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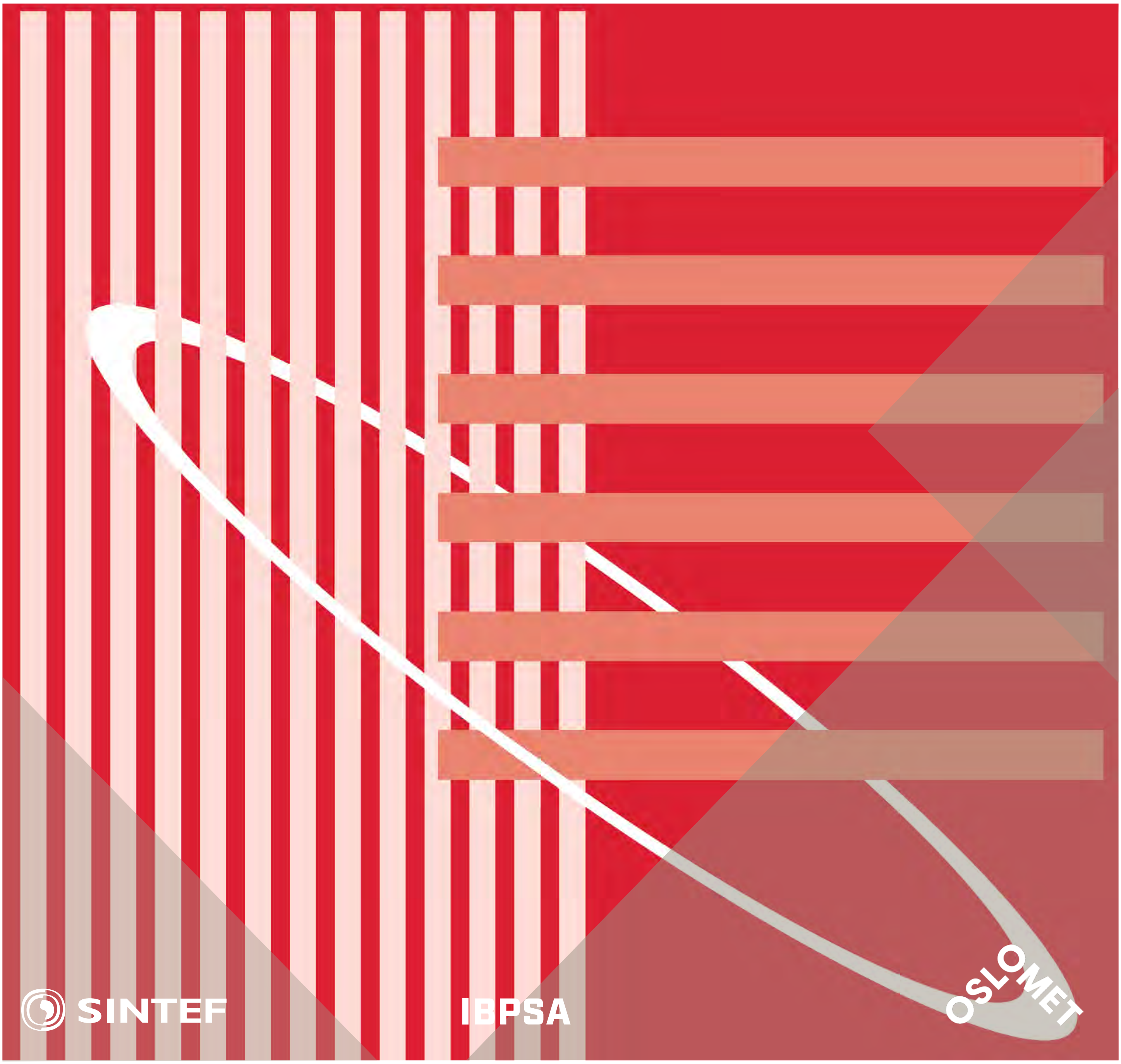

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Editors:
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Data-based calibration of physics-based thermal models of single-family houses

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Abstract

The calibration of building energy simulation models is crucial for addressing the issue of the discrepancy between the simulation output and real-world measurements. The majority of current research studies have used monthly utility bills as calibration data. In this study an automated optimization algorithm was implemented to calibrate an energy model of a single-family house using daily and hourly energy consumption data. The performance of the calibrated model was tested on a different dataset and the simulation output matched the measurements with a daily CV(RMSE) of 14%. This study demonstrates that the calibration using currently available district heating data can significantly improve the performance of building energy simulation.

Introduction

Building energy simulation can be classified in two main categories: physics-based models, which apply physical laws to predict the system behaviour, and data-based models, which estimate the system properties based on statistical analysis of measured data. The advantage of (detailed) physics-based models is the ability to predict the system behaviour under previously unseen boundary conditions. Physics-based building energy simulation tools are therefore suitable for predicting the thermal performance of buildings e.g. during the building design process, in energy retrofit projects, and for various research purposes like testing and developing predictive control systems. However, many studies have documented that there are often significant discrepancies between simulation results and measurements (Coakley et al. 2014; Petersen et al. 2012). The major reason is that the inputs to the simulation model does not correspond to the actual conditions. Therefore, current literature describes different approaches for the calibration of the simulation model to fit the measured data.

The calibration methods are divided by Coakley et al. (2014) into two main approaches: manual and automated. Current research has investigated different methods for automated calibration; among these are optimization-based methods. Optimization methods normally consist in a minimization problem where an optimal set of parameters is found in order to minimize an objective function stating the deviation between the simulated output and the measurements. Sun and Reddy (2006) developed a four-step approach that consist in sensitivity analysis, identifiability analysis, uncertainty analysis and optimization with a gradient-based algorithm. In order to avoid the risk of local minima which are typical of gradient-based methods, different algorithms based on global search have been investigated in other studies. In Asadi et al. (2019), the implemented method is a Harmony Search algorithm, which generates the next iterations either with a random solution or choosing the saved solution with the lowest simulation error. Other studies used population-based approaches, where a group of solutions is generated in each iteration, for example using a particle swarm algorithm as in Yang et al. (2016) or a genetic algorithm as in Martínez et al. (2020). To take the uncertainties of the under-determined calibration process into consideration, Reddy et al. (2007) selected a small number of the best solutions to predict the energy use of the model instead of choosing only one solution.

Current research studies have generally used utility bills on a monthly basis as calibration data (Coakley et al. 2011). Recently, the development and roll-out of e.g. smart heat meters and IoT-based sensors technology has made data with higher resolution more available, data that potentially can improve the robustness of model calibration. In the study by Monetti et al. (2015) hourly data were used to calibrate a building energy model coupling the EnergyPlus building simulation tool and the GenOpt optimization program. The case study was a small building used exclusively for indoor climate experiments, without any occupant and conditioned by means of electric resistances. The validation was based on performance limits set out by ASHRAE Guideline 14 and the results of the calibrated model were found consistent with those thresholds. Another calibration study that utilized hourly data was performed by Asadi at al. (2019). The case study was a large office building and one hundred different independent variables were calibrated. The calibrated model was able to predict the electricity consumption with a proper accuracy after 500 iterations.

In contrast to the previous mentioned studies, the aim of this study is to develop a calibration method that can be suitable for single-family houses, addressing the issue of the low resolution of district heating data and unmeasured indoor temperature, while at the same time keeping the computational complexity low.

Methodology

The calibration method applied in this study was an iterative process between the calibration algorithm and the building energy simulation model made in EnergyPlus, a high-fidelity building energy simulation tool (Crawley et al. 2001). The model was used for co-simulation with Matlab where the calibration algorithm was implemented. The procedure used was similar to the optimization program GenOpt for the minimization of an objective function evaluated by an external simulation program (Wetter 2016). A first input file for the EnergyPlus model was written assigning initial guess values to the calibration variables. Based on output from EnergyPlus, the Matlab code calculated the new input parameters and wrote them in the input file for the next EnergyPlus simulation in the calibration iteration. The process continued until the maximum number of iterations was reached or the convergence criteria were met. The flow diagram is shown in Figure 1.

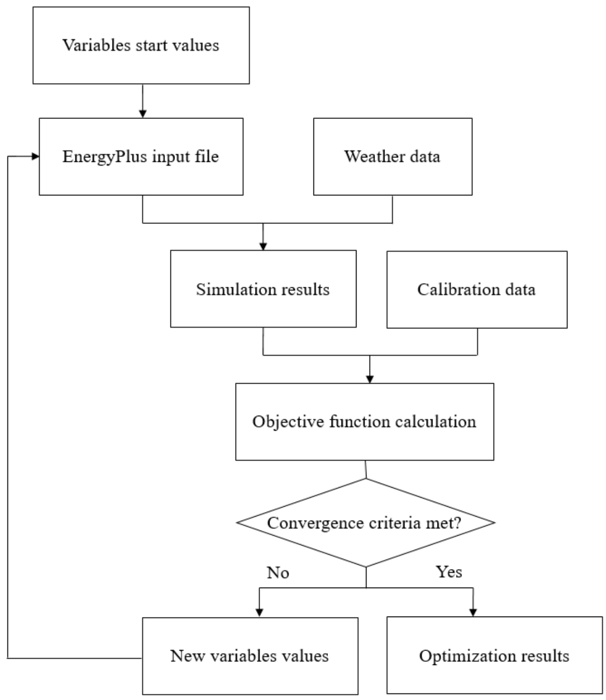

Figure 1: Flow diagram of the calibration process

Building model

The first step of the methodology was to build an energy simulation model using all the information currently available about the building. The case study is a typical single-family house from 1968 located in Aarhus, Denmark, occupied by four people (two adults, two children). The floor area is approximately 180 m^2 and has 15 rooms distributed on one floor. District heating supplies the radiator-based space heating and domestic hot water. The geometry and initial assumptions about the thermal properties of the constructions was based on as-built drawings. In order to reduce the complexity of the model, the building was modelled as one thermal zone, while the walls that separate the different rooms were considered as internal mass. Since EnergyPlus models the heat conduction through surfaces is modelled as a one-dimensional problem, thermal bridges cannot be directly modelled. Instead, the contribution of thermal bridges was accounted for with an additional heat loss through the building envelope, hence by increasing the thermal conductivity of the materials.

Hourly electricity consumption data were used to generate a daily profile of the internal heat gains. The heat dissipated by lighting and other electrical equipment was assumed to be a fraction of the electricity consumption recorded every hour, and the daily pattern observed in the data was used as schedule throughout the year for the heat gains in the EnergyPlus model. The occupancy schedule was determined from the time of the day when electrical appliances were used and from the assumptions that all occupants are present during the night.

The weather data included were the outdoor air temperature and the global solar radiation, with a resolution of $1 \cdot 10^{-9}$ °C and $1 \cdot 10^{-9}$ W/m^2, respectively, measured by a near-by weather station. Other meteorological data such as humidity and wind speed were set to standard values in the EnergyPlus model because they were not measured, and it was assumed that they do not have a major impact on heat consumption.

Calibration data

The output data used to calibrate the model is the energy consumed for space heating. The data available was the cumulative district energy consumed, recorded on an hourly basis with a reading resolution of 1 kWh. This resolution does not give the true hourly value as there might be a consumption of 1 kWh spread across several hours. Two different possibilities were investigated to overcome this issue in the calibration: 1) The hourly truncated data were aggregated into larger time resolutions, as in Kristensen et al. (2017); 2) the data were smoothed using a moving average.

The available district heating data was the sum of space heating and domestic hot water. Domestic hot water consumption thus had to be disaggregated from the total. For a daily resolution, the domestic hot water consumption was calibrated assuming the consumption was constant in each day. For an hourly resolution, different approaches were used in an attempt to identify the profile of the consumption during the day: 1) analysing the district heating data measured during the summer when the radiators are switched off; 2) Indoor air relative humidity logged every 5 minutes in the bathroom was used to detect the time of the day when occupants took showers. However, a clear daily pattern could not be seen in summer, and it was not possible to identify a sound correlation between energy consumption peaks and periods with high/peak humidity. This can be explained to some extent by the low reading resolution of the heating energy meter. Therefore, a constant value was assumed for this study, while a more accurate way to separate the domestic hot water consumption will be the object of future work.

Sensitivity analysis

The calibration of building energy simulation models is an over-parameterized problem where the parameters cannot be uniquely defined. Therefore, it is crucial to reduce the number of parameters to be calibrated. The first task of the study was to identify the set of parameters that drive the majority of the model output variation. The method used was the screening method by Morris (1991), which is the most common screening technique used for sensitivity analysis in relation to calibration of building simulation models (Fabrizio et al. 2015). First, a minimum and maximum value for each input parameter x_i for $i = 1,2, \dots, k$, where k is the number of parameters included was defined. These ranges were divided into p=4 number of points, called levels, equally distant from each other, forming a grid of input parameter values, Ω. The Morris method then employs a random one-at-a-time (OAT) sampling procedure to generate trajectories through Ω with each trajectory comprising $k+1$ random model realisations from Ω. The sampling procedure was repeated for r=100 trajectories creating a global set of $r\cdot(k+1)$ building energy models to be simulated. The elementary effect EE_i of each input parameter x_i for every set of k+1 models was calculated from the ratio between the variation in output and the variation in input:

$$EE_i = \frac{Y(x_1,\dots,x_i+\Delta,\dots,x_k)-Y(x_1,\dots,x_i,\dots,x_k)}{\Delta} \quad (1)$$

where $Y(x_1, \dots, x_k)$ is the simulation output, in this case the heating demand, and Δ is the distance between each parameter level.

Finally, the influence of each parameter μ_i can be ranked by calculating the absolute mean of the elementary effects following different trajectories (Saltelli et al. 2004):

$$\mu_i = \frac{\sum_{t=1}^{r}|EE_{i,t}|}{r} \quad (2)$$

The chosen values of p and r are aligned with the findings of Petersen et al. (2019) who found that a reliable outcome of deploying the Morris method for SA applied to a high fidelity BEM (like Energy Plus) is generated by choosing $p\geq4$ and then run simulations for $r\geq100$.

The selection of the parameters to include in the Morris analysis was made based on literature review and on the quality and reliability of the available building information. The geometric properties of the building were known with high degree of confidence because they were determined from direct measurements and drawings and therefore they were not included. Instead, there was more uncertainty involved with the thermal properties of the building envelope, such as the U-values and the heat storage capacities. Therefore, the sensitivity of the simulation output to the thermal conductivity and to the specific heat of the insulation material of the main structures was analysed. The set of studied parameters was extended with the infiltration flow rate, the solar transmittance of the window glazing, the internal heat gains intensity and the set-point temperature for space heating. The heat gains from lighting and other electrical equipment were combined in one parameter. As mentioned in the previous section, a scalable equipment schedule was estimated from the electricity consumption data, and the maximum intensity was the parameter used for the sensitivity analysis. The level of occupancy outside of working hours was known and the heat gains from occupants were not analyzed in this study. The results obtained are shown in Table 1.

From the assessment of the results of this analysis the parameters with the highest influence are: the conductivity of the external wall insulation, the infiltration rate, the heating set-point temperature and the domestic hot water consumption. These parameters were selected as calibration variables.

Table 1: Results from sensitivity analysis

Parameter	Unit	Minimum	Maximum	μ
Set-point temperature	°C	18	24	2.030
Infiltration flow rate	$l/(s\cdot m^2)$	0.32	1.28	0.544
External wall insulation conductivity	W/(m·K)	0.02	0.07	0.244
Domestic hot water consumption	kWh/h	200	700	0.130
Window glazing solar factor	-	0.30	0.80	0.085
Window glazing conductivity	W/(m·K)	0.03	0.07	0.053
Roof insulation conductivity	W/(m·K)	0.02	0.07	0.052
Internal heat gain maximum intensity	W/m^2	0.80	1.50	0.024
External wall specific heat	J/(kg·K)	400	1200	$2.375\cdot10^{-3}$
Internal wall specific heat	J/(kg·K)	400	1200	$9.765\cdot10^{-5}$

Optimization algorithm

The objective function to be minimized is a goodness-of-fit function which is calculated combining the mean bias error with the coefficient of variation of root mean squared error. The mean bias error (MBE) is calculated from the sum of the differences between the observed and simulated values, normalized by the sum of the observed values, as follows:

$$MBE\ [\%] = \frac{\sum_{t=1}^{T}(y_t - \hat{y}_t)}{\sum_{t=1}^{T} y_t} \cdot 100 \quad (3)$$

where $\hat{y}_t$ is the simulated output at time step t, y_t is the measured value at time step t, and T is the total number of time steps.

CV(RMSE) is calculated by normalizing the root mean squared error to the mean of the observed values, as in the following equations:

$$CV(RMSE)\ [\%] = \frac{RMSE}{\bar{y}} \cdot 100 \quad (4)$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{T}(y_t - \hat{y}_t)^2}{T}} \quad (5)$$

$$\bar{y} = \sum_{t=1}^{T} \frac{y_t}{T} \quad (6)$$

The goodness-of-fit function is calculated from a weighted sum of the CV(RMSE) and the MBE.

$$GOF = \sqrt{\frac{w_{CV}^2 CV^2 + w_{MBE}^2 MBE^2}{w_{CV}^2 + w_{MBE}^2}} \quad (7)$$

where (w_{cv} + $w_{mbe)}$ = 1. The ratio between the weighting factors was chosen to be w_{cv}:w_{mbe} = 1:3 as in Reddy at al. (2007).

Different algorithms can be applied to minimize the objective function, some of which evaluate the gradient of the objective function, while others are stochastic meta-heuristic methods (Wetter et al. 2004). Based on the assumption of an objective function without discontinuities, a simple gradient descent algorithm was implemented. The variables of each iteration are changed by moving in the direction of the negative of the gradient of the objective function. The step size for moving is proportional to the gradient and to a defined learning rate. Thus, the values are updated using the following equation:

$$x_{i,t} = x_{i,t-1} - \alpha \frac{\delta}{\delta_{x_i}} GOF(x_{1,t-1}, \dots, x_{N,t-1}) \quad (8)$$

Where $x_{i,t}$ is the value of the variable x_i in the iteration t, α is the learning rate, N is the number of variables and $\frac{\delta}{\delta_{x_i}} GOF(x_i, \dots, x_N)$ is the partial derivative of the objective function with the respect to the calibration variable x_i. Since the analytical gradient calculation was not practicable, an approximate derivative was calculated using finite difference with a proper step size.

Results

The algorithm was run using a training period which extends from the 25th of September 2018 to the 28th of March 2019. The objective function was evaluated using two different dataset: daily aggregated data or hourly data. It was found that after the tenth iteration the GOF function only improved by a negligible amount and therefore the calibration algorithm was run for 10 iterations.

The error indices obtained are shown in Table 2. In addition to MBE and CV(RMSE), the third metrics introduced for model validation is the fit ratio, which is calculated as follows:

$$FIT\ [\%] = \left\{1 - \frac{\sqrt{\sum_{t=1}^{T}(y_t - \hat{y}_t)^2}}{\sqrt{\sum_{t=1}^{T}(y_t - \bar{y})^2}}\right\} \cdot 100 \quad (9)$$

The fit ratio is a measure of the performance of the model compared to a benchmark naive model where the prediction is the mean of the observations. It is positive when the RMSE of the model is lower than the standard deviation, which is the RMSE of the benchmark model.

The results in Table 2 show that the optimization algorithm succeeded in eliminating the mean bias error and in reducing considerably the CV(RMSE).

The measured and simulated energy consumption with a daily and hourly temporal resolution can be observed in Figure 2 and 3, respectively.

The values of the calibration parameters before and after the calibration can be read in Table 3. It can be immediately seen that the solutions obtained do not show a significant variation depending on the temporal aggregation used.

Table 2: Error indices (training dataset)

	Daily data		Hourly data	
	Initial model	Calibrated model	Initial model	Calibrated model
CV(RMSE) [%]	31.99	13.03	43.65	21.47
MBE [%]	- 28.21	- 0.11	- 36.35	0.09
FIT[%]	- 0.06	56.52	- 26.36	37.37

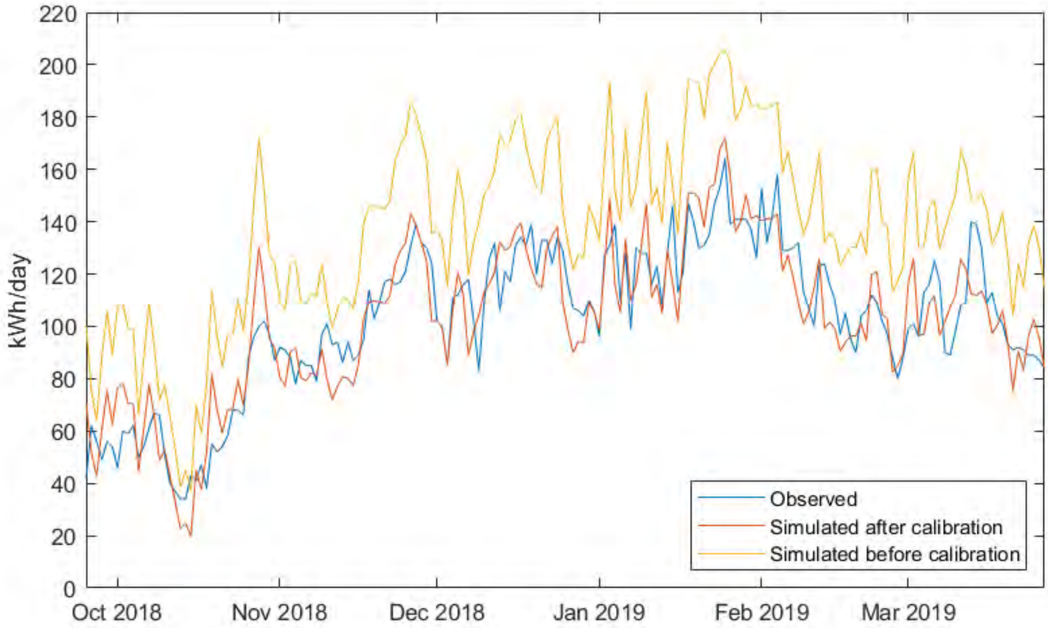

Figure 2: Observed and simulated data with daily resolution (training dataset)

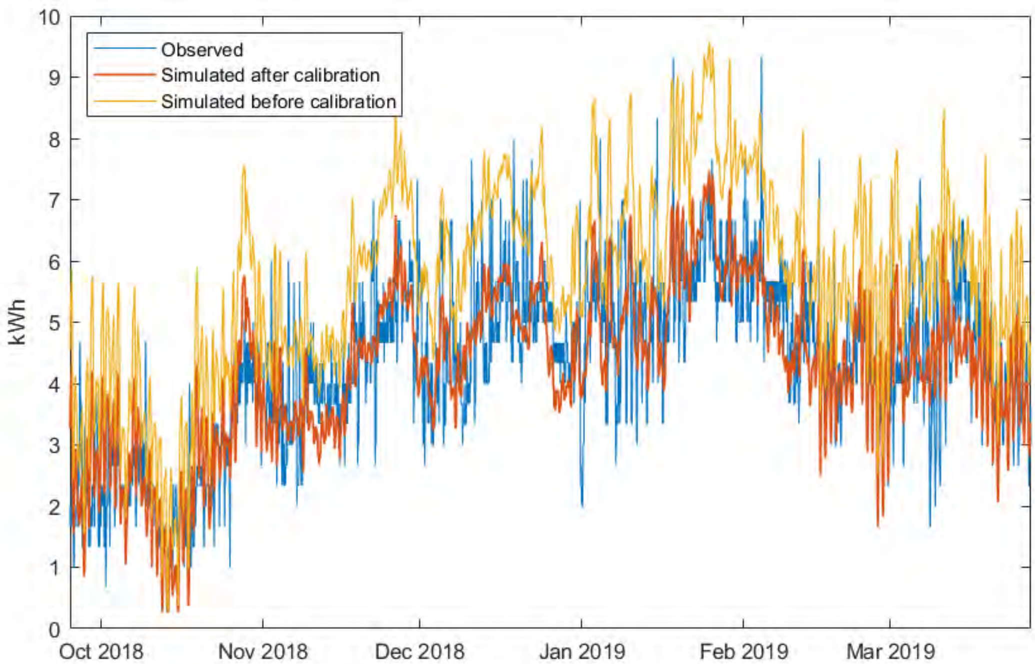

Figure 3: Observed and simulated data with hourly resolution (training dataset)

Table 3: Values of the calibration variables (training dataset)

	Initial model	Calibrated model	
		Daily data	Hourly data
λ_{wall} [W/mK]	0.045	0.0424	0.0423
Infiltration [l/(sm^2)]	0.960	0.705	0.704
S.P. temp. [°C]	21.000	19.736	19.750
DHW [kWh/day]	7.200	6.557	6.471

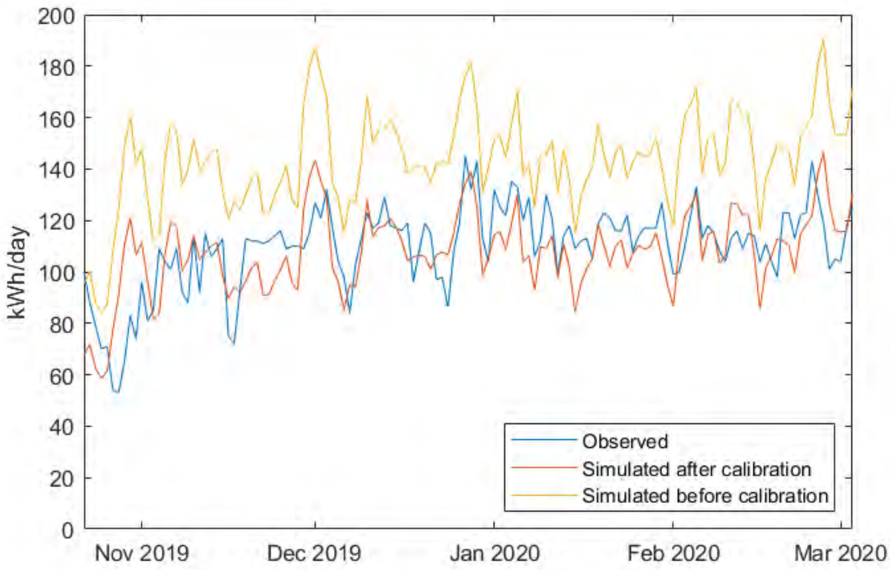

Figure 4: Observed and simulated data with daily resolution (validation dataset)

The robustness of the method was evaluated by testing the performance of the calibrated model with a different dataset. The parameters values estimated on the training dataset were used as input values and a simulation was performed using the data of four months of the heating season 2019/2020, from the 22th of October until the 3rd of March. The set of parameters selected was the one obtained with daily aggregation because it was the one fitting best the training dataset. The model was used to make predictions on a daily basis. The simulation output and the observations are shown in Figure 4 and the statistical indices obtained are summarized in Table 4.

Table 4: Error indices (validation dataset)

	Initial model	Calibrated model
CV(RMSE) [%]	36.54	13.97
MBE [%]	- 26.19	2.04
FIT[%]	- 127.49	12.46

The residuals normalized by the maximum value of the observations are plotted in Figure 5 and in Figure 6 as a function of the outdoor temperature and of the solar radiation rate transmitted through the window. The residuals are positively correlated with the outdoor temperature (the correlation coefficient calculated is 0.46), while there is a negative correlation with the solar radiation (the correlation coefficient is -0.49).

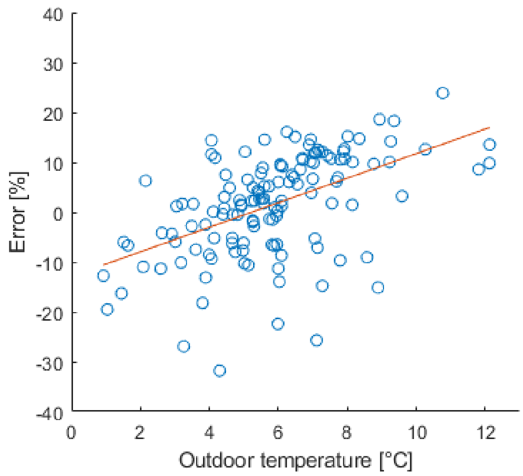

Figure 5: Residuals as a function of the outdoor temperature (validation dataset)

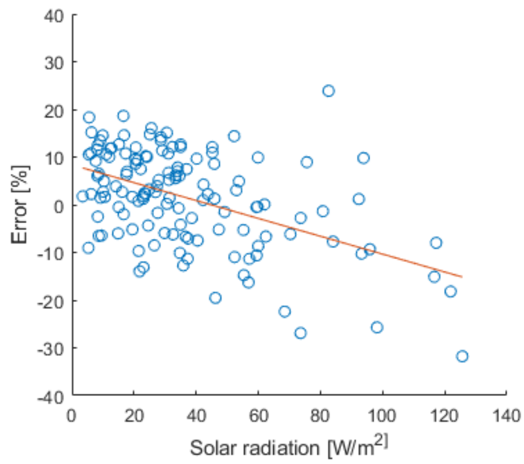

Figure 6: Residuals as a function of the solar radiation (validation dataset)

Discussion

From the assessment of the statistical indices of the residuals and of the final parameters values several considerations can be made about the calibration process.

As expected, the simulation error increases with the temporal resolution because of the larger dataset to fit and because of the significant noise present in the hourly data. Furthermore, there is more uncertainty involved with hourly data because a profile for the domestic hot water consumed during the day was not defined. However, the final values of the calibration variables obtained using different temporal aggregations do not differ significantly from each other.

The energy consumption of the initial model was higher than the measurements. The positive mean bias error was removed by the algorithm by choosing a lower insulation conductivity, infiltration rate, temperature set-point and domestic hot water consumption. Despite that, the final values are still comparable with the initial guesses, that were based on prior information. This demonstrates that the building descriptions and the initial assumptions were valid to some extent.

The calibration parameters were tuned to minimize the discrepancy between the simulation output and the training dataset. However, the goal of a building energy model is the ability to predict the system behaviour under any unseen condition. Although the model performance is reduced on the validation data compared to the training data, the performance is still signicantly better than the one of the not calibrated model. Nevertheless, the mild correlation between residuals and outdoor temperature and solar radiation suggests that the model does not perfectly describe how these inputs relate to the output.

Conclusion

The aim of this paper was to develop and test a calibration method for a single-family house using district heating data. The approach implemented was a calibration algorithm based on numerical optimization. The calibration was performed on a training dataset of six months and the performance of the calibrated model was tested on a different dataset of four months. The validation of the model was based on the assessment of the mean bias error and of the normalized root mean square error on a different dataset.

The calibration method significantly improved the performance of the uncalibrated model both on the training and on the validation dataset. Furthermore, the parameters estimated were not strongly affected to changes in temporal resolution of the calibration data.

Several challenges and possible improvements have been identified for future work. The study has highlighted the limits of the calibration data due to the truncation and to the indeterminacy of the share of domestic hot water in the total energy consumption, especially on an hourly level. The issue could be solved in future studies by utilizing meters with higher reading resolution and separate sensors for the domestic hot water circuit.

Furthermore, there is a level of uncertainty involved with the estimated values of the calibration parameters, because a solution that yields to a good model fit could be a local optimum (Reddy et al. 2007). The optimization algorithm implemented could be improved and used in combination with other algorithms in order to ensure the convergence to a unique optimal solution.

Finally, since the simulation error is correlated to the weather input data even after the calibration, the model could be further improved by extending or modifying the set of calibration parameters (for example including the glazing solar factor).

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