

A MULTI-STAGE APPROACH FOR BUILDING AND HVAC MODEL VALIDATION AND ITS APPLICATION TO A SWISS OFFICE BUILDING

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ABSTRACT

In the Swiss research project OptiControl (www.opticontrol.ethz.ch), new predictive building control strategies are developed and applied to a fully occupied, well instrumented demonstrator building. Here we report on the development and validation of the EnergyPlus building energy performance simulation model used in the project. Validation was done in three stages: (i) plausibility testing, (ii) tuning of room temperature dynamics based on HVAC excitation experiments, (iii) comparison of longer-term net energy and room temperature statistics in different operation modes. The mean and variability of spatially averaged indoor temperatures were generally well reproduced. Simulated total heating and cooling net energy usage showed however in many cases deviations > 50%. They were traced plausibly (but not conclusively) to specific modeling and input assumptions. Validation results depended strongly on incorporation of controller feedback in the simulations. The used validation strategy helped to improve the model and advanced the understanding of the building.

INTRODUCTION

Predictive control presents a promising option to enhance the energy efficiency and comfort of buildings, and to reduce their peak power demand at modest additional cost. The Swiss project OptiControl deals with the development and testing of predictive building control solutions. These are currently being tested on a representative, well functioning, fully occupied office building.

To support the development of the control algorithms and to overcome the limitations of field experiments (particular weather conditions, effects of user interactions etc.) the project heavily relies on computer-based modeling and simulation.

Energy modeling of a building typically presents an iterative process consisting of alternating model development and model validation phases. In model validation independent data are used to check in as far the model meets certain requirements. The results are then normally used to further improve the model, e.g. based on the refinement of submodels, the adjustment of key input assumptions, or the tuning of model parameters.

Here we present a three-stage model development and validation procedure that we used to structure our overall model construction process. The goal of the paper is to report the capacity of the (tuned) multizone building and HVAC model to predict room temperatures and net energy usage, and to discuss the model's strengths and limitations with regard to controller development.

MATERIAL AND METHODS

Building

The target building (Figure 1) was a typical Swiss office building located in Allschwil close to Basle, Switzerland. Constructed in 2007, the building has six levels with a conditioned floor area of ~6'000 m², a typical Swiss thermal insulation level (U-value 0.32 Wm⁻²K⁻¹), insulation glazing (U-value 1.34 Wm⁻²K⁻¹, total solar heat transmittance 60%), and a window area fraction of 50%. The usage is representative for an office building.



Figure 1 View of the target building from the south

The HVAC system consists of the following components: (i) thermally activated building system (TABS), i.e. pipes buried in the concrete slabs of the floors carrying hot/cold water; (ii) a central air handling unit (AHU) with a heat exchanger for return air heat/cold recovery, a heating coil in the supply air, and an evaporative cooler in the return air; (iii) radiators in the corner offices and the lounge; (iv) centrally controlled external blinds.

A gas boiler generates the hot water for the TABS, the AHU heater and the radiators. The cold water for the TABS comes from a dry cooling tower, which is only operated at night.

There is only one TABS zone, i.e. the TABS massflow rate and supply water temperatures are determined globally for the entire building. The AHU provides all zones with a constant minimum outdoor air flow rate. It is operated during working hours only. Supply air temperature is determined globally for the entire building. There are no local reheating coils. For the radiators thermostatic control is used. The blinds are set on working days three times a day on a per façade basis. Their position can be overridden by the occupants. The windows can be opened manually.

Measurements

The following measurements were used for model tuning and validation: Whole-building heating energy consumption by TABS, radiators, and ventilation; whole-building cooling energy consumption by TABS; electrical consumption for the entire second floor and for lighting and equipment in each individual office of that floor; room temperature, presence, illuminance and window opening state in each office of the second floor.

The measurements were originally available at irregular points in time, mostly at a sub-hourly sampling rate. For comparison with the simulated data they were interpolated to hourly totals or hourly mean values, depending on the physical variable.

High-quality hourly weather data for the years 2011 and 2012 were obtained from the MeteoSwiss weather station Basel Binningen at a few kilometers distance from the building site. The following variables were used as an input to the simulations: dry bulb and dew point temperature, and direct normal and diffuse horizontal radiation that were derived from global horizontal radiation.

Model Description

The simulation model represented the target building's entire second floor (Figure 2). The model was implemented using the EnergyPlus (EP) Version 7.0 software (EnergyPlus, 2013). EP is a simulation engine for building energy performance analysis and thermal loads of buildings.

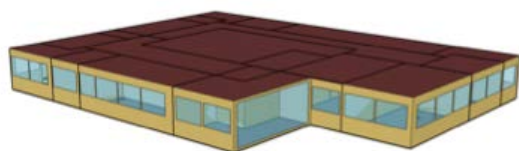


Figure 2 Geometrical model and zoning of the second floor

The second floor is mainly used for office space. It was subdivided in 20 thermal zones (Figure 2). Zoning was initially based on façade orientation, but additional subzones for the non-corner zones were necessary to accurately model mechanical ventilation and the use of the hall as a return air plenum. All zones were thermally coupled assuming adiabatic

boundary conditions for the floors and ceilings. Additional floors and neighbouring buildings were considered for shading calculations.

All HVAC components were scaled such as to fit the needs of the second floor only. Internal gains due to occupancy, lighting and electric equipment were introduced based on number of workplaces, installed equipment and Swiss standard usage schedules as provided by SIA (2006). Infiltration was taken into account, using a constant value of 0.1 h^{-1} (after final tuning). Natural ventilation due to possible window openings by occupants was neglected.

Set-Up of Simulations

In order to drive the EP model with measured external data and to be able to use precisely the same control as implemented in the target building we coupled EP to the MATLAB scientific computing environment (MathWorks, 2013). This was accomplished with the Building Controls Virtual Test Bed middleware (BCVTB; Wetter, 2011). Details on the used modeling and simulation environment can be found in Sagerschnig et al. (2011).

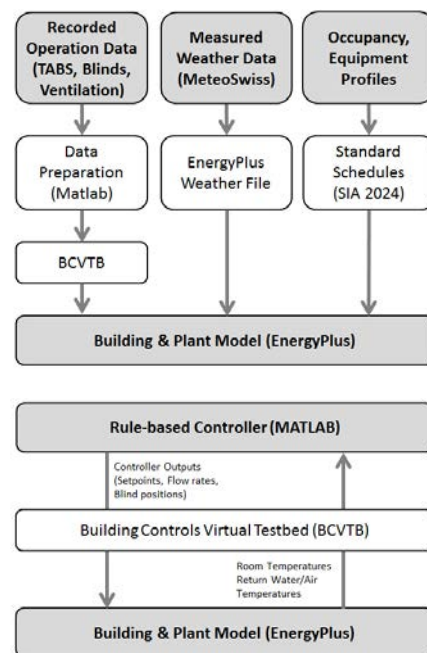


Figure 3 Signal flows in open (top) and closed loop control (bottom) simulations

We performed two kind of simulations: Open loop control (OLC) simulations, where the model was entirely driven by measured control signals for TABS, blinds and ventilation; and closed loop control (CLC) simulations where the model was controlled by the same rule-based control procedure as used in the real building (Figure 3). Details on the used control strategy can be found in Gwerder et al. (2010 and 2013). Both kinds of simulations were driven by measured weather data plus pre-determined, weekly recurring hourly schedules for occupancy and internal loads.

The simulations were run for 2011 and 2012, but depending on the availability of measurements only selected time windows could be used for validation.

All simulations were done at a 15 minutes time step and their outputs were aggregated to hourly totals or averages. The 15 minutes time step was chosen to minimize computational effort for model integration and co-simulation. Use of shorter time steps down to one minute was found to have no significant effect on the key statistics reported here.

Model Development and Validation

The used procedure for model development, validation and tuning was characterized by the fact that detailed measurements from the building became increasingly available during the course of the project. Overall, we developed three main model versions, Models A–C in chronological order, as shown in Table 1.

Table 1
Model Versions

MODEL	MAIN INPUTS USED FOR MODEL DEVELOPMENT AND VALIDATION
A	Planning data, standard weather data, standard internal load profiles, out-of-the-box controls.
B	Measured room temperatures from AHU and TABS excitation experiments; measured weather; measured control signals; realistic control. Tuning of time-mean room operative temperatures.
C	Same as B, but model extended/tuned with focus on room temperature dynamics.

We distinguished three validation stages, as follows:

Stage 1: Initial modeling and plausibility testing. Result: Model A. The initial model was constructed based on planning data and best practice guesses where no such data were available. It was tested for general correctness and plausibility in simulation studies covering a few days to a whole year using design reference weather data, standard internal load profiles, and out-of-the-box controls. The simulations were analyzed to make sure that the model (i) is implemented correctly, (ii) shows a physically plausible and consistent behaviour, (iii) processes external controller outputs accurately, and (iv) yields room temperatures and energy consumption that were roughly within the observed range.

Stage 2: Tuning of operative room temperatures. Result: Models B and C. Tuning was done by driving the models with measured weather data and realistic controls and then comparing the simulated hourly mean operative room temperatures with the room temperature measurements from two multi-day periods (Periods I and II, cf. Table 2). To maximize the information content of the measurements during these periods we performed two open-loop control experiments, as follows.

In the first experiment we investigated the building’s thermal response to an AHU supply air temperature

excitation. We employed two doublet signals (+15/-20/+5 K, and -5/+20/-15 K), as shown in Figure 4 (top). The second experiment allowed us to measure responses from step changes in the TABS supply water temperature. The TABS were first operated at maximum cooling capacity for three days, after that maximum heating was switched on (Figure 4, bottom). During both experiments the blinds were kept generally closed to minimize the influence of solar gains on the measured temperature trajectories.

Stage 3: Comparison of long-term energy and operative room temperature statistics. Result: Final validation statistics. Here we applied the model to three further periods (Periods III–IV, Table 2) of several weeks length each. During these periods the building was operated normally. Simulation results for these periods were compared to measured data for both, operative room temperatures, as well as net heating/cooling energy usage.

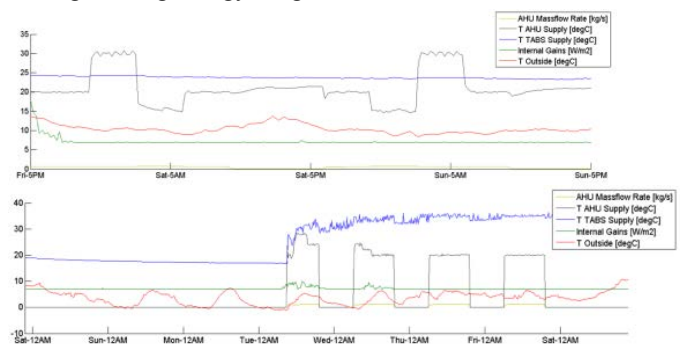


Figure 4 HVAC actuation, and measured outside air temperature and internal gains during the AHU (top) and the TABS (bottom) excitation experiments

Tuning Procedure

Tuning of all three models was done in an iterative manner by matching qualitative model behaviours to expected outcomes based on expert knowledge, by rough quantitative comparisons with measured data, and by visual matching of simulated and measured trajectories. Detailed statistical analyses were undertaken for the Stage 3 validation, as explained later.

Model B resulted from Model A based on a tuning exercise that aimed at reducing the average difference between the simulated and the measured room temperatures. We employed the following adjustments:

- Modification of the assumed construction of the floor covering/internal ceiling;
- Removal of insulation layer in the internal walls;
- Raising of radiator setpoints in the corner rooms;
- Reduction of infiltration and internal gains in the core zone;
- Introduction of base load in equipment schedules based on measured electricity consumption.

Note that these modifications affected only issues where no planning data were available. Where planning data were available (such as for the façade construction) they were not modified.

Development of Model C was motivated by the fact that Models A and B were both found to only poorly reproduce the room temperature dynamics from the AHU step experiment (see Figure 5).

Additional measurements during a two-week special monitoring phase showed that the air temperature at the office zones' air outlets differed from the measured supply air temperature that is set in the AHU located at the building's basement by up to 2-4 K. A closer investigation showed, firstly, unexpectedly high heat losses during the transport in the shaft. Secondly, we discovered that the ducts to the offices are partially embedded in the concrete core of the ceiling, such that the supply air is apparently strongly conditioned towards the concrete temperature.

Unfortunately, EP does not support the use of two heat sources (such as TABS water pipes plus supply air ducts) within a single construction. Therefore in order to be able to simulate the thermal implications of the embedded ducts we resorted to the following approach: The supply air temperature entering the room was modified as a function of supply air temperature in the basement based on linear regressions fitted to data from the special monitoring phase. This modification was implemented by introducing virtual heating and cooling coils that were acting on the supply air in the model. The coils' energy consumption was not considered in the AHU's final energy usage statistics. However, it was used to compute at each time step a corresponding adjustment of the TABS supply water temperature to impose appropriate heat gains or losses and associated temperature modifications to the concrete ceiling. The TABS' final energy usage was evaluated based on the unmodified supply water temperatures.

This procedure clearly presented but a rough approximation of the physical processes in the building. This was because it assumed the same average effect on the concrete temperature for all zones, and because the used modification of the supply air temperature did not depend on the concrete core temperature.

Model C incorporated one further refinement as compared to Model B: It accounted for the fact that the outdoor air travels to the AHU via an earth embedded duct of several meters length. To predict the air temperature at the AHU supply air inlet we used a first-order model that was tuned to several months of hourly temperature measurements. This extension influenced the heating and cooling energy used by the AHU, but otherwise it did not affect the model's dynamical behavior.

Comparisons

Comparisons between measured and simulated hourly data were done for five selected periods, as summarized in Table 2.

Period I included the weekend from Nov. 4th-6th, 2011, where the AHU supply air temperature

experiment was performed (see Figure 4). Period II covered the TABS experiment that was executed during Dec. 23-31, 2011 (see Figure 4). Periods III and IV were heating periods, whereas cooling was active during the warm Period V.

Table 2
Validation periods.
 T_{out} : Mean outside air temperature.

PERIOD	TIME WINDOW	T_{out} [°C]	DESCRIPTION
I	Nov. 2-8, 2011	10.2	AHU experiment
II	Dec. 20-31, 2011	3.5	TABS experiment
III	Jan. 26-Feb 17, 2012	-4.5	Cold period
IV	Mar 1-Apr 19, 2012	8.6	Mild period
V	Aug 8-Sep12, 2012	19.5	Warm period

Deviations between simulated (s) and measured (m) hourly time series were assessed quantitatively by the mean error (ME) and the mean absolute error with the bias removed (MAE):

$$ME = 1/n \sum (s_i - m_i) \quad (1)$$

$$MAE = 1/n \sum |(s_i - ME) - m_i| \quad (2)$$

Here n and i denote the sample size and the time step index, respectively. ME measures the time-averaged deviation over the comparison period, whereas MAE measures the average deviation in the simulated signal's dynamical behavior after it has been shifted to have the same time-mean as the measurements.

The following quantities were analyzed: the area weighted mean operative temperature of all offices plus the meeting room of the second floor (T_{RM}), the net energy usage for TABS heating and cooling (H_{TABS} , C_{TABS}), and the net energy usage for AHU (H_{AHU}) and radiator heating (H_{RAD}). The total heating energy usage by TABS, AHU and radiators is denoted as H_{TOT} . Energy measurements were scaled to the second floor based on its fraction of the total building's conditioned area.

RESULTS

Figures 5 and 6 compare the measured temperatures for two selected office rooms with the simulated operative temperatures for the corresponding model zones during Periods I and II, respectively.

It can be seen that during Period I (Figure 5) all three models overestimated the amplitude of the room temperature responses to the imposed changes in AHU supply air temperature. Model C was however clearly the best.

Quite differently, in Period II (Figure 6) this model showed the poorest performance in reproducing the effect of the imposed TABS heating step.

Figures 7 and 8 show the ME and MAE of T_{RM} for all model versions and periods, respectively. They confirm the findings from Figures 6 and 7 for the entire second floor.

Figure 8 further shows that the simulated T_{RM} were cooler than the measurements for all models and validation periods, except for the OLC cases in Period V. Also, the magnitude of the ME was mostly smaller for the CLC as compared to the OLC cases.

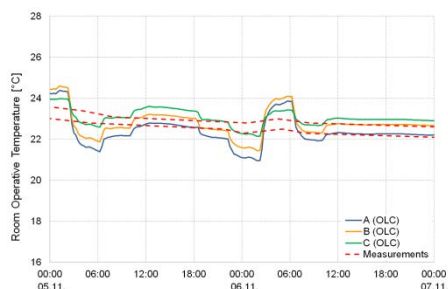


Figure 5 Measured office room temperatures (red) and simulated operative temperatures in Period I (AHU experiment). A–C: Model versions. Data refer to two selected office rooms and the related model zone with façade orientation “West”



Figure 6 Same as Figure 5, but for Period II (TABS experiment)

From Figure 8 can also be seen that the MAE of the simulated T_{RM} was generally below 0.6 K, the only exception being Model C in Period II. For comparison note that the mean absolute deviation of the measured T_{RM} data from their respective period mean was for Periods I, III and IV ~ 0.36 K, for Period II 2.11 K, and for Period V 0.77 K.

All T_{RM} comparisons showed a statistically significant linear relationship between the measured and simulated time series. This relationship was always stronger for the OLC as compared to the CLC cases (results not shown).

Figure 9 juxtaposes the measured and simulated net energy usages for the Periods III–V. Relative deviations are given in Figure 10. It can be seen that the simulations got the differences between the different validation periods and between the total heating and cooling demand roughly right (Figure 10). However, except for Period III, relative deviations from the measured values were found to be large, often $> 50\%$ (Figure 10).

Figure 11 shows the average daily cycles of T_{RM} and H_{TABS} during the cold Period III. It can be seen that all simulations were not only too cool (cf. Figure 7), but also that they showed a much larger daily T_{RM} amplitude than the measurements.

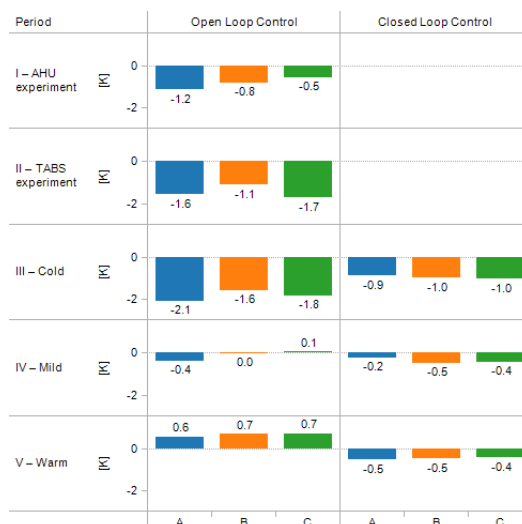


Figure 7 Mean error (ME) from the comparison of measured and simulated room operative temperatures T_{RM} . A–C: Model versions

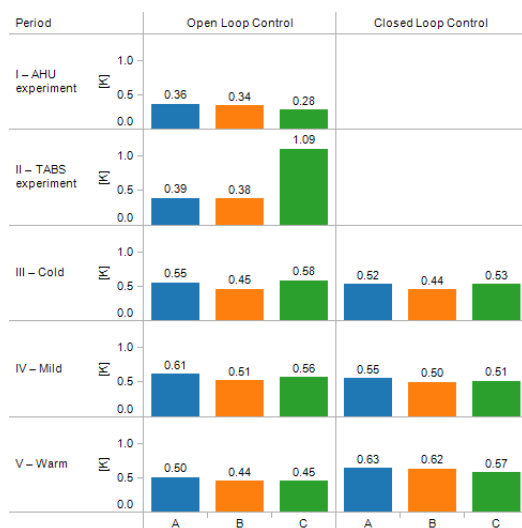


Figure 8 Same as Figure 7, but for the mean absolute error with the bias removed (MAE)

From Figure 11 can further be discerned that the average diurnal course of H_{TABS} in the OLC simulations showed an intermittent behavior, similar to the one found in the measurements. Under CLC, however, the TABS heat delivery showed a basically different, much more continuous pattern.

Figure 12 presents a similar analysis as Figure 11, but for the warm Period V. Here T_{RM} was higher than measured for the OLC and lower than measured for the CLC simulations (cf. Figure 7). Again, all simulations overestimated the amplitude of the T_{RM} daily cycle.

Both the measurements and the simulations showed qualitatively similar diurnal cycles for C_{TABS} (Figure 12, bottom) that reflected the fact that the dry cooling tower is only operated during night-time. The real building required less cooling energy than suggested by the simulations (cf. Figure 10, bottom).

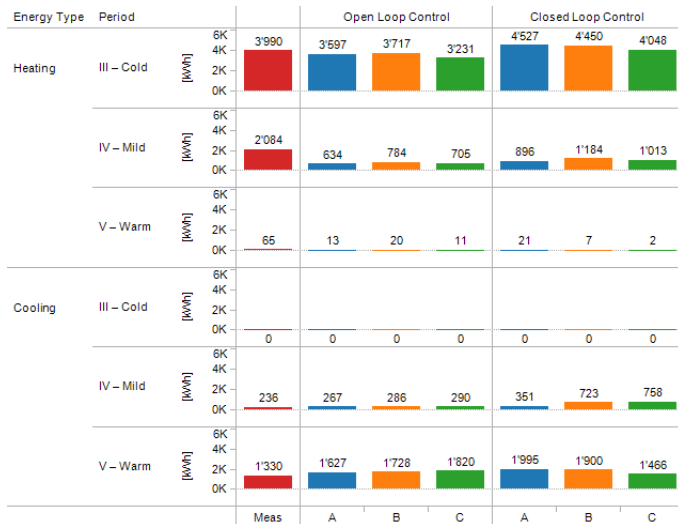


Figure 9 Measured (Meas) and simulated total net energy usages for heating (H_{TOT} , top) and cooling (C_{TABS} , bottom). A–C: Model versions.

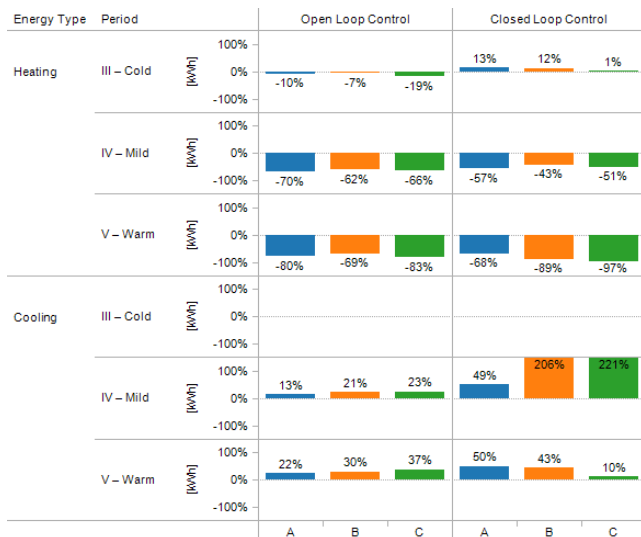


Figure 10 Percent deviations of simulated total net energy usages from the measured values.

DISCUSSION

The validation exercise revealed a very varied picture about the three model’s ability to predict measured room temperatures and net energy usage.

Overall, Model B gave the best results with regard to reproducing the dynamics (Figures 5, 6 and 8) and long-term means (Figure 7) of the measured T_{RM} . In terms of simulating net energy usage Model B proved to be the best in 3 of the 5 available OLC comparisons, and in one of the 5 available CLC comparisons (heating energy in Period IV, Figures 9 and 10). However, this ranking is of secondary importance given that all simulated energies showed large deviations from the measured data, except perhaps for heating energy in Period III (Figure 10).

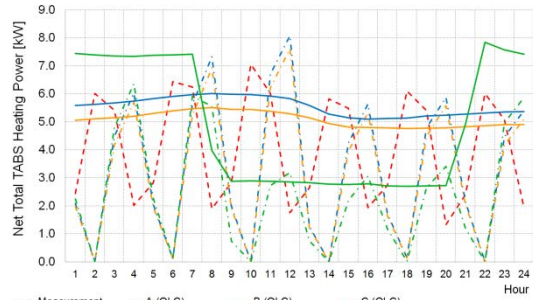
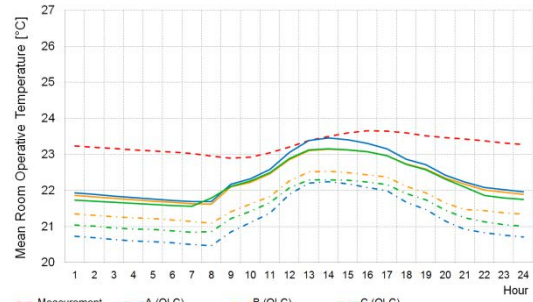


Figure 11 Comparison of measured and simulated average diurnal cycles for room operative temperatures (top) and TABS heating power (bottom) during the cold Period III. A–C: Model versions; OLC/CLC: Open/closed loop control.

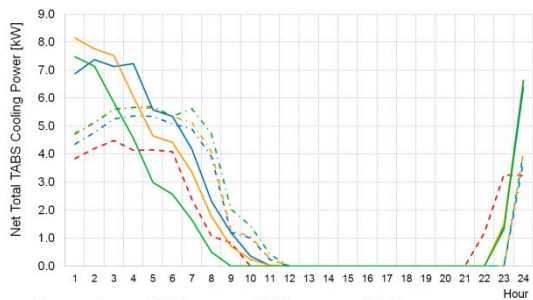
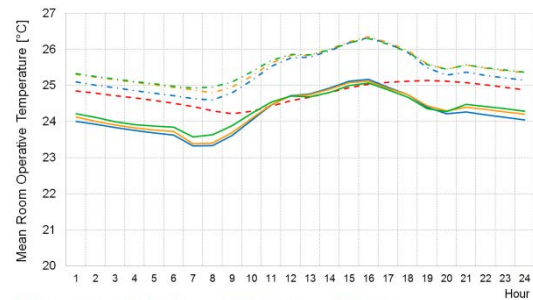


Figure 12 Comparison of measured and simulated average diurnal cycles for room operative temperatures (top) and TABS cooling power (bottom) during the warm Period V. A–C: Model versions; OLC/CLC: Open/closed loop control.

A further salient feature of our results are the found large differences between the OLC and CLC simulations (Figures 7–12).

All these findings depended on a multitude of modeling decisions, input data sets and assumptions that made it difficult to trace the individual deviations to a single cause. Nevertheless, several specific statements can be made.

Too low average T_{RM} in the cold Period III (Figures 7 and 11): A closer analysis showed that for both, OLC and CLC, H_{AHU} was reproduced to within ca. $\pm 10\%$. However, the three OLC simulations were found to underestimate H_{TABS} by 18–39% and to overestimate H_{RAD} by 13%–65%. CLC showed opposite trends of similar magnitude. Moreover, in all simulations the average diurnal cycles for H_{RAD} were found to differ strongly from the measured ones (not shown), as this was also the case for the average diurnal H_{TABS} patterns, in particular under CLC (Figure 11).

The operation of the TABS and the radiators in the real building as well as in the models depends on operating modes and setpoints (high-level control) that are being tracked by low-level controllers. In the simulations the high-level control signals were either prescribed by measurements (in case of OLC) or computed online (in case of CLC; cf. Figure 3). Quite differently, the low-level control was completely left over to the EP simulation engine. We therefore suspect that the various deviations found in Period III were at least partially caused by differences in low-level control. Sources of error are for instance the radiator setpoints (that we had to guess) and differences in the sensed temperatures used by the radiator thermostats and the TABS control algorithm (e.g., due to differences in real vs. modelled sensor locations).

Underestimation of heating energy usage in the mild/warm Periods IV and V (Figure 10): As shown in Figure 7 during these periods the average room temperature level was quite well reproduced. Accordingly, the reduced energy usage in the model is indicative of too high internal and/or solar gains. The latter depend crucially on the positioning of the blinds. During working days the blinds are set by the building's automation system three times per day, but the occupants may override the automatic settings at any time. Unfortunately, no data was available that would have allowed us to account for the occurrence of manual blind repositioning and the resulting modification of solar heat gains in the simulations.

Overestimation of cooling energy usage in Periods IV and V (Figure 10): This result could have been caused, firstly, again by too high internal and/or solar gains. Secondly, it could be due to the fact that cooling by natural ventilation was not considered in the simulations. An analysis of window contact sensor data (not shown) suggested that during August and September 2012 on ca. 45% of all days where an office was occupied at least one window had been

opened for at least 5 hours. For a single opened window we estimate for a single office of the target building the resulting heat flux to be somewhere between a few W/m^2 and several tens of W/m^2 , depending on the size of the window opening, the temperature gradient and the resulting outdoor air change rate. Considering that the measured peak C_{TABS} in Period V was 20–25 W/m^2 (time-average: 2.13 W/m^2 ; cf. Figure 12) it can be stated that natural ventilation has probably contributed significantly to reducing the measured cooling energy demand.

Differences between open and closed loop control (Figures 8–13): The OLC simulations accounted implicitly for occupancy-induced internal loads and the possible blind repositioning or opening of windows by the occupants because the recorded control sequences included the control system's response to these disturbances. In contrary, the CLC simulations depended entirely on the assumed internal loads schedules and did not account for windows and blinds operation by the occupants. Given the aforementioned importance of natural ventilation this difference in the two set-ups might well have contributed to the found smaller C_{TABS} deviations in the OLC as compared to the CLC simulations (Figure 10). Note that the overestimation of C_{TABS} in the CLC simulations was particularly large for the mild Period IV where comparatively large outdoor-indoor air temperature gradients yielded a very high cooling potential by natural ventilation.

Deterioration of Model C temperature dynamics during the TABS experiment (Figure 6): This result showed that the used correction for the thermal interaction between the supply air and the concrete floor was either too crude and/or not general enough. Note that in our simple model fix we modified TABS supply water temperature rather than the concrete temperature directly. This probably explains the much delayed room temperature response of Model C as shown in Figure 6. Moreover, the used regression models were fitted to data measured in May 2012, whereas the validation was applied to the much cooler TABS experimental period in December 2011.

Further factors that may have contributed to the found deviations between measurements and simulations are the limited accuracy of the room temperature measurements; the use of non-local weather inputs in the simulations (possibly affecting solar gains and temperature gradients, e.g. with implications for cooling tower operation, cf. Figure 12); various assumptions on construction details that are very difficult to check; the assumed boundary conditions to the adjacent floors; the lack of realistic submodels for air and water transport; the use of a quasi-steady-state submodel for the radiators; the need to rescale HVAC design values and measured energies to the 2nd floor; and finally limitations of the EP software such as the inability to simultaneously model TABS and embedded air ducts, limitations in

the simultaneous use of the TABS heating and cooling loops, and the limited ability of EP users to influence the software's low-level control.

The three-stage validation approach presented here appears suitable for application also to other modeling projects. At Stage 1 one will typically produce a first guess (Model A), essentially based but on planning data. In Stage 2 first improvements (e.g., Models B and C) can be developed thanks to initial measurements. Here we found that the use of excitation experiments (Figure 4) was essential with regard to motivating the development (Period I) of possibly improved models (e.g., Model C) and to test the various model's performance (Period II). The poor response of Model C to the TABS excitation would have probably gone undetected if validation data had been only available from the standard operation Periods III–V (cf. Figures 7 and 8). Our results further suggest that it was wise to test the updated models in a further stage (Stage 3, but possibly also in further stages) using longer-term measurements that reflect a wide range of operating conditions.

The increasing availability of measurements during the course of a project such as the one presented here can in principle be exploited to tune model parameters using automated algorithms such as GenOpt (2013). However, our findings suggest that such tuning exercises require careful examination of all relevant disturbances (related, e.g., to internal or solar gains and natural ventilation) in order to avoid spurious agreement between reality and simulations.

CONCLUSION

The model development, tuning and validation process described here proved very challenging. The model's predictive accuracy for room temperature dynamics and net energy usage was found to depend as much on the correctness of the building and HVAC submodels, as on control details and the choice of various input data sets and assumptions.

We found (once more) that measurement-driven tuning may improve some aspects of the model while worsening others. This highlights the need to carefully trace the effects of possible model adjustments by considering several variables, operation modes and statistics. Targeted HVAC excitation experiments can provide valuable insights and validation datasets otherwise not available from normal building operation.

While average measured temperatures and temperature dynamics could be reproduced well, the validation revealed large deviations between simulated and measured energy usages. These can be traced plausibly (but not conclusively) to a series of specific modeling and input assumptions. Simulation models like the one developed here are often used to investigate long-term differential effects on the building's energy usage due to alternative building,

HVAC or control designs. The magnitude of the found errors suggests that in our case to allow firm conclusions with regard to the real building's energy usage any such differential results should be tested under a variety of parameter uncertainty and disturbances scenarios (related, e.g., to windows opening, blinds operation, occupancy etc.).

Overall, the proposed validation approach provided important insights into the building and its control. These insights, together with the ability to conduct simulation experiments using a reasonably realistic model (Model B) allowed us to successfully develop and implement new control strategies in the real building (Gwerder et al, 2013; Sturzenegger et al., 2013). The model's limited predictive accuracy proved not too critical since the developed control solutions were robust and general enough not to depend on the details of the target building.

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