Modeling and calibration of the energy systems of a high-rise building

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Abstract

Energy modeling of buildings plays an essential role in system design optimization and performance assessment. However, in high-rise buildings, noticeable differences between the prediction of the simulation models and their actual performance often happen. These disparities can be due to the complexity of these buildings and the limitations in the available data for model creation. In this paper, we propose a calibration process as per ASHRAE Guideline 14 for a high-rise building, comparing the prediction results of EnergyPlus simulation model with building automation system (BAS) data. This study improves the accuracy of the high-rise energy model, enabling practitioners to make informed decisions in energy system design alternatives.

Introduction

High-rise buildings have several features that clearly distinguish them from low-rise buildings of similar purpose. An increase in urban land values has made high-rise buildings more attractive and necessary in many cities. The adoption of a vertical rather than horizontal building layout can offer considerable savings in terms of land area. High-rise buildings of a certain purpose are also designed to be iconic and have aesthetic appeal. This has major implications for building architects and subsequent building energy consumption. High-rise buildings are commonly designed with a glass façade to enhance aesthetic appeal and to offer occupants expansive views. However, glass has low thermal insulation properties. Additional features of high-rise buildings include a central core and multiple zonal usages with different set point requirements [1]. These lead to the complexity of energy systems and huge energy consumption in high-rise buildings.

The escalating energy consumption worldwide has encouraged researchers to detect and minimize energy waste in various applications. This is particularly so in the case of heating, ventilation, and air-conditioning (HVAC) systems, which generally account for 40% to 60% of the total energy consumed in high-rise buildings [2, 3]. With the increasing pressure to reduce consumption of energy, HVAC systems are a prime starting point, given their significant potential for energy and cost savings. Reducing energy consumption has been a topic of interest for a long time, with research focusing on redesigning systems and adjusting operational schedules. New trends are now turning to artificial intelligence and machine learning methods for energy management in buildings. This research will look at the modeling and calibration process to produce a reliable energy model for the *UdeS Longueuil campus* to apply the model predictive control strategies based on the machine learning technology and investigate how machine learning can be used to reduce energy consumption in an HVAC system in a high-rise building [4].

The objective of developing a precise energy model is to be the "simulation engine" to test MPC strategies based on machine learning models. Model predictive control (MPC) plays an important role in optimizing the efficiency of HVAC and extensive energy systems. By using machine learning algorithms, MPC can identify energy consumption for complex building environmental conditions, which allows for more accurate predictions and management decisions regarding HVAC systems. ML-based MPC not only reduces energy consumption but also maintains occupant thermal comfort in real-time by adjusting set-points, airflow rates, and other parameters. Furthermore, when applied to an energy system furthermore, ML-based MPC can improve the efficiency of HVAC systems and other energy-consuming systems, ML-based MPC can contribute to significant energy savings, carbon emissions decreased, and improve overall system performance.

Methods

Case study building

The building that we studied is the Université de Sherbrooke (UdeS) Longueuil campus of the as shown in Figure 1. which located in Longueuil, Québec, Canada. It has a total built up area of 54,000 m² approximately and the building has 19 floors. the lowest three basement floors are utilized for car parking, while front of house application are located

at the higher 16 floors as follow. The ground level mainly is used utilized for commercial purposes such as café and restaurants and. Then starting the 2nd level to the 6th level, spaces are mainly used for classrooms. higher than the 6th floor, spaces are used as offices.

Figure 1. Case study building (UdeS Longueuil campus).

Table 1 provides the main classification of the spaces usage for each level that has been modeled in the energy plus simulation model.

Table 1. Building floor's application.

Floor	Application
Level 1	Retails
Level 2	Retails
Level 3	Classrooms / Cafeteria
Level 4	Classrooms
Level 5	Classrooms
Level 6	Classrooms
Level 7	Office / Classrooms
Level 8	Classrooms
Level 9	Office / Classrooms
Level 10	Office / Classrooms
Level 11	Office / Classrooms
Level 12	Office Rooms
Level 13	Office Rooms
Level 14	Office Rooms
Level 15	Office rooms
Level 16	Equipment rooms

UdeS Longueuil campus building has been air conditioned via central cooling system consists of sets of chillers, cooling and chilled water pumps, and cooling towers. the cooling system consist of three water cooled chillers, having standard cooling capacity is 1970 kW for chiller 1, while chiller 2 has 910 kW, and the third chiller has 251 kW respectively. chilled water pumps having flow rate of 60.5 L/S for pump 1, while pump 2 has 28 L/S, and the third pump has 7.7 L/S respectively, all the equipment is located in an equipment room, which are located at 16th level, there are two cooling towers on the roof with total cooling capacity of 3800 kW.

Modelling

There are several energy simulation programs, but in this study we used an open source which is EnergyPlus simulator, it is a powerful building performance simulation tool developed by the U.S. Department of Energy [5], EnergyPlus has the feature of the integration between external tools and libraries allowing for advanced analysis, which assist to enhance machine learning-based model predictive control for HVAC systems in high-rise building [6]. for simulating the UdeS Longueuil campus, it has been divided to five thermal zones per floor (four perimeter zones + one core zone) as shown in figure 2; this approach is a common practice in identifying thermal zones in high-rise buildings. Perimeter zones include indoor rooms up to 15 ft (4.6 m) away from the façade. In the case of the 1st to 3rd floors, additional zones have been identified considering the larger surface of these floors.

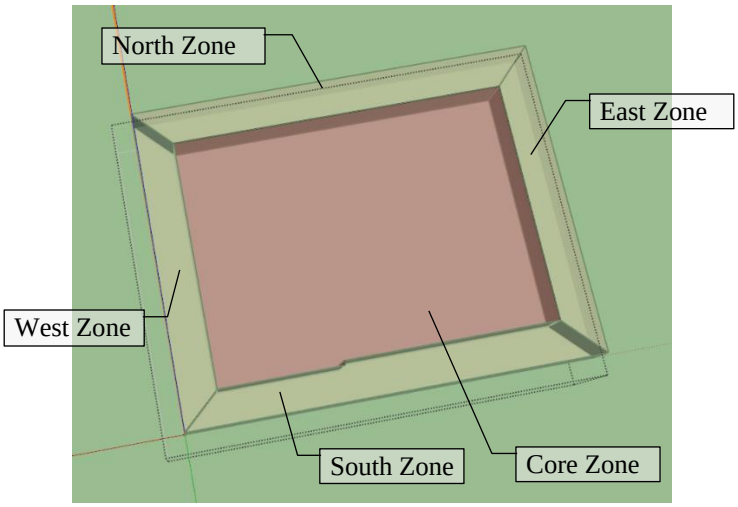

Figure 2. Zones arrangement inside typical Floor.

Figure 3 shows sample of the architectural floor plans that have been modelled in the SketchUp model to model all floors of the building as per the architectural layouts based on each room applications.

People Occupancy, lightning, and electrical equipment profiles of operations are based on ASHRAE default values. Space type and infiltration rates are also based on ASHRAE default values. These values were iteratively modified through the calibration process.

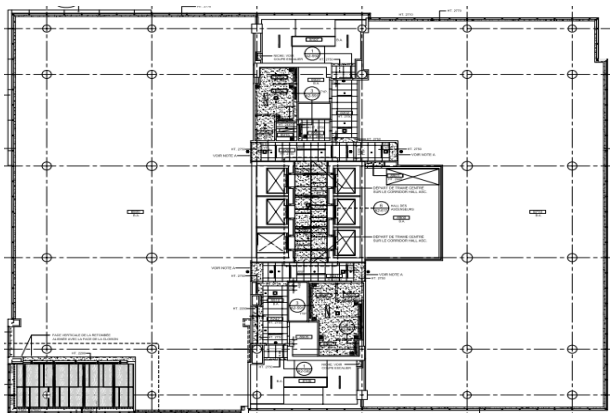

Figure 3. Architectural layout, floor sample.

Since January 2019, the Building Automation System (BAS) at UdeS Longueuil campus has been diligently tracking the performance of its HVAC system components. This detailed monitoring laid the groundwork for a crucial task: calibrating the building energy model. Beginning in the summer of 2019, we focused on refining the model specifically for cooling load demand for the period from June 2019 to September 2019. This calibration process is pivotal as it forms the basis for fine-tuning the energy model to encompass the heating and cooling load demand for the entire year of 2019 and beyond. The objective is to develop a reliable calibrated energy model that serves as a reliable foundation for implementing a model predictive control strategy. By accurately predicting energy demands and optimizing HVAC operations, UdeS Longueuil campus aims to enhance energy efficiency, reduce costs, and bolster its commitment to sustainable practices in the years to come.

For calibrating the energy model related to the building, which is used for simulating the building's energy performance by merging external weather conditions, building thermal envelope properties, and HVAC systems, The results of cooling load demand were compared with real measured data from the Building Automation System (BAS). The building's internal loads of people, lighting, electrical equipment, and profile of operations are initially set to the default values (for instance, default profiles). The initial simulation results were far from the measured cooling demand of the building: the overall initial values of CV (RMSE) and MBE were about 100% for the simulation period. Then, the operations profiles were edited hourly to fulfil the hourly cooling load demand of the building. This was an ongoing process until we achieved a satisfactory match with the real building performance. This iterative process aims to attain a high level of accuracy according to the ASHRAE Guideline 14 requirements, normally with a coefficient of variation root mean square error (CV (RMSE)) of less than 30%. MBE is less than ± 10% for hourly base analysis. The building's energy model is a precious tool for predicting and optimizing energy consumption, contributing to the development of energy-efficient strategies while retaining the thermal comfort of the occupants. The process of calibration is summarized in Figure 4.

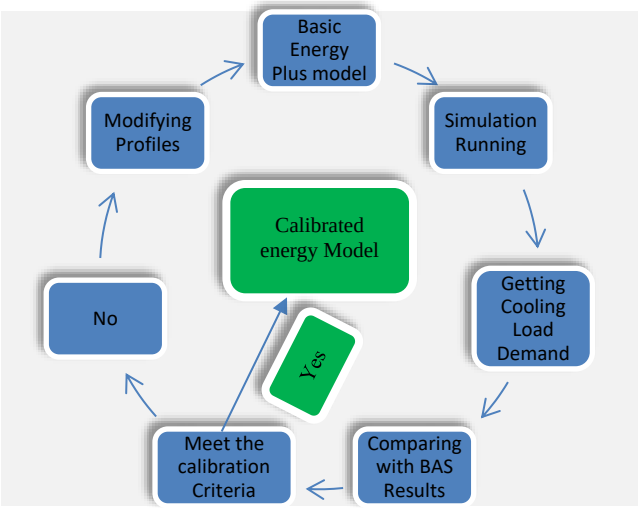

Figure 4. calibration process Flow diagram.

The calibration process begins with the creation of a basic energy model, accurately designed to reflect the interaction of the HVAC system under investigation. This initial model acts as the basis upon which subsequent adjustments are made. Once the energy model is established, simulations are executed to simulate the system's behaviour under the external and internal design conditions. These simulations yield essential data points that serve as the basis for analysis and comparison with real-world BAS information.

A key output from these simulations is the cooling load demand, a critical metric used to evaluate the model's accuracy. This demand becomes a reference point for evaluating the effectiveness of the calibration process. Subsequently, simulated results are compared with data obtained from the BAS, enabling a thorough examination of any disparities. This comparative analysis allows for the identification of areas within the model that require adjustment. calibration criteria, typically defined by Mean Bias Error (MBE) and Coefficient of Variation Root Mean Square Error (CV RMSE) methods, are then applied to assess the model's performance. If the model meets the predefined calibration standards, indicating alignment within acceptable margins according to the ASHRAE Guideline 14 requirements, it proceeds to the calibration phase. In instances where the model does not meet calibration criteria, adjustments are made to its profiles and applied them to people's occupancy, lighting density, fresh air requirement for occupancy and electric equipment load. These modifications are tailored to address discrepancies identified during the comparison process, aiming to improve the model's fidelity to real-world data.

The updated profiles are integrated into the Energy Plus model, replacing the original settings. Subsequent simulations are conducted to evaluate the impact of these adjustments on the model's performance. This iterative process of simulation, analysis, and adjustment continues until the energy model meets the calibration criteria specified by MBE and CV RMSE. Each iteration refines the model's representation of the system, progressively enhancing its predictive capabilities and ensuring its compatibility with observed data. Through this systematic approach, the energy model achieves calibration, providing a reliable basis for decision-making and optimization of system performance.

Table 2 shows the major energy model's inputs that have been included during the simulation period, such as the external weather conditions, internal loads of people, lighting, and electric equipment loads.

Table 2. Energy model's inputs.

Inputs	Value
Simulation Period	June to September, 2019
Weather conditions	Actual weather data measured on the building
Profiles of operation	Initial default profile (1.0), then modified based on the calibration process.
Thermal envelope	as per architectural layouts of the building.
Rooms and glazing	as per architectural layouts of the building.
internal loads	People, lighting, electric equipment, ventilation, and infiltration demand. are default values for each application based on ASHRAE fundamental handbook
Thermostats set points	Thermostats are set to AHSRAE design values, 24 °C in cooling mode [7].
HVAC system	HVAC system is assigned to ZoneIdealLoadsAirSystem

The setpoints implemented adhere to the guidelines outlined by ASHRAE, aligning with the standard operating temperature of 24°C as well as the parameters recorded by the Building Automation System (BAS). These setpoints represent recommended values endorsed by ASHRAE for optimal thermal comfort and energy efficiency in indoor environment.

Comparison between simulation and measured data

By using the historical measured data of the Building Automation System (BAS) available for the building HVAC systems, we got the required information for our research. especially, our concentration was related to cooling load demand, a precise calculation derived from measured system inputs. which is mainly cover chilled water supply temperature, chilled water flow rate, in addition to and chilled water return temperature. By using this data, we obtained idea about the details of our plant cooling demand of the building, enabling us to make informed decisions about allocating resource and system optimization, such as this approach underlines our commitment to using an accurate information foundation that will be used later for the energy model calibration process.

There are two criteria: CV (RMSE) (coefficient of the Variation of the Root Mean Square Error) and MBE (Mean Bias Error), are selected to assess the quality of the results and whether the simulated and measured cooling loads demand or energy are acceptably close to each other. Those criteria have been used in multiple studies [8], and recommended by ASHRAE Guideline 14 [9].

CV (RMSE) is the average sum of square error divided by the mean measured cooling loads that evaluate the variability between measured and simulated data and is calculated using Equation (1) [9].

$$CV(RMSE) = \frac{\sqrt{\sum_{j=1}^{N} \frac{(E_{\text{measured}}(j) - E_{\text{simulated}}(j))^2}{N-1}}}{\bar{E}_{\text{measured}}} \times 100 \quad (1)$$

where N represents the number of time samples (hours) within the period, $E_{simulated}$ is the simulated data (cooling energy demand) and $E_{measured}$ is the measured data from the BAS.

MBE represents the overall deviation of the model. MBE is calculated using Equation (2) [9]:

$$MBE(\%) = \frac{\sum_{j=1}^{N} E_{\text{measured}}(j) - E_{\text{simulated}}}{N} \times 100 \quad (2)$$

To be able to consider that the energy model is calibrated when those two criteria are satisfied according to the tolerances of 30 % CV (RMSE) and ± 10 % for MBE as specified by ASHRAE Guideline 14 [9].

Results

It is clear that the cooling load demand within a building is a critical aspect of its energy consumption, especially regarding the internal load of the building. This internal load includes several elements, such as the occurrence of occupants, lighting, electric equipment, and ventilation requirements. Together, these internal loads form a major part of the total cooling load demand. Understanding and managing this internal cooling demand is critical for optimizing cooling load demand, energy efficiency, and overall operational costs.

The most critical element that affects the internal cooling demand is the profile of the operation. This profile indicates the occurrence of internal loads during the day and is quantified on a scale ranging from 0 to 1.0, representing the percentage of occurrence. The profile of operation varies based on factors like patterns of occupancy, light distribution, working hours, and electric equipment usage within the building.

In the course of energy modelling, Figure 5 shows the initial values for the profile of operations applied to people's occupancy, lighting density, fresh air requirement for occupancy, and electric equipment load. in the energy model, set regularly at 1.0 for all 24 hours of the day sample. However, through the process of calibration, these values and profiles of operations are modified to express the actual operating conditions. The calibrated profile of operations accounts for variations in the internal loads over the cycle of the day, as specified during analysis with data gathered from BAS and other monitoring tools.

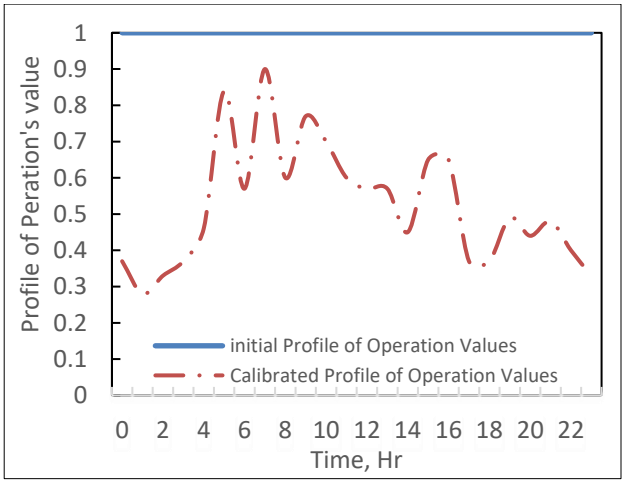

Figure 5. Profile of operation of the initial and calibrated energy models (21st June 2019).

Figure 6 gives an idea of the effect of both the initial and calibrated profiles of operation on the energy model calibration process. By comparing the performance of the initial and calibrated profiles of operation, it becomes clear how modifications to the profiles of operation can affect the accuracy of the energy model in predicting cooling load demand. The process of calibration itself involves improving the applied profile of operation for internal loads while maintaining external weather conditions and the heat gained by the building's thermal envelope. This process guarantees that the energy model precisely reflects the building's actual cooling requirements under various operating conditions.

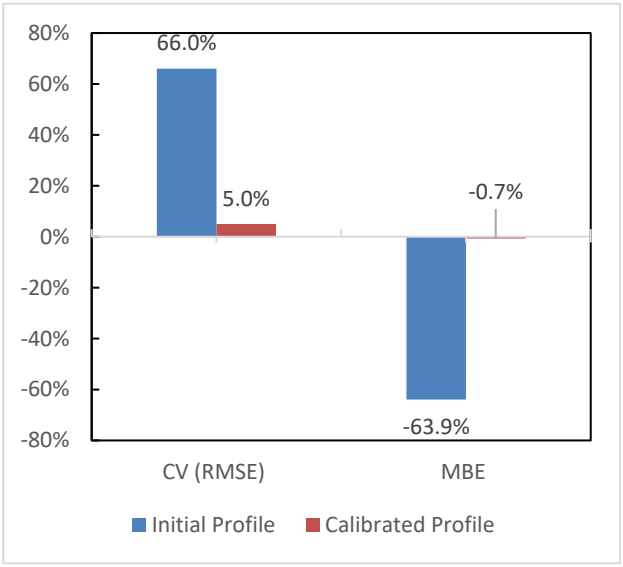

Figure 6. Impact of the profile of operation on the energy model calibration.

We can conclude from the above descriptions that it is recommended to accurately analyse the profile of operation and consider changing it to achieve a calibrated energy model. the operational profile is indeed crucial, as it governs all internal loads encompassing people's occupancy, fresh air intake, lighting usage, and electric equipment consumption. Consequently, internal loads constitute a substantial portion of the total building load, thereby significantly influencing the overall energy demand and the energy model calibration process.

By integrating external weather conditions and accounting for external heat gain through the building's thermal envelope (such as walls, floors, glazing, and roofs), the calibrated energy model provides a more trusted basis for making informed decisions regarding an efficient energy measurements and operational strategies within the building. This approach ultimately leads to improved performance and reduced energy consumption over the long term.

Figures 7-8 show the conclusions of the calibration process, derived from data collected during the duration of four months, starting from June to September 2019, and offer an overall understanding of the simulation's performance.

Causing, both CV (RMSE) and (MBE) match with the accepted criteria mentioned in ASHRAE guideline 2014. months of June and September have better results, indicating successful calibration. However, July and August have higher CV (RMSE) and MBE values, suggesting the possibility of more adjustment through additional iterations to lower these metrics. It becomes evident that the profile of operations is the primary affecting factor, exerting a significant impact on the internal load demand of the building, the next mission will focus on the calibration of the heating energy model during the winter months, an important step for obtaining a completely calibrated annual energy model. This quest allows for the enhancement of enhance the accuracy and reliability of the simulation across varied seasonal conditions.

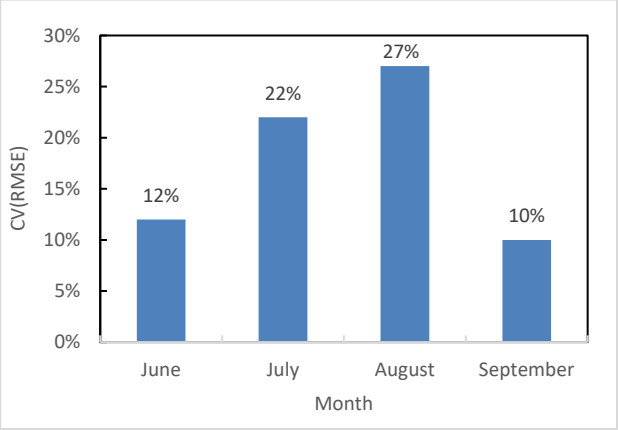

Figure 7. CV(RMSE)Results for the summer season, 2019.

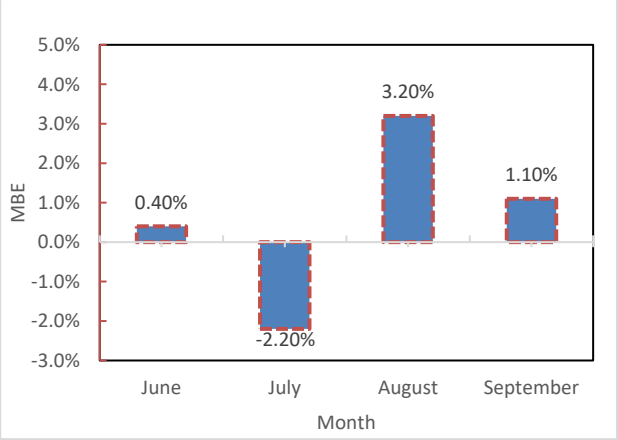

Figure 8. MBE Results for the summer season, 2019.

Figures 9-10 show a detailed comparison between the hourly outputs of the calibrated energy model and the actual measured data obtained from the Building Automation System (BAS). This analysis related to a sample of the four months, June 2019, with a focus on the 21st of that month.

Figures 9 and 10 show how the simulated energy model aligns with the real measured data, confirming the efficacy of the calibration process. The calibrated model not only demonstrates its fidelity for June but also extends its accuracy to subsequent months. This achievement confirms the robustness and reliability of the calibrated energy model, affirming its ability to accurately predict cooling demand usage and enhance the efficiency of energy management systems. Through precise calibration and validation processes, the model achieves a level of accuracy that renders it a valuable tool for optimizing cooling demand and energy consumption and improving building performance across different temporal scales.

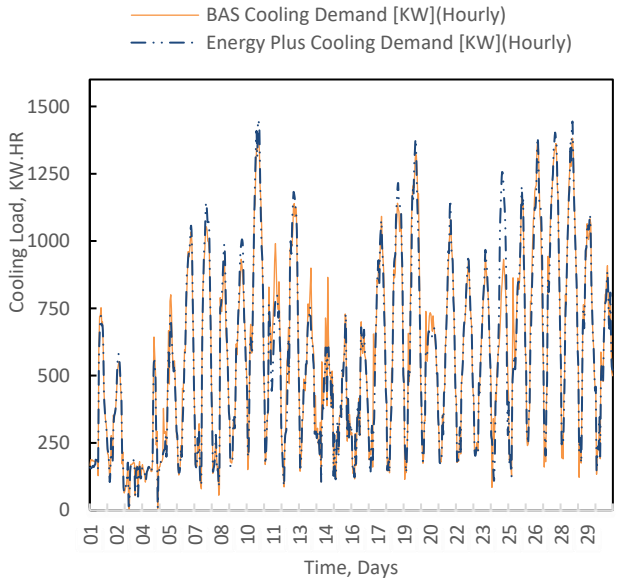

Figure 9. Comparison between BAS data and calibrated energy model for June 2019.

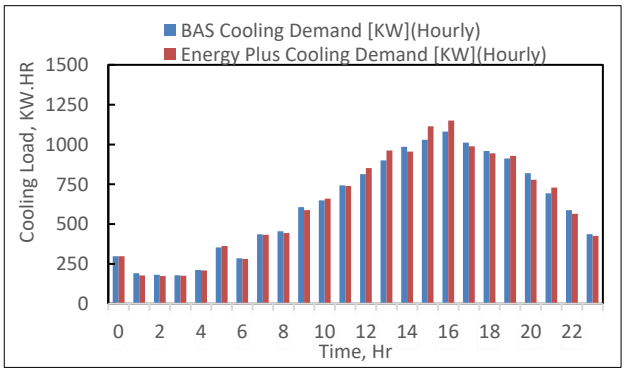

Figure 10. Comparison between BAS data and calibrated energy model for 21st June 2019.

Conclusion

It's a crucial and challenging task to calibrate the energy model for HVAC systems in high-rise buildings. To improve the energy model's accuracy and reliability, it must be calibrated by modifying and fine-tuning it to accurately represent actual measured data. A deep grasp of the intricate dynamics underpinning cooling demand and control within such intricate building systems is necessary to achieve this. The goal of our cross-examination iterations is to refine the model to closely match real measured data by integrating empirical evidence with practical assumptions. The operating profile has the greatest impact on the internal cooling load demand, which affects this calibration process.

When it comes to HVAC systems in high-rise buildings, the calibration procedure is more than just a technical exercise—it is proof that theory and practice can coexist. In order to guarantee the energy model's effectiveness in practical situations, the calibration aims to match the model's predictions with actual measured data. The importance of using both empirical data and theoretical frameworks to provide a reliable and correct depiction of cooling load demand, energy consumption, and thermal dynamics within high-rise structures is confirmed by this exact approach.

At the end of the calibration procedure, a significant advancement in HVAC system modeling and simulation is shown. The calibrated energy model is proof of the unrelenting quest of precision and dependability in computational models. The calibrated model achieves a respectable degree of precision, varying from 10% to 27% for (CV) (RMSE) and from -2.2 to 3.2% for MBE during the simulation period.

The calibration process's success attests to the multidisciplinary character of building energy modeling and simulation. It demonstrates the harmonic convergence of theoretical frameworks, empirical data, and computational approaches to show the intricate dynamics of HVAC systems in high-rise buildings. A new era of sustainable building management and design is also promised by the calibrated energy model, which is a crucial instrument for investigating creative control tactics and maximizing energy efficiency in high-rise buildings.

The iterative nature of the energy model calibration process can be time-consuming and demands careful consideration of factors influencing cooling load demand. As this process typically unfolds through continuous iterations, there is potential to explore alternative approaches to expedite it. One such avenue involves harnessing the capabilities of machine learning and artificial intelligence. By proposing the development of algorithms tailored to this purpose, a new approach may emerge, promising accelerated execution of the calibration process.

While our results demonstrate the effectiveness of the calibrated energy model in predicting cooling load demand, conducting a sensitivity analysis would provide additional insights into the model's performance under varying input parameters. By systematically varying key factors such as occupancy patterns, lighting density, and equipment usage, sensitivity analysis can elucidate the model's sensitivity to changes in these parameters and identify any potential areas of improvement. Future research endeavors will include a comprehensive sensitivity analysis to enhance the reliability and confidence in our calibrated energy model.

References

[1] C. Bedon and S. J. B. Mattei, "Facial expression-based experimental analysis of human reactions and psychological comfort on glass structures in buildings," vol. 11, no. 5, p. 204, 2021.

[2] A. Akgüç and A. Z. J. J. o. B. E. Yılmaz, "Determining HVAC system retrofit measures to improve cost-optimum energy efficiency level of high-rise residential buildings," vol. 54, p. 104631, 2022.

[3] N. Asim *et al.*, "Sustainability of heating, ventilation and air-conditioning (HVAC) systems in buildings—An overview," vol. 19, no. 2, p. 1016, 2022.

[4] Y. Himeur, K. Ghanem, A. Alsalemi, F. Bensaali, and A. J. A. E. Amira, "Artificial intelligence based anomaly detection of energy consumption in buildings: A review, current trends and new perspectives," vol. 287, p. 116601, 2021.

[5] U. S. D. o. Energy, "EnergyPlus simulator " 2022.

[6] N. R. E. L. (NREL), "Python Opens Up New Applications for EnergyPlus Building Energy Simulation," 2022.

[7] T. Reddy, J. F. Kreider, P. S. Curtiss, and A. Rabl, *Heating and cooling of buildings: principles and practice of energy efficient design*. CRC press, 2016.

[8] J. E. Pachano, C. F. J. E. Bandera, and Buildings, "Multi-step building energy model calibration process based on measured data," vol. 252, p. 111380, 2021.

[9] A. J. A. g. Guideline, "Measurement of energy, demand, and water savings," vol. 4, pp. 1-150, 2014.