Calibration of the Energy Simulation Models using Tikhonov-Type Regularization: Application to a Residential Building Apartment

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Abstract

It is well known that the calibration of building energy models is an under-determined problem, whether subjected to hourly or monthly calibration criteria. In fact, while it is possible to identify a large number of calibrated models, it is not clear which offer a good representation of the building behaviour. For a calibration methodology of building energy models to be effective, it should automate and speed-up calibration processes. This is especially important when the number of model parameters is too large to tune manually. Moreover, when the number of model parameters is too large, the probability to find the real parameter combination using statistical sampling methods is very small. Instead, we suggest performing a guided search of the parameter space, e.g. solving a parameter optimization problem. Since Tikhonov-type regularization has been applied successfully to many ill-posed inverse problems, we propose adopting the same methodology to find optimal parameters for building energy models. The regularization term can be interpreted as imposing certain a-priori distributions on model parameters as identified by an energy audit. As an illustration, the study case of a residential apartment is calibrated and we show that regularization more accurately predicts the energy demand estimate after the retrofit of the study case.

1. Introduction

It is well known that the calibration of building energy simulation models against the monitored energy demand, is an under-determined problem (Alifanov et al., 1995), whether subjected to hourly or monthly calibration criteria. To account for model uncertainty, the identification of more than one calibrated model is advised (ASHRAE, 2002). While it is possible to identify a large number of calibrated parameter sets, it is not clear which offer a reasonable representation of the real building. The importance of reducing parameter uncertainty in building energy models, lies in the increased confidence in the calculation of savings for the intended energy conservation measures (Heo et al., 2012), as well as in the reliable prediction for model predictive controls (Schirrer et al., 2016), to name just a couple of applications.

In order to rank different calibrated models, Reddy et al. (2007) introduce an aggregated index incorporating a number of statistical indicators representing the agreement between simulation data and data reported on monthly utility bills. However, the calibration process can result in large standard deviations for certain influential model parameters. Caucheteux et al. (2013) calibrated an energy simulation model for a house based on hourly monitoring data. They noticed that, although the deviation of some influential parameters seems to decrease as the calibration period increases, some parameters can cancel each other out, thus a significant parameter deviation remains. Alternatively, Heo et al. (2012) proposed a probabilistic approach based on the Bayesian calibration of energy models to match monthly gas consumption values. Unlike deterministic methods, in a Bayesian approach a distribution function of each model parameter is sought, it directly provides the quantification of uncertainty.

Recently, optimization-based approaches have been utilized in simulation model calibration (Tahmasebi et al., 2012), where the cost function sums up the discrepancy between simulation and monitoring data. Solving an optimization problem for a parameter combination which optimally matches the monitored data, leads to further automatization of the

calibration process. However, the danger of the cancellation effect of two or more parameters remains. In this way, parameters may also reach the boundaries of the predefined parameter range, thus taking on less plausible values.

Regularization has already been successfully applied to many ill-posed inverse problems including the calibration of financial market models (Crépey, 2003), geophysical models (Zhdanov, 2002), and even in meteorology and oceanography (Navon, 1998). We propose adopting the Tikhonov-type regularization to find optimal parameters for building energy models. When regularization is applied, priority is given to those solutions which are ranked closer to the modeller's initial guess.

In Section 2 we introduce the proposed methodology, and its application to a residential building apartment is presented in Section 3. Finally, the conclusion and the discussion on further research are given in Section 4.

2. Calibration Methodology

The goal of developing an effective calibration methodology for building energy models is to automate and speed-up the calibration process, which is especially convenient when the number of model parameters is too large to tune manually. In the literature, there is a clear consensus that the first phase of the calibration procedure consists in an energy audit of the building and the acquisition of monitoring data, followed by an initial model development and the identification of uncertain model parameters (Coakley et al., 2012; Raftery et al., 2011). In the second stage, the dimension of the parameter space is typically reduced using a sensitivity analysis, and the calibration criteria are chosen (and potentially the validation criteria) based on the acquired monitoring data and the simulation results of the initial model (Fig. 1). However, a number of different methods for the final calibrated energy model(s) identification are used in the literature. Not all include a validation step. In earlier approaches, the parameters were tuned manually, based on the expertise of the modeller. This process was later automatized, mostly using the statistical sampling of the parameter space to evaluate different parameter combinations.

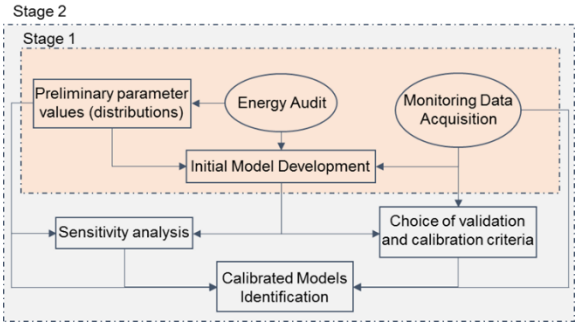

Fig. 1 – Typical building energy model calibration procedure

The calibration process can be further automatized using a guided search (e.g. optimization algorithm) to directly identify optimal parameter combinations. In the rest of this chapter, we present a regularization-augmented optimization-based approach to building energy model calibration. This approach aims at reducing the model uncertainty that arises from common practice.

2.1 Parameter Space and Probability Distribution

We assume we have an initial simulation energy model of the building, and that the number of model parameters was reduced by sensitivity analysis. Let $p = (p_1, \dots, p_n) \in \mathbb{R}^n$ be the model parameter vector, where $p_k \in [p_k^{min}, p_k^{max}]$ lies in the realistic range chosen by the modeller based on an energy audit and/or various datasheets on material properties, internal gains, etc.

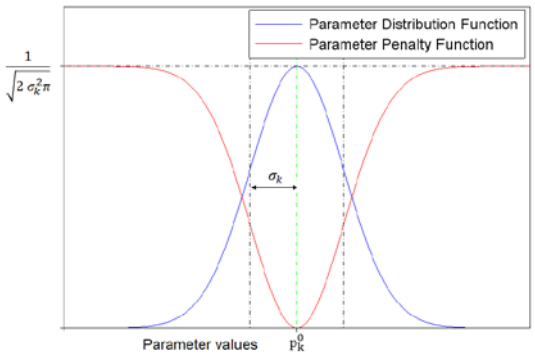

Fig. 2 – Parameter distribution and penalty function

Parameter ranges should be chosen wide enough to include all plausible values for the given case, even if their probability is low. We also assume that for some parameters it was possible to give an initial guess p_k^0 as well as choose an a-priori probability distribution function. For example, the normal distribution $p_k \sim N(p_k^0, \sigma_k)$ can be assumed (Fig. 2), where a modeller provides an appropriate deviation estimate σ_k. The higher the certainty of the initial guess p_k^0, the lower the deviation σ_k.

2.2 Optimization Problem

In order to identify the parameter vector p that fits the monitoring data, a constrained optimization problem is defined to minimize the error between the monitored and simulated energy demand:

$$\min J(p), \quad \text{where } p_k \in [p_k^{min}, p_k^{max}] \qquad (1)$$

In order to optimally represent the building under consideration, the cost function should also include an a-priori knowledge on the parameter probability. Hence, the cost function $J(p)$ is designed as summation of the cumulative absolute simulation error for temperature and heating demand, and a regularization term representing penalization depending on parameter probability:

$$J(p) = \sum_{j=1}^{N}\left(w_T\left|T_j^m - T_j^s\right| + w_Q\left|Q_j^m - Q_j^s\right|\right) + \sum_{k=1}^{N} w_k \, f_{pen,k}(p_k). \qquad (2)$$

Here, T and Q denote indoor air temperature and cumulative heating demand, respectively. Superscripts m and s represent measured and simulated values respectively, and subscript j denotes the corresponding value at the jth time step. Since scales for the temperature and heat demand vary largely, the corresponding error terms should be balanced using appropriate weights w_T and w_Q. However, since the goal of the calibration is to accurately predict the heating demand, the corresponding error should still be dominant. Adding a regularization term can be interpreted as imposing certain a-priori distributions on model parameters. Here $f_{pen,k}(p_k)$ and w_k denote the penalty function and weight for each parameter p_k. The penalty term $f_{pen,k}$ should increase as $|p_k - p_k^0|$ increases, i.e. when parameter p_k takes less probable values. For this reason let

$$f_{pen,k}(p_k) = \tilde{f}_{pen,k}(|p_k - p_k^0|) \qquad (3)$$

such that $\tilde{f}_{pen,k} : \mathbb{R}^+ \to \mathbb{R}^+$ is a monotonically increasing function. Hence, it could be defined as (Fig. 2):

$$f_{pen,k}(p_k) = \frac{1}{\sqrt{2\,\sigma_k{}^2}}\left(1 - e^{-\frac{(p_k - p_k^0)^2}{2\,\sigma_k^2}}\right). \qquad (4)$$

Since the penalty term not necessarily needs to be defined as a weighted norm, it represents a generalization of the Tikhonov regularization. The problem (1) can be observed as a multi-objective optimization problem, where a trade-off is made between minimizing the simulation error and maximizing the parameter probability.

3. Study Case Model Calibration

In this section, the methodology introduced in Section 2 is illustrated on a residential building apartment model. The presented results offer evidence of regularization benefits on the retrofit prediction and model parameter estimation.

3.1 Study Case Description

The residential building under consideration is located in the south of Madrid, Spain. Built in the 1960s, with poorly fitted windows, no insulation and cracks around doors, windows, and foundations, it was deemed suitable for retrofit. On the eastern side, it is attached to a twin residential building (Fig. 3).

Fig. 3 – Study case residential building

Each block contains five 50 m² apartments. The study case apartment is located in the west block on the last floor (Fig. 4).

It used a gas boiler with five water radiators for the heating in winter and a split unit for the cooling in summer. Monitoring data is available for one year before the retrofit (September 2014 — September 2015), and two months after the installation of new windows and insulation layers on the envelope (January 2016 – March 2016).

The acquired real-time data with 15 min samplings include internal (IAT) and external (EAT) temperatures, global solar radiation, CO_2 concentration, and electric consumption. A heat meter on supply and return pipes of the gas boiler was also installed to monitor the heating energy. The heating demand at each time step is easily calculated as the increase in the measurement of heating energy. The internal temperature of the apartment below was monitored as well, but not the one of the apartment adjacent on the eastern side.

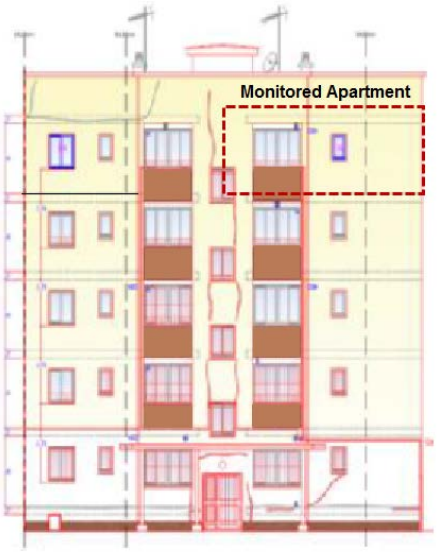

Fig. 4 – Front view

3.2 Initial Building Energy Model

The initial energy model for the whole building was developed in the dynamic environment of TRNSYS Simulation Studio (Klein et al., 2010), where the building geometry was developed in Google SketchUp and set up in TRNBuild. The model is based on the information provided by the energy audit (Garcia et al., 2014), including building plans, envelope structure, openings, air tightness, internal partitions, shading elements, and occupancy. Each apartment is divided in two thermal zones, north and south oriented (see Fig. 5). Since the heating setpoint of the apartment is unknown, we assume an ideal heating. An infiltration coefficient is used when the windows are closed, and another when windows are open. Internal heat gains from occupants and equipment are included, where 75 W/person is assumed and heat gain from electric appliances is estimated based on real-time electric meter measurements and guidelines by ASHRAE (1985). The shading model is based on an on/off differential controller that takes into account the indoor air temperature and solar irradiance at each window according to its orientation. Shading is activated when both indoor temperature and solar irradiance on horizontal plane exceed a certain threshold. The threshold for the temperature controller is equal to the calibration parameter p_4, and 250 W is chosen for the solar irradiance controller. The external shading factor is the calibration coefficient p_3 taken to be the same for all windows in the apartment. The new control value for each controller is the output control signal from the previous time step, by introducing a hysteresis effect. Therefore, both lower and upper deadband for the difference between actual and threshold values, also need to be defined. These deadbands are chosen to be -0.5 °C and 0.5 °C for the temperature controller, and -50 W and 0 W for the solar radiation controller. The shading activation is an adaptation of the controller values defined by Dott et al. (2013).

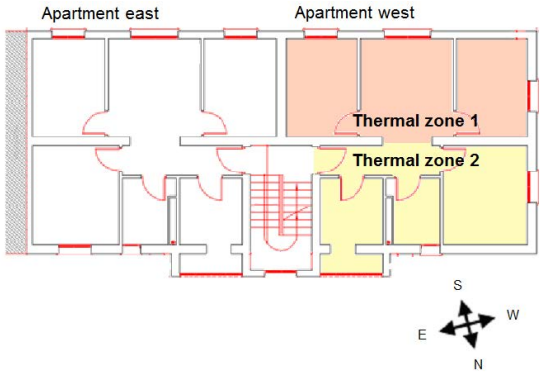

Fig. 5 – Building cross-section

The sensitivity analysis was performed using the Morris method (Saltelli, 2008), and significant

model parameters for the energy demand assessment were identified (Table 1).

Table 1 – Significant model parameters

Parameter	Description [Unit]
p_1	Internal temperature of the adjacent apartment [°C]
p_2	Occupancy multiplication factor [-]
p_3	Shading factor [-]
p_4	Shading activation temperature [°C]
p_5	Infiltration with windows closed [ACH]
p_6	Total infiltration and ventilation with windows open [ACH]
p_7	Conductivity of the concrete layer in the external walls [W/(m K)]
p_8	Conductivity of the concrete layer in the internal partitions, floors and ceilings [W/(m K)]
p_9	Conductivity of the concrete layer in the roof [W/(m K)]
p_{10}	Window U-value [W/(m² K)]

The outcome shows that the IAT of the adjacent apartments (p_1) has a strong influence on the heat demand. Parameter p_2 represents the correction factor for the assumed occupant's heat gain. In addition, the parameters of the shading model (p_3, p_4) are mostly significant in the summer and swing period. Infiltration parameters (p_5, p_6) turn out to have a strong effect on both IAT and heat demand, as expected. To account for possible errors in layer description of the external and internal walls, floor and roof, and the fact that walls are reinforced, we have included the conductivity of the concrete as uncertain model parameters (p_7, p_8 and p_9). Parameter p_{10} represents the windows U-value. Since for a number of apartments in the building, additional windows were already installed, we want to prove our hypothesis that the monitored apartment has double windows. As an initial point, minimum and maximum values of each parameter were defined (Table 2), based on the energy audit and by consulting various standards and datasheets.

Table 2 – Parameter range and initial guess

Parameter	p_k^{min}	p_k^{max}	p_k^0	σ_k
p_1	17.6	24.6	18.6	-
p_2	0.5	2	1	0.3
p_3	0	1	0.5	-
p_4	22	32	25	-
p_5	0.15	0.75	0.4	0.6
p_6	0.4	5.2	3	-
p_7	0.8	2.5	1.13	0.35
p_8	0.8	2	1.13	0.35
p_9	0.8	2	1.13	0.45
p_{10}	2.74	5.68	2.83	-

In particular, the initial guess for the infiltration parameter (p_5) is based on the blower-door test which was performed during the energy audit (Table 3).

Table 3 – Blower-doors test results

ΔP [Pa]	Flow [m³/h]	ACH
20	200	2.0
30	276	2.8
50	382	3.9
65	471	4.7

The airflow through the building envelope and the pressure difference across it are known to have the following relationship (Sherman, 1987):

$$q = \mathrm{C}\,(\Delta \mathrm{P})^n \qquad (5)$$

Here ΔP is the induced pressure difference (in Pa), q is the airflow through the building envelope (in m³/h), and C is the air leakage coefficient. To determine the parameters n and C, the least-square tech-

nique is applied to the blower-door test results following ISO standard (ISO/TC 163/SC 1, 2015). The reached values $n = 0.67$ and $C = 260$ have a standard deviation estimate 0.02 and 3 respectively, and $r^2 = 99.7$ %. In order to estimate the average air infiltration, stack-dominated and wind-dominated components are evaluated separately (Klems, 1983). From one year measurement data, the average indoor air temperature, the temperature difference between the indoor and external air, and the air density were obtained and used to calculate the average stack effect pressure difference to be $\Delta P_{se} = 1.03$ Pa. From the meteorological data, the average wind speed in Madrid is estimated to be 2 m/s, implying a wind pressure difference equal to $\Delta P_w = 1.23$ Pa. Hence, the stack effect air infiltration and the infiltration due to the wind are equal to 0.3 ACH and 0.27 ACH respectively, which implies an infiltration rate of 0.4 ACH (Klems, 1983). The occupancy multiplication parameter p_1 is estimated to be equal one, where we assume that 75 W/person provided by ASHRAE (1985) is a well-studied approximation. The conductivity of the concrete found in the walls, floors and partitions (p_8, p_9 and p_{10}) is provided by the refurbishment architect during the energy audit (Garcia et al., 2014). These initial guesses are considered reliable and are assigned a divergence factor. The corresponding penalty is added to the cost function of the optimization problem. The window U-value and the shading coefficient are estimated with less certainty by inspecting the windows and the indoor temperature. Since ventilation rates with open windows (p_6) cannot be easily estimated, a wide parameter range was chosen and the approximate mean value was selected as the initial guess. Initial guesses that are not reliable are not included in the regularization term.

3.3 Calibration and Validation Procedure

The monitoring data was divided into three periods: the calibration period (September 11, 2014–January 31, 2015), and the validation period before (February 01, 2015–April 12, 2015) and after the renovation (January 21, 2016–March 29, 2016). Opening of the windows and occupancy in the apartment were identified on the basis of CO2 levels. Measured IATs were set as the heating setpoint in the monitored apartment and for the apartment below. However, the IAT measurement is not available for the apartment adjacent on the eastern side, which is therefore treated as an unknown model parameter (p_1). Although the whole building is simulated, the results for the monitored apartment were considered just in the cost function. The heating demand and the average indoor air temperature during the heating season are summarized in Table 4.

Table 4 – Monitoring data summary

Period	Heat demand [kWh]	Average heating IAT [°C]
Calibration	3755	21.91
Validation 1	2252	21.76
Validation 2	1222	22.62

Since the ideal heating is assumed and the IAT is taken as the setpoint, the temperature error is negligible in the heating periods. Therefore, it is included in the cost function only when there is no heating. Used weight coefficients are $w_T = 0.65$ and $w_Q = 5.7e-3$, in order to approximately achieve a 1:4 ratio between temperature and energy demand error. For a regularized solution $w_k = 100$ is taken. As soon as the optimization problem was solved, the models were validated on a new set of monitoring data. Since the average measured heating power was 1.9 kW, the sensor resolution of the heating demand (1 kWh) was not suitable to take into consideration the normalized mean bias (NMB) and the coefficient of variation of root mean square error (CVRMSE) on an hourly basis. Instead, the daily NMB and CVRMSE were reported. The recommended calibration criteria per ASHRAE (2002) for hourly values are NMB ≤±10 % and CVRMSE ≤30 %, and NMB ≤±5 % and CVRMSE ≤15 % for monthly data. However, according to the knowledge of the authors, there are no standard criteria for daily values. Hence, as daily criteria we use a combination of ASHRAE defined criteria: NMB ≤±5 % and CVRMSE ≤15 % for calibration, and NMB ≤±5 % and CVRMSE ≤30 % for validation. For model validation after the renovation, models were

adapted to include new windows, the corresponding infiltration parameter and insulation layers, as specified in the manufacturers' datasheets.

3.4 Regularized and Non-Regularized Solution

Hybrid algorithm combining Particle Swarm optimization and Hooke-Jeeves optimization algorithms from GenOpt (Wetter, 2009) were used to solve the optimization problems. Regularized and non-regularized solution models were obtained using the same algorithm parameters and the initial parameter set, solving optimization problem (1), where the cost function (2) in the former case includes also the regularization term. The obtained parameter sets are reported in Table 5. Both models yield zero shading since otherwise the simulated IAT would be much lower than monitored. However, four parameters of the non-regularized model reach boundary values of the pre-defined parameter range. For example, when the windows are open infiltration reaches minimal 0.4 ACH, thus contradictory since it is smaller than the infiltration with windows closed (0.62 ACH).

Table 5 – Calibrated model parameters

Parameter	Regularized	Non-regularized
p_1	18.08	18.6
p_2	1.25	2
p_3	0	0
p_4	28	30
p_5	0.35	0.62
p_6	1.46	0.4
p_7	1.13	0.88
p_8	1.51	1.99
p_9	1.13	1.99
p_{10}	2.74	2.74

We also note that the conductivity of the concrete in internal partitions and roof also reaches the maximum value of the interval. Compared with the regularized solution, these values are significantly larger and result in larger transmission losses through the roof. And also, a larger infiltration when windows are closed results in a larger infiltration loss compared to the regularized solution. These losses are counterbalanced by a higher gain from the occupants (150 W/person, maximum value), a reduced infiltration when windows are closed, and less transmission losses through external walls. The parameters of the non-regularized model that reach minimum or maximum values represent possible, but highly unlikely, scenarios. Table 6 summarizes the calibration results for both models. Both models satisfy the calibration criteria. Also the average absolute error (AAE) for cumulative heat demand and temperature calculated at 15-minute intervals is considered.

$$AAE\ Heat = \frac{\sum_{k=1}^{n} \left| \int_{t_0}^{t_k} (\dot{Q}^s - \dot{Q}^m)\,\mathrm{dt} \right|}{n} \frac{100}{\int_{t_0}^{t_n} \dot{Q}^m\,\mathrm{dt}} \qquad (6)$$

$$AAE\ Temp = \frac{\sum_{k=1}^{n} |T_k^s - T_k^m|}{n} \qquad (7)$$

$\dot{Q}_{sim}$ and $\dot{Q}_{mea}$ are simulated and measured heating power. Average absolute heating demand error amounts to 0.45 % and 0.34 % of the total measured heating energy demand (3755 kWh, see Table 4) for the regularized and non-regularized solution.

Table 6 – Calibration error (Sep 11, 2014 – Jan 31, 2015)

	Regularized	Non-regularized
NMB	-0.85	-0.47
CVRMSE	9.57	10.3
AAE Heat [kWh]	11.64	12.6
AAE Temp [°C]	1.24	1.09

Table 7 reports the error for both solutions in the validation period before the renovation.

Table 7 – Pre-renovation (Feb 01, 2015 – Apr 12, 2015) validation results

	Regularized	Non-regularized
NMB	-3.97	-3.53
CVRMSE	22.38	22.98
AAE Heat [kWh]	82.12	78.09
AAE Temp [°C]	0.92	0.82

The total measured heating demand for the validation period reads 2252 kWh, and the values predicted by the regularized and the non-regularized solution are 2150 kWh and 2157 kWh, which represents under-prediction of 4.44 % and 4.22 % respectively.

Both models satisfy the validation criteria. The regularized solution has a slightly better performance with respect to NMB and CVRMSE, while the non-regularized solution has lower average absolute errors. The model predictions for the post-retrofit period are given in Table 8. The total monitored heating demand in that period is 1222 kWh. The predictions obtained by regularized and non-regularized solution read 1173.8 kWh and 1099 kWh, hence the models under-predict the demand by 3.9 % and 10.1 %, respectively. The regularized solution yields a better estimate of the building energy demand after the renovation. The non-regularized solution underestimates the heating demand by over 10 % because it overestimates the occupant internal gain, while it underestimates the infiltration losses.

Table 8 – Post-renovation (Jan 21, 2016 – Mar 29, 2016) validation results

	Regularized	Non-regularized
NMB	-3.66	-10.1
CVRMSE	25.3	29.9
AAE Heat [kWh]	19.66	47.9
AAE Temp [°C]	0.89	0.76

4. Discussion and Further Research

We have illustrated how calibrated and validated building models do not necessarily provide good renovation savings estimates. The parameter optimization method for complex building energy models presented in this work aims to reduce the parameter uncertainty and thus the prediction error by utilizing regularization. The proposed method is in general useful when the number of model parameters is large, since the chances to perform a good search of the parameter space by using statistical sampling, is small and the model uncertainty increases. The performance of a guided search of the parameter space instead is advantageous, e.g. it solves a parameter optimization problem.

This work also highlights the importance of a good preliminary estimation of the building parameters; otherwise, unrealistic parameter combinations may emerge as optimal in the calibration phase.

The success of the regularization strongly depends on the choice of the penalty weight in the cost function. How to optimally choose this value has not been considered here and is a topic for further research. A possible approach is to address (1) as a multi-objective optimization problem and evaluate different Pareto optimal solutions. Finally, although only the heating demand was considered, this method naturally extends to the calibration of the models with respect to both the heating and the cooling demand.

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Nomenclature

Symbols

C	Air pressure leakage coefficient
$f_k(p_k)$	Penalty function for kth parameter
$J(p)$	Cost function
n	Air pressure exponent coefficient
p_k	kth model parameter
p	Parameter vector
q	Air flow through building envelope
Q	(Cumulative) Heating demand
$\dot{Q}$	Heating power
T	Indoor Air temperature
w_k	Weight for kth parameter p_k penalty function
w_Q	Weight for heating demand error
w_T	Weight for temperature error
ΔP	Induced pressure difference

Subscripts/Superscripts

j	Value at the jth time step
m	Monitored value
s	Simulated value
se	Stack-effect dominated value
w	Wind dominated value

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