Wizard interfaces, which lead the user through the steps of building a model for a specific type of study; 2) the Standard interface, for users to formulate a simulation model using domain specific concepts and objects, such as zones, radiators and windows; 3) Advanced level interface, where the user is able to custom the mathematical model of the system [23].

- **IES (Virtual Environment)**

IES is an integrated tool and it is composed by different modules. The main goal of the program is to provide an environment for the detailed evaluation of building and system designs, allowing them to be optimized in terms of comfort criteria and energy consumption [23].

- **PowerDomus**

PowerDomus is a whole-building simulation tool for analysis of both thermal comfort and energy use. It provides to the users several reports about the zone temperature and relative humidity, the Predicted Mean Vote (PMV) and the Percentage of Person Dissatisfied (PPD), thermal loads statistics, temperature and moisture content [23].

- **SUNREL**

SUNREL is an hourly building energy simulation program. Usually, it is used for designing small energy-efficient buildings where the loads are mostly affected by the dynamic interactions between the building's envelope, occupant behaviors and location [23].

- **TAS Version 9.0.7.**

TAS was a commercial software during the past twenty years in UK and around the world. It is a suite of packages, which perform a building dynamic thermal simulation and a system simulation. This tool combines dynamic thermal simulation of the building structure with natural ventilation calculations, which include advanced control functions on aperture opening and the ability to simulate complex mixed mode systems. The software has heating and cooling plant sizing procedures, which include optimum start [23].

- **TRANCE 700**

This tool has been developed based on four different calculation phases: Design, System, Equipment, and Economics. During the Design phase the program first calculates building heat gains for conduction through building surfaces as well as heat gains from people, lights, and appliances and impact of ventilation and infiltration. Finally, the program sizes all coils and air handlers based on these maximum loads.

During the System phase, the dynamic response of the building is simulated for an 8,760-h (or reduced) year by combining room load profiles with the characteristics of the selected airside system to predict the load imposed on the equipment. Later then, the Equipment phase uses the hourly coil loads from the System phase to determine how the cooling, heating, and air moving equipment will consume energy. Finally, the Economic phase combines economic input supplied by the user with the energy usage from the Equipment phase to calculate each alternative's utility cost, installed cost, maintenance cost and life cycle cost [23].

- **TRNSYS**

TRNSYS is a transient system simulation program with a modular structure that implements a component-based approach. TRNSYS components may be as simple as a pump or pipe, or as complex as a multi-zone building model.

The TRNSYS simulation engine uses algebraic and differential equations that represent the whole energy system to run the dynamic simulations. The modular nature of TRNSYS facilitates the addition of new mathematical models to the program [23].

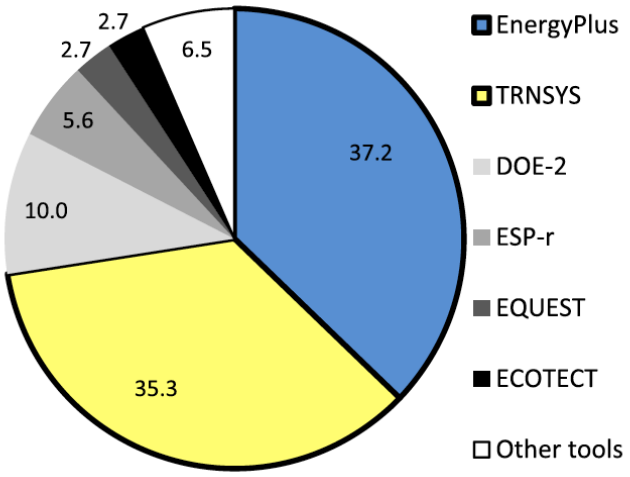

Figure 1: Utilization share of major simulation programs in building optimization research.

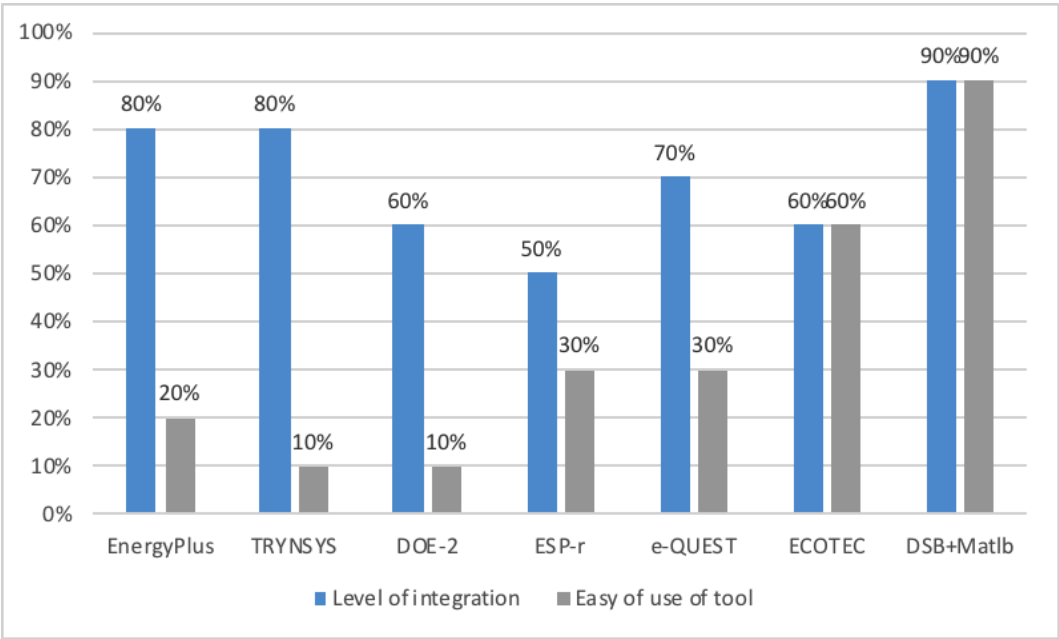

Table 1: Level of integration and complexity of common performance simulation tools during the design phases.

Building Simulation Tools
Building loads Analysis and System Thermodynamics(BLAST) Energy-10 BSim Designer's simulation toolkits (DeST) ECOTEC DOE 2.1 e-QUEST Ener-Win EnergyExpress Energy Plus ESP-r Hourly Analysis Program (HAP) HEED IDA Indoor Climate and Energy (IDA ICE) IES(Virtual Environment) PowerDomus SUNREL TAS TRANCE TRNSYS
Building Simulation Plug-in and On-line tool
MIT Design Advisor Building Design Advisor (BDA) SEMPER VA114

Table 2: Building performance simulation tools available.

	BLAST	Energy -10	Bsim	DeST	ECOTECT	DOE -2.1E	Ener -Win	Energy Express	ESP-r	HAP	HEED
Zone loads, Building Envelope, Daylight and Solar											
Interior Surface Convection											
Dependent on temperature	×		×						×		×
User-defined coefficients (constants, equations or correlations)			×	×	×	×			E		×
Internal thermal mass	×	×	×	×	×	×	×	×	×		×
Automatic design day calculation for sizing											
Dry bulb temperature	×	×	×	×	×	×	×	×		×	×
Dew point temperature or relative humidity				×		×	×	×		×	×
User-specified steady-state, steady-periodic or fully dynamic design conditions			×							×	×
Outside surface convection algorithm	×	×		×		×	×		×		×
Inside radiation view factors			×	×					×		
Radiation-to-air component separate from detailed convection (exterior)			×	×					×		
Solar gain and daylighting calculations account for inter-reflections from external building components and other buildings			P		×				×		

	BLAST	Energy -10	Bsim	DeST	ECOTECT	DOE -2.1E	Ener -Win	Energy xpress	ESP-r	HAP	HEED
Infiltration, ventilation, rom air and multi-zone airflow											
Single zone infiltration	×	×	×	×	×	×	×	×	×	×	×
Natural ventilation			×	P					×		
Multi-zone airflow			×	P					×		
Control window opening based on zone or external conditions				×			×		×		
Mix of flow networks and CFD domains				×					E		

Table 3: Summary of the works that focused on the intelligent control of energy and comfort managen

	BLAST	Energy -10	Bsim	DeST	ECOTECT	DOE -2.1E	Ener -Win	Energy xpress	ESP-r	HAP	HEED
HVAC systems/components and renewable energy systems											
Renewable Energy Systems	×	×	×	×	×	×	×	×	×	×	×
Idealized HVAC systems	×			×	×		×		×		
User-configurable HVAC systems			×	×					×	×	×

Table 4: HVAC systems/components.

	BLAST	Energy -10	Bsim	DeST	ECOTECT	DOE -2.1E	Ener -Win	Energy Express	ESP-r	HAP	HEED
Economic evaluation											
Simple energy and demand charges		×	×	×	×	×	×	×	×	×	×
Complex energy tariffs			×	×		×	×	×		×	×
Scheduled variation in all rate components			×	×		×				×	×
User selectable billing dates						×				×	

Table 5: Economic evaluation.

3. CALIBRATION AND VALIDATION APPROACH OF DYNAMIC BUILDING SIMULATION MODEL

3.1 Introduction

Nowadays, current government policies have introduced, in US and EU, sustainability guidelines, including construction of sustainable buildings and renovation of older ones. Their major aim is focused on the reduction of energy consumption and, at the same time, the improvement of indoor thermal comfort. For example, the Energy Independence and Security Act of 2007 requires that all new commercial buildings have a zero-net-energy balance by 2025 and that all buildings do so by 2050 [28].

In order to achieve high and ambitious sustainability goals, the building design process has been recently subjected to changes that involve the building performance simulation (BPS). It plays an important role for designing and renovating buildings that comply with these requirements because it provide the guidance to virtually test several design strategies.

On the other hand, BPS has to face an issue about the real building performance. Because, most of the time, buildings do not perform as well as forecasted [29]. In fact, different studies [29, 30] have shown high disagreement between simulated and actual building performance. For this reason, research about building performance simulation have been grown in interest and importance, especially, in real-monitoring and operation diagnostic field. To understand the disagreement between simulated and measured data and reduce the discrepancies, a calibration and validation methodology is needed to highlight these differences and to help and improve design BPS models.

Additionally, the feedback loop between design, goals, decision, assumptions made, and operation is rarely closed, prolonging inefficient practices and slowing the pace of performance improvement and adoption of appropriate innovations.

In addition, building models are complex and composed by a large number of input data. In fact, each building has a specific number of floors, which contain a number of

spaces, HVAC (heating, ventilation and air conditioning) systems, several thermal loads, different materials and occupancy habits. The designer and stakeholders need to take into account all those input data to run simulation that reach the real building performance and provide an optimal strategy to decrease energy consumption and increase indoor thermal comfort. Usually, this type of approach is driven by assumptions that have a direct impact on the simulation results. So, for this reason, the accuracy related to the ability of the users to input the parameters (input data) plays an important role.

This chapter aims to show a picture of the state of art of calibration methodologies in order to reach the building performance assessments. Several studies related to calibration have been carried out to show standard criteria for calibrating and validating a model. [31-36]

Calibration of BPS models is usually related to the building project and system levels planned at the early design-stages. For reaching a predefined statistical characteristic (e.g., 5% error margin), the calibration approach could involve an important shortcoming of these methods: the final calibrated model may include compensation errors at the building level [15]. For example, an oversized pump may compensate for the error caused by an undersized fan. It means that significant differences between the building model and the measured data may be hidden at the building level and can only be understood and found if more details are added at the component level. Sun and Reddy [37] show in their research that the problem, in calibrating models, is highly underdetermined and brings to a non-unique solution due to the large amount of input variables compared to collected data [38]. So, with the availability of more affordable measured data, the number of missing data points can be reduced.

Calibrated simulation is often related on a top-down approach, which involve the compensation error issue. Limitation about the collection of actual and simulated data present challenges that make comparing the data difficult. One of the most issue is that both collected and forecasted data are only representations of the real-world building. This constrain affects the accuracy and quality of any comparison. Limitations of simulation tools influence the results and thus impact simulated performance data significantly.

Additionally, these limitations are either embedded in the simulation tool or caused by the particular use of a tool. The knowledge about these limitations is pivotal for studying and analyzing simulated performance data.

As previously explained, the measurement and simulation limitations involve assumptions, approximations, and simplifications. They provide to the designer and the building physics engineer a background that is needed to understand differences between measured and simulated data.

In the literature, there are several researches [29, 39, 40] that have introduced assumptions to justify and describe discrepancies between actual and predicted data on a project-specific basis. An example of a measurement assumption is the use of spot measurements that are representative of the actual quantity [41]. With knowledge of these measurement assumptions and simulation, it is possible to assess differences and explain whether a difference is plausible because of the assumptions or whether it is a symptom of a performance problem.

The remainder of this chapter is organized as follows. Section 3.2 provides criteria about calibration and validation of a building performance simulation model. Section 3.3 presents an overview a literature review of the main calibration approaches used, while Section 3.4 shows the methodologies followed to develop a calibrated model.

Finally, Section 3.5 and Section 3.6 explain the pivotal role of the building performance simulation in the early and late design stages the decision model and the optimization algorithms.

3.2 Criteria for the Model Goodness-of-fit

The statistical indices are the basic criteria involved in the evaluation of calibration accuracy and whether or not a model should be considered calibrated. These criteria determine how well simulated energy consumption matches the measured utility data at the selected time interval. They do not constitute a methodology for calibrating buildings models, but rather a measure of the goodness-of-fit of the building energy model.

The statistical indices have become the international reference criteria for the validation of calibrated models.

They are recommended by the following bodies:

- American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE)

Guidelines 14 [42];

- International Performance Measurements and Verification protocol (IPMVP) [43];
- M&V guidelines for FEMP [44].

During calibration two main sets of data are needed: the simulation data set, from the building model created, and the metered data set, from the real building monitoring. The building model data set is composed of large quantity of data, among which, the most influencing parameters have to be selected in order to find a matching between simulated and measured energy consumption. Commonly the Mean Bias Error (MBE) and the Coefficient of variation of the Root Mean Square Error (Cv(RMSE)) are the two statistical indices used. The consideration of both indices allows preventing any calibration error due to errors compensation [29]. MBE measures how closely simulated data corresponds to monitored data. It is an overall measure of how biased the data are. MBE is calculated, as reported in Equation (1), as the total sum of the difference between measured and simulated energy consumption at the calculation time intervals (e.g., month) of the considered period. The difference is then divided by the sum of the measured energy consumption.

$$\text{MBE (\%)} = \frac{\sum_{P} (M - S)}{\sum_{P} M} \times 100\% \qquad (1)$$

Where:

- M is the measured energy data point during the time interval;

- S is the simulated energy data point during the same time interval.

Due to a compensation effect (positive and negative values contribute to reduce MBE final value), MBE usually is not a “stand-alone” index, but it is assessed together with the Cv(RMSE). The Root Mean Squared Error (RMSE) is a measure of the sample deviation of the differences between the measured values and the values predicted by the model. The Cv(RMSE) is the Coefficient of Variation of RMSE and is calculated as the RMSD normalized to the mean of the observed values. Cv(RMSE) is either a normalized measure of the variability between m[45]easured and simulated data and a measure of the goodness-of-fit of the model. It specifies the overall uncertainty in the prediction of the building energy consumption, reflecting the errors size and the amount of scatter. It is always positive. Lower Cv(RMSE) values bring to better calibration. It is calculated as follows in Equations (2)– (4):

$$\text{Cv(RMSE)} = \frac{R\text{[illegible]}Poe}{\text{[illegible]}Poe} \text{x } 100 \qquad (2)$$

$$\text{RMSE}_{\text{Period}} = \sqrt[2]{\frac{\sum(\text{[illegible]} - \text{[illegible]})^2}{\text{[illegible]}}} \qquad (3)$$

$$A_{\text{period}} = \frac{\sum P\text{[illegible]}Poe\text{[illegible]}}{\text{[illegible]}} \qquad (4)$$

where $N_{Interval}$ is the number of time intervals considered for the monitored period.

In addition, Reddy et al. [6] have proposed an aggregated index that considers all three main types of the building energy uses (electricity in kWh, demand in kW, gas use in m^3). It is a weighted mean of MBE and Cv that takes into account the weight of each energy quantity on the total annual energy cost. In order to consider a model calibrated, a threshold limit of the MBE and the Cv(RMSE) must be respected. Depending on the time interval for the calibration (monthly or hourly) and in compliance with the requirements of the Standard/Protocol considered, the limit threshold is subjected to slight differences, as reported in Table 6.

	Monthly Calibration			Hourly Calibration		
	ASHRAE 14	**IPMVP**	**FEMP**	**ASHRAE 14**	**IPMVP**	**FEMP**
MBE [%]	±5	±20	±5	±10	±5	±10
Cv(RMSE)[%]	15	-	15	30	20	30

Table 6 Threshold limits of statistical criteria for calibration.

If a model is calibrated in compliance with these limits, "it is sufficiently close to the physical reality that it is intended to simulate" [36]. However, these thresholds represent a first guidance for the building calibration and should not be taken as definite values. The presented statistical indices are related only to the predicted building energy consumption. The compliance with the thresholds can also be achieved with different models, as the solution is not unique and may not guarantee that all the model input data are correctly tuned. As stated before, calibration is an underdetermined problem.

Moreover, it is important to note that this validation approach does not take into account uncertainties in the model and takes no notice of other influent parameters, such as indoor condition, temperature trend and occupancy.

3.3 Typical Calibration Issues

Disagreement between simulated and metered data energy consumption and thermal comfort represent a common issue in building simulation.

The metric used to assess thermal comfort is the so-called predicted mean vote (PMV), based on Fanger's model. PMV is representative of what a large population would think of a thermal environment, and is used to assess thermal comfort in standards such as ISO 7730 [46] and ASHRAE 55 [45]. The PMV model predicts the thermal sensation as function of **activity**, **clothing** and four classical thermal behaviors: **air temperature**, **mean radiant temperature**, **air velocity** and **relative humidity.** Its major benefit is that is a flexible tool that includes all the major variables influencing thermal sensation.

The PMV index predicts the mean response of a large group of people according to the ASHRAE thermal sensation scale [45].

$$PMV = 3{,}155\ [0{,}303\ e^{-0{,}114 M} + 0{,}028]\ L \qquad (5)$$

Where L is a thermal load on the body, defined as the difference between internal heat production and heat loss to the actual environment for a person hypothetically kept at comfort values of t_{sk} and E_{rsw} at the actual activity level. PMV ranges from -3 (too cold) to +3 (too warm).

After estimating the PMV with the Equation (1), the Predicted Percent Dissatisfied (PPD) with a condition can, also, be estimated. In fact, Fanger [46], in his research, related the PPD to the PMV as follows:

$$PPD = 100 - 95\ e^{-(0{,}03353\ PMV^4 + 0{,}2179\ PMV^2)} \qquad (6)$$

PMV value of zero is expected to provide the lowest percentage of dissatisfied people (PPD) among a population [47].

Fanger explained in his study that the variation of PPD as function of PMV can be approximated by an analytic expression that corresponds to a curve whose appearance is similar to an inverted Gaussian distribution.

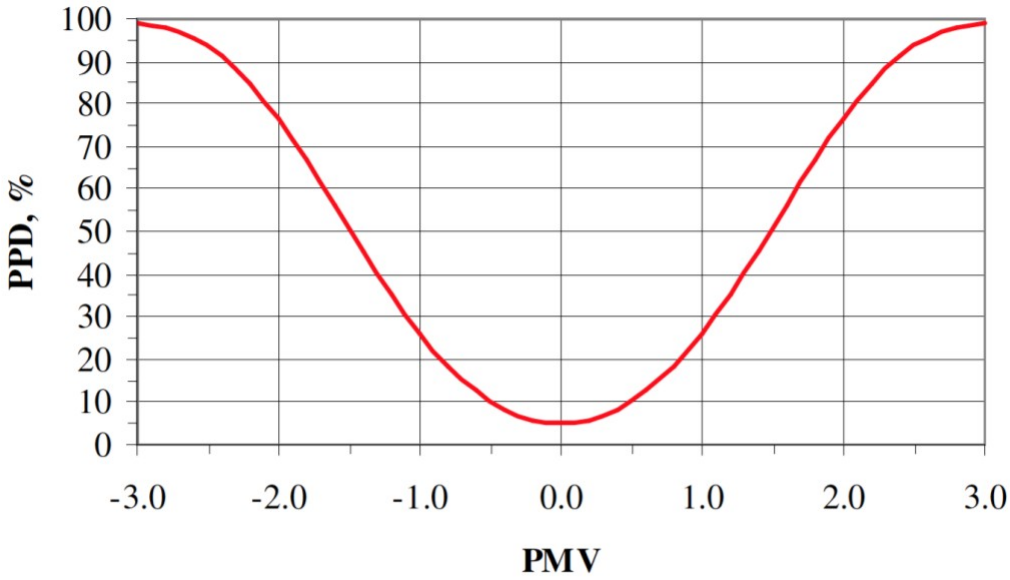

Figure 2: Predicted percentage dissatisfied (PPD) as a function of predicted mean vote (PMV).

A PPD of 10% corresponds to the PMV range of ±0,50, and even with PMV=0, about 5% of the people are dissatisfied.

In BPS, the discrepancies depend on the large number of parameters involved in the model and on the ability of the user to make some assumptions regard input data.

Usually, the "trial and error" approach is used to calibrate a building model. This technique may be a time-consuming method, because it is driven by assumptions that may bring inexperienced users to unfeasible solutions. In fact, as explained previously, the assumptions affect directly the simulation outputs. Moreover, the process of modeling becomes more difficult during calibration. Consequently, in order to control the model complexity, the customizing process of the model parameters needs experts' knowledge.

At the beginning, it is pivotal understand the level of calibration to work on and, to verify if the measured data are acceptable for performing the calibration. For this reason, in order to compare predicted building performance with actual performance, temperature and relative humidity data, utility bills, questionnaires about occupancy behaviors and As-built drawings are necessary. The collecting period of them should be minimum one-year-long. In fact, the type of data and the collecting period are important requirements for calibrating a model trough measurements and history data in order to generate feasible results.

Moreover, based on input data available, several levels of calibration can be listed [38], as shown in Table 6.

According to Fabrizio et al. [29], Level 1 represents a preliminary calibration founded on incomplete information such as utility bills and As-built data. In the next step, level 2, site visits or inspections allow checking as-built data and collect more information. In Level 3, which is based on detailed audit of the specific building, on-spot measurement of the building operation, indoor thermal comfort and energy consumption data are collected.

Finally, Level 4 and 5 are based on short-term and long-term monitoring and they are the most detailed levels of calibration.

The calibration process presents high difficulties and it is usually based on the users' experience. Many problems can be faced when dealing with calibration. In literature, there are several researches [30, 31, 38, 43, 44, 48] that study calibration applications focusing on the main issues that characterize them.

The following list, proposed by Coakley et al. [43], shows the main issues affecting calibration:

- **Calibration costs**: The modeling process is not an easy step, even for building simulation that does not need calibration. Calibrated models are more complicated and, for this reason, they need higher costs than "uncalibrated" models. If the calibration is not automated, it is, even, as highly time-consuming. Moreover, time and expenses to record sub-metered data affect the total calibration cost.
- **Model input data.** the building model process involves a large amount of input data. However, the quantity may vary depending on the level of model details and on the data availability Measured data are sometime used for providing the model with further information, such as building occupancy and temperature, during validation of the calibrated model based on statistical indices.
- **Standardization.** Statistical criteria are used for understanding whether or not a building model can be considered calibrated. On the other hand, they do not reveal an approach that shows how calibrating a building model.
- **Model complexity.** It depends on two main aspects: the type of model designed and its complexity, the number of input data. Usually, steady-state and

quasi-steady models are simpler than dynamic model. The degree of simplification of the building model concerns directly the input data, as the more complex the models is, the larger amount of input data is required.

- **Automation.** So far, no approved automated methodology for calibration has been used. Nowadays, they introduction of automated methodology have decreased expenses and also attempted to wider the knowledge of calibration to other professionals.
- **User's experience.** Another issue is the user's experience. Reddy et al. [48] claims that "calibration is highly dependent on the personal judgment of the analyst doing the calibration". Even with automated process, users are still responsible of CS and a more than basic knowledge of the building simulation domain is required for applying the procedure.
- **Uncertainty in building models.** When manual calibration is performed, a deterministic approach is usually adopted. However as not all input data affect the investigated building performance in the same ways. So, for this reason, it is pivotal the identification of parameters that influence the most the building model and define their level of uncertainty.
- **Discrepancies identification.** Issues concerning the reason of discrepancies between simulated data and measured ones is often encountered during calibration. Experienced users should understand the underlying causes of the mismatch due to their building simulation skills and knowledge. These disagreements may be linked to several reasons or errors in building model definition or also to measurements mistakes.

3.4 Calibration Methodologies for Building Simulation Problems

In literature, there are three main categories of calibration approach, as proposed by Clark [39] and revised also by Reddy [36]:

1. Manual iterative calibration;
2. Graphical-based calibration and analytical methods;
3. Automated methods.

These approaches are not exclusive and different method can be coupled during the same calibration process.

- **Manual Calibration Methods**

This first type of calibration methods is usually involved in the analysis process without a systematic way or an automated procedure. It includes "trial and error approach", which are performed by an iterative manual adjustment. In fact, many stakeholders use this way to tune the input parameters related to the building model based on their experience and judgment.

An important research about the manual iterative calibration is the one developed by Pan et al. [32] The main aim of the study is the calibration of a commercial building placed in Shanghai by an e-Quest model. The author made some assumptions and simplifications about the building geometry for saving simulation time. The model was developed in four major steps:

- Collecting 2004 weather data for Shanghai and replacing TMY weather data with them;
- Defining HVAC schedules according to site survey;
- Defining indoor loads based on site investigations;
- Tuning infiltration rate thanks to on-site observations.

The calibration conducted by Pan is completely heuristic without any logical or systematic procedure and it does not achieve common calibration standards, even if some conclusions regarding the discrepancies are proposed in the paper.

Moreover, Pedrin et al. [49] introduce a general calibration approach based on three main steps:

- Running simulation from building documentation;
- Test-auditing:
- Collecting end-use energy measurements.

The proposed methodology is used for calibrating DOE2.1 model to several case studies but it is very general and is not as systematic as it could be.

Additionally, Westphal et al. [50] presents a calibration method closed to the research developed by Pedrini et al. [49]. This approach involves EnergyPlus software with the audit techniques and sensitivity analysis. It combines a simple sensitivity analysis with the calibration process. Moreover, numerous hypotheses are needed at the beginning of the calibration process and make the methodology not easily reproducible.

Finally, Raftery et al. [51] designed a calibration methodology for improving and optimizing the operation of the HVAC using a "key factors" methodology [52]. The developed approach is intended to be used with the EnergyPlus software with three fundamental principles:

- Using of a detailed building simulation model;
- Reproducibility and Repeatability;
- Collecting utilities measurements.

From the conducted literature review, it is possible to understand that manual calibration corresponds thus to subjective and ad-hoc approaches.

- **Graphical Techniques and Statistical Methods**

Innovative methods have been also employed, apart the manual calibration technique, based on graphical representations and comparative displays of the simulation outputs. They can be listed in two main categories:

- 3D comparative plots;
- Calibration and Characteristic signature.

The first approach has been introduced to determinate the hourly discrepancies, during a specific simulation time, between forecasted and actual data. The 3D comparative plot takes into account the time-dependent inputs. Moreover, this type of display has also been coupled with statistical index for evaluating the goodness-of-fit of the building model.

Haberl [40], in his research, explain a novel calibration method including comparative analysis on different timescales and statistical indices, such as MBE and CV(RMSE). This methodology was introduced to calibrate a building designed with the DOE2 tool and placed in Washington.

In addition to time-series plots and scatter plots, the authors involved the using 3D surface plots and statistical indices for providing a whole view about discrepancies between measured and computed hourly values for understanding seasonal or daily patterns.

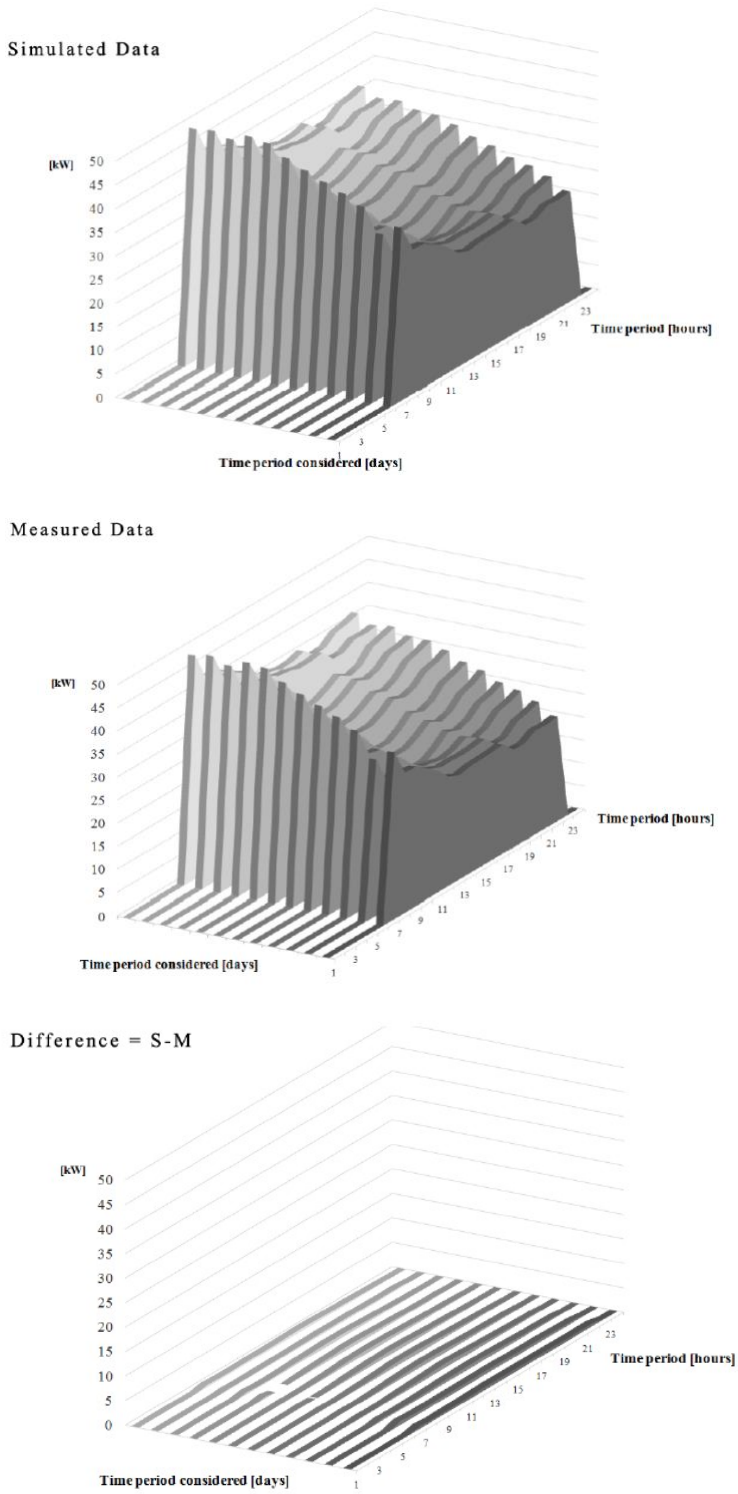

Figure 3: Example of comparative plot [29].

Moreover, another research by McCray et al. [53] proposes another graphical method to calibrate a DOE2.1 model to an entire year of hourly or 15 minute metered whole-building energy use: Visual Data Analysis (VDA) approach. It allows coupled the results and tuning parameters of the model during a calibration process. Even in this case, the criteria of accuracy is based on classical statistical indices (MBE and CV(RMSE)).

The graphical methods proposed by Haberl [40] and McCray et al. [53] suit well with the calibration of simulation models to hourly measured data. With only whole-building monthly data, these advanced graphical methods are of less help and a very systematic and logical calibration method has to be applied to limit the number of simulation runs and make the calibration process efficient.

Their approach is based on designing a DOE2.1 model to an entire year of hourly collected building energy use. The Visual Data Analysis (VDA) method allows quickly comparing the results and reviewing the parameters of the model during a calibration process. Once again, the accuracy is based on statistical indices, such as MBE and CV(RMSE).

Another important calibration method is the "signature method". It was introduced by Wei et al. [54]. The author found that calculating, normalizing and plotting the difference between measured and predicted heating and cooling consumptions as function of the outdoor temperature was useful to help in calibrating building simulation models.

$$\text{Residual} = S - M$$

$$\text{Calibration signature } = \frac{R\text{\textcircled{}}sPeu\text{\textcircled{}}\text{\textcircled{}}}{\text{\textcircled{}}m\text{\textcircled{}}xPmum} x\ 100\%$$

In each point of the temperature, the discrepancies between measured and simulated values, divided by the

maximum measured value and multiplied by 100%, is plotted and compared to the temperature for drawing the signature path.

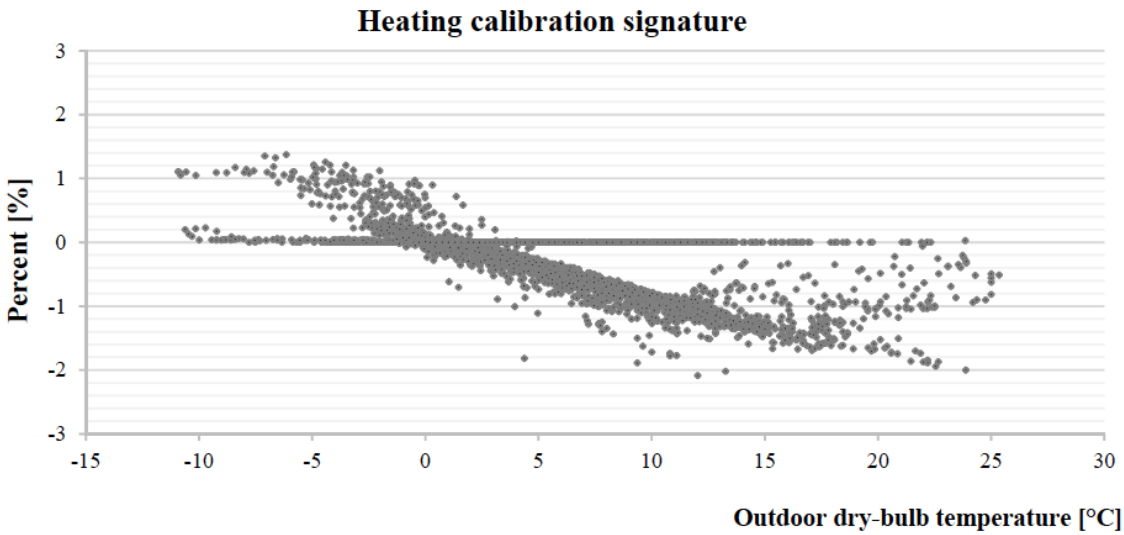

Figure 4: Example of calibration signature.

Another signature should be defined for comparing values from two distinguished simulations, instead of values from measured and simulated data. The characteristic signature should be taken as reference or baseline for the measured values. Characteristic signatures are generally calculated based on a daily average basis and are denoted by a characteristic shape due to the climate and the system type considered.

$$\text{Characteristic signature} = \frac{\text{Power consumption}}{\text{Maximum Power}} \times 100\%$$

When assessing both characteristic and calibration signatures, the differences between the two curves help users detect errors in the simulation inputs for calibrating the model. It is thus possible to study the effect of the input parameters variation in the building models looking at the calculated signature.

Liu et al. [55] used the signature approach to calibrate simplified building and AHU energy consumption models. The model designed is based on two-zone (interior –exterior) building model with AHU model. The two-level calibration method focuses on the weather dependence of the model (1 st level) and on the time schedule dependency (2 nd level) and uses measured hourly values of heating and cooling energy consumptions. So, "characteristic signatures" can be generated and plotted for different systems and climates

by varying important parameters one-at-a-time and plot the % of variation as function of the outdoor temperature.

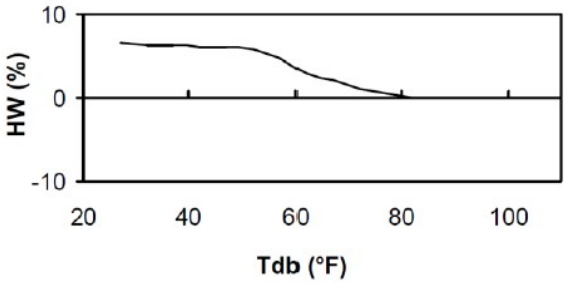

Figure 5: Example of heating calibration signature. Liu [56]

Then, the comparison of the "calibration signature" to this "characteristic signature" can help in performing the calibration of the model.

The method is easy to follow and generalize but is actually based on data currently not available (hourly or daily hot water and chilled water consumptions).

Unfortunately, the authors recognize that this signature method cannot be transposed to more common cases where only whole-building monthly consumption data are available [57]. In his research, Liu mentions the integration of sensitivity issues as a possible improvement for the method.

Heo [58] proposes an interesting Bayesian approach to calibrate a simple normative simulation model based on CEN standards. This is a statistical method that employs probability theory to compute a posterior distribution for unknown parameters given by observed data. It is used for calibration purposes for incorporating directly uncertainties in the process [10, 59]. Traditionally, the Bayesian technique was used for the model predictions in other domains (such as geochemistry [60] or geology [61, 62] rather than in building physics simulation). However, recently different studies [63-65], have focused on the application of this technique to the building simulation domain. Based on the Bayesian theory [66], a set of values of the uncertain parameters θ of the energy model is formulated in order to find a matching between the simulation outcomes and the measured data y. Three different sources of uncertainty are investigated: parameter uncertainty in the energy model; discrepancy $\delta(x)$ between the energy model and the real building behavior; observation error $\varepsilon(x)$.

- **Automated Calibration Methods**

The automated calibration methods include all the techniques that cannot be considered user driven and are built on sort of automated procedures.

Carroll and Hitchcock [67] show, in their research, the development of automatic calibration methods for the retrofit energy saving estimation model tool based on the ASHRAE modified bin method [68]. The aim of the calibration is minimizing an objective function designed as a weighted sum of the difference between computed and recorded data. In the algorithm, input parameters are ranked in "high-level" and "low-level". At the beginning, the stakeholder is allowed to choose and tune the "high-level" characteristic suspected to be the reason of the differences and, consequently, the developed algorithm costumes the "low-level" parameters linked to the high-level input. The authors suggest to start the calibration process selecting the most influential parameters thanks to the users' experience and the sensitivity analysis to for saving simulation-time and minimizing the objective function in a certain amount of time.

Lately, Reddy and Maor [69]have developed a calibration method funded on the same approach as the one proposed by Carroll and Hitchcock [67] but, in this case, the authors involved the hourly simulation tool (DOE2.1), performed monthly calibration simulations and included sensitivity analysis for generating a feasible set of building solutions instead of one hypothetical optimal solution. Because, Reddy and Maor [69] believe that using a small number of possible solutions is more useful than using only one optimal calibration solution to reach some predictable forecasts.

This automated calibration procedure is developed in three steps:

- Defining of a set of influential parameters;
- Using advanced analytical methods such as Monte-Carlo method of optimization algorithms;
- Running simulations.

This partially "black-box" calibration method allows identifying a subset of most plausible solutions to this under-determined problem. But, on the other hand, this method is very complicated to handle due to the multiple steps.

Additionally, Lavigne [70] in his research, has developed a semi-automatic calibration procedure with DOE2.1 software. It requires monthly electricity consumption, electricity

peak demand and real local weather data and uses common engineering rules and optimization algorithms.

Two steps are involved in this calibration process:

- Pre-calibration: requiring the analysis of the available recorded data to extract useful information and identifying critical parameters such as ventilation rate and envelope performance.
- Calibration: involving an optimization method in order to minimize an objective function defined as a sum of differences between measured and computed data.

So, coupling intuitive and analytical approaches for calibrating building simulation models is an attractive solution to the calibration problem and an interesting compromise between black-box methods and full manual iterative processes. But, the main issue related to these methods is that some hypotheses on the available data have to be done and some parameters cannot be changed during the automated calibration in an easy way.

4. THE ROLE OF BUILDING PERFORMANCE SIMULATION TOOLS IN THE DESIGN PROCESS.

4.1 Introduction

The design of buildings is a complex process. To ensure that a building can satisfy the needs of occupants, it is essential that during the design stages, all environmental factors that affect the performance of the building are carefully considered.

To provide a better understanding of the impact of such environmental factors, various methods have been developed to simulate the effects of such elements. The most fundamental approach involves the building of physical scale models and studies their behavior under the various weathering elements. Various tools have also been developed to simulate those kinds of effects.

In fact, the building simulation tools have the capability to predict the usage of various building systems such as air conditioning systems, artificial lighting, sound sources, and so forth and, over the past decade, the design and performance evaluation of buildings has become increasingly complex. One of the main challenge is to understand the interaction between various aspects of building performance and their implications on complex control. For this reason, the pressure for competitive differentiation is leading property developers and designers to include novel and innovative design features in the core design work. Unfortunately, there is considerable uncertainty in assessing the performance of designs if the dynamic and integrated response of the building and its environmental systems is not taken into account.

Nowadays, the main designers' goal is to develop a sustainable design process useful to achieve several aims, in terms of energy efficiency, passive building, and ecologically friendly projects.With the increasing complexity involved in building design and performance evaluation of buildings, the need for the use of BPS to evaluate and introduce support tools throughout the process is recognized. Those kinds of tools allow the building designers to evaluate the impact of design on the various performance.

Moreover, they are able to replace expensive and time-consuming field tests and provide a comprehensive range of test conditions. Also, they are especially important for making preliminary evaluation of different complex design strategies.

Throughout the design process, the various aspects of building performance such as comfort, economics, code compliance, energy requirement, environmental impact, esthetics, and so forth must be considered.

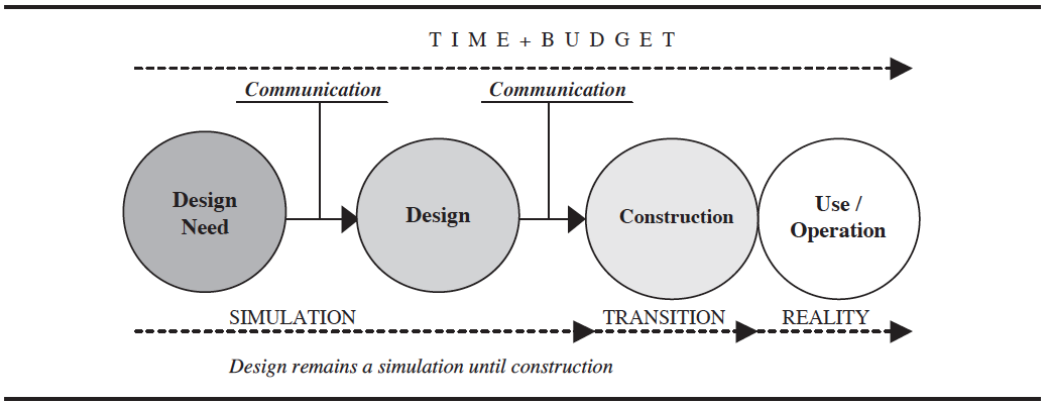

Figure 6: Design simulate reality.

Therefore, as shows in Figure 6, the building design process can be seen as a dynamic process of generating ideas that involve specific strategies and technologies and then estimating and evaluating their performance related to several considerations within the specific design context. To estimate the performance of building designs, designers need to simulate the operation of the building using various types of modeling techniques.

The performance evaluation process requires the comparison of multiple alternative design schemes as well as the performance of existing buildings. This is because the current simulation tools are mostly developed based on one single aspect of building performance, although such tools can facilitate the evaluation process by the provision of appropriate user interface that generates graphical representation of the output data and allows direct comparison of multiple solutions with respect to multiple performance consideration.

4.2 Design problem, process and support tool

The design process can be considered as a vehicle to move from a design problem to a design solution that meets the stakeholders' needs. The ability of the design solution to fulfill the stakeholders' needs defines the value of the design to the stakeholders. Those require a specific functionality of the integrated building concept. However, design problem characteristics necessitate a number of design solutions to be synthesized and evaluated. To be able to successfully use a BPS-tool to evaluate design alternatives, it desires to be able to represent the elements used to summarize design options in design practice.

4.3 Building design phases

A sustainable design needs an integrated design process and a more involved approach than a conventional design process. Ensuring the high quality of design is to ensure an approach based on building performance, an integrated and interdisciplinary project team-working through an integrated planning and preparing a project to its best performance.

Thus, the design process is crucial because most decisions that will determine building performance in use will be made at this stage. Normally, a building project is developed by a sequence of phases. The concept of design phases is related to a set of consecutive actions that guides the development process. These actions are grouped in stages by their level of priority. It is important to consider the value of each action/goal/objective, predicting its importance on buildings performance and its influence on the projects final cost in order to implement each one in the best way.

The project starts with the definition of its objectives and with the moment where the client meets the project team and exposes the goals for the building. During this initial phase, clients and design team share information seeking to develop the building's concept. The architectural programming is required to define key requirements and constraints towards project quality. Type of architecture formal and functional aspects must be discussed as well as indoor and outdoor quality desired by the client. Information of the site must be available and if it is not appropriate for construction, elsewhere should be suggested; subjects as room and building functional, environmental, and spatial

performance, comfort practices, energy requirements, and so forth should be addressed, as well as concerns on building use, heating, cooling, lighting, ventilation, water, waste, site works, and materials. Additionally, it is at this stage that procurement method, project and sustainability procedures, building design life time, maintenance, project cost, and timescale are dealt with. The following project step is the implementation of the earlier defined objectives. At this phase, all clients' interests and design team-members are involved. This initial phase puts into practice the clients' instructions and exposes the project team proposal; decisions at this early stage are of the utmost importance while project is provisional and open to change.

Hence, it is hereby understood as the preliminary design phase of the building, in which the overall system configuration is defined, and schematic drawings and layouts will provide an early project configuration. At this stage, the availability of data is very poor and any assessment has to be based mainly on assumptions. The only information about the building shape is the area of construction and the height of the building. From these elements, all other data need to be estimated. Based on the available input data, the following aspects need to be fulfilled in this stage: the selection of the type of the superstructure of the building; a bill of materials for the structure (estimation) and a bill of materials for the envelope.

The next stage of the project begins after the approval of sketch studies; the design team commences the implementation of the working drawings for the construction of the project. At this moment, the general shape of the building is developed through plans, sections, and elevations; the provisional information addressed in earlier phases is confirmed or modified. The actual/chosen solution must be compatible with initial requirements and within the various applicable regulations; the functional relationships between different elements, spaces, and volumes must be examined, as well as the base programming, according to any amendments agreed between the client and the design team.

Type of construction is generally defined and the materials are proposed during meetings with the clients. Aspects like exterior and interior wall finishing, flooring, plumbing fixtures, hardware design, and so forth shall be decided in this stage. Building equipment as types of windows and doors and their manufacturer, the elevator type and manufacturer, the mechanical system, and electrical fixtures are also to be identified in this phase.

This kind of information, when taken together, facilitates an estimate of construction cost. Still, work of every technical specialist must be coordinated; the public authorities must be consulted and initial investigations of comfort and environment should be confirmed. The data available at this stage enables a better definition of the structural system. In this stage, it is expected to have information (drawings) about the plans and elevations of the building. The detail level of the building enables a much more accurate definition of the bill of materials. Based on the available input data, the following aspects need to be fulfilled in this stage: a complete bill of materials for the structure and envelope and the definition of the building orientation.

Figure 7 summarizes the sequence of the phases, moments, and data improvement of a building project.

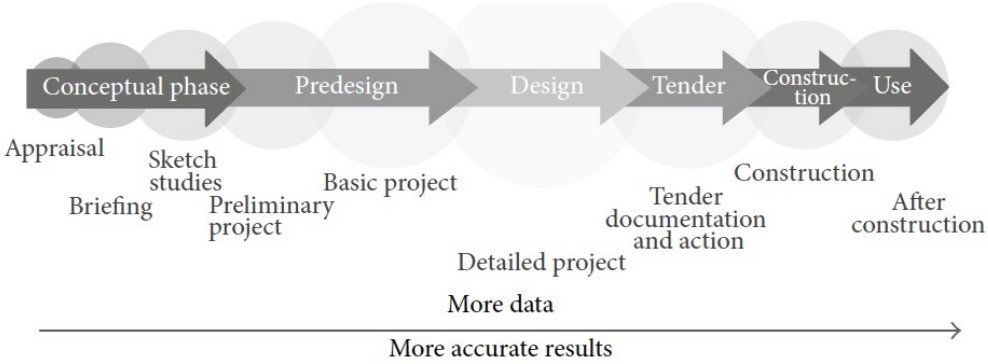

Figure 7: Design stages of a building. [reference 36]

Each phase is characterized by a set of key tasks that lead to gathering information needed and to the development of the building architecture and features. In a conventional design process, these steps can be understood as a linear process, but sequential work routines may be unable to support any adequate design optimization efforts during individual decoupled phases, which of course lead to higher expenditure.

In this approach, the architect and the client agree on a design concept, consisting of a general massing schema, orientation, fenestration, and (usually) the general exterior appearance, in addition to basic materials. The structural, building physics, mechanical, and electrical engineers are then asked to implement the design and to suggest appropriate systems. Although this is vastly oversimplified, this kind of process is the one that is followed by the overwhelming majority of general purpose design firm.

On the other hand, a sustainable design needs an integrated design process; it requires the involvement of the whole design team and the iteration between phases. The design team must maintain a high level of communication throughout the design process and must work well together to resolve all issues and concerns on the project. Accordingly, the attitude of the design team is critical and their members must be able to establish a collaborative framework for the project.

4.4 Role of performance evaluation at early design stages

As previously presented, BPS involved computer-based models that reveal performance aspects such as energy consumption and thermal comfort.

On the other hand, BPS is still not usually used in building design stages. Typical design assessment criteria are cost, future flexibility, energy efficiency, environmental impact as well as productivity and occupants' comfort. The goal of design phases is developing a functional building that meets a set of predefined performance criteria. To achieve that goal, it is necessary for the design team members to share information throughout the design process [71]. Within this building design process, a number of design stages can be distinguished that are shown in Figure 8: decision, program of requirements, preliminary design, final or detailed design, and the contract documents and papeprworks.

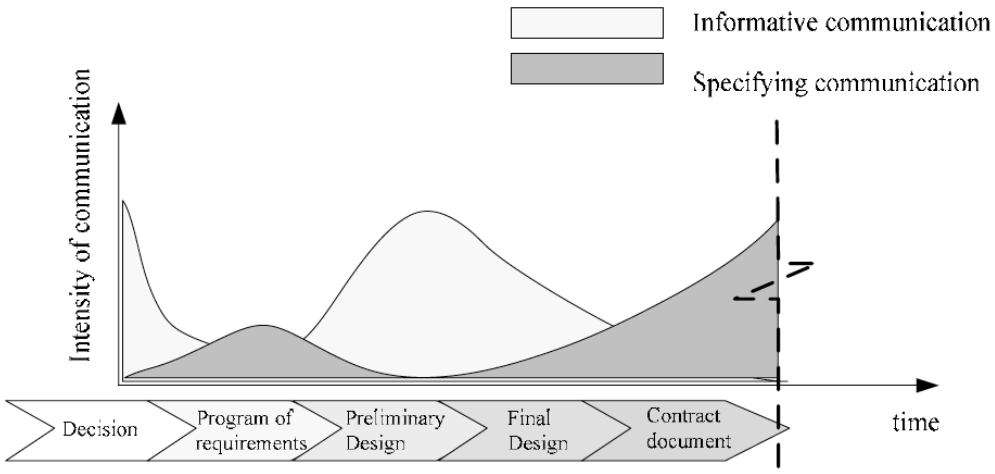

Figure 8: Illustration of the relationship between communication and simulation during the design process [72].

In the program of requirements, the objectives and necessities are defined. In the conceptual or preliminary design stage the main systems are selected and a number of concepts is developed. In the detailed or final design stage the development and integration of design elements to operate design solutions takes place. While, in the last stage, the contract document or the specification, the production of site drawings (As-Built), product specification and construction resource documentation are finalized.

The different experience from stakeholders concerning the design stages is shown in Figure 8. In fact, Stoelinga [72], in his studies, categorizes the communication form during the design process into "informative" and "specifying".

The informative information should answer questions such as "would it work" or "how does it perform" [72]. There is a demand to use BPS for design support in particular for the generation and selection of alternative design concepts during early phases in the design process, where decisions have to be made with limited resources and on the basis of limited knowledge.

While, the specifying communication is more quantitatively as it is considered in the context of specifications in the later design phase. In the final design stage there is a peak of informative communication and another peak value of specifying communication which should be supported by the use of simulation or other tools. In current practice the connection between simulation tools as an evaluation procedure and the design analysis communication is poorly developed. The need for BPS is very strong in the final design stages in order to support the particularizing communication. One means of better connection should be provided by the simulation tools in providing a better insight into the role of uncertainties and unknowns on the evaluation results. BPS tools should therefore provide support to perform uncertainty and sensitivity analyses and communicating them with other design partners leading to informed decision making, and optimization.

For this reason, BPS should be an essential part in the building design process. But, actual applications do not fulfill the needs considering the support of design decision making or the seamless integration of optimization techniques.

The building design process needs to foresee how the detailed specific decisions relate to the resulting performance of the entire building or its functional components [73]. In this respect, long term concerns such as life performance, durability and life cycle costs have a

higher value than short term arguments such as direct costs, construction process for instance [73].

To sum up, a problem in current design assessment is the lack of ability to explicitly deal with the varying expectations, needs, and requirements throughout the design process. Tools and methods for different design stages should address this diversity of needs and enhance the communication required.

In the beginning of the design process less information is available because of many issues are undecided. This leads to many input unknowns when studying and analyzing the potential impact of design alternatives. Under certain constraints these can be interpreted as uncertainties, which will diminish as design evolution proceeds.

However, even in the detailed design the building is not without uncertainty as there is imprecision in the construction process and natural variability in the properties of building components and materials. Many external factors that influence the performance of the building are unpredictable.

For this reason, the combined assessment of the lack of knowledge and the external factors cause the uncertainty in the building performance.

4.5 Role of performance evaluation in late design stages

The information required in the final design stage is more detailed and needs to be treated more accurately. For example, similar options with slight changes in the layout might be compared. The exact specification of the options and the selection of all parameters used are therefore very important. Besides, selecting properties, requires close coordination with the architect or the design engineer [18].

The following list summarizes possible applications in the final design by Olsen and Iversen [18]:

- Applying optimization as support also for decision aid in comparing different schemes, options, and systems.
- Improvement of envelope performance through energy studies determining and optimizing material properties such as insulation or glazing performance via uncertainty/ sensitivity analysis.
- Selection and observation of, e.g., different HVAC systems enabling the overview and comparison of energy use.

According to Olsen and Iversen [18] in the final design are:

- Scheduling uncertainty (time requirement vs. mistakes).
- Consideration of design team cooperation and coordination. Design team members need to be aware of how decisions might affect each other. A model that is affected by several disciplines is going to enlarge this problem.
- Evaluating of different trade-offs through different options. If different performance aspects are considered, it might be that one scenario performs well in one aspect whilst another performs better in another one. Multiple choices with no clear-cut best solution can complicate the decision process.

5. COMPUTATIONAL OPTIMIZATION METHODS FOR BUILDING ENERGY AND COMFORT ANALYSIS: STATE-OF-ART

5.1 Introduction

Buildings consume a significant amount of energy, which is around one-third of the total primary energy resources. This has increased several problems for energy suppliers and concerns over rapid energy resource depletion, rising building service demands, improved comfort life styles along with the increased time spent in buildings; consequently, this has shown a rising energy demand in the close future.

However, contemporary buildings' energy efficiency has been fast tracked solution to cope/limit the rising energy demand of this sector. Building energy efficiency has turned out to be a multi-faceted problem, when provided with the limitation for the satisfaction of the indoor comfort index.

Moreover, the comfort level for occupants and their behavior have a pivotal effect on the energy consumption pattern. It is generally perceived that energy unaware activities can also contribute to one-third to building's energy performance.

Buildings are generally built for human's habitation. Moreover, approx. 90% of people spend most of their time in buildings [74]. Indoor comfort has a significant role and poses a huge impact to preserve inhabitant's health, morale, working efficiency, productivity and satisfaction [75]. There has been an increasing demand by inhabitants for the improvement of indoor environmental comfort, whilst reducing energy consumption and CO2 emissions during the previous decade.

The optimization methods have a main aim, maximizing the occupant's expected comfort index whilst minimizing energy consumption with regard to the energy price variation during the building operation period.

Many researchers have been working with this issue for over a decade, but, yet it remains an important challenge.

In this chapter, a literature review about optimization methods with a specific focus on the Genetic Algorithm is carried out using the search engines, such as web knowledge, IEEE explore digital library, Science Direct library and Google Scholar. The key terms related to this topic include: “energy”, “comfort”, “building simulation” and “optimization”.

The remainder of this chapter is organized as follows. Section 5.2 provides an overview about the computational optimization methods used for the building performance simulation model and validation of a building performance simulation model. Section 5.3 presents an important algorithm, called the Genetic Algorithm, involved in the problem optimization for minimize the energy consumptions and the energy demand and improve, at the same time, the thermal comfort.

Finally, Section 4.4 explains the using of different optimization tools for the BPS.

5.2 Computational Optimization Methods: State-of-Art

Various engineering, research and industry applications involve simulations, certain modeling, data analysis and computational optimizations. These aspects with the limited resources of time and money lead, consequently, to the optimization practice.

Nowadays, engineers and researchers try to optimize systems, whether to minimize cost and energy consumption or alternatively, to maximize output, efficiency, profit and performance. Modeling, computation and search algorithms are the integrated components of an optimization process.

An optimization problem can be formulated in numerous ways; by far most broadly, the formulation of the optimization problem is non-linear as shown below:

$$\text{Minimize} \quad f_i(x) \quad (i=1,2\ldots.M)$$

Subject to the bound constrains:

$$h_j(x) \quad (j=1,2\ldots.J)$$

$$g_k(x) \geq 0 \quad (k=1,2\ldots.K)$$

Whereas f_i, h_i and g_i are usually non-linear function. The design vector $x = (x_1, x_2 \ldots x_n)$ can be discrete, continuous or mixed in an n-dimensional space. The function f_i is the cost or objective function and if M > 1, the optimization would be multi-criteria or multi-objective. Whereas $h_i(x)$ and $g_i(x)$ are equality and inequality constraints. Yet in building applications, optimization studies employ a single objective and constitute almost 60% of the studies; this means that in an optimization run, only one cost function can be optimized. Nevertheless, building energy research deals with conflicting issues for optimization [76, 77], such as the minimum energy consumption vs. the maximum comfort (i.e., thermal, visual, air quality, humidity, plug loads, etc., may include individually or in combination) and vs. the tariff costs, vs. renewable energy trade-offs, etc. Therefore, a multi-objective approach seems more relevant than a single objective. Various methods have been proposed to solve multi-objective problems; however, the scalarization is the simplest over others. In this, each cost function is assigned a weight factor and is simplified through the criteria of the weighted summation [78]. Thus, it transforms the multi-objective into a single objective problem with the help of linear scalarization as depicted in the following equation:

$$\text{Minimize} \quad \sum_{P=1}^{M} \omega_P f_i(x) \quad (i=1,2\ldots.M)$$

Whereas ω_P is the weight factor of the ith objective function ($\omega_P > 0$)

Generally, objective functions are equally significant and probably in conflict. In addition, usually, no single optimal solution is common for all the objectives. Therefore, multi-objective optimization looks for trade-offs, rather than a single solution. Multi-objective optimization includes:

- The search for the Pareto optimality set of non-dominated solutions with negotiations among different objectives;
- The selection and evaluation of the respective solutions based on further information availability, prioritization, cost opportunity and satisfactions.

Although various optimization techniques have been established and reviewed [79, 80] the genetic algorithm (GA) is the most recognized technique in building performance analysis. Dalamagkidis et al. [77] utilized the detached dwelling optimization of 3-phase

GA; whilst Griego et al. [81] employed the GA method for energy and thermal comfort with feedback control including occupant preference. Guillemin et al. [82] employed ANN training and validation, and coupled it with GA for the optimization of thermal comfort and energy consumption. Huang et al. [83] used GA with a contribution ratio of each optimization parameter of energy, thermal and humidity levels; whereas [84] employed GA for fuzzy optimization to balance energy and comfort, which included air quality, illumination and thermal factors.

The multi-objective genetic algorithm (MOGA) has been used with schedule control and discrete predictive models [85-87] for the trade-offs between energy and thermal and illumination comfort conditions. Safdar and DoHyeun [88] utilized the multi- islanded property of GA (MIGA) for energy and the comfort index. The exceptional feature was that the population had been divided into sub-populations and thus genetic operators were independently executed on this sub-population. This depicts quite a slow recovery issue in comparison to GA. However, the energy consumption is quite less or may be equal to the GA technique, NSGA- II, in optimizing energy consumption vs. visual and thermal comforts [89]. Being population-based methods, GAs is well suited to solve multi-objective optimization problems. The performance has been evaluated for three multi-criteria algorithms [89], which were NSGA-II, aNSGA-II and pNSGAII, based on the building optimization and two benchmark test problems. This supported NSGA-II for its high-quality true trade-off solutions with very few evaluations runs and it attained better convergence.

Various other strategies have included the Multi-Objective Particle Swarm Optimization (MOPSO) in optimizing thermal, illumination and air quality comfort and building energy consumption [90-92] and have also provided the opportunity for occupant preferences. Hooke–Jeeves [93, 94] utilized an algorithm for optimal solutions among energy and comfort in low energy buildings. A comparison of the Hooke–Jeeves algorithm with the GA, PSO, Coordinate search algorithm, Hybrid PSO-HJ algorithm, Simplex algorithm of Mead and Nelder, Discrete Armijo gradient algorithm and PSO mesh search for the optimization of energy consumption in buildings has been performed in [95, 96]. It has been found that GA outperformed in all comparisons and as close to the best minimum, consistently; however, the HJ algorithm was trapped at the local minimum. The hybrid HJ-PSO attained the overall best cost decrement though only after a lot of simulation runs.

Consequently, the other algorithms' performances were not satisfactory and were found to be unstable. Further, the implementation of the simplex algorithm and Discrete Armijo gradient algorithm has not been suggested for building optimization problems.

Linear programming optimal solutions ought to occur on the exterior point when each function and constraint is linear [97]. Non-linear programming allows a range of non-linear objective functions and constraints [98, 99]. Differential evolution [100] and hill climbing [101] algorithm values of the variables are perturbed with introducing modules of other solutions to enhance the performance index in the optimization strategy. Whereas evolutionary programming (EP) [102] and genetic programming (GP) [103] provide a hierarchical representation of the variables that have been allowed by the tree-structure. In general, variable values are altered in EP and GP; whereas the tree structure also varies along with the variables. Bellman–Ford's algorithm [104, 105] and optimal search min–max algorithm [78, 84, 106] have been employed for the optimization strategy of the energy and thermal comfort levels utilizing scheduling schemes. In simulated annealing [107], solutions have been perturbed far from their previous positions and retained the probability for better solutions that steadily enhanced with time.

Other strategies for optimization in the literature are the anytime optimization (AO) [108], ordinal optimization (OO) [109], femicon [77, 110] and meta-analysis [111]. It has been generally perceived from these studies that the utilized methods have aimed at making a Pareto optimal representative subset from which an appropriate solution can be driven by the decision-makers of the selected problem.

5.3 Genetic Algorithm in Building Performance Simulation

The Genetic Algorithm is one of the most important algorithms used in the BPS for running the optimization method. Usually, in these cases, the optimization process is based on two variables (multi-objective) which define a good solution of a model χ^2 and CV(RMSE)). According to Golberg [112] describes, there are ‘‘three main types of search methods: calculus-based, enumerative and random”. Pernodet et al. [113] give a brief explanation of each, emphasizing random or stochastic methods. There are different strategies related to random method, with names related to the phenomena used to optimize them. The genetic algorithm is an evolutionary algorithm that operates on a finite set of simulations (population). In each iteration (generation) there is a competition between the different subjects (particular models) of the population, and the algorithm selects the ones that fit best with the objective. It then generates a new population for the next generation with the best subjects and new random ones. In the BPS, the process, usually, starts with the first script which reproduces ‘‘internal climate” before the calibration period (to start with the correct thermal inertia); then starts the free-floating period where the second script performs uncertainty analysis; finally, the results of the uncertainty analysis are exported as outputs. The process continues with the evaluation of these results by the genetic algorithm which, if the range is under the number of generations, creates a new set of parameters to simulate taking into account the results during evaluation. The best ranking of parameters is always updated in each results evaluation. When all generations are performed, the process stops and the best models are stored as calibrated models. During the process bad solutions are removed and optimal ones are saved. There are several studies that use genetic algorithms: Charron and Athienitis [114] optimize the design of low and net zero building using electricity consumption; Wang et al. [115] design a green building with two objectives, life-cycle cost and life-cycle environmental impact; Chantrelle et al. [116] propose different multi-criteria sets of optimizations, with two and three criteria relating to investment, energy consumption and thermal comfort. The particular multi-objective evolutionary algorithm that is usually involved in BPS optimization process is

the NSGA-II (Non-Sorting Genetic Algorithm II); its advantages compared to other algorithms are explained by Deb et al. [117]. The most important is that it uses a non-dominated sorting approach that obtains a better spread of solutions and convergence than other multi-objective evolutionary algorithms (MOEAs) such as the Pareto Archived Evolution Strategy (PAES) and Strength Pareto Evolutionary Algorithm (SPEA).

5.4 Simulation tools for BPS optimization

Due to the diverse complexity and heterogeneity of the control schemes and optimization algorithms in BPS as well as the vigorous interaction and needs of the occupants, cost functions, accuracy and time constant, there should have been a clear strategy for the affordable and easy to use simulation tool. With the development of control systems, researchers have tried to negotiate between the conflicting challenges in buildings. This has let the researchers to have a certain simulation platform to evaluate and analyze control system optimization strategies.

Building simulation programs were traditionally written with imperative languages that are FORTRAN (FORmula TRANslation), which is primarily suited to scientific and numeric computations, and C and C++ [82], which generally facilitate structured programming capabilities. They employ various iterative algorithms including the Runga–Kutta method, Newton Raphson. However, traditional programming languages allow further development in new versions of software for ease of use; these comprise ESP-r, DOE-2 and Energy Plus [118]. A program developer composes a sequence of instructions, which assign values in a predefined order of execution of variables. These platforms typically write amalgamated codes; thus, they determine the physical processes for the resolution of a numerical problem and data management [118].

However, at present there have been some packages, which offer a platform for multi-criteria optimization. The MATLAB optimization toolbox contains the MOGA algorithm, Min–Max, FMINCON, artificial neural network (ANN), fuzzy inference system (FIS) and Simulink toolbox. Fuzzy inference systems with various conventional controllers have been widely employed in SEBs as discussed in the above section. ANNs have also been widely employed for environmental and building performance predictions. ANN prediction models of indoor building environmental discomfort and energy consumption have the potential for control setting optimization in an on-line method [119]. The prime goal of replacing models with ANNs reduces efforts for physical model development, regulation and validation. Building simulations can also be carried out with the HYBCELL numerical model comprising coupled models, thermal models and pressure airflow models [120].

This tool has been developed in the MATLAB/SIMULINK environment and is an open source. This can be coupled with controllers, such as ON/OFF, PID and fuzzy, and can be optimized easily within the same platform.

TRNSYS (a Transient System Simulation Program) has been utilized for the dynamic simulations for cooling-down and heating-up thermal building zones and control systems [121]. This tool allows researchers and scientists to save effort in the building model's creation and replicates time constants through existing building data. Magnier and Haghighat [122, 123] used TRNSYS simulations for the training of an ANN and coupled the trained and validated ANN with the GA for the optimization of energy consumption and thermal comfort index. This was performed due to the decreased time for the generation of a database; otherwise, TRNSYS and GA direct coupling could have taken 10 years instead of 3 weeks. However, the simulation time was very small.

The Energy Plus simulation package is a stand-alone module and does not possess a 'user friendly' graphical interface. Integration of the optimizing algorithm into the Energy Plus package for the reduction of the occupants' effort for coupling between this tool and the optimal algorithm has been proposed [124]. Direct search family optimization algorithms were integrated, which greatly limited the search performance. Automated coupling of this engine with formal optimization techniques with an impartial data standard have been used with the Ar-DOT program for seamless integration [125]. The support vector machine (SVM) technique has also been employed for producing various meta-models for the Energy Plus building models [126]. A sensitivity analysis has been performed for selecting the most influential variables for further optimization. This resulted in equivalent optimized solutions with both meta-models and Energy Plus.

Other complex building emulators have included electrical consumption, which can be programmed in the object-oriented modeling language Modelica, with Dymola being a software package, which supports the Modelica modeling language. Dymola software has been generally employed for the object-oriented modeling of complex systems [125]. It has been utilized in various domains (e.g., electronics, physics, etc.). ATplus, another general purpose commercial simulation software designed to simulate building thermal models dynamically, comprises thermal storage and heat flow balances. In [125], these simulation engines constitute the predefined HVAC components and various control schemes for

heating systems, i.e., discrete, continuous and fuzzy controllers. It allows coupling of weather models into computations, such as weather relative influences, solar radiation, etc.

BEopt [127] and Op-E-Plus [128] offer multi-criteria platforms, explore vast parameter space and search for economically effective energy conservation solutions. The two engines exploit DOE-2 and/or Energy Plus and a sequential search method for the simulation and optimization, respectively. These computational programs possess user-friendly interfaces and are fully functional simulation–optimization search platforms, which can be employed for building design practice. The zero energy building design support tool (ZEBO) facilitates the benefits of building performance simulations for early design stages of projects in hot and humid environments [129]. Thus, an added contribution for the integrated building simulation and optimization method resolved a barrier. The SIMBAD (SIMulator for Buildings and Devices) environment allows various plug loads for the simulation and optimization purposes. However, very little attention has been given to real time building simulations, which allow for physical devices and real conditions [130]. This has been provided for through the Power Hardware-in- the-loop (PHIL) for the SEB's testing and validation.

An ACHE system aims for energy conservation and personal comfort [131]. It learns the personal preferences through the behavior of the persons inside the buildings. However, the ACHE system is unable to identify and locate occupancy; therefore, it is unable to deal properly with the occupants' preferences. It develops a surrogate optimization method with the application of polynomial regression to the computational fluid dynamic (CFD) simulation output. This is in order to derive explicit cost functions thus optimizing them by employing a simple deterministic method. Dynamic simulations are also performed with HVACSIMþ [109, 132, 133]. They simulate any system of discrete components and are determined with a set of non-linear ordinary differential and algebraic equations. Another generic multi-parameter optimization engine for building system optimizations is GenOpt (Generic Optimization Program) [76]. Main goal of this optimization tool is to determine the best values of the design parameters within no time. Cost function optimization is generally evaluated with external simulation engines such as Energy Plus, TRNSYS, IDA-ICE, DOE-2, or Dymola. Thus, they are developed where cost function derivatives are not available/exist and are computationally exclusive. AMPL is also an influential modeling language for optimization problems of both linear and non-linear cost functions [134]. It is

not capable of solving optimization directly; however, it requires solvers, such as KNITRO, LANCELOT, SNOPT, MINOS, IPOPT, CPLEX, etc. AMPL is a global solver; therefore, it is not concerned about reaching the local extreme point.

6. CASE STUDY: SOLATRIUM HOUSE

6.1 Introduction

Building Performance Simulation Models (BPSM) have gained an important role during the building design phase. However, due to the complexity related to the large number of input parameters involved, the disagreement between predicted and collected energy consumption data or thermal comfort results represents a common issue in dynamic BPSM. Model calibration methodologies can lead to more accurate simulation results by bringing simulation predictions closer to the actual energy consumption and environmental targets, such as predicted air temperature or relative humidity.

Important approaches to model calibration were introduced by Clarke et al. [39] and implemented in a later study by Reddy [31]. They classified the calibration approaches into four main categories: 1) manual iterative methods; 2) graphical representation and comparative displays; 3) special tests and analytical procedures; 4) automated methods based on mathematical models. Different methods, from the four main categories, can be involved in the same calibration process. In fact, it was found that approaches to the matching of model prediction to collected data could employ, at the same time, either the manual calibration method with the graphical one or the automated approach in synergy with the analytical procedures [29]. The first calibration method performs all the calibration processes without a systematic or an automated technique. These methods are based on "trial and error" and rely on an iterative manual customization of the model inputs parameters. As shown in the studies conducted by Fabrizio et al.[29], the second class of calibration approaches is based on a graphical representation to illustrate the difference between actual measured data and predicted results. The comparison could be presented in several modes but the most common ways are: (i) scatter plots, (ii) time-series, (iii) 3D comparative plots, and (iv) calibration signature. The third calibration category uses analytical procedure in combination with actual test data, such as results from blower door tests or wall thermal transmittance measures, to support or compliment the calibration process. Finally, automated methods are similar to the third approach but develop a synergy between tools to facilitate the calibration process and increase its accuracy.

Passive solar Design (PSD) principles can be used to help attain thermal comfort in buildings by balancing heat loss through the building envelope with solar energy input, while also using thermal mass, shading, and/or ventilation to dampen diurnal thermal swings. Passive solar buildings may not require HVAC systems to attain thermal comfort, which poses unique challenges to model calibration as current methods typically require energy consumption utility data. Here we explore a methodology to demonstrate achievement of architectural design criteria for passive-solar buildings when there is a lack of energy consumption data. Some of the key factors that influence the thermal performance of passive solar buildings include building orientation, weather, thermal mass, thermal and optical performance of the transparent and opaque building fabric, and shading devices. PSD strategies can greatly help with reaching energy-efficiency in buildings by reducing energy consumptions and increasing thermal comfort for the occupants [135]. The proposed model calibration approach verifies the scientific basis for developing a passive solar building through air temperature analysis and constrains imposed by ASHRAE Standard 55 protocols for this type of design.

This case study describes a process for calibrating building simulation models based on indoor air temperature data collected in a real passive-solar house located in Datong, China. A manual iterative method with the introduction of statistical indices for validating the model was chosen, and this method was used in conjunction with the Design Builder building energy simulation software. The arrangement of real-time measurements for building air temperature and weather monitoring provides basis data to support the proposed methodology. The Hobo U12 data loggers, shown in Figure 1, were used to collect the indoor and outdoor air temperature. They permit for measurement of air temperatures in a range between -20°C and 70°C, with a precision of ± 0,35°C in a range between 0°C and 50°C [136]. For this reason, thanks to the Hobo U12 behaviors, a long monitoring period of one year was investigated for model calibration based on an hourly basis.

The remainder of this chapter is organized as follows. Section 6.2 explains the methodology used for the calibration and validation approach. While Section 6.3 and 6.4 describes the Solatrium House and its Design Builder model. From Section 6.4 to Section 6.7, the results of the calibration and validation and their trends are carried out. While

Section 6.8 up to the end of the chapter, the study about the parametric analysis is revealed for better understand a possible integration of BPS with a parametric analyzer based on automatic process for achieve the optimization problem's goals.

Figure 9: Onset Hobo data logger: temp/RH

6.2 Methodology

The goal of this research is to propose a simple methodology for calibrating and validating the predictions of a dynamic building simulation model against actual indoor air temperature as a data-driven approach to connect the monitoring phase and the initial design stage. The presented method is based on measured data collected by temperature sensors to achieve a high degree of accuracy. A real case study has been selected to demonstrate the methodology. It is a prototype house, called "Solatrium", designed for the Solar Decathlon China Competition (2013) by a student and faculty team from three universities: Worcester Polytechnic Institute (US); NYU Poly (US) and Ghent University (Belgium). The purpose of this case-study is to illustrate how the methodology could be performed for obtaining a calibrated model with great accuracy through a dynamic simulation software: Design Builder.

The proposed approach is built on six step-methodology. In Step 1, the evaluation of on-site collected building data is carried out by using data logger software (Hobo U12). Step 2 consists in the development of an initial building simulation model and the creation of a representative weather file for the specific Solatrium location.

According to Heo Y, during the calibration process, the presence of input data affected by uncertainty should require sensitivity analysis. In Step 3, due to the large computational time linked to the use of Design Builder, sensitivity and uncertainty analyses are not

conducted but, based on the user experience, a set of input parameters is defined to perform the building simulation. Each parameter is constrained in a range between a lower and upper bound. During Step 4, the model calibration is performed over one entire year through Design Builder simulations: the input parameters are changed based on the constrains until the output (forecasted indoor air temperature) matches with the target (collected indoor air temperature).

Finally, Step 5 processes the output data for validating, in a specific summer and winter period, the calibrated model based on its accuracy.

This process helps to evaluate the input correctness in order to calibrate and validate the building energy model. Steps 1 and 2 are crucial, the first represents the target to be reached while the second affects the accuracy and simulation precision.

In addition, Step 1 is important for Step 2, as measured outdoor data is used for customizing a weather file retrieved from the adjacent airport station. Step 3 and 4 represent the core of the calibration process, while, Step 5 validates the model thanks to agreement evaluation of simulated and measured data through the use of the Mean Bias Error (MBE), the Root Mean Square Error (RMSE) and the Coefficient of Variation of the Root Mean Square Error (CV(RMSE)) in a certain period.

6.3 Case Study: Solatrium House

The case study is a single-family house, "Solatrium", which was designed and built to compete at the first Solar Decathlon Challenge held in Datong, China, in 2013. To achieve the project requirements mandated by the competition, the design of the house is based on modularity and ease of assembly. As shown in Figure 7, it has a compact shape (11.25 m x 11.25 m x 2.3 m) that develops its spaces around a central atrium (6 m x 6 m) characterized by a ceiling designed one meter higher than the rest of the house to increase the natural convection. The atrium is flanked by roof windows made from multi-skin acrylic glazing to enable day-light penetration (with a solar control film). The window-to-wall ratio is more than 50% and the walls are constructed of sandwich fiber-reinforced panels while a Low-E double glazing system is used for the vertical windows. As a passive solar house prototype, Solatrium is built around an atrium surrounded by two main zones: living and sleeping areas. The first one is composed by a dining room and a saloon located on the south and the west side of the building respectively, and a kitchen, including a mechanical room, on the east side. The second zone, entirely placed on the north side of the building, is made up by the two bedrooms and one bathroom. The floor of the house is covered with 3.8 cm thick concrete tiles containing 13.5% of micro-encapsulated phase change materials.

6.4 Building simulation model

The geometry of the case study house and all its important physical features were modeled in the Design Builder Software (version 5.0.3.007). Thanks to a complete as-built documentation and the relatively small dimension of the house, the building model was quite detailed. As pictured in Figure 10, three thermal zones were defined with their associated loads, functions and occupancy behaviors. In the aftermath of the competition Solatrium was used as an office space for security personnel and thermal comfort data was collected (temperature and relative humidity) by sensors inside the house. Outdoor temperature and relative humidity was also measure next to the house.

The main building simulation inputs are listed in Table 7, based on the technical documentation provided by the designers. During the process, each parameter, involved in

the calibration, was altered, including the occupancy schedule and the cooling temperature set point.

The infiltration air flow was set to 0,7 ac/h. Based on the hourly air temperature analysis, the natural ventilation was not considered during the winter season. Three split systems with dehumidification served thermal zone 1 and 2. Data analysis showed that these units were used occasionally for cooling purposes during the summer months only and no heating systems were used during the 1-year monitoring of the house. As presented in Table 3, the monitoring period lasted from the 3rd of August 2014 to the 27th of October 2015 while the analysis period extends from March1 st to March 30 th 2015 for the winter and from July 1st to 31st 2015 for the summer. Figure 11 and 12 show the indoor air temperature of the "uncalibrated" energy model simulations, and these reveal large differences between actual and simulated results while Figure 13 and 14 presents the outputs from the calibrated models.

Figure 10: Solatrium plan-view (above) and section-view (below).

Envelope Component	
Ground Slab	
U-value [m^2k/W]	3,8431
Transonite	
Conductivity [W/mk]	0,043
Solar Absorptance	0,8
Thermal Absorptance	0,9
Low-E double glazing system	
Conductivity [W/mK]	1,82
Solar Heat Gain Coefficient (SHGC)	0,72
Visible Transmittance	0,76
Multi-skin acrylic glazing system	
Solar Heat Gain Coefficient (SHGC)	0,3

Table 7: Thermal features of the main Solatrium envelope components.

6.5 Use of monitored data

According to step 2, the collected meteorological data from the nearby airport weather station was adapted for creating a more actual-weather file to run the dynamic simulations, instead of using a typical EPW weather files. For the model calibration purposes, the collected indoor temperature and the relative humidity from the thermal sensors located in the three thermal zones were used and the dynamic simulations were performed for the two validation periods (March and July)(Table 8).

Run Periods	Start Date	End Date
Calibration	08.03.2014	10.27.2015
Validation (winter period)	03.01.2015	03.31.2015
Validation (summer period)	07.01.2015	07.31.2015

Table 8: Specification of run periods.

6.6 Calibration Process

The calibration process involves two main sets of data: the simulation outputs, from the developed numerical model, and the measured data, from building monitoring. In the case study, the simulated outputs are composed of large quantity of data that represent the indoor air temperature and the relative humidity.

During the calibration process, a set of input parameters were considered to have greater influence on building performance. For each of them, the variation constrains (upper and bonds) were set, while the thermal behavior of the ground slab and the multi-skin acrylic glazing system, listed in Table 7, were kept constant.

During step 5, the calibration was performed based on the thermal simulation results provided by Design Builder. At the end of each simulation, each input value was changed

manually, directly, into the software to make the simulated results match the collected ones. The process was stopped when the evaluation of the discrepancies between the two outputs were minimized, specifically, when the simulated data matched closely with the monitored one.

The discrepancies are defined as the reference value (measured) subtracted from the model forecast (simulated) and, in the case study, they were constructed for the two streams of data (winter and summer period) under analysis using the following Equation:

$$\text{[illegible]} = \text{[illegible]} - \text{[illegible]} \quad (7)$$

Where:

S_i are the simulated air indoor temperature points during the simulation period;

M_i are the measured air indoor temperature points for the same simulation period.

For the purpose of the error analysis, three statistical indices (MBE, RMSE, CV(RMSE)) were used as reference criteria for evaluating the model accuracy. They reveal how well simulated outputs match the actual measurements at a specific time interval to represent the goodness-of-fit of the simulated model [137].

As shown in Equation (8), the first statistic index, Mean Bias Error (MBE), is calculated as a ratio between the total sum of the hourly or monthly discrepancies in a specific period and the sum of the actual outputs.

$$\text{[illegible]} = \frac{\sum \text{[illegible]}}{\sum \text{[illegible]}} \times 100\% \quad (8)$$

Where:

M is the collected air indoor temperature point during the time interval;

S is the predicted air indoor temperature point for the same time interval.

It estimates how close the two data-sets are but it does not take into account the effect of the compensations due to the positive and negative values that contribute to reduce the MBE final value.

In order to control this effect, the RMSE and the CV(RSME), presented in Equation (9) and (10), were introduced. The former evaluates the discrepancies deviation while the latter is a normalized measure of the variability between collected and predicted data, and it is used to determinate the goodness-of-fit of the model. In fact, lower values of CV(RMSE) confirm a better calibration.

$$R\text{[illegible]} = \sqrt{\frac{\sum(\text{[illegible]} - \text{[illegible]})}{\text{[illegible]}}} \quad (9)$$

$$\text{[illegible]}(R\text{[illegible]}) = \frac{R\text{[illegible]}}{\text{[illegible]}} \quad (10)$$

Where:

$N_{Interval}$ is time number of time intervals considered for the collected period;

$$\text{[illegible]} = \frac{\sum \text{[illegible]}}{\text{[illegible]}}$$

For estimating the model accuracy, a limits constraint of the MBE and CV(RMSE) must be respected. They depend on the time interval of the calibration (monthly or hourly), as listed in Table 9:

Statitial Indiiei	Monthly Calibraton	Hourly Calibraton
MBE [%]	±5	±10
CV(RMSE) [%]	±15	±30

Table 9: Limits of statistical criteria for calibration.

As expected, the calibration process is a highly determinate problem that leads a non-unique solution because the agreement of the designed model with the thresholds does not confirm the existence of an exclusive input combination. In fact, a good fit can be reached with several combinations. The use of statistical indices can determinate the variability of the errors between the simulated temperature (S_i) and the measured temperature (M_i) provided by one of the possible input-combinations that can satisfy the calibration problem.

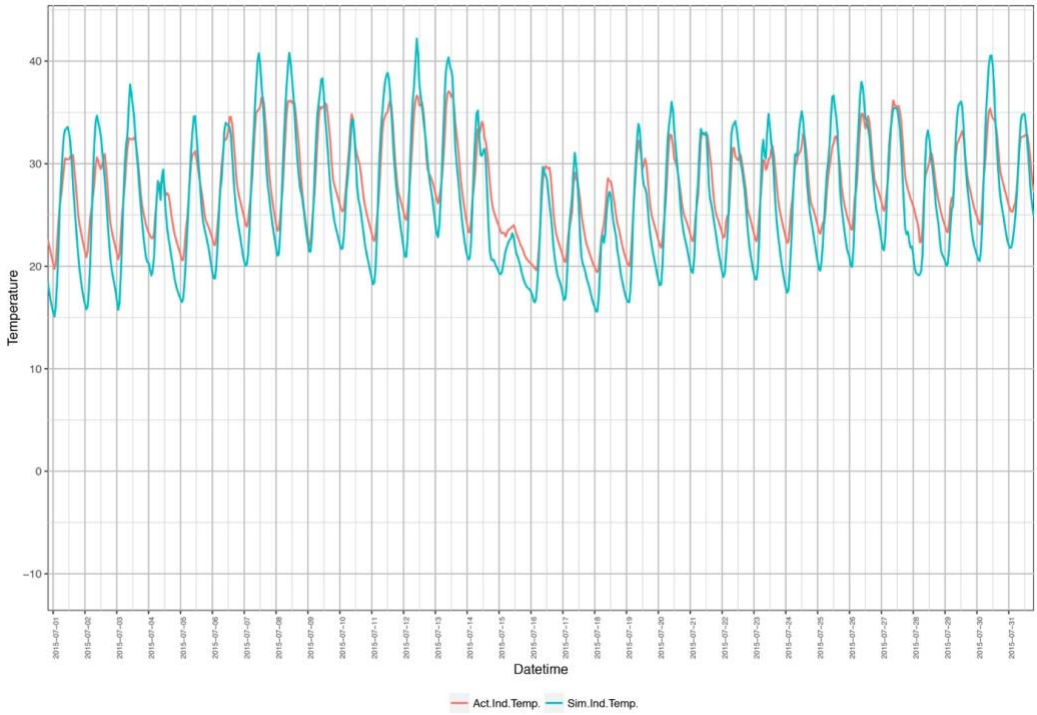

Figure 11: Actual and simulated indoor temperature variation during March (uncalibrated model).

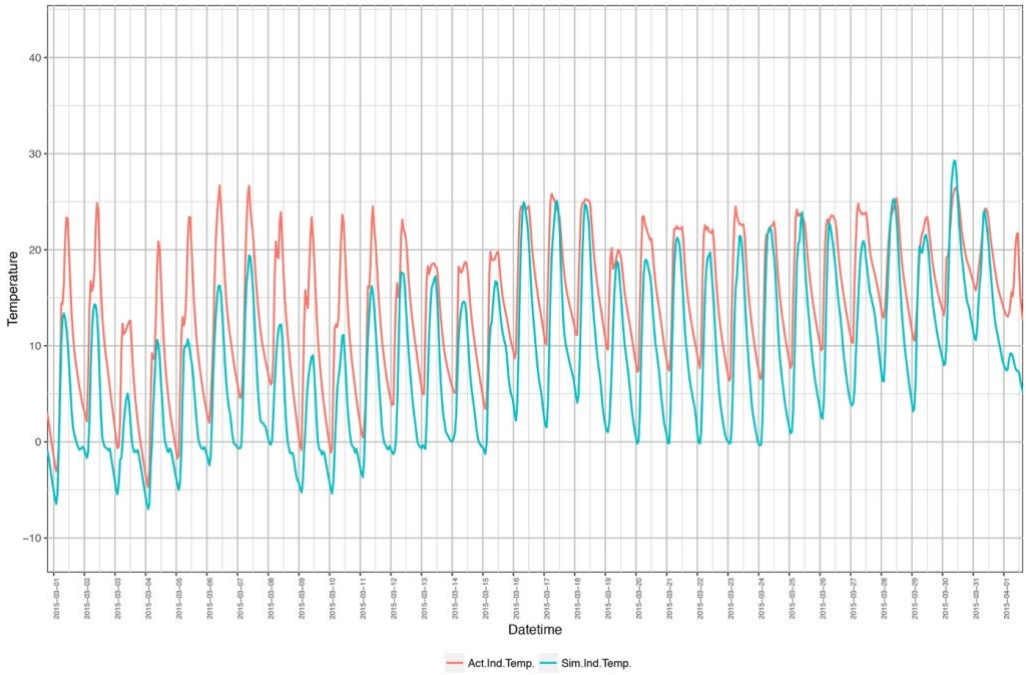

Figure 12: Actual and simulated indoor temperature variation during July (uncalibrated model).

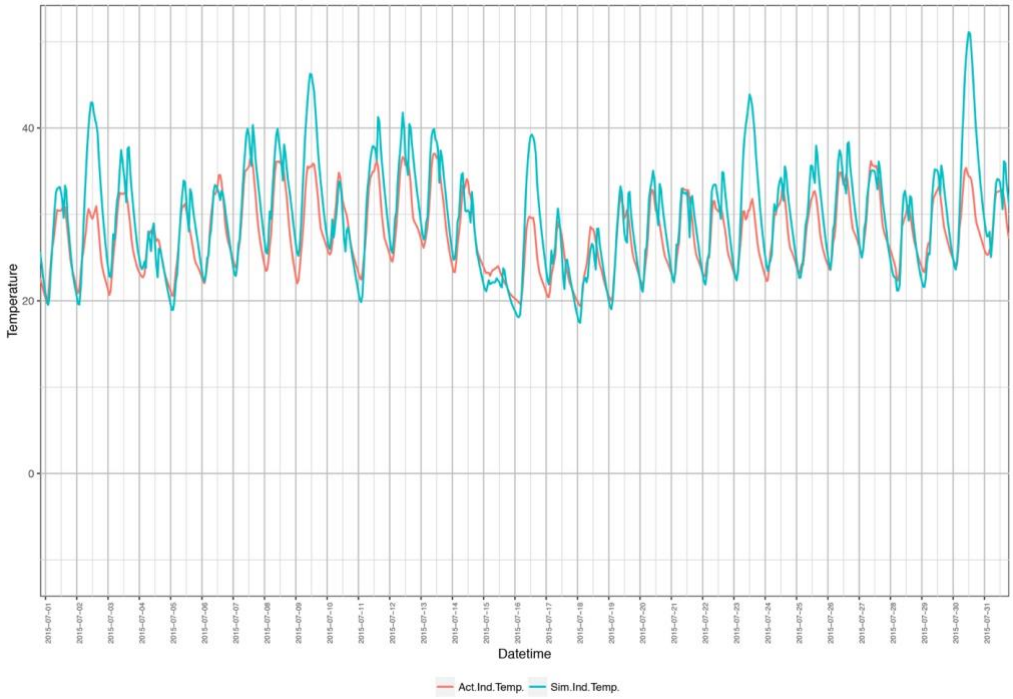

Figure 13: Actual and simulated indoor temperature variation during March (calibrated model).

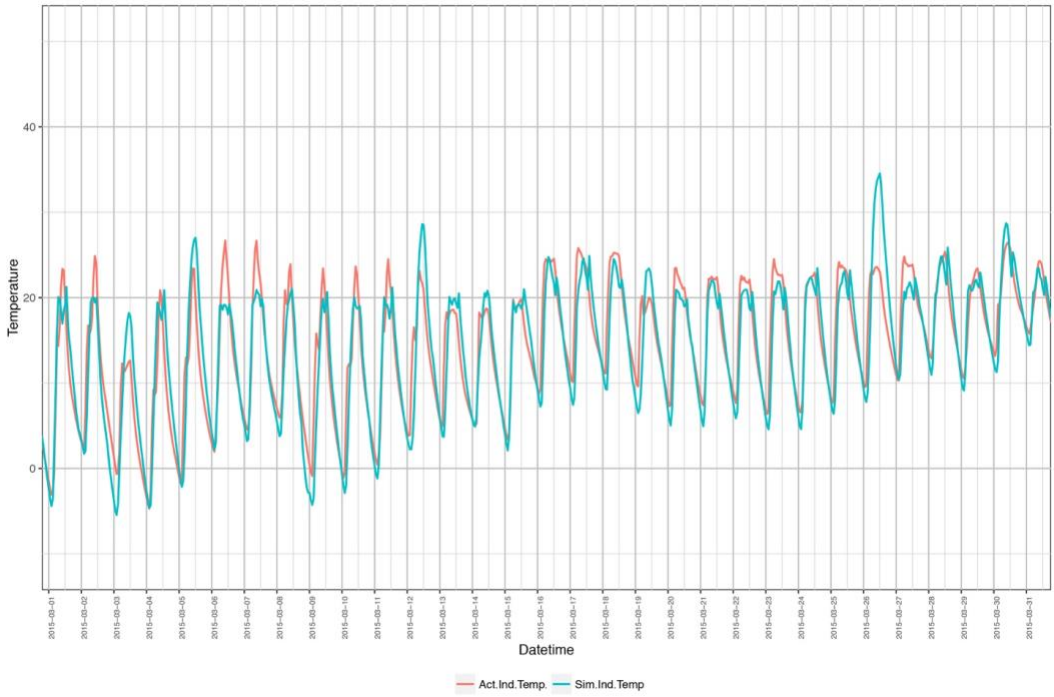

Figure 14: Actual and simulated indoor temperature variation during July (calibrated model).

6.7 Simulation Results

Actual recorded air temperature over the two validation periods (winter and summer) were used to examine the ability of the model to predict the indoor temperature. The histogram in Figure 15 shows the error-frequency for the winter period with almost an equal distribution on both sides of the peak. Its standard deviation (SD) is ±3.27 °C with 66.3% of the errors (as defined in Equation 1) fall within ± 2.5°C.

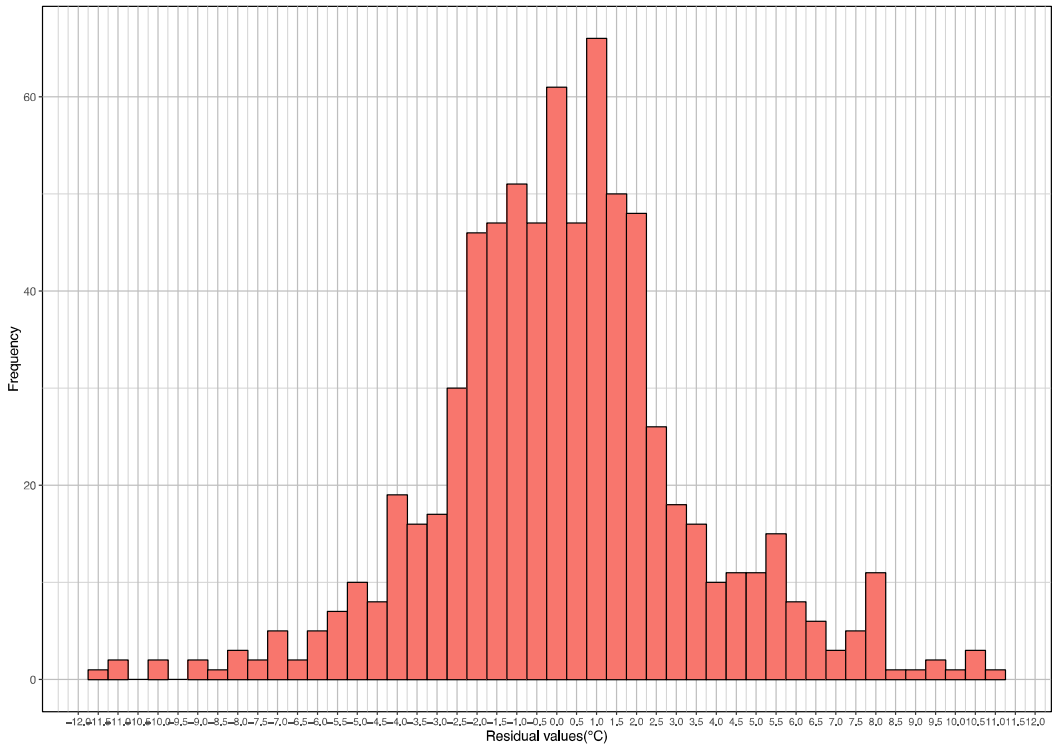

Figure 15: Errors frequency (winter period).

The histogram in Figure 16 represents the frequency spread of Design Builder space temperature prediction from corresponding actual values during the summer time. In that case the standard deviation (SD) is ± 2.07°C with 70% of the errors fall within ±2.3°C. Additionally, the density-plot on Figure 17 presents the error-density for both validation periods, which reveals that the Design Builder model has a better error-distribution, that influence the accuracy level of the model, across the summer period.

According to step 6, MBE, RMSE and CV(RMSE) were determined and verified for the case study. About 45 calibration runs were performed to reach the indoor air temperature target and, for each run, the Design Builder model was recalled and the main input parameters were changed to achieve the hourly air temperature objective.

Table 10 shows the list of parameters involved in that process and their constraints used to perform the dynamic simulations: the initial value (uncalibrated model), the defined constraints (lower and upper bonds) and the final value (calibrated). Additionally, Table 11 reports the statistical indices related to run 15 (1 st stage) and the run 45 (5 th stage) that describe the accuracy of the design model.

The ASHRAE Guideline 14 defines acceptable limits for hourly calibration data. It states that MBE must be within ±10% and $CVRMSE_{hourly} < 30\%$. These were selected as the acceptance criteria for this case study to validate the designed building model. With regard to the variation of the parameter-values during the calibration runs, the most stable parameters are those related to the building envelope, whose final values have light deviations from the initial ones. On the other hand, the mostly unstable parameters are those related to the ventilation rates and ground temperature.

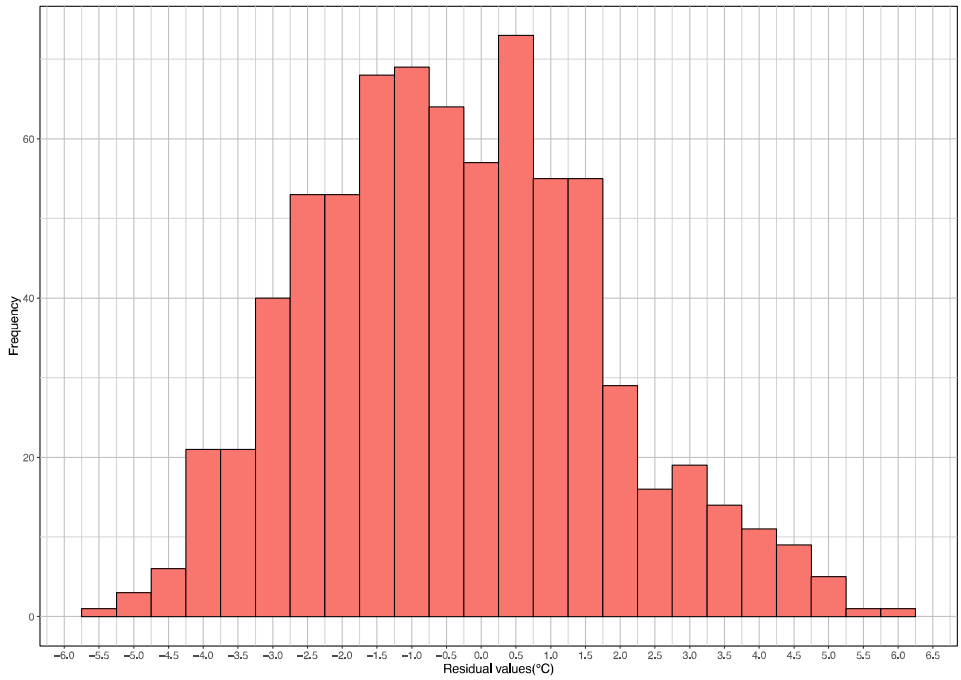

Figure 16: Errors frequency (summer period).

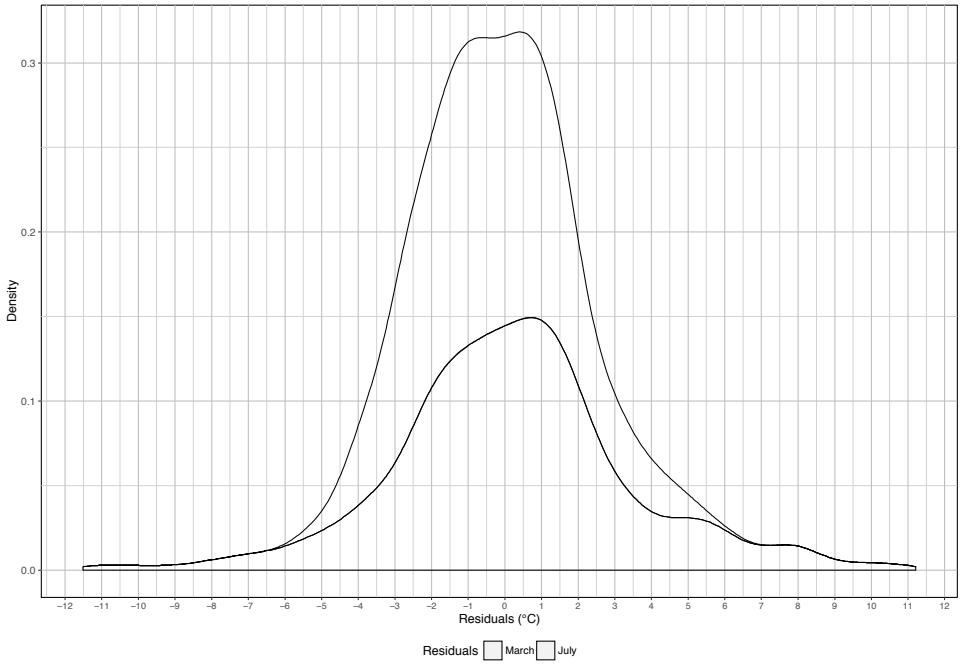

Figure 17: Errors density.

	Initial value	Lower Bound	Upper Bound	Final Value
Exposition				
Exposed to the wind	Normal	Sheltered	Exposed	Exposed
Ground Temperature				
Core	-2° below G.L.	-1° below G.L.	-4° below G.L.	-2,5° below G.L
Ventilation				
Infiltration [ac/h]	0,50	0,40	0,90	0,70
Transonite				
Conductivity [W/mk]	0,057	0,057	0,08	0,043
Solar absorptance	0,70	0,70	0,90	0,90
Thermal absorptance	0,90	0,70	0,90	0,80
Low-E window glazing				
SGHC	0,72	0,59	0,85	0,69
Light transition	0,70	0,65	0,8	0,76
U-value [W/m^{2}K]	1,80	1,70	3,31	1,88

Table 10: Thermal features of the main Solatrium envelope components for the Calibration process.

Indoor Air Temperature		
	MBE [%]	**CV(RMSE) [%]**
Uncalibrated Model(winter)	48,96	64,45
Run 4 (winter)	48,96	64,45
Run 17 (winter)	-1,54	22,96
Uncalibrated Model(summer)	-15,65	20,34
Run 27(summer)	8,95	15,29
Run 45 (summer)	1,31	7,59

Table 11: Validation results: MBE and CV(RMSE) in calibration run 4 and 17 for the winter time and 22 and 45 for the summer time.

As a result, a manual calibration and validation process were introduced for testing with a user-friendly simulation software the accuracy of a building model for a passive solar house. The validation of the building model was determined with the threshold hourly limits of the MBE and CV(RMSE) statistical index. Certainly, further developments can be introduced to improve the calibration process because the indoor air temperature is an instable objective function affected by several building and environmental parameters. This methodology should be performed on monitored buildings equipped with different sensors that collect all the involved variables for long monitoring periods.

7. SOLATRIUM HOUSE: PARAMETRIC ANALYSIS

7.1 Introduction

In this case study, a parametric analysis was carried out to introduce a decision support tool, aimed at helping designers/practitioners in evaluating and ranking the choice of implementing different building components (e.g., insulation foams, glazing systems and window-wall rates) and estimating their benefits in terms of thermal comfort and energy savings through a real building energy model.

The proposed tool is intended to play an important role in the early design phase, when it is well known that parametric analysis is useful for evaluating high-level conceptual design choices and building components benchmarking. On the other hand, the complexity related to the large number of variables affecting the building behavior prevents achieving a precise picture of the real-world building operation. To address such an issue, the proposed method enables powerful parametric studies in a reasonable time. The main feature of the proposed tool is the integration of the definition of the building model including the calibration and validation procedures, with a sensitivity analyzer based on an automatic process.

7.2 Scheme of the building model

In parallel to the continuous more stringent energy requirements to new buildings, it is fundamental to renovate the existing ones. The comparison of the potential impact on energy use and cost-efficiency of different measures for ex-novo design as well as renovation is not a straightforward task and has been the topic of substantial research effort. By the way, the potential improvement in the building design varies from building to building. For energy- and cost-efficient measures to be taken both in existing and in new buildings, it is crucial to understand which parameters largely influence the energy demand.

Unfortunately, the energy demand in a building depends on a number of factors, which can be schematically grouped in the following categories:

Climatic factors, such as environment temperatures and their yearly distribution, humidity and its distribution, solar radiation intensity and distribution and wind intensity and distribution.

Design building parameters: Geometrical parameters, e.g. building orientation and shape, percentage of glazed surface on the building enclosure and orientation; Thermo-physical properties of the building, like transmittance of external walls, roof and external floors, building thermal mass, transmittance and Solar Heat Gain Factor of the transparent surfaces. User-dependent parameters, such as set-point temperatures, internal gains and ventilation rate.

While the climatic conditions are determined by the building location, the user-dependent parameters depend on the destination use of the building, which often yields regulatory constraints on it. The building designer has more design freedom on geometrical and thermo-physical parameters.

However, when a multiplicity of parameters is to be analyzed, approaches capable to identify the relevant input parameters and to quantify their impact are crucial to improve the design of the building.

Typical helpful analyses in such a task are the Multivariate analysis (MVA) and the multiple-criteria decision analysis (MCDA). On one hand, multivariate analysis is based on the statistical principle of multivariate statistics, which involves observation and analysis of more than one statistical outcome variable at a time. In design, the technique is used to perform trade studies across multiple dimensions while taking into account the effects of all variables on the responses of interest. On the other hand, multi-criteria approaches aim at finding the optimal renovation options by considering the effect of each renovation measure on several different and non-homogeneous outputs, such as energy use, environmental impact, indoor thermal comfort or costs.

Independently from the considered analysis, the building modeling for energy demand calculation can be simplified with the block scheme in Figure 18.

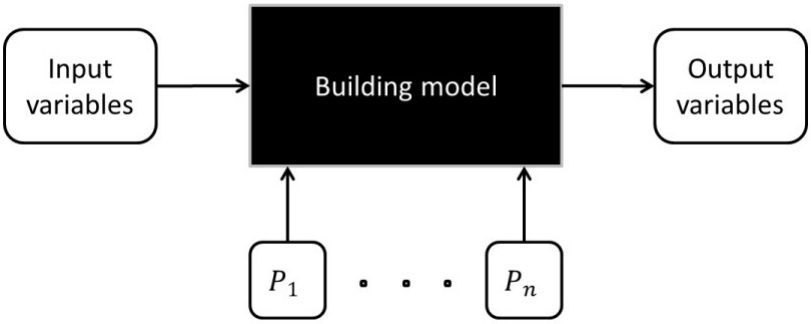

Figure 18: Scheme of Building modeling.

A set of input variables, such as temperatures and solar radiation, determines through the transfer function the output variables, e.g., the energy demand and the occupants internal comfort. The transfer function is determined by the building model. In building simulations, such a function is usually not explicitly known and it is described by a set of building parameters $P_1,..., P_n$. This set of building parameters includes geometrical parameters, like walls and windows surfaces, and thermo-physical ones, such as walls and windows U-values. Due to the implicit character of the transfer function, the output variables are determined with software simulations. The variation of a parameter P_P determines a change in the modeled building which also yields a variation in building performances. Determining the extent of this variation is crucial to identify which parameters influence most the potential to improve the design of the building. Parametric analysis approaches can quantify the effect on the output variable of the change of a parameter within a given interval.

7.3 Features of the proposed tool

Sensitivity analysis methods are among the parametric approaches. A sensitivity analysis can determine the contribution of a individual design variable to the total performance of the design solution. This is done by varying the input parameters selected for the study within a range and then comparing the variation in the input. This variation is carried out in one parameter each time in the so called One-At-a-Time (OAT) simulations.

The focus will be put on three types of sensitivity analyses: the screening analysis, the local sensitivity analysis and the factorial sampling.

Screening analysis

Screening analysis is an approach used to identify which input parameters the output function, e.g. the energy demand, is most sensitive to. The parameters to study are varied one at a time between two values and the variation on the output is compared to find the ones that cause the largest variation of the output. Since the number of simulation runs needed is limited to twice the number of parameters studied, this approach is particularly effective with complex systems computationally expensive to be evaluated.

To perform a screening analysis in a building the following steps are taken:

- Define an initial building configuration with n parameters to study. The initial building configuration is characterized by a value assigned to each parameter of the building;
- Assign a minimum value and a maximum value to each of the parameters to study;
- Simulate the building in the initial configuration;
- Simulate the building varying the parameter to its minimum and maximum value while holding the other ones' constant to their initial value;
- Analyze the results.

7.4 Local sensitivity analysis

A Local Sensitivity Analysis, quantifies the dependence of the output function on an input parameter. Similarly, to the screening analysis, the local sensitivity analysis is a one-at-a-time approach. To perform a Local Sensitivity Analysis, the following steps are taken:

- Define an initial building configuration with n parameters to study. The initial building configuration is characterized by a value assigned to each parameter of the building;
- Identify an interval L comprised between a minimum and a maximum value for each of the parameters to study and subdivide the interval in a number of values m to be used for the parametric study, Li={ pi,1, … , pi,m };
- Simulate the building in the initial configuration;
- Simulate the building varying the parameter within the interval from its minimum to maximum value, while holding the other ones' constant to their initial value;

For instance, this analysis is capable to identify the intervals where the analyzed building parameters are most effective in reducing the energy demand.

7.5 Factorial sampling

In this analysis, parameters are associated with discrete possible values or "levels". Then, simulations take on all possible combinations of these levels across all such parameters. Factorial experiments allow the analyst studying the effect of each factor on the response variable, as well as the effects of interactions between factors on the response variable.

This analysis is a global method. While in the local methods the parameters are varied around the initial configuration, with global parametric methods the variation of building parameters is carried out for different building configurations.

7.6 The simulation tools

Parametric analyses have been performed in a multi-platform environment. In particular, a Matlab test-bed has been developed for co-simulation with the whole-building energy simulator EnergyPlus.

Two design principles have been pursued in the tool development:

- Ease-of-use. The user should be enabled to use the program without any particular competence in macros coding.
- Flexibility. The user should be capable of adding and removing a virtually unlimited number of parameters to study without modifications in the macro.

7.7 Description of used software tools

7.7.1.1 Matlab

MATLAB (matrix laboratory) is a multi-paradigm numerical computing environment. A proprietary programming language developed by MathWorks, MATLAB allows matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs written in other languages, including C, C++, C#, Java, Fortran and Python.

7.7.1.2 Energy Plus

EnergyPlus is a whole building energy simulation program that engineers, architects, and researchers use to model both energy consumption — for heating, cooling, ventilation, lighting, and process and plug loads — and water use in buildings. Its development is funded by the U.S. Department of Energy Building Technologies Office. EnergyPlus is a console-based program that reads input and writes output to text files. Several comprehensive graphical interfaces for EnergyPlus are also available.

The main features of Energy Plus software are:

- Integrated, simultaneous solution of thermal zone conditions and HVAC system response that does not assume that the HVAC system can meet zone loads and can simulate un-conditioned and under-conditioned spaces;

- Sub-hourly, user-definable time steps for interaction between thermal zones and the environment; with automatically varied time steps for interactions between thermal zones and HVAC systems;
- Heat balance-based solution of radiant and convective effects that produce surface temperatures thermal comfort and condensation calculations;
- Atmospheric pollutant calculations;
- Anisotropic sky model;
- Combined heat and mass transfer model that accounts for air movement between zones;
- Heat transfer model;
- Simulation based on climate zone;
- Advanced fenestration models including controllable window blinds, electro chromic glazing, and layer-by-layer heat balances that calculate solar energy absorbed by window panes;
- Component-based HVAC that supports both standard and novel system configurations.

7.8 Description of the test-bed

The development of the simulation tool has regarded the implementation of parameters management program, including the front-end in order to facilitate the configuration process in defining the building model and listing the associated building parameters needed for the co-simulation.

An arbitrary number of parameters to be included in the analysis is assigned by the user, together with the minimum and maximum values and the parameter location in the software. After completion of the simulations the performance indicators are calculated for each building parameter and a ranking based on these parameters is created.

A high-level scheme of the developed tool is shown in Figure 20.

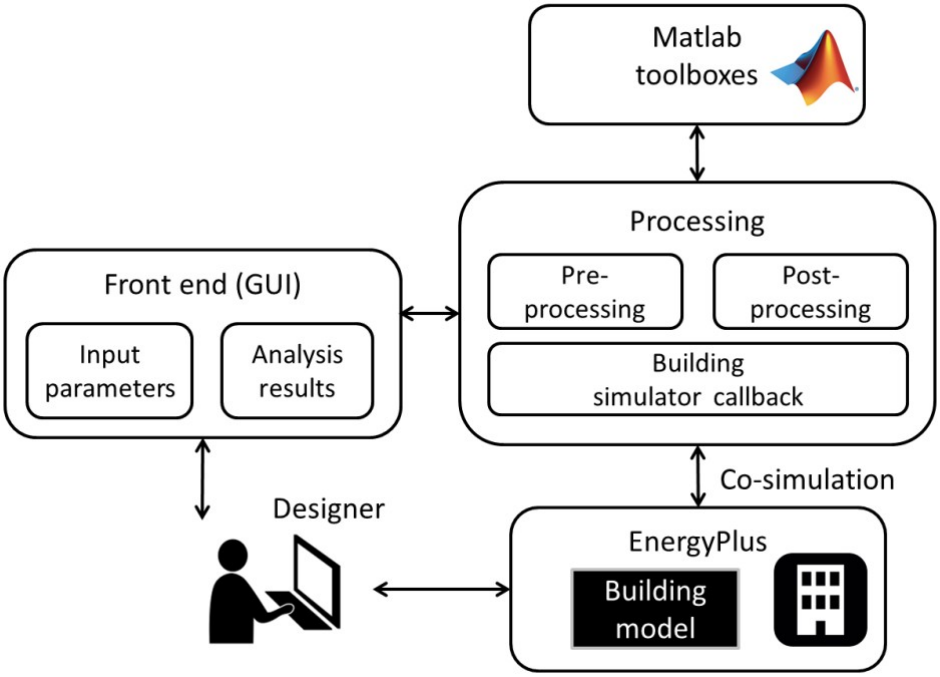

Figure 19: Conceptual scheme of the developed test-bed.

8. COST OPTIMAL-ANALYSIS OF A SUSTAINABLE BUILDING

8.1 Introduction

Combining cost-optimal solutions to reach a sustainable building design process in compliance with European policies is an ongoing challenge. Energy consumption can be reduced evaluating different configurations at the design stage and implementing the most appropriate solutions according to the building and the location.

In this chapter, a description has of simulation-based optimization framework of cost-optimal choices and energy efficiency measures for new buildings has been developed. The proposed model combines energy and cost simulations using a sequential search technique to find the most effective combination of energy efficiency starting from a base configuration. Based on the literature review, the method is applied to a residential building prototype, taking into consideration hourly climatic data, construction methods, cost data and energy consumption.

Results highlight how the cost-optimal measures change based on climate and how in each location final selected options differ. Insulation and building tightness appear essential in colder climates, while efficient appliances and lighting are key measures in warmer locations. A key finding of the research is that a source energy reduction of 90% and beyond is feasible for new constructions in all locations. Results also show how efficient lighting and appliances considerably impact the building energy performance.

8.2 Economic analysis

A building design strategy depends on a complex interaction of factors including location, climate, costs, available resources and materials. Since the building design has a big impact on the environmental and economic life-cycle, it is important to assess the effectiveness of potential solutions in a comprehensive manner.

Based on various algorithms and assumptions, a simulation-based optimization method can be used to derive the cost-optimal solution exploring several design options in more locations [138].

The optimization approach is based on a computer model running a building simulation program coupled to an optimization engine [139]. An iterative method driven by optimization algorithms progressively solves the analyzed problem. The solution is gradually approached until it is reached and it is established as the level that satisfies an optimality condition selected by the user [129]. Simulation-based methods have increasingly revealed their effectiveness in decreasing energy consumption in buildings at the design stage [140].

Different design variables can be analyzed with the purpose of reducing energy consumption in buildings [141, 142]. Applications deal with exploiting the efficiency of HVAC systems and ventilation or on optimizing a single building component, such as windows or envelope [116, 143], internal comfort and relative humidity [83, 144]. Some applications also consider costs while optimizing high-performing buildings. Znouda et al. [145] optimized energy and costs in a Mediterranean climate building, while Bambrook et al. focused on an Australian low energy house [146]. Ferrara et al. [147] developed a simulation-based optimization model with the aim of increasing the analyzed design options and dealing with a large number of simulations. They demonstrated the feasibility of the method in dealing with a large number of packages of measures while maintaining a manageable calculation scheme and minimizing the complexity of the global cost function. A simulation-based optimization approach has the advantage of evaluating more design options providing a better approximation of the cost-optimal configuration for the reference building [148, 149].

8.3 The methodology

The methodology proposed is based on the optimization design of a residential building prototype placed in different climate locations. Given the potential complexity of housing, the model is focused on a single family detached structure, although the methodology could be extended to other building types and orientations. The building has been modelled to evaluate, from an energy and economic prospective, several configurations obtained by a

combination of different design options. EnergyPlus and Design Builder have been used to carry out the dynamic simulations of the building together with the optimization process based on the parametric analysis set in Matlab.

The methodology identifies the lowest cost path to decrease the energy consumptions and its costs based on some assumptions (Table 12).

Application Area	New buildings
Building Type	Single house (120 m2)
Climatic Conditions	Amsterdam, Athens, Berlin, Bucharest, Dublin, Larnaca, Lisbon, Madrid, Milan, Paris, Rome, Stockholm
Categories of measure options	Envelope, insulation, airflow, windows, shading, heating and cooling systems, lighting, appliances
Building lifetime	30 years
Calculation of energy needs	Dynamic simulations with EnergyPlus and Design Builder
Solving method	Optimization technique with parametric analysis
Energy uses	Heating & cooling
Costs	Energy, labor, materials, maintenance, replacement, disposal and taxes

Table 12: Research assumptions.

8.4 Building model

The developed BPS model calculates energy savings with respect to a user-defined base case. It estimates hourly household heating, cooling and appliance loads. Fundamental building thermodynamics are estimated via finite difference conduction functions based on a multi-zone representation that allows a robust evaluation of transient thermal phenomena. The results of the simulations compared to real buildings measured data verified its potential to replicate measured energy use both in cold and in hot climates [150].

The design tool allows to directly assess the cost-effectiveness of energy efficiency measures. Even in cold climates, this method offers some advantages as it shows that it is possible to reach zero energy performance at relatively lower cost [151].

The simulation has been adapted to perform in European climates by adding hourly International Weather for Energy Calculations (IWEC) weather data files [152]. The proposed approach is consistent with the established design process use to achieve a sustainable projects and cost-optimality aims. The parametric analysis searches for the most cost-effective options across a range of categories (e.g. walls, floor and ceiling insulation levels, window glass type, HVAC type) to identify the optimal building design able to reach the target performance at the lowest cost. These measures are evaluated against the cost of electricity and natural gas bought from the utility companies. Once evaluated the energy generated by an initial design of the building, all the other design combinations are compared in a series of parametric evaluations with energy saving results calculated and stored for each implemented measure, as reported in the following equation (Equation 9):

$$E_{n,i} = (E_{n} - E_{n,i}) \quad (9)$$

where:

$E_{n,i}$ = Energy savings within optimization iteration 'n' evaluated for option 'i'

E_{n} = calculated energy use of the base building at the beginning of iteration 'n'

$E_{n,i}$ = estimated energy use of the base building with measure 'i' installed within iteration 'n'.

The simulated energy demand from each energy option together with cost data are used to analyze the cost-effectiveness of individual measures. This has been derived by estimating the net present value (NPV) of the cost of the improvement or change over the life of the building consistent with established method of evaluating design optimizations. This is compared with the cost of the evolving base building through the optimization process.

$$P_{n,i} = (C_{n,i}) \quad (10)$$

$$P_{n} = (C_{n}) + \sum_{n=1}^{N} (C_{n} + R_{n}) \sum_{n=1}^{N} \sum_{i=1}^{I} P_{n,i} \quad (11)$$

where:

PV = total present-value of life-cycle costs before taxes, associated with a given energy system;

I = total first costs associated with energy saving measure, including purchase, installation, building modification, and improvement;

V_n = residual or salvage value at year n, the last year in the evaluation (30 years);

a = single-present-value formula computed for a designated year from j = 1 to n, and discount rate d; i.e. $a^j = (1 + d)^{-j}$;

M_j = maintenance costs in year j;

R_j = repair and replacement costs in year j;

P_k = the initial price of the kth type of conventional energy carrier for energy types k = 1 to H;

Q_k = the quantity required of the kth type of energy;

b^j = the formula for finding the present value of an amount in the jth year, escalated at a rate Θ_k, where k denotes the kth type of energy carrier, and discounted at a rate d.

Each option, in each iteration, has a calculated NPV or the combination cost of the purchase and ownership of the measure as well as the costs for energy needs associated with the measure. The total costs over the life of the analysis are then annualized to a yearly cost of energy [153, 154].

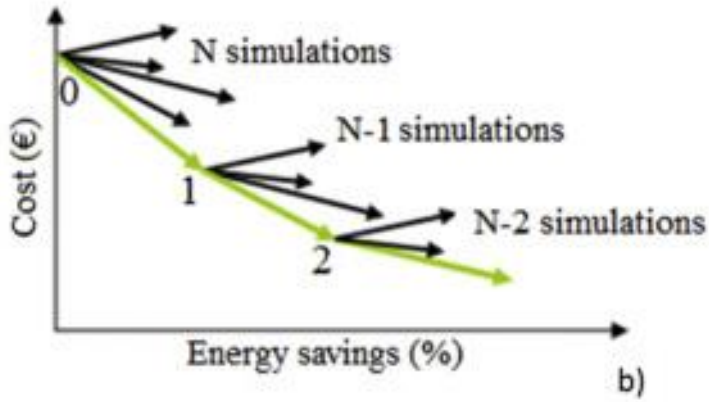

Figure 20: the sequential search process to decrease the energy consumption.

Within the optimization process, the base building is modified by adding the selected most cost-effective option at the end of an iteration and before proceeding to the next. All remaining options are then re-evaluated until the performance target is reached or the cost-effective options are exhausted.

The sequential search technique has a number of advantages. It allows to reach the established target and locates the least expensive path to achieve it. It further locates intermediate optimal points along the path, i.e. minimum-cost building design at different energy savings levels. Another advantage is that single building options are evaluated reflecting realistic features of available technologies. Finally, near-optimal alternative designs are identified within the optimization process. This is important since many competing solutions may be very close to the optimum while costs may be uncertain or variable for some options.

8.5 Economic Parameters

Uniform costs of measures are not seen across European zones, and a detailed knowledge of all measure costs is subject to an extremely high level of variation at European level. Differences exist especially for energy and technologies, but variability can be also found within the same country in relation to economical or labor costs. In the present work, average costs, conditions and building variants are assumed to obtain comparable results and an overview of the potential savings that can be reached. The approach allows the analysis to focus on realistic influences of climate on potential options with a consistent set of potential costs.

The cost calculations are based on the present value considering Standard EN 15459 [153]for energy systems and projections over an analysis period of 30 years. Sensitivity analysis performed on calculation periods revealed that increasing the calculation period decreases the cost-optimal target until the year 31. The assumed economic parameters are shown in the following table (Table 13):

Category	Rate
General Inflation Rate (GR)	2.00%
Energy Price Inflation Rate (ER)	3.00%
Financing Interest Rate (MR)	5.00%
Discount Rate	5.00%
Down Payment with Financing	10.00%

Table 13: Economic parameters for the optimization.

8.6 Building prototype: Economic analysis

The Solatrium House has been considered for the economic analysis. The prototype is similar to a sample developed in a recent study by Ecofys GmbH and the Danish Building Research Institute [155] with some additional details on lighting and appliances. Improved appliance efficiency alters building internal heat generation rates and the resulting heating and cooling needs. Its main characteristics are summarized in Table 14. The same table reports system properties, insulation levels, and airtight equipment efficiencies.

Characteristics of the base building	
House Size	120 m^2 with heating equipment
Neighbors	Similar neighboring buildings on the two sides of the house
Envelope	
Windows	23 m2 with double clear glass (2.2 W/m2K)
Walls	R 1.3 Insulated perlite filled masonry walls (~0.8 W/m2K)
Attic	R-5.3 insulation (~0.18 W/m2K)
Doors	Insulated wood entry door (~0.8 W/m2K)
Air leakage	Standard construction (4 ACH at 50Pa blower door pressure)
System	
Heating	COP 4.1 mini-split heating system
Cooling	COP 4.1 mini-split cooling system
T° Set point	20 °C for heating, 23 °C for cooling

Table 14: Characteristics of the base building.

The base building represents a standard energy performance starting point in the optimization process. Particular care was made in specifying occupancy related parameters as these potentially exhibit an extreme influence on building energy consumption. A minimum air change at maximum occupation rate has been considered, coherently with occupation levels and ventilation design rates proposed by Standard EN 15251 [156] for very low-polluted buildings. This value represents the average rather than specific conditions for an individual building.

Both a heating and cooling system are potentially available in all climates. Some measures, such as window solar heat gain selection, will involve a trade-off between the balance of heating and cooling. The chosen building is intentionally simplified so that results will focus on the influence of climate and the solar resource on the potential optimization problem.

As previously shown, a set-point of 23 °C has been adopted in line with recent climate change predictions. This accounts for the likelihood that cooling loads could grow with warmer temperatures. A mini-split cooling system has been included the optimization for all locations. This has the important advantage of balancing options that might reduce heating but can adversely impact cooling loads. The exclusion of a cooling system would have favored options that may lead to overheating.

The energy consumption results from Design Builder as interpreted within Matlab code will seek to balance various building elements to address heating, cooling and appliance uses to best reduce energy costs for the cost-optimal selection. The analysis tends to encourage efficiency options such as shading, insulation and low surface solar absorption that can significantly reduce cooling needs. The proposed design approach with a wide range of commercially available technologies can help effectively minimize a building's energy costs. An important concept in energy-efficient design is integrating the building's architectural and mechanical features to minimize energy use and reduce cost while maintaining comfort.

This integration is best done during the very early stages, when the most cost-effective holistic system can be designed. Although some energy-efficiency strategies result in slightly higher first costs, the resulting annual cost savings result in lower maintenance costs.

To illustrate this concept, the Solatrium House has been analyzed in terms of energy costs that could be saved by using the developed approach linked with the parametric analysis to evaluate different architectural choices. To conduct this type of analysis, the case study is modeled to meet the levels of energy efficiency in the American Society of Heating, Refrigerating and Air Conditioning Engineers (ASHRAE) 90.1-1999 standard.

The average total construction cost has been estimated at $90,000.00. Using the building energy simulation model (EnergyPlus) and standard costing approaches, the incremental first cost, the annual energy cost savings and the payback periods has been evaluated, for a combination of two different wall solutions, optimized for the lowest energy use through the parametric analysis. The final results indicate that annual energy costs could be reduced 37% below the base case by introducing a new type of envelope technology, based on a fiber-glass wall, at a total first cost increase of about $8,000.00 (adding 8.8% to total first costs). The overall simple payback for the new system was estimated to be 8.7 years, and the sustainable building had a net lifecycle savings of over $23,000 during the assumed 25-year lifetime.

The energy-efficiency analysis of the prototype indicates that significant amounts of energy can be reduced within an acceptable payback period. The proposed analysis demonstrates how significant energy was saved using the described technique, including the parametric analysis and the energy optimization.

	Base Case	Sustainable Building
Total first cost of building	$90,000.00	$98,000.00
Annual energy cost		
Dollar amount	$11,800	$7,490
Percent change from base case	NA	-36.70%
Economic metrics		
Simple payback period	NA	8.65
Savings to investment ratio	NA	1.47
Energy use		
Million BTU	370	117
Percent change from base case	NA	-34.6
* Value have been rounded to three significant figures. **NA= not applicable		

Table 15: Prototype Building Analysis: Costs and Benefits of Energy-Efficiency Measures.

CONCLUSION

Currently few buildings have calibrated energy models, perhaps due to the complexity of the process involved. However, the growth of technology (better computers), and the rise and optimization of

simulation tools enable the realization of calibrated models. Moreover, the calibration and validation technique introduced in this thesis could be used to design model for real-time control, analyze thermal energy storage in buildings as a system dynamic, for on-going commissioning and for existing building commissioning, where the model may be used as a diagnostic aid and to predict the savings that will be achieved from implementing commissioning measures.

Any improvement in the accuracy of the model means that the model will respond better to the applications requirements. The use of different algorithms to find calibrated BPS models intends to make the process affordable due to the reduction of the time involved (automated process).

The methodology presented in this thesis and explained through the case study shows that the use of the novel approach to obtain calibrated models or to improve existing ones is not only feasible, but also that the models obtained are predictive models of real building behavior. The use statistical index means that the model simulation obtained is a BPS calibrated model that has captured the dynamics of the building. In fact, the real model has a strong correlation between simulated and measured values.

The following summary is a list of the benefits related to the proposed methodology and the parametric analyzer:

- Free oscillation advantage. Use of free floating time-periods to calibrate models reduces the number of parameters needed. The methodology needs a continuous period of free floating and it is not always possible to have two full weeks as in this study. Small periods (weekends) may be enough to calibrate models but the period needs to have thermal amplitude and to be long enough to discharge the energy stored in the building. The methodology described here could be fully functional with the building in use, but in that case time-step data of energy consumption and internal loads should be taken into account.

- The use of temperature sensors reduces the investment needed for the calibration process because they are cheap and easy to place and to read. But it is important to study where they are placed so as to prevent measurement errors due to solar radiation and air flow;
- Usefulness of parametric analysis to reduce the search space. Fewer possibilities, in addition to being less time-consuming, show the parameters that need more attention because they produce major variations in the building energy behavior. Information is also given on the building parameters that need to be improved if retrofitting measures are to be implemented.
- Automatic process, no skill needed. The proposed tool is fully automated. It merely requires the values of measured temperatures, a baseline model and the parameters which the algorithm can vary to find the solution.
- This methodology attempts to solve the difficulties in obtaining a calibrated model. The benefits offered by a calibrated model make the effort of obtaining them worthwhile. Parametric analysis, and the algorithm developed are the active tools that will make this process affordable.

The research presented in this thesis have left many open problems and paved the way for novel research directions in calibration methodologies and parametric analysis:

- The main limitations of the presented calibration approach is related to the assessment of uncertainties that affect the prediction of the building simulation model. Future research will be devoted to overcoming the identified limitations about considering uncertainty on environment parameters and modeling uncertainties that affect the estimation of other devices;
- Future extensions will also address the Integration of the building model with an optimization tool for the identifying the optimal parameters of of building components.

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11. BIBLIOGRAPHY

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