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A CASE STUDY OF OPTIMIZATION-AIDED THERMAL BUILDING PERFORMANCE SIMULATION CALIBRATION

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ABSTRACT

Building performance simulation is being increasingly deployed beyond the building design phase to support building operation. Specifically, the predictive feature of the simulation-assisted building systems control strategy provides distinct advantages in view of building systems with high latency and inertia. Such advantages could be exploited only if model predictions could be relied upon. Hence, it is important to calibrate simulation models based on monitored data. In the present paper, we report on the use of optimization-aided model calibration in the context of an existing university building. Thereby, our main objective was to deploy data obtained via the monitoring system to both populate the initial simulation model and to maintain its fidelity through an ongoing optimization-based calibration process. The results suggest that the calibration can significantly improve the predictive performance of the thermal simulation model.

INTRODUCTION

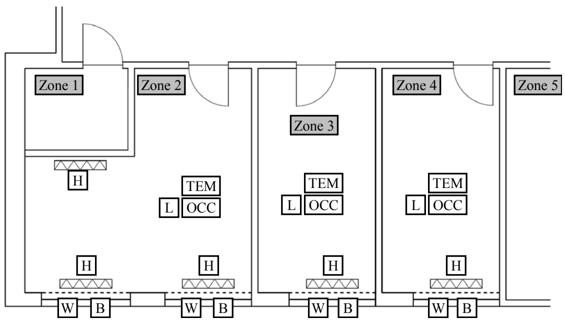
Building performance simulation tools are conventionally used to predict the future performance of building designs. More recently, however, the potential for the deployment of simulation in the buildings' operation phase is being explored. Needless to say, the quality of any simulation-based building operation system greatly depends on the reliability of the deployed simulation model (Mahdavi 2001).

Thus, to ensure that predictions are dependable, applied simulation models must be calibrated. Moreover, given the dynamic nature of building operation, some input parameters of the model may have to be subjected to calibration on a recurrent basis (Mahdavi and Tahmasebi 2012). This circumstance implies that the calibration task cannot be approached as an ad hoc or one-time activity. Rather, it needs to be conducted on a systematic basis. Consequently, the entire calibration process should be preferably automated to ensure efficiency and consistency (Tahmasebi et al. 2012). Given this background, the present contribution reports on a case-study of monitoring-based optimization-aided thermal performance model calibration.

METHODOLOGY

The monitored building

An existing office building in Vienna, Austria, was selected as a case study to evaluate the potential of an optimization-aided thermal simulation model calibration. This building was equipped with a monitoring infrastructure in the course of a previous research project. Thus, various streams of data are gathered from three offices within the building, including time-varying parameters such as the state of windows (open/closed), blinds (open/closed), lights (on/off), occupancy (absence/presence), and heat emission of the radiators. Figure 1 shows the floor plan of the building and the thermal zoning in the simulation model. The Figure includes also the location of the installed sensors.



Window contact	[W]	Heat power	[H]
Occupancy	[OCC]	Light	[L]
Blind	[B]	Temperature	[TEM]

Figure 1 Building floor plan, thermal zones and installed sensors

The building model

The whole-building simulation engine EnergyPlus 7.0 (EnergyPlus 2012), was used in the case study. In order to create the initial model, first building geometry and thermal properties of components were specified. Each monitored room was modeled as a separate thermal zone (zones 2, 3, 4 in Figure 1). Moreover, the adjacent non-monitored zones were included in the model, because they are used in a number of calibration scenarios to control the boundary conditions of the monitored spaces.

As the second step in developing the initial model, we populated the model with the above-mentioned streams of data provided by the monitoring system. Incorporating the values of time-varying input parameters into the model was accomplished with the aid of a Matlab script (Matlab 2012). This program calls different streams of monitored data from building management system database and converts them to compact schedules using EnergyPlus input file syntax. These schedules are later assigned to the corresponding input parameter in the model.

Run periods

The model calibration and validation process involved a monitoring period of five months including two summer and two winter periods. Table 1 demonstrates these run periods.

Table 1 Run periods

PERIODS	START DATE	END DATE
1. 1st summer period	10.06.2011	23.07.2011
2. 2nd summer period	24.07.2011	26.08.2011
3. 1st winter period	15.02.2011	24.03.2011
4. 2nd winter period	15.02.2012	24.03.2012

Optimization-aided calibration

In an optimization-aided simulation model calibration, the objective function addresses the error in simulated output (in this case zone mean air temperature). A number of input parameters of the model are systematically varied within specified ranges, in order to minimize the objective function. To execute the optimization process, the generic optimization tool Genopt (LBNL 2012) was selected. This tool supports the efficient inclusion of simulation data from applications such as EnergyPlus in the course of the optimization (Wetter 2001).

The optimization algorithm was the hybrid generalized pattern search with particle swarm optimization algorithm. This is one of the recommended generic algorithms for problems, where the cost function cannot be explicitly stated, but can be approximated numerically by a thermal building simulation program (LBNL 2012).

Calibration studies

To arrive at a calibrated simulation model of the offices under study, a sequence of simulation and calibration studies was conducted in terms of the following steps:

1. A single zone model (zone 3, Figure 1) was generated based on available information about the building and the monitored data. The monitored air temperature of the adjacent offices was used as boundary conditions of the zone. This model was simulated for all specified run periods (Table 1). The model evaluation statistics were derived based on the monitored and simulated zone mean air temperature.
2. The single zone model was calibrated for the first run period (1st calibration). In this calibration, eight input parameters of the model were subjected to the optimization-based calibration (Table 2). Subsequently, the calibrated single zone model was evaluated for all run periods.
3. A three-zone model of the building was developed (zones 2, 3 and 4, Figure 1). This model was fed with the optimized values of the eight input parameters that were calibrated in step 2. The model was simulated and evaluated for entire run periods.
4. The three-zone model was calibrated for the first summer period (2nd calibration) and validated for the second summer period. In this calibration step, only the infiltration and ventilation rates were subjected to optimization.
5. The three zone model was calibrated for the first winter period (3rd calibration) and validated for the second winter period. Similar to step 4, this calibration had two variables, namely infiltration and ventilation rates.
6. A five-zone model was generated by adding the adjacent unmonitored spaces (zones 1 and 5, Figure 1). The mean air temperature of these two zones during the 1st summer period was subjected to the 4th calibration. The resulting model was validated for the 2nd summer period.
7. Using the five-zone model, the mean air temperature of the adjacent zones (zones 1 and 5, Figure 1) during the 1st winter period was subjected to the 5th calibration. The resulting model was validated for the 2nd winter period.

Calibration variables

As thermal performance simulation models involve numerous input parameters, subjecting all these variables to an optimization-based calibration is computationally expensive. Methods such as sensitivity analysis can be deployed to find to most influential parameters, thereby limiting the number of variables in the optimization process (Reddy et al. 2007, Tahmasebi and Mahdavi 2012). For the purposes of the present study, the calibration variables and their associated variation ranges were selected based on the authors' previous experiences.

For the first calibration, eight input variables were selected (see Table 2), which address the heat transfer processes in the building, namely conduction, convection (air infiltration and ventilation), and solar radiation. For the second and third calibrations, only the infiltration and ventilation rates were subjected to calibration. The next two calibrations only tune the average indoor temperature of the adjacent zones during summer and winter. Table 2 demonstrates the included calibration variables together with their initial values and variation ranges.

Table 2
Initial values (together with lower and upper limits) of the variables subjected to calibrations

Calibration variables			Units	Lower limit	Initial value	Upper limit	Calibration				
							1st	2nd	3rd	4th	5th
Solar transmittance											
	Green 6mm glass		-	0.34	0.48	0.62	×				
	Clear 6mm glass		-	0.54	0.78	0.85	×				
Thermal conductivity											
	Mineral wool		$W.m^{-1}.k^{-1}$	0.031	0.039	0.047	×				
	XPS		$W.m^{-1}.k^{-1}$	0.03	0.05	0.07	×				
Density											
	Ceiling concrete		$kg.m^{-3}$	1260	1800	2340	×				
	Wall concrete		$kg.m^{-3}$	980	1400	1820	×				
Infiltration rate											
	Summer		h^{-1}	0.1	0.2	0.4	×	×			
	Winter		h^{-1}	0.1	0.2	0.4			×		
Ventilation rate											
	Summer		h^{-1}	0.5	1.0	3.0	×	×			
	Winter		h^{-1}	0.5	1.0	3.0			×		
Mean air temperature											
	Zone 1	Summer	ºC	23.6	26.7	28.3				×	
		Winter	ºC	19.6	24.2	26.3					×
	Zone 5	Summer	ºC	23.6	26.6	28.3				×	
		Winter	ºC	19.6	23.9	26.3					×

Cost function

In an optimization-aided calibration, the cost function addresses the difference between the measured and simulated values. In the present study this was calculated for the zone mean air temperature.

To address the error in the cost function two model evaluation statistics were used. The first statistic is the "Coefficient of Variation of the Root Mean Squared Deviations" (Equations 1 & 2). CV(RMSD) aggregates the runtime individual time step errors into a single dimensionless number (Polly et al. 2011, Tahmasebi et al. 2012).

$$RMSD = \sqrt{\frac{\sum_{i=1}^{n}(m_i - s_i)^2}{n}} \qquad (1)$$

$$CV\left(RMSD\right) = \frac{RMSD}{\overline{m}}.100 \qquad (2)$$

The other deployed statistic is the "coefficient of determination" denoted by R^2. R-squared describes the proportion of the variance in measured data explained by the model (Moriasi et al. 2007). The coefficient of determination ranges from 0 to 1. An R^2 of 1.0 indicates that the regression line perfectly fits the data. Therefore, R^2 value is to be maximized in the optimization process. Van Liew, et al., 2003 concluded that the values more than 0.5 can be counted as acceptable. R^2 was calculated via Equation 3:

$$R^2 = \left(\frac{n\sum m_i s_i - \sum m_i \sum s_i}{\sqrt{\left(n\sum m_i^2 - (\sum m_i)^2\right)\cdot\left(n\sum s_i^2 - (\sum s_i)^2\right)}}\right)^2 \qquad (3)$$

In Equations 1 to 3, m_i is the measured air temperature at each time step, s_i is simulated air temperature at each time step, n is the total number of time steps, and $\overline{m}$ is the mean of the measured values.

The defined cost function f takes into account the CV(RMSD) and R^2 in an equally weighted manner (Equation 4).

$$f_i = 0.5\cdot CV(RMSD)_i + 0.5\cdot(1-R_i^2)\cdot\frac{CV(RMSD)_{ini}}{(1-R_{ini}^2)} \qquad (4)$$

In Equation 4, $CV(RMSD)_i$ is the coefficient of variation of the RMSD at each optimization iteration, R_i^2 is the coefficient of determination at each optimization iteration, $CV(RMSD)_{ini}$ is the coefficient of variation of the RMSD of the initial model, and R_{ini}^2 is the coefficient of determination of the initial model.

In case of models with multiple thermal zones, the statistics are calculated for each zone and the cost function is calculated based on the averaged statistics.

To efficiently manage the repetitive process of varying the input parameters' values, the calculation of the cost function was tightly integrated with the simulation application. To accomplish this, the monitored indoor air temperatures were incorporated into the model input stream. EnergyPlus runtime language (DOE 2011) was used to calculate the cost function after each run of the model.

RESULTS

As shown in Table 2, six variables, which are related to physical properties of the building, were calibrated in the course of the first calibration (first run period).

Table 3 includes the respective results. Note that these values were not changed in the course of later calibration runs.

Table 3
The optimized values of physical properties of the model in the first calibration

Calibration variables	Units	Optimized Value
Solar transmittance		
Green 6mm glass	-	0.34
Clear 6mm glass	-	0.54
Thermal conductivity		
Mineral wool	$W.m^{-1}.k^{-1}$	0.031
XPS	$W.m^{-1}.k^{-1}$	0.03
Density		
Ceiling concrete	$kg.m^{-3}$	1260
Wall concrete	$kg.m^{-3}$	980

However, the infiltration and ventilation rates, as time-varying input parameters, were calibrated in the single-zone model in summer conditions (1st calibration), as well as in the three-zone model in summer and winter conditions (2nd and 3rd calibration). The mean air temperature of the adjacent zones was also calibrated separately for summer and winter conditions (4th and 5th calibration). The respective calibrated values are summarized in Table 4.

Table 5 includes the model evaluation statistics used in the weighted cost function, for the initial and calibrated models during different run periods.

DISCUSSION

The results suggest that the 1st calibration exercise (single-zone model) significantly improved model predictions (see Table 5, STEP 2, 2nd to 4th run periods): CV(RMSD) values for the calibrated model are smaller than their non-calibrated counterparts, whereas R^2 values are higher. The initial three-zone model did not perform very well, even though it inherited calibrated variable values derived in the 1st calibration run (see STEP 3, Table 5). The reason for this may be the uncertainty regarding the boundary zone assumptions. Internal walls separating zones 1 and 2 as well as zones 4 and 5 were assumed to be adiabatic. Calibration of infiltration and ventilation assumptions did not improve the model's performance in a noteworthy manner (see Table 5, STEP 4 and 5). Only when assumptions regarding indoor temperature of zones 1 and 5 were subjected to calibration, a better model performance could be achieved (Table 5, STEP 6 and 7).

The performance of optimization-based calibration approach could be improved via more case studies. Moreover, to further rationalize the calibration process, methods like sensitivity analysis could be deployed to identify a subset of the input variables most likely to influence the simulation results.

Table 4
The optimized values of time-varying input parameters in performed calibrations

Calibration variables		Units	Performed calibrations				
			1st	2nd	3rd	4th	5th
Infiltration rate							
Summer		h^{-1}	0.40	0.12	-	0.12	-
Winter		h^{-1}	-	-	0.28	-	0.28
Ventilation rate							
Summer		h^{-1}	0.50	0.59	-	0.59	-
Winter		h^{-1}	-	-	0.50	-	0.50
Mean air temperature							
Zone 1	Summer	°C	-	-	-	28.0	-
	Winter	°C	-	-	-	-	25.4
Zone 5	Summer	°C	-	-	-	26.9	-
	Winter	°C	-	-	-	-	26.0

Table 5
Model evaluation statistics of the initial and calibrated models in different run periods

Step	Models	1st run period		2nd run period		3rd run period		4th run period	
		CV(RMSD)	R^2	CV(RMSD)	R^2	CV(RMSD)	R^2	CV(RMSD)	R^2
1	Initial single-zone	4.5%	0.77	4.9%	0.94	15.1%	0.26	16.3%	0.69
2	1st calibrated single-zone	1.4%	0.88	2.2%	0.96	4.4%	0.35	5.5%	0.81
3	Initial three-zone	7.6%	0.69	7.3%	0.89	19.4%	0.50	13.2%	0.61
4	2nd calibrated three-zone	5.1%	0.68	4.4%	0.86	-	-	-	-
5	3rd calibrated three-zone	-	-	-	-	12.0%	0.48	7.3%	0.60
6	4th calibrated five-zone	3.8%	0.68	3.8%	0.89	-	-	-	-
7	5th calibrated five-zone	-	-	-	-	6.6%	0.48	6.1%	0.63

CONCLUSION

A case study of an optimization-based calibration method for a thermal performance model of a building was presented. In the course of multiple simulation and calibration steps, ten simulation input variables were subjected to calibration, using monitored data (measured room temperatures). The optimization-based calibration process utilized a cost function that considered both the goodness of fit of the model and error minimization (difference between monitored and simulated values). The results suggest that the predictive performance of simulation models can be noticeably improved, given monitored data to support an optimization-supported simulation model calibration.

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