A Calibrated RC Model for Data-Driven Retrofit Analysis of a Residential Building

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Abstract

Among other reasons, the low building retrofit rate in Switzerland is attributed to modeling barriers: a lack of accurate assessment of building energy performance in the pre-retrofit phase as well as the difficulty to model the energy performance in the post-retrofit phase. We propose a novel resistor-capacitor (RC) model that is calibrated with geometric and physical building information (area specifications and U-values) as well as hourly in-situ measurement data over three weeks. The calibrated RC model is able to accurately simulate not only the thermal behavior of the current building state but also the energy savings for different retrofit strategies, and can thus serve as a data-driven decision-tool in the building retrofit process.

Introduction

The construction and operation of buildings accounted for 36 % of the global final energy consumption and 39 % of greenhouse gas (GHG) emissions in 2017 (IEA, 2018a). In order to limit global warming, a global shift to energy-efficient and low-carbon buildings is therefore essential. However, due to the slow turnover of the building stock it is not sufficient to only focus on new buildings. There is an equally critical need for widespread deep retrofits of existing buildings (IEA, 2018a,c). However, the current retrofit rate is very low; in Switzerland, for example, it is only about 1 % (IEA, 2018b). There are several reasons for this low retrofit rate. One major obstacle is the performance gap, which consists of prebound effects and rebound effects (Sunikka-Blank and Galvin, 2012). The prebound effect describes the phenomenon when buildings consume less heating energy than the calculated energy performance rating. In 2012, a study examined 3'400 German buildings and showed that the actual energy consumption was, on average, 30 % lower than the calculated rating (Sunikka-Blank and Galvin, 2012). Studies in Switzerland also showed that the actual energy consumption of Swiss buildings is often considerably below or above the calculated rating (Reimann et al., 2016; Lehmann et al., 2017). The rebound effect, on the other hand, describes the phenomenon when the energy consumption after a building retrofit is higher than the calculated rating, i.e., higher than expected. A study on retrofitted multi-family buildings in Switzerland showed that, on average, only 42 % of the calculated energy saving potential could be achieved (Khoury et al., 2016). Sunikka-Blank and Galvin (2012) observed similar effects for buildings in several European countries. Reasons for both pre- and rebound effects include the use of inaccurate standard values and assumptions, limited building energy models with uncertain input data and occupant behavior (Khoury et al., 2016). Both pre- and rebound effects reduce the calculated energy savings of building retrofits and therefore increase the uncertainty over future cost savings.

Our goal is to overcome such modeling barriers by precisely simulating the dynamic thermal behavior of a building, not only in the current (pre-retrofit) state but also for different retrofit strategies. Therefore, we develop a thermal resistor-capacitor (RC) model, in which retrofit measures on the building envelope can be integrated. The model parameters, i.e., the resistances and capacities, are determined with building measurement data from a wireless sensor network (WSN) and some geometric building information during the calibration stage. A single-family house in Switzerland is used as a case study building to test the developed model. Following calibration, the RC model is able to depict the thermal behavior of the current building state, i.e., the internal air temperature as well as the heating demand, and the effects of potential envelope retrofit measures on the heating demand. The accuracy, along with the scalability of the modeling approach suggests that the proposed RC model can serve as a data-driven decision tool for retrofit analysis.

Methods

RC modeling

According to Foucquier et al. (2013), building energy modeling methods can be divided into three categories: white-box, grey-box, and black-box modeling. White-box models use detailed physical equations to predict the thermal behavior of a building. Such a forward modeling approach requires very detailed information about the building, which is sometimes difficult to obtain for older buildings to be retrofitted (Li and Wen, 2014). Furthermore, white-box models do not address the performance gap issue since no measurement data is required (Li and Wen, 2014). Black-box models, on the other hand, are purely data-driven models that use statistical methods and machine learning techniques to predict the thermal behavior of a building (Dimitriou, 2016). Their main advantages are that the physical features of the building can be disregarded along with their high prediction accuracy. However, black-box models are based exclusively on measurement data and are tied to the operating conditions they have been trained for. It is therefore challenging to simulate and assess retrofit measures. Grey-box models are hybrid models that combine the other two approaches (Braun and Chaturvedi, 2002). First, a simplified physical model is developed. Then, statistical methods and measurement data are used to calibrate the model, i.e., to identify the relevant model parameters. This reduces the amount of physical building information and measurement data that is required. Furthermore, grey-box models often allow for physical interpretation of the results (Dimitriou, 2016).

In grey-box modeling, a simplified physical model that approximates the thermal characteristics of the building is first created. For this purpose, RC models, also known as lumped parameter models, are often used (Madsen et al., 2016). They are based on a simple network with resistors and capacitors and are the thermal equivalent to the electrical circuit. Buildings are modeled as dynamic thermal systems which consist of a distributed set of thermal nodes, whereby the building elements are treated as if they were lumped into one node with uniform temperature (Roels and Senave, 2018). Therefore, RC models rely on the following two assumptions (Dimitriou, 2016):

- Multilayer building elements can be adequately represented by lumped parameters
- The heat transfer processes within the building are linear

The number of nodes, also called states, defines the order or complexity of the RC model. Figure 1 shows an example node e with a temperature T_e [K] and thermal capacity C_e [J/K]. The example node e is connected to the two adjacent nodes T_1 and T_2 via the resistances $R_{1,e}$ and $R_{e,2}$ [K/W]. In addition,

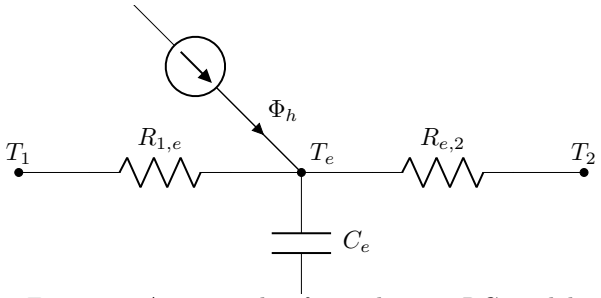

Figure 1: An example of a node in a RC model.

there is a heat input Φ_h [W] at node e. RC models are mathematically modelled by ordinary differential equations (ODEs), which define how the nodes are linked. For each thermal node the energy balance is formed, which is shown in Equation (1) for the example node e in Figure 1.

$$C_e \frac{dT_e}{dt} = \frac{1}{R_{1,e}}(T_1 - T_e) + \frac{1}{R_{e,2}}(T_2 - T_e) + \Phi_h \quad (1)$$

RC models are usually used to simulate the indoor air temperature or the heating load/demand. The main advantage of RC models is their ability to accurately describe the dynamic thermal behaviour of buildings (Madsen et al., 2016). This is not the case with simple steady-state models that disregard the heat stored within the building elements. However, the model order as well as the network topology can vary greatly depending on the area of application.

In a second step, a linear stochastic state-space model is created based on the physical RC model (Madsen et al., 2016). In continuous-time, a linear stochastic state-space model has the following form (MathWorks, 2019):

$$\dot{x}(t) = Ax(t) + Bu(t) + Ke(t) \quad (2)$$

$$y(t) = Cx(t) + Du(t) + e(t) \quad (3)$$

$$x(0) = x_0 \quad (4)$$

where t is time, $x(t)$ is the state vector containing the node temperatures, $u(t)$ is the known input vector, $y(t)$ is the output vector containing the measured states, i.e., the measured node temperatures, and $e(t)$ is Gaussian white noise. A, B, C and D are matrices with elements that are functions of the R and C parameters. K is the disturbance matrix and x_0 defines the initial states. Stochastic state-space models consist of two parts: the system equation (2) and the measurement equation (3). The system equation is a set of stochastic differential equations (SDEs) which describe the dynamics of the states in continuous-time. The SDEs are formed from the ODEs which describe the underlying RC model, with a noise term simply added to each ODE. The measurement equation describes how the observation measurements are linked to the states of the model. The next step is the model estimation or model calibration where the

Table 1: Retrofit measures on the building envelope.

Envelope component	Retrofit measure	U-value [W/(m² K)]
Roof	Inter-rafter insulation with 20 cm mineral wool	0.18
External walls	Ventilated curtain facade with 16 cm expanded polystyrene	0.19
Cellar ceiling	Insulation with 16 cm mineral wool	0.19
Windows	Replacement with triple-glazed windows	0.76

stochastic state-space model is calibrated to measurement data (Deconinck, 2017). This process is also called parameter identification since the model parameters, i.e., the R and C parameters of the underlying RC model, are estimated. Typically, this is done by means of a maximum likelihood estimation (Deconinck, 2017; Madsen et al., 2016; Roels and Senave, 2018; Bacher and Madsen, 2011). In this way, the estimated parameters lead to the best agreement between the output of the stochastic state-space model and the observed measurements. In a final step, the estimated model is validated using different statistical model evaluation tools. Madsen et al. (2016) give a detailed overview about different validation techniques. Particularly important is to check whether strong correlations exist between estimated parameters. The correlation coefficient of two parameters should be less than |0.98| (Madsen et al., 2016). Otherwise, these two parameters are strongly linked and the number of estimated parameters should be reduced, e.g., by fixing one parameter to a physically meaningful value. After the model has been successfully validated, it can be used to predict the thermal behavior of the building under consideration.

Retrofit strategies

According to Sigrist et al. (2019), the following retrofit measures on the building envelope are most frequently undertaken in Switzerland and thus considered in the proposed RC model: roof insulation, external wall insulation, cellar ceiling insulation and window replacement. Furthermore, Sigrist et al. (2019) determined the cost-optimal variant (in terms of insulation type, material and thickness) for each of the four building envelope measures. These four cost-optimal retrofit measures are shown in Table 1 and used in the case study.

Case study building

The case study building is a single-family house in the canton of St. Gallen, Switzerland, which was built in 1953 in timber construction and has three floors. The basement (i.e., the cellar) is completely concreted and contains only one heated room. The roof, external walls and cellar ceiling are only minimally insulated with mineral wool. The case study building is shown in Figure 2a. Additionally, a large, glazed winter garden was added to the building in the 1990s, which is depicted in Figure 2b. An oil boiler with a maximum heating capacity of 28 kW generates heat for space heating and radiators are used for heat dissipation.The energy audit report of the case study building indicates an overall heat loss coefficient (HLC) of 512 W/K and heating demand of 39 170 kWh/a (calculated according to the Swiss standard SIA 380/1:2009). Heat for domestic hot water (DHW) is separately generated by an electric boiler. The following time series consisting of one hour average values are used to calibrate and validate the RC model:

- T_e [°C]: External air temperature
- $\dot{V}$ [m³/s]: Flow rate of heating water
- T_{supply} [°C]: Supply temp. of heating water
- T_{return} [°C]: Return temp. of heating water
- DNI [Wh/m²]: Direct normal irradiance
- DHI [Wh/m²]: Diffuse horizontal irradiance
- T_i [°C]: Internal air temperature

All variables described above were measured over six weeks from February 2 to March 15, 2019 using a WSN. The details of the WSN can be found in Frei et al. (2020). The first three weeks form the training period (for both model calibration and validation), while the last three weeks form the test period (only for model validation). A training period of only three weeks is applied, as longer training periods resulted in an overtrained model.

The calibrated and validated RC model is then used to simulate the heating demand over one year. T_i therefore becomes an input while $\dot{V}$, T_{supply} and T_{return} are no longer inputs. For the heating demand simulation, a day profile of the T_i is calculated based on the measurement data. This reference profile (of 24 hourly internal air temperatures) is then used for each day of the year. As hourly values over one year for T_e, DNI and DHI, hourly ten-year average values (from 2000 to 2009) are used. Data on T_e is obtained from the climate station in St. Gallen, while the CAMS is used for DNI and DHI.

Proposed RC model

Modeling framework

The RC model must be able to accurately predict not only the thermal behavior of the building in its current state, but also the effects of changes in the building envelope on the thermal behavior. This leads to the following consequences:

- The underlying RC model must depict the components of the building envelope individually. This is the only way to later integrate retrofit

(a) West and north facade.

(b) Winter garden.

Figure 2: Case study building.

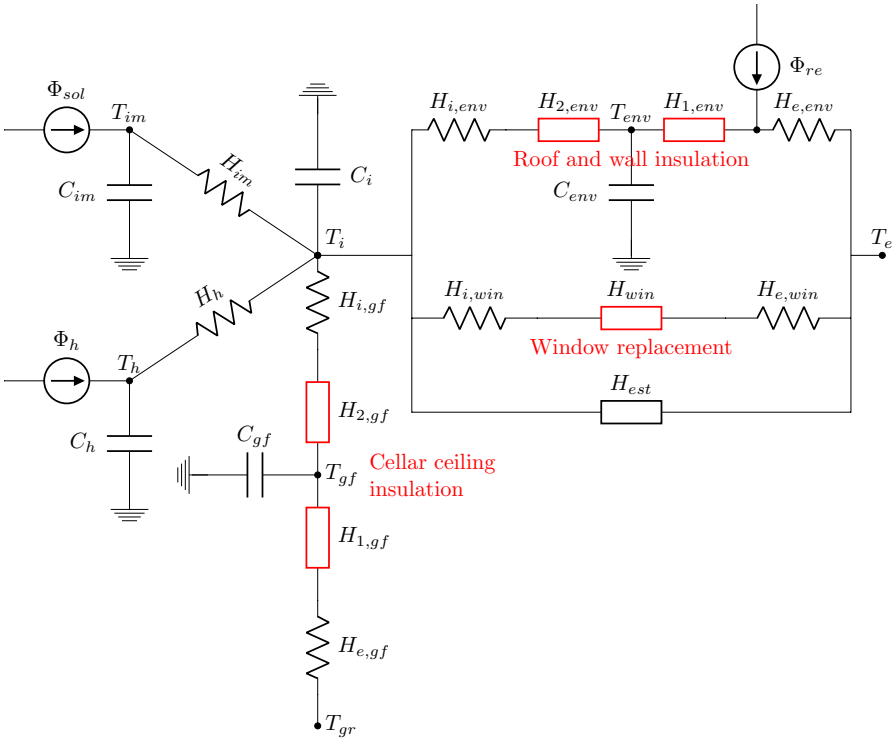

Figure 3: Proposed RC model with retrofit measures.

measures that affect one particular building envelope component. A rather high model order is therefore required. Several previous studies confirmed the feasibility of complex, i.e., high-order RC models that depict building envelope components individually (Braun and Chaturvedi, 2002; De Rosa et al., 2014; Andrade-Cabrera et al., 2016). The studies further showed that high-order RC models are able to simulate the thermal building behavior well, regardless of whether a white-box (calculation of parameters) or grey-box modeling approach (estimation of parameters) was chosen. Yet, grey-box models, i.e., estimated parameters, lead to more accurate model outputs. The performance of white-box models can, however, be significantly improved if individual parameters are estimated.

- Not all model parameters, i.e., R and C parameters, can be estimated using measurement data. No measurement data is available for (future) retrofit measures on the building envelope, so that the model parameters affected by those retrofit measures must be calculated theoretically. Bacher and Madsen (2011), Reynders et al. (2014) and Deconinck (2017) showed that only in higher-order RC models the estimated parameters can be interpreted in physical terms, i.e., they correspond to their theoretically calculated values. Consequently, if some model parameters are to be calculated (based on their physical properties) instead of estimated, a high model order is required. This was successfully demonstrated by (Dimitriou, 2016), who combined estimated and calculated parameters in the same

model, which produced a very accurate output.

- However, Sonderegger (1977), Penman (1990), Bacher and Madsen (2011), Dimitriou (2016), Hedegaard and Petersen (2017) and Bagheri et al. (2018) showed that in high-order models only the estimated R parameters are consistently in good agreement with their calculated values, i.e., can be interpreted in physical terms. The estimated C parameters, on the other hand, can often not be interpreted in physical terms, i.e., they differ from their calculated values in many cases. Accordingly, only R parameters should be calculated in the proposed RC model whereas all C parameters should be estimated. The same studies further showed that even if a single estimated R parameter deviates from its calculated value, the sum of the estimated R parameters is very close to the sum of the calculated values. Accordingly, at least one of the R parameters of the proposed RC model should be estimated.
- Finally, the number of identifiable parameters, i.e., R and C parameters to estimate, should not exceed the number of known input variables and measured state variables (Brastein et al., 2018). Otherwise, the model is over-parameterized and the estimated parameters cannot be interpreted in physical terms, i.e., they strongly deviate from their theoretical/calculated value.

Fifth-order RC model for retrofit analysis

Based on the previously presented modeling principles and the number of known input variables and measured state variables from the case study building, a single zone, fifth-order RC model (five unknown temperature nodes/states) as shown in Figure 3 is proposed. To avoid over-parameterization, the roof and external walls are modeled together as a lumped envelope element (env) with a single thermal capacity. The same applies for the ground floor which is represented with element gf. The windows, on the other hand, are modeled as a lumped element without any thermal capacity (win). Both the internal mass (im) and heating system (h) are modeled as lumped elements with single capacities. Ventilation, infiltration, thermal bridges and doors are represented together with element est. All elements are connected to the internal air node with temperature T_i [°C] and thermal capacity C_i [J/K]. There are five input variables, i.e., heat sources and ambient temperatures: external air temperature T_e [°C], ground temperature at 2 m T_{gr} [°C], heat input from heating system Φ_h [W], solar heat input through windows Φ_{sol} [W] and solar heat input on external surfaces Φ_{re} [W]. While T_e is directly measured, all other inputs are calculated using the measured variables $\dot{V}$, T_{supply}, T_{return}, DNI and DHI. T_{gr} is calculated according to Zürcher and Frank (2018) and the solar heat inputs Φ_{sol} and Φ_{re} according to standard ISO 52010-1:2017. Instead of thermal resistances, heat transfer coefficients are used ($H = 1/R$ [W/K]). The H parameters, which are displayed by serrated resistances, represent surface heat transfer coefficients, while those shown as rectangles represent heat transfer coefficients of building elements. Furthermore, the serrated resistances represent convective (and sometimes radiative) heat transfer while the rectangular resistances represent heat transfer through thermal conduction, i.e., transmission heat gains or losses. The external heat transfer coefficients $H_{e,bec}$ as well as internal heat transfer coefficients $H_{i,bec}$ of building envelope component bec are calculated by multiplying the building envelope area with the appropriate heat transfer coefficient taken from the standard ISO 52016-1:2017. The heat transfer coefficients of the heating surface H_h and internal mass H_{im} are calculated in the same way, estimating the surface areas based on the ground floor area, number of floors and type of heat dissipation system. The following model parameters are estimated using measurement data (grey-box modeling approach): H_{est}, C_{env}, C_{gf}, C_h, C_{im} and C_i. Initial and boundary conditions taken from the standard ISO 52016-1:2017 are used for the estimation to ensure that the estimated parameters lay within a physically plausible range. Model parameters affected by retrofit measures (depicted red in Figure 3) are calculated based on their physical properties, i.e., their surface area and U-value, according to standard ISO 13370:2017. The U-values are reduced by retrofit measures on the respective envelope component, whereas their impact on the heat capacity is neglected. This assumption seems reasonable in view of the low density of the retrofit insulation materials and their small volume. The heat transfer coefficient of the lumped envelope element H_{env} is affected by both retrofit measures on the roof and the external walls.

Results

Model validation

The correlation coefficients of each two estimated parameters are below |0.98| indicating that the model is not over-parameterized. The estimated H_{est} together with the calculated H parameters lead to an HLC of 484 W/K. The simulated hourly internal air temperature (T_i) over the training period is shown in Figure 4. The corresponding results for the test period are shown in Figure 5. The mean value of the simulated temperatures (21.90 °C) over the training period deviates by −0.68 % from the mean value of the measured temperatures (22.05 °C). For the test period, the mean value of the simulated temperatures (21.64 °C) deviates by −1.27 % from the mean value of the measured temperatures (21.91 °C).The model performance in terms of hourly output, i.e., the agreement between the simulated hourly T_i and the measured hourly T_i, is described by the MAE, MAPE and

MSE, which are shown in Table 2.

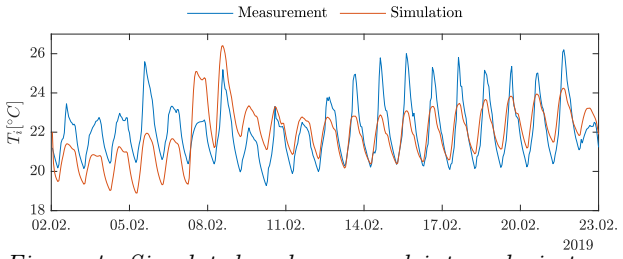

Figure 4: Simulated and measured internal air temperature during the training period.

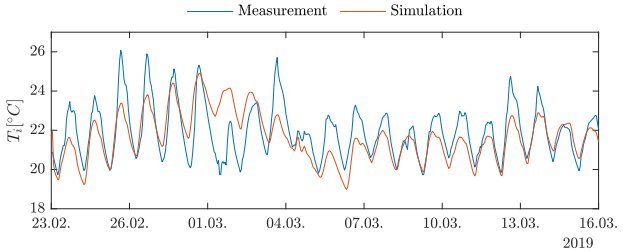

Figure 5: Simulated and measured internal air temperature during the test period.

Table 2: Model performance for T_i.

	MAE [°C]	MAPE [%]	MSE [°C]
Training period	1.06	4.79	1.58
Test period	0.86	3.92	1.25

Heating demand simulation

Figure 6 shows the simulated heating demand compared to the heating demand calculated according the Swiss standard SIA 380/1, which is given in the energy audit report of the case study building. Both heating demands, accumulated over the whole year, are shown in Figure 7. The simulated heating demand amounts to 28 630 kWh while the heating demand according to the standard amounts to 39 170 kWh. Additionally, the measured heating energy consumption of 30 660 kWh is indicated by a red line. However, the measured heating energy consumption does not yet take into account the efficiency of the oil boiler, i.e., the actual heating demand is lower. Consequently, the simulation yields a heating demand which is much closer to the real heating demand than the heating demand calculated according to the Swiss standard SIA 380/1.

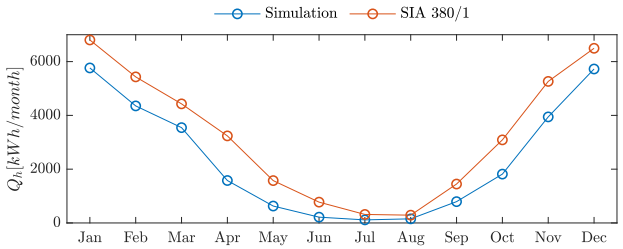

Figure 6: Simulated heating demand compared to Swiss standard SIA 380/1 heating demand.

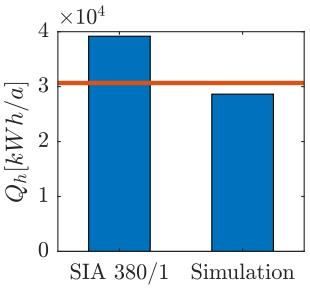

Figure 7: Comparison of annual heating demands with measured consumption (red line).

Retrofit analysis

The annual heating demand was simulated for each of the 16 combinations of retrofit measures on the building envelope shown in Table 3. For each combination, which is defined with a code, it is indicated which components of the building envelope are retrofitted. The retrofit measures themselves are described in Table 1. The simulated heating demands for each retrofit strategy are shown in Figure 8. If all four building envelope components are retrofitted (code 4), the heating demand is reduced by 48 %.

Table 3: Different retrofit strategies.

Code	Roof	Walls	Windows	Cellar ceiling
0				
1a	✓			
1b		✓		
1c			✓	
1d				✓
2a	✓	✓		
2b	✓		✓	
2c	✓			✓
2d		✓	✓	
2e		✓		✓
2f			✓	✓
3a	✓	✓	✓	
3b	✓	✓		✓
3c	✓		✓	✓
3d		✓	✓	✓
4	✓	✓	✓	✓

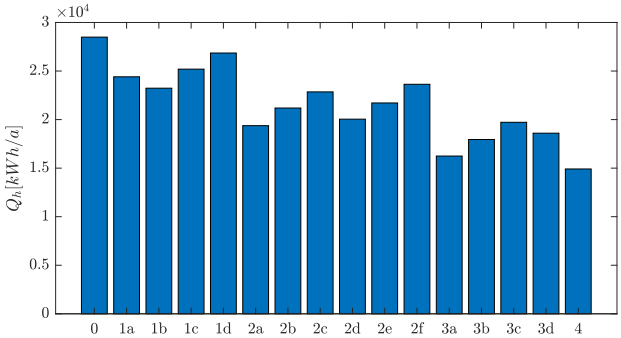

Figure 8: Heating demand of retrofit strategies.

Discussion

The proposed RC model is not over-parameterized as none of the model parameters are strongly correlated. This means that the same RC model structure, i.e., the same network topology, can be used for further simulations. The estimated H parameter, H_{est}, leads to a physically meaningful result: the overall HLC amounts to 484 W/K, which is only 5 % below the value from the energy audit report. Since the RC model was calibrated using in-situ measurements, it is assumed that the estimated HLC is more accurate than the calculated value from the energy audit report. This is supported by the fact, that the report also clearly overestimates the heating demand compared to the measured energy consumption.

For the T_i simulation, the RC model needs a few days until it is calibrated or "trained": the model output is quite inaccurate during the first six days of the training period. However, this effect is only visible during the training period. In the test period, the model output is accurate from the start, as the state temperatures have already stabilized around an equilibrium. Except for the first few days in the training period, the RC model simulation yields good results. The course of the temperature fluctuations is well simulated. It must be emphasized that this is not a 1-step prediction, but that the internal air temperature is predicted for three weeks, which corresponds to a total of 504 steps. The RC model shows deficits especially at the temperature peaks at noon, which are not well simulated. The temperature peaks are due to the high solar heat inputs, which are caused in particular by the glazed winter garden. Since the building is modeled as a cuboid, such special geometries (as the attached winter garden) are not taken into account properly. The fact that the temperature peaks are not fully simulated is also shown by the MAE, MAPE and MSE. However, the simulated T_i deviates on average only by 4.8 % from the measured temperature. Considering that the MAPE of the simulated T_i is below 5 % and the unusual geometry and high glazing of the building, the model performance can thus be rated high. Additionally, the fact that the model output for the test period is more accurate than the output for the training period confirms that the model is not over-trained. Otherwise, the training period would have had to be shortened.

Over the year, the simulated heating demand follows a similar trend as the heating demand calculated according to the Swiss standard SIA 380/1. However, the simulation output is constantly lower than the standard value. This is also reflected in the annual total: the simulated heating demand is almost 27 % below the standard value. A comparison with the actually consumed heating energy shows that the RC model simulation is much more accurate. If the efficiency of the oil boiler is also taken into account, the actual or "true" heating demand is probably even lower than the simulated one. Consequently, the RC model yields a very accurate annual heating demand.

For the 16 different retrofit strategies, the RC model delivers realistic results which, unfortunately, cannot be verified using measurement data. Further case studies are therefore required, where the buildings can ideally be examined before and after a retrofit. This would allow to validate how well the RC model simulates retrofit measures. Nevertheless, the RC model seems to yield plausible results. Depending on the type and number of retrofit measures, the heating demand is significantly reduced. If all four components of the building envelope are retrofitted, the heating demand is almost halved. In the energy audit report of the case study building a reduction of 35 % (compared to the original heating demand from the report) is calculated for the retrofitting of roof, windows and floor. This corresponds to combination 3c, for which a reduction of 31 % is simulated with the RC model (compared to the originally simulated heating demand). Although both results are in the same range, the model predicts lower savings, which seems realistic as energy performance ratings often overestimate savings (rebound effect).

One limitation of the proposed model is that the occupant behavior is partially neglected. The heating behavior of the occupants and their favoured room temperatures are taken into account, but short-term ventilation is not. Long-term ventilation (e.g., when a window is constantly tilted), in contrast, can be taken into account by the model.

Conclusion

We propose a fifth-order RC model that is able to simulate not only the thermal behavior of the current building state but also the energy savings of different retrofit strategies. Geometric and physical building information (area specifications and U-values) as well as hourly in-situ measurements are required to set up and calibrate the model. In a case study, the RC model was successfully calibrated, validated and applied in heating demand simulations for different retrofit strategies. The proposed RC model seems to prevent prebound effects as it does not over-estimate the current heating demand. This makes it a valuable tool to fight the performance gap. It also estimates lower energy savings than the energy performance rating which might indicate that it also prevents rebound effects. However, this needs to be verified with post-retrofit measurement data first. Nevertheless, we see great potential in the proposed RC model as a data-driven decision-tool in the building retrofit process.

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