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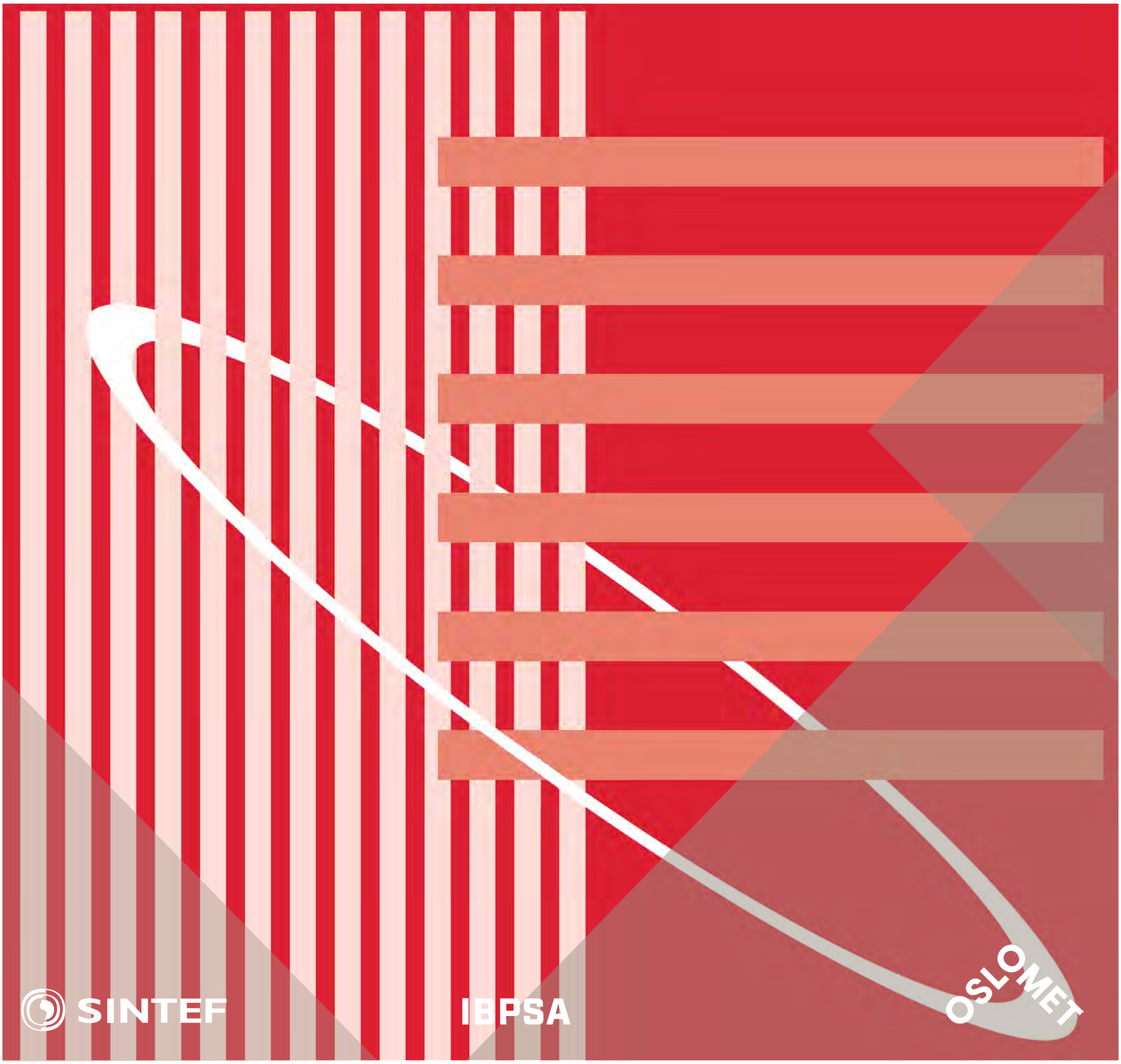

SINTEF Proceedings

Editors:
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Keywords:
Building acoustics, Building Information Modelling (BIM), Building physics, CFD and air flow, Commissioning and control, Daylighting and lighting, Developments in simulation, Education in building performance simulation, Energy storage, Heating, Ventilation and Air Conditioning (HVAC), Human behavior in simulation, Indoor Environmental Quality (IEQ), New software developments, Optimization, Simulation at urban scale, Simulation to support regulations, Simulation vs reality, Solar energy systems, Validation, calibration and uncertainty, Weather data & Climate adaptation, Fenestration (windows & shading), Zero Energy Buildings (ZEB), Emissions and Life Cycle Analysis

Cover illustration: IBPSA-logo

ISSN 2387-4295 (online)
ISBN 978-82-536-1679-7 (pdf)

SINTEF Academic Press
Address: Børrestuveien 3
PO Box 124 Blindern
N-0314 OSLO
Tel: +47 40 00 51 00

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Digital twin of the Live-In Lab Testbed KTH: development and calibration

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Abstract

In the last decade, the development of Information and Communication Technology (ICT) has enabled unprecedented possibilities to tackle worldwide ambitious sustainability targets. Demonstration facilities like the KTH Live-In Lab are fundamental for the adoption of ICT solutions for energy efficiency and sustainability in buildings. The Live-In Lab monitoring infrastructure enables the creation of a digital-twin, which facilitates a cost effective development, testing and implementation of advanced control and fault detection strategies.

The paper proposes a calibration methodology for the thermal model (energy and comfort) of the Live-In Lab, developed in IDA-ICE, to be deployed as a digital twin. The methodology first screens the parameters with most impact on energy use and then calibrates the model minimizing the error in both indoor comfort and energy use with a weighting parameter β. Calibration results are then validated against the measured data.

The results of this paper will be instrumental to the improvement of control systems and it will facilitate the study of behavioral aspects of the energy use.

Introduction

The recent development of ICT has originated an exceptional potential for cost-effective improvement of energy efficiency in buildings, providing tools for more advanced building monitoring and building data analysis, more advanced control architectures and fault detection.

Nevertheless, large scale implementation of ICT-related solutions in buildings need to be well proven and smart building demonstrators are required. Emerging tools to gain better and more realistic insights on the potential of ICT in buildings are virtual testbeds and digital twins.

According to the CIRP Encyclopedia of Production Engineering (Stark and Damerau 2019) the definition of a digital twin can be given as:

"A digital twin is a digital representation of an active unique product (real device, object, machine, service, or intangible asset) or unique product-service system (a system consisting of a product and a related service) that comprises its selected characteristics, properties, conditions, and behaviors by means of models, information, and data within a single or even across multiple life cycle phases."

In a recent review, (Jones et al. 2020) identify 13 characteristics common to digital twins; according to (Jones et al. 2020) all digital twins share, among other characteristics, a physical entity (e.g., a building), the virtual entity or twin (e.g., the building model of the building), a physical and virtual environment (e.g. the weather and the weather monitored data), a physical-to-virtual connection and twinning, i.e., the act of synchronizing virtual and physical states. An interesting example of implementation of a digital twin for buildings can be found in (Lydon et al. 2019); they present a coupled simulation for the thermal design of a space heating and cooling integrated in a lightweight roof structure to support design improvements.

In building design and operation, digital twins can serve as an invaluable tool to test the effectiveness of advanced control architectures in reducing energy use and providing improved comfort, to test cost-efficient fault detection schemes, to generate realistic data for benchmarking of algorithms and to investigate potential privacy risks related to the increasing sensing and monitoring capabilities.

The KTH Live-In Lab ("KTH Live-In Lab"), whose monitored data will be used as benchmark in this paper, has evolved from a single building (now Testbed KTH) to a set of demonstration buildings with the goal of testing and demonstrating the impact of ICT-based solutions in the building to facilitate innovation in the building industry. The testbed KTH is configured as a smart building; a key element to foster research is the creation of its energy digital twin. The first step in the creation of the digital twin is the implementation and the calibration of an energy model: this paper deals with the process of calibration and introduces a methodology considered particularly suitable to the specific requirements of a digital twin.

The capability to accurately predict energy use and temperature is crucial. Prediction discrepancies in building simulation models typically arise from uncertainties in input data relative to the building enclosure, like for instance geometry, air-tightness and wall insulation, to the HVAC system, control setting, e.g. temperature setpoints, and to the building usage, i.e.

internal gains from people, light and equipment. The issue of reliable data retrieval for simulations may be even more problematic for older buildings, where such information may not be available at all – thus relying on an assessment based on expert knowledge. In addition, the monitoring of certain environmental conditions, like solar radiation, can be impracticable, expensive or not commonly available; similarly, certain variables like occupancy estimation in time may not be accurate. All these uncertainties are likely to result in a relevant mismatch between the building and the building model it represents. Building models calibration against measured data has proven an effective way to improve the prediction accuracy of the models. Important contributions in the literature on thermal model calibration will be briefly summarized in this section.

The calibration of a building energy model can be used as a first step towards the evaluation of energy savings measures: examples can be found in (Ascione et al. 2019) that perform a calibration for the whole building model – a university building- on the available monthly energy data (gas and electricity) after a preliminary investigation on the prevalent indoor conditions, with errors after calibration below recommended thresholds.

(Coakley, Raftery, and Keane 2014) provide an exhaustive overview of challenges, software tools, procedures and methods in matching building energy simulation models to measured data. Building energy performance simulation calibration approaches are grouped in analytical tools, mathematical and statistical techniques, manual calibration approaches and automated calibration approaches, which include optimization-based techniques and Bayesian techniques. The application of optimization techniques to building simulations is object of the review by (Nguyen, Reiter, and Rigo 2014), who stress the growing number of publications and illustrate the main challenges related to the topic.

Bayesian approach for building model calibration and parameter ranking is used by (Yuan et al. 2017) in an existing building in Singapore, based on monthly electricity data. Other successful examples of Bayesian calibration are found in (Chong et al. 2017), who apply it to two building cooling plants, in (Kristensen, Choudhary, and Petersen 2017), who investigate the effect of aggregation of smart meter data on the calibration of a building energy model and in (Zhu et al. 2020), who propose a new Bayesian calibration approach combined with machine learning. Finally, guidelines for the implementation of Bayesian calibration are provided by (Chong and Menberg 2018) to ease general users from its complexity and need of specific information due to its statistic formulation, which make it non-trivial for building designers and consultants.

Compared to Bayesian approaches, optimization-based calibration methodologies have the advantage of a being more intuitive and have been widely used in literature.

(Asadi et al. 2019) deal with the calibration of the cooling energy of a building in a temperate zone (Doha), with hourly electricity monitoring, using a Harmony search optimization algorithm. (Mustafaraj et al. 2014) perform a two-step calibration of the model of a large university building in Ireland to evaluate potential energy savings measures; two steps are required due the complexity of the model and satisfactory results are reached after the second step of the calibration.

(Yang et al. 2016) applies a calibration method based on sensitivity analysis and Particle Swarm Optimization to a building in Shanghai to improve the prediction accuracy of the model. The model is developed using eQUEST and the calibration, which is performed on monthly energy data on HVAC, lighting and equipment, manages errors below the recommended thresholds.

(Chaudhary et al. 2016) propose an "Autotune" calibration methodology and test it on a deliberately de-tuned building model and on a manual calibration approach, yielding accurate results and time efficient operation.

(Monetti et al. 2015) perform a calibration of a test building model of approximately built around a climatic room. Given the limited dimensions (160 m^2) of the building, a thermal zone was defined for each of the rooms, for a total of seven thermal zones. Most calibration parameters are given a variation range of 25%. The hybrid generalized pattern search with Particle Swarm Optimization was used in a two steps calibration: first with time-varying parameters (like equipment and infiltrations) and then building envelope parameters, for a total of 11.

A slightly different approach is used by (Allesina et al. 2018), who opt to calibrate a building model, a 3600 m^2 retail store building from the 70's in Italy. The calibration is based on the energy signature of the whole building and data recovered from gas bills; instead of using heuristics, they create a mesh of 176 configurations of the building model, built with EnergyPlus.

As model calibration may involve numerous parameters in the optimization process, refined methods include a screening analysis before the calibration process. (Zuhaib, Hajdukiewicz, and Goggins 2019), for instance, perform a Morris analysis to isolate parameters with significant impact on the model thermal dynamics, and then perform a two steps optimization. Similarly, (Li et al. 2018), use Morris analysis to reduce the number of parameters in the optimization from 15 to 6; after calibration, the discrepancy between monitored and predicted energy (CV) in the validation period decreases from 84% down to 16%. Sensitivity analysis is used also by (Ascione et al. 2020) to validate the model of an industrial building in Southern Italy and evaluate different retrofit measures with a Pareto frontier.

Calibration processes can also be extended to aggregated set of buildings: (Taylor et al. 2019), for instance, propose a method to calibrate an aggregate energy demand model.

(Li et al. 2018) stress that current calibration practice is mostly carried out on monthly data with fewer studies with hourly calibration. In building energy models to be deployed as digital twins, calibrations with higher time resolutions are preferable, but there is a trade-off between effort and calibration resolution. The necessary data may not be available, it may be costly to obtain or it may come with high uncertainty. It is often challenging to get data with the desired time resolution and spatial resolution; a temperature sensor may be available for only a room in a large space or set of rooms.

It is commonly found in literature that uncertainty is related to occupancy related dynamics, including gains from occupants, equipment and lighting, and energy flows from demand-controlled ventilation. In this work, high resolution data from the Live-in Lab Testbed KTH enables the evaluation of a calibration methodology with a detailed model, with a zone for each room, and hourly resolution. The testbed monitoring platform includes motion sensors; such data is used to estimate occupancy patterns and evaluate the impact of occupancy in the calibration of the model; furthermore, the calibration methodology introduces a weight factor β to enable the evaluation of the errors of both energy and indoor environment in the cost function of the calibration.

The following paragraphs of the paper include a methodological section, with a description of the building to be calibrated and the methodology proposed, based on a screening analysis and an optimization algorithm based on sequential search technique; the results of the calibration are then presented. The discussion of the results follows and a conclusion section ends the paper.

Method

The building energy model and the measurements refer to the Live-In Lab Testbed KTH (Figure 1). The Testbed KTH is a residential building for students located in the KTH Main Campus. The Testbed KTH premises feature total of 305 square meters distributed over approximately 120 square meters of living space, split into four apartments; each apartment is divided into a living room, a kitchen and a bathroom. The remaining space is used as technical space and an office. The testbed is designed to be energetically independent, with dedicated electricity generation systems through PV panels, a heat generation system (ground source heat pumps), and energy storage (electricity and heat). Sensors are extensively used to improve energy efficiency and indoor comfort, study user behaviour and to improve control and fault detection strategies. Indoor environmental quality is continuously monitored via multiple temperature, relative humidity, CO_2 and VOC sensors in each room. Additional sensors include, for instance, occupancy detectors and magnetic sensors to detect the opening of windows. Space heating energy is distributed through the ventilation system and both ventilation and energy are continuously monitored at the apartment level; in addition, electricity consumption is also logged per apartment.

A building model, to be used as a digital twin has been created in the IDA-ICE 4.8 simulation environment (“IDA ICE - Simulation Software | EQUA”). The IDA-ICE release 4 has been validated according to EN 15255-2007 and performs within given error boundaries (0,5 Kelvin for operative temperature and 5 % for maximum and average cooling power) in all but one test cases; validation scores according to EN 15265 are A in most of the heating cases (Equa Simulation AB and Equa Simulation Finland Oy 2010). To enhance the model accuracy, the simulation model features a zone per each room of the apartments; all apartments share the same layout with a living room, a kitchen/entrance and a bathroom.

Figure 1: Computer generated view of the Testbed KTH building [source: property developer Einar Mattsson] and the building model generated in IDA-ICE.

The methodology for calibration discussed in this paper pivots around two crucial steps: a screening analysis and the actual calibration.

The screening analysis is a fundamental step to evaluate the impact that the parameters have on the thermal dynamics, i.e. indoor temperature and energy demand, of the model. The impact of each single parameter can differ significantly from building model to building model.

The ranking of the parameters is primarily intended to limit the calibration process to a more restricted subset; this is two-fold beneficial, speeding up the calibration process and avoiding that a too large set of parameters to calibrate might become intractable. In this screening analysis each parameter is varied one at a time with respect to the initial configuration of the building model. Each parameter is varied only between a given minimum and maximum value. A performance indicator, the Sensitivity Index S.I. (Heiselberg et al. 2009), is defined by:

$$S.I.(\%) = \frac{E_{max} - E_{min}}{E_{min}} \quad (1)$$

where E_{max} and E_{min} represent the energy demand relative to the maximum and minimum parameter value.

Upon completion of the screening process, the selected parameters are used in the calibration process, which is essentially an optimization problem.

The software architecture is displayed in Figure 2, where the monitored building (blue box) constitutes the basis for calibration. A simulation manager, based on an ad-hoc code developed in Python, launches the simulation model (yellow box) and evaluates the outputs of the IDA-ICE simulation model against the monitored building; the difference between the simulated results and the monitored data is the error, i.e. the cost function to minimize.

To maximize model fidelity, a climate file derived from the weather station installed in the monitored building is used as input for the simulation model; similarly, internal loads and occupancy schedules are reconstructed based on metered electricity consumption and motion detector sensors.

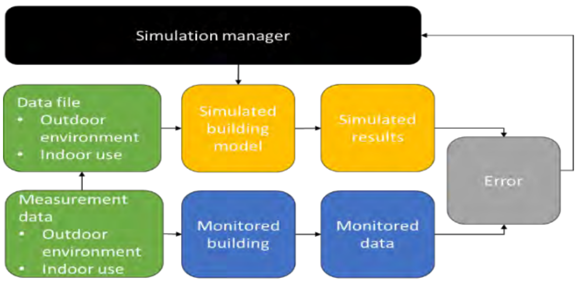

Figure 2: illustration of the simulation conditions and workflow.

The algorithm used for optimization is the one proposed by Box in (Box 1965); the algorithm is capable to escape global maximum of a multivariable non-linear function subject to non-linear constraints. The optimization algorithm is based on a sequential search technique, proven effective in solving problems with non-linear objective functions and without requiring the calculation of derivatives. The optimization procedure is initialized with a set of K points randomly scattered throughout the feasible region of the N independent variables (Box 1966). The required dimension of the set of points is K≥N+1, while the dimension of the points is N.

Common performance indicators for calibration accuracy used in literature are the Mean Biased Error, MBE, and the Coefficient of Variation (Root Mean Square Error), CV(RMSE), defined in (2) and (3), (Ruiz and Bandera 2017)

$$MBE(\%)=\frac{\sum_{i=1}^{N_p}(m_i-s_i)}{\sum_{i=1}^{N_p}(m_i)} \quad (2)$$

$$CV(RMSE)(\%)=\frac{\sqrt{\sum_{i=1}^{N_p}(m_i-s_i)^2 / N_p}}{\bar{m}}\cdot 100 \quad (3)$$

m_i and s_i denote respectively the measurement m_i and the simulated output s_i at the same timestep i, which is sampled on an hourly basis; N_p is the number of samples in the considered sampling interval. Recommended maximum errors for calibration depend on whether calibration is carried out hourly or monthly and are given in Table 1.

Table 1 Suggested values for maximum error for calibrated models according to different sources, from (Ruiz and Bandera 2017).

Guideline	Hourly (%)		Monthly (%)	
	MBE	CV(RMSE)	MBE	CV(RMSE)
ASHRAE	±10	30	±5	15
IPMMVP	±5	20	±20	
FEMP	±10	30	±5	15

The proposed calibration approach aims at the minimization of the error of energy and room indoor temperature the overall error to minimize in the cost function is reduced to a scalar through the weight factor β, introduced in equation (eq. 4) and set prior to the calibration run. For β=0 the cost function is evaluated through the error on energy only; for increasing values of β, the weight of the temperature error in the cost function grows.

$$Weighted\ CV(RMSE)=CV(RMSE)(T)\cdot(\beta) + CV(RMSE)(En)\cdot(1-\beta) \quad (4)$$

Results

To speed up the optimization problem, a screening analysis has first been carried out to identify and rank the variables with the largest impact on the building thermal dynamics and to rule out the parameters with marginal impact on the model calibration. Since the calibration process considered in this work only focuses on thermo-physical properties of the building envelope, set-points and parameters of the heating and ventilation system and internal gains, the building geometry has been excluded from the calibration process; the rationale for this decision is building geometry can usually be estimated with good accuracy either through building drawings or with in-situ measurements. Table 2 shows the list of the variables and the resulting ranking. The large impact of the efficiency of the heat recovery system is largely due to the large airflows required by the full-air heating system. Similarly, the transmittance of the windows has a large impact because of the high windows-to-walls ratio. On the opposite, the impact of the cooling setpoint is due to the simulation period, March. Windows G-value and insulation on external walls show a similar S.I.; insulation was chosen for the calibration due to less reliable information available. Occupant gains in kitchen and bathroom result in no impact due to the spaces being barely used. Living rooms feature variable ventilation between minimum and maximum airflows; in the screening analysis the values minimum and maximum airflows are varied. Kitchens and bathrooms instead use a constant ventilation strategy, i.e the ventilation flow is kept constant within a simulation; in the screening analysis the value of the ventilation flow is varied. The S.I. of kitchen and bathroom heating setpoints is due to constant ventilation flow scheme. Heat capacity of the thermal envelope, which has been dealt varying the thickness of the external walls, resulted in a limited impact in the screening analysis.

To showcase the method, parameters have been divided into three groups: building envelope (*BENV*), HVAC system (*HVAC*), and building occupancy and behaviour (*BEHV*). Two parameters per group have been chosen, for a total of six parameters; insulation thickness and windows U-value for the building envelope; heat recovery system and airflows for the HVAC, and occupancy gains and temperature set-points for the third group.

Table 2: Results from the screening analysis; selected parameters for calibration are highlighted.

Type	Parameter	S.I.	Selected
HVAC	Heat recovery efficiency	117.2%	Y
BENV	Windows U-value	14.9%	Y
HVAC	Living room minimum airflow	11.9%	N
HVAC	Living room maximum airflow	9.3%	Y
BENV	Windows G-value	8.7%	N
BENV	Insulation thickness	8.3%	Y
HVAC	Kitchen airflows (constant)	8.3%	N
BEHV	Living room heating setpoint	5.7%	Y
HVAC	Bathroom airflows (constant)	5.7%	N
BENV	Infiltrations	4.7%	N
BEHV	Living room occupant gains	4.4%	Y
BEHV	Living room equipment gains	0.8%	N
BEHV	Living room light gains	0.8%	N
BEHV	Bathroom light gains	0.8%	N
BEHV	Kitchen light gains	0.7%	N
BEHV	Bathroom equipment gains	0.7%	N
BEHV	Kitchen equipment gains	0.7%	N
BEHV	Living room cooling setpoint	0.6%	N
BENV	Building envelope heat capacity	0.2%	N
BEHV	Kitchen occupant gains	0.0%	N
BEHV	Bathroom occupant gains	0.0%	N
HVAC	Bathroom cooling setpoint	0.0%	N
HVAC	Bathroom heating setpoint	0.0%	N
HVAC	Kitchen cooling setpoint	0.0%	N
HVAC	Kitchen heating setpoint	0.0%	N

The calibration algorithm has been tested to benchmark its optimization performance. Arbitrarily de-tuned simulation building model building configuration have been used as initial values for optimization, which used a reference building configuration as a "ground truth". Starting from the initial configuration, the optimization algorithm efficiently converged to the target –benchmark- configuration even with several parameters, without getting stuck in local minima.

Table 3 shows the cumulated errors on energy and temperature after calibrations for different values of the weight parameter β. Weighted CV(RMSE) is the overall error; the lowest weighted CV(RMSE) after calibration is equal to 6% and is found for β=0.75; this value is below the recommended values found in literature and summarized in Table 1, and it ensures that the calibration is satisfactory for both energy and indoor environment.

Table 3: Coefficient of variation for energy and temperature mapped for different values of the parameter β.

β	0.25	0.5	0.75
MBE Energy [%]	-8%	-3%	-2
MBE Temperature [%]	2%	-2%	-2
CV(RMSE) Energy [%]	16%	14%	13%
CV(RMSE) Temperature [%]	3%	3%	3%
Weighted CV(RMSE) [%]	13%	9%	6%

Figure 3 shows measured and simulated trends for averaged temperature and overall energy in the apartments in the initial configuration; these results, before calibration, are for the period between 07-03-19 and 11-03-19. Although the temperature trends almost overlap, the time series illustrates clear discrepancies energy; the CV(RMSE) Temperature is 2%, the CV(RMSE) Energy is 46% and the Weighted CV(RMSE) is 13%.

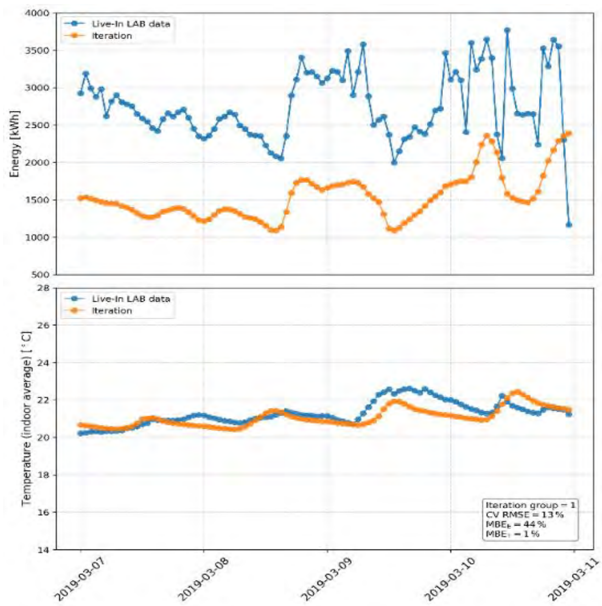

Figure 3: Comparison of energy use (top) and average indoor temperature (below) with hourly resolution in the period between 07-03-19 and 11-03-19 before calibration. Energy and temperature measured are plotted against the actual monitored values.

Figure 4 shows measured and simulated trends for averaged temperature and overall energy in the apartments for the same period after calibration for β=0.75. The Weighted CV (RMSE) is 6% and the time series shows almost overlapping trends for both.

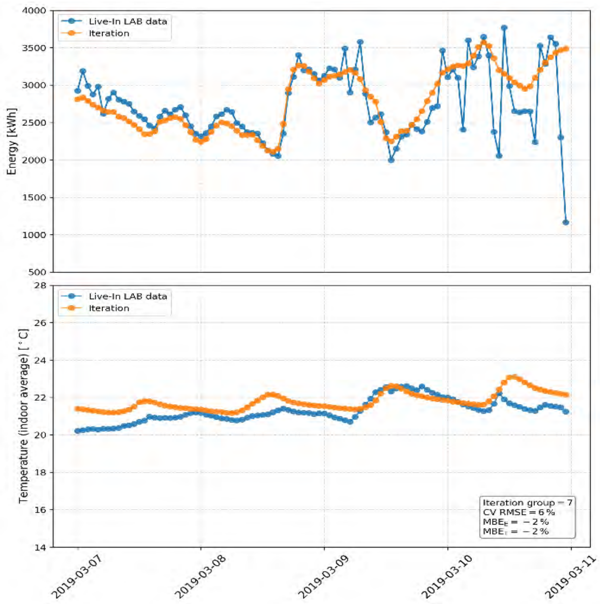

Figure 4: Comparison of energy use and average indoor temperature with hourly resolution in the period between 07-03-19 and 11-03-19 after calibration.

Table 4 summarizes the values of the parameters included in the calibration process for the initial and calibrated configuration for β=0.75.

Table 4: Initial and optimized values for the considered variables.

Parameter	Initial value	Calibrated value
External walls insulation [m]	0.05	0.10
Windows U-value [-]	1.4	1.87
Living room maximum airflow [l/sm^2]	2.0	2.0
Air heat recovery efficiency [%]	0.85	0.60
Heating set-point [°C]	22	18
Occupants gain [n_{people}]	1.0	1.5

Discussion

The screening analysis has a two-fold importance. First, selecting only the parameters with the most impact on the thermal dynamics, it reduces the number of variables to optimize for; this speeds up the overall simulation time and reduces the risk of local minima. Furthermore, including parameters with low impact in the calibration is likely to result higher uncertainty in such calibrated parameters, due to the limited sensitivity that they have in the cost functions. Although the selection of the parameters to calibrate can – and usually is – be done based on expert knowledge of the impact that each parameter has on thermal dynamics and the uncertainty that exists on that parameter, the impact of each parameter on a building model can vary significantly in building and important parameters may be overlooked and excluded from the validation; the sensitivity analysis mitigates this risk.

The simple screening approach used still has a degree of subjectivity, based on expert knowledge, in the choice of minimum and maximum values of the parameters, which in turn influences the sensitivity index. Another limitation of the chosen screening approach is that, given that it is a local sensitivity analysis approach, the initial configuration has an impact on the results of the screening analysis. A global sensitivity analysis, like the Morris method, can be a more accurate tool the problem but at a cost of a higher computational burden.

Upon completion of the calibration, the implemented methodology has been shown to decrease significantly the discrepancy between measured and simulated data for both energy and temperature. The initial value of CV (RMSE) was 2% for the temperature and 46% for energy with an overall error, CV (RMSE), of 13%; this error has decreased down to 6%, CV (RMSE), with 2% and 13% respectively for a value of the weighting factor β of 0.75. These calibrated values are below the suggested thresholds found in literature and are satisfactory for the chosen hour time resolution.

The introduction of the weighting factor β is considered central in the context of digital twins. Calibration procedures may disregard to quantify the error in the indoor conditions. Qualitative assumptions on indoor temperatures may be sufficient for calibrations for models used for energy auditing or the evaluation of renovation measures. Instead, for digital twins the capability to fine tune the model accounting for both energy and temperatures is expected to deliver a superior model to generate synthetic data to support a better understanding of the behaviour dynamics in relation to advanced control and fault detection schemes, calibrated models are needed for both energy use and indoor environment. In this context, detailed calibrated models with hourly time resolution can be an optimal trade-off between prediction accuracy and the cost to produce them. More refined time resolution calibrations require higher resolution datasets that are often not available, e.g., outdoor data from existing weather stations, prone to errors, like motion detectors sensors or more costly to manage, like indoor data with higher resolution.

Advanced monitoring platforms, like the one of the Testbed KTH, that includes the continuous measurement of indoor environmental variables, occupancy and internal gains from detailed electricity readings, are powerful tools for model calibration and advance the implementation of models for building digital twins. Sensors with low sampling time, occupancy detectors and electricity monitoring can provide useful information to reconstruct the occupancy patterns and estimate internal gains.

An immediate practical extension of the use of the calibrated parameters is to support fault detection and predictive maintenance; for instance, significant discrepancies in a parameter like external wall transmittance above the design values can pinpoint a problem with the building envelope insulation characteristics, and trigger further investigation.

However, caution should be used, as results presented here are only preliminary; in this case, for instance, parameters are calibrated only on a limited time series to show the viability of the proposed approach and the advantages of calibrating a model with both temperature and energy in the cost function. Given the observation window, the calibrated parameters – though realistic- may change in a calibration carried out over different seasons.

Conclusion

This paper has showcased an innovative calibration procedure for the calibration of building energy models, validated against preliminary data from the Live-In Lab, a recently built residential building testbed in the KTH Main Campus in Stockholm. A detailed building energy model has been created in IDA-ICE and has been calibrated with hourly sampling, which is the current state-of-the-art resolution.

The calibration methodology consists in a screening analysis to select a subset of parameters to optimize and subsequently an optimization process. The implemented calibration minimizes the error between the model and the monitored data with a multi-objective cost function based on the discrepancy between indoor temperature and the energy demand. In the calibration process the user can set a parameter β to weigh the relative importance of the temperature and energy error.

The calibration process has proved to be straightforward and after calibration the overall error has been reduced from 13% to 6%, while guaranteeing that both errors on energy and indoor temperature trends are minimal. For optimized configurations, the proposed procedure has managed to yield a calibration error below the recommended thresholds in the literature.

Although the monitored dataset is currently limited in extension, the observed dynamics in the model follow closely the monitored temperature and energy trends, which is a key feature for the adoption of the model as digital twin.

The sensor platform of the Testbed KTH, which includes the continuous monitoring of indoor comfort conditions, occupancy and internal gains from detailed electricity readings, has proved an invaluable tool to provide the necessary data for calibration and in the evaluation of the impact of user activities.

Future development of this work will include a calibration with extended datasets to study seasonal effects.

Acknowledgements

The work in this paper has been carried out within the project Kostnads- och energieffektiva styrsystem i byggnader - (Cost-and Energy-Efficient Control Systems for Buildings), financed by the Swedish Energy Agency and IQ Samhällsbyggnad under the E2B2 program, project number 47859-1 – and within CLAS: Cybersäkra lärande reglersystem – financed by the SSF, Swedish Foundation for Strategic Research, reference number RIT17-0046.

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