ABOUT UNCERTAINTIES IN SIMULATION MODELS FOR BUILDING SYSTEMS CONTROL

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ABSTRACT

This paper presents the process and the results of a calibration effort of a thermal simulation model of an existing office building in Vienna, Austria. The model is an integral component of the building's innovative model-based control logic for the operation of windows and shades. To achieve the desirable level of accuracy, sources of uncertainty in the simulation model are identified and treated. In the present contribution, we focus on two sources of uncertainty namely the prediction capability of a calibrated simulation model, and errors in weather predictions.

INTRODUCTION

In previous research and the respective publications, we have introduced and described the concept and various implementations of a simulation-based approach to building systems control (Mahdavi 2008). In this approach, control decisions are made based on a proactive comparison of simulated implications of alternative control actions. The best-performing control option can thus be identified and executed on a regular basis. In a recent implementation effort, we implemented and started to test such a simulation-assisted control system for effective passive room cooling in an office building, in which three rooms were selected and equipped with motorized windows and automated blinds (Pröglhöf et al. 2010, Orehounig et al. 2010). Thereby the control scheme was as follows: at a specific point in time in a typical summer day, the control unit applies simulation to predict how various window and shade operation regimes would affect the indoor temperature over the course of the following hours. The essential advantage of this method is the possibility to bypass conventional air-conditioning systems and harness instead the naturally occurring day-night temperature difference toward free space cooling.

To endow the window and shade operation unit with predictive capabilities, we developed simulation models for the office spaces using a numeric simulation application. The initial testing phase of the system's operation highlighted the importance of the accuracy of the simulation model's predictions. To achieve the desirable level of accuracy, sources of uncertainty in the simulation model must be identified and treated. In the present contribution, we focus on two sources of uncertainty in the simulation process:

i) Simulation model requires input data regarding window positions towards the estimation of the resulting air change rates. We illustrate the potential for the calibration of the simulation process based on the comparison of measured and predicted air change rates given a set of input assumptions.

ii) Simulation model's prediction of the future conditions in the office spaces uses weather data forecast as input assumption. Our experiences so far suggest that the implications of weather forecast errors for the reliability of the control system are significant. Preferably, weather predictions should be based on data obtained from a local weather station at the close proximity of the building.

METHODS

In a recent implementation effort, we started to test a simulation-assisted control system for effective passive room cooling in an office building. The object is a University building located in Vienna (see Figure 1), in which three adjacent rooms were selected and equipped with motorized windows and automated blinds. These three rooms are south facing (Figure 2) and are referred to as R1, R2 and R3. R1 acts as a reference room and was left untouched. The room is equipped with manual internal, simple venetian blinds. The users can open the windows manually. In R2 and R3 the existing windows were partly motorized. R2 was equipped with automated internal venetian blinds and R3 with automated external venetian blinds (Figure 2).

Additionally, offices were equipped with indoor environmental sensors for air temperature, humidity, illuminance, flow velocity, and surface temperatures (Figure 3). External environmental data such as temperature, relative humidity, wind speed, wind direction, global horizontal radiation, and diffuse horizontal radiation were collected. Moreover, window opening and shading positions were recorded. As to the external environmental conditions, a weather station was installed on the roof of a close-by building.

Figure 1 External view of the selected building

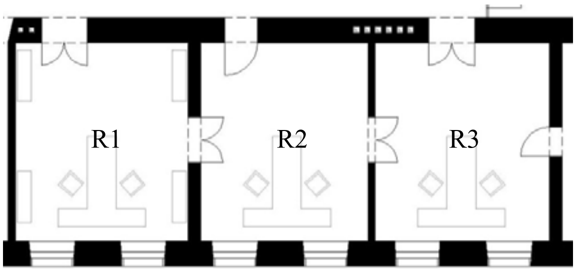

Figure 2 Floor plan of the three offices

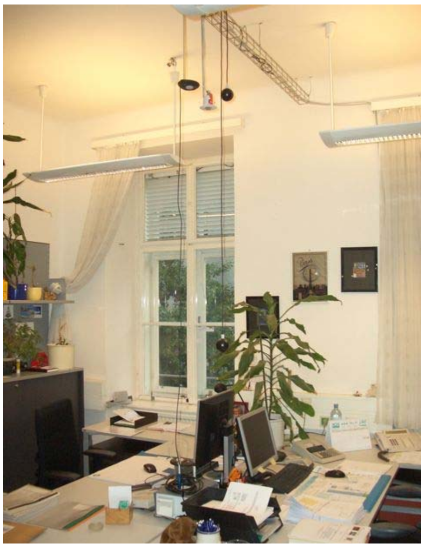

Figure 3 Workplaces in R2 with motorized window, internal venetian blinds, and sensors

Control approach

The potential for the application of a simulation-based natural ventilation control strategy has been addressed, in principle, in our previous publications (Mahdavi & Pröglhöf 2004, 2005, Mahdavi 2008, and Mahdavi et al. 2009). The idea was to utilize the day-night difference in outdoor air temperature toward passive space cooling via optimized operation of natural (window) ventilation. Therefore a simulation model was generated and calibrated for the above mentioned building.

As to the control scheme approach: At a specific point in time in a typical summer day (d_j), the control unit applies simulation to predict how various window operation regimes would affect the indoor temperature in a building over the course of the following day (dj+1). An "operation regime" denotes in this context which windows, when, how long, and to which extent, are opened. To compare and rank the performance of various control options (alternatives), we applied in this case the Mean Overheating (OHm) of the indoor air in selected spaces (see Equation 1) as the relevant performance indicator.

$$OH_m = \sum_{i=1}^{n} \frac{\theta_i - \theta_r}{n} \qquad (1)$$

Where θ_i denotes indoor air room temperature (°C) at hour i in day d_{j+1}, θ_r the reference indoor air temperature for overheating (°C), and n the total number of considered hours in day d_{j+1}. This number was considered to be 10 for the office spaces. Note that the term $\theta_i - \theta_r$ (in Equation 1) is considered only for those hours when $\theta_i > \theta_r$. In our illustrative example, the reference overheating temperature (θ_r) was assumed to be 26 °C. In the control situation, weather forecast information for the following day is used as input information for the simulation runs. In the present emulations, weather predictions are taken at 18:00 for the following 24 hours. These weather predictions were derived from a web-based service (Weather channel 2009). Thus, amongst a number of discrete alternative window operation scenarios, one could be selected, which, according to simulation results, would minimize the overheating of the indoor air in the following day. To illustrate this process, Table 1 shows a number of alternative window operation scenarios (schedule and degree of window opening).

Simulation process

The initial testing phase of the system's operation highlighted the importance of the accuracy of the simulation model's predictions. To achieve the desirable level of accuracy, sources of uncertainty in the simulation process must be identified and treated. In the present contribution, we focus on two sources of uncertainty in the simulation process:

1. Simulation model uncertainties: The simulation model, which is used for the control strategy was generated based on building information (geometry and construction) using a numeric simulation application (EDSL 2007, 2008). Material properties such as thermal conductivity and specific heat capacity were based on in-situ observations and applicable document archives. Information regarding occupancy, lighting,

equipment, window positions, and shades position was based on monitoring in the office spaces. Air change rates were computed by the simulation application based on input data on window opening positions. To calibrate this computation, measured values of air change (in room R2 and R3) for various window positions on two days in June 2009 were used. Simulated and measured air change rates were compared to calibrate the window opening degree. Simulations were run using weather files specifically generated based on data obtained from the local weather station. Simulation results were compared with corresponding measurements (such as room air temperature), resulting in a calibrated simulation model.

2. Weather forecast uncertainties: The weather forecast information used for the simulation-assisted passive cooling in buildings, is derived from a web-based meteorological weather service (for the city of Vienna), which provides hourly data regarding air temperature, humidity, wind speed, wind direction, probability of precipitation, and sky condition for the next 48 hours (Weather channel 2009). Typical weather files for building performance simulation require air temperature, humidity, wind speed, and wind direction. Moreover, information is needed regarding global horizontal radiation, diffuse horizontal radiation, and cloud cover, which was not provided by the web based service. Instead, this service provides sky condition information in verbal terms such as "clear sky", "partly cloudy", "mostly cloudy", and "sunny". These terms typically refer to the fraction of the sky obscured by clouds (e.g., 0: clear sky, 10: overcast sky). We used this information to estimate the cloud cover values and further to estimate input data for global and diffuse horizontal radiation. Subsequently, global horizontal irradiance ($E_{G,H}$) was approximated as a function of cloud cover (CC) and global clear sky irradiance ($E_{G,C}$) according to the relationship which we derived based on empirical data (see Equation 2). Diffuse horizontal radiation was further calculated based on the clearness index, which takes the temperature, humidity, extraterrestrial radiation, and global horizontal radiation into account (Reindl 1990).

$$E_{G,H} = -0.0085 \cdot CC^2 \cdot E_{G,C} + 0.0174 \cdot CC \cdot E_{G,C} + 0.8288 \cdot E_{G,C} \quad (2)$$

To further explore the extent of weather forecast errors, weather predictions were compared to actual data (for August 2009). We used the outcomes of this analysis to further adjust weather predictions (which are generated for the city of Vienna) to the location of our building.

RESULTS

Control method implementation

To test the simulation-based control system's operation, different scenarios were generated (see Table 1) and simulated every evening at 18:00 for the next 24 hours (using the respective weather forecast information). Figure 4 shows, for R3, the predicted indoor air temperature resulting from these alternative control scenarios. Table 2 shows calculated Mean Overheating values for these scenarios. Scenarios with better performance (highlighted in grey in Table 2) were implemented in the actual operation.

Figure 5 shows measured indoor air temperatures in all three offices together with the outdoor air temperature for the test period. R3 and R2 were controlled by the simulation-based method. R1 acts as a reference room and remained mostly unoccupied with closed windows.

Table 1

Illustrative alternative control scenarios (s1 to s7) for window (W) operation ("f": fully open, "p": 40% open, "c": closed) in selected offices. The operation of the blinds (B) is specified either as "f" (fully open) or "c" (80% closed).

	s1		s2		s3		s4		s5		s6		s7	
hr	**W**	**B**	**W**	**B**	**W**	**B**	**W**	**B**	**W**	**B**	**W**	**B**	**W**	**B**
19	p	c	p	c	p	c	p	c	c	c	c	c	p	f
20	p	c	p	c	p	c	p	c	f	f	f	f	f	f
21	p	f	p	f	p	f	p	f	f	f	f	f	f	f
22	p	f	p	f	f	f	p	f	f	f	f	f	f	f
23	p	f	p	f	f	f	p	f	f	f	f	f	f	f
00	p	f	p	f	f	f	p	f	f	f	f	f	f	f
01	p	f	f	f	f	f	f	f	f	f	f	f	f	f
02	p	f	f	f	f	f	f	f	f	f	f	f	f	f
03	p	f	f	f	f	f	f	f	f	f	f	f	f	f
04	p	f	f	f	f	f	f	f	f	f	f	f	f	f
05	p	f	f	f	f	f	f	f	f	f	f	f	f	f
06	p	f	f	f	f	f	f	f	f	f	f	f	f	f
07	p	f	f	f	p	f	f	f	f	f	f	f	f	f
08	p	f	f	f	p	f	f	f	f	f	f	f	f	f
09	p	f	f	f	p	f	f	f	f	f	f	f	f	f
10	p	c	f	f	p	c	p	c	f	f	f	f	f	f
11	p	c	f	f	p	c	p	c	f	f	f	f	f	f
12	p	c	f	f	p	c	p	c	c	c	f	f	f	c
13	p	c	c	c	p	c	p	c	c	c	f	c	f	c
14	p	c	c	c	p	c	p	c	c	c	p	c	p	c
15	p	c	c	c	p	c	p	c	c	c	p	c	p	c
16	p	c	p	c	p	c	p	c	c	c	p	c	c	c
17	p	c	p	c	p	c	p	c	c	c	c	c	c	c
18	p	c	p	c	p	c	p	c	c	c	c	c	c	c

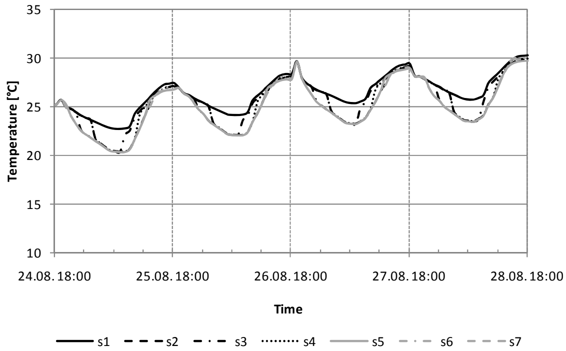

Figure 4 Simulation-based predictions of the indoor air temperature in R3 (day d_{j+1}) for alternative control scenarios (s1 to s7 as per Table 1) for four days in August 2009

Table 2

Comparison of control scenarios (Table 1) based on predicted Mean Overheating (OH_m in K)

	OH_m [K]						
	s1	s2	s3	s4	s5	s6	s7
24.8.	0.5	0.4	0.4	0.4	0.3	0.3	0.3
25.8.	1.2	1.0	1.1	1.0	0.9	0.9	0.9
26.8.	2.1	1.6	1.9	1.8	1.6	1.6	1.5
27.8.	2.9	2.2	2.6	2.3	2.1	2.3	2.2

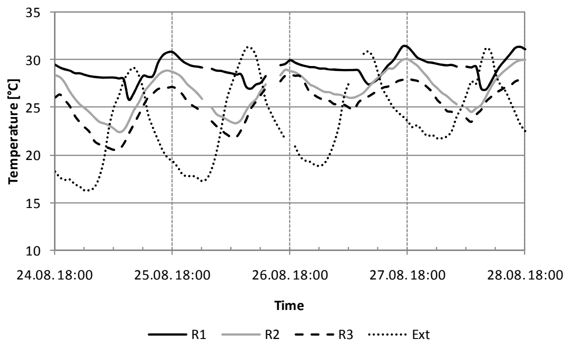

Figure 5 Measured indoor air temperature in rooms R1 to R3 together with external temperature over the test period

Simulation calibration

The operation of the system, as documented in the above results, was based on multiple runs with a calibrated simulation engine. As previously noted, the simulation model applied uses window opening degrees (in %) as input information. As part of the simulation calibration process, we compared the results of air change measurements with corresponding simulation results. Measured air change rates for R2 and R3 are shown in Table 3. Table 4 includes, for these, a summary comparison of measured and simulated air change results. We consider these results satisfactory, given the considerable uncertainties involved in simulating air change rates in buildings. Note that, in the present case, the simulation application's default standard pressure coefficient values were used. We would expect, that even a better reproduction of measured values could be achieved, if pressure coefficients would be computed in a detailed manner using CFD (or empirically obtained via wind tunnel tests).

Table 3

Measured air change rates in office R2 and R3 on 16th and 17th of June 2009

Room	Window position	ACH [h^{-1}]	Wind speed [$m.s^{-1}$]	Wind dir. [°]
	open	8.6	6.8	270
R2	partly open	1.6	6.8	270
	closed	0.3	3.2	270
	open	8.3	2.7	315
R3	partly open	1.1	2.5	45
	closed	0.3	1.7	135

Table 4

Simulated versus measured air change rates in office R2 and R3 on 16th and 17th of June 2009

Room	Window position	Measured ACH [h^{-1}]	Simulated ACH [h^{-1}]	Window opening degree [%]
	open	8.6	7.6	40
R2	partly open	1.6	1.5	8
	closed	0.3	0.3	1.3
	open	8.3	8.0	40
R3	partly open	1.1	1.3	8
	closed	0.3	0.3	1.3

To address the extent of weather forecast errors, weather predictions were compared to actual data (for August 2009). Figure 6 shows the Mean relative error of outdoor temperature and irradiance predictions as a function of prediction time horizon (from 1 hour to 18 hours ahead). Predicted temperatures show an error of about -5% fairly independent of the prediction time horizon. Thus, as part of the simulation process calibration, this systematic error was reflected in the simulation input assumptions regarding weather information. Consequently, Figure 7 shows the comparison between the predicted (locally adjusted weather forecasts from the web-based service) and the measured (weather station based) outdoor temperatures for four days in August 2009. Predictions were made every day at 18:00 for the following 24 hours.

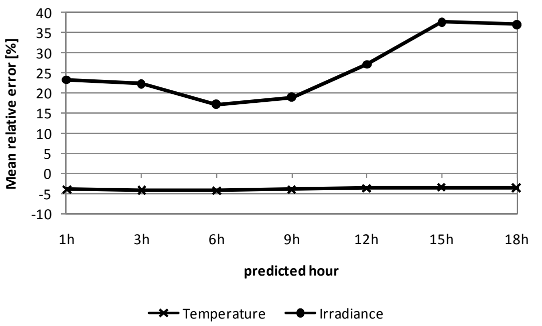

Figure 6 Mean relative error of outdoor temperature and irradiance predictions (August 2009) as a function of prediction time horizon (from 1 hour to 18 hours ahead)

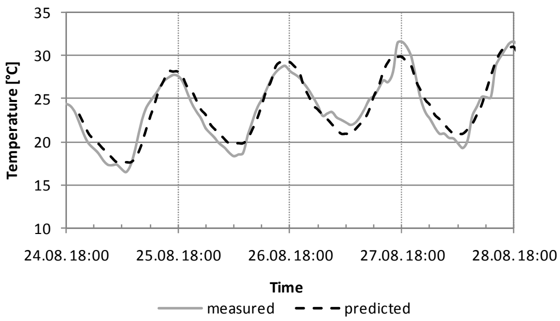

Figure 7 Comparison predicted and measured outdoor temperature over a period of 4 days in August 2009

Having thus calibrated the simulation model in view of ventilation rates and weather conditions, we could compare measured and predicted indoor air temperatures in the test space (R3). To demonstrate this point, Figure 8 shows, as an example, simulated and measured indoor air temperatures for the actually selected scenarios (grey areas in Table 2) for the four day test period in office R3.

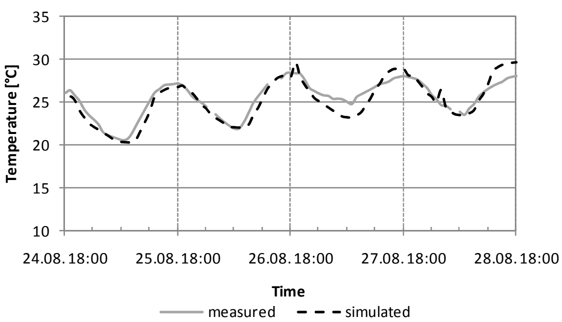

Figure 8 Comparison simulated and measured indoor air temperature R3 resulting from the system's operation

DISCUSSION AND CONCLUSION

In this paper, we presented the process and the results of a calibration effort related to a thermal simulation model of an existing office building in Vienna, Austria. This model is an integral component of the building's innovative model-based control logic for the operation of windows, shades, and lights. To enhance the prediction capability of the simulation model, it was subjected to a systematic calibration effort.

Results of the implementation effort suggest that the predictive simulation-based control approach toward intelligent space cooling is feasible. As Figure 5 suggests, indoor temperatures in R3 (equipped with external shades) display lower values than in R2 (equipped with internal shades), followed by R1 (reference room). Mean Overheating was calcuated for this observation period as 2.9 K in R1, 1.9 K in R2, and 0.9 K in R3 during occupancy hours.

The quality of the system operation depends on the reliability of the simulation application's algorithms, relevant input assumptions, as well as input data regarding window positions towards the estimation of the resulting air change rates. The predictive accuracy of the simulation models can be improved via calibration. In the present implementation, we illustrated the potential for the calibration of window position assumptions based on the comparison of measured and predicted air change rates. Likewise, we argued that a good predictive performance of the simulation application requires high-quality and locally adjusted weather forecast data.

The resulting calibrated simulation model provided reliable predictions: for the 4-day period depicted in Figure 8, compared pairs of measured and simulated room temperature values showed a mean relative error of -1.2% (simulated values were in average 1.2% lower than the measured values). The corresponding error in terms of RMS amounted to 0.54 K.

We are currently exploring potential toward fine-tuning of system performance through more frequent control state updates. In the implementation illustrated in this paper, simulation-based assessment of alternative control options was conducted once each day (in the afternoon) for the following day. However, such assessments could be performed more frequently (e.g. every hour). This continuous mode of operation with shorter intervals would make it possible to examine, evaluate, and revise control decisions regularly. Moreover, refinements of control scenario generation and selection process are being undertaken using stochastic search routines and genetic algorithms.

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