Universidade de Aveiro Departamento de Ambiente e Ordenamento
2020

Elisa de Moura Scortegagna

Calibração Baseada em Evidências de Modelo de Desempenho Energético do Edifício com Análise de Incerteza e Sensibilidade

Evidence-Based Calibration of a Building Energy Performance Model with Uncertainty and Sensitivity Analysis

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Evidence-Based Calibration of a Building Energy Performance Model with Uncertainty and Sensitivity Analysis

Dissertação apresentada à Universidade de Aveiro para cumprimento dos requisitos necessários à obtenção do grau de Mestre em Sistemas Energéticos Sustentáveis, realizada sob a orientação científica do Doutor Nelson Amadeu Dias Martins, Professor Auxiliar do Departamento de Engenharia Mecânica da Universidade de Aveiro

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agradecimentos

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palavras-chave

Processo de Calibração Baseado em Evidências,
Análise de Incerteza,
Análise de Sensibilidade,
Modelo de Desempenho Energético de Edificações,
Qualidade Ambiental Interna.

resumo

A simulação dinâmica de edifícios é uma prática cada vez mais comum em engenharia e arquitetura. Embora os simuladores atualmente utilizados sejam cada vez mais poderosos, a complexidade dos edifícios leva à necessidade de simplificações que podem ter um impacto relevante na qualidade dos resultados obtidos. Vários estudos realizados recentemente enfatizam discrepâncias consideráveis entre o desempenho energético medido e simulado do edifício. Como os edifícios geralmente não apresentam o mesmo desempenho durante a operação que o previsto na fase de projeto, foi instigado um amplo interesse no monitoramento real de edifícios, e a lacuna entre os dados de consumo de energia medidos e simulados tornou-se uma preocupação elementar na construção de domínio de simulação. Por esse motivo, a calibração dos modelos de simulação de construção é de crescente interesse. O objetivo deste trabalho é usar os dados das medições de Qualidade do Ambiente Interno (QAI) e as medições reais de uso de energia, consumo de eletricidade e aquecimento durante um ano de um apartamento residencial em uso recém construído de baixo carbono no oeste de Londres - Reino Unido, para a calibração e validação de um modelo de desempenho energético. Para conseguir isso, os desempenhos de alguns apartamentos típicos foram analisados e um modelo de energia foi criado no DesignBuilder usando a documentação da fase de projeto, medições de dados pós-ocupação, juntamente com dados de QAI de zonas típicas. Uma metodologia sistemática, baseada em evidências, foi usada para calibrar um modelo representativo de energia de apartamentos com base nos dados mensais de consumo de energia. Os resultados da simulação de energia do modelo calibrado foram comparados com os dados reais de energia medidos, em seguida as causas das discrepâncias entre os dois resultados foram elaboradas e a diferença entre esses dois desempenhos foi analisada para prever possíveis determinantes. A análise de incerteza e de sensibilidade (UA/SA) foi realizada após a conclusão do modelo calibrado, a fim de verificar e quantificar o grau de incerteza e as variáveis mais influentes e determinantes em um modelo de desempenho energético. O modelo calibrado criado foi validado pelos critérios mensais de calibração conforme a Diretriz 14 do IPMVP/ASHRAE, de CV (RMSE) <15% e NMBE <± 5%. A lacuna remanecente do desempenho energético entre as medições reais e os resultados da simulação do modelo calibrado é indicada e explicada. O trabalho também reflete sobre aspectos práticos da coleta de dados, como deficiências na medição, monitoramento e observações que poderiam ser abordadas para uma calibração do modelo mais precisa. Algumas melhorias nas limitações encontradas neste trabalho são recomendadas: mais rigidez nos padrões de validação de modelos calibrados; e métodos existentes para calibração; e a redução da incerteza nos parâmetros de entrada do modelo.

keywords

Evidence-based Calibration Process,
Uncertanty Analysis,
Sensitivity Analysis,
Building Energy Performance Model,
Internal Environmental Quality.

abstract

Dynamic simulation of buildings is an increasingly common practice in engineering and architecture. Although the simulators currently used are increasingly powerful, the complexity of buildings leads to the need for simplifications that can have a relevant impact on the quality of the results obtained. Several studies performed recently have emphasized considerable discrepancies between measured and simulated building energy performance. As buildings usually do not present the same performance during their operation as the one predicted in the design phase, a broad interest in building real-monitoring has been instigated and the gap between measured and simulated energy consumption data has thus become an elementary concern in the building simulation domain. For this reason, the calibration of building simulation models is of growing interest. The objective of this work is to use the data from the Indoor Environmental Quality (IEQ) measurements and the actual energy use measurements, electricity and heating consumption for one year of an in-use low-carbon newly built residential apartment in West London - UK, for the calibration and validation of an energy performance model. To achieve this, performances of some typical apartments were analyzed, and an energy model was created in DesignBuilder using design stage documentation, post-occupancy measurement and metering along with IEQ data from typical zones. A systematic, evidence-based methodology was used for calibrating one representative apartment energy model-based to monthly energy consumption data. The outcomes from the calibrated model energy simulation were compared with the actual measured energy data, then the causes of discrepancies between the two results were elaborate and the gap between these two performances was analysed to predict possible determinants. Uncertanti and Sensitivity Analysis (UA/SA) were conducted after the completion of the calibrated model in order to verify and quantify the degree of uncertainty for and the most influential and determinants variables in an energy performance model. The calibrated model created was validated by monthly calibration criteria as per IPMVP/ASHRAE Guideline 14, of CV(RMSE) <15% and NMBE<±5%. The energy performance remaining gap between the actual measurements and the calibrated model simulation results are than point out and explained. The work also reflects on practicalities of data collection such as shortcomings in the metering, monitoring and observations that could be addressed for model calibration more accurate. Some improvements in the limitations found in this work are recommended: more rigidity in the validation standards of calibrated models and existing methods for calibration; and the reduction of uncertainty in the model's input parameters.

SUMMARY

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LIST OF ABBREVIATIONS

ASHRAE	American Society Heating, Refrigerating and Air-Conditioning Engineers
BREDEM	BRE Domestic Energy Model
BEMS	Building Energy Management System
BEM	Building Energy Modelling
BEPM	Building Energy Performance Model
BEPS	Building Energy Performance Simulation
BPS	Building Performance Simulation
BRE	Building Research Establishment
BS	Building Simulation
CS	Calibration Simulation
CV(RMSE)	Coefficient of Variation of Root Mean Square Error
DAs	Devolved Administrations
DSA	Differential Sensitivity Analysis
DHW	Domestic Hot Water
DS	Dynamic Simulation
DSM	Dynamic Simulation Modelling
EMS	Energy Management System
EPA	Energy Performance Analysis
EPC	Energy Performance Certificate
EPBD	Energy Performance of Buildings Directive
IEQ	Indoor Environmental Quality
IPCC	Intergovernmental Panel on Climate Change
IAQ	Internal Air Quality
IEA	International Energy Agency
MBE	Mean Bias Error
MHCLG	Ministry for Housing, Communities, and Local Government
NCM	National Calculation Method
RH	Relative Humidity
RMSE	Root Mean Square Error
SA	Sensitivity Analysis
SAP	Standard Assessment Procedure
UA	Uncertainty Analysis

1. INTRODUCTION

Dynamic Simulation (DS) of buildings is an increasingly common practice in engineering and architecture. Although the simulators currently used are increasingly powerful, comprehensive and subject to standardized validation and verification processes, the complexity of buildings as a thermal system leads to the need for simplifications and adjustments that can have a relevant impact on the quality of the results obtained.

By constructing simulation models that mimic complex real-world physical processes, it is virtually impossible to evaluate all possible variations because of the large number of interdependent input variables. The Uncertainty Analysis (UA) and the Sensitivity Analysis (SA) of the simulation results seek to evaluate the impact of the variations on the input parameters in the outputs, in order to propose simplification models by identifying the most sensitive inputs which propagate the uncertainty in the results. Thus, it is possible to obtain simplified Dynamic Simulation Models (DSM) that properly represents the analysed building.

1.1. Research Background

In the mid-1970s, a wave of energy conservation activities, especially promoted by federal and state agencies, was triggered by the oil shock. This led to the generalized initiation of demand-side management projects geared specifically to the small commercial and residential buildings stock [1]. In this scenario, Building Simulation (BS) has emerged, used initially throughout the design process, from the early stages to detailed construction phases, as an endeavour to imitate reality and improve on traditional manual methods in order to study and optimize the energy performance of buildings and systems [2]. Subsequently, in 1980, building professionals started becoming aware of the potential and magnitude of energy conservation saving in large buildings [1] and, thereafter, the BS domain has grown and continuous improvements are being made to software features and, above all, to the building models robustness [2].

Many initiatives have been developed to build more sustainable buildings since the construction sector are responsible for almost 40% of total final energy consumed in the world [3]. An example of this effort is that in the European Union all new buildings must reach a “nearly zero energy” performance by 31 December 2020 [4]. In response to current high and ambitious sustainability goals, as the main focus is to reduce the energy demand of the buildings and optimize its energy performance, the building's design has been recently subjected to changes and BS is of growing importance as a clear response to this issues [2]. Nevertheless, it is much more common to see BS applications in construction or advanced design phases rather than in early phases as in concept design, which shows that its potential is not fully exploited, and its uptake is still restricted.

Several studies performed recently have emphasized considerable discrepancies between measured performance and simulated building energy performance [5–7]. As buildings usually do not present the same performance during their operation as the one predicted in the design phase, a broad interest in building real-monitoring and operation diagnostic has been instigated and the gap between measured and simulated energy consumption data has thus become an elementary concern in the BS domain. For this reason, the calibration of building simulation models is of growing interest [2].

Despite the recent increasing importance and application of calibration due to the interest in studies concerning the disagreement between measured building energy consumption and predicted energy consumption by building energy simulation programs, the lack of a harmonized and officially recognized procedure for performing calibration of building energy models still remains a major issue [2].

UA and SA perform an essential part of the modelling process, especially for calibrated simulation, as they represent a key function in building model accuracy. The UA intends to quantify the output variability, while the SA seeks to identify the impact on the output variability according to the variation of input data, in other words, how the uncertainty in the model output can be allocated to different sources of uncertainty in the input of the model [2]. The SA aims to identify the most influential parameters on energy consumption to simplify the statistical model by eliminating non-influential inputs or grouping correlated inputs. Understanding what is influencing the levels of the key parameters and their interactions is important in order to reduce their uncertainty and provide only relevant information on the model [4]. In doing so, UA and SA should be integrated within calibration methodologies for tuning the most important parameters.

1.2. General Objective

- This work purpose is to use the data from the Indoor Environmental Quality (IEQ) measurements and the actual energy use measurements, electricity and heating consumption for one year of an in-use low-carbon newly built residential apartment in West London - UK, for the calibration and validation of an energy performance model.

1.2.1. Specifics Objectives

- Develop existing analytical methodologies which may be applied to calibration models to achieve a greater degree of correlation between the real-world and simulation model, thereby increasing the reliability of the final calibrated model.
- Perform UA and SA of DS results of energy response and comfort in buildings.

1.3. Thesis Contribution

This research contributes for the selection of methods and tools, according to the available measured data, for the calibration process and preparation of a model that can lead to optimized retrofit interventions and rationalization of building management and operation. In order to determine whether low-carbon buildings actually operate with the lowest expected carbon content, to discover problems and address improvements in energy performance, it is necessary to assess the energy performance of buildings and to reduce existing gaps in energy consumption.

Since most of the surveys that assessed building performance focused on commercial buildings, and among those that assessed residential buildings, most chose homes as case studies, the focus on assessing performance in residential apartment blocks is considerably reduced. Therefore, this dissertation comes to remedy the obvious lack of comprehensive studies on the evaluation of the building performance of apartment buildings.

1.4. Organization of the Work

This document is organized into eight chapters. The first one 1. Introduction, a small contextualization it's made, sequentially the work objectives are pointed out, the contribution of this work and the scope and limitation of the project. The second chapter 2. Literature Review, the recent main researches in this field are presented, as well the main methods applied for Calibration Simulation (CS), UA and SA and the additional work required is presented. In the third chapter 3. Methodology, the overall methodology is described, the case study is presented in detail, as well as the data measurements which were made in order to access the building actual performance information. In this same chapter, the modelling and the calibration processes are described related to the base model and calibrated model. Chapter 4. Base Model describes in detail the input data which were used to generate the base energy model simulation, the results obtained from this simulation, a comparison of this results with the actual energy consumption and an analysis of the performance gap founded between these values. Sequent, in chapter 5. Calibration Process, all the changes made on the base model input during the calibration process are described in detail, based on evidence. Chapter 6. Uncertainty and Sensitivity Analysis describes the methodological process and the results for the analysis of the uncertainty and the most sensitive variables in the model. On chapter 7. Results and Discussion, a comparison made between the results founded with the calibrated model simulations and the actual performance is taken, followed by an analysis of what are the probable causes of the remaining energy performance gap. In the end, the conclusions from this work are presented in Chapter 8. Conclusion, and some considerations for future works. The References and Attachments are presented in sequence.

2. LITERATURE REVIEW

This chapter aims to deepen the knowledge related to Building Energy Performance Simulation (BEPS) and calibration of Building Energy Performance Models (BEPM) by assisting UA and SA. A literature review of the main authors on the subject is carried out in order to know the available methods, the most used methodology and what research has been developed in this field in recent years. The literature review considered the fundamental authors on the theme and the researches made in the last ten years, from searches made for scientific articles in open access platforms.

Firstly, this chapter presents a general comprehension about the scope of Energy Performance Analysis, including the UK regulations, procedures and methods, the BEPS concept, the model calibration and its issues. Subsequently, the CS is approached with its methods and classifications. Likewise, the UA and SA methodology and classifications are presented. Finally, the additional work required in this field is discussed.

2.1. Energy Performance Analysis

Both the International Energy Agency (IEA) and Intergovernmental Panel on Climate Change (IPCC) report of 2015 emphasize that the potential of achieving energy efficiency in buildings to reach global energy reduction targets is significant, as buildings are long-term assets, and, therefore, should be short-term targets to prevent lock-in of a stock of inefficient buildings [3]. This significant potential is further evidenced by the fact that the residential sector accounts for about 25% of the world's primary energy consumption and that this consumption is steadily growing on a global scale at an average annual rate of over 2% over the past four decades [8].

In the residential sector, BEPM is generally used to evaluate energy-saving policies, analyse the impact of future energy consumption conservation measures and predict future energy demand of buildings. After 1990, simulation tools were mostly used during later stages of the project, and, as in this late phase design decisions with the greatest impact on the building's energy performance have already been made, such as form, construction and operation of the building, the effectiveness of simulation tools is usually lower [9]. Although in recent years several BEPM have been developed, the amount and type of input data required creates difficulties in modelling and obtaining accurate results from simulations [8]. Building energy simulation in the early design stages has the potential to provide a means of quantifying and evaluating the energy efficiency of design alternatives and guiding future decisions [10].

Commonly, buildings are delivered without any feedback on measured operational performance and actual energy consumption, which is not the case in other industrial sectors such as the automotive industry. This situation is clearly unsustainable when real improvements in actual performance are intended. For high-quality, low-energy buildings to be designed, feedback on the measured operational performance of real buildings is required, which is only possible from organized energy monitoring systems and CS of BEPM [11]. Unfortunately, BEMS are expensive and many homeowners find the required investment prohibitive.

2.1.1. Standard Assessment Procedure – SAP

Standard Assessment Procedure (SAP) is the methodology, developed by the Building Research Establishment (BRE) for the former Department of the Environment in 1992, based on the BRE Domestic Energy Model (BREDEM) framework for calculating the energy consumption of dwellings. This methodology is used by the United Kingdom (UK) Government to assess and compare the energy and environmental performance of dwellings in order to help deliver its energy efficiency policies. SAP purpose is to provide accurate and reliable assessments of dwelling energy performances that are needed to underpin energy and environmental policy initiatives.

This procedure, based on standardized assumptions for occupancy and behaviour, assess how much energy a dwelling will consume when delivering a defined level of comfort and service provision. These indicators of performance are based on estimates of annual energy consumption for the provision of space heating, domestic hot water, lighting and ventilation. SAP enables a comparison of dwelling performance quantifying it in terms of energy use per unit floor area, and determine related factors, such as a fuel-cost-based energy efficiency rating (the SAP Rating) and emissions of carbon dioxide, CO_2, (the Environmental Impact Rating) from the assessment [12].

SAP, as a simplified tool to reflect the theoretical energy performance of a building in compliance with UK building regulations, is used in building dynamic modelling since this has a significant role in evaluating the in-use building energy performance.

2.1.2. National Calculation Method – NCM

The Ministry for Housing, Communities, and Local Government (MHCLG) in consultation with the Devolved Administrations (DAs), defined the National Calculation Method (NCM) for the Energy Performance of Buildings Directive (EPBD), which, besides indicate the procedure for demonstrating compliance with the Building Regulations for buildings other than dwellings by calculating the annual energy use for a proposed building and comparing it with the energy use of a comparable 'national' building, contains standard sets of data for different activity areas and call on common databases of construction and service elements. These standard sets of data are used as a base model and are default schedules templates for dynamic simulation on DesignBuilder Software [13].

2.1.3. Building Energy Performance Simulation (BEPS)

In order to understand the overall energy consumption in buildings, since the buildings energy flows can be very complex, energy modelling of buildings becomes necessary. BEPS is a detailed analysis of the energy use of a building and/or its energy-using systems, carried through the computer-based simulation software. It could be performed a building-wide simulation [14–16] as well as detailed component analysis using specialized simulation software tools which works by creating a mathematical model that gives a rough representation of the building.

BEPM can generally be classified as: diagnostic models, used to identify the nature or cause of some phenomenon and to better understand the laws that govern a given system; or prognostic models, used to predict the behaviour of a complex system given a set of well-defined laws. The BEPM can further be classified into Law-Driven (or forward) models, which predict a system behaviour given its properties and conditions by applying a given set of laws; or Data-Driven (inverse) approaches, which produce models that are capable of accurately predicting system behaviour by using monitored data from the building. The data-driven methods can be used to describe a system with a minimal set of adjustable inputs [17].

Inverse models, in the context of energy performance estimation, can be used in detailed model calibration. In this approach, a fully descriptive law-driven model of a building system has its various inputs tuned to match the measured data. The detailed model calibration allows assessing the impact of changes in specific physical parameters of construction, system and environment, and provides a more detailed prediction of building performance as it has high-quality input data available. However, because this approach is over-parameterized and under-determined, it requires significant experience, time and effort for its development [17].

2.1.4. Issues with Building Energy Performance Simulation and Model Calibration

Aspiring to maximize the benefit of the simulation and for it to be employed successfully at the beginning of the design process, decisions with the biggest effect on performance must be made at the initial stage, such as form and materials. In this case, it is necessary to know the details of the construction, which does not correspond to reality in most cases [9].

BEPS models need to have a certain degree of confidence in order to the existing model closely represent the actual behaviour of the building under study. However, significant discrepancies between BEPS model-predicted and the actual metered building energy use (often up to 100% differences) have been observed recently in numerous studies [17]. Since Calibration is known as the reconciliation of model outputs with measured data, achieving more accurate and reliable results, it's the best method to reduce the discrepancies between BEPS prediction and measured building performance.

As synthetized by Coakley, Raftery, & Keane [17], the BEPS modelling and calibration face some issues. The problems relate to modelling are:

- The lack of understanding and consistent use of standardized methods;
- The time, knowledge, expertise and cost required to develop accurate models of building geometry and HVAC systems;
- The poor integration between various 3D modelling software packages (such as Autodesk Revit and ArchiCAD) and BEPS packages (such as EnergyPlus, DesignBuilder).

The BEPS calibration issues are:

- The lack of explicit standards for calibration criteria;
- The expense and time needed to obtain the required hourly sub-metered data, which is usually not available;
- The few measurable outputs to thousands of model inputs;
- The lack of high-quality input data required for detailed models;
- The few studies which account for uncertainty in model inputs and predictions, what leads to a lack of confidence in BEPS outputs;
- The difficulty in identifying the underlying causes of discrepancies between model predictions and measured data; and
- The lack of integrated tools and automated methods that could assist calibration.

2.2. Calibration Simulation

Usually, only very scarce and limited information about the building and its performance, such as as-built files and energy billing data, are available. It contrasts with the simulation packages with a high number of details and parameters to adjust and aspects that cannot be investigated in practice, as they have been developed to support the design of new buildings. [14]. This situation indicates how the calibration of a simulation model to an existing situation usually is highly underdetermined problem.

In literature [1,17] it's possible to find four main proposed BEPS model calibration methodologies: manual calibration methods based on an iterative and pragmatic approach; graphical-based calibration methods, suite of informative graphical comparative displays; calibration based on analysis procedures and special test; and automated techniques for calibration, based on analytical and mathematical interventions.

Several studies based on CS have been carried out in the past decades but till the moment no formal and recognized methodology has been presented. The lack of a universal consensus guideline makes CS a process highly dependent on the user's judgments and skills, highly timing consuming and far more complicated, requiring higher expenses than "uncalibrated" models.

User's knowledge and skills constitute an imperative and elementary factor for performing calibration. As issues concerning the reason of divergencies between simulated consumption and measured consumption are often encountered during CS, users should be able to identify the underlying causes of the mismatch due to their building simulation knowledge and skills. Regardless of the calibration method used and the accuracy of the building models accomplished, the user's skills also impact directly on the calibration running time [2].

Nevertheless, there are standard criteria that characterizing the calibration process for validating a calibrated model: the calibration methodology adopted; the calibration level pursued; the model complexity; the simulation tool used; and the integration of SA/UA in the calibration process [2]. The same calibration process can adopt different methods from the four main categories in order to improve the calibration.

2.2.1. Calibration Methods

The BEPS model calibration is notoriously known as a complex and highly undetermined problem for feature an important number of parameters to calibrate in comparison with the very limited amount of data available, even if special attention be paid to select parameters with a physical meaning easily identifiable.

Considering the complexity of the problem, when performing a model calibration, is crucial ensuring the method is systematic and may be applied to numerous cases, keeping the reproducibility and robustness of the approach. In the same way, is important consider issues regard to sensitivity, distinguishing influential and non-influential parameters; uncertainty, quantifying the final uncertainty on the model's outputs; and accuracy, defining the calibration criterion that will be used to estimate the quality of the calibrated model [14].

As BEPS is still a relatively rare practice, it’s also unlikely to find an initial model available, hence often one has to be created according to design documentation and, in the absence of these, program defaults [15].

The calibration process begins by configuring the initial as-built input file based on the available information, such as architecture plans, built files and technical sheets. The next steps of the calibration methodology involve selecting the sources of information explored to identify the model input parameters. From the as-built files, there is a hierarchy between the sources of information, subsequently: inspection through visits to the building and installation, a survey of installed equipment and analysis of the Building Energy Management System (BEMS); monitoring using a power measurement and analyse equipment with short or long term measurements; questionnaire-based occupancy survey. Along this process, priority is always given to physical observations and measurements rather to architecture/engineering plans or specification sheets.

The adjustment of a parameter is done when it represents an improvement in the reliability of the model, only if the updated value came from a more reliable source of information and has a physical meaning, such as direct measurement at the expense of on-site observation. In order to help define a hierarchy between influential and non-influential parameters, sensitivity analysis can be used. The non-influential parameters are set to their best-guess value and the influential parameters are ranked in order of importance [14,15].

At each stage of the calibration process, an analysis of the calibrated model accuracy is done using statistical criteria and visual verifications, in order to point out possible problems to be investigated for the model continuous improvement. Depending on the size and complexity of the modelled construction and systems, the amount of information available at each stage of the calibration process and the number of iterative process steps, a greater or lesser number of revisions and analysis of the calibrated model will be necessary.

2.2.2. Manual Calibration

Manual Calibration category is the most used in simulation applications, includes all CS applications without a systematic or an automated procedure through mathematical/statistical methods or otherwise. The input data are altered based on users’ knowledge about the building, experience and judgment, relying on iterative pragmatic intervention by the modeller. A manual calibration method may avoid the use of highly complex models once they are hard to handle [2,17].

2.2.3. Graphical Techniques

Graphical Techniques are based on graphical representations and comparative displays of the results. The graphical methods may also avoid the use of highly complex models.

3D Comparative Plot

This method is applied for calibrating time-dependent parameters, has been established to analyse hourly differences, during the entire simulation period, between simulated and measured data, for instance, schedule loads. Hourly values are computed and compared in the plot.

Calibration Signature

Calibration Signature corresponds to a graphical representation of the differences between the predicted and simulated energy consumption, as a function of the outdoor air temperature.

2.2.4. Analytical Procedures

This method is based only on analytical test and procedures, such as short or long-term monitoring periods, it does not utilize mathematical or statistical procedure in the calibration process.

2.2.5. Automated Techniques

Automated techniques can be described as having some form of automated process to assist or complete model calibration, these approaches are based either on mathematical procedures, as Bayesian calibration, or in analytical approaches. Include all procedures that are built on sort of automated procedures which cannot be considered as user-driven.

Automated methods may bring a reduction on the computational time of the calibration process, once they tend to use simplified models, rather than more detailed ones. As complex models are hard to handle and tune, they can provide guidance that could represent too complex procedures, bringing users to a confusing and unorganized process. Even though the current trend is the search for and use of automated methods, based on the implementation of sensitivity and uncertainty analysis, to fine-tune the models and improve thus their accuracy [2,17].

Bayesian

Bayesian analysis is a statistical method which computes a distribution for unknown parameters (θ) given the observed data (y), from preceding probability theory. It is employed for calibration purposes for incorporating uncertainties directly in the process.

Meta-model

A meta-model is a mathematical function in which a limited number of input and output combinations serve as the basis for determining the coefficients.

Optimization-based

Optimization-based methods are settled on the combination of a building simulation software, such as DesignBuilder, EnergyPlus, etc., and as optimization program which employs optimization algorithms, such as GenOpt.

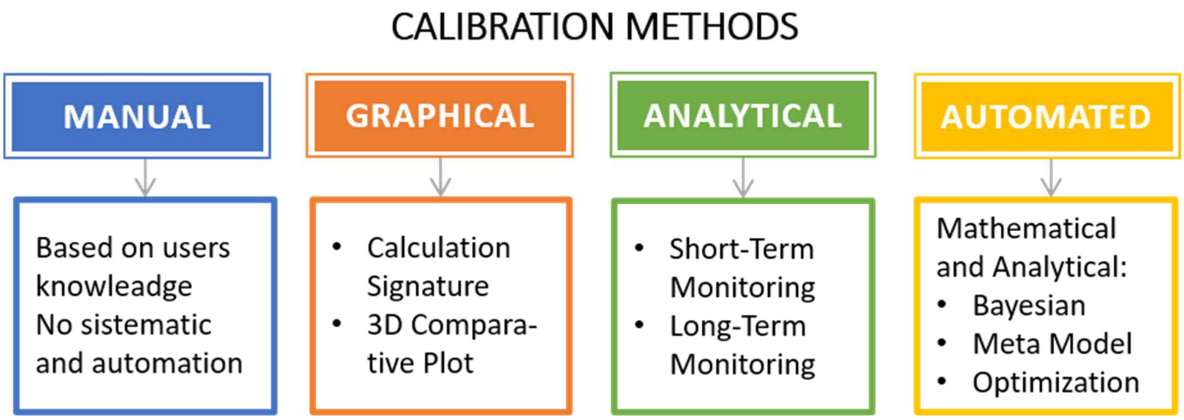

Figure 1: Calibration Methods

The Figure 1 above briefly presents the main methods for carrying out the calibration process, which are detailed in this chapter.

2.2.6. Obtaining input data and assessing calibration performance

Calibration methodologies and results are often not discussed in detail in many case studies, which leads to a lack of explicit standards for calibration criteria. Current guidelines do not account for input uncertainty, sub-metering calibration, or zone-level environmental discrepancies, there are currently few studies which account for uncertainty in model inputs and predictions, thus leading to a lack of confidence in BEPS outputs.

The most common approach is which the analyst tunes some of the countless input parameters until the model meets the acceptance criteria is commonly used. Manual approaches to model calibration generally rely on manual pragmatic user intervention to 'fine-tune' individual parameters to achieve a calibrated solution. However, these changes are often not tracked or recorded and are rarely reported. This results in a situation whereby the calibration process relies heavily on user knowledge, experience, statistical expertise, engineering judgement, and an abundance of trial and error.

In order to improve the reliability and reproducibility of the calibration process, it is necessary to bring the scientific method of evidence-based decision-making to the process. All changes to the input parameters must be made according to a clearly defined hierarchy of priorities, so that simulation becomes more of a science than an art. Changes in the model must be documented, keeping an up-to-date history of the decisions made along with the evidence on which these decisions were based [11,17].

Although several authors have worked on defining a criterion to assess the quality of the calibration, defining a general criterion, ensuring the proper calibration of a given simulation model for a given existing situation, is a difficult if not impossible task. The current guidelines specify only acceptable error intervals for the annual or monthly simulation of the entire building, through the calculation of statistical indices such as Mean Bias Error (MBE) and Coefficient of Variation of the Root Mean Square Error (CVRMSE) (ASHRAE, 2002). However, these calibration criteria are usually considered too cold or not very representative of the quality of the calibrated model [14].

Building energy simulation models are generally considered 'calibrated' if they meet the criteria set out by ASHRAE Guideline 14 / IPMVP protocol [18], [19], [20]. Mean Bias Error (MBE) (%), Root Mean Square Error (RMSE) (%) and Coefficient of Variation of Root Mean Square Error CV(RMSE) (%) are the most common calculations to check the model calibration.

2.3. Uncertainty Analysis

Uncertainty analysis has received increasing attention and becomes an active research field in buildings energy assessments because a number of variables influencing energy use and thermal performance in buildings are inherently uncertain [21].

The UA effort involves the designation of a mathematical description to the uncertainty in the parameters of the model previously identified as sources of uncertainties, in other words, it assesses the consequences of a lack of knowledge about the input parameters on model outputs.

The variety of approaches that have been used for uncertainty characterization and the complexities associated with them is showed with the analysis of each uncertain parameter, the most commonly utilized approaches are the simple ones, using PDFs, while more advanced models have been considered only for some parameters [22].

No standard framework for uncertainty quantification in building energy models is curently available, uncertainty modeling it is often based on literature and expert judgment and the attention on the use of measured data is limited [10]. However, as enough applications of statistical methods of uncertainty analysis in buildings energy assessment and thermal performance are available and mature, these methods have been ready to become the mainstream approach. In order to provide more flexible analysis for achieving sustainable high-performance buildings, it's necessary to create more connection between the characteristics of building energy analysis and the fundamentals of uncertainty quantification [21].

Many studies demonstrate the relevance of uncertainty analysis in building performance assessment in four out of several discussed applications [23,24], such as:

- Building stock analysis;
- HVAC system sizing;
- Variations of sensitivity indicators;
- Optimization under uncertainty.

2.3.1. Uncertainty Analysis Methods

There are two principal types of uncertainty analysis methods [4]: local approximations, such as Taylor decomposition, and sampling methods, as Monte Carlo and Latin Hypercube Sampling. The uncertainty analysis can also be categorized by the way they propagate in numerical models, which could be forward and Inverse.

Forward uncertainty analysis, to obtain variations of energy use, propagates input uncertainty through building energy models. Heo et al. [21] discuss three types of approaches for forwarding analysis (Monte Carlo, non-sampling, and non-probabilistic) in order to provide sufficient choices of uncertainty methods depending on the purpose and specific application of a building project. Because it is an intuitive method and only requires running energy models a few times, the sampling-based Monte Carlo method proved to be the most widely used forward uncertainty method in the field of building energy assessment among the quantification methods studied.

Inverse uncertainty analysis can deduce unknown input factors through building energy models based on previous information and energy data. Recent researches of inverse analysis have concentrated more on Bayesian computation once this method can make full use of prior information on unknown variables, from previous studies, site surveys, and industry standards, incorporating this information on building energy models data [21].

Some distributions are suggested [9] to uncertainty modelling in the construction of energy systems according to the objective of the work:

- Discrete distribution, parametric or non-parametric, is limited to a finite number of options;
- Uniform distribution is a limited continuous distribution, whose probability of the variable assuming a value between the limits is equal;
- Normal distribution is most appropriate for measured physical data, such as measured lengths or temperatures in the case of simulation of healthy buildings;
- Log-normal distribution is when two or more variables normally distributed are combined as a product, not being able to produce negative quantities and being unlimited to the positive infinity, as in the case of the area, the result of the product of two length measurements will be normally distributed;
- Triangular distribution is a limited continuous distribution, suitable as an intermediate step between uniform and normal distributions, is often used in fuzzy logic applications.

2.3.2. Sources of Uncertainty

Uncertainty analysis is an important technique and can be used in simulation to address problems such as: the model's degree of realism, how well the model represents reality and with what resolution; choice of input parameters, which values should be used in the absence of measured data; stochastic processes, how much the forecasts are affected by the assumptions made in relation to future climatic, occupation and operational factors; features of the simulation program and the uncertainties associated with the specific choice of algorithms for the various heat and mass transfer processes; and design variations and the effect of changing an aspect of the design [9]. Uncertainties are inherent to modeling techniques, however analysis methods must be available to assess their effects.

The main sources of uncertainty in the buildings energy models are related to physical domain of the buildings and generally arise from four main sources [2,17]:

- Scenario uncertainty, external conditions imposed on the building, including outdoor weather conditions, building usage and occupancy schedule;
- Building physical and operational specification uncertainty, due to incomplete or inaccurate specification of the building or modeled systems, which includes any model parameters exposed, such as geometry, building envelope properties, internal gains, HVAC systems specifications, operation and control settings;
- Model inadequacy and modeling uncertainty, due to inadequate simplifications and assumptions of complex physical processes, these assumptions can be explicit for the modeler, such as modelling assumptions, zoning and programming of stochastic processes, or hidden by the tool, as ignored phenomena in the calculation algorithm;
- Numerical uncertainty, errors introduced in the discretization and simulation of the model due to the lack of robust and precise numerical algorithms, such as observation error and metered data accuracy.

2.3.3. Assessing Uncertainty Analysis

Due to the lack of knowledge about the input parameters, as detailed information on building materials, components and systems specification needed for energy simulation, in many cases the characterization of the uncertain parameters couldn't be backed up by actual data, which requires assumptions based on the modeller’s experience and their best guesses, default values or on empirical information. Relying on assumptions made by the modeller, even if's more valuable compared to neglecting uncertainty completely, it's not the optimal solution for the input data, thus adequate effort should be placed towards obtaining data to support these assumptions, in order to increase the transparency of uncertainty investigations [9,10,22].

The complexity of building systems often lead to simplifications into the simulation. Furthermore, most researches have considered all uncertain model parameters as independent instead of looking upon parameter correlations which might, in some cases, lead to erroneous conclusions. The assumption of parameters independence and the simplifications made due to the complexity of building systems, add to the uncertainties in the simulation outcome [10,22].

Another complex factor that has a significant impact on uncertainty analysis in building energy performance is occupants behaviour. Probably, soon, implicit models will remain dominant in simulating the variations of occupant behaviour. Specialized tools have been developed to generate samples from specified uncertainty distributions, such as Matlab, R, and jEPlus. Those tools also create and run a large number of building energy models for uncertainty analysis [21].

The decision in selecting an appropriate UA method for the uncertain model parameters it’s a difficult part of the modeller's work. This difficulty can contribute to a modeller’s decision to pursue deterministic modelling. Furthermore, in many cases, a considerable obstacle is established by the structure and the complexity of the modelling tools used for different functions. Due to this complexity, a modeller could be discouraged to consider uncertainty in the process of energy performance evaluation, which emphasize the need of facilitated data exchange between the different tools [22].

Aiming to more truthful uncertainty investigations, every uncertain parameter should be considered, although, it also leads to more complex and more computationally intensive model formulations. As the design progresses, the uncertainty will generally decrease, since the design decisions are made concerning the uncertain data.

In order to allow the appropriate concentration of design effort, its necessary identify those parameters that most strongly impact on performance, this could be done by assessing the uncertainty in simulation outputs [9]. One approach to minimize the number of uncertain parameters is the "manual" elimination based on the modeller's experience, and an alternative to avoid this approach is the use of screening Sensitivity Analysis techniques like the Morris method [22]. Screening techniques require only a small number of Monte Carlo model evaluations because it's able to identify the uncertain parameters whose uncertainty can be safely ignored.

2.4. Sensitivity Analysis

As described before, sensitivity analysis is a useful device for energy simulation models and, in order to seek the characteristics of building thermal performance, has been extensively adopted in different types of applications, such as, calibration of energy models, building design, building retrofit, building stock and the impact of climate change on buildings [25].

Aiming to provide more robust results for sensitivity analysis, the variations of sensitivity index need to be computed. This uncertainty and probability distributions of input factors for different research proposes is often not emphasized enough or even overlooked in the building analysis field [25].

2.4.1. Sensitivity Analysis Methodology

In order to get sensitivity analysis implemented in building energy performance analysis, the methodology that should be used is basically the same in different types of application, the variations of input factors, in other words, uncertainty or probabilistic distribution, is the main difference for diverse research purposes. This methodology follows those typical steps: determine input variations; create building energy models; run energy models; collect simulation results; run sensitivity analysis; and presentation of sensitivity analysis results [25].

The building performance analysis methods could be firstly divided into internal and external methods. This work focusses on describing and analysing the external ones. The external methods could be categorized into local and global sensitivity analysis, both methods provide a quantitative result on determining the influence of each input variable on the outputs. The global methods could be further divided into four approaches: regression, screening-based, variance-based, and meta-model sensitivity analysis.

According to other studies, [25] the choice of which method should be used in sensitivity analysis depends on many factors, such:

- The research purposes,
- The number of input variables,
- The computational cost of energy models,
- The analyst's time for a project,
- The familiarity of sensitivity methods, etc.

2.4.2. Local Analysis

The simplest method but still very useful in building performance analysis is local sensitivity analysis. This method focuses on the impact of the inputs on a specific area of the input space. The restraint of local analysis is that it only explores a small portion of the possible space of input value, but even with its shortcomings, the method is low computational cost, simple implementation, and easy interpretation [25].

Differential Sensitivity Analysis

Differential Sensitivity Analysis (DSA) is the best known of the local methods, described as the backbone of all sensitivity analysis methods. The DSA is a robust method and capable of accurately quantifying the uncertainty in the model output, in each parameter independently, thus being suitable for use in the construction simulation.

It is based on calculating the effect of changing each uncertain parameter in isolation. An initial simulation is performed and, for each uncertain parameter, two simulations are performed by changing a model parameter from its initial value to its extreme, upper and lower values, while all other parameters remain at their initial values. From the comparison of the results of these simulations with those of the initial simulation, the effect of uncertainty is calculated [9].

Despite its ease of application and interpretation of results, since the differences are entirely due to the only parameter that was disturbed, the effects of uncertainties are assumed to be independent of all other parameters.

Some methods, such as the Factorial (which includes interactions between parameters), the Cotter and the Morris, were other local methods derived from the differential sensitivity analysis. However, as these methods are more appropriate for identifying critical parameters than for quantifying the effect on output, care must be taken when selecting and applying the correct one, a general difficulty encountered in the selection of statistical methods [9].

2.4.3. Global Analysis

Aiming to identify the key variables affecting building thermal performance, global sensitivity analysis methods have been increasingly adopted in building energy analysis, being the focus of recent researches.

It is due to their capability to explore the whole input space; they give more accurate results and many methods allow the self-verification. These methods drawback is that they require a larger number of simulations, so it's hard to implement those methods on building simulation programs with only graphical user interface when it is necessary to automate the process of creating energy models and collecting the results from simulation in order to more simulation runs for global sensitivity analysis [25].

Regression Method

Regression analysis is a statistical method which "aims to estimate the relationships between different variables in a model, investigating how a dependent variable change based on the variation of an independent variable" [25]. It provides sensitivity and input correlation information and requires moderate computational cost, which put him in one of the first-choice methods.

This method could be applied in the early design phase, considering different design scenarios and their impact on the building energy consumption, or also in post-construction phase, for assisting the calibration of building models [2].

Screening-based Method

It's important to identify the parameters that influence the most in building model and define their level of uncertainty, as not all input data affect the investigated energy consumption in the same ways. Throughout a screening analysis, it's possible to identify the most important or influent parameters to be considered in further global SA [2].

Screening methods are local sensitivity analyses which provide qualitative results of the inputs influencing on output, highlighting parameters with important or negligible effects relative to each other, without knowing their global impact. They are often used before uncertainty or sensitivity analysis to exclude negligible inputs [4].

The most common Screening techniques are Elementary Effects, also known as the Morris method, subsequently, we also have Sensitivity Index and Differential Sensitivity Analysis.

Morris method is recommended in the case of an inherent non-smoothness in the model and for high computational energy models, when there are a large number of input variables and the analyst only needs qualitative analysis [4,25].

Variance-based Method

Variance-based methods aim to decompose the uncertainty of the outputs over the input variables, giving more reliable results at the cost of increased computational time [25]. There are two main sensitivity measures that are assessed within this type of technique: first-order index and total order index. They represent correspondently: the effect of the input parameter Xi on output variation y; and the measurement of the effect of the parameter alone and the sensitivity of the interaction of the parameter with all other parameters [2].

The most common Variance-based techniques are ANOVA and FAST methods. The FAST allows apportioning the output variance to the variance in the input parameters, computing the individual contribution of each input factor, referred as “main effect” in Statistics, to the output variance, which is why it is considered superior to other local SA methods [2].

Meta-Model Sensitivity Analysis

The meta-model sensitivity analysis can be used to determine the most influential factors in the analysis of the results from regression method indicating there is a large proportion of the output variance unexplained by regression models, without running extra energy simulation [25]. It could be a good choice to quantify the variance of output for every input, and also it is possible with this method to replace the physical model by running a swift code that performs a building simulation in less than one second [4].

Monte Carlo

The Monte Carlo method (MC), which is one of the most commonly used techniques for carrying out global sensitivity and uncertainty analysis, is broadly used in the building field to achieve the propagation of uncertainty by analysing distribution or dispersion [4].

This analysis is based on a repeated number of simulations with a random sampling of the model's input, each uncertain model input is defined through a probability distribution, all input parameters are then varied simultaneously. MC assesses an estimate of the overall uncertainty in the model predictions based on the uncertainties in the input parameters [2].

The random samples of the model inputs could be replaced for low discrepancy sequences, built deterministically to present a low dispersion, such as stratified sampling and Latin Hypercube Sampling. This is the principle of the quasi-Monte Carlo method [4].

Sampling

Sampling methods, which consist in carrying out a large number of simulations using different ways to create the input samples, are the better option when a model has more than 4 discrete parameters or outputs since their disadvantage of high computational time is no longer comparable to the other methods [4].

Latin Hypercube

Latin Hypercube enables to cover the input space and the convergence is fast, providing the probability density of the outputs. This is the reason that if the total distribution is desired to set the threshold, LHS is preferred against the standard Monte Carlo method.

LHS method is very similar to Stratification method, except that "the points for LHS method are not selected in each stratum but in a subset, such that no pair of subassemblies should have the same value for the same parameter" [4].

There are other methods to access meta-model sensitivity analysis, they are: Quadratic Combination method, FORM/SORM, Sparse Polynomial Chaos, MARS, ACOSSO, SVT OU SVM and Gaussian method.

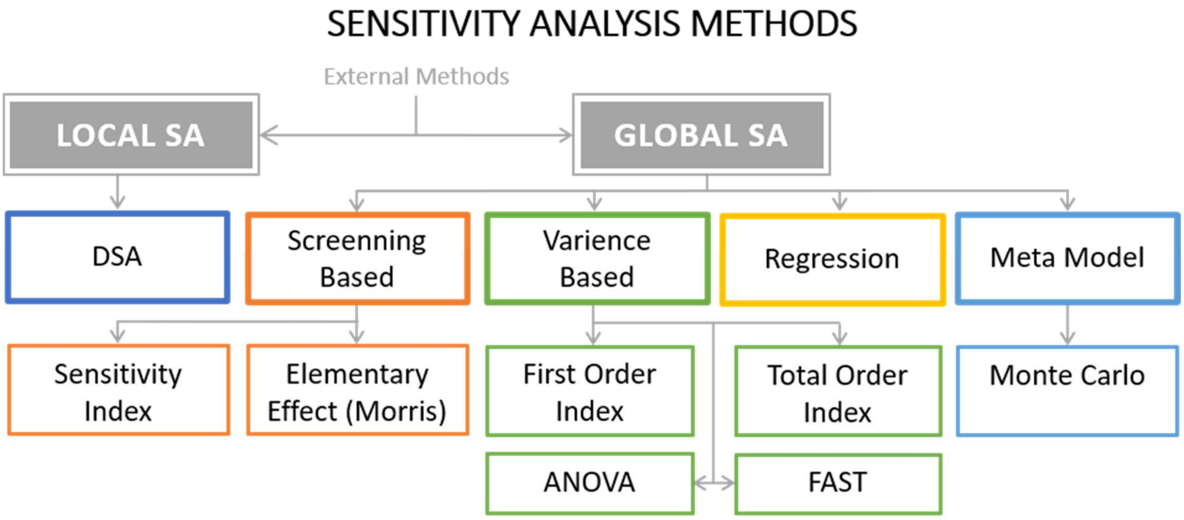

Figure 2: Sensitivity Analysis Methods

The Figure 2 above briefly presents the main methods for carrying out the sensitivity analysis detailed in this chapter.

2.5. Additional Work Required

Regarding to Uncertainty Analysis, Mavromatidis, Orehounig, and Carmeliet [22] pointed as an additional work required two approaches which could facilitate the workflows between DES design models, UC approaches and modelling techniques. “The first approach involves the integration of many different modules into a single framework, implemented in a common environment. An alternative approach is to host individual models, each implemented in a different environment, in a multi-model ecology".

More effort still needs to be placed on the most difficult task in ensuring the quality of uncertainty analysis results, which is the rigorous quantification of the input parameters uncertainty. It's necessary to construct the databases for quantifying uncertainty input parameters in terms of diverse indicators, such as building types, climate characteristics, and new or existing buildings [21].

Related to the occupant behaviour, many issues still need to be addressed to better simulate stochastic occupant behaviour and their interactions with other systems in buildings by using both implicit and explicit occupant models.

Further research on the sampling-based methods is required to present clear guidance on the sampling size in order to produce converged probabilistic outcomes for building energy analysis.

For the 2D Monte Carlo method, further studies are required once this approach can be used to represent both epistemic and aleatory uncertainty in building energy assessment. It's necessary to explore new visualization methods to show uncertainty results.

Regarding Bayesian inverse computation, more attention should be paid in applying this method, since it's important to clearly understand how the posterior distributions of input variables, defined from Bayesian computation, is affected by the availability of energy use data in combination with prior beliefs specified as precedent distributions.

Many new methods haven't been sufficiently explored to test the relevance in calibrating building energy models, such as Hamiltonian Monte Carlo. Further research is required on optimization under uncertainty (robust design) for low-energy buildings, considering a number of uncertain factors at the design stage [21].

3. METHODOLOGY

This chapter describes the methodology which will be followed in the case study developed in this work. The findings obtained and described in the previous chapters were used to instruct the procedures of modelling and calibrating in this chapter, in order to develop an accurate model which reflect the actual performance gap.

The overall methodology which will be followed in this work is described first. In the following, the building case study and the reference apartment were described in detail. Next, the information on which data were measured and in which way is summarized. And finally, the way that models were created, and the steps of calibration are described.

3.1. Overall Methodology

This work focus is on building performance calibrated modelling through dynamic simulations in order to estimate its predicted energy performance at in-use status. A systematic, evidence-based methodology was used for calibrating one representative apartment energy model-based to monthly energy consumption data, through measured actual energy performance.

The energy supplied to the apartment, both the electric gas and the natural gas for heating, as well as IEQ measurements, like internal temperature, CO_2 concentrations and relative humidity, were measured for a study conducted by researchers from a joint research project between UCL and Tsinghua University, entitled 'The Total Performance of Low Carbon Buildings in China and the UK'. The energy supply has been measured since (02/08/2016) to obtain the current energy performance, and the IEQ began to be monitored (27/09/2016).

The model was created in DesignBuilder Software version 6 in two phases, a base model and a calibrated model. Initially, to generate the parameters, profiles and schedules in the base model, NCM database and SAP worksheets were used. The calibrated model was obtained by modifying the base model according to findings obtained from residents' feedbacks, actual IEQ and energy measured conditions.

As noted in the previous chapter, it is extremely important to monitor and control all steps of the calibration process for later analysis and reproduction. As a result, during the modelling process, the calibration settings for each phase were listed and the impacts of these adjustments were analysed.

The outcomes from the base model energy simulation were compared with the actual measurement energy data and elaborate on the causes of discrepancies between the two results. The calibrated model results, in the same way, were compared with actual energy consumption, and then the gap between these two performances was analysed to predict possible determinants.

UA and SA were conducted after the completion of the calibrated model in order to verify and quantify the degree of uncertainty for and the most influential and determinants variables in an energy performance model. Finally, some hypothesis were created to explain the energy performance remaining gap between the actual measurements and the calibrated model simulation results.

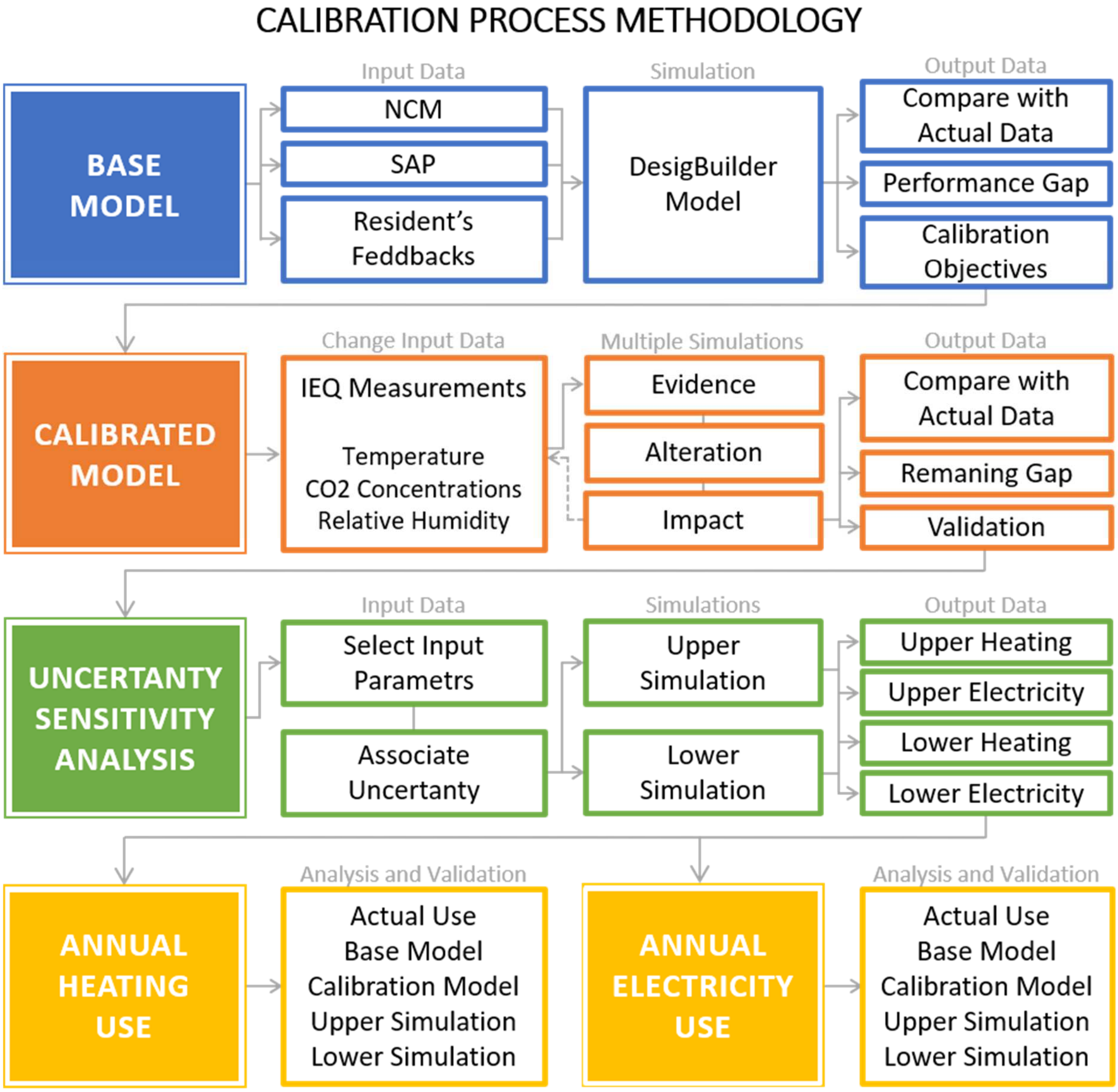

Figure 3: Calibration Process Methodology

The Figure 3 above briefly presents the general methodology of the calibration process used in this research.

3.2. Case Study: Apartment Blocks in East London, United Kingdom

The chosen case study building consist of two low-energy apartment blocks located in East London, England. The buildings were completed in 2015, they attain high sustainability standards (Code for Sustainable Homes Level 4) and are mixed-use buildings since the ground and first floors accommodate offices.

These two buildings provide in total 98 highly efficient residential homes, as well as community infrastructures like offices and a community centre on the ground and first floors. Block A is a fourteen-storey high-rise building including 48 apartments, and Block B is a ten-storey low-rise building with 34 apartments and 16 maisonettes.

The building is plugged into a district heating system, have the electricity consumed by appliances, equipment and lighting supplied from the Grid, and heating and domestic hot water are supplied by the centralized boiler system. The heating energy and electricity data of all the apartments in this condominium are metered by E.ON[1], one of the UK's leading power and gas companies.

All the apartments have radiators installed in most of the rooms for space heating, no mechanical cooling system is used. Mixed-mode ventilation strategy, which uses both natural and mechanical ventilation with heat recovery, is present in all the flats, each one with its own MVHR unit with stale air extracted vents and fresh air incoming vents in the flat. In order to maintain the user's health and well-being, the MVHR system operates continuously, providing enough fresh air inside as recommended by the WHO [26].

Only the residents of five apartments among the total 98 flats allowed the monitoring of Internal Air Quality (IAQ) and thermal comfort conditions in their homes. Because of that, the present work chose one of those flats as a typical one by a probabilistic sampling in order to evaluate its performance. The Figure 4 below shows the spread of energy use in all the flats, with the average being of 2437 kWh and standard deviation of 1575 kWh. The representative flat selected for calibration and detailed analysis has energy use of 2581 kWh, near the average value across the apartment block. The red line in the figure highlights the energy use of the representative apartament that was selected for detailed assessment.

[1] https://www.eon.com/en.html

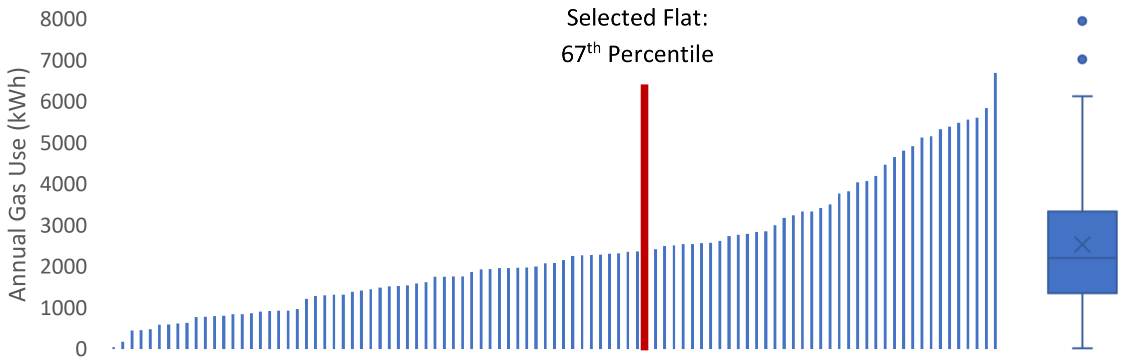

Figure 4: Spread of actual gas use of all flats in the apartment block

The apartment analysed is inhabited by five people, three adults and two children, it's located on the eighth floor of Block A, facing southwest and southeast orientations, whith total floor area of 98.3 m² and storey height of three meters. It has eight zones, which include three bedrooms, living room, kitchen, bathroom, toilet and circulation, represented in Figure 5.

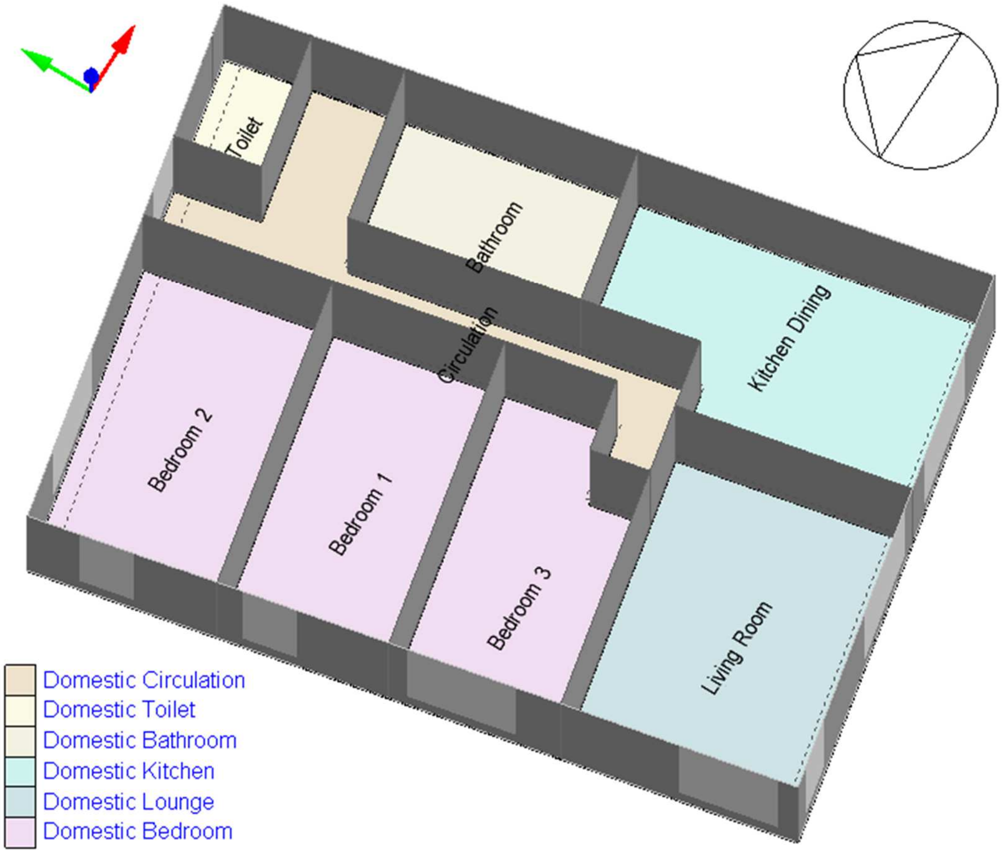

Figure 5: Apartment's DesignBuilder 3D

3.3. Data Collection for Actual Performance

The three monitored environmental parameters, indoor air temperature, Relative Humidity (RH) and CO_2 concentration, were collected from the on-site measurement in the flat. The measurement, started in September 2016 and still going on, have a time gap for data logging of 5 minutes, uses Eltek data loggers[2] installed on the walls of one bedroom, the living room and the kitchen in the flat for monitoring of environmental parameters.

The the equipment's sensor measures: for temperature, range of -30 to 65°C, resolution of 0.1°C and accuracy of ± 0.4°C (+5 to + 40°C), ± 1.0°C (-20 to +65°C) and ± 1.5°C (-30 to -20°C); for relative humidity, range of 0-100%, resolution of 0.1% and accuracy of ± 2% (10 to 90% RH) and ± 4% (0 to 100% RH); and for CO_2 concentration range of 0-5000ppm, resolution of 3% and accuracy of ± 50ppm. The heating energy and electricity supplied are measured by its own energy meter installed by E.ON and the usage data of the case study flat could be directly read from meters. Actual Performance.

The year selected from the current measurements to serve as the database for the simulations was 2017, as it has the most complete electricity data, providing the highest accuracy / resolution power consumption data. Electricity consumption data were obtained from the electricity meter of the apartment located in the building during site visits, which contributed to the non-regularity of the electricity consumption information as those visits took place according to the availability of the team that monitors this building. The available data is for the months of Jan, February, April, May, September, November and December, with intervals between measurements ranging from 30 to 90 days.

Measurements of natural gas for heating, used for DHW heating and space heaters in the room, were taken from the meter of the selected apartment and have uninterrupted daily accuracy throughout the year. The data obtained from the IEQ measurements inside the apartment to be modelled has a big gap between the months of April to July (12/04 - 01/07), and this interval between measurements occurs again in September (28/08 – 28/02). Table 1 shows the treated measured data for monthly consumption of heating (gas) and electricity for the year 2017.

[2] http://eltekdataloggers.co.uk/index.html

Table 1: Building Measured Data - Heating (Gas) and Electricity Actual Consumption

Building Measured Data				
Months	Heating (Gas)		Electricity	
	kWh	kWh/m²	kWh	kWh/m²
Jan/17	822	**8.36**	330.88	**3.36**
Feb/17	659	**6.70**	269.28	**2.73**
Mar/17	488	**4.96**	259.16	**2.63**
Apr/17	220	**2.23**	311.62	**3.17**
May/17	254	**2.58**	303.15	**3.08**
Jun/17	372	**3.78**	289.66	**2.94**
Jul/17	396	**4.02**	299.32	**3.04**
Aug/17	317	**3.22**	265.81	**2.70**
Sep/17	277	**2.81**	255.75	**2.60**
Oct/17	377	**3.83**	271.25	**2.75**
Nov/17	509	**5.17**	323.10	**3.28**
Dec/17	882	**8.97**	338.34	**3.44**
Total	**56.69**	**56.69**	**3517.35**	**35.78**

3.4. Modelling and Calibration Process

Hereafter, the methodology in each step of the modelling and calibration process is described. The steps include the base model, the calibrated model with available information, uncertainty analysis, sensitivity analysis and hypothesis conception for the energy performance gap of the studied apartment, with the development of a calibrated final model.

As outlined in the previous chapter, tracking and recording of input data as well as changes in each phase, especially in the model calibration phase, is crucial to the reproducibility of the survey and the results obtained.

3.4.1. Base Model

The base model was created using DesignBuilder software from design project information and drawings and from design parameters in SAP and NCM dwelling templates already embodied in DesignBuilder software. The SAP worksheet provides design parameters of systems and construction such as infiltration rate, air change rate and efficiency. NCM templates included relevant defaults on power consumptions and operation profiles of lighting and equipment, operation and set-point profiles of heating system, consumptions and use patterns of Domestic Hot Water (DHW) and occupancy patterns. Other information was taken from the drawings and specifications of the design project as the U-value.

The weather file used for the dynamic simulation is provided by DesignBuilder software and corresponds to actual weather measurements for the simulated year, 2017, for the studied building location.

3.4.2. Calibration Process

The calibrated model was generated from the base model by adjusting the input values to match the information found from the actual data analysis. In order to assist in the calibration process of the model's operational profiles, IEQ was used to establish occupancy profiles from ambient CO_2 concentration data and space heating setpoints temperature from indoor temperature measurements.

3.4.3. Uncertainty and Sensitivity Analysis

The UA was conducted by assigning a degree of uncertainty for those variables who present the major probability of uncertainty according to the literature. A DSA was the methodology used to access the most influence and determinants variables in an energy performance model.

3.4.4. Performance Gap Hypothesis

After knowing the most relevant variables in the calibrated model, some hypothesis for the remaining gap between the actual and the simulated energy consumption were developed, and a final calibrated model was created.

4. BASE MODEL

In this chapter, the construction of the base model of the building under study will be described step by step. First, the parameters and variables considered in the model as well as the respective sources will be listed. Next, the model and the initial simulation results will be presented, along with the verification criteria used to check the input information to validate the base model. Finally, the comparison between the results of electricity consumption and natural gas for heating obtained with the simulation of the base model will be compared with the actual consumption of the apartment in the same period of time and the gap between the current and simulated consumption will be shown.

4.1. Input Data

The base model was directly built on DesignBuilder software based on the drawings and design projects of the selected apartment and the building. Data on the dimensions, size and quantity of the openings and U-value of the exterior walls, floors and openings were obtained from drawings. Infiltration rate, air exchange rate, the efficiency of system and construction were extracted from the SAP calculation table [27] as shown in Table 2.

Other data, such as occupancy by day of week and space usage, DHW consumption, room heating setpoints temperatures, etc., were obtained from the NCM database [28], already incorporated into DesignBuilder software as in Table 3.

The tables below contain the input data, their values and their sources, used as input to build the base model. The Figure 6 and Figure 7 beneath show the model design in the software as per drawings and design projects of the selected apartment. The attachment shows an exemple of the input data in the DseignBuilder Software.

Table 2: SAP Model Information

SAP MODEL INFORMATION

BASE MODEL	External Wall U-value	Windows U-value	Airtightness	Lighting Power Density	Auxiliary Energy	MVHR
Units	W/m²·K	W/m²·K	ac/h	W/m²	W/m²	-
Values	0.18	0.92	0.1	7.5	1.5	0.74

Table 3: NCM Model Information

NCM MODEL INFORMATION								
BASE MODEL	Metabolic Rate	Outdoor Air Per Person	Illumi-nance	Equip-ment	Occupancy Density	Set back Tempe-rature	Heating Set-point	Min Natural Ventila-tion[3]
Units	W/person	l/s - person	lux	W/m²	people/m²	°C	°C	°C
Lounge	110	10	150	3.90	0.01	12	21	21
Kitchen	160	12	300	30.28	0.02	12	18	18
Bathroom	120	12	150	1.67	0.01	12	18	18
Toilet	140	12	100	1.61	0.02	12	18	18
Circulation	180	10	150	1.57	0.01	12	18	18
Bedrooms	90	10	100	3.58	0.02	12	18	18

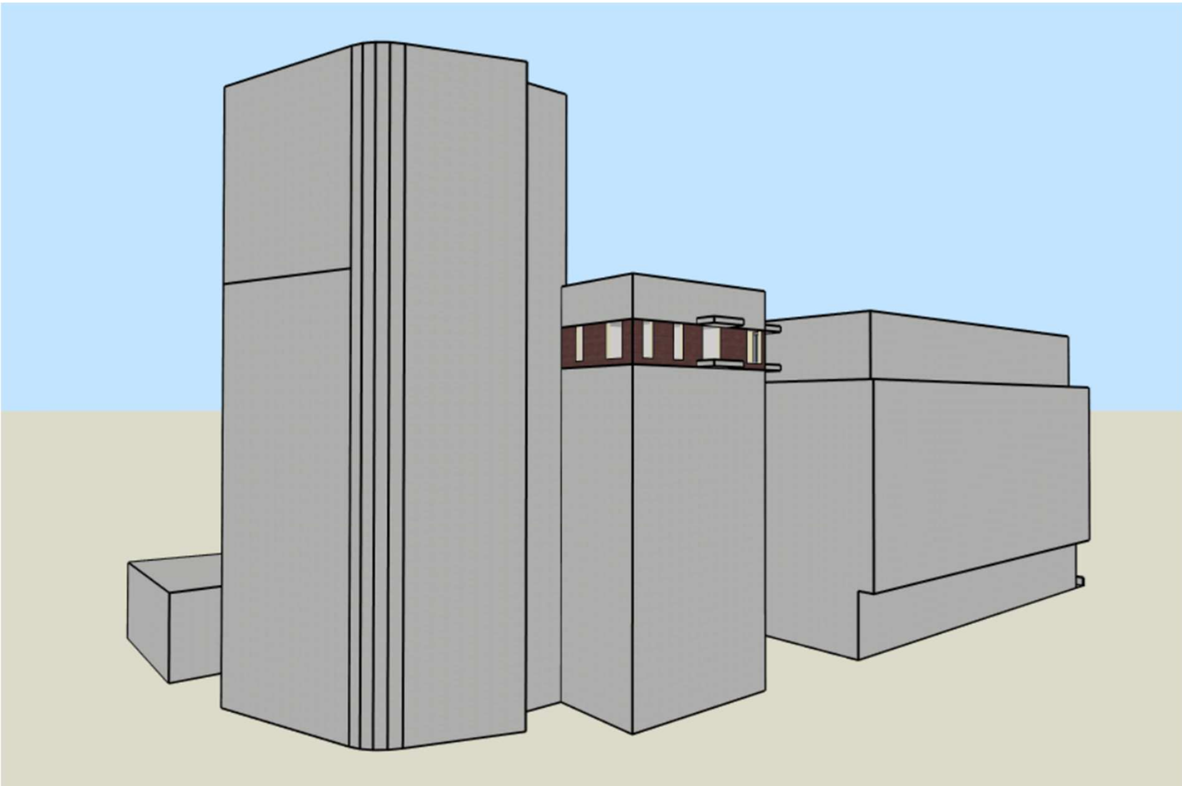

Figure 6: Building 3D Model

[3] Minimum temperature at which natural ventilation is used as a cooling method.

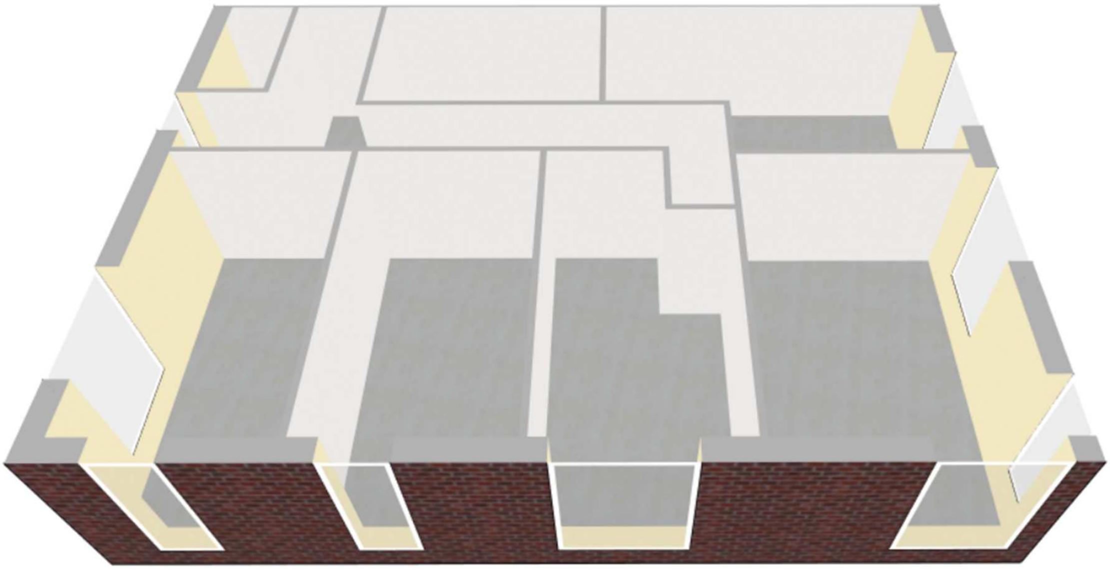

Figure 7: Apartment 3D Model

4.2. Energy Model Simulation Output Data

After simulating the base model, the results obtained were validated by checking hourly indoor temperatures for each ambient, heat gains, mechanical and natural ventilation operation and energy consumption for heating demand and electricity. The next simulations in the model calibration phase will also aim to adjust the input data to avoid overheating, low temperatures, simultaneous natural ventilation and space heating, etc.

4.3. Performance Gap

The final calculated values for heating and electricity consumption were compared with the actual measured values in order to access the energy performance gap between the calculated energy consumption at project's phase, meeting local requirements and standards, and the actual energy consumption at an in-use building. The gap found with this comparison is evident in Figure 8 and Figure 9.

The CV(RMSE) and NMBE values are calculated for the base model as per ASHRAE Guideline 14 / IPMVP protocol, in order to quantify the performance gap already known by the graph comparison. To validate a monthly calibration, the criteria of CV(RMSE) and NMBE is to be <15% and <±5% respectively. For these values, the base model reached CV(RMSE) of 9.97%

and NMBE 3.42% for electricity consumption results and CV(RMSE) of 56.21% and NMBE 45.31% for heating consumption results.

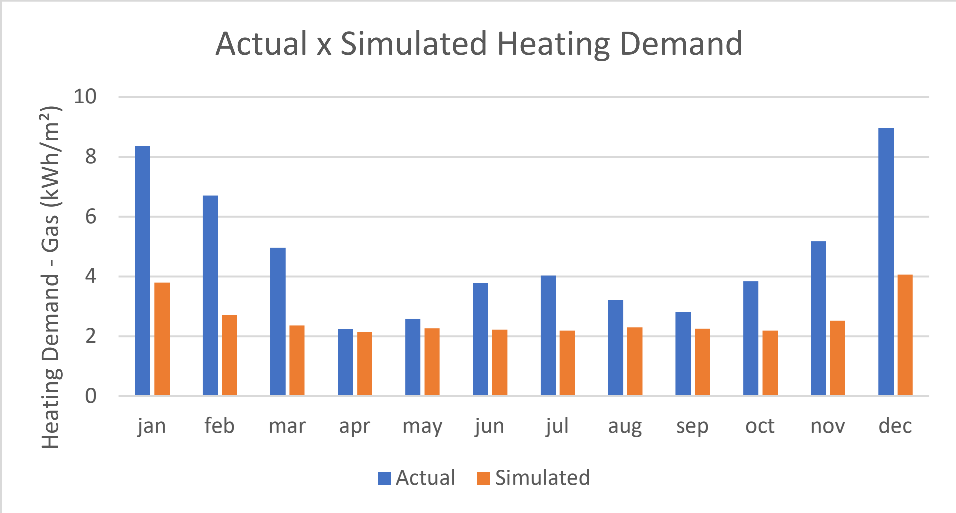

Figure 8: Actual x Simulated Energy Consumption - Heating Demand (Gas)

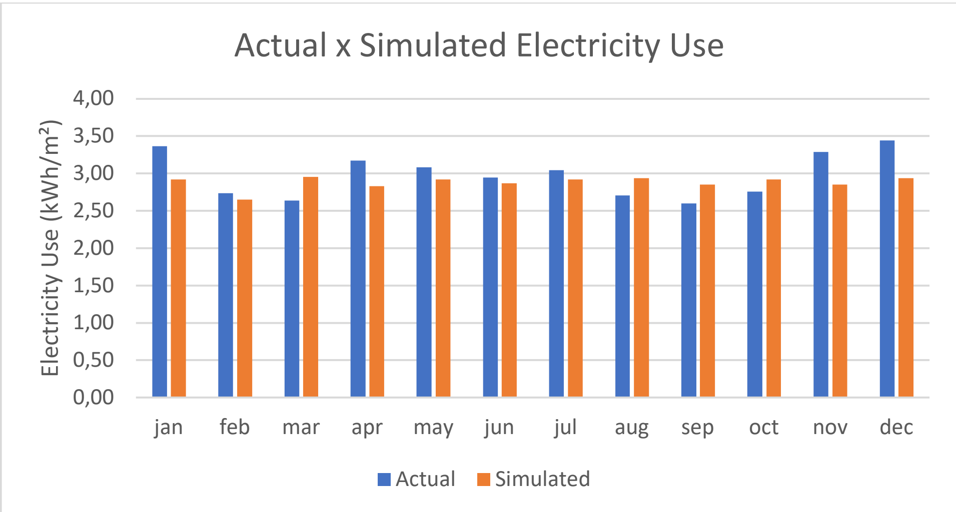

Figure 9: Actual x Simulated Energy Consumption - Electricity Use

4.4. Calibration Objectives

After analysing the base model simulation results and comparing it with the data of the current IEQ measurements and electricity and heating consumption, some variables to be changed in the calibration process were identified. These variables essentially include changing the space heating setback and setpoint temperatures and the space occupancy patterns and use. The aim of these changes is, in addition to getting closer to the actual user profile of the apartment, to avoid phenomena diagnosed in the analysis of the base model simulation results, described in this chapter: keep internal simulated temperatures close to the internal measured temperatures, avoid the overheating and overcooling and avoid simultaneous space heating and natural ventilation. These and other questions regarding the calibration process will be addressed in detail in the following chapter.

5. CALIBRATION PROCESS

This chapter describes the framework of the model calibration process. All changes made to the base model for fine-tuning the variables are introduced separately, along with figures and tables that justify each change and present the results in the simulation for each of them. The framework of the model calibration process attends the following steps:

1. The evidence found in the analysis of the IEQ data is presented;
2. It's presented what alteration this evidence entails, showing the initial First value of the base model and the value to be altered;
3. After the simulation is performed, the impact of the change is evaluated and the impacted results are presented compared to the previous ones.

5.1. Heating Set Back Temperature

5.1.1. Evidence

By analysing indoor temperature data in the apartment rooms, whose IEQ data were being measured, it was possible to conclude that no temperature, at any time, in any room, during the entire year, fell below 18°C. The Figure 10 below shows the internal temperature measurements results for each of the three rooms, living room, kitchen and bedroom, for one representative month, January, as the coldest month in the year for the site location respectively.

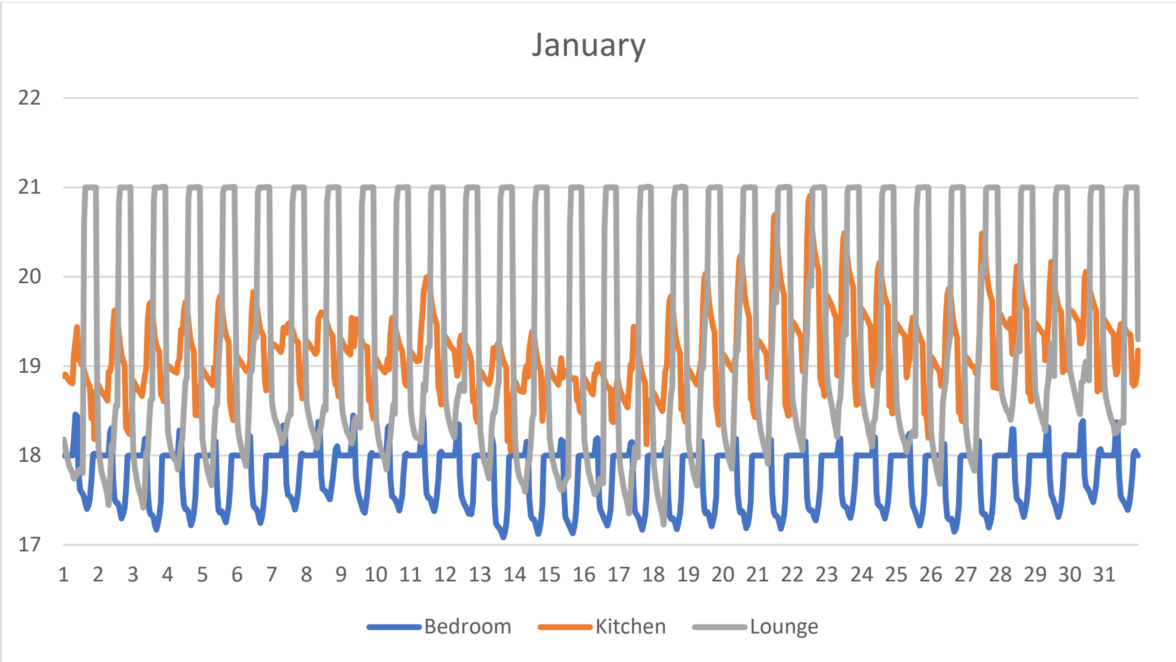

Figure 10: Base Model Internal Temperatures in January for Each Ambient

5.1.2. Change

Based on the evidence shown above, the initial value on the base model for heating setback temperature, which was 12°C, was changed for the minimal temperature that was measured inside the rooms, 18°C. After this alteration have been made, the model was again simulated on DesignBuilder software.

5.1.3. Impact

The Figure 11 below compares the base model simulated internal temperature, per room and per representative month, with the first version of the calibrated model simulated internal temperature, the same way per room and per month. Is possible to perceive that in the base model simulation there were some temperatures previously below 18°C, and after the change made, all the internal temperatures are above 18°C.

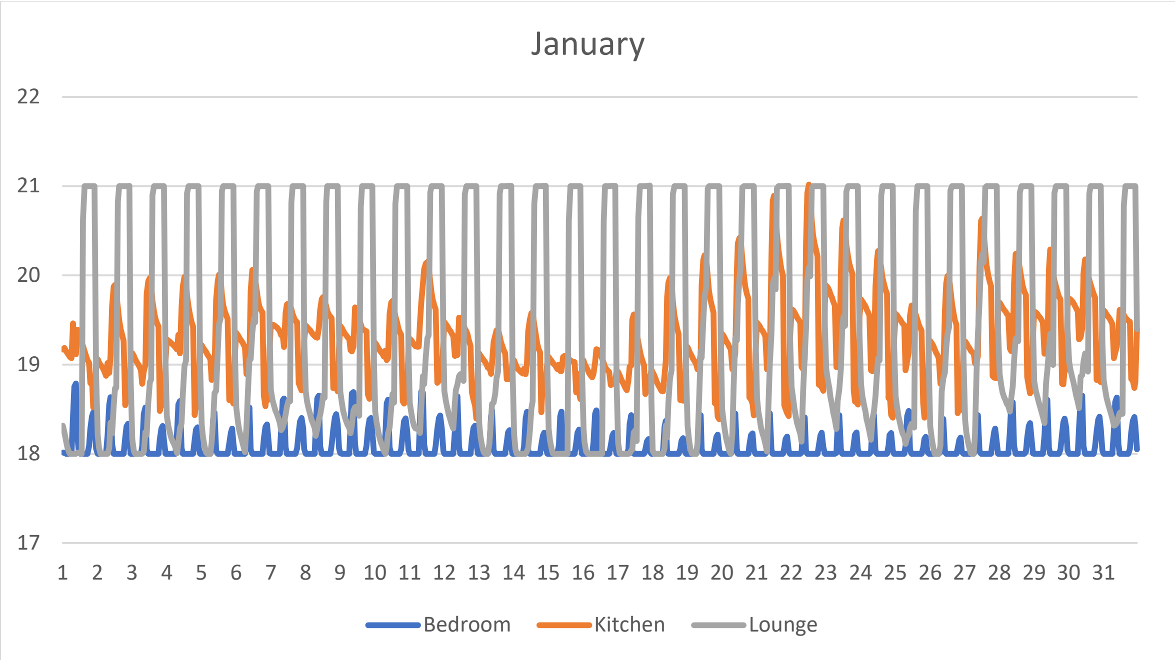

Figure 11: Simulated Internal Temperatures in January for Each Ambient

5.2. Occupancy

5.2.1. Evidence

Based on feedback from residents’ interviews, the actual number of inhabitants became known. In the apartment live five people, 3 adults and 2 children.

5.2.2. Change

The value for residents’ number on the apartment in the base model was four people, two adults and two children. This value, based on the NCM database, was changed for the actual number of inhabitants, evidence out of the residents’ feedback, five people, three adults and two children.

The number of residents was then fine-tuned directly into the software, having as a base the first version of the calibrated model. The total value was then divided by each room so that the sum of the maximum number of people in each room does not exceed the total number of the apartment's inhabitants. The number of maximum occupation in the living room is the same as the number of residents, the kitchen occupancy is the same number as the adults living in the apartment and the bathroom, the toilet and the circulation were kept with only one occupant as the maximum occupancy. The maximum number of occupants for each ambient of the apartment is described below in Table 4.

Table 4: Occupants Number for Each Ambient

Living Room	Kitchen	Bathroom	Toilet	Circulation	Bedroom 1	Bedroom 2	Bedroom 3
5	3	1	1	1	2	2	1

5.2.3. Impact

The alteration of the number of residents in the apartment had a significant impact on the simulation results. Analysing all the heat flux that the increase in the number of occupants in each room generated, was possible to confirm that the occupancy gains increase, as well as the gains by mechanical ventilation, once this parameter is dependent of the occupancy, while the total heating consumption decrease lightly. The figures below, Figure 12, Figure 13, Figure 14, Figure 15, Figure 16, Figure 17 and Figure 18, illustrate the occupancy heat gains for two representative months, January and July, for each of the ambientes analysed.

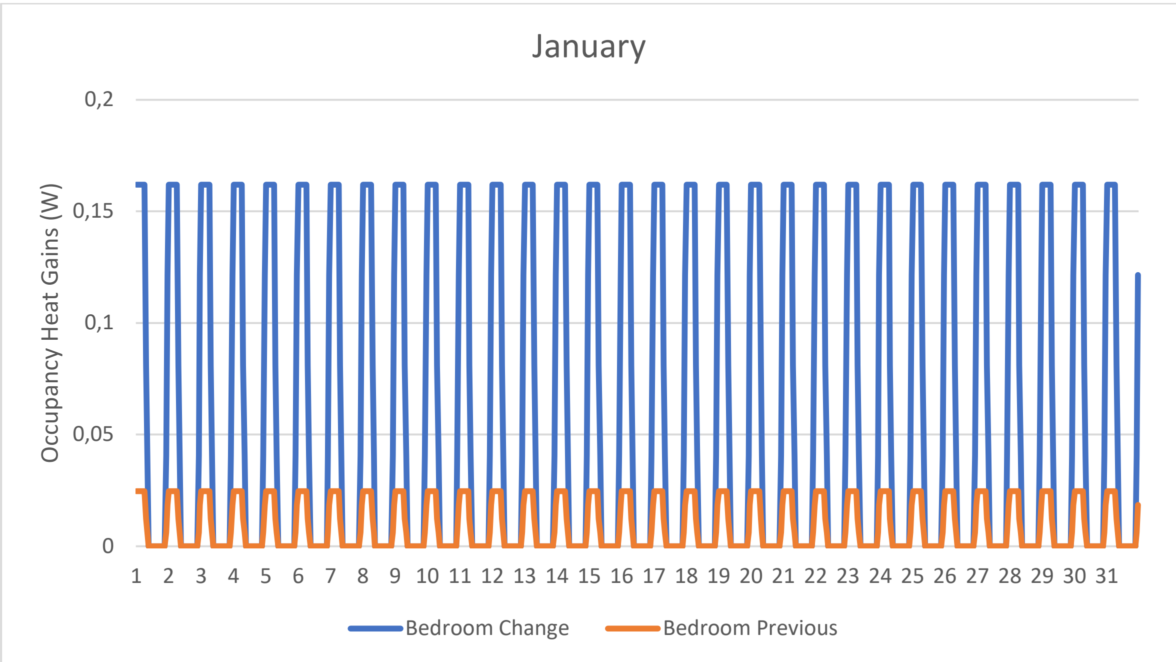

Figure 12: Occupancy Heat Gains in January for Bedroom

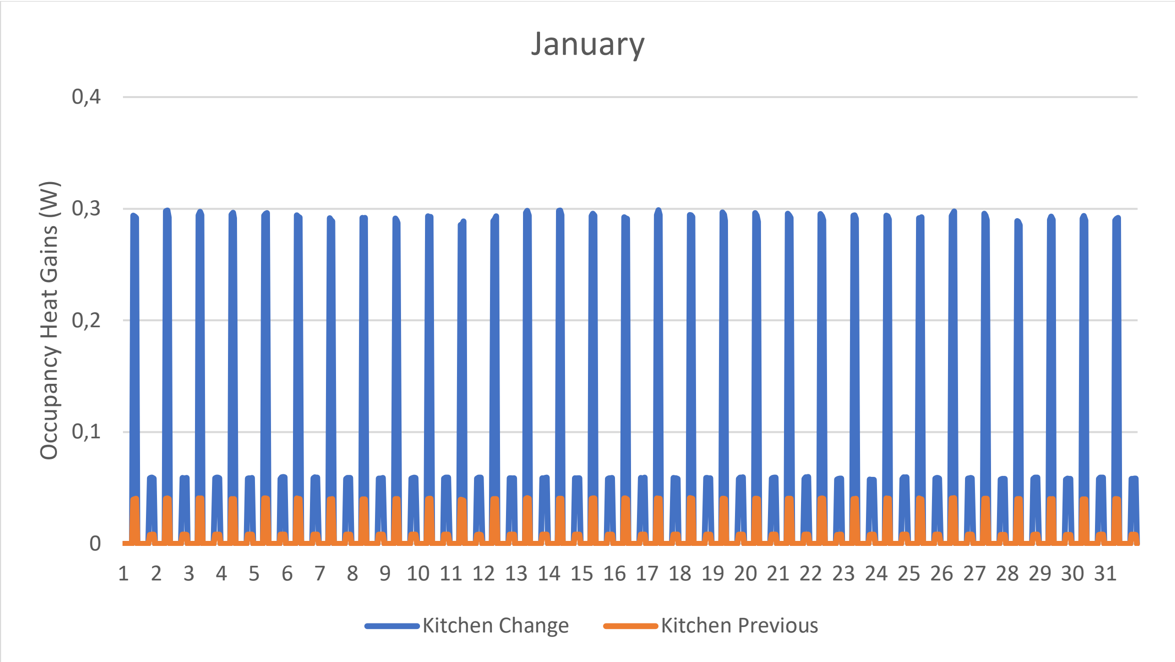

Figure 13: Occupancy Heat Gains in January for Kitchen

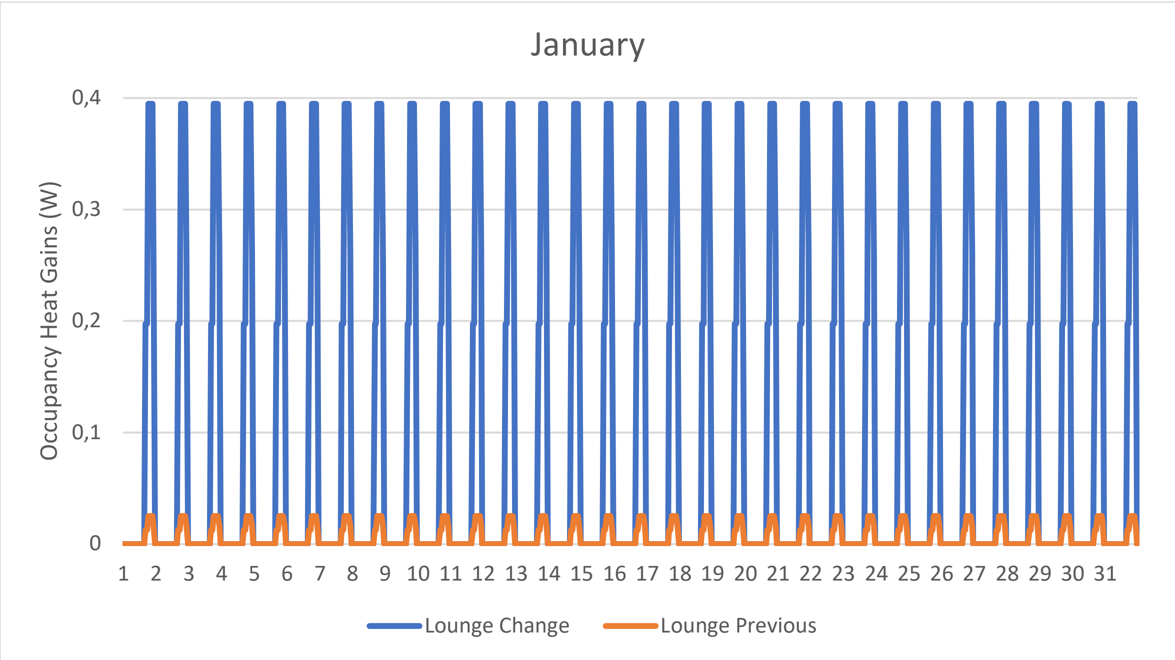

Figure 14: Occupancy Heat Gains in January for Lounge

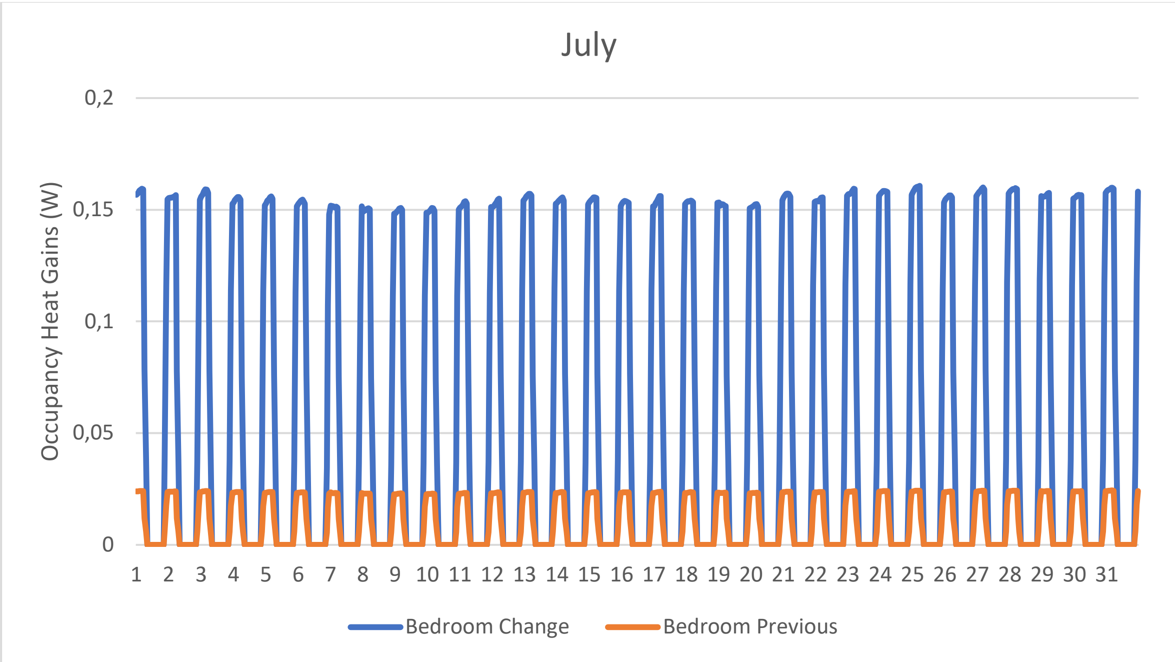

Figure 15: Occupancy Heat Gains in July for Bedroom

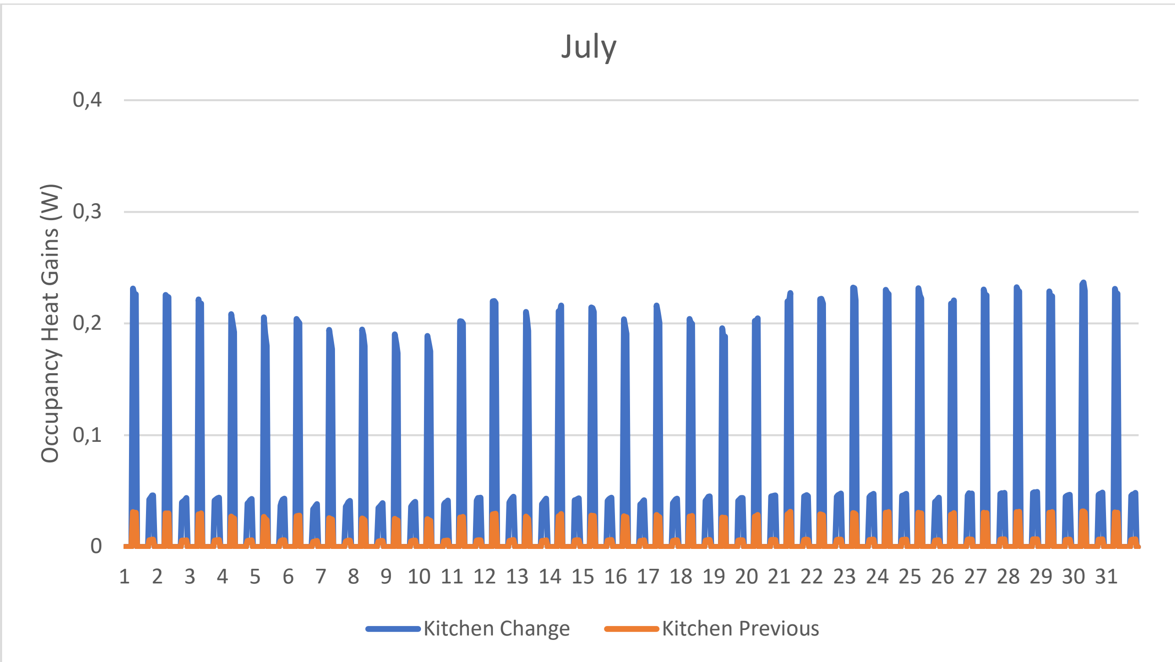

Figure 16: Occupancy Heat Gains in July for Kitchen

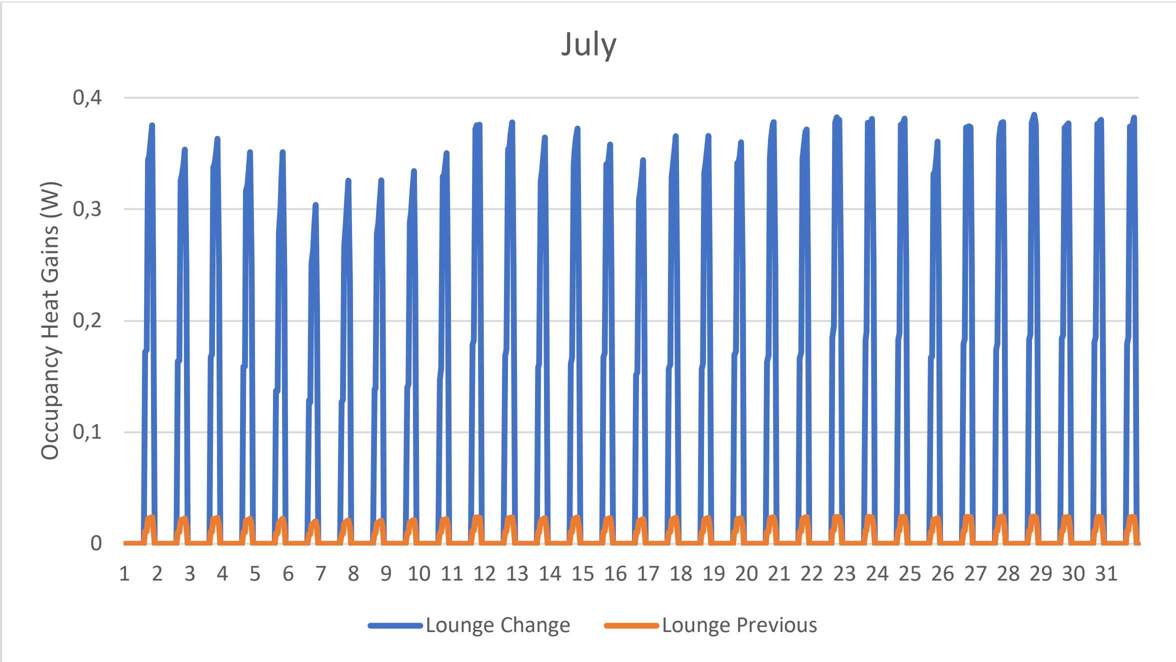

Figure 17: Occupancy Heat Gains in July for Lounge

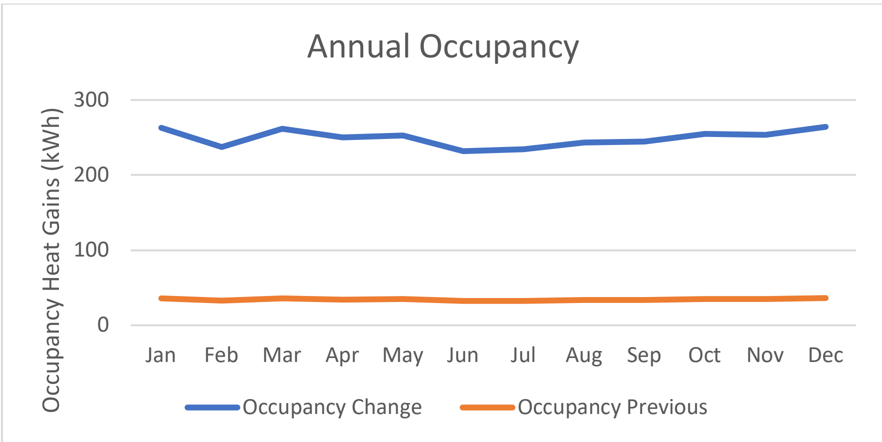

Figure 18: Total Occupancy Heat Gains – Annual

5.3. Schedules - Occupancy

5.3.1. Evidence

By analysing CO_2 concentration measurements data in the apartment rooms whose IEQ data were being measured, it was possible to establish occupation patterns for the living room, the kitchen and the bedrooms.

The Figure 19, shows the CO_2 concentration for the bedroom for the month of January, while Figure 20 and Figure 21 show the CO_2 concentration for the bedroom for a representative week in the year, the second week of January. Initially, it is possible to distinguish two patterns of occupation, one on weekdays and another on weekends. On the weekdays the residents use to stay longer in the bedroom in the mornings and come back earlier during the afternoon and the evenings on the weekdays, compared with the NCM database in base model. On the weekends the residents remain in the bedroom till late in the morning, and the occupancy during the afternoon and evening remain the same as during the weekdays.

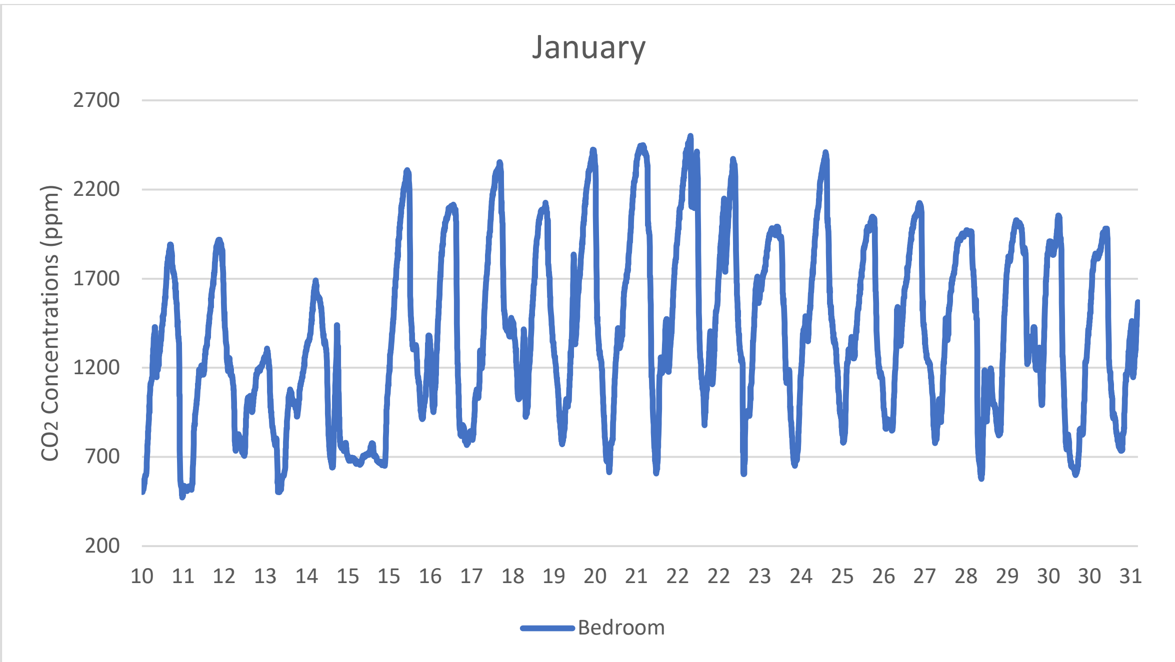

Figure 19: CO_2 Concentration in January for Bedroom

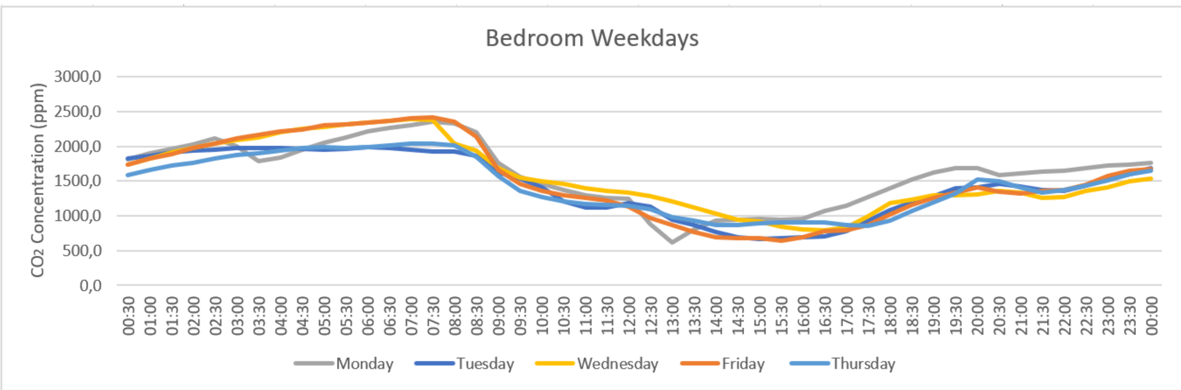

Figure 20: CO_2 Concentration in Weekdays in January for Bedroom

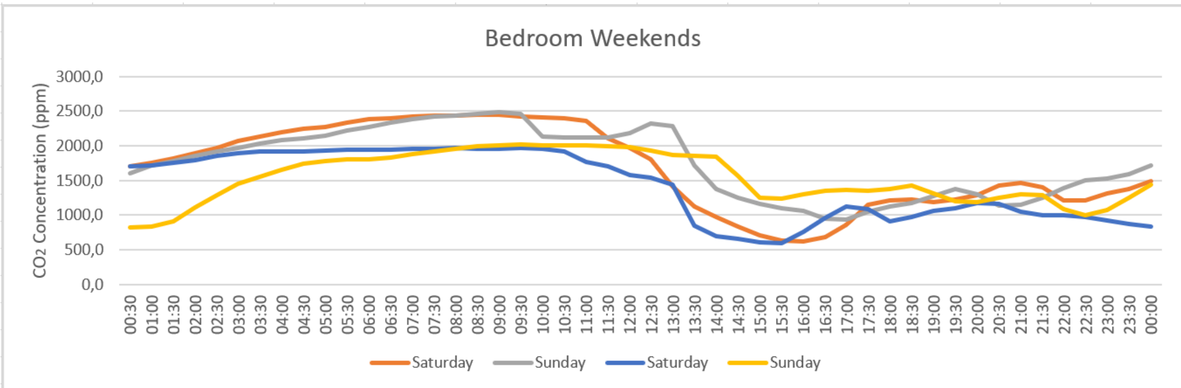

Figure 21: CO2 Concentration in Weekends in January for Bedroom

In the same way, the CO_2 concentration for the living room and the kitchen were analysed, and Figure 22 shows the CO_2 concentration for these spaces in January, and Figure 23 to Figure 26 show these values for the same representative week in the year, the second week of January, in order to determine the occupancy patterns. The same way as the data for the bedroom, the data for the common areas of the apartment evince that it is possible to distinguish weekdays and weekends occupation patterns, and both have thereabout similar occupancy.

On weekdays, these common spaces are occupied for a few hours in the early morning and from mid-afternoon, with a peak of occupancy in the evenings. On weekends, the occupancy take place in the late morning and again from the mid-afternoon, also with the peak of occupancy in the evenings. Those pieces of evidence could be perceived in the figures below.

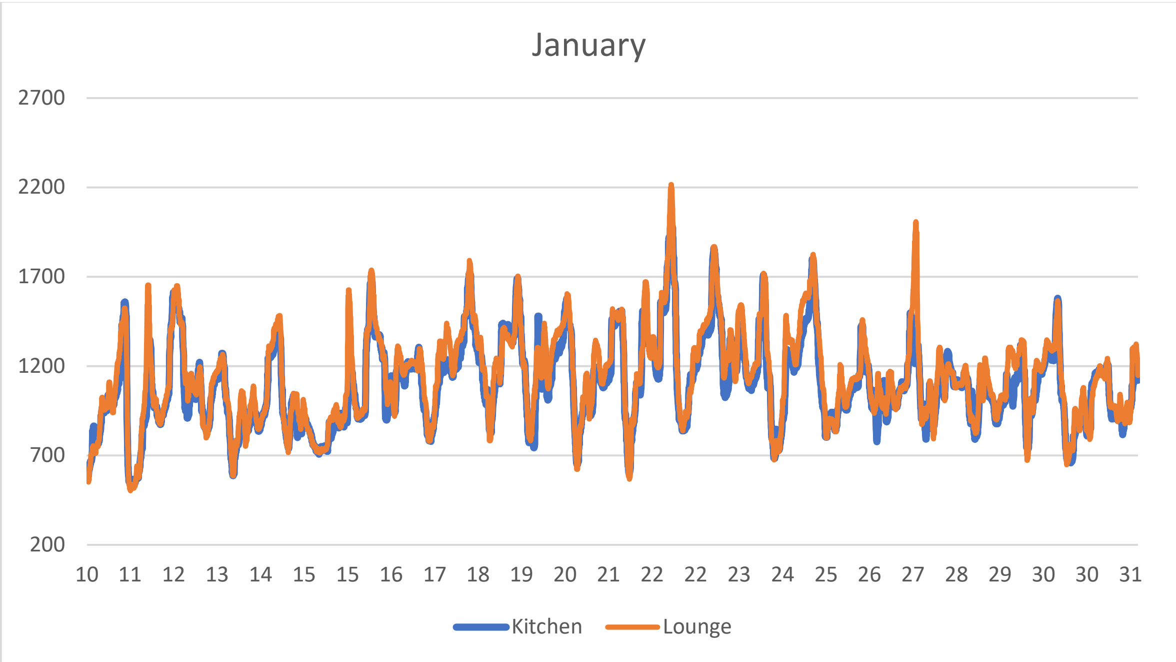

Figure 22: CO_2 Concentration in January for Kitchen and Lounge

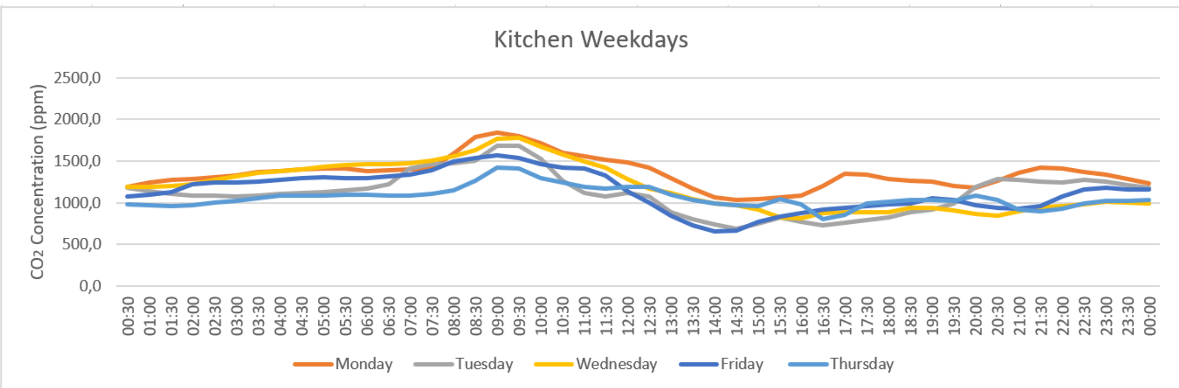

Figure 23: CO_2 Concentration in Weekdays in January for Kitchen

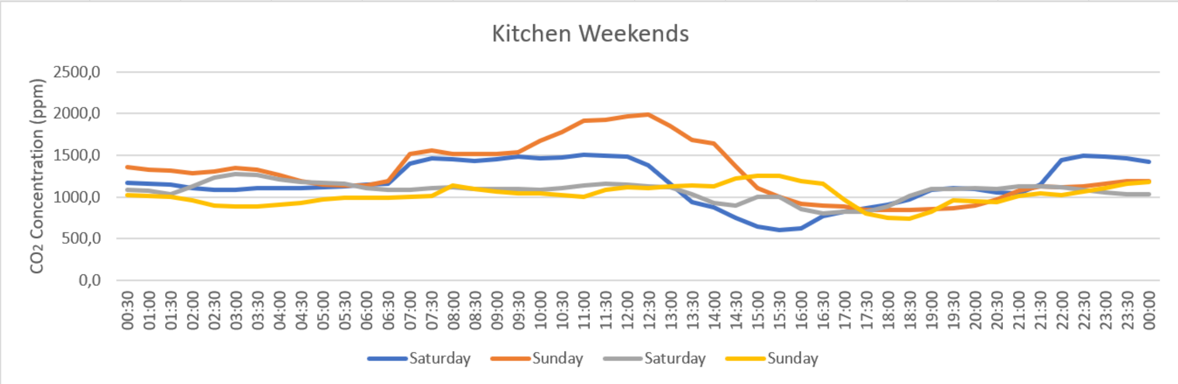

Figure 24: CO_2 Concentration in Weekends in January for Kitchen

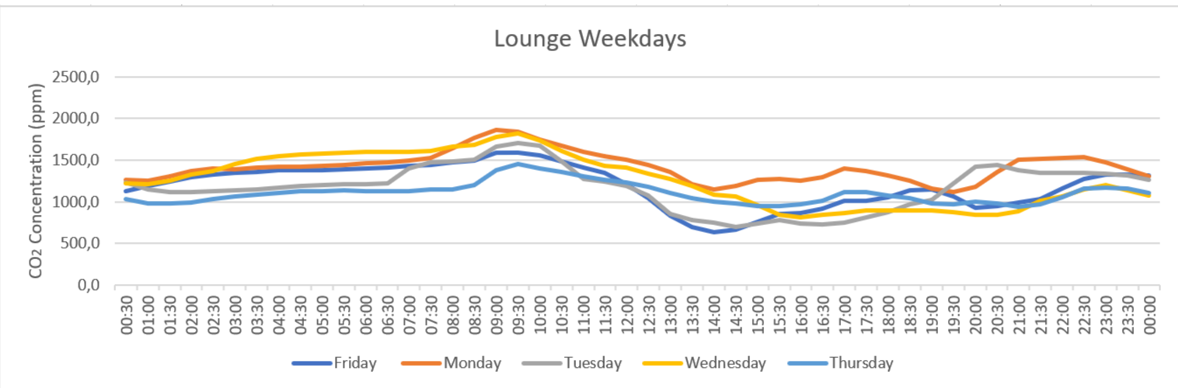

Figure 25: CO_2 Concentration in Weekdays in January for Lounge

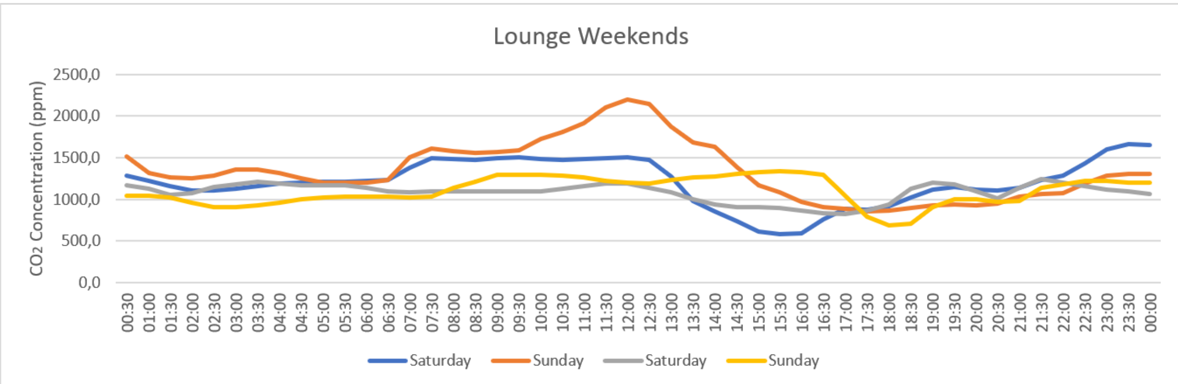

Figure 26: CO_2 Concentration in Weekends in January for Lounge

5.3.2. Change

From the evidence mentioned above, the occupancy schedules assigned to each apartment space per day of the week have been changed as needed. The Figure 27 and Figure 28 hereafter shows the previous occupancy values, used in the base model, and the Figure 29 and Figure 30 the new designated values according to the findings by analysing the CO_2 concentration measurements, to each of the rooms.

It is important to note that the change made in the occupancy profiles for all apartment spaces leads to changes in the energy consumption of all parameters whose thermal load is affected by the occupancy of the spaces. In this sense, the schedules related to space heating, lighting, use of equipment and others, will be changed.

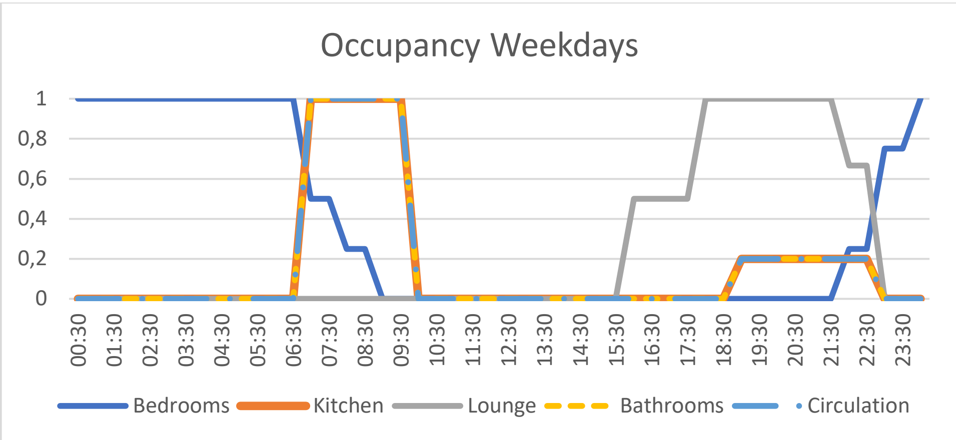

Figure 27: Previous Occupancy Patterns in Weekdays

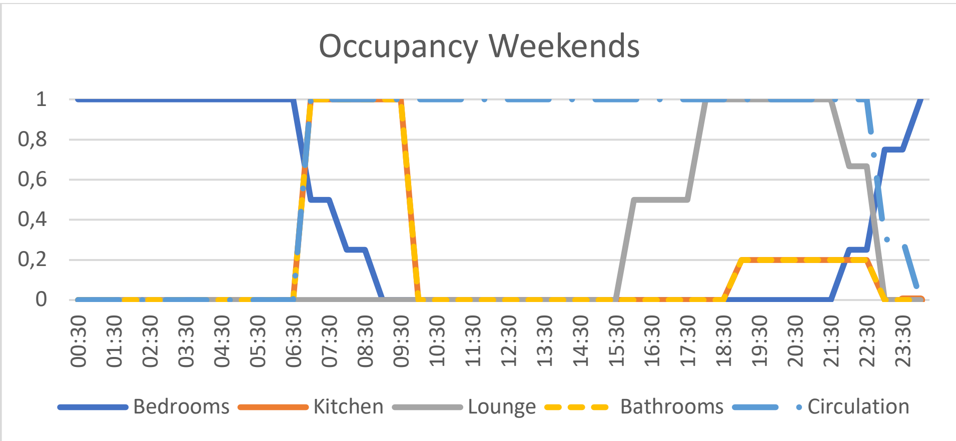

Figure 28: Previous Occupancy Patterns in Weekends

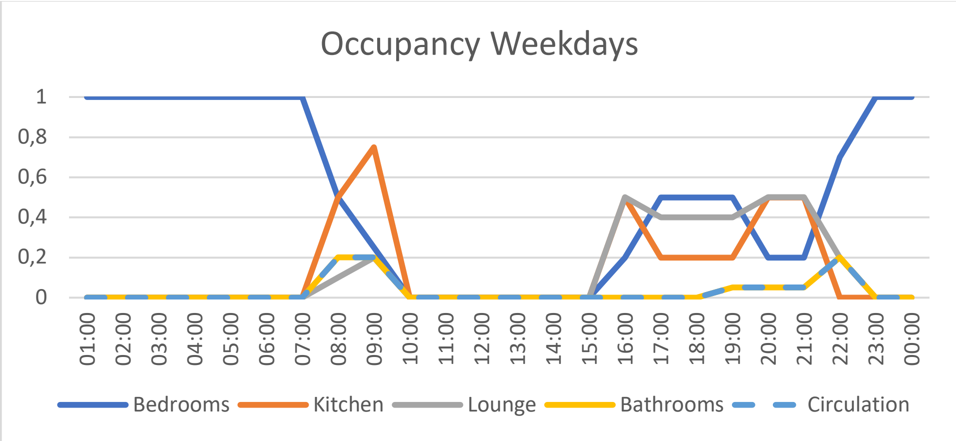

Figure 29: Changed Occupancy Patterns in Weekdays

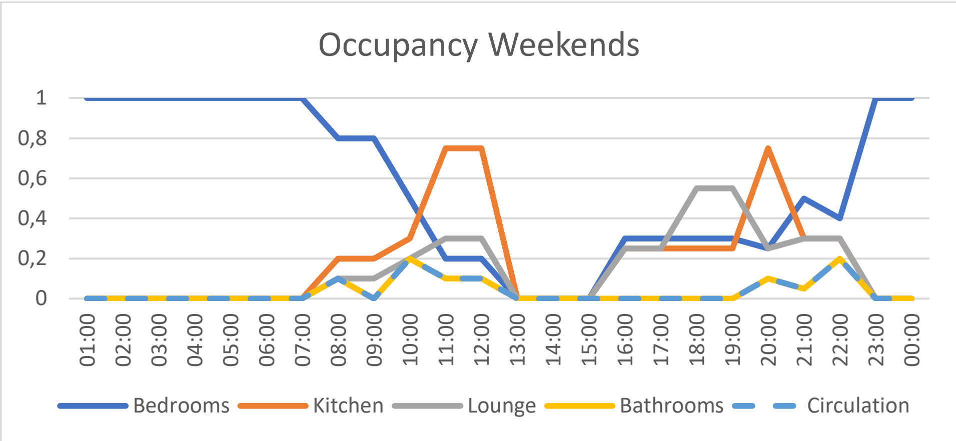

Figure 30: Changed Occupancy Patterns in Weekends

5.3.3. Impact

Analysing the simulation results of the third version of the calibrated model, after changing the occupancy profiles for all apartment spaces, which would have an effect on the heating profile, equipment use and lighting, among others, there is a significant increase in energy consumption compared to the previous calibrated model version. The increase in total energy consumption is due to the significant increase in the occupancy heat gains.

5.4. Holidays

5.4.1. Evidence

By analysing the CO_2 concentrations for the living room, between fourth and twelfth day of April, the only available measured data for this month, it was noted that the CO_2 concentration levels between seventh and twelfth day of April for the living room were closer to the external average concentration level of CO_2 in that region, 406.5 ± 0.1 ppm (parts per million in dry air) according with Mauna Loa CO_2 concentration records. Combined with this finding, the variation of these levels inside the room during the day was almost null.

That evidence, illustrated in Figure 31 below, associated with the fact that the heating daily use for those days also presents a significant drop, made believe that the family didn't use the living room at those, at least, five days. As the living room is a central room in the house and, based on previous analysis, with a significant use by the residents either during the weekdays or during the weekends, most probable the family wasn't at home during these days.

To validate this hypothesis, those days, seventh to twelfth day of April, coinciding with the School Easter Holidays according with the school term dates by local Council which are from April 7th to 24th, with Easter being the April 16th. It's not possible to determine if the family was at the apartment after twelfth of April, once there is not enough data to assert itself for sure.

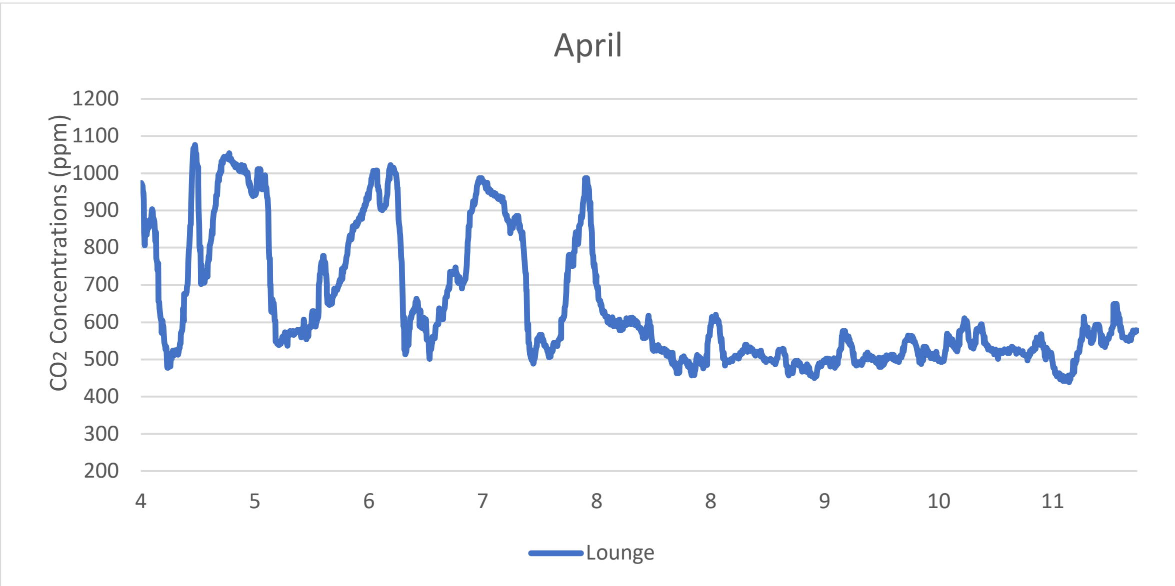

Figure 31: CO_2 Concentration in April for Lounge

5.4.2. Change

Family vacations were determined during the 7th and 12th of April, based on the evidence mentioned above.. The occupancy schedules for these days, assigned to each space of the apartment, per day of the week, have been changed to no occupancy. As was done in the previous change in the calibrated model, change in the occupancy schedules, the schedules for equipment use, lighting, space heating among others, need to be changed for no occupancy during those days in April.

5.4.3. Impact

Figure 32 shows the impact of the holiday alteration in the fourth version of the calibrated model, April seventh to twelfth, made in the living room heat flux compared with the previous model heat flux. The total heating consumption for April had a considerable reduction (from 25.6 kWh to 20.7 kWh). These drop-in heating consumption come across the actual heating demand measurements, which, once more, reinforce and validate the found evidence.

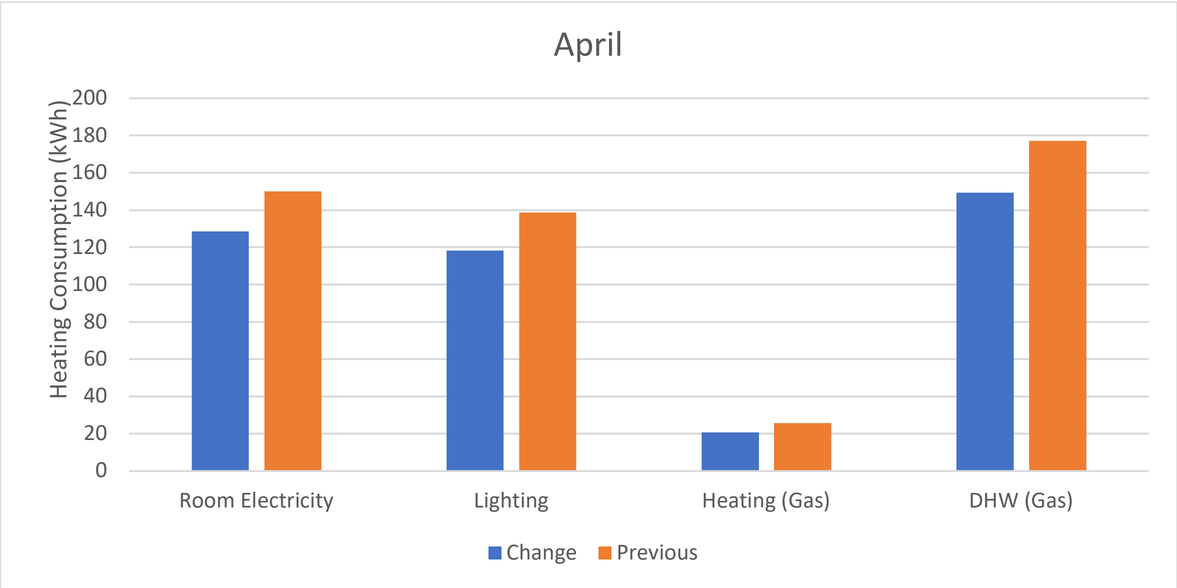

Figure 32: Previous versus Changed Simulated Heating Consumption in April

5.5. Heating Setpoint Temperature

5.5.1. Evidence

By analysing indoor temperature data for each month in the apartment rooms whose IEQ data were being measured, was possible to identify the average temperature per room. In order to access more accurate results, the hourly indoor temperature average values were compared with the occupation hours of the rooms. This way the average hourly data of the rooms' internal temperatures during their occupation periods were gotten.

The Figure 33, Figure 34 and Figure 35 presented here, demonstrate the comparison of the internal temperature measurements results during a representative week for each month and for each of the rooms, against the occupancy pattern in the correspondent space and month, as well as the value of the average temperatures in the occupation periods.

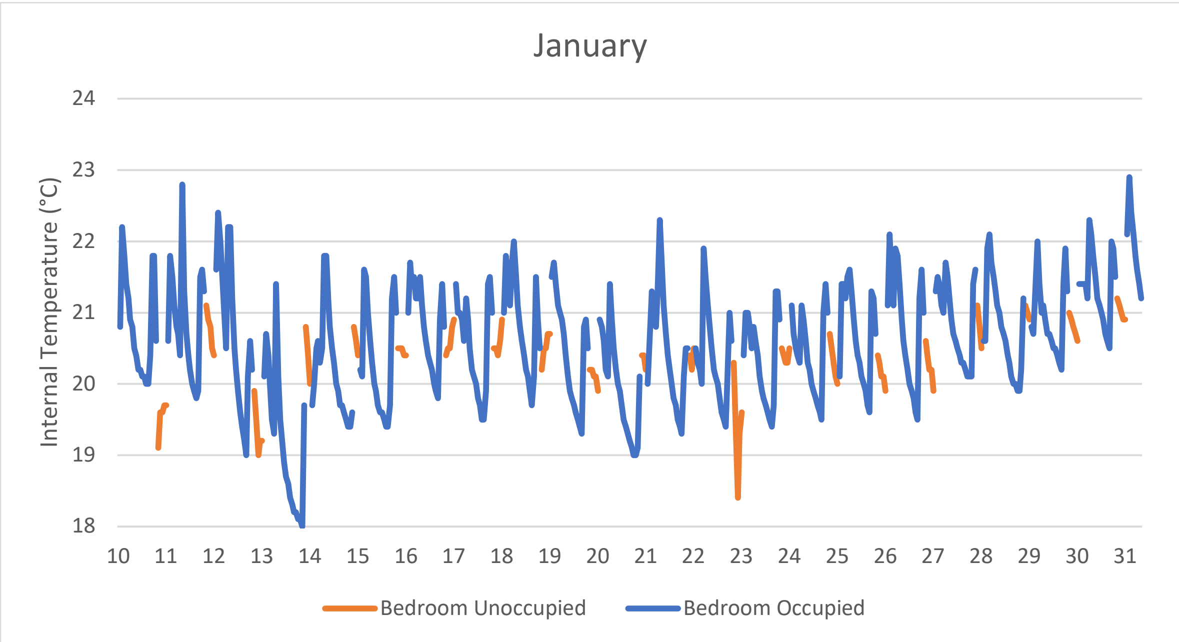

Figure 33: Internal Temperatures by Occupancy Pattern in January for Bedroom

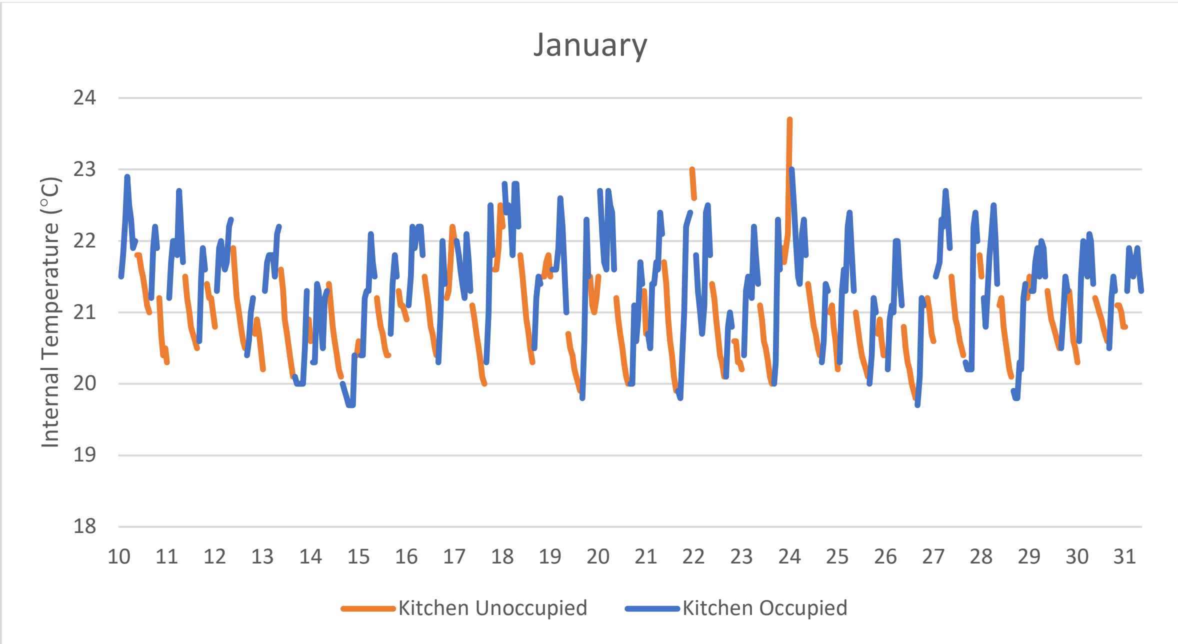

Figure 34: Internal Temperatures by Occupancy Pattern in January for Kitchen

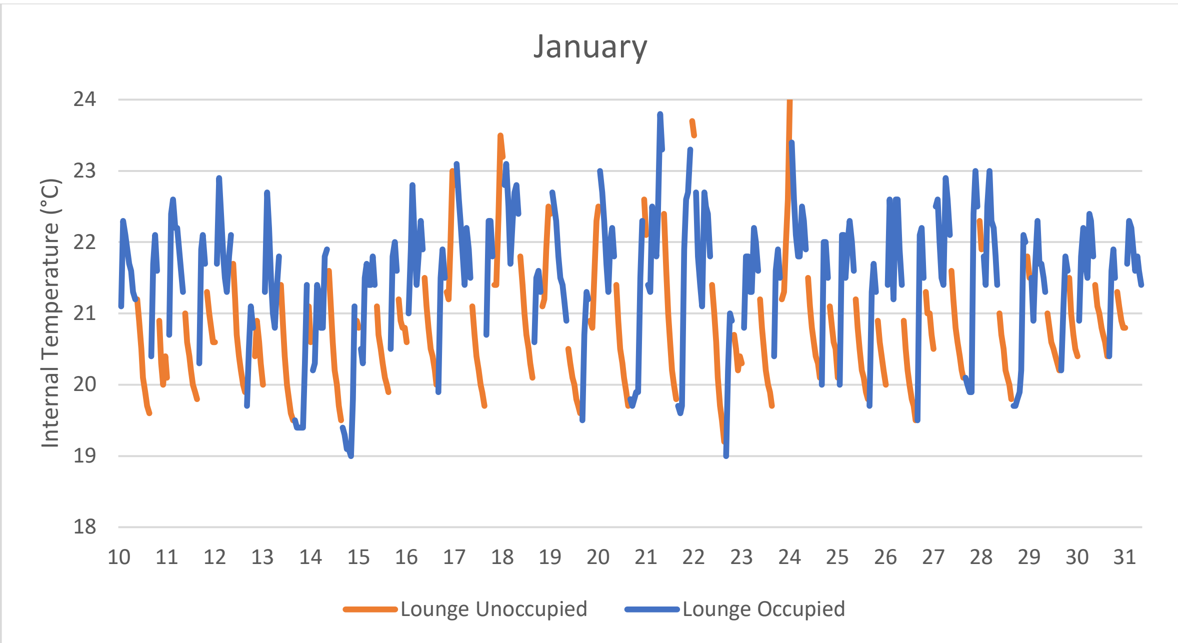

Figure 35: Internal Temperatures by Occupancy Pattern in January for Lounge

5.5.2. Change

The heating setpoint temperatures were changed to correspond the average indoor temperature values measured for each space of the apartment following the evidence shown above, from 18°C in each room, except in the living room, which was 21°C, to the temperatures described below. As there was not enough measured data for the months of March, April and September, and absolutely no collected data for the months of May and June, those months, described below underlined, were simulated with estimated values to follow a pattern between the temperatures.

- January 21°C
- February 22°C
- March 22°C
- April 22°C
- May 23°C
- June 24°C
- July 24°C
- August 24°C
- September 23°C
- October 23°C
- November 21°C
- December 21°C

To accomplish this, in a faster and more efficient way, in dynamic simulation, an Energy Management System (EMS) was created, providing thus custom simulation runtime control to override selected aspects of standard software behaviour, like the heating setpoint temperature different for each month.

Once the heating setpoint temperatures were changed, and one of the objectives of the calibrated model dynamic simulation avoids the simultaneous heating and cooling by natural ventilation, the minimum external temperature, used as a setpoint for opening windows, allowing natural ventilation cooling is also changed in this model version. The rule followed here was fixed the minimal external temperature setpoint at four degrees below the heating setpoint temperature, and the values are specified below:

- January 17°C
- February 18°C
- March 18°C
- April 18°C
- May 19°C
- June 20°C
- July 20°C
- August 20°C
- September 19°C
- October 19°C
- November 17°C
- December 17°C

In this way it is possible to prevent the entry of external air much colder than the internal temperature being maintained in the room, avoiding a sudden cooling of the internal temperature in the spaces and consequently the unnecessary use of heating energy to raise the internal temperature again. An EMS script was created so that the necessary changes were made in the most efficient way.

5.5.3. Impact

Figure 36 below shows the impact that the change made in version five of the calibrated model reverberated in the indoor temperatures. In the results it is possible to realize that the internal temperatures of the rooms, after the changes, increase regarding the previous values, getting closer to the measured real temperatures. This conclusion is evident in the figure below, which compares the measured internal temperature in the bedroom in one representative month of the coldest period of the year, January, with the fifth (changed) and forth (previous) version of the calibrated model simulated internal temperature, for the same room and period of the year.

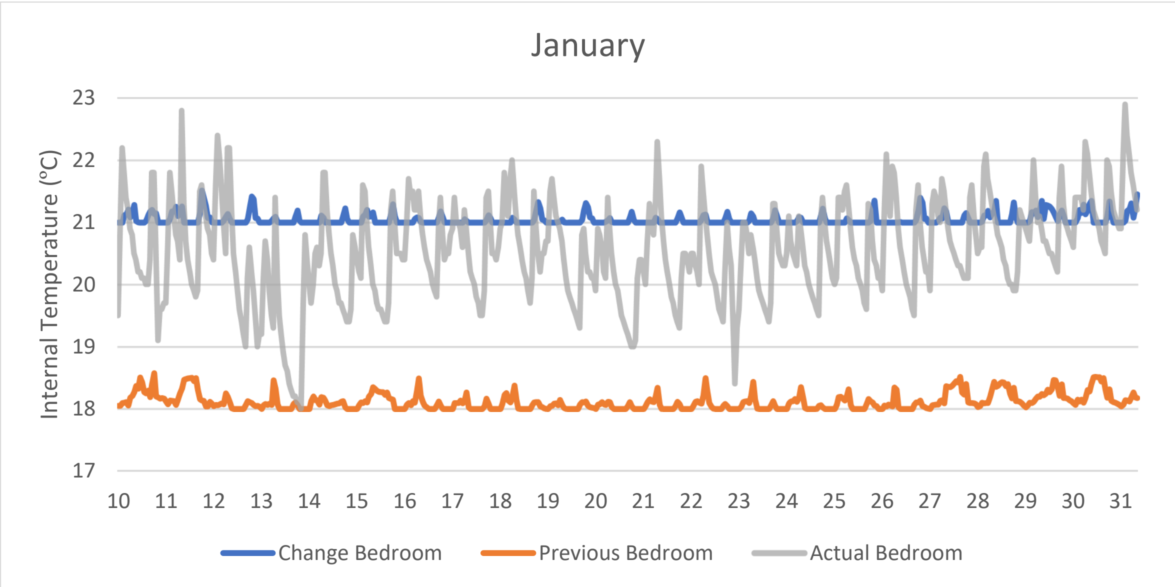

Figure 36: Actual x Simulated Internal Temperature in January for Bedroom

5.6. Validation as per ASHRAE Guideline 14 / IPMVP protocol

The monthly calibration was validated as per ASHRAE Guideline 14 / IPMVP protocol criteria of CV(RMSE) <15% and NMBE<±5%. The actual heating and electricity consumption is compared with the simulation values of heating (gas) and electricity demand of the calibrated model, as shown in the Figure 37 and Figure 38 below.

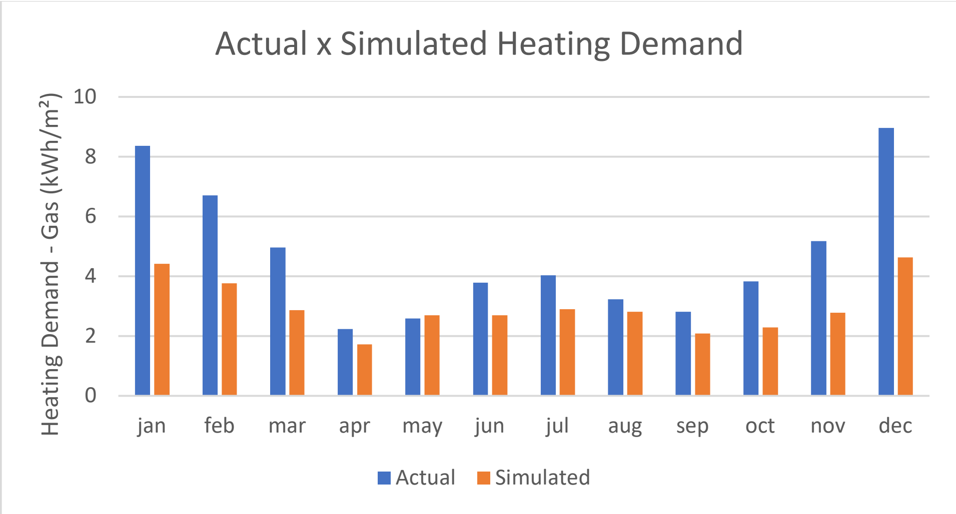

Figure 37: Actual x Simulated Heating Demand - Calibrated Model

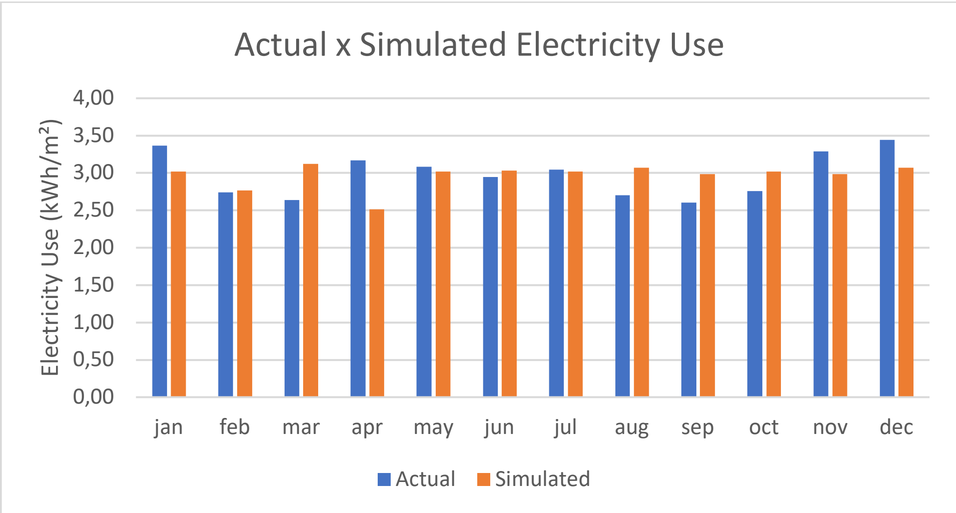

Figure 38: Actual x Simulated Electricity Use - Calibrated Model

The calibration model was validated using the ASHRAE Guideline 14 / IPMVP protocol. The CV(RMSE) and the NMBE are respectively 46.924% and 37.090% for heating (gas) and 11.359% and 0.462% for electricity. However, to account for various uncertainties in the building operations, a probabilistic approach was also used for validating the model as will be described in the next chapter.

6. Uncertainty and Sensitivity Analysis

Since all empirical data has been exhausted, and no other statement can be made with certainty based on the available data, other methods, such as uncertainty and sensitivity analysis, can help and facilitate obtaining a calibrated energy performance model.

6.1. Uncertainty Analysis

The methodology applied to perform the UA is based on literature and previous case studies [29,30]. For the UA accomplishment, were selected the input parameters whose values interfere on the results of the electricity and heating energy consumption and which are passive of uncertainty, such as external U-values, infiltration, natural ventilation, heating setpoint, occupancy, equipment and lighting power density and DHW consumption. For each of those variables, were associated with uncertainty values, lower and upper values, according to the designated distribution based on literature and case studies researches. The actual values for each parameter and their associated uncertainty are described in the Table 5.

The uncertainty values designated for each parameter were based on literature [4,31]. The study developed by Rivalin et al. [4], performs thermal simulation couple to various uncertainty and sensitivity methods, then these methods are tested and compared on a case study and the resulting recommendations can be applied to any building, depending on the model regularity, the number of uncertain parameters and the objective of the study.

Table 5: Designated Uncertainty for Each Parameter - Best versus Worst Scenario

BEST x WORST CENARIUM				
Parameter / Variable	**Unit**	**Actual**	**Lower**	**Upper**
External Wall U-value	W/m²·K	0.18	0.16	0.55
Infiltration (DB Template Slider)	-	Good	Good	Medium
Natural Ventilation				
Jan/Nov/Dec	°C	17	20	17
Feb/Mar/Apr	°C	18	20	17
May/Sep/Oct	°C	19	20	17
Jun/Jul/Aug	°C	20	20	17
Heating Setpoint				
Jan/Nov/Dec	°C	21	21	24
Feb/Mar/Apr	°C	22	21	24
May/Sep/Oct	°C	23	21	24
Jun/Jul/Aug	°C	24	21	24

Occupancy (Schedule)				
Living Room	Num.	5	4	6
Kitchen	Num.	3	2.4	3.6
Bathroom	Num.	1	0.8	1.2
Toilet	Num.	1	0.8	1.2
Circulation	Num.	1	0.8	1.2
Bedrooms	Num.	5	4	6
Equipment Power Density				
Living Room	W/m²	3.9	3.51	4.29
Kitchen	W/m²	30.28	27.25	33.30
Bathroom	W/m²	1.67	1.50	1.83
Toilet	W/m²	1.61	1.44	1.77
Circulation	W/m²	1.57	1.41	1.72
Bedrooms	W/m²	3.58	3.22	3.93
Lighting Power Density	W/m²	7.5	6.75	8.25
DHW Consumption				
Living Room	l/m² day	0.72	0.57	0.86
Kitchen	l/m² day	1.05	0.84	1.26
Bathroom	l/m² day	1.05	0.84	1.26
Toilet	l/m² day	4.85	3.88	5.82
Circulation	l/m² day	2.62	2.09	3.14
Bedrooms	l/m² day	0.53	0.42	0.63

6.2. Sensitivity Analysis

As all the measured data were exhausted or its not available, literature and past case studies on uncertainty quantification would be used to assign the subjective variables of an appropriate probability distribution [10]. The methodology followed is according to case study present in literature [29,30].

To access the SA, two simulations were performed using DesignBuilder software and the uncertainty values assigned to the parameters listed above: one of the simulations was performed to evaluate the scenario that would present the lowest possible energy consumption for the studied apartment, the best scenario, using the best and lowest uncertainty values for each parameter; the other simulation was performed with the uncertainty values per parameter that would result in the scenario of the highest possible energy consumption for this apartment, the worst scenario, concerning both electricity and space heating consumption. The result of these two simulations is presented in Figure 39 and Figure 40 below.

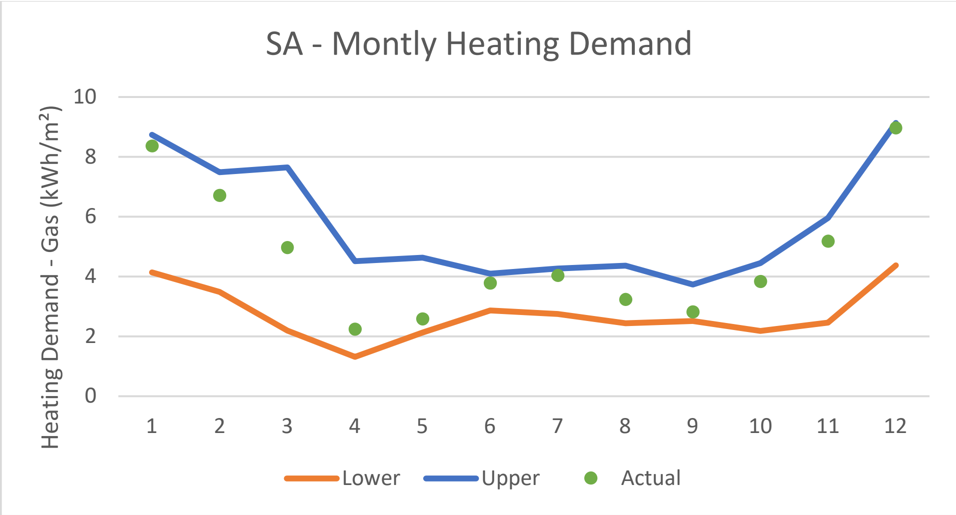

Figure 39: Sensitivity Analysis Heating Demand versus Actual Consumption

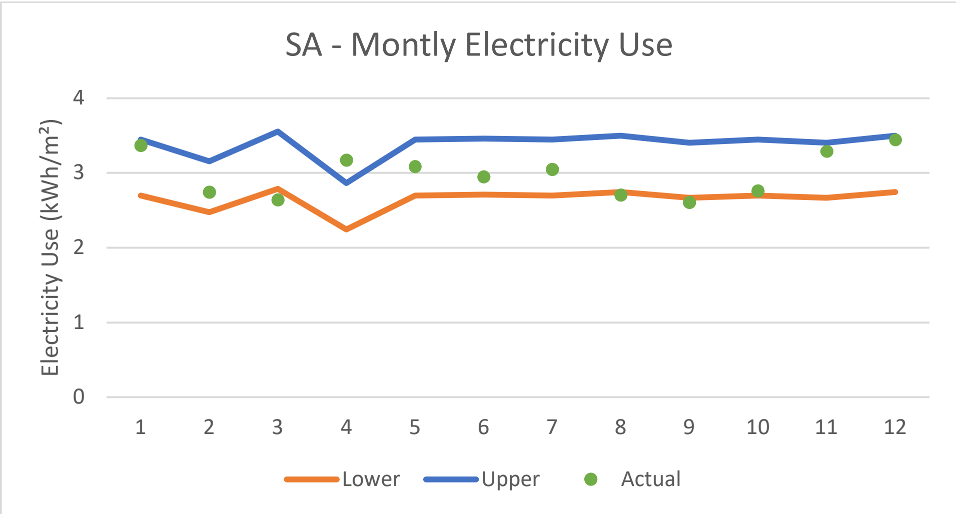

Figure 40: Sensitivity Analysis Electricity Use versus Actual Consumption

It is possible to see in the images above that, when considering the possible uncertainty for each parameter, the variation in simulated heating and electricity consumption, in general, ends up encompassing the values of each month of current consumption.

Regarding the heating consumption (gas), most of the monthly consumption values were close to the maximum estimates for energy demand. In the months with the most extreme, coldest temperatures (Jan, Feb, Mar, Oct, Nov, Dec) as well as in the two hottest months of the year, Jun and Jul, actual consumptions are closer to the maximum consumptions, the worst scenario, according to studies by UA and SA. As for the months with the mildest temperatures, Apr, May, Aug and Sep, current consumption for heating and electricity has come closer to the minimum values of energy demand, the best scenario.

Regarding electricity consumption, the months of Mar and Apr are the only ones that still present lower and higher current consumption values than the minimum and maximum values of each month respectively. In a similar way, results found in SA for electricity consumption reveal that the months with the most intense temperatures of cold (Jan, Nov and Dez) and of heat (Mai, Jun and Jul) kept the actual consumptions data close to the maximum estimated values and average consumption values respectively. While the months of milder temperatures, Feb, Mar, Aug, Set and Out, the actual consumption are very close to the simulated minimum consumption.

When analyzing the Table 6 and Table 7 below, it is possible to notice that the energy performance gaps may be closer or larger than the final gaps shown in the calibrated model. This is due to the fact that the energy results have significant uncertainties, as evidenced in the Table 5 above, due to uncertainties in the specifications, especially those related to construction and envelope.

Table 6: Annual Heating Consumption Discrepancies compared to SA Values

Annual Heating Consumptions							
2017	**Consumption Values**			**Lower**		**Upper**	
	Actual Data	**Lower Value**	**Upper Value**	**Absolute Error**	**Relative Error**	**Absolute Error**	**Relative Error**
Unity	**kWh/m²**	**kWh/m²**	**kWh/m²**	**kWh/m²**	**%**	**kWh/m²**	**%**
jan	8.36	4.14	8.73	-4.22	-50.49	0.37	4.46
feb	6.70	3.48	7.49	-3.21	-47.96	0.78	11.73
mar	4.96	2.19	7.64	-2.77	-55.87	2.67	53.91
apr	2.23	1.31	4.51	-0.92	-41.37	2.27	101.64
may	2.58	2.12	4.63	-0.45	-17.67	2.04	79.27
jun	3.78	2.86	4.09	-0.91	-24.25	0.30	8.08
jul	4.02	2.74	4.26	-1.28	-31.84	0.24	5.96
aug	3.22	2.43	4.36	-0.78	-24.46	1.13	35.28
sep	2.81	2.51	3.73	-0.30	-10.78	0.92	32.67
oct	3.83	2.18	4.45	-1.65	-43.13	0.61	16.07
nov	5.17	2.46	5.95	-2.71	-52.48	0.77	14.96
dec	8.97	4.37	9.13	-4.60	-51.27	0.16	1.78

Table 7: Annual Electricity Consumption Discrepancies compared to SA Value

Annual Electricity Consumptions							
2017	Consumption Values			Lower		Upper	
	Actual	Lower	Upper	Absolute Error	Relative Error	Absolute Error	Relative Error
Unity	**kWh/m²**	**kWh/m²**	**kWh/m²**	**kWh/m²**	**%**	**kWh/m²**	**%**
jan	3.36	2.70	3.44	-0.66	-19.79	0.07	2.29
feb	2.73	2.47	3.15	-0.26	-9.74	0.41	15.11
mar	2.63	2.78	3.55	0.15	5.74	0.91	34.85
apr	3.17	2.24	2.86	-0.92	-29.18	-0.30	-9.68
may	3.08	2.70	3.44	-0.38	-12.45	0.35	11.65
jun	2.94	2.71	3.45	-0.23	-7.97	0.51	17.37
jul	3.04	2.70	3.44	-0.34	-11.33	0.39	13.08
aug	2.70	2.74	3.49	0.04	1.47	0.79	29.40
sep	2.60	2.66	3.40	0.06	2.55	0.80	30.78
oct	2.75	2.70	3.44	-0.05	-2.16	0.68	24.78
nov	3.28	2.66	3.40	-0.61	-18.83	0.11	3.52
dec	3.44	2.74	3.49	-0.69	-20.28	0.05	1.66

7. DISCUSSION

This chapter presents and discusses the results of the efforts exerted this project. First, it summarizes the general results of the calibration process, then makes a critical discussion about the limitations at different stages of this project and explain the concept of 'A' Calibrated Model. Finally presents the potential determinants of energy performance discrepancies and final performance gaps in this case study.

7.1. Overall Results

After obtaining the final calibrated model, the energy performance results of heating and electricity consumption for different stages of the calibration process are established in Figure 41 and Figure 42. As described in the previous chapters and evidenced by the figures below, the energy consumption values simulated in the calibrated model do not accurately represent the actual consumption data. There is a common variation pattern followed between the results of actual consumption and base model and the results of the base model and calibrated model, for heating consumption and for most months of electricity consumption. The base model energy demand presents a lower value regarding both the real consumption and the calibrated model. The simulated values for energy consumption in the calibrated model are still lower than the actual values, especially for heating consumption.

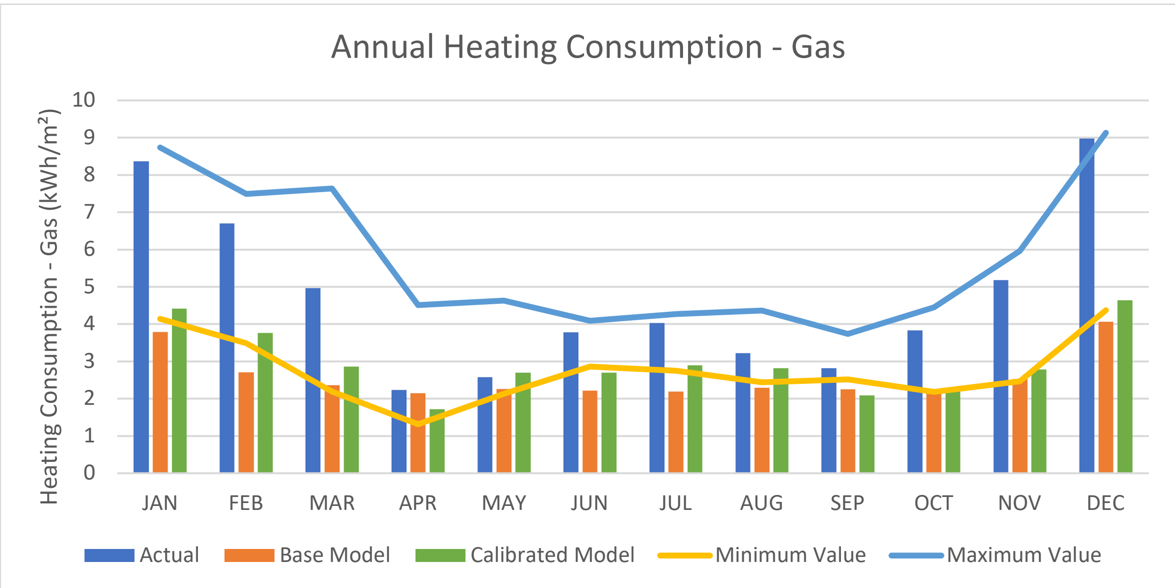

Figure 41: Annual Heating Consumption Summarized

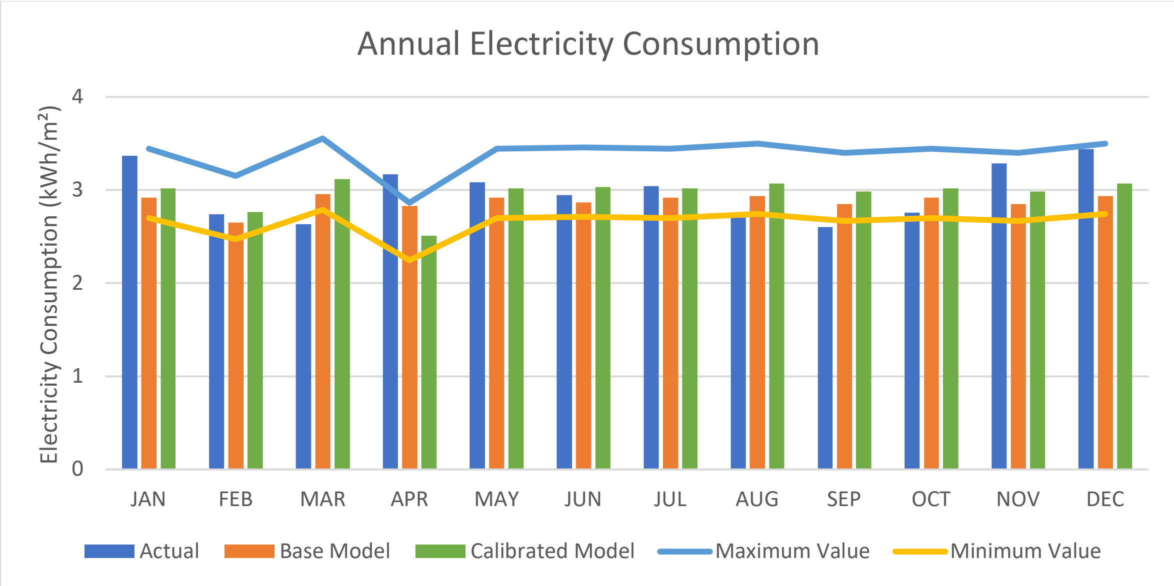

Figure 42: Annual Electricity Consumption Summarized

After adjustments in the number of occupants, DHW consumption, usage schedules, set back, setpoint and natural ventilation temperatures, the simulated heating energy demand in the calibrated model has an obvious growth and electricity has a slight growth in the majority of months. The final predictions of the calibrated model wavered to varying degrees in electricity consumption.

When specifically evaluating the heating (gas) consumption data Figure 41, it is noted that the consumption values of the base model present a discrepancy in relation to the actual consumption, which can reach almost 60% less. The months with the most extreme temperatures, of cold and of heat, present respectively more than 50% (Jan, Feb, Mar, Nov, Dec) and 40% of the variation (Jun and Jul).

After the changes made during the calibration process, the heating demand values of the calibrated model presented smaller discrepancies when compared to the actual consumption values. The months with colder temperatures showed reductions in values greater than 40%, while the months from Apr to Sep the differences were around 20% lower than the actual values. Even with the reduction in the existing gaps between real and simulated heating demand, the discrepancies are still very high. The only month that significantly approached actual consumption was the month of April, after the change in the apartment occupation during the Easter holidays.

The gaps between simulated and real electricity consumption are considerably smaller when compared to the gaps in heating demand. In the base model simulations, the largest discrepancy was 13% and 14% in the winter months, while in the calibrated model simulations it was 18% and 20% in the months of Mar and Apr. In both cases electricity consumption gaps are admissible values regarding the validation of the calibrated model.

The gaps and discrepancies between simulated energy predictions in two stages, base model and calibrated model, and actual energy performance are worked out in Table 8 and Table 9, as well as the CV(RMSE) and NMBE values for model validation.

Table 8: Annual Heating Consumption Discrepancies

Annual Heating Consumptions						
Against Actual Data	**Base Model**	**Change 1**	**Change 2**	**Change 3**	**Change 4**	**Calibrate d Model**
Consumption (kWh/m²)	31.00	30.97	29.39	30.68	30.35	35.66
Absolute Error (kWh/m²)	25.68	25.71	27.29	26.01	26.33	21.02
Relative Error (%)	45.31	45.36	48.15	45.88	46.45	37.09
CV(RMSE)	56.20	54.85	59.29	56.42	56.49	46.92
NMBE	45.31	45.35	48.15	45.87	46.45	37.09

Table 9: Annual Electricity Consumption Discrepancies

Annual Electricity Consumption						
Against Actual Data	**Base Model**	**Change 1**	**Change 2**	**Change 3**	**Change 4**	**Calibrate d Model**
Consumption (kWh/m²)	34.55	34.55	34.55	36.04	35.61	35.61
Absolute Error (kWh/m²)	1.22	1.22	1.22	-0.25	0.16	0.16
Relative Error (%)	3.42	3.42	3.42	-0.72	0.46	0.46
CV(RMSE)	11.35	9.97	9.97	9.67	11.35	11.35
NMBE	3.42	3.42	3.42	-0.72	0.46	0.46

Analysing the discrepancies in the different steps of the calibration process, the result is not ideal. The simulated values of annual heating consumption, Table 8, shows different degrees of variation throughout the calibration process. Initially, the base model, built with NCM data, comprised in the DesignBuilder software, information from SAP table and project drawings, had a consumption of 31 kWh/m², 45.3% less than the actual heating consumption of 56.69 kWh/m², which resulted in a CV(RMSE) of 56.2%. Increasing the setback temperature, the space occupation data and DHW consumption, the simulated heating consumption decreased by 5.2%. Subsequently, with the changes in the schedules and natural ventilation and setpoint temperatures, the heating demand reached 35.66 kWh/m², 37% less than the current consumption, which resulted in a CV(RMSE) of almost 47%, well above the maximum value of 15% according to ASHRAE Guideline 14 / IPMVP protocol.

Evaluating the discrepancies in the simulated electricity consumption of each stage with the actual annual consumption, of 35.78 kWh/m², it was noted that the consumption increased by 4.3% when the occupancy schedules of the spaces were changed, and, after the insertion of the Easter holiday, consumption decreased slightly, reaching acceptable values of CV (RMSE) and NMBE, of 11.35% and 0.46% respectively.

The uncertainties in the construction specifications have significant impacts on the modelled energy results, as shown in the analysis process, so the energy performance gaps can be smaller or larger than the final gaps of the calibrated model.

As already shown, the SAP table forecasts are not representative of the actual operating conditions since there are huge discrepancies in the heating energy predictions of the base model and a lack of estimates on electricity consumption. Bearing in mind that the real operating conditions of a building are dynamic, forecasts based on standardized conditions in the SAP tables, which use a quasi-steady state calculation method, are not suitable to be treated as expected energy performance.

Likewise, the NCM database used in the construction of the base model presents irrational parameters that do not fully represent the real values. In this sense, the differences between the actual consumption data and the predictions of the base model, do not accurately reflect the real performance gaps. Considering that the base model is the foundation for the calibration process, the parameters in the base model that would not be calibrated or modified in later stages should reflect the actual in-use conditions.

As NCM modelling guide, the source of inputs parameters in the model was initially a procedure for demonstrating compliance with the Building Regulations for buildings other than dwellings, the analysis of residential buildings using NCM database might not be as comprehensive, sufficient and representative as on non-domestic buildings.

An example of NCM defaults in the case study which not accurately represent the actual case was the people density template. They were evidenced to be unreasonable and unprocurable, as the number of occupants in all the rooms of five flats are below one after calculation.

For those building parameters and operational profiles which lack actual metered or better references, such as consumptions and profiles of DHW and equipment, their values are maintained using dwelling templates in NCM, what generates considerable uncertainties and impairs the determination on the accuracy of the final model. Those are a non-negligible factor of the final energy performance gap.

7.2. Creating 'A' Calibrated Model

Building model calibration is essentially an undetermined problem due to a large number of building inputs in a BEPM. Therefore, the quality of a manual calibration is highly dependent on the experience and expertise of the analysts performing the calibration. With this method, one can get any calibration result desired but the solution that results may not be the true solution.

With currently available tools and the lack of access to more accurate measurements and data regarding building information, it is difficult to calibrate a BEPS model in a cost-effective manner. Many discrepancies in the model could be due to the assumptions and simplifications made by the simulation engine as well as poor estimates for some parameter values.

In this case study, despite the level of calibration effort, the results still show a significant amount of discrepancy between measured and simulated heating consumption values. Although even if the model meets the most stringent monthly acceptance criteria, it could not accurately represent the building, as already evidenced by some studies [15]. Monthly acceptance criteria do not adequately capture how well the model matches the measured data.

Considering all the above, the calibration process of energy performance models does not reveal absolute truth, but one of many alternatives whose simulated output values are close to the actual energy consumption values of the analysed building. The final objective of the calibration simulation is to create 'A' calibrated model, which is within the limits of validation of existing models, knowing that one cannot pretend to create 'THE' calibrated model.

8. CONCLUSION

The focus of this dissertation is placed on the analyses of the energy performance gap and the corresponding determinants as well as potential improvements, using evidence-based calibration process, fine-tuning the dynamic model with data from the IEQ measurements and the actual energy use measurements, electricity and heating consumption for one year in an in-use low-carbon newly built residential apartment in West London, UK.

To estimate the theoretical energy performance of a low-carbon residential building by a case study is an essential approach to, in order to narrow the gaps in buildings energy performance, assess whether buildings operate as they are anticipated to, and discover the problems and address the improvements on energy performance.

This approach happens by comparisons between energy results from calibrated BEPM and actual energy performance. An UA and SA assists the assessment of total variations of energy and the estimation of the maximum and minimum possible consumption for each month due to the input parameters uncertainties.

In the fine-tuning process, several building specifications, occupancy number and patterns, DHW consumptions, heating system set-point and setback, lighting density and profiles are adjusted and calibrated in the dynamic model from subjective feedbacks and objective measurements.

The results of the energy performance evaluation are far below expected due to some limitations. The biggest limitation was related to obtaining continuous and discriminated data on electricity consumption and heating. Another major drawback, limiting the work to be done, were discontinuities present in the IEQ measurements within the apartments.

Even with this limitations, the evaluation process applied in this case study is reasonable and necessary to modify the incorrect initial forecasts and reflect on the flexible and diverse real conditions of use in this apartment. This calibration methodology can be used in other projects for assessing the energy performance of residential buildings, however, it is recommended some improvements in the limitations found by this work.

The analysis evidence that the range of energy performance gaps could be either closer or wider due to uncertain inputs specifications causing uncertain energy outputs. In order to improve the energy performance analysis process of residential buildings by dynamic simulation, there are two approaches that can be proposed: more rigidity in the validation standards of calibrated models and existing methods for calibration; and the reduction of uncertainty in the model's input parameters, based on the facilitation of access to consumption, usage and performance data in buildings, and improvement in the data availability and granularity obtained by measurements.

The first proposed approach require improvements on the guidelines and protocols used for determining when a simulation is calibrated. As the overestimated end-use consumption in one area can offset underestimates in other areas, to yield a reasonable correlation at the utility level, explicitly measurement of the energy consumption by the end-user is recommended. A reduction in the acceptable MBE and CV(RMSE) values is suggested given the number of solutions yielded by the current acceptance criteria and hourly measured data over the calibration period is endorsed since some issues were encountered when using only monthly data for comparison.

Regarding the second approach, the level of measures need to improve are:

- Infiltration rate of the building fabric should be technically monitored;
- Scarcity of IEQ data such as data losses need to be overcome;
- More detailed sub-meters on DHW and small power appliances is necessary;
- The indirect calibration on lighting profiles based on occupancy patterns need to be avoid as it cause lack accuracy;
- The impact of occupants-related activities has to be paid more attention, such as, heating system controls, supplementary heating system usage and weather activities like opening and closing windows; etc.

Directly objective measurements are always a better option to estimate the actual uses and operations when calibrating.

More research and case studies are necessary in the quantification of these uncertainties in order to test the robustness of the proposed method and to increase the adoption of the presented framework in building energy performance simulation.

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ATTACHMENTS

Example of Base Model Input Data in DesignBuilder Software

Activity Template	
Template	Domestic Bedroom
Sector	Residential spaces
Zone type	1-Standard
Zone multiplier	1
☑ Include zone in thermal calculations	
☐ Include zone in Radiance daylighting calculations	
Occupancy	
☑ Occupied?	
Occupancy density (people/m2)	0,0229
Schedule	Dwell_DomBed_Occ
Metabolic	
Activity	Bedroom (dwelling)
Factor (Men=1.00, Women=0.85, Children=0.75)	0,90
CO2 generation rate (m3/s-W)	0,0000000382
Clothing	
Comfort Radiant Temperature Weighting	
Contaminant Generation and Removal	
DHW	
Consumption rate (l/m2-day)	0,530
Environmental Control	
Heating Setpoint Temperatures	
Heating (°C)	18,0
Heating set back (°C)	12,0
Cooling Setpoint Temperatures	
Cooling (°C)	25,0
Cooling set back (°C)	28,0
Humidity Control	
Ventilation Setpoint Temperatures	
Minimum Fresh Air	
Fresh air (l/s-person)	10,000
Mech vent per area (l/s-m2)	0,000
Lighting	
Target Illuminance (lux)	100
Default display lighting density (W/m2)	0
Computers	
Office Equipment	
☑ On	
Power density (W/m2)	3,58
Schedule	Dwell_DomBed_Equip
Radiant fraction	0,200
Miscellaneous	
Catering	
Process	