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ASSESSING INDOOR AIR TEMPERATURE IN EDUCATIONAL BUILDINGS: A CASE STUDY AT JAZAN UNIVERSITY, SAUDI ARABIA

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Abstract

Energy model calibration is essential in assessing building energy performance and developing effective energy management strategies. To enhance calibration scenarios worldwide, the adaptability of building components, such as indoor air temperature (IAT) and heating, ventilation, and air conditioning (HVAC) systems, must be evaluated across diverse building types, including educational buildings. However, this aspect remains underrepresented in existing studies. Evidence suggests that combining simulated and measured data improves calibration accuracy in building energy simulations, ultimately leading to optimized energy management and thermal comfort. Given the above-mentioned information, this study introduces a methodological approach to energy model calibration for educational buildings. The main objectives are to establish a reliable baseline model, to design a robust IAT measurement framework, and to integrate measured and simulated data for model calibration. The proposed approach incorporates architectural drawings, building envelope properties, and comprehensive data collection as key inputs for developing a reliable energy model baseline. The methodology also includes a detailed data measurement framework that specifies the duration, instruments, and sensor placements to ensure robust results. EnergyPlus simulation software was used to create the baseline model, integrating standardized parameters, such as thermostat setpoints. Furthermore, two sets of IAT measurements were collected using data loggers placed in the southern and northern zones of the building, respectively. The findings reveal a strong correlation between *Sensor-S1* and *Sensor-S2* measurements, thereby validating their reliability for monitoring IAT. Baseline calibration under stable conditions also demonstrated the model's effectiveness, while measurements during transient events highlighted the importance of real-time monitoring, sensor placement, and adaptive HVAC strategies. The study's findings underscore the importance of incorporating dynamic behaviours and occupancy data to improve accuracy in educational buildings. This calibrated energy model also serves as a valuable tool for benchmarking and predicting energy performance, thus offering a foundation for future research and enhanced energy management strategies across diverse building types.

Keywords: Actual measurement, Educational buildings, Energy modelling, Indoor air temperature, Model calibration.

1. Introduction

Requirements for building energy performance have escalated in recent years, especially in regions with substantial cooling and heating demands. Building sectors significantly affect global energy demands, increase carbon emissions, and intensify global warming potential [1]. The international semi-annual electricity market report published by the International Energy Agency (IEA) projected a nearly 5% increase in global electricity demand in 2021 and a 4% increase in 2022 - both fuelled by economic recovery [2]. Notably, it has been reported that the US building sector is responsible for 40% of total energy use and about 40% of carbon emissions [3]. Although many developing countries are seeing economic growth and increasing energy demand, most of their energy resources are derived from finite sources [2].

In Saudi Arabia, building energy demands have significantly increased, accounting for approximately 30% of total energy production [4]. The residential sector alone is responsible for nearly 50% of this consumption, with cooling workloads being the primary driver of energy use [5]. Saudi Arabia relies on cooling energy to achieve occupants' thermal comfort [2]. Although the country supports climate action and has committed to reducing carbon emissions to zero by 2060, its extremely hot climate has imposed several challenges. Related to this, enhancing the energy efficiency of buildings via energy modelling is considered a solution for reducing energy demands and associated carbon emissions [3]. At the same time, it highlights the need for building energy evaluation studies to reduce the impact of carbon emissions on the built environment.

In light of the complex process involved in evaluating building energy performance in real-world applications, energy modelling techniques have been proposed. For instance, since the 1920s, building energy modelling techniques have been used to calculate thermal heat flow. Many companies and institutions, along with engineers and academics, have used modelling techniques because they offer various energy efficiency scenarios for evaluation [6]. Building energy modelling or simulation is crucial for predicting energy performance and developing energy conservation strategies to help reduce operational loads on building systems [7]. Energy policies also encourage the use of modelling to reduce costs [1]. However, in using modelling techniques, numerous variables and data inputs must be considered, and effectively capturing these variables is essential for constructing accurate energy simulation models [6].

Furthermore, data input in building energy modelling is critical, as it must reflect actual buildings to ensure that energy behaviours are effectively simulated. Researchers often use various tools for data collection to replicate real-world conditions. One study reported that measuring environmental factors, such as indoor air temperature (IAT), is essential for enhancing the accuracy of these models [6]. The IAT measurements of actual buildings are typically used by monitoring devices employed in simulation processes. The simulation uses specific energy performance software, such as EnergyPlus, DOE, and TRNSYS [8]. Thus far, most studies in this field have focused on residential and commercial buildings worldwide [9].

The primary objective of this study is to evaluate the IAT performance of educational buildings in the Jazan region under very hot-dry conditions. Specifically, the study aims to first, establish a reliable baseline energy model using architectural drawings and building envelope properties; second, design and implement a comprehensive IAT measurement framework; and third, integrate simulated and measured data for model calibration and validation. Accordingly, the study aims to address the overarching research question: How can a calibrated energy model accurately predict IAT performance in educational buildings? The novelty of this study lies in the integration of real-time sensor measurements with simulation-based calibration using EnergyPlus, combined with an analysis of IAT, in the specific context of an educational building in Saudi Arabia's very hot-dry conditions. This combination provides a unique methodological and contextual contribution, as most existing studies have focused primarily on residential and commercial buildings.

1.1. Literature review

As the assessment of building energy performance has been extensively researched, several approaches have been proposed over the past few decades. Prior studies have mostly concentrated on determining the most effective methods for reducing energy use without compromising indoor comfort [10]. At the same time, simulation approaches make it possible to analyse multiple design scenarios and estimate how energy performance changes based on different circumstances [11, 12]. Integrating the two approaches has proven to be productive, providing adjustability and precision in building performance optimization [12]. Furthermore, previous research has strengthened energy models using reliable calibration methods. For instance, by detecting typical modelling flaws that can be improved in design-stage models, one study found that calibration greatly increases the reliance on energy simulation packages [13]. Another study created an automated calibration process to help energy models correctly depict heating, ventilation, and air conditioning (HVAC) and building systems [3].

1.1.1. Building energy model validation

The building energy model (BEM) method is widely used and requires calibration and validation processes. Building model calibration is a measure of model accuracy and is conducted by comparing measured data against simulation model outputs to check for variability. Model calibration refers to the process of adjusting the model's variables and settings in the simulation package to match actual building energy performance or what we see in experiments. Integrating simulated and measured data dramatically enhances a model's calibration. Royapoor and Roskilly [6] calibrated the model using ASHRAE Guide 14 indices, and found that further scientific work using actual hourly data is significant to ensure proper model energy performance. Meanwhile, Kim et al. [7] developed office building models for calibration using occupant schedules and hourly electricity use. Their results showed that the accuracy of BEM improved significantly when occupancy schedules were incorporated. Pachano and Bandera [1] highlighted the gaps between simulated and actual energy performance in buildings and introduced a multistep calibration method for HVAC systems. Their findings significantly improved HVAC parameter adjustments in EnergyPlus simulations and demonstrated promising results. Their research is insightful due to its use of actual IAT data for calibration.

Moreover, model validation evaluates how accurately a model represents real-world conditions for its intended purposes, while model verification ensures that the model implementation presents an accurate reflection of the developer's description and proposed solutions [14]. Earlier efforts to validate building thermal performance predictions emphasized the need for more observed data to enhance comparisons. For example, Tsioptsias et al. [15] reviewed the literature on model validation using simulation techniques, focusing on operational research, modelling, simulation, and computer science. They examined validation approaches, test types, and common practices, thus highlighting the necessity of empirical studies for collaboration. Model validation lacks universal definitions and standards, with inconsistent terminologies often causing confusion about validity types.

Kim et al. [8] conducted an empirical study that validated whole-building energy simulation outputs against measured data for accuracy. Their validation employed statistical indices, including normalized mean bias error (NMBE) and the coefficient of variation of the root mean square error (CV-RMSE), to assess simulation accuracy. They addressed gaps in data availability for small buildings, which often lacked empirical data for comparison, and demonstrated that accurate thermal performance predictions can be achieved through robust validation efforts. Their findings also highlight the importance of continuous and empirical validation to ensure the reliability and accuracy of BEMs [8].

1.1.2. Data measurement and input parameters

Measuring data for building energy performance evaluation requires monitoring influential parameters that directly impact buildings' energy performance and indoor thermal comfort. These parameters, which include IAT, relative humidity (RH), occupancy, system scheduling, and others, are critical as they significantly impact model predictions and may introduce considerable uncertainty if neglected. However, many studies, such as those of Royapoor and Roskilly [6], Pachano and Bandera [1], and Kim et al. [7], have primarily relied on IAT as the core parameter for comparing actual data with model predictions. The high variance between the measured and simulated IAT values indicate the need for model recalibration to minimize discrepancies. In accordance with the ASHRAE guidelines, acceptable levels of accuracy for model calibration require an mean bias error (MBE) within ± 10% for monthly data and ±5% for hourly data, while the CV-RMSE should be within 15% for monthly data and 30% for hourly data [16].

1.2. Gaps and limitations from literature

Overall, existing studies have conclusively demonstrated that merging simulated and measured data helps improve the accuracy and reliability of model calibration procedures in *BEM*, resulting in more effective energy management shown in Table 1. However, it remains unclear whether earlier studies are required to define the requirements and degrees of model accuracy for much deeper research in future endeavours, such as optimization and control techniques, Energy Conservation Measures (*ECM*) and technology applications, and renewable integration. Furthermore, to explore a broader range of calibration scenarios in energy models, future research must examine the adaptability of several different building components, such as IAT and HVAC systems, in building types apart from residential and commercial structures worldwide. This is critical because the performance of models with various parameter subsets must be evaluated more thoroughly. In addition, a standardized calibration technique is required to ensure the consistency and dependability of the obtained results across studies.

The theoretical framework of this study is based on the premise that accurate calibration enhances the predictive reliability of building energy models, which is essential for guiding energy efficiency improvements. Accordingly, the study aims to demonstrate that integrating actual data measurements with advanced simulation techniques yields a more robust and replicable calibration approach for educational buildings. Additionally, dynamic factors such as occupancy patterns, user behaviour (e.g., opening doors and windows), and diverse space usage (classrooms, studios, and laboratories) must also be recognized as theoretical indicators, since they affect internal heat gains, airflow, and thermostat setpoints, thereby driving variability in IAT and influencing model accuracy. Therefore, this study investigates the building modelling and calibration of an educational building at Jazan University through the integration of actual data measurements and advanced simulation techniques for more efficient energy performance evaluation and improvements.

In contrast to previous studies that have predominantly concentrated on residential or commercial buildings, the present research employs an integrated methodology that combines real-time sensor data with simulation-based calibration in EnergyPlus. The approach explicitly incorporates the analysis of IAT within an educational building situated in very hot-dry conditions. This dual emphasis on sensor-informed calibration and contextual application enhances the fidelity of the model and ensures a more accurate representation of the building's actual thermal dynamics.

Table 1. Summary of key studies on building energy simulation calibration and identified gaps.

Author(s), (Year)	Focus of Study	Approach/ Method	Key Findings	Identified Gaps/ Limitations
Royapoor and Roskilly (2015) [6]	Calibration of building energy model (office building)	EnergyPlus calibration using hourly data and ASHRAE Guide 14 indices	Improved accuracy in predicting air temperature and retrofit savings	Need for more annual data cycles; limited to office buildings
Kim et al. (2017) [7]	Occupancy schedules and energy calibration	Linked hourly electricity data with space occupancy types in office buildings	Occupancy schedules significantly improved *BEM* accuracy	Focused on commercial offices; limited application to educational buildings
Pachano and Bandera (2021) [1]	Multistep calibration of HVAC systems	Empirical test data with EnergyPlus calibration	Reduced energy performance gap; maintained IAT within limits	Limited to HVAC calibration; not extended to broader building performance
Kim et al. (2022) [8]	Validation of whole-building energy simulation	EnergyPlus v23.2.0 + *OpenStudio*; statistical indices (*NMBE*, *CV-RMSE*)	Demonstrated reliable validation methods for small buildings	Lack of empirical validation data for larger/educational buildings
Abha School Study (2020) [9]	Energy use in Saudi schools, zero-energy design	Measured two years of electrical data; active vs passive design	Active design (PV) is more effective than passive design	Focused on energy use, not calibration; limited to one case study
Meta-analysis of *BEM* calibration models [14]	Review of calibration approaches	Meta-analysis of existing *BEM* models	Identified flaws in calibration reporting and reliance on monthly stats	Lack of standardized calibration requirements; poor reporting consistency

1.3. City and location

The building studied in this research is located in Jizan City, within the Jazan region, Saudi Arabia. Due to the building's high occupancy levels, continuous operational schedules, and substantial contribution to cooling energy demand, it is a critical sector for improving building energy performance in a very hot-dry climate. However, researchers identified Jizan as a hot, humid region due to the elevated level of humidity [17]. The annual humidity ratio in Jizan is very high, with 64% or above (the muggier period of the year lasts for 10 months), accompanied by a lack of precipitation, resulting in an annual average of 27.61mm (1.09 in). At the same time, the average yearly temperature ranges from 32°C to 29 °C.

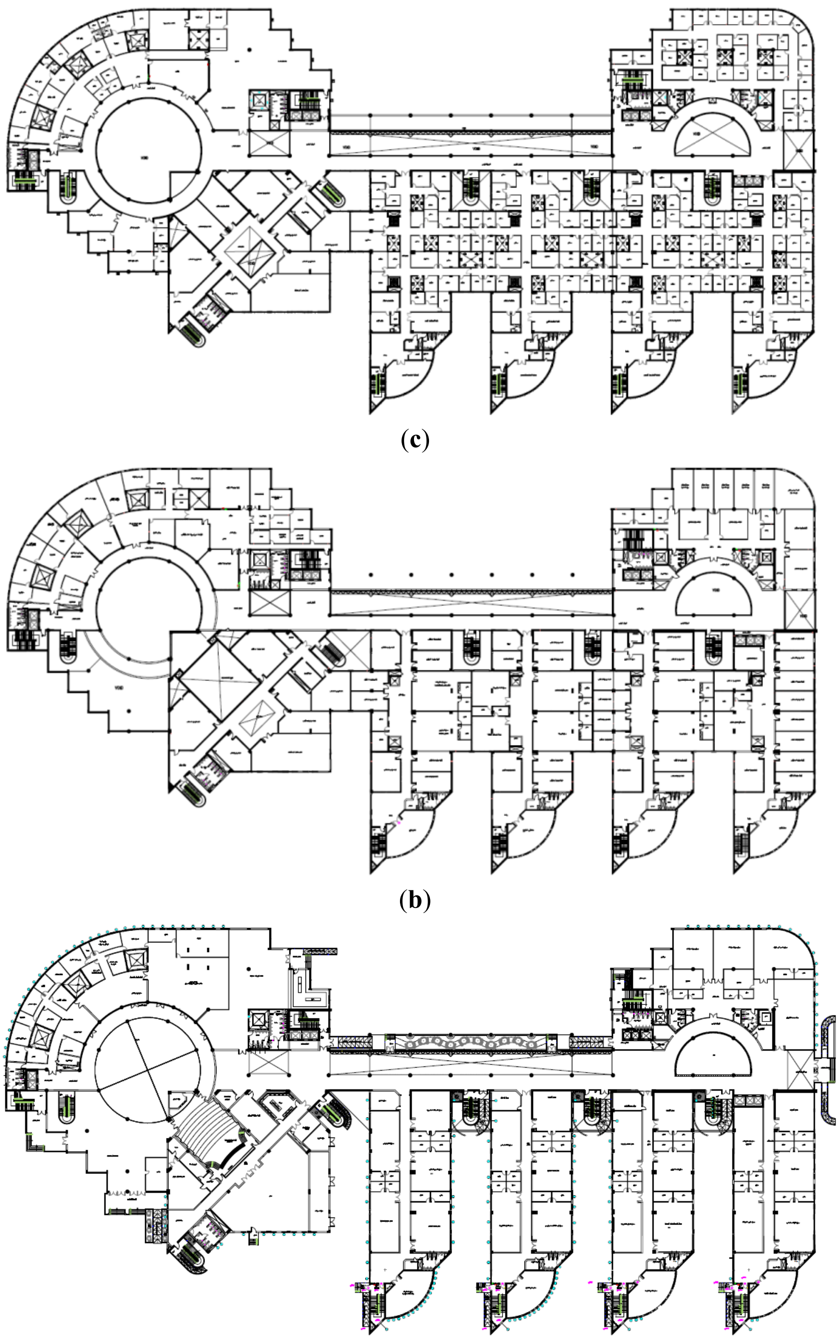
In accordance with the Saudi Building Code and International Climate Zone Definitions, Jazan's climate zone belongs to Zone "1B" (Very Hot-Dry), which describes a climate characterized by high temperatures and humidity [18]. Average summer temperatures in this region often exceed 40°C, and humidity levels can surpass 80% [19]. These climatic conditions and the location of Jizan make it a crucial area for energy efficiency studies, particularly in evaluating cooling loads and ensuring indoor thermal comfort. Additionally, Jizan is an essential regional centre that connects various towns and facilitates economic and academic activities. With a population of approximately 1.5 million people [20]. The city plays a significant role in local development and urbanization, further emphasizing the importance of efficient building design and energy management [21].

1.4. Case study description and building description

To embrace the practical application of the calibration methodology introduced in the methodology section, this study used the College of Engineering and Computer Science (CECS) building at Jazan University, which was constructed in 2017. This building is a modern educational facility designed to support academic activities for students and faculty. It is the central hub for the university's Engineering and Computer Science Programs, encompassing lecture halls, laboratories, and faculty offices. The building is equipped with centralized HVAC systems and advanced infrastructure and is designed to provide a comfortable and efficient environment for its occupants.

This research focuses on the CECS building - a three-story structure with a total floor area of 34,168 m^2 and a building volume of 204,907 m^3 as shown in Fig. 1. A notable feature of the building is its extensive glazing, with windows covering 3,640 m^2, accounting for 24.5% of the total envelope area of 14,836 m^2. The eastern façade, in particular, has the highest window-to-wall ratio (WWR), featuring 1,080 m^2 of glazing. These architectural characteristics, especially the large-window areas, significantly affect the building's thermal behaviour and energy performance, making it an ideal case study for detailed energy modelling and analysis.

The main corridor of the CECS building has a total height of 17.2 meters, with floor heights varying across different zones. The ground and first floors each have a height of 5.0 meters, while the second floor has a height of 4.5 meters. This variation in ceiling heights influences the thermal dynamics and airflow within the building, thereby contributing to the overall complexity of energy modelling and indoor environmental analysis. Therefore, the combination of diverse space usage, advanced HVAC systems, and significant glazing presents a complex environment for thermal dynamics. Such complexity offers a valuable opportunity to assess the influence of building design on energy consumption and indoor environmental quality through energy simulations.



(**c**)

(**b**)

(**a**)

Fig. 1. Floor plans of the College of Engineering and Computer Science (CECS) building (a) Ground floor plan; (b) First-floor plan; (c) Second-floor plan [22].

2. Material and methods/experiment

The present research employed a quantitative methodology structured into three key sections. Section A outlines the collection of building-specific data, including architectural drawings, envelope configurations, and material properties, which are essential for establishing an accurate energy model foundation. Section B details the data measurement process, which includes data measurement, the instruments used, and the placement of sensors throughout the building. Section C describes the development of the energy model baseline using EnergyPlus simulation software, with standardized parameters, such as thermostat setpoints.

The methodology began with data collection, which involved gathering the critical information required for measurement and energy modelling as shown in Fig. 2. Such information included details about building construction, such as material properties and structural specifications, thermal properties of the building envelope (e.g., insulation and U-values), weather data specific to the building's location, and site-related parameters. Additionally, IAT measurements were collected using devices (*Sensor-S1* and *Sensor-S2*) placed in the south and north zones of the building, respectively. To ensure their accuracy, these devices were validated systematically, thus identifying and addressing any errors before formal data measurement began.

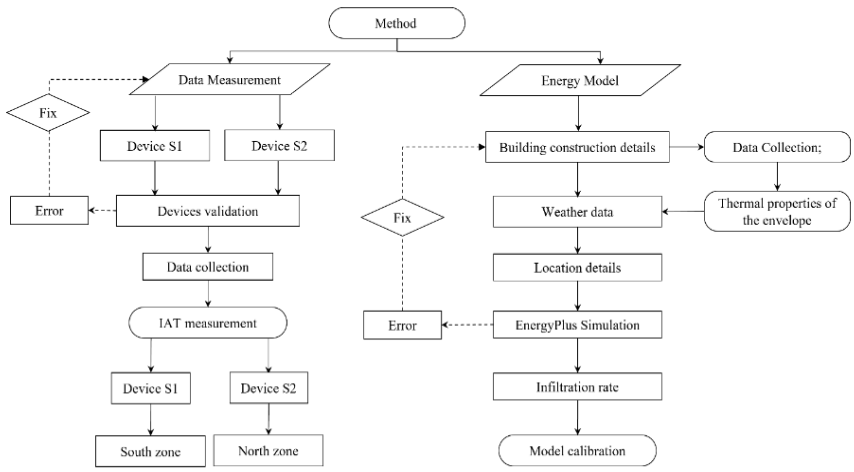


Fig. 2. A flowchart of the study's research methodology, including an overview of the calibration methodology.

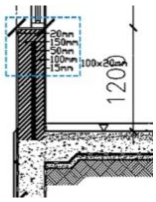
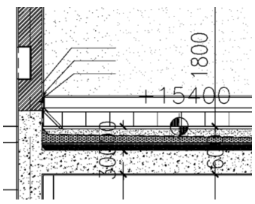
Once reliable IAT data were collected, the energy modelling process was initiated. The collected data served as inputs for the EnergyPlus simulation tool, which was used to model the building's energy performance. To predict IAT under various conditions, key factors such as infiltration rates, weather conditions, and thermal envelope properties were included in the simulation. The final step involved model calibration, during which the simulated results were compared to the actual measured data. This step involved fixing the energy model by adjusting its inputs to minimize discrepancies between the predicted and observed results. A robust and reliable building energy model can be developed through this integrated approach of comprehensive data collection, precise measurements, and calibrated energy modelling.

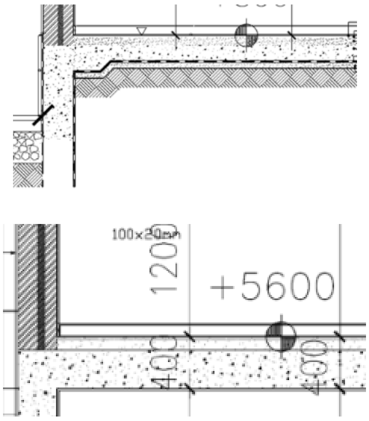
2.1. Data collection

Data on the CECS building's architectural details were meticulously gathered from the Project Management Office at Jazan University [22]. This comprehensive data collection encompassed a range of critical components, including complete architectural drawings, detailed floor plans, cross-sectional views, and elevation drawings. Furthermore, data acquisition extended to the specifications of the building envelope system, capturing essential attributes, such as wall thickness, material types, door configurations, and WWR. Such a comprehensive dataset served as a foundational element for the energy modelling process, facilitating a thorough analysis of the building's thermal performance and energy efficiency. A summary of these architectural details is presented in Table 2, which consolidates the key information for reference and further analysis.

Meanwhile, Table 2 summarizes the construction details and thermal properties of the CECS building envelope at Jazan University. These characteristics were documented from the Project Administration at Jazan University [22] because they represent the primary indicators affecting building thermal performance and IAT. Specifically, the U-values of walls, roofs, floors, and glazing quantify the conductive heat transfer through each component, while the *WWR* and glazing type influence solar heat gain and daylighting.

Table 2. Actual building construction details and descriptions of construction materials (building envelope). The CECS building has three stories with a total floor area of 34,168 m² [22].

Building model	Details	Drawing details	U-value (W/m²-K)
Wall construction	Outer whites are 20mm, building wall thickness is 150mm, heat insulator is 50mm, building wall thickness is 100mm, and inner whiteness is 15mm.		0.498
Roof construction	Reinforced concrete tiles 300mm, Heat insulation 70mm, moisture insulation (cerublast) 20mm, Concrete protection layer 5mm, Concrete Tendencies 60mm, and 115mm, Mortar pastes tiles, cement tiles (flooring) 30mm.		0.234

Floor construction	• Ground Floor: Concrete bench 55mm Moisture insulation cerublast 20mm, concrete 150mm, sand 80mm, mortar 10mm, floor tiles 10mm. • 1st and 2nd Floor: Moisture insulation cerublast 15mm, concrete 300mm, sand 80mm, mortar 10mm, floor tiles 10mm.		0.531
Glazing	Double-Clear		1.624
Window-to-Wall Ratio	24.5%	-	-
Air infiltration	0.8 *ACH*	-	-

Air infiltration rate was included due to its significant impact on cooling loads and transient fluctuations in IAT, particularly in very hot-dry conditions. Recording these parameters provides the essential baseline for developing and calibrating the EnergyPlus model and for analysing the relationship between building envelope characteristics, HVAC operation, and measured indoor air conditions, thereby directly supporting the study's objective of establishing a reliable baseline model for calibration.

To further enhance the understanding of the building's attributes, site visits were conducted so that interior and exterior photographs could be taken. These visual records served to document the architectural features, spatial layouts, and overall condition of the structure. By integrating these images with architectural data, this research aims to provide a more nuanced analysis of how the CECS building's physical characteristics influence its energy performance and indoor environmental quality.

Within the theoretical framework, such indicators, including envelope properties, spatial configuration, and material composition, are essential because they govern heat transfer, solar gain, and airflow patterns, which ultimately affect IAT and the reliability of energy model calibration. This comprehensive approach facilitates a thorough evaluation of the building's energy dynamics, thus contributing to the overall objectives of the study.

Notably, despite the comprehensive data collected for this research, several critical factors remain absent, particularly air infiltration rate, along with other related variables, such as occupancy patterns and internal heat gains. Due to the absence of these critical elements, assumptions were used in the energy modelling process, which could have significantly influenced the overall accuracy and reliability of the results. For example, the infiltration rate is crucial for understanding how air exchange affects indoor air quality and energy performance [23].

2.2. Data measurement

The data measurement involved using temperature sensors to measure the actual IAT within the CECS building. HOBO data loggers were employed and strategically distributed across various building zones to capture real-time temperature variations. This arrangement allowed for a comprehensive assessment of the building's indoor thermal environment, enabling the analysis of how different areas within the building respond to changes in occupancy and external conditions.

2.3. Measurement period

The study aimed to provide insights into the CECS building's IAT and thermal behaviour over time by collecting data across different days. This methodology facilitated a comprehensive analysis of the building's thermal performance and observations of IAT fluctuations under varying conditions. The data collection also involved field measurements to assess the building's IAT. As such, the study was conducted over two separate days to capture variability in environmental conditions and to enhance accuracy and reliability. This step allowed for a more comprehensive analysis and minimized the potential for day-specific anomalies to skew the findings. The observation days were the 8^{th} and 26^{th} of March 2024, with each measurement session lasting 24 hours. During these sessions, the temperature sensors recorded real-time variations at intervals of 10 minutes.

Although measurements were conducted in March, this period still represents the very hot-dry conditions of Jazan; however, it is acknowledged that peak summer conditions may present more extreme thermal loads. This limitation is noted, and the methodology can be extended in future studies to include additional summer observations for further validation. Additionally, data collection during the summer was not feasible because building operations were significantly reduced, preventing the systems from running under normal conditions and thereby limiting the validity of measurements during that period. Future studies are therefore recommended to extend the analysis to summer observations for further validation.

2.4. Measurement instruments

This research used two devices, Onset HOBO U12-012 temperature data loggers (*Sensor-S1* and *Sensor-S2*), which were previously used in previous studies. These data loggers are compact and efficient devices designed for environmental monitoring and can measure temperatures ranging from -20°C to 70°C, with an accuracy level of ±0.5°C. These have been shown to provide comprehensive data collection in diverse settings [24, 25]. Furthermore, these devices can store up to 8,000 readings, facilitating long-term monitoring, which is essential for various applications, such as HVAC performance analysis and indoor air quality assessment. Their user-friendly design and compatible software enable easy data visualization and analysis; thus, they are widely considered effective tools by researchers and engineers engaged in evaluating building performance and energy modelling.

2.5. Instruments placement

To understand the CECS building's thermal performance comprehensively, it is essential to distribute sensors across various zones. During the first measurement session, *Sensor-S1* was placed on the second floor on the southern side of the building at the height of 1.0 meter in the centre of the office's wall. This was done to accurately record IAT within a typical occupancy zone, thus reflecting the thermal environment experienced by occupants. The second floor was selected over the other floors because it offered a more balanced perspective on temperature variations. The middle floor experiences heat transfer from the upper and lower floors, making it an ideal location for capturing thermal equilibrium and understanding how the entire building behaves thermally. Some external variables, such as direct sunlight or ground temperature, also have less intense effects on the middle floors.

Sensor-S2 was positioned at a height of 0.5 meters in the same office to capture variations in IAT at different levels. This methodology was designed to ensure that the collected data accurately represented conditions experienced by individuals working in the office, thereby facilitating a more realistic assessment of the building's thermal performance and contributing to the overall analysis of indoor environmental quality [26]. In the second measurement session, the placement of Sensor-S2 was adjusted to a height of 1.0 meter and relocated to the northern side of the building on the middle floor. The north side was selected to capture IAT variations in different zones and because it represented typical office occupancy patterns. The placement of sensors allows for a thorough examination of thermal behaviour across various building areas, enhancing the reliability and applicability of the research findings [27], shown in Figs. 3 and 4.

2.6. Energy model

Developing the energy model requires a bottom-up engineering approach that emphasizes integrating specific physical characteristics and empirical data from the building to enhance the accuracy of simulations. This methodology is beneficial in understanding the complex interactions of different variables within the building's systems and provides a detailed analysis of IAT and energy consumption patterns. This method requires individual application of each building component, such as walls, insulation, windows, and HVAC systems and setpoints, to be separately analysed and quantified. Doing so allowed for the construction of a highly detailed model that reflected real-world conditions and operational characteristics [12].

In the current research, the energy model development used the EnergyPlus *version 23.2.0* (U.S. Department of Energy, 2023) tool over other simulation tools because it can account for its ability to calculate heat building transfer and time lag, damping effects that may occur naturally due to heat transfer and temperature difference (ΔT). Also, it has robust capabilities for dynamic building energy simulation and wide adoption in calibration studies. The building energy model was designed with a detailed division into 31 distinct zones, each representing specific areas within the building as shown in Fig. 5. This zonal approach allowed for a refined analysis of building energy performance, while considering variations in occupancy, usage patterns, and thermal conditions across different spaces [28]. All zones were conditioned, indicating that they were equipped with air conditioning to maintain a comfortable indoor environment.

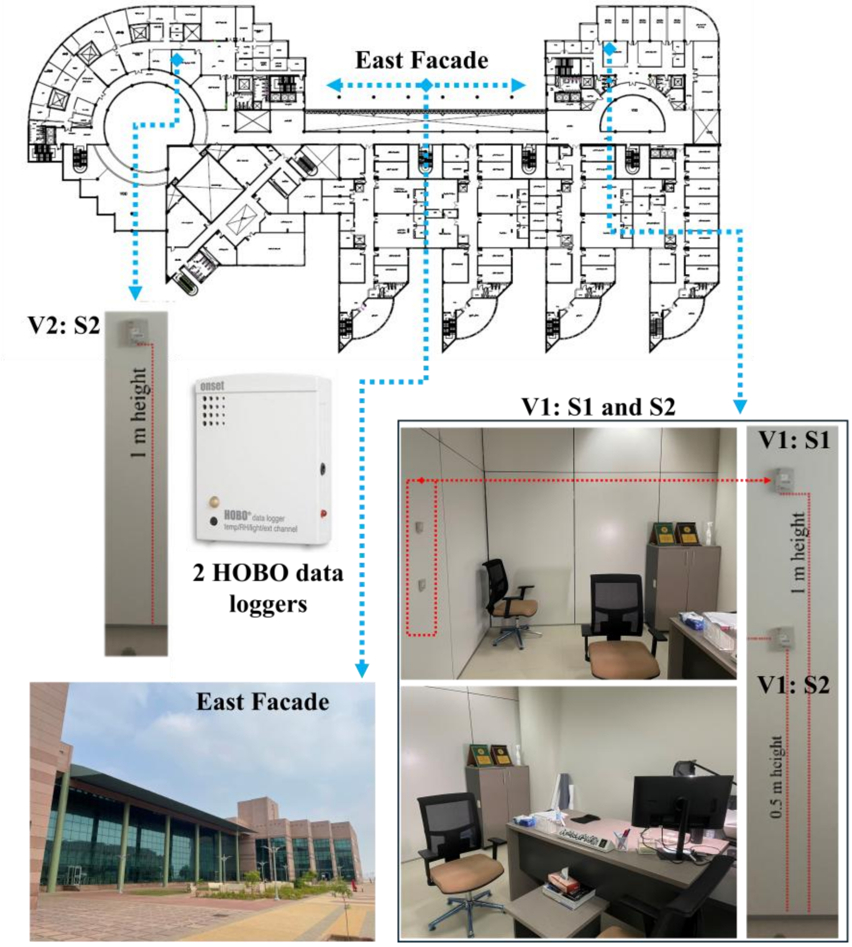


Fig. 3. HOBO data loggers and installation of measurement devices on the first floor (faculty offices) [22].

Fig. 4. Multiple views of the CECS building at Jazan University (Photo by the authors, September 2024).

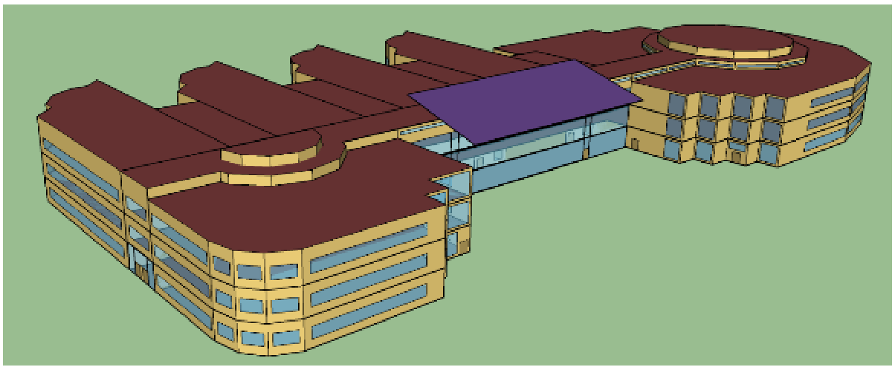


Fig. 5. The college building model is designed for effective energy simulation (Created by the authors, September 2024).

Next, an energy model baseline was developed using the ideal load air system (*ILAS*), a widely adopted approach in building performance simulations for modelling thermal loads. *ILAS* offers a simplified and controlled method for comparing building designs by simulating idealized heating and cooling demands without incorporating the complexities of specific HVAC systems. This approach is essential for isolating a building's intrinsic thermal performance, thus providing a consistent framework for evaluating energy efficiency under ideal operational conditions. For this model, the cooling setpoint was standardized at 22.5ºC. While individual rooms and zones in practice may have distinct thermostat setpoints reflecting varying occupancy patterns and user preferences, using a uniform setpoint in the simulation allowed for more accurate comparisons and analyses of the CECS building's energy performance across different operational scenarios. Furthermore, this form of standardization ensured clarity in assessing the building's thermal behaviour and helped improve energy performance modelling.

Due to limited available data and the absence of direct measurements of air infiltration rates in Saudi Arabia, an infiltration rate of 0.8 air changes per hour (*ACH*) has been assumed as a representative value for energy modelling in educational buildings in Saudi Arabia. This rate effectively accounts for air leakage through the building envelope, which is crucial in determining indoor air quality and overall energy performance. Research indicates that an infiltration rate of 0.8 *ACH* aligns well with the climatic conditions typical of the region, which are characterized by high temperatures and elevated humidity levels that necessitate efficient ventilation strategies [5]. The Saudi Building Code also supports this assessment, categorizing infiltration rates within this range as suitable for educational facilities. Although certain assumptions, such as the air infiltration rate, were necessary to complete the model, they are acknowledged as limitations of the current study. Future research will seek to validate these parameters through extended field measurements to further enhance model accuracy.

This framework also enables a realistic evaluation of thermal comfort and energy consumption, ultimately facilitating the design and operation of energy-efficient educational environments. By adopting an infiltration rate of 0.8 *ACH*, energy models can achieve greater accuracy, thereby reflecting practical observations while accounting for the intrinsic characteristics of the building envelope. Furthermore, such an approach enhances the reliability of the energy modelling process and highlights the importance of adequate ventilation in optimizing indoor environments for educational settings [29].

Additionally, we sourced weather data for this region from the EnergyPlus weather database, which compiles representative meteorological data spanning 20-30 years. This extensive dataset provides comprehensive information regarding temperature, humidity, wind speed, and solar radiation, among other climatic variables. Such historical data are crucial for accurate energy modelling, as they enable the assessment of the CECS building's performance under varying weather conditions, thereby enhancing the reliability of simulations and analyses [30].

3. Results and discussion

Figure 6 presents a scatterplot comparing IAT readings from *Sensor-S1* and *Sensor-S2*, with a fitted linear regression line to assess the relationship between the two datasets. The equation $y = 0.8783x + 2.4111y$ and the coefficient of determination (R^2) of 0.84 indicate a strong positive correlation between the sensors. Approximately 84.41% of the variation in *Sensor-S1* readings can be explained by *Sensor-S2* measurements, thus demonstrating a high level of agreement and consistency between the two sensors. A slope of 0.87 suggests that while *Sensor-S1* readings are strongly correlated with *Sensor-S2*, a slight systematic offset exists, possibly due to calibration variations or environmental factors that affect each sensor differently. At the same time, the clustering of data points along the regression line reflects the sensors' reliability in terms of measuring IAT under similar conditions. However, some scatter around the line may indicate minor variability in measurement accuracy or environmental influences.

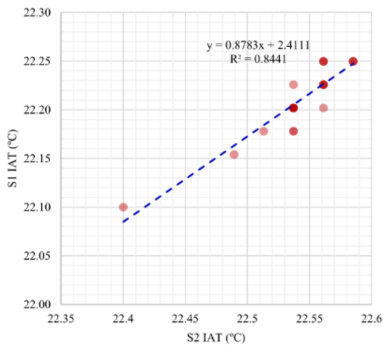


Fig. 6. Data validation of *Sensor-S1* and *Sensor-S2*.

Descriptive statistics for the recorded IAT data are summarized in Table 3. These statistics include measures of central tendency (mean and median), variability (standard deviation and range), and distribution (skewness and kurtosis). The high level of agreement between the two sensors is further supported by these metrics, as they consistently reflect similar thermal patterns across the monitored zones. This analysis confirms that *Sensor-S1* and *Sensor-S2* can be effectively used together for monitoring IAT, providing consistent and reliable data for energy modelling and thermal performance evaluations. Moreover, the high correlation reinforces the validity of using these sensors in studies aimed at optimizing building energy efficiency and occupant comfort.

Table 3. Descriptive statistics of the measuring sensors.

Descriptive Statistics	Data logger: *Sensor-S1*	Data logger: *Sensor-S2*
Mean	22.30	21.92
Standard Error	0.01	0.03
Median	22.32	22.03
Mode	22.25	22.08
Standard Deviation	0.07	0.18
Sample Variance	0.00	0.03
Kurtosis	-0.13	-1.04
Skewness	-0.57	-0.75
Range	0.311	0.50
Minimum	22.10	21.58
Maximum	22.41	22.08
Sum	535.40	526.26
Count	24.00	24.00
Largest Value	22.41	22.08
Smallest value	22.10	21.58

3.1. Descriptive statistics and data representation

Figure 7 illustrates the time-series comparison of IAT measurements from *Sensor-S1* and *Sensor-S2* against simulated data from the energy baseline model over a 24-hour period. The blue line represents IAT recorded by *Sensor-S1*, the red line corresponds to *Sensor-S2*, and the dashed black line depicts the simulated data. As indicated in the results, both sensors exhibit consistent trends, with *Sensor-S1* consistently reporting slightly higher IAT values than *Sensor-S2*. Such a discrepancy may be attributed to differences in sensor placement, sensitivity, or exposure to localized environmental factors, such as proximity to heat sources or airflow patterns. Furthermore, the alignment between the measured data from the sensors and the simulated data demonstrates the energy model's reliability, confirming its ability to accurately predict IAT under real-world conditions.

The IAT values also remain relatively stable throughout the day, indicating effective HVAC system performance in maintaining a consistent thermal environment. This stability is essential for ensuring thermal comfort, particularly in educational settings in which steady indoor conditions are crucial for occupant productivity and well-being. At the same time, slight reductions in IAT during certain hours may reflect transient factors, such as door openings or thermostat adjustments, which introduce variability into the thermal environment. The occasional deviations between the measured and simulated data also highlights the dynamic interplay between occupant behaviour, external environmental conditions, and HVAC control strategies. These findings demonstrate the importance of precise energy modelling and monitoring systems in optimizing building energy performance while maintaining occupant comfort.

Overall, Fig. 7 validates the accuracy of the energy baseline model, the reliability of *Sensor-S1* and *Sensor-S2*, and the effectiveness of the CECS building's HVAC system. These findings provide valuable insights into opportunities for further enhancing energy efficiency, such as through the improved calibration of the energy model and the introduction of dynamic HVAC controls tailored to real-time occupancy and environmental conditions.

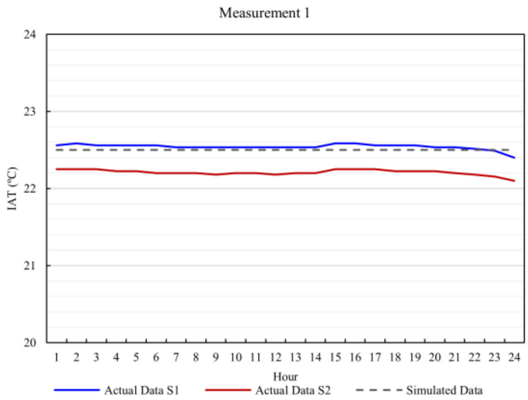


Fig. 7. IAT **of the energy model baseline and *Sensor-S1* and *Sensor-S2* in the first measurement session.**

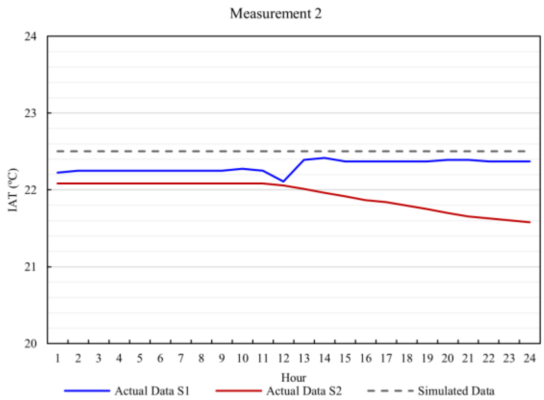


Fig. 8. IAT **of the energy model baseline and *Sensor-S1* and *Sensor-S2* in the second measurement session.**

Next, Fig. 8 presents a time-series comparison of IAT measurements from *Sensor-S1* and *Sensor-S2* with simulated data for a second measurement period. The blue and red lines correspond to *Sensor-S1* and *Sensor-S2* readings, respectively, and the dashed black line illustrates the simulated IAT values. Similar to the first measurement, *Sensor-S1* consistently records slightly higher IAT values than *Sensor-S2*. However, a notable feature of this dataset is the sudden dip and subsequent spike in *Sensor-S1* readings around midday, which contrasts with the smoother trend observed in *Sensor-S2* data. This midday fluctuation in *Sensor-S1* can be attributed to transient events, such as the opening of an office door, resulting in convective air exchange between the office and the adjacent corridor. Such interaction leads to a temporary disruption in thermal equilibrium, leading to a rapid decrease, followed by a stabilized IAT.

Conversely, *Sensor-S2* displays a gradual decline in IAT over time, which is likely due to an intentional thermostat setpoint adjustment to improve thermal comfort, thus reflecting deliberate control measures within the zone it monitors. The simulated data remains relatively stable and aligns closely with the overall trends of both sensors, further validating the energy model's ability to predict thermal performance. However, the simulated data do not account for the localized and transient events captured by *Sensor-S1*, thus indicating an opportunity to further refine the model by incorporating dynamic occupant behaviours and real-time environmental factors.

Overall, the graph highlights the critical role of accurate sensor placement and monitoring in capturing transient thermal phenomena, as well as the importance of adaptive HVAC strategies in maintaining consistent thermal comfort. Together, these findings emphasize the need to further refine the energy model to include real-time variability factors. In doing so, the model's predictive accuracy and utility in optimizing energy efficiency are improved, along with increased occupant satisfaction in similar building environments.

3.2. Model validation

The calibration accuracy of the energy model was evaluated in accordance with ASHRAE Guideline 14, Measurement of Energy, Demand, and Water Savings [31, 32]. This standard specifies that acceptable model calibration criteria are a normalized mean bias error (*NMBE*) within ±5% and a coefficient of variation of the root means square error (*CV-RMSE*) ≤ 15% for monthly data, or an *NMBE* within ±10% and a *CV-RMSE* ≤ 30% for hourly data. As this study utilized hourly IAT measurements, the hourly thresholds were applied. The calibrated model achieved *CV-RMSE* values of 0.58% for the test day on 8 March 2024 and 0.93% for the test day on 26 March 2024, both of which are well below the ASHRAE limits, thereby demonstrating excellent agreement between the measured and simulated IAT values. The hourly calibration results for two test days are presented in Table 4.

Table 4. Hourly calibration results for selected test days (ASHRAE Guideline 14 criteria).

Date	Max (°C)	Min (°C)	Sum square	Count (hrs.)	*RMSE* (°C)	*MAE* (°C)	*CV-RMSE* (%)	Average (°C)
Mar.8 (Day 1)	22.42	22.25	0.40	24.00	0.13	0.12	0.58	22.38
Mar.26 (Day 2)	22.22	22.11	1.02	24.00	0.21	0.19	0.93	22.31

A sensitivity analysis of the hourly calibration results was conducted for both test days. On 8-March-2024, deviations between measured and simulated IAT values ranged from -0.08 °C to -0.25 °C, with an average deviation of -0.13 °C. On 26-March-2024, deviations ranged from -0.08 °C to -0.39 °C, with the largest deviation occurring at 11:00 AM. Despite these minor fluctuations, the overall calibration remained robust, with *RMSE* and *CV-RMSE* values well within ASHRAE Guideline 14 thresholds. These results demonstrate that the model shows low sensitivity to hourly variation and reliably predicts IAT under both tested days conditions.

3.3. Summary

The analysis of the two measurement charts highlights the strong agreement between *Sensor-S1* and *Sensor-S2*, thus validating their reliability for monitoring IAT. Measurement-1 demonstrates consistent trends, with minor offsets between sensors, while the simulated data closely align with actual measurements, thus validating the energy baseline model under stable conditions. In Measurement-2, a transient midday event, which is likely caused by door openings, caused *Sensor-S1* to record a noticeable dip and spike, while *Sensor-S2* showed a gradual decline due to thermostat adjustments. While the simulated data remains stable, they do not capture these localized fluctuations, thus revealing limitations in the model's ability to account for dynamic factors.

In summary, both measurements emphasize the importance of sensor placement, real-time monitoring, and adaptive HVAC strategies in optimizing thermal comfort and energy efficiency. While the energy baseline model performs well under stable conditions, its predictive accuracy and practical application in educational buildings can be further improved by incorporating transient behaviours and real-time occupancy data.

3.4. Zonal temperature variations and thermostat regulation

The data analysis reveals significant zonal variations in IAT, which can be attributed to differences in thermostat setpoints across the building. Each office or room is equipped with an individual thermostat, allowing occupants to regulate their specific thermal environments. Such decentralized control facilitates tailored temperature management, promoting occupant comfort while potentially reducing overall energy consumption. In Fig. 8, a distinct drop in IAT recorded by *Sensor-S1* during the midday break is evident. This drop correlates with the opening of an office door, which leads to convective air exchange between the office and the adjacent corridor. The influx of cooler or warmer air into the zone temporarily alters the local thermal balance, as described by the principles of thermodynamics and fluid dynamics.

Specifically, the opening of the door introduces advection and mixing, which disrupt the steady-state thermal equilibrium of the office. Conversely, *Sensor-S2* recorded a continuous decline in IAT, which aligns with a deliberate adjustment of the thermostat setpoint to 21.5ºC. Such deliberate intervention reflects an intentional strategy to improve thermal comfort within the zone, as lower setpoints are associated with higher levels of occupant satisfaction in warmer climates. The gradual decline observed suggests a controlled and consistent cooling process governed by the HVAC system's operational efficiency and the thermal mass of the surrounding materials.

3.5. Implications for energy efficiency and thermal comfort

The abovementioned findings illuminate the complex interplay between occupant behaviour, thermostat settings, and resultant indoor thermal conditions. The ability to dynamically regulate temperatures based on zone-specific needs is a critical component of energy-efficient building design. Such a design not only enhances thermal comfort but also minimizes unnecessary energy expenditure by reducing heating or cooling loads in unoccupied or less critical zones. Overall, the results emphasize the importance of advanced monitoring systems and calibrated models in understanding and optimizing energy use in buildings. The observed variations in thermal comfort across different zones highlight the potential for implementing zonal control strategies, such as occupancy sensors and adaptive HVAC systems, to further enhance energy efficiency [5].

Furthermore, in educational environments where thermal comfort is directly linked to productivity and learning outcomes, maintaining optimal IAT through precise control mechanisms is particularly significant. By integrating insights from the present study, building managers and designers can develop targeted strategies to reduce energy consumption and improve occupant satisfaction, thus contributing to the overarching goals of sustainability and environmental stewardship.

3.6. Discussion and limitations

Measurements 1 and 2 were conducted in occupied zones, in which daily operational changes influenced IAT measurements. Certain factors, such as occupancy fluctuations, human activity (opening doors and windows), and varying indoor activities, affect the accuracy of the measurements. For example, diverse activities, such as lectures, lab sessions, and design studio work across different departments, lead to variability in indoor conditions. Additionally, occupancy patterns directly affect IAT, as the CECS building features a range of spaces, from professors' and administrative offices to classrooms and laboratories, each with distinct activities and usage patterns.

Various assumptions, such as infiltration rate and occupancy behaviour, introduce uncertainty into the simulation results. These uncertainties are acknowledged as limitations of the present study. Future research will seek to conduct detailed sensitivity analyses to quantify their effects and improve the robustness of model calibration. One of the key assumptions in the energy model is a uniform cooling setpoint of 22.5°C across the entire building. However, such an assumption does not reflect the real-world scenario, wherein each zone has its thermostat and is subject to different setpoints based on the specific needs of each space. For instance, architectural engineering students spend significant time in studio environments, which differ from other departments with regular classrooms or labs. These distinct spaces and their varied occupancy schedules introduce fluctuations in thermal conditions, which lead to decreased accuracy of the uniform set point assumption in terms of representing actual energy use.

While the validation between *Sensor-S1* and *Sensor-S2* reveals a strong correlation, areas for improvement have been found in the measurement process and the energy modelling framework. The first area for enhancement is the spatial distribution of sensors. Expanding the network of temperature sensors throughout the CECS building would provide a more comprehensive dataset, accounting for more significant spatial variability in IAT across zones. Such viability would offer a clearer understanding of temperature distributions and facilitate more accurate representations of thermal behaviours in diverse building zones. Although the standardized cooling setpoint of 22.5°C provides a valuable reference for simulations, the variability in thermostat setpoints and occupancy patterns in real-world applications must be acknowledged. This is because each zone or room may be subject to different user preferences and activity levels, which significantly affect energy consumption and occupant comfort levels. Future iterations should thus incorporate these distinct setpoints and patterns to better represent the building's operational dynamics and improve the model's accuracy.

Additionally, in depth sensitivity analyses can be conducted in future works to identify the most influential factors that affect energy performance. This step would involve systematically varying key parameters, such as the thickness and thermostat type of thermal insulation, occupancy levels, cooling setpoints, and external weather conditions. Sensitivity analyses could also improve the model's predictive accuracy and offer insights into further optimizing HVAC operations and improving overall energy efficiency.

Although this study employed a dynamic simulation approach, the transient variations observed in the measured IAT were not fully captured by the calibrated model for longer periods of time. Future research will therefore focus on integrating advanced transient simulation modules and real-time modelling techniques to better represent rapid fluctuations associated with HVAC system performance and occupant-driven loads. This enhancement is expected to strengthen the accuracy and responsiveness of the model in reflecting dynamic thermal behaviours. Furthermore, subsequent studies will seek to extend the proposed framework to a wider range of building types and climatic conditions, thereby broadening its applicability. The framework will also be expanded to incorporate optimization algorithms that support energy conservation strategies and facilitate the integration of renewable energy systems, with particular emphasis on improving energy efficiency in educational facilities.

Finally, it should be acknowledged that the calibration and validation of the model were performed using data from two days in March (8 and 26 March 2024). While these datasets provided reliable validation under occupied conditions, they do not capture the full seasonal variability of thermal loads, particularly during the peak summer months when external heat gains are more pronounced. As such, the model's performance under extreme summer conditions cannot be assumed based solely on the March validation. Future work will extend the calibration process to longer monitoring periods and across multiple seasons, with emphasis on summer extremes, to further test and strengthen the robustness of the model. This extension will also broaden the applicability of the framework to other building types and climate zones and facilitate its integration with optimization algorithms for energy conservation strategies and renewable energy adoption in educational facilities. Although certain variables, such as infiltration rate and occupancy patterns, were assumed, their impact on the main conclusions is limited, as the model still achieved excellent calibration accuracy within ASHRAE Guideline 14 thresholds. Future studies will seek to explicitly measure and incorporate these factors to further refine model performance.

4. Conclusion

This research establishes a comprehensive methodology for developing an energy model - one that serves as a benchmarking tool and a predictive framework for building energy performance. Detailed data collection, robust validation processes, and an advanced simulation technique were integrated to provide a reliable and adaptable approach for analysing IAT and enhancing building energy efficiency. Using EnergyPlus, key parameters, including IAT, building construction details, and thermal envelope properties, were systematically gathered and incorporated into a calibrated energy model. The calibration ensured that the proposed model closely reflected actual building performance, thus significantly enhancing its predictive accuracy.

In line with the study's objectives, a reliable baseline energy model was developed from architectural drawings and envelope properties supported by a comprehensive IAT measurement framework. Real-time sensor data were integrated with simulation-based results for calibration and validation, which represents an important methodological advancement. This approach applied in the underexplored context of an educational building in the very hot-dry conditions of Jazan demonstrates that sensor-informed calibration can improve the fidelity of energy models in predicting thermal dynamics.

The findings also indicate that the developed energy model functions as an effective tool for benchmarking energy performance, facilitating comparisons across different buildings and identifying inefficiencies within the built environment. Furthermore, the model's predictive capabilities offer a robust foundation for evaluating the potential impacts of design modifications, operational strategies, and retrofitting measures on future energy performance. This research also advances the understanding of energy-efficient building design and provides a practical framework for the further exploration of innovative approaches, including renewable energy integration, optimized retrofitting strategies, and climate-resilient building designs.

Finally, by offering substantial contributions to sustainable building practices, this study bridges the gap between theoretical energy modelling and real-world applications. Thus, the present work lays a strong foundation for future research to refine, expand, and implement these methodologies in support of global energy efficiency and sustainability goals.

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Abbreviations

ACH	Air changes per hour
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
BEM	Building energy model
CECS	College of Engineering and Computer Science
CV-RMSE	Coefficient of variation of the root mean square error
ECM	Energy conservation measures
HVAC	Heating, ventilation, and air conditioning
IAT	Indoor air temperature, ºC
IEA	International Energy Agency
ILAS	Ideal load air system
MBE	Mean Bias error
NMBE	Normalized means bias error
R^2	Coefficient of determination
RH	Relative humidity, %
RMSE	Root means square error
WWR	Window-to-wall ratio

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