

Simulation model calibration for a multi-purpose building on an hourly basis

Hamed Amini ^{1*}, Tikka Maria ¹, Kari Alanne ¹, and Risto Kosonen ¹

¹ Department of Mechanical Engineering, Aalto University, Finland

Abstract. When developing digital twins for buildings, the calibration of simulation models on an hourly basis is essential to maintain the fidelity of the virtual representation and to enable real-time monitoring and analysis in the operational phase. Achieving such a high accuracy in building performance simulations (BPS) calls for novel calibration strategies with enhanced effectiveness. In this regard, this paper outlines a calibration strategy that makes use of hourly measurements to improve the fidelity of energy simulation models. The proposed approach includes a hierarchical structure involving data acquisition and management, setting unknown weather parameters, sensitivity analysis, calibration of fixed parameters, and hourly calibration of dynamic variables. Here, acquired data from the building's sensor are refined to enable hourly demand calibration, and an accurate weather data file is gathered. Next, sensitivity analysis is conducted to identify the key fixed parameters for the calibration process. Following the calibration of these fixed parameters, the final level involves the calibration of dynamic variables to achieve a robust hourly agreement between simulated and measured data. The developed strategy is implemented in a multi-purpose building located in the Aalto University campus in Finland. The building is simulated as a simplified five-zone model developed in the whole-building simulation software IDA-ICE, including various educational sections, workshops, a shopping center, and a metro station. Sensors and meters are used to measure the hourly indoor air temperature by zone, whereas the calibration aims at minimizing the difference between measured and simulated heating and cooling energy demands. In conclusion, the proposed calibration strategy appears to be successful in facilitating hourly synchronization between simplified simulation models and multi-purpose buildings.

1 Introduction

Today, building energy simulation (BES) models are increasingly calibrated against measured data from actual buildings to improve the fidelity of the forecasting ability of the BES model [1].

Calibration of multipurpose building models, in turn, poses an extra challenge to the calibration process. Complex and multipurpose building complicate the calibration process because there are numerous parameters and variables to be selected and calibrated. This type

* Corresponding author: hamed.amini@aalto.fi

of a simulation problem calls for enhanced identification of calibratable parameters and variables and a calibration strategy where the calibration process is divided into appropriate stages. In this regard, Chong et al. [1] identified a lack of scalable calibration algorithms which can utilize several data sources and research gaps around them.

Even though multi-stage calibration has been implemented in several studies, there is still a lack of established approaches that account for all the key aspects required for digital twinning. According to [1], most multi-stage calibration strategies (e.g. [2]) are based on calibration during free-floating time periods i.e. night and weekend times when there are none or low utilization and occupation rate and HVAC system is shut down and don't affect the indoor temperatures. One advantage of this type of strategy is that one of the most difficult inputs to be calibrated, the occupation schedule, is ruled out [3]. However, the drawback is that implementing in free-floating time periods is not always possible. Therefore, a more generic calibration strategy is required to cope with occupancy.

Chong et al. [4] identified an inconsistency when using schedules as calibratable parameters. Several studies determined schedule modification as an important part of the calibration process. For example, Chong, Augenbroe, & Yan [5] reduced the coefficient of the variation of the root mean square error (CV(RMSE)) between simulated and measured energy use from 37 % to 24 % by changing the ASHRAE 90.1 standard occupation schedules to building level occupancy schedules collected from Wi-Fi usage. Kim et al. [6] had even more drastic results in their study where they acquired occupation schedules from electricity use data. In their three test buildings the CV(RMSE) values of total building hourly electricity use decreased from 21 % to 12 %, 128 % to 31 % and 156 % to 16 %. Although this type of results is available, Chong et al. [1] found that often the studies (e.g., [4], [7], [8], and [9]) do not consider schedules in their calibration. According to [1], the most probable reasons for this inconsistency are the increasing computational costs and the intention to prevent over-parameterization. Schedules are typically simplified or selected from some list or standard of typical use for the type of building in question [10]. So, developing a strategy considering schedule calibration without imposing high computational efforts is advantageous.

Chong et al. [1] studied the critical features, model input(s), and output(s) of BES models and they observed that the most used measured input data for model calibration is the local weather data (outdoor dry bulb temperature, relative humidity, solar radiation, and wind data). The study discovered that measured indoor conditions were often required to increase the accuracy of the model at the zone level. For example, [9] calibrated their model at zone level with hourly indoor dry bulb temperature achieving CV(RMSE) values between 4.51 % – 5.36 % and goodness of fit (GOF) value of 3.2 %. In addition, internal load quantities, construction material characteristics, and infiltration rate are commonly used as calibratable inputs [1]. For example, the blower door test results were commonly used to determine the infiltration rate of the building.

Chong et al. [1] established that in most of the reviewed papers (62%) the BES model was calibrated against one output parameter and only 29% of the studied papers calibrated their BES model against two output parameters and even less (8 % and 1%) calibrated against three or more output parameters. At building scale models, the hourly indoor dry bulb temperature and monthly electricity consumption were the most frequently used measured data to calibrate the model.

For the calibration process, the resolution of the measured data needs to be determined. The selection of the resolution depends on the data availability and the model complexity which affects the computational expenses of the calibration process. According to [1], the resolution of the measured output data used for the calibration process decreases when moving from small-scale models (e.g. system scale) to large-scale models (e.g. urban scale). At the building scale, the resolution of the measured data used for calibration varies between hourly and monthly data. They also noted that the calibration procedures need further research and

development, and they concluded that there are no widely accepted explicit instructions or guidelines for calibration processes and the calibration cases continue to be very subjective and technically unfeasible to replicate.

In this research, we aim to contribute to the research by proposing a comprehensive calibration strategy and demonstrating its implementation for a multi-purpose building. This consistent and holistic strategy can be utilized as a part of the digital twinning of buildings. The additional value of this study lies in the hierarchical structure defined as the calibration strategy to hourly synchronize the building simulation model with the actual multi-purpose building across multiple spatial or temporal levels. To boost the computational efficiency, a sensitivity analysis is performed to identify the most influential parameters conducted to pinpoint and prioritize within the calibration process.

This article is organized as follows. Section 2 provides information about the methodology and materials used for the calibration. Section 3 mentions sensitivity analysis results as the basis for developing the calibration strategy. Section 4 discusses the strengths and weaknesses of the proposed strategy through implementation in a case study; Section 5 provides a conclusion for the study.

2 Methods and materials

Required methods and materials for developing the calibration strategy are introduced in this section.

2.1 Calibration strategy

As demonstrated in Fig. 1, the proposed strategy is built upon five levels. This hierarchical approach is developed based on reviewing the literature, reasoning, and experience alongside studying the sensitivity of variables in the real simulation case study. It offers a versatile framework for calibrating different building types, wherein the selection of calibration steps is tailored to the specific characteristics of the target model. The proposed approach aims to achieve acceptable hourly accuracy for the model while minimizing computational time. According to ASHRAE Guide 14, the acceptable range for hourly CV-RMSE and mean bias error (MBE) are below 30% and within $\pm 10\%$, respectively.

The calibration process is described as a pyramid, at the bottom of which measured data is acquired using sensors and energy meters implemented in the building. Prior to exploiting the collected data for hourly demand calibration, data management is needed, particularly addressing missing data and standardizing time steps. Second, unknown weather parameters are to be determined to create an accurate weather file corresponding to the building site. Weather files can be gathered through nearby weather stations and temperature sensors (if available). At the third level, as the calibration process involves many optimization runs for minimizing the deviation between simulation and measured data, prioritizing the extensive list of unknown simulation design parameters is essential. So, to minimize the computational expenses, key parameters are identified by sensitivity analysis. Subsequently, key fixed parameters of the simulation model are calibrated to enhance the model's fidelity and align it as closely as possible with the measured data. Finally, to maximize the model's accuracy, it is recommended that dynamic variables (e.g., schedules) are calibrated in addition to the fixed parameters. These variables that change during the building operation are tuned in the final hierarchical level (top).

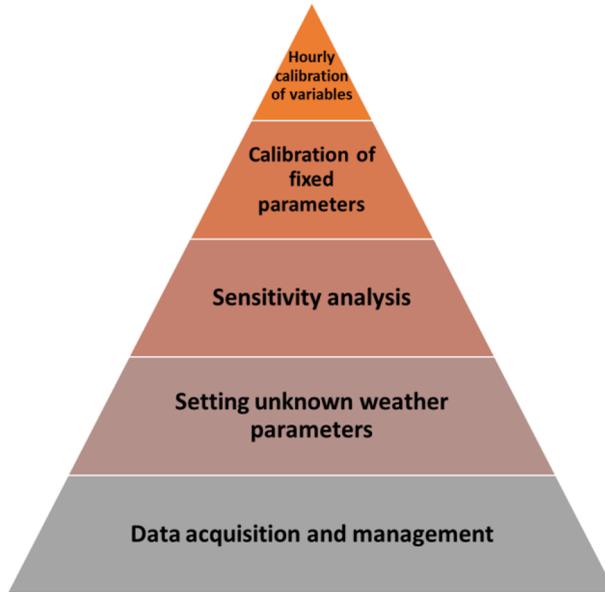


Fig. 1. Proposed hierarchical calibration strategy.

2.2 Building characteristics

The “Väre” building, constructed in 2018 and covering the total floor area of 47,500 m² located in the Aalto University Campus in Espoo, Finland, was chosen to represent a multi-purpose building for simulation and calibration in this study. The target building consists of a shopping center, a metro station, and educational sections. The diverse functionalities of the building, especially the existence of a metro station alongside commercial and educational sections, increase complexity and pose challenges to accurately simulate its energy performance. However, the building is densely equipped with sensors and energy meters, so the necessary instrumentation is in place for accessing high-quality measured data. Fig. 2 demonstrates the full geometric model of the target building.



Fig. 2. General schematic of the target building (image courtesy of Tekla, Finland).

Both heating and cooling energy are distributed via air-conditioning and low-temperature radiant heating/cooling panels in room spaces, using water as the heat carrier. In this regard, the actual building’s heating and cooling load supplied by either radiant panels (zone heating/cooling) or air handling units (AHU heating/cooling) recorded over two years (2021-

2022) are utilized for calibration. Furthermore, hourly air temperature is measured using building sensors to create an accurate weather file.

2.3 Simulation descriptions

IDA indoor climate and energy tool (ICE) is used for simulating the target building and identification of key parameters. IDA ICE, developed by EQUA Simulation AB, is a whole-building simulation tool with the capability of modelling buildings, their systems, and controllers in various time steps. The validation of IDA ICE has been done in many studies [11-13]. Also, [14] used the IDA ICE for conducting the sensitivity analysis.

There are three models with various levels of detail to simulate the energy performance of the target building. Table 1 shows the main characteristics and computational time of the three IDA-ICE simulation models. According to the high computational time of the detailed model (126 zones), it was not considered useful for further applications e.g., optimizations or developing digital twins.

The simple model (5 zones) consists of a box geometry building where zones are multiplied by calculation to correspond to the real floor area of the building complex. The semi-detailed model (21 zones) contains a detailed geometry of the whole building complex, but the zones are simplified according to the floor level and the purpose of use (university, and commercial areas). The detailed model (126 zones) has both, detailed geometry, and detailed zones (only one part of the building complex, the School of Business). The 24-hour whole building energy simulation conducted for all the different models is demonstrated in Table 1 (The computational time of the calibration will follow the computational time of the simulation). Accordingly, the simple (5-zone) model [15] is chosen for sensitivity analysis and calibration.

Table 1. simulation models with different levels of simplification

Simulation approach	Simulation time (24-h simulation)	Number of zones
Simple	54 [sec]	5 zones
Semi-detailed	234 [sec]	21 zones
Detailed	1744 [sec]	126 zones

Fig. 3 and Fig. 4 illustrate the floor plan of the 5-zone model. Also, Table 2 contains the simplified model's geometry parameters.

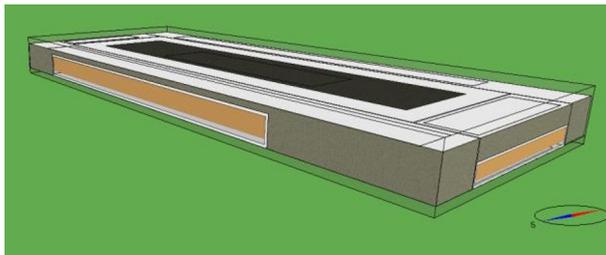


Fig. 3. Simplified shoebox model.

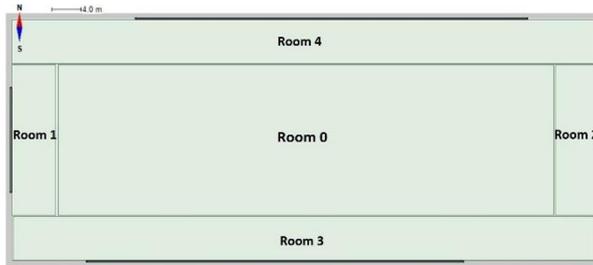


Fig. 4. Simplified building's floor plan.

Table 2. Simplified model's geometry parameters.

Model's characteristics	Value
Length	80.2 [m]
Width	32.7 [m]
Height	4.6 [m]
Zone multiplier	18.35
Net floor area	47502 [m ²]
Window to envelope ratio	17.3 [%]

2.4 Data acquisition and management

The measured data has been gathered automatically to a web server by the Aalto University Campus & Real Estate (ACRE). For the calibration process, the required energy data (heating and cooling energy for zones and AHUs) was manually collected from the server, processed, and transformed to .prn files for the IDA ICE simulation model. The data was inspected for measurement errors and then transformed from sub-hourly timesteps to hourly timesteps, from cumulative MWh meter readings to hourly kWh and kW values, and from UTC time zone to UTC+2 (Helsinki) time zone.

The hourly weather data was collected from the FMI open-source data service (Finnish Meteorological Institute (FMI), 2023). The downloaded data included relative humidity, air dry bulb temperature, wind direction, and wind speed from Espoo Tapiola station and direct solar radiation and diffuse radiation from Helsinki Kumpula station. The weather data was inspected for measurement errors. If there were missing hours in data files they have been handled accordingly: temperature, humidity, and wind data 1 to 4 hours missing data filled with average of previous and forward hour data, more than 4 hours missing data or all missing solar radiation data filled with previous days similar hours' data.

2.5 Sensitivity analysis

Calibrating all unknown parameters is not appropriate, because that would heavily increase the computational effort, whereas the impact on the model fidelity would remain negligible. In contrast, an efficient calibration strategy aims at minimizing the difference between the simulated output and measured variables with respect to the most influential key parameters only. The identification of these key parameters, in turn, requires sensitivity analyses.

Table 3 shows the unknown design parameters recognized in our case study as well as their pre-defined range of variation. To eliminate biases arising from various ranges and units of parameters, all parameters normalized within a certain range ([0, 1]), using:

$$X_{new} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

The sensitivity analysis is conducted to assess how changing these design parameters impacts the desired target objectives (simulation outputs corresponding to energy measurements available in the measured data set). This procedure involves varying one of the parameters at a time, while others are fixed. IDA-ICE's parametric run and sensitivity analysis tools are used for performing these analyses. Finally, the relation between each changing parameter and the objective is addressed by computing slope and R^2 (R-squared) related to the linear regression model between them. The slope indicates the rate of change in the output by a unit change in the parameters while the R-squared shows how well the regression model fits the data.

Table 3. List of unknown parameters and their range in sensitivity analysis

Parameters	Range of values
Supply air flow rate (all rooms)	[1, 4] L/s.m ²
Number of people (Room 0)	[150, 350]
Number of people (Room 1-4)	[75, 150]
Occupants' activity level	[1, 4] Met
Number of lights (Room 0)	[75, 150]
Number of lights (Room 1-4)	[40, 100]
Number of equipment (Room 0)	[45, 85]
Number of equipment (Room 1-4)	[10, 30]
Loss factor (Room 0)	[5, 20] W/K
Loss factor (Room 1, 2)	[2, 8] W/K
Loss factor (Room 3, 4)	[5, 20] W/K
Leakage infiltration	[1, 4] m ³ /hr.m ²
Distribution losses to zones	[0, 6] %
Solar radiation level at which integrated shadings are drawn	[100, 200] W/ m ²
ETA of heat exchanger	[0.5, 0.8]
ETA AIR_Heating coil	[0.8, 1]

3 Results

The first presentation in this section focuses on the sensitivity analysis results and identification of the key parameters. Subsequently, it is presented how the calibration strategy is applied to the specified case study.

3.1 Sensitivity analysis results

The sensitivity analysis is conducted for each target meter (AHU heating, Zone heating, and total cooling loads) separately to provide comprehensive insights for selecting parameters that should be calibrated. The convergence of the sensitivity results gives rise to identifying final calibration parameters.

Fig. 5 shows the result of the sensitivity analysis for the top 40% of parameters affecting on AHU heating load. The values on the X-axis quantify the extent of AHU heating load variation (kW) resulting from altering each parameter within its defined range (parameters are normalized). Therefore, the parameters on the right side of the graph have the greatest impact on the AHU heating load. In this regard, Table 4 ranks the most influential ten fixed design parameters sorted in order of their impact on the air handling unit (AHU) heating load. The name of the parameters is based on their name in the IDA-ICE software interface.

Accordingly, the supply airflow rates of room_0 comes to prominence as the most influential parameter. Notably, a balanced ventilation system and constant air volume (CAV) air conditioning system is considered in the analysis. Based on the high rank of supply air for each zone, two different parameter selection approaches can be chosen, affecting the calibration time directly. The first method involves a more detailed approach where the supply air for each zone is calibrated separately (different zones possess different functionalities and schedules). The second one simplifies by calibrating the average supply air flow rate (L/s.m²) for all zones, reducing five parameters to just one in the calibration process. Moreover, the effectiveness of the AHU's heat exchanger is recognized as the second most influential parameter that should be calibrated to decrease the difference between measured data and simulated results. Heat exchanger effectiveness represents the percentage of the maximum possible heat that is transmitted from exhaust to supply air. Finally, the occupants' activity level is another potential candidate for the calibration process.

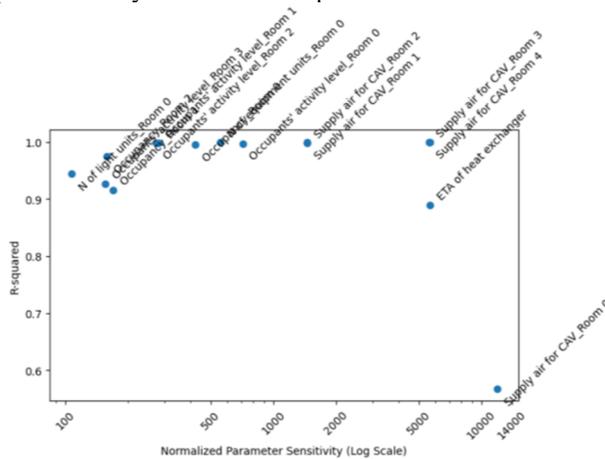


Fig. 5. Sensitivity analysis results for normalized parameters (top 40%) affecting AHU heating.

Table 4. IDA-ICE simulation parameters sorted by their impact on AHU heating.

Rank	Parameters
1	Supply air for CAV Room 0
2	ETA of heat exchanger
3	Supply air for CAV Room 4
4	Supply air for CAV Room 3
5	Supply air for CAV Room 1
6	Supply air for CAV Room 2
7	Occupants' activity level_Room 0
8	N of equipment units_Room 0
9	Occupancy_Room 0
10	Occupants' activity level_Room 1

Fig. 6 and the contents of Table 5 list meaningful parameters with respect to heating power emitted from heating panels (zone heating). Like the analysis regarding the AHU heating, supply air flow rates are the most influential parameters that should be included in the calibration. In addition to that, the loss factors of Room 0 and Room 2 need to be addressed. It is calculated based on heat losses and heat transfer coefficients of walls, windows, roofs, thermal bridges, etc. So, it directly affects the heating and cooling loads of the building as presented in the sensitivity analysis results.

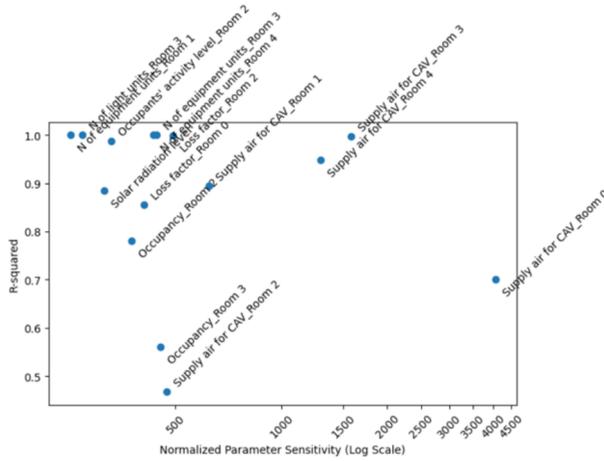


Fig. 6. Sensitivity analysis results for normalized parameters (top 40%) affecting zone heating.

Table 5. IDA-ICE simulation parameters sorted by their impact on zone heating.

Rank	Parameters
1	Supply air for CAV_Room 0
2	Supply air for CAV_Room 3
3	Supply air for CAV_Room 4
4	Supply air for CAV_Room 1
5	Loss factor_Room 2
6	Supply air for CAV_Room 2
7	Occupancy_Room 3
8	N of equipment units_Room 3
9	N of equipment units_Room 4
10	Loss factor_Room 0

In addition to heating, calibrating the cooling demand of the building is another objective of this study. In this regard, Fig. 7 and Table 6 show the design parameters that appear to have the highest impacts on the total cooling of the building. They emphasize the importance of supply air flow rates and heat losses as key parameters in the calibration process.

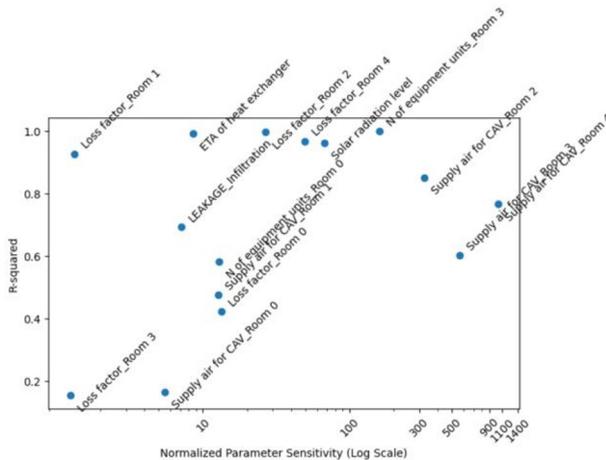


Fig. 7. Sensitivity analysis results for normalized parameters (top 40%) affecting total cooling.

Table 6. IDA-ICE simulation parameters sorted by their impact on total cooling.

Rank	Parameters
1	Supply air for CAV_Room 4
2	Supply air for CAV_Room 3
3	Supply air for CAV_Room 2
4	N of equipment units_Room 3
5	Solar radiation level for shading
6	Loss factor_Room 4
7	Loss factor_Room 2
8	Loss factor_Room 0
9	N of equipment units_Room 0
10	Supply air for CAV_Room 1

The synthesis of the sensitivity analyses on various target meters results in identifying supply airflow rates (all zones or one average), heat exchanger's effectiveness, occupants' activity (Rooms 0 and 2), and loss factor (Room 2). In general, supply airflow rates can be highlighted as a potential key parameter for calibrating various simulation models. Also, the number of occupants and equipment in zones can be addressed through schedules in the final calibration level (calibrating dynamic variables).

3.2 Case-specific strategy implementation

For validation purposes, the calibration strategy is implemented to a limited extent via a case study including a simplified simulation model. This sub-section maps how the proposed strategy is implemented in the model (as demonstrated in Fig. 8).

Accordingly, after acquiring and managing the measured data as described in the methods and materials section, unknown weather parameters are determined to create an accurate weather file for the building site to be utilized in the IDA-ICE directly as the first step of the simulation and calibration process. Based on the results of the sensitivity analysis, key parameters are determined for calibrating the fixed parameters and variables,

The next level contains four different steps for calibrating the fixed design parameters. In the first step, the average value of the supply air flow rate (for all zones) is adjusted in a way that the discrepancy between measured data and simulation results is minimized. Then, the calibrated value of the heat exchanger effectiveness is calculated to increase the accuracy achieved in the previous step. This process continues for the occupancy activity of rooms 0 and 2, and the loss factor of room 2 in the next steps. Consequently, the model's accuracy increases step by step through discovering the calibrated values of fixed simulation parameters.

To maximize the model's accuracy as much as possible, dynamic variables (e.g., schedules) are calibrated in the final stage. The occupancy schedule and ventilation schedule are variables that are calibrated against hourly observations in the final phase. To implement the final level in IDA-ICE, multiple schedules are defined for the calibration process to identify the most optimal schedule that minimizes errors.

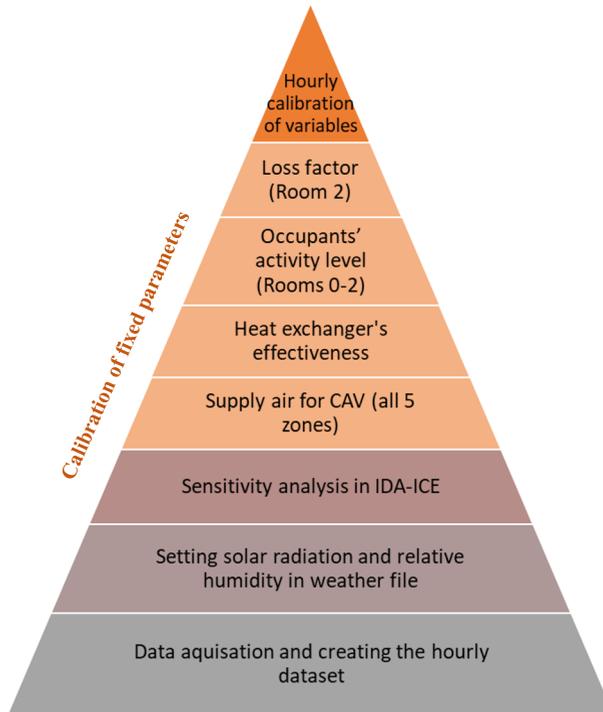


Fig. 8. Proposed hierarchical calibration strategy implemented in the case study.

4 Discussion

The developed calibration strategy (Fig. 1) can be utilized as a framework for calibrating simulation models in multiple stages. This strategy can apply to various types of buildings (especially complex and multi-purpose buildings) and simulation models with different levels of simplification. The strategy indicates the necessary levels for implementing an efficient calibration process (achieving high fidelity with low computational time) in a way that the accuracy of the simulation model improves gradually to generate a virtual replica of the building, i.e., its digital twin. The developed strategy benefits the engineering work by saving time and effort and laying a basis for automation applications.

Achieving hourly agreement between the simulation models and collected data from the complex buildings demands substantial effort and computational resources even if simplified models are used. Reducing the number of calibration parameters has a direct impact on the computational time of the calibration process. So, performing sensitivity analyses to identify the key calibrated parameters potentially improves the computational efficiency of the calibration process. In addition, multi-stage calibration of the fixed key parameters, as well as dynamic variables, can result in a low discrepancy between simulation results and measured data in hourly time steps. In our case study, a simplified approach for calibrating dynamic variables (the final stage of the calibration strategy) was employed to demonstrate the suggested approach. Rather than determining the hourly value of variables (e.g., occupancy) in the calibration process, the most suitable schedule for each variable (such as an occupancy schedule) was selected from a set of predefined schedules.

While the proposed approach endeavours to decrease the computational time required for calibration, it may still encounter challenges, especially when dealing with complex models. Additionally, it relies on a considerable amount of high-quality measured data which may

not be available for all buildings. So, as a future suggestion, the applicability and computational efficiency of the proposed approach can be enhanced by reducing the reliance on comprehensive and large measured datasets by e.g. data management and reconciliation (DVR) procedures [16] as well as implementing the steps of the pyramid selectively. Also, the effectiveness of the proposed calibration framework will be further enhanced by developing a method to dynamically calibrate variables in hourly time steps, rather than solely relying on identifying the best pre-defined schedules in the final phase.

5 Conclusion

In this study, we proposed a multi-step calibration strategy to enhance the accuracy of the building simulation models using hourly measurements. The strategy was developed based on reasoning and learned experiences through implementation in a real case study.

The proposed calibration approach includes a hierarchical structure involving five levels, namely, i) data acquisition and management, ii) setting unknown weather parameters, iii) sensitivity analysis, iv) calibration of fixed parameters, and v) hourly calibration of dynamic variables.

A case study was presented for a multi-purpose building (including various educational sections, workshops, a shopping center, and a metro station) to demonstrate the implementation of the calibration strategy. The simulation was conducted using simplifications within the IDA-ICE software.

Following managing and refining the collected measured data, a sensitivity analysis was conducted to identify the most influential parameters for each objective with an aim to optimize the computational efficiency of the calibration process by excluding less significant parameters. In the case study, the supply air flow rate and effectiveness of the AHU's heat exchanger appeared to be the key parameters for the calibration process.

Overall, the proposed calibration strategy, enabling hourly synchronization between simplified simulation models and multi-purpose buildings, can be utilized as a part of the digital twinning of complex buildings and lay a basis for automation applications. Achieving a robust hourly agreement between simulated and measured data, that may lead to some computational challenges, need to be addressed in further studies.

References

- [1] A. Chong, Y. Gu, H. Jia, Calibrating building energy simulation models: A review of the basics to guide future work, *Energy and Buildings* **253**, 111533 (2021). <https://doi.org/10.1016/j.enbuild.2021.111533>
- [2] J. Cipriano, G. Mor, D. Chemisana, D. Pérez, G. Gamboa, X. Cipriano, Evaluation of a multi-stage guided search approach for the calibration of building energy simulation models, *Energy and Buildings* **87**, 370-385 (2015). <https://doi.org/10.1016/j.enbuild.2014.08.052>
- [3] D. Yan, W. O'Brien, T. Hong, X. Feng, H.B. Gunay, F. Tahmasebi, A. Mahdavi, Occupant behavior modeling for building performance simulation: Current state and future challenges, *Energy and Buildings* **107**, 264-278 (2015)
- [4] A. Chong, K. Menberg, Guidelines for the Bayesian calibration of building energy models, *Energy and Buildings* **174**, 527-547 (2018)
- [5] A. Chong, G. Augenbroe, D. Yan, Occupancy data at different spatial resolutions: Building energy performance and model calibration, *Applied Energy* **286**, 116492 (2021)

- [6] Y.-S. Kim, M. Heidarinejad, M. Dahlhausen, J. Srebric, Building energy model calibration with schedules derived from electricity use data, *Applied Energy* **190**, 997-1007 (2017)
- [7] D.H. Yi, D.W. Kim, C.S. Park, Parameter identifiability in Bayesian inference for building energy models, *Energy and Buildings* **198**, 318-328 (2019)
- [8] T. Yang, Y. Pan, J. Mao, Y. Wang, Z. Huang, An automated optimization method for calibrating building energy simulation models with measured data: Orientation and a case study, *Applied Energy* **179**, 1220-1231 (2016)
- [9] A. Figueiredo, J. Kämpf, R. Vicente, R. Oliveira, T. Silva, Comparison between monitored and simulated data using evolutionary algorithms: Reducing the performance gap in dynamic building simulation, *Journal of Building Engineering* **17**, 96-106 (2018)
- [10] S. Martínez, E. Pérez, P. Eguía, A. Erkoreka, E. Granada, Model calibration and exergoeconomic optimization with NSGA-II applied to a residential cogeneration, *Applied Thermal Engineering* **169**, 114916 (2020)
- [11] S. Moinard, G. Guyon, Empirical validation of EDF ETNA and GENEC test-cell models, *Subtask A* **3**, 912 (1999)
- [12] J. Traversi, G. Maxwell, C. Klaassen, M. Holtz, G. Knabe, C. Felsmann, M. Achermann, M. Behne, Empirical validation of Iowa energy resource station building energy analysis simulation models, *IEA Task* **22** (2001)
- [13] P. Loutzenhiser, H. Manz, IEA Task 34—Testing of Building Energy Simulation Tools Project, International energy agency: Paris, France (2014)
- [14] H. Eggebø, Sensitivity analysis for investigating the energy performance of a retrofitted kindergarten under different weather scenarios, NTNU, 2017.
- [15] T. Xue, V. Nadas, J. Jokisalo, R. Kosonen, M. Vuolle, M. Virtanen, Optimal dimensioning power of GSHP with district heating in an educational building, CLIMA 2022 conference (2022). <https://doi.org/10.34641/clima.2022.115>
- [16] O. Todorov, K. Alanne, M. Virtanen, R. Kosonen, A novel data management methodology and case study for monitoring and performance analysis of large-scale ground source heat pump (GSHP) and borehole thermal energy storage (BTES) system, *Energies* **14**, 1523 (2021)