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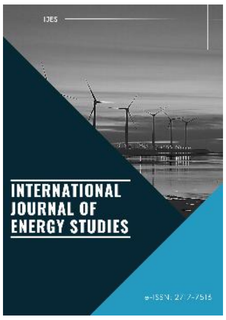

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Calibration of building energy simulation models for energy-efficient retrofitting: A residential case study in Samsun-Havza

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Highlights

- Discrepancies between model and actual data often stem from data gaps, model simplifications and operational uncertainties.
- Misuse of MBE and NMBE formulas can make it difficult to accurately assess model calibration.
- Iterative adjustments of operational uncertainties within acceptable ranges are commonly applied to enhance model accuracy.

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ABSTRACT

Considering today's technological developments, it can be said that academic interest in intelligent systems that provide data about human living spaces has increased significantly. In the energy sector, the growing availability of data from smart evaluation systems and advanced devices, combined with progress in energy modeling software, has notably enhanced the effectiveness of energy modeling and efficiency improvement efforts. Calibration of Building Energy Simulation (BES) models is crucial for ensuring the accuracy required for implementing and evaluating energy efficiency strategies. Organizations such as ASHRAE 14-2014, IPMVP and FEMP are developing model validation methods in this context. This study addresses methodological challenges and reduces uncertainties encountered during the calibration processes of BES models. The primary objective of the research is to contribute to optimizing energy efficiency strategies. Integrating systematic calibration approaches and uncertainty assessment methods is anticipated to enable more accurate energy performance analyses. Methodologically, the study presents an approach to resolve errors in validation measurements within calibration processes. On the empirical side, the applicability of the systematic calibration methodology was successfully tested using forty days of hourly recorded indoor temperature data and indoor temperature data obtained from the EnergyPlus program via DesignBuilder; and validated with N(MBE) and CV(RMSE) uncertainty indices.As a result of the analysis, it was determined that the total final energy consumption (heating, DHW, electricity) of the building in question was 128.31 kWh/m², and approximately 72% of this was heating energy. Calibration results indicated that N(MBE) was 1.68% and CV(RMSE) was 13.86%, both within the thresholds set by ASHRAE 14, FEMP and IPMVP. This result shows that in terms of applicability, the calibrated model can be a practical tool that can be successfully used in energy efficient retrofit proposal development and implementation research.

Keywords: Building Energy Simulation (BES), Energy-efficient retrofitting, Calibration, Validation

1. INTRODUCTION

Globally, energy consumption continues to rise exponentially due to increasing population, economic growth, and energy demand [1]. This increase necessitates countries and communities to take measures on energy consumption, develop policies and strategies, and manage the growing energy demand sustainably while combating the climate crisis. As a critically important resource, energy is indispensable due to its diverse applications ranging from industry to transportation and agriculture to buildings. Consequently, ensuring energy efficiency in areas of high energy usage and achieving energy savings are vital for countries and communities to meet their energy security goals [2].

The World Economic Forum (WEF) emphasized the energy-saving potential of industrial, transportation, and building sectors, which constitute 94% of global energy demand, in its "Transforming Energy Demand" report published on January 8, 2024. The report highlights that by improving existing buildings, which account for approximately 30% of global energy demand and about one-third of global greenhouse gas emissions, building energy intensity can be reduced by around 38%, thereby lowering global energy demand by 12%. Additionally, the report underscores that among the three sectors, buildings have the most significant potential for energy savings [3].

Given the economic, social, and environmental impacts of energy consumption in buildings, energy-efficient retrofitting practices are becoming increasingly important. Building simulation models play a critical role in assessing the energy performance of buildings, estimating energy consumption, and analyzing the effects of various design or operational strategies to minimize these impacts [4], [5].

These models not only evaluate the energy performance of buildings but also play a significant role in improving energy efficiency from the design stage to the operational phase of buildings, reducing operational costs, and achieving sustainable building design goals. They are mathematical and dynamic tools created based on inputs such as the structural features of the building, the characteristics of mechanical systems, climatic data, user behavior, and occupancy [5].

Building Energy Simulation (BES) programs are software tools that enable rapid assessment of the environmental performance of new and existing buildings. BES has been developed and enhanced for practical purposes such as architectural design, HVAC design and operation, retrofit analysis, building operational optimization, urban-scale energy efficiency analysis, Life Cycle Assessment (LCA), and Life Cycle Cost (LCC) analysis [6]. The model's accuracy is a decisive factor for all these applications, making it essential to employ calibrated models [7].

A review of the relevant literature reveals a substantial number of studies focusing on the calibration of building energy models. However, significant deficiencies have been observed that may adversely affect the calibration outcomes, particularly regarding the accurate calculation of uncertainty indices, conceptual clarity, and the practical demonstration of methods.

Cacabelos, Eguía, Febrero, and Granada [8] developed a multi-stage calibration methodology and applied it to the HVAC system of a public library to validate the procedure. However, although the N(MBE) index was presented using the correct formula, it was labeled as MBE or MBE (%), leading to a conceptual inconsistency. Similarly, Brunelli, Castellani, Garinei, Biondi, and Marconi [9] proposed a multi-objective optimization procedure for sustainable building design, but misapplied the MBE formula during the model validation phase. Raftery, Keane, and O'Donnell [10] introduced an evidence-based methodology for calibrating whole-building energy models; however, the mathematical formulas used to calculate uncertainty indices were omitted, and only the final values were reported. This hinders the traceability of the verification process. Choi, Joe, Kwak, and Huh [11] investigated the actual behavior of a multi-story double-skin façade in an office building in South Korea during the heating season. Yet, in the validation of the simulation model, they neglected the impact of cancellation errors in the MBE analysis. Sahin, Arsan, Tuncoku, Broström, and Akkurt [12] presented an interdisciplinary approach for the energy-efficient retrofitting of a historical building, but did not normalize the MBE value during the validation phase of the case study.

The common feature among these studies is the presence of various shortcomings and misapplications in the calculation of uncertainty indices used during the validation process. In this context, the present study provides a novel contribution to the literature by addressing such widespread errors, particularly in the calculation of frequently used indices such as N(MBE) and CV(RMSE).

This research aims to minimize methodological challenges and uncertainties encountered during the calibration processes of building energy simulation models. To this end, it examines the definition and scope of calibration, analyzes uncertainty evaluation methods for calibrated models, defines the steps of the calibration methodology for model validation, and applies these steps to a residential building.

2. BUILDING ENERGY SIMULATION MODEL CALIBRATION

Variables such as user behavior, which has one of the most significant impacts on building energy consumption, can cause substantial differences between model simulation and real-world data. In their systematic review of key aspects of building energy simulation calibration, Chong et al. [6] identify the "leading causes of discrepancies between predicted and actual energy performance" in the literature as follows:

- "Specification uncertainty due to assumptions arising from information gaps.
- Model inadequacy resulting from simplifications and abstractions of actual physical building systems.
- Operational uncertainty caused by the lack of feedback regarding actual building usage and operations.
- Scenario uncertainty stemming from the specification of model conditions such as weather and building occupancy" [6].

When looking at these factors, it can be said that most of them are uncertainties related to internal processes that are directly related to building design and operation. On the other hand, weather conditions are related to external factors that create scenario uncertainty in the modeling process as the effect of climatic variables and environmental conditions on the simulation. Building energy simulations are usually based on a specific climate data set obtained from meteorological stations, satellite observations or climate data banks, and therefore the climate data used in simulations is an important factor that greatly affects the accuracy and reliability of building energy modeling.

From a computational simulation and engineering perspective, the concept of calibration is not about proving the accuracy of a scientific theory but rather assessing and measuring whether the model is acceptable and suitable for the intended purpose. At this point, the calibration approach gains importance as a measure of the accuracy of the building model and, consequently, the simulation data. Calibration is "adjusting numerical parameters by matching simulation results with actual data to establish model reliability" [6].

This specific application of building simulation is called calibrated simulation (CS). This term corresponds to "fine-tuning or calibrating simulation inputs so that observed energy consumption aligns closely with those predicted by the simulation program” [13]. In this way, predictions closely match observed energy use. Ultimately, the calibration process is a procedure that “relies on user knowledge, experience, statistical expertise, engineering measurement, and a considerable amount of trial and error” [14].

The building energy model calibration process can generally be divided into three stages:
Modeling and data collection: Developing the building simulation model and collecting real-time data such as energy consumption, indoor environmental conditions, and climate data necessary for calibration.
Comparison and Error Analysis: Running the simulation model, comparing the outputs with accurate data, and determining error rates.
Iteration and Verification: Adjusting the parameters in the simulation model to align with accurate data until the error rates between simulation and measured results reach an acceptable level, re-simulating and verifying the model.

Calibration is defined in ASHRAE Guideline 14 as "the process of reducing model uncertainty by comparing the predicted output of the model under a specific set of conditions with actual measured data for the same set of conditions" [15]. As such, a calibrated model can reproduce measured data under the same set of conditions, with its accuracy measured through an uncertainty analysis.

ASHRAE Guideline 14 [15] describes uncertainty analysis as "the process of determining the degree of confidence in the true value when measurement procedures and/or calculations are used" [7]. The three primary sources explaining how this "degree of confidence," or uncertainty, is determined are:

“ASHRAE Guideline 14, published by the American Society of Heating, Refrigerating, and Air-Conditioning Engineers” [15].
“Federal Energy Management Program *(FEMP)* Measurement and Verification Guidelines” [16].
“International Performance Measurement and Verification Protocol *(IPMVP)”* [17].

These sources use simplified methods to measure uncertainty in savings calculations. The primary uncertainty indices employed are [8], [9], [10], [11], [12]:

Normalized Mean Bias Error *(NMBE)*;
Coefficient of Variation of the Root Mean Square Error *(CV(RMSE))*.

Other uncertainty indices used in the literature include *RMSE* (Root Mean Square Error), *MBE* (Statistical Mean Bias Error), *GOF* (Goodness of Fit), and the cost function fi. However, this study employs *NMBE* and *CV(RMSE)*, which are most used and can complement each other effectively when addressing calibration errors in combination.

NMBE (%) measures the difference between measured and simulated data for each hour and serves as a good indicator of overall bias in the model. It can be either negative or positive, with positive values indicating that the model underestimates measured data and negative values indicating overestimation. However, an essential issue with this index is its susceptibility to cancellation errors, where the sum of positive and negative values reduces the overall value. Therefore, it is not recommended to use this index alone. *CV(RMSE) (%)*, on the other hand, captures compensatory errors between measured and simulated data and determines how well a model fits the data. It is always “positive and not susceptible to cancellation errors” [18].Combining both indices is considered more accurate to prevent potential calibration errors.

During calibration, two primary datasets are required: the "simulation dataset" from the generated building model and the "measured dataset" from the real building monitoring system. The building model dataset consists of a large amount of data, from which the most influential parameters must be selected “to find a match between simulated and measured energy consumption” [8]. These can include monthly energy consumption data from utility bills or hourly measured indoor environment data.

2.1. Calculation and Evaluation of Uncertainty Indices

N(MBE) is the normalized form of Mean Bias Error *(MBE)*. *MBE* is the mean of errors across a sample space. It is generally a good indicator of the overall behavior of simulated data concerning the regression line of the sample [7] (Equation 1).

$$MBE = \frac{\sum_{i=1}^{n}(m_i - s_i)}{n-p} \times 100\ (\%) \quad (1)$$

Accordingly, the *N(MBE)* index must be scaled to make *MBE* results comparable. It is calculated by dividing the *MBE* index by the mean of the measured values ($\bar{m}$) and provides the global difference between actual and predicted values. By substituting the mean measured value ($\bar{m}$) into the formula and simplifying by taking p=0, the *N(MBE)* formula is derived (Equation 2). According to this formula, the calculation is completed by first adding the difference between the measured and simulated energy consumption in the time intervals of the considered period (e.g., monthly) and then dividing this result by the total of the estimated energy consumption. It is important to note that, in the literature, the *N(MBE)* formula (Equation 2) is often referred to as *MBE*. However, as detailed above, the uncertainty index is taken into account for calibration, and this index is mentioned as (MBE), (Normalized Mean Deviation Error) in Standards/Protocols *(ASHRAE 14, FEMP, IPMVP).*

$$N(MBE) = \frac{1}{\bar{m}} \cdot \frac{\sum_{i=1}^{n}(m_i - s_i)}{n-p} \times 100\ (\%) \rightarrow \ \bar{m} = \frac{\sum_{i=1}^{n}(m_i)}{n}$$

$$N(MBE) = \frac{\sum_{i=1}^{n}(m_i - s_i)}{\sum_{i=1}^{n}(m_i)} \times 100\ (\%) \quad (2)$$

Where:

- *m*: measured energy data over the time interval.
- *s*: simulated energy data for the same time interval.
- *n*: number of observations.
- *p*: number of adjustable model parameters, ideally zero for calibration purposes.

When calculating N(MBE), $p = 0$ is recommended [19] as cited by [20].

Another uncertainty index, *CV(RMSE)*, is derived by normalizing the *RMSE* value. Firstly, the sum of squared differences between measured and simulated values is divided by the number of observations. The square root of this result gives the *RMSE* (Equation 3). Finally, dividing the *RMSE* by the mean of measured values ($\bar{m}$) yields *CV(RMSE)* (Equation 4).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(m_i - s_i)^2}{n-p}} \times 100\ (\%) \quad (3)$$

$$CV(RMSE) = \frac{1}{\bar{m}} \sqrt{\frac{\sum_{i=1}^{n}(m_i - s_i)^2}{n-p}} \times 100\ (\%) \quad (4)$$

Where:

- *m*: measured energy data over the time interval.
- *s*: simulated energy data for the same time interval.
- *n:* number of observations.
- $\overline{m}$*:* mean of measured values.
- *p:* number of adjustable model parameters, ideally zero for calibration purposes.
-

For *CV(RMSE)* calculation, $p = 1$ is recommended [19] as cited by [20].

A threshold limit must be met in the *N(MBE)* and *CV(RMSE)* values to consider a model as calibrated. Depending on the time interval for calibration (monthly or hourly) and compliance with the requirements of the considered Standard/Protocol *(ASHRAE 14, FEMP, IPMVP)*, the threshold limit varies slightly (Table 1).

Table 1. Statistical criteria thresholds for calibration [15], [16], [17].

	Statistical Indicators (%)	**ASHRAE**	**FEMP**	**IPMVP**
Monthly	*N(MBE)*	±5	±5	±20
	CV(RMSE)	15	15	-
Hourly	*N(MBE)*	±10	±10	±5
	CV(RMSE)	30	30	20

2.2. Approaches to Calibration and Challenges Encountered

The first research on building energy model calibrations was conducted in the late 1970s by Diamond and Hunn, who calibrated seven different building types (a restaurant, a single-story office building, a retail store, a hospital, a multi-story office building, a school, and a solar-heated and cooled building) using one-year monthly energy bills [21]. Over time, existing calibration methods have been improved, and many new techniques and approaches have been introduced into the literature, particularly in the last two decades.

The classification of standard approaches to calibrate simulation models against measured data is given by Reddy [22] as follows:

- ***“Manual, Iterative, and Pragmatic Intervention Calibration***, where the procedure adopted to calibrate the parameters iteratively is user-specific, and the inputs and parameters are adjusted through trial and error, and therefore largely intuitive.
- ***Based on Informative Graphical Comparison Calibration***, visuals, which involve using specific types of visual graphs created with specialized toolsets, in addition to the manual, iterative, and pragmatic calibration approach, are beneficial for hourly data calibration, where analysts face numerous data points and find it challenging to pinpoint exact discrepancies;
- ***Based on Special Tests and Analytical Procedures Calibration***, which includes interventions such as intrusive Blink Tests, STEM Tests, Signature Analysis Methods, Macro Parameter Estimation Methods, and unique approaches involving monitoring data,
- ***Analytical/Mathematical Calibration is*** an optimization problem based on minimizing the monthly (or even hourly) mean square errors between measured and simulated energy usage data.”[22]

These methods can be used independently or in combination to support each other.

It should be noted that building energy model calibration is heavily dependent on user knowledge and experience. It is also challenging and time-consuming, based on trial, error, and expertise-requiring process.

However, the lack of any generally accepted standard in calibration procedures and methods makes this process more difficult and complex. Coakley et al. [18] identified the fundamental problems related to calibration under seven main issues:

- ***“Standards:*** The lack of a universally accepted standard for calibration leads users to perform calibration based on their experiences.
- ***Cost:*** The energy modeling process requires substantial time and cost.
- ***Simplification***: Simulations require many inputs, but measuring and obtaining all these data is impossible.
- ***Inputs:*** The model's accuracy depends on the data quality used. When it is not possible to measure all inputs accurately, achieving reasonable accuracy becomes difficult.
- ***Uncertainty:*** Some inputs impact the modeling process more than others. The uncertainty of these inputs affects the accuracy of the results.

- ***Identification:*** Identifying the causes of inconsistencies between simulations and actual measurements is often an under-defined process based on expert knowledge.
- ***Automation:*** The lack of a method to automate the calibration process results in the need for manual interventions, making it more difficult and time-consuming." [18].

In addition, there are some errors related to the verification measurements used in the validation and calibration of building energy models. These technical errors can prevent the correct assessment of whether the energy models are calibrated, especially regarding the use and representation of the *MBE* and *N(MBE)* formulas. Ramos Ruiz and Fernandez Bandera [7] have revealed these errors in a very comprehensive study and compiled them with examples as follows:

1. Although the *MBE* mathematical formula is correct, converting it to a percentage has not been explained [23].
2. The *MBE* value has been expressed as a percentage, but the necessary normalization procedures have not been applied [12].
3. In the *MBE* analysis, the cancellation errors' effect was ignored, and direct use was made [11].
4. The *MBE* values are percentages without a mathematical formula. This makes the verification process impossible [10].
5. The mathematical formula used to calculate *MBE* is incorrect [9].
6. *MBE* Although the mathematical formula is correct, the methodological explanation has been incorrect [24].
7. As the most common error, the *N(MBE)* index was given with the correct formula, but it was called the *MBE* or MBE (%). This leads to a confusion of concepts [8].

In addition, while it is stated in [19] (as cited in [20]) that the p-value in the formula should be taken as p=1 when calculating *CV(RMSE)*, it has been observed that the use of p=0 is quite common in the literature.

In the sections so far, the definition and scope of calibration, its importance in evaluating building energy performance, and the stages of calibration of a BES model have been given; uncertainty assessment methods used to assess the accuracy of a calibrated model have been introduced; tools and techniques used for calibration of BES models have been presented, and difficulties encountered in the calibration process of a building model errors in calculations have been mentioned.

In the next section, as an example, the energy simulation model of an existing residential building with ground + 3 floors located in Samsun–Havza was calibrated and verified.

3. METHOD

3.1. Case Study-Calibration of the Building Simulation Model

The method of this study is based on the calibrated simulation approach, one of the three approaches outlined in ASHRAE 14-2002. This guideline is a reference for determining acceptable minimum performance levels in energy demand and building savings. The three approaches Whole-building metering, retrofit isolation metering, and Whole-building calibrated simulation-include minimum compliance requirements to ensure acceptable error rates. The method consists of five steps:

1. Defining the steps of the calibration process.
2. Collecting data related to the building.
3. Developing a numerical energy model.
4. Comparing simulation results with measurement results.
5. Improving the energy model until it reaches an acceptable error margin.

The energy model was developed within this framework by inputting the data obtained during the creation and validation phases into the Design Builder and EnergyPlus programs. Analytical calibration was applied based on accurate data collected through measurements and observations. The process was completed following the steps outlined below (Figure 1).

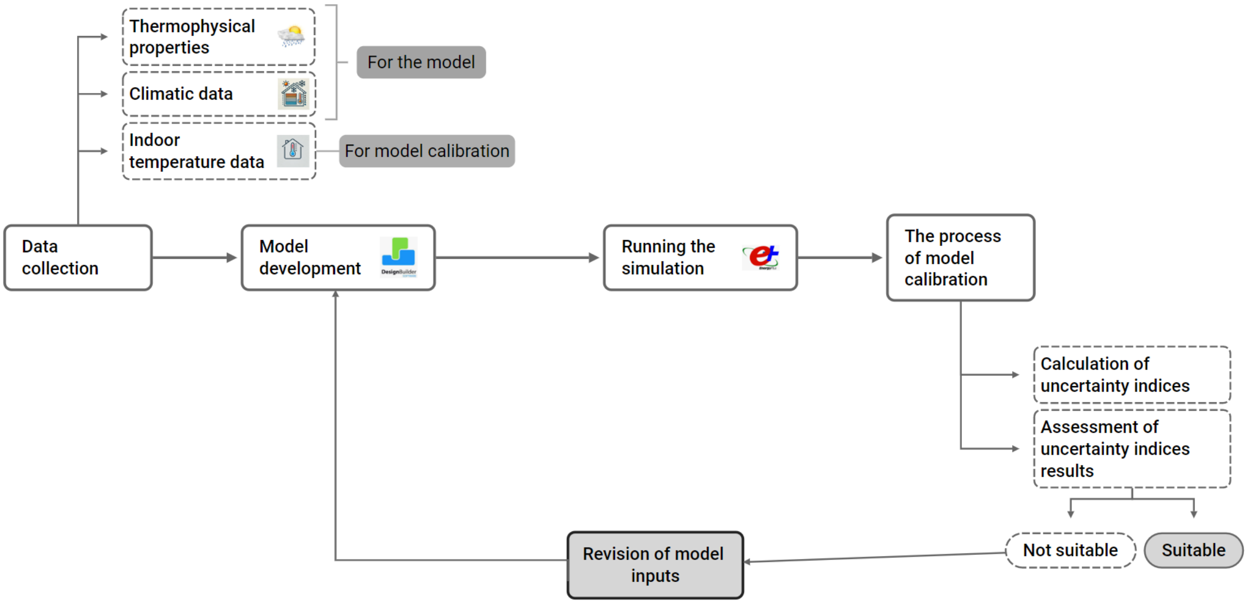

Figure 1. Flowchart of the model creation and calibration process

3.2. Introduction of the Existing Building and Development of the Energy Model

As part of the study, a residential building constructed in 1988 and located in parcel 54/1 in the Havza district of Samsun was selected to represent a significant portion of the building stock in the area (Figure 1). This building, constructed without insulation during the pre-2000 period when the TS 825 standard was not mandatory for buildings, underwent a suboptimal external cladding application in recent years.

Initially, the implementation project for the building was accessed. The selected building has a base area of 243 m². The structure consists of a basement, ground floor, and three additional floors, built with a reinforced concrete skeleton system. Each floor contains one Type T1 (3+1) apartment with an area of 116 m² and one Type T2 (2+1) apartment with an area of 95 m² (Figures 2 and 3).

Figure 2. Residential building for case study

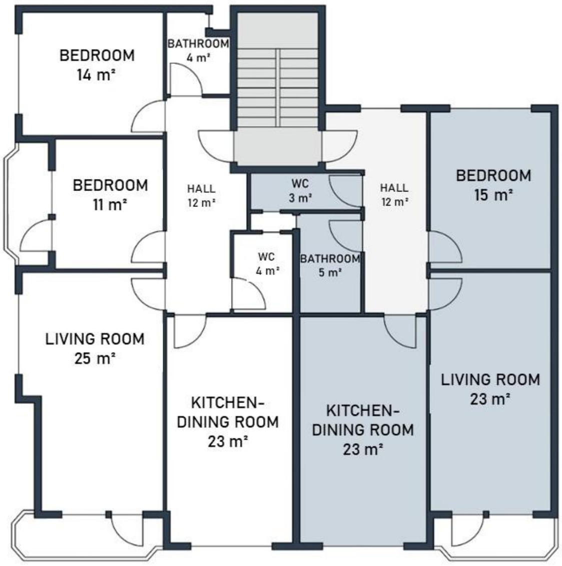

Figure 3. Typical floor plan

The ground floor comprises five partitioned retail spaces with a total area of 216 m². The ceiling heights of the typical floors are 3 m, while the ground floor and basement have ceiling heights of 3.5 m and 2.6 m, respectively. The building is on a corner plot with northern and western facades and adjacent buildings on the other sides. Typical floors have 30% glazed facades, whereas the ground floor has 60%. Using this data, the Design Builder program modeled the building geometry (Figure 4).

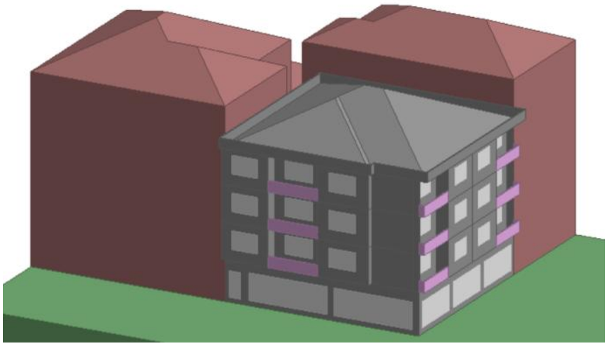

Figure 4. 3D model of the selected building

Subsequently, the detailed building information provided in Table 2 was entered into the program, preparing the simulation model.

Table 2. Structural and Technical Information of the Building

Building Geometry	Orientation	Northeast
	Number of Floors	Basement + 4 floors
	Facade Area (excluding basement) (m²)	581.69
Windows	Transparency Ratio of Typical Floor Facades (%)	30
	Transparency Ratio of Ground Floor Facades (%)	60
Building Area (m²)		1065,73
General Description of the Building	Structure Type/Material	Reinforced concrete skeleton
	Outer Wall Material	Brick
	Air Tightness Level	0,5

General Features of Building Technology and Systems	Occupancy Density (person/m²)		0,0188
	Building Age		36
	Building System	Heating	Individual boiler
		Heating Equipment	Radiator
		Heating Fuel	Natural gas
		Heating System Efficiency	0,85
		Hot Water System	Boiler
		Hot Water Fuel	Natural gas
		Hot Water System Efficiency	0,85
		Cooling	-
		Ventilation	Natural
	Thermal Transmittance Coefficients of Opaque Components	U_{wall} (W/m²K)	1,258
		U_{roof} (W/m²K)	1,425
		U_{floor} (W/m²K)	1,932
	Transparent Component Properties	Window Area (m²)	148.94
		U_{window} (W/m²K)	2.72

Information was collected regarding the occupants' daily routines, equipment, and lighting habits. Additionally, the operational schedules of the mechanical systems in the building were determined. These insights, obtained through on-site observations and interviews with the building occupants, were input into the simulation program to perform the simulation.

Table 3. Current energy performance

Annual total heating energy demand (kWh)	98258,06
Annual total cooling energy demand (kWh)	-
Annual total energy demand (kWh)	136746,1
Total building area (m²)	1065,73
Heating energy demand per m² (kWh/m²)	117,60
Heating energy demand per m² for heated spaces (kWh/m²)	92,20
Total energy demand per m² (kWh/m²)	128,31

According to the simulation results presented in Table 3, the total final energy consumption (heating, domestic hot water, electricity) is 128.31 kWh/m². Heating accounts for the largest share at approximately 72%. The heating energy demand per m² for heated spaces is 92.20 kWh/m².

3.2. The Calibration Process

As emphasized in Chapter 2; using accurate, up-to-date, and locally relevant climate data plays a critical role in ensuring the accuracy and reliability of the simulation model. Therefore, in order to obtain a more precise and realistic simulation model, the study utilized PVGIS (Photovoltaic Geographical Information System), an online program that provides information on solar radiation and photovoltaic system performance for much of Europe, Africa, Asia, and America. By entering the building's latitude and longitude information into the system, microclimate data specific to the building's location was obtained on a daily, monthly, and yearly basis, which was then incorporated into the DesignBuilder database.

The indoor temperature data required for calibration were recorded hourly over approximately forty days using temperature and humidity measurement devices placed in the living area of an apartment (T2) on the second floor.

The simulation results obtained with the EnergyPlus program of the case study in which the energy simulation model was created were calibrated using indoor temperature measurement data. Calculations were carried out using the *N(MBE)* and *CV(RMSE)* formulas detailed above.

The operations were conducted on 1008 data obtained by hourly measurements in the existing building between April 20, 2024, and May 31, 2024.

The uncertainty parameters given in Table 4 on the building energy model were changed manually and iteratively within appropriate value ranges, and each time, a new simulation was performed to ensure that the measured and simulated values were within the appropriate range. The calibrated values resulting from the repeated operations are shown in Table 4.

Table 4. Uncertainty parameters and the calibrated values

Uncertainty Parameters	**Value Range**	**Calibrated Value**
Heating System Efficiency	85-95	85

Air Tightness (ac/h)	0,1-0,5	0,5
Heating Setpoint (°C)	23-25	23

According to Equation 2, the total difference between each measured and simulated data was divided by the total of the measured data, and the *N(MBE)* value was found to be -1.68 percent (Table 5).

Table 5. Calculation of *N(MBE)*

$\sum_{i=1}^{n}(m_i - s_i)$	-331,51
$\sum_{i=1}^{n}(m_i)$	19651,50
$\sum_{i=1}^{n}(m_i - s_i)/\sum_{i=1}^{n}(m_i)$	-0,0168
×100(%)	-1,68

Subsequently, the *CV(RMSE)* value was calculated. First, the squared differences between each measured and simulated data were summed and divided by 1,007, the total number of data points minus one, as per Equation 3. The square root of this result yielded the *RMSE* value. Then, as seen in Equation 4, the *RMSE* was divided by the mean of the measured values ($\bar{\boldsymbol{m}}$) to calculate the *CV(RMSE)* value as 13.86% (Table 6).

Table 6. Calculation of *CV(RMSE)*

$\boldsymbol{\sum_{i=1}^{n}(m_i - s_i)^2/(n-p)}$	7353,45 /1007
$\boldsymbol{\sqrt{\sum_{i=1}^{n}(m_i - s_i)^2/(n-p)}}$	2,70
$\boldsymbol{{}^1/_{\bar{m}}\sqrt{\sum_{i=1}^{n}(m_i - s_i)^2/(n-p)}}$	0,1386
×100(%)	13,86

$\boldsymbol{p = 1}$

$\boldsymbol{n = 1008}$

$\boldsymbol{\bar{m} = 19{,}4955}$

Based on the indoor temperature measurement data, the *N(MBE)* and *CV(RMSE)* values were within the acceptable thresholds (Table 7). Therefore, the calibration process was considered completed.

Table 7. Evaluation of Uncertainty Index Results

Statistical Indicators		*N(MBE)*	*CV(RMSE)*
Value (%)		-1,68	13,86
Hourly	**ASHRAE**	±10	30
	FEMP	±10	30
	IPMVP	±5	20
Result			Acceptable

Compared to similar studies, the calibration of the energy simulation results in Table 3 shows consistent performance based on statistical indicators. As highlighted in Reddy's analysis, the primary challenges encountered during the calibration process stem from user behavior and operational uncertainties.

Additionally, lack of information, simplification of the physical model, and operational uncertainties were the parameters that were iteratively varied at appropriate intervals to improve the accuracy of the model, which were highlighted as the main reasons for the differences between model simulation and accurate data in the systematic review by Chong et al. [6].

In cases where the measurement results are above the threshold values that must be provided or where it is desired to increase the accuracy, iterations can be performed by making appropriate changes to these inputs.

This study also serves as a comprehensive guide to addressing various methodological issues in calibrating building energy models, as identified by Ramos Ruiz and Fernandez Bandera [7]. The NMBE value was calculated as -1.68% with the mathematical formula and percentage conversion explicitly defined, ensuring the proper normalization process. Hourly measurements were conducted with 1,008 data points, considering the impact of cancellation errors. The verification process concerned the thresholds specified in the *ASHRAE 14*, *FEMP*, and *IPMVP* standards was completed. This study's methodology and mathematical formulas were clearly defined, eliminating conceptual ambiguities.

4. CONCLUSION AND RECOMMENDATIONS

The growing interest in energy consumption optimization and measurement and verification protocols highlights the importance of calibrated energy models. Understanding the validation requirements of building energy models is critically important in this context. However, the academic literature has identified errors and inconsistencies in the validation measurements (uncertainty indices) used in model calibration processes. In this regard, this study focuses on reducing the methodological challenges and uncertainties/inconsistencies in the calibration processes of building energy simulation models, which are crucial for evaluating building energy performance.

This study contributes to the theoretical and practical aspects of calibrating building energy simulation models, a highly parameterized process. Fundamental concepts related to the calibration of building energy simulation models, calculating and evaluating uncertainty indices, common approaches to calibration, and the challenges encountered have been comprehensively addressed. Through a case study, systematic calibration approaches and the integration of uncertainty evaluation methods have been applied to validate the energy simulation model of an existing building. This process has resulted in a manual application example for performing building energy simulation model calibrations more effectively and reliably, yielding a model capable of conducting precise energy performance analyses.

The lack of a universally accepted standard for building simulation model calibration, the reliance on user knowledge and experience, the presence of numerous inputs and uncertainties, and the necessity for manual intervention are factors that further complicate the process, while the main reason for the inconsistencies between the sources is that the researchers misuse different uncertainty calculation criteria. This error directly affects the accuracy of the building energy simulation model calibration.

As a result, this study, which addresses the inconsistencies and errors between similar studies in the academic literature and presents a correct example application with a case study, is a basic example for handling Building Energy Simulation model calibrations more reliably and effectively. These findings can contribute to the creation of strategies that will ensure more efficient use of energy by providing a guide for both energy efficient retrofit processes in existing buildings and energy modeling in new buildings.

In future studies, in addition to manual studies that will consider more comprehensive inputs, especially user behavior, with larger sample groups, it is recommended to disseminate automatic calibration examples that will increase both process efficiency and accuracy levels by providing the capacity to evaluate a wide parameter area. In particular, the integration of machine learning and artificial intelligence algorithms can accelerate the calibration process, minimize user errors and increase model accuracy. Thus, the energy modeling process can be made more adaptive, and more precise results specific to different building types and climate conditions can be obtained. In addition, there is a need to develop calibration systems based on real-time data flow that can provide more reliable analyses by updating energy simulations with instant data.

On the other hand, comprehensively addressing the uncertainties in the calibration process, integrating user behavior into energy simulations, and deepening uncertainty analyzes are important research areas that will allow energy efficiency targets to be determined more effectively by increasing the accuracy of calibration.

NOMENCLATURE

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

BES : Building Energy Simulation

CV(RMSE) : Coefficient of Variation of the Root Mean Square Error

FEMP : Federal Energy Management Program

GOF: Goodness of Fit

HVAC: Heating Ventilating and Air Conditioning

IPMVP: International Performance Measurement and Verification Protocol

LCA : Life Cycle Assessment

LCC : Life Cycle Cost

MBE: Statistical Mean Bias Error

N(MBE) : Normalized Mean Deviation Error

RMSE: Root Mean Square Error

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DECLARATION OF ETHICAL STANDARDS

The authors of the paper submitted declare that nothing which is necessary for achieving the paper requires ethical committee and/or legal-special permissions.

CONTRIBUTION OF THE AUTHORS

Sinem Tozlu: Analysed the case, wrote and edited the manuscript.

Ayşenur Coşkun: Analysed the case, wrote the manuscript.

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CONFLICT OF INTEREST

There is no conflict of interest in this study.

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