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Monitoring-based optimization-assisted calibration of the thermal performance model of an office building

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1 ABSTRACT

This paper reports on a case study of monitoring-based optimization-assisted calibration of a thermal simulation model for an office building. Such a calibrated model could effectively support the operation of the building. For example, it could be deployed toward diagnostics, fault detection, preventive maintenance, and a model-based building systems control. To explore the potential of optimization-assisted calibration in a realistic setting, we selected an actual office. This facility is equipped with a monitoring infrastructure, which provides various streams of data about outdoor and building conditions. Our intention was to deploy data obtained via the monitoring system to both populate the initial simulation model and to maintain its fidelity through a systematic calibration process. The initial simulation model used, asides from static physical building information, dynamic monitored data including electrical plug loads, occupancy, and state of devices such as luminaires and windows. In the optimization-assisted calibration, a weighted cost function was defined, which addressed the bias error between measured and simulated indoor temperature and the goodness of fit of the model. A limited number of model input parameters were varied in the optimization process toward minimizing the cost function. The resulting calibrated model showed noticeable accuracy improvement and the optimization-assisted method displayed a promising potential as a systematic calibration method in model-based predictive systems control.

2 INTRODUCTION

The potential of performance simulation tools are being explored recently in predictive building systems operation. In this approach, simulation engines can be incorporated as an integral component of a building's control system [1]. However, whole-building simulation applications require extensive input data to accurately model the buildings' thermal performance [2]. Insufficient information on the physical and behavioral aspects of buildings limits the capabilities of building automation systems [3]. Hence, effective use of simulation-based building systems control approach requires that buildings possess comprehensive monitoring systems to collect data on indoor and outdoor environmental conditions, systems' energy use, occupants' presence and control actions, etc.

Needless to say, the quality of a simulation-based control system greatly depends on the reliability of the deployed simulation model. To ensure that the model-based predictions are reliable, applied simulation models must be calibrated. Moreover, given the dynamic nature of building operation, the calibration task cannot be approached as an ad hoc or one-time activity. Rather, it needs to be conducted on a systematic basis to ensure efficiency and consistency. Consequently, the entire simulation model calibration process should be preferably automated to ensure efficiency and consistency. Given this background, the present contribution explores the potential of an optimization-assisted approach to simulation model calibration.

3 METHODOLOGY

3.1 The Monitored Building

To explore the potential of 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. This monitoring infrastructure provides various streams of data, including indoor climate, outdoor weather conditions, energy delivery via the building's heating system, energy use for lighting and equipment, occupancy presence, and the opening state of windows and doors.

The monitored data was used to: *i)* create a weather file based on local data instead of using a predefined "typical" year; *ii)* populate the initial building model with dynamic data regarding internal loads, device states, and occupancy processes; *iii)* to calibrate the initial model (see Table 1).

Use of data	Monitoring System Data point	Unit
Creating local weather data file	Global horizontal radiation	[W.m^{-2}]
	Diffuse horizontal radiation	[W.m^{-2}]
	Outdoor air dry bulb temperature	[^{o}C]
	Outdoor air relative humidity	[%]
	Wind Speed	[m.s^{-1}]
	Wind direction	[degree]
	Atmospheric pressure	[Pa]
Creating the initial model	Electrical plug loads	[W]
	State of windows and doors (open/closed)	[-]
	State of the lights (on/off)	[-]
	Occupancy (presence/absence)	[-]
Calibrating the model	Indoor air dry bulb temperature	[^{o}C]

Table 1: Use of monitored data in the calibration process

3.2 The Building Model

The building was modelled in EnergyPlus v7.0 [4]. The office is situated between two conditioned floors and it has been assumed that the floor and ceiling surfaces of the office are adiabatic. In the zoning scheme, the open south and north-oriented spaces were separated from the central corridor. Figure 1 illustrates the building floor plan and the thermal zoning of the building model.

The monitored data were incorporated into the EnergyPlus input stream as some schedules. Since writing schedules manually in EnergyPlus, and likely in any other text-based simulation program, is a time-consuming and error-likely process, a simple program was written in Matlab to generate an event-based "compact schedule" for each data point.

The present study focuses on the performance of the building during summer. Therefore, the model does not include the operation of the heating system ("free-running period"). A 2-month period (7 May to 7 July 2011) was assigned to the calibration of the model and another 2-month period (8 July to 7 Semptember 2011) was set aside for validating the calibrated model.

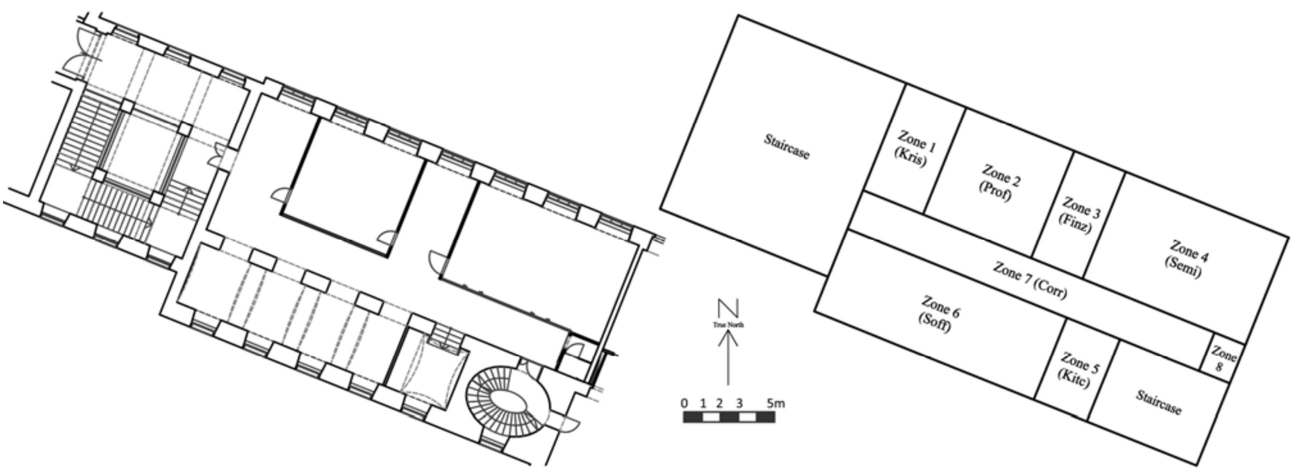

Fig. 1: Building floor plan (left) and the thermal zoning of the building model (right)

3.3 Optimization-assisted calibration

3.3.1 Overview

In an optimization-assisted approach, calibration is cast as an error-minimizing process. In this kind of optimization problem, the cost function addresses the difference between measured and simulated data such as indoor air temperature. The variables in the optimization algorithm include a number of model input parameters. The attributes of these variables will be varied toward minimizing the cost function.

To accomplish the optimization in a way that works smoothly with the EnergyPlus model, authors used Genopt, which is a generic optimization program. Genopt has been developed to conveniently find the independent variables that yield better performance of a system. Genopt optimizes a user-supplied cost function, using a user-selected optimization algorithm [5].

Algorithm used for the optimization was the hybrid generalized pattern search algorithm with particle swarm optimization algorithm, as it is one of the recommended generic algorithms for problems where the cost function cannot be evaluated, but can be approximated numerically by a thermal building simulation program [5].

3.3.2 Variables

The problem of large search space and multiple possible solutions has been addressed in previous research. Methods such as sensitivity analysis have been proposed to limit the number of variables in the optimization process [6, 7, 8, 9]. In the present research, the variable selection was based on previous heuristically-based experience of the authors. Consequently, a limited number of static input variables were selected, which address the heat transfer processes in the building, namely conduction, convection (air infiltration and ventilation), and solar radiation. A variation range of 20% was applied to the variables representing conduction and solar heat gain. In case of external walls, only the thermal property of this component's dominant layer (brick) was subjected to variance. For the "Air Mass Flow Coefficient" through cracks a wider range was selected based on the template libraries of DesignBuilder [10]. For open windows, the entire possible range of the "Discharge Coefficient" was allowed. The variables of the optimization process and their variation ranges are given in Table 2.

Variables	Unit	Initial value	Lower band	Upper band
External windows: air mass flow coefficient, when closed	$[kg.s^{-1}.m^{-1}]$	0.00014	0.00001	0.003
External windows: discharge coefficient, when open	[-]	1.0	0.0	1.0
External windows: glazing solar transmittance	[-]	0.837	0.670	1.000
External walls: thermal conductivity (brick layer)	$[W.m^{-1}.K^{-1}]$	0.7	0.56	0.84
External walls: density (brick layer)	$[kg.m^{-3}]$	1700	1360	2040
External walls: specific heat (brick layer)	$[J.kg^{-1}K^{-1}]$	920	736	1104

Table 2: The variables of the optimization process and their ranges

3.3.3 Cost Function

To minimize the bias error between monitored and simulated values, and to keep the "goodness of fit" of the model at the same time, a weighted function of two different indicators was defined as the cost function. The first indicator is the "Coefficient of Variation of the Root Mean Squared Deviation" (Eq. (1) & Eq. (2)). CV(RMSD) serves to aggregate the individual errors between measured and simulated values at any time step into a single dimensionless number [11].

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

$$CV(RMSD) = \frac{RMSD}{\bar{m}} \times 100 \qquad [\%] \qquad (2)$$

The other indicator used in the cost function is the "coefficient of determination" denoted by R^2. This indicator has been deployed because the main purpose of the developed model is the prediction of future outcomes and R^2 provides a measure of how well future outcomes are likely to be predicted by the model. In other words, R^2 is a statistic that will give some information about the goodness of fit of a model. 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 it is preferable to maximize the R^2 value in the optmization process. While there are different definitions of R^2, here it has been calculated by Eq. (3):

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

In Eq. (1) to Eq. (3), m_i is the measured air temperature (averaged over all office zones) at each time step, s_i is simulated air temperature at each time step, n is the total number of time steps, and $\bar{m}$ 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 (Eq. (4)).

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

In Eq. (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.

To efficiently manage the repetitive process of varying the input variables' attributes, 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 input stream and the EnergyPlus runtime language [12] was used to calculate the cost function by the EnergyPlus engine after each run of the model.

4 RESULTS

The optimized values of the model input variables are given in Table 3. Table 4 presents values of the two indicators used in the weighted cost function, before and after the calibration. Moreover, Figure 2 and 3 compare monitored office temperature with initial and calibrated model results, during 9-day periods of calibration and validation.

Variables	Unit	Optimized value
External Windows: Air Mass Flow Coefficient When Closed	[$kg.s^{-1}.m^{-1}$]	0.000159
External Windows: Discharge Coefficient When Open	[-]	0.475
External Windows: Glazing Solar Transmittance	[-]	0.847
External Walls: Thermal conductivity (brick layer)	[$W.m^{-1}.K^{-1}$]	0.58
External Walls: Density (brick layer)	[$kg.m^{-3}$]	1360
External Walls: Specific Heat (brick layer)	[$J.kg^{-1}K^{-1}$]	736

Table 3: The optimized values of the model input parameters

Period	Initial Model		Calibrated Model	
	R^2	CV(RMSD)	R^2	CV(RMSD)
Calibration Period (2 months)	0.81	7.60	0.88	3.26
Validation Period (2 months)	0.85	5.11	0.84	2.35

Table 4: Comparison of R^2 and CV(RMSD) in the initial and calibrated model

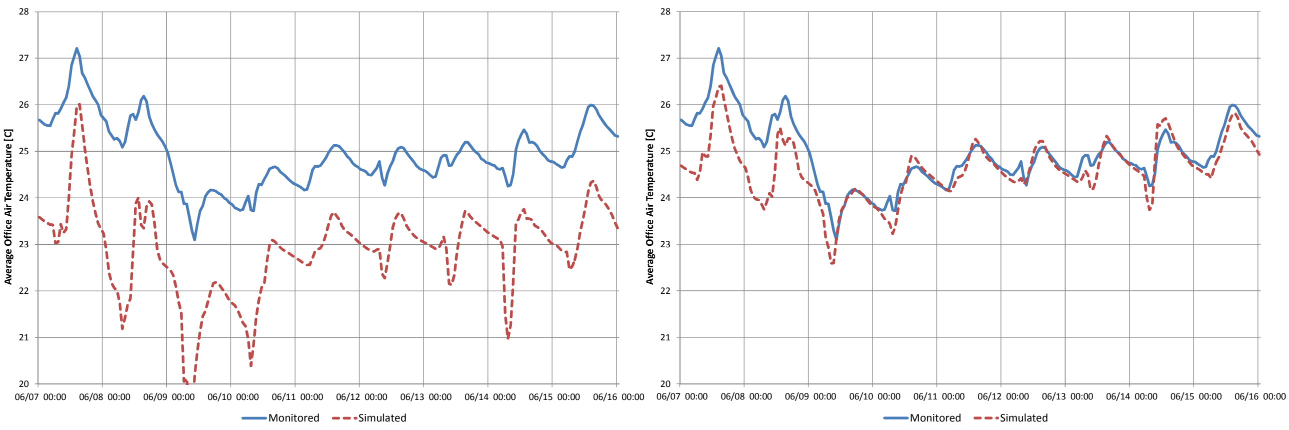

Fig. 2: Monitored & simulated office temperature in calibration period: initial model (left), calibrated model (right)

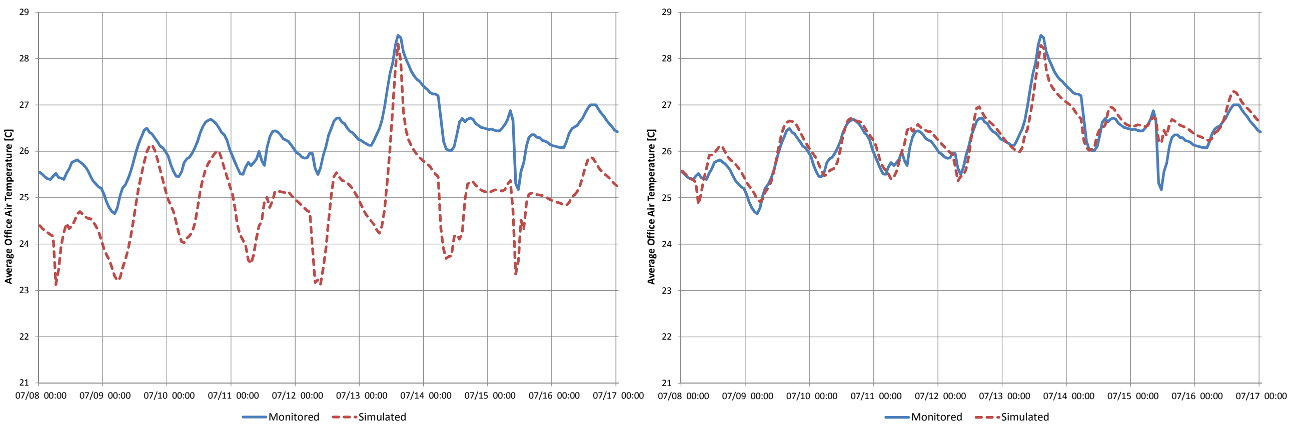

Fig. 3: Monitored & simulated office temperature in validation period: initial model (left), calibrated model (right)

5 DISCUSSION

As it can be seen from Table 4, the initial model generated outputs with relatively high R^2 values in both the calibration and validation periods. The automated calibration, however, could effectively reduce the error in terms of CV(RMSD). Thereby, R^2 value could not be further improved, but remained essentially the same as before. Figures 2 and 3 provide an impression of the significant predictive improvement of the simulation model as a result of the calibration process. Thus, the present study points to the promising potential of monitoring-based optimization-assisted simulation model calibration. The performance of the approach could be further improved via a more detailed process for the determination of the cost function and associated weights. Note that the convergence-based approach to the definition of the values of model input parameter in the course of the optimization process does not mean that "true values" for such parameter are found. Rather, optimization exploits the uncertainty potential in our knowledge of the exact values of such parameter to provide a better fit to the monitoring results. It is thus important, that care is taken while defining the permissible variations from the initial values of model input parameter.

6 CONCLUSION

We demonstrated the use of a monitoring-based optimization-assisted calibration of the thermal performance model of an office building. Data obtained via the monitoring system were deployed to both populate the initial simulation model and to maintain its fidelity through a systematic optimization-assisted calibration process. To perform the optimization-assisted calibration, a cost function was proposed, which equally weighted an error and a goodness of fit indicator. The results showed noticeable improvement of the predictive potency of the calibrated model. Hence, the optimization-assisted model calibration method represents a promising possibility to be applied in building automation, diagnostics, and model-based systems control.

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