A TWO-STAGED SIMULATION MODEL CALIBRATION APPROACH TO VIRTUAL SENSORS FOR BUILDING PERFORMANCE DATA

Farhang Tahmasebi and Ardeshir Mahdavi

Department of Building Physics and Building Ecology
Vienna University of Technology, Vienna, Austria

ABSTRACT

In existing buildings, monitored data can support the process of simulation model calibration and validation. Such calibrated models could be effectively applied in building management and systems operation processes. The present contribution focuses on a specific problem faced by a monitoring-based optimization-assisted simulation calibration: In many realistic circumstances, it is not possible to install monitoring systems with full building coverage. To address this issue, we explore the potential of simulation model calibration based on monitored data obtained from a selected sub-set of building zones. Thereby, we demonstrate that the resulting calibrated simulation model can provide, via virtual sensors, information from building zones, which are not actually monitored.

INTRODUCTION

In the past few years, research and development regarding the deployment of building performance simulation in the building operation phase has gained on momentum. Specifically, simulation routines have been successfully applied in the conception and implementation of predictive methods for building systems control (Mahdavi 2001). As we have argued in previous publications (Mahdavi et al. 2012), the quality and effectiveness of such a predictive control system depends on the reliability of the integrated simulation models. Thus, to ensure that predictions are dependable, the incorporated simulation models need to be calibrated. Moreover, given the dynamic nature of building operation and the boundary conditions (e.g., weather, occupancy), the calibration task cannot be approached as a kind of ad hoc activity. Rather, it needs to be conducted on a systematic and regular basis. In previous publications (see, for example, Tahmasebi et al. 2012), we examined the potential of an optimization-based simulation model calibration to maintain the model's fidelity through a recurrent calibration process.

The present contribution focuses on a specific problem faced by a monitoring-based optimization-assisted simulation calibration: In many realistic circumstances, it is not possible to install monitoring systems with full building coverage. To address this issue, we explore the potential of simulation model calibration based on monitored data obtained from a selected sub-set of building zones. Thereby, we demonstrate that the resulting calibrated simulation model can provide, via virtual sensors, information from building zones, which are not actually monitored.

To explore the possibility of using a calibrated thermal performance simulation model for virtual building zone monitoring, a university campus office area with existing monitoring infrastructure was selected.

METHODOLOGY

The building model

To explore the potential of monitoring-based optimization-assisted calibration in a realistic setting, we selected an actual office in a building of the Vienna University of Technology, which is equipped with a monitoring infrastructure (see Figure 1).

The building was modeled in the building energy simulation tool EnergyPlus v7.0 (EnergyPlus 2012). In order to create the initial model, first building geometry and thermal properties of building components were specified. In the zoning scheme, the open-plan south and north-oriented spaces were separated from the central corridor. However, using the network-based multi zone airflow model of EnergyPlus (Gu 2007), the airflow between these connected spaces was simulated. Figure 1 illustrates the building floor plan and the thermal zoning of the building model. Zones 1, 2, 3, 5 and 6 represent the offices of building and zone 4 is a seminar room.

As the second step in developing the initial model, the monitored data was incorporated in the model in terms of schedules for time-varying input parameters, namely occupancy, lighting, electric equipment, and state of the windows. The heat delivery rate of the hydronic heating system was also calculated based on the measured radiator surface temperatures (Tahmasebi et al. 2012).

Use of moniored data

The data from the building's weather station (see Table 1) was used to create a real-year weather data file based on local data instead of using a typical meteorological year weather data file.

Next, we populated the initial model with various streams of data from selected monitored spaces (Table 1). Thereby, we deployed monitored data only from zones 1, 4 and 5 (actual monitored zones). For other offices of the building, namely zones 2, 3, and 6, we used the monitored input data from adjacent zones (Zone 1 data was used for zones 2 and 3, whereas zone 5 data was used for zone 6).

For model calibration purposes, the measured indoor temperature from the actual monitored zones was used. Available measured temperatures for other zones were only used to evaluate the performance of the calibrated model's virtual sensors.

Run periods

The model calibration and validation process involved a monitoring period of nearly three months consisting of two 44-day periods (Table 2). The sensitivity analysis was also performed for the calibration period.

Optimization-based calibration approach

In an optimization-based simulation model calibration, the objective function addresses the difference between measured and simulated values (in this case zone air temperature). A number of input parameters of the model (selected via sensitivity analysis) are then 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).

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

Sensitivity analysis of calibration variables

The problem of large search space and multiple possible solutions has been addressed in previous research (see, for example, Reddy et al. 2007). As examined in a previous publication (Tahmasebi & Mahdavi 2012), to identify a subset of the input variables most likely to influence the simulation results, first, the large number of candidate model parameters was reduced to a certain extent via heuristically-based considerations. This subset included 23 model input variables (Table 3). Secondly, these variables were subjected to a Monte Carlo-based sensitivity analysis.

The performed sensitivity analysis included four steps. In the first step a range was selected for each variable (Table 3). Secondly, a sample of points was generated from the distribution of the inputs using the Latin hypercube sampling method, which is a particular case of stratified sampling (Saltelli et al. 2011). The result was a sequence of 690 sample elements (for all variables). In the third step, the model was populated with the sample elements and a set of model outputs (building heating load) was produced.

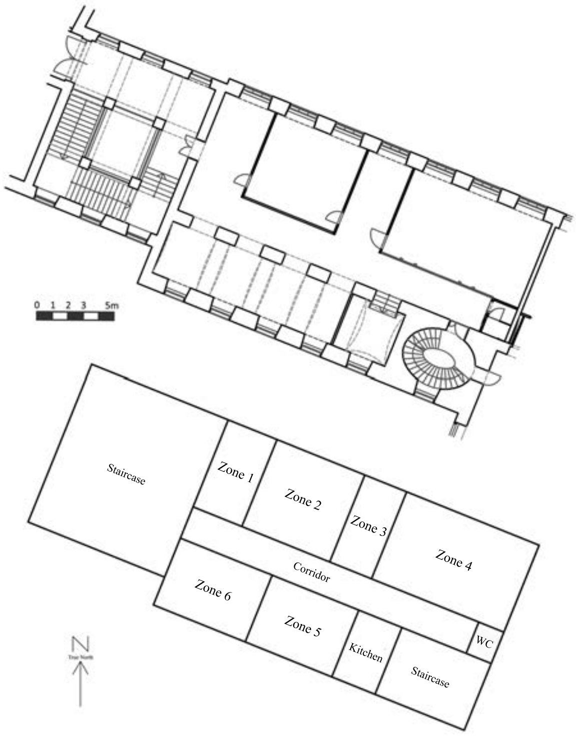

Figure 1 Floor plan and thermal zoning of the model

Table 1
Monitored data used in the calibration process

Use of data	Data point	Unit
Creating real-year local weather data file	Global horizontal radiation	W/m^2
	Diffuse horizontal radiation	W/m^2
	Outdoor dry bulb temperature	^oC
	Outdoor air relative humidity	%
	Wind Speed	m/s
	Wind direction	degree
	Atmospheric pressure	Pa
Creating the initial model	Electrical plug loads	W
	Occupancy (presence/absence)	-
	State of the lights (on/off)	-
	State of openings (open/closed)	-
	Radiators' surface temperature	^oC
Calibration	Indoor air temperature	^oC

Table 2
Specification of run periods

Run periods	Start date	End date
Calibration	15.02.2011	30.03.2011
Validation	27.04.2011	09.06.2011

Running the generated models with randomly selected input parameters' values, a mapping was created from the space of the inputs to the space of the results that was used in the fourth step as the basis for sensitivity analysis. By solving a multiple linear regression model using least squares (Saltelli et al. 2011), the absolute value of Standard Regression Coefficient (SRC) was calculated for the variables as a quantitative sensitivity measure. Table 4 shows the variables in order of the absolute value of SRC.

Based on these results, the first four variables, which have SRC values higher than 0.1, were chosen to be subjected to optimization-based calibration in the next stage. Three additional calibration variables were defined due to the circumstance that the surface temperatures of radiators in virtual monitored zones were assumed to be related to those in the actual monitored zones. Hence, we defined three correction factors in terms of calibration variables. The calibration variables, their initial values, and their allowed calibration ranges can be seen in Table 5.

Calibration cost function

For the purpose of building performance analysis, error can be defined as the difference between a predicted value and a measured value (Polly et al. 2011). In the present case, the error was calculated and accumulated for the indoor air temperature of the actual monitored zones (zones 1, 4, and 5).

Two model evaluation statistics were used to address the error in the cost function. The first statistic, CV(RMSD), aggregates time step errors over the runtime into a single dimensionless number:

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

$$CV(RMSD) = \frac{RMSD}{\overline{m}} \cdot 100 \tag{2}$$

The other model evaluation statistics used in the cost function is the "coefficient of determination" denoted by R^2. Coefficient of determination 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. R^2 has been calculated via Equation 3.

Table 3 Variables subjected to SA and their ranges

Variables	Min. Value	Max. Value
White painted gypsum - Thermal conductivity	0.336	0.504
White painted gypsum - Density	960	1440
White painted gypsum - Thermal absorptance	0.82	0.93
White painted gypsum - Solar absorptance	0.24	0.36
White painted stucco - Thermal conductivity	0.576	0.864
White painted stucco - Density	1485	2227
White painted Stucco - Thermal absorptance	0.82	0.93
White painted Stucco - Solar absorptance	0.24	0.36
External walls brick layer - Thermal conductivity	0.56	0.84
External walls brick layer - Density	1360	2040
Wood parquet - Thermal absorptance	0.664	0.996
Wood parquet - Solar absorptance	0.48	0.72
Glazing - Solar transmittance	0.56	0.84
Glazing - Front side infrared emissivity	0.837	0.898
Glazing - Back side infrared emissivity	0.837	0.898
Glazing – Thermal conductivity	0.72	1.08
Windows frame - Thermal conductance	1.816	2.724
Outside windows discharge coeff. when open	0.64	0.96
Inside windows discharge coeff. when open	0.64	0.96
Outside closed openings air mass flow coeff.	0.00011	0.00017
Outside closed openings air mass flow exponent	0.52	0.78
Inside closed openings air mass flow coeff.	0.016	0.024
Inside closed openings air mass flow exponent	0.56	0.84

Table 4 Variables in order of absolute value of SRC

Variables	| SRC |
External walls brick layer - Thermal conductivity	0.7735
Outside windows discharge coefficient when open	0.4128
Glazing - Solar Transmittance at Normal Incidence	0.3660
Outside openings air mass flow coeff. when closed	0.1132
Glazing - Front Side Infrared Emissivity	0.0831
Inside openings air mass flow coeff. when closed	0.0760
Inside openings air mass flow exponent when closed	0.0663
Glazing - Back Side Infrared Emissivity	0.0626
White-painted Stucco - Solar absorptance	0.0592
Glazing - Thermal conductivity	0.0374
White painted gypsum - Thermal conductivity	0.0369
White painted Stucco - Thermal absorptance	0.0314
Brick - Density	0.0314
Windows frame - Thermal conductance	0.0285
White painted stucco - Thermal conductivity	0.0218
Outside openings air mass flow exponent when closed	0.0152
White painted gypsum - Thermal absorptance	0.0145
Inside windows discharge coefficient when open	0.0104
Wood parquet - Solar absorptance	0.0090
White painted gypsum - Solar absorptance	0.0058
Wood parquet - Thermal absorptance	0.0038
White painted gypsum - Density	0.0015
White painted stucco - Density	0.0010

Table 5 The calibration variables

Variables	**Unit**	**Initial value**	**Lower band**	**Upper band**
Thermal conductivity of external walls (brick layer)	$W.m^{-1}.K^{-1}$	0.70	0.56	0.84
Discharge coefficient for windows when open	-	0.80	0.00	1.0
Glazing solar transmittance at normal incidence	-	0. 837	0.56	0.85
Air mass flow coefficient for windows when closed	$kg.s^{-1}.m^{-1}$	1.4×10^{-4}	1.4×10^{-5}	0.003
Correction factor of radiator's surface temperature in zone 2 (CF_{1-2})	-	0.5	1	2.0
Correction factor of radiator's surface temperature in zone 3 (CF_{1-3})	-	0.5	1	2.0
Correction factor of radiator's surface temperature in zone 6 (CF_{5-6})	-	0.5	1	2.0

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

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).

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

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.

RESULTS

The optimized values of the calibration variables are given in Table 6. Table 7 presents the values of evaluation statistics for the initial and calibrated models in the calibration period. Table 8 shows the evaluation statistics in the validation period.

DISCUSSION AND CONCLUSION

As it can be seen from Table 7, the calibration process improves the model performance (calibration period) both for actual and virtual monitored zones. More importantly, the calibrated model shows for the validation period (Table 8) a considerably better performance as compared to the initial model, again for both actual and virtual monitored zones. In this period, the calibrated model has an error of less than 7.7% in actual monitored zones and less than 6.4% in virtual monitored zones. The coefficient of determination is between 0.60 and 0.83 in the actual and virtual monitored zones.

The results thus point to the promise of a two-step (sensitivity analysis, optimization) simulation model calibration process toward establishing virtually monitored building zones. Thereby, partial monitoring results can be harnessed toward effectively calibrated models that can provide reliable predictions of performance indicators (e.g., room temperatures) even for those zones where no monitored data exist. Ongoing studies further probe and document the potential of the proposed approach in providing a set of virtual sensors for salient building performance indicators towards application scenarios in building management and simulation-based building systems control.

NOMENCLATURE

Coeff.	= coefficient
CV(RMSD)	= coefficient of variations of root mean squared deviations
RMSD	= root mean squared deviations
R^2	= coefficient of determination
SRC	= Standard Regression Coefficient

Table 6 The optimized values of the model variable.

Variables	Unit	Optimized value
Thermal conductivity of external walls (brick layer)	$W.m^{-1}.K^{-1}$	0.778
Discharge coefficient for windows when open	-	0.153
Glazing solar transmittance at normal incidence	-	0.677
Air mass flow coefficient for windows when closed	$kg.s^{-1}.m^{-1}$	4.0×10^{-5}
Correction factor of radiator's surface temperature in zone 2 (CF_{1-2})	-	0.97
Correction factor of radiator's surface temperature in zone 3 (CF_{1-3})	-	0.80
Correction factor of radiator's surface temperature in zone 6 (CF_{5-6})	-	0.95

Table 7 The evaluation statistics of the initial and calibrated models for the calibration period

Models	Evaluation Statistics	Actual monitored zones			Virtual monitored zones		
		Zone 1	Zone 4	Zone 5	Zone 2	Zone 3	Zone 6
Initial model	CV(RMSD)	4.1%	11.0%	5.4%	9.9%	5.5%	5.4%
	R^2	0.40	0.17	0.34	0.32	0.28	0.27
Calibrated model	CV(RMSD)	3.0%	5.4%	4.4%	9.9%	3.9%	4.6%
	R^2	0.78	0.62	0.56	0.41	0.52	0.46

Table 8 The evaluation statistics of the initial and calibrated models for the validation period

Models	Evaluation Statistics	Actual monitored zones			Virtual monitored zones		
		Zone 1	Zone 4	Zone 5	Zone 2	Zone 3	Zone 6
Initial model	CV(RMSD)	7.6%	10.4%	7.5%	6.3%	7.5%	8.0%
	R^2	0.35	0.46	0.33	0.35	0.43	0.33
Calibrated model	CV(RMSD)	6.3%	7.7%	5.7%	5.4%	5.9%	6.4%
	R^2	0.66	0.83	0.72	0.71	0.69	0.60

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