SIMULATION ASSISTED IMPLEMENTATION OF A MODEL BASED CONTROL PARAMETER FINE-TUNING METHODOLOGY FOR A NONRESIDENTIAL BUILDING WITH A COMPLEX ENERGY SYSTEM

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ABSTRACT

In order to improve the energy efficiency, while still insuring indoor comfort for a new non-residential building, a model-assisted fine-tuning methodology for control parameters was implemented. During offline experiments, where no control parameters are sent to the building, the method was configured according to the particularities of the building. To this purpose we used a co-simulation, where the optimization algorithm for the control parameters was connected to a simulation model of the building and its technical equipment. The offline experiments show promising results regarding energy savings when compared to good rule-based controllers. The transition to online experiments is more challenging as it depends on the way the whole building system behaves.

INTRODUCTION

Modern non-residential buildings have to mediate the trade-off between high energy efficiency and quality of the indoor climate, as the first is imposed by the current energy saving policies (European Union, 2012) and the latter has a direct influence on the workers' productivity (Seppanen et al., 2004). The problem gets more challenging in the case of buildings with complex energy systems using renewables, as no clear methodology for designing their control strategy exists. In this paper we present the way simulation can assist in devising controllers for such buildings using a model-assisted control parameter fine-tuning methodology. The results presented in the paper were generated in the project PEBBLE (Positive Energy Buildings thru Better controL dEcisions) funded through the Seventh Framework Programme of the European Union.

PEBBLE is an international project that aims to achieve maximal net energy produced for buildings by using an intelligent control process. The challenge lies in the ability of the building's control system to make (almost) real-time decisions under the constraints of unpredictable user behavior, occupancy scheduling or weather conditions. Seven partners from Austria, France, Germany, Greece and Switzerland are involved in the project, including the RWTH Aachen University. The new building of the E.ON Energy Research Center is used as a demonstration building, being the most complex of all three demonstration buildings in the project.

At the core of the energy concept of the building lies a highly efficient turbo compressor driven heat pump process that uses geothermal energy as a heat source. The geothermal field has 40 boreholes, each 100 m deep. The base load for heating or cooling is covered by a concrete core activation system (CCA), whereas the peak load and the air quality are achieved in each office with a façade ventilation unit (FVU).

For the PEBBLE project we chose to focus on the north concrete core activation area (Figure 1), which stretches over all three floors of the building and includes 45 offices.

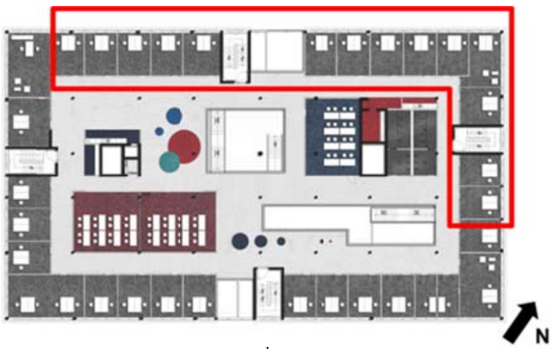

Figure 1 Floor plan 2nd floor with CCA zone north marked

A building automation system (BAS) is installed. However its programming is not yet complete as the complexity of the systems proves challenging. The programming relies on a series of rule-based controllers, which sometimes come into conflict with each other. PEBBLE proposes an optimization algorithm that uses the BAS as an interface to communicate with the building.

For the control strategy a model assisted fine-tuning methodology is employed, named cognitive adaptive optimization (CAO) (Giannakis et al., 2011). The method uses weather and occupancy prediction just like model predictive control (MPC) methods. MPC methods are quite popular for building control (Široký et al., 2011) and have already been employed as early as 1985. Building up a state-space model for an MPC model can be time consuming and the modeling assumptions can lead to sub-optimal controllers for a real building. CAO on the other hand uses a simulation model of the building that does not need to be further translated in a state-space representation.

CAO's goal is to optimize a cost function for the energy demand under the constraint of user comfort. It is an iterative method that estimates the effect of a certain control strategy by using a simulation model of the building and its technical equipment.

The method has the following advantages:

- Convergence is guaranteed under a general set of assumptions (Kosmatopoulos, 2009)
- It can be used for any type of building, regardless of its size or installed technical equipment, as long as a simulation model can be built for it
- Additional constraints are easily added

The paper continues with the presentation of the control problem, the models and the interface for the co-simulation. The offline experiments for the configuration of the controller are detailed. We then discuss the results from both offline and online experiments.

SIMULATION

Control problem

We decided to implement the PEBBLE system for temperature control in the offices, because their climatisation concept offers an interesting problem to tackle. The CCA system is located in the massive concrete ceiling and can be used for cooling or heating. It is a slow system and as such used for covering the base load. The switch from cooling to heating for the CCA is done according to the ambient temperature. The flow temperature for the CCA system is set for a whole group of offices, of which the building has two: north and south. The heating fluid (water) is then distributed through the system, with approximately one CCA circuit per office. No further control of the flow or temperature of the CCA happens on a room level. The FVU is a much more dynamic system, because it heats or cools the air directly and is thus used for covering the peak load. The FVU can both cool and heat during the course of a day, as it is equipped with two heat exchangers. The room air temperature is controlled by adjusting the rotational speed of the ventilators and the valves positions of the heat exchangers. The challenge is to have the systems working together and not against each other, as this is inefficient.

We decided on the following control parameters:

- the set temperatures for the FVUs
- the flow temperature for the CCA

Over the whole demonstration area this leads to 46 (45 FVUs + 1 temperature CCA) control parameters. As we control each room temperature individually, each room has to be modeled in detail. However such a simulation model would lead to very long simulations, so simplifications need to be made. As the building is well insulated (U_{walls} = 0.2 W/m K, U_{window}= 1.2 W/m K) and all the offices have a similar use, we assume the main factor that differentiates them is their orientation. So instead of simulating all 45 rooms, only exemplary rooms with different orientations are simulated. To this purpose we build "tower" models. A tower stretches over all floors of the building and thus has three rooms, on top of each other, one on each floor. The boundary conditions towards neighboring offices are considered adiabatic. Figure 2 shows the name and the orientations of the resulting three towers. While the results for Tower Corner can be used only for these rooms in the real building, the results for the other two towers can be used for all the rooms with that orientation. For one tower we have four (three FVU temperatures and one CCA temperature) control parameters.

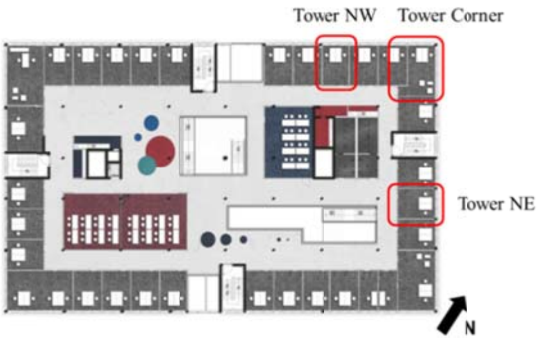

Figure 2 Name and orientation of the three towers

The cost function of the optimization algorithm is the minimization of the energy demand, which is the thermal energy from the FVUs and the CCA. The main constraint is the indoor comfort. For the quantification of indoor comfort we use the Fanger PPD (Predicted Percentage Dissatisfied) index (Fanger, 1970). The Fanger PPD index depends on the air temperature, the mean radiant temperature, the air velocity and the vapor pressure of air in the room and also on the cloth index, which is a function of outside temperature. We formulate the constraint as:

$$PPD \leq 15\% \qquad (1)$$

The constraint can be violated, however for no more than 15 minutes during a simulation run, in our case two days.

The controller is a P-controller, which calculates the control parameters (four for one tower) as a linear combination of states in the building:

$$U = \theta X \qquad (2)$$

where $U = [u_1, u_2, u_3, u_4]^T$ are the control parameters, $X = [x_1, x_2, x_3, x_4, x_5, x_6]^T$ are the states in the building and $\theta \in R^{4\times6}$ is the matrix of the gains with which each state factors into each controller. The θ matrix is continuously improved during the optimization algorithm, until an optimum of the cost function is found.

The states used for the controller are detailed in Table 1. More details about the way the states were selected for the final controller are given in the controller fine tuning chapter.

Table 1 States for calculating the control parameters

State	Description
x_1	Ambient temperature in °C
x_2	Wind speed in m/s
x_3	Diffuse solar radiation in W/m
x_4	Beam solar radiation in W/m
x_5	Room air temperature in °C
x_6	Presence as Boolean (0 or 1)

For the set temperature in each room, the corresponding room air temperature and presence for that room are considered. For the CCA (u_4) the mean room air temperature of all three rooms is used.

The optimization algorithm is implemented in MATLAB.

Co-Simulation

The simulation model was build using the modeling language Modelica in the simulation environment Dymola. For connecting the optimization algorithm with the simulation model we used the BCVTB (Building Controls Virtual Test Bed) software (Wetter and Haves, 2008).

The optimization algorithm runs iteratively and uses a simulation model to calculate the energy demand and the comfort level determined by a θ matrix. We use a simulation period of two days for such a test. At the beginning of each iteration a new matrix θ is generated, the co-simulation runs and at the end of it the cost function and constraints are evaluated. Afterwards the θ matrix is improved by the optimization algorithm and tested in a new iteration. During the co-simulation the model exchanges data with the optimization algorithm every ten minutes simulation time. The model sends the building states, as well as the current values for the energy consumption and the PPD index. Using this data the optimization algorithm calculates the new values for the control parameters and sends them back to the simulation model. The new values for the control parameters are set in the simulation and new states are generated.

Models for the building and technical equipment

A detailed thermal simulation model for the selected area is a prerequisite for the building's optimization and control process. The model takes into account geometries, building physics, installed HVAC and energy generation systems. It has a degree of detail that allows a thorough validation, as well as acceptable simulation durations.

The tower model was done using components from our Modelica libraries (Müller and Badakhshani, 2010). Each wall, window and door is individually modeled. The air volume in each room is modeled as one node. One typical office room with an outer wall (Tower NW and Tower NE) has a floor area of 19 m with a height of 3 m and a window area of 8 m . The Tower Corner has larger rooms with two outer walls and a floor area of 32 m . The windows are equipped with external blinds, which activate once the incident solar radiation exceeds 180 W/m .

The following internal loads are considered: humans, machines and lights as convective and radiant heat loads and humans as CO_2 sources (VDI 2078, 1996).

The technical equipment is modeled in detail. The model for the CCA is a physical model, with the pipes inserted between the concrete layers. The FVU can heat, cool and ventilate the rooms. The control strategy is modeled exactly as in the actual unit. During night time, when the office is not used, the set temperatures are adjusted, so that the unit remains in standby. For cooling the set temperature is increased with 5 K, and for heating it is decreased with the same amount. The heater, cooler and ventilator models are almost ideal; meaning once they are activated the reaction in the room temperature is fast. In reality we would have a delay caused by several factors: the furniture in the room, the opening of a window etc. The simplification of using just one air node per room and the goal of achieving short simulation durations justifies in this case the selection of almost ideal components.

The verification of the simulation model with measurement data is only partially possible. The building has several sensors installed in each room (presence, window opening, temperature, CO_2-concentration). Weather data is provided by a nearby weather station. However we have no information about the position of the blinds, the number of people who are in the room at one time, or the number and type of machines which are in use. For such a well-insulated building these types of internal gains have a considerable effect on the room air and radiant temperature. Several rooms are reference rooms, where extra measuring equipment was installed to measure the energy fluxes in the room (CCA and FVU). Figure 3 presents the comparison between the simulated and the measured room air temperature for a reference room for one winter day.

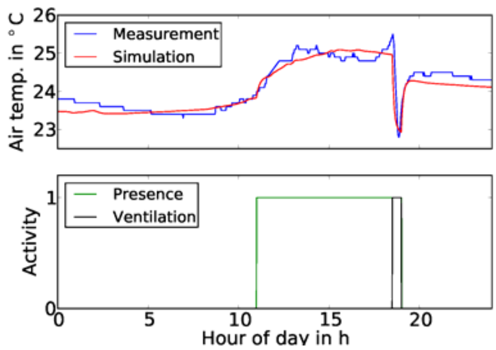

Figure 3 Comparison between simulation and measurement for a reference room

The temperature drop during the time the window was open was achieved only by iteratively adjusting the air exchange rate until we had a good fit. The number of persons in the room was set according to the room book. We consider this to be a good fit. The amount of work needed to adjust the value for the air exchange rate in this case and the uncertainties about other influences over which we have no information (e.g. blinds) do not allow at this time for a more detailed verification of the model with measured data.

Controller fine-tuning

A deciding factor when starting to fine tune the controller is the number of iterations needed to achieve a (local) optimum. First a number of initial iterations are used for the controller to explore the area around its initialization point (initial controller). These are arbitrarily generated. After that, more iterations are used to identify the right "way" towards the optimum, by using Support Vector Machines (Bishop, 2006). Although the problem of determining the minimum sample size to perform multiple regression analysis has no unique answer, since the statistical properties of each application domain prevent definition of a general rule, several rules of thumb have been proposed in literature (Green, 1991). In our case, using these rules as a guideline and under specific assumptions on the statistical correlation of the available data samples along with a trial-and-error process during the application of the method to all PEBBLE project test buildings, the following rules have been adopted for determining the number of necessary iterations:

$$Nr_{Ini.It.} = 1.5 \cdot Nr_{States} \cdot Nr_{Ctr.Par.} \quad (3)$$

$$Nr_{Max.It.} = 2.5 \cdot Nr_{States} \cdot Nr_{Ctr.Par.} \quad (4)$$

For one tower this means 60 iterations. Furthermore the optimization algorithm runs four times, each time with 60 iterations, in order to make sure the algorithm did not get stuck, leading to a total of 240 iterations.

The number and type of states is a more complicated problem, which we solved by testing different combinations of states and comparing the end results (energy demand and comfort violations). At first we varied the type and number of states, for example considering only some of the ambient conditions. Then we substituted some states with other similar states, like using diffuse and beam radiation instead of the total radiation on the outside wall; or considering just the room air temperature and not also the air temperatures in the neighboring offices. Both of these considerations led to better controllers. Lastly we developed controllers where we used the square of the room temperature. This approach did not improve the controller. We forgo at this point the presentation of these results. Earlier work (Constantin et al., 2012) is available, where an earlier version of the simulation model and of the control problem is presented. The current version improves upon those results.

Another important factor is the exploration area around the initial controller, used as a starting point in the optimization. If the search area for the initial explorations is wide enough, even a 'naïve' initial controller which only uses maximum allowed values can be optimized. Too wide an area is counterproductive, because the initial number of iterations might be insufficient to explore it correctly. We decided on the following rule: an exploration area is wide enough if the algorithm reaches similar results, when starting from three different initial controllers (C1, C2, and C3). C1 is similar to a state-of-the-art rule-based controller, which takes the ambient temperature as the main parameter for calculating set values. Figure 4 presents the dependence on the ambient temperature for the set temperature for a FVU and for the flow temperature of the CCA. The curve for the CCA is exactly the one implemented in the BAS – system. Between 18 °C and 22 °C ambient temperature the switch between heating to cooling mode occurs and the CCA is not used.

The curve for the FVU does not allow the temperature to drop under 22 °C or rise above 26 °C. Furthermore between 22 °C and 26 °C the room air temperature follows the ambient temperature. In the actual building the FVU uses a simpler control strategy, with a fixed set point (by default 22 °C), which the user can adjust. The C1 rule-based controller will be used further as a reference for comparing the results from the CAO algorithm for offline experiments.

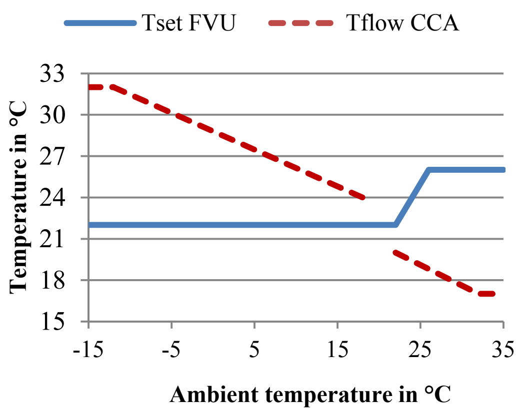

Figure 4 Dependence on ambient temperature for the C1-Controller

The C2 and C3 controllers are 'naive' controllers which use fixed set points for the control parameters ($T_{set,FVU}$ and $T_{flow,CCA}$). The C2 controller leads to lower energy demand, the C3 controller to higher energy demand. Table 2 presents the two controllers for two test cases: one in winter and one in summer.

Table 2 Overview of the C2 and C3 controllers for the summer and winter test cases

Controller	$T_{set, FVU}$	$T_{flow, CCA}$
C2 – Summer	26 °C	20 °C
C3 – Summer	22 °C	17 °C
C2 – Winter	22 °C	25 °C
C3 – Winter	24 °C	32 °C

The tests were offline experiments, each two days long. The Tower NW was used. Further details about the simulation setup are given in the next chapter.

The results for the energy demand for the whole tower are presented in Figure 5 and Figure 6.

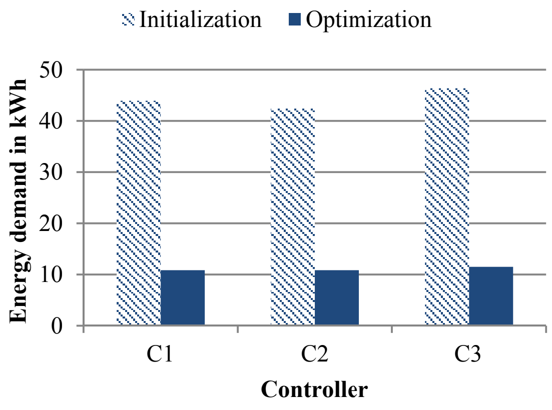

Figure 5 Results when starting from three different initial controllers for the summer test case

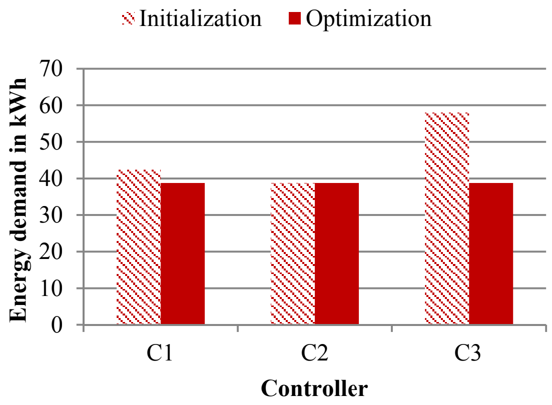

Figure 6 Results when starting from three different initial controllers for the winter test case

With the exception of the C3 controller, all other controllers have no violations of the comfort constraint at the initialization. For the summer test case the initializations with C1 and C2 lead to the same result (10.85 kWh), whereas C3 leads to a worse result (11.5 kWh). For the winter test case all three controllers lead to the same result (38.74 kWh). As the C3 controller is the worst initial controller of the set, the 6% difference to the optimization results with the other controllers is considered acceptable and no further tests are needed for the exploration area.

For all tests the CAO algorithm leads to an improvement on the initial case. In the case of C1 the control strategy is even better than the one currently implemented in the real building. As the C1 – controller can be used as a reference for the results of the optimization algorithm and it is close to a real case, it was made the default initial controller.

EXPERIMENTS

Offline experiments

Offline experiments are experiments where no control parameters are sent to the building. Here we also only refer to experiments where no other information from the building is used. Instead standard weather data and occupancy profiles are used. For the weather data we used the test reference year, TRY 05, for the area of Aachen (DWD, 2010). For the occupancy profiles we assumed continuous occupation according to the room book, between 9 a.m. and 6 p.m. The machines are on when the users are in the building, and go on standby during the night.

The purpose of the offline experiments was to assess how fast the simulation runs and how good it works for all three towers. Summer and winter tests were done. For each test a period of two days was simulated, producing one set of controllers. To produce a set of controllers for one tower takes around 2.5 hours.

Online experiments

Online experiments are the experiments where data is exchanged between the co-simulation and the building (Figure 7).

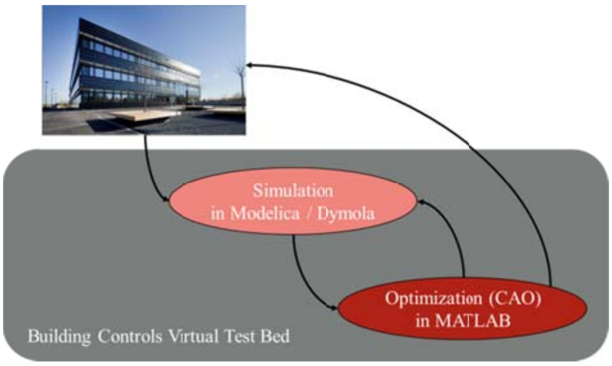

Figure 7 Data exchange flows during online simulations

Controllers are developed and deployed continuously. They are developed with the help of a two day simulation but will only be used for three to four hours real time, during which a new controller is generated with improved prediction data for the near future. The simulation uses weather prediction data (updated hourly) and occupancy profiles. The occupancy profiles are similar to the ones used for offline simulations, but are further adapted to take into consideration the weekends.

The initial state of the simulation has to be the current state of the building, especially when dealing with the thermal mass of the concrete activated ceiling. To this effect, a "warm up" of the model occurs before each new set of controllers is determined. Monitoring data for the last 72 hours is used: room air temperatures, ambient conditions, presence, and flow temperature of the CCA. The optimization then runs like in an offline experiment.

At the end of the optimization the θ matrix is generated. Using actual measurements for the building's states, the control parameters are calculated and sent to the building. Analogous to the data exchange rhythm in the co-simulation, new control parameters are calculated and sent to the building every ten minutes.

A problem of the offline experiments is the evaluation. Only six offices in the building are reference rooms, where the energy consumption of the CCA and FVU can be measured. No two such rooms on the same floor have the same orientation. The occupancy profiles and the indoor comfort preferences of the people working in the offices are also different.

The first online experiments involved only three rooms in a tower of type Tower NW, where the office on the 1st floor is a reference room. Only the set temperatures for the FVUs were controlled. We evaluated the trends in set temperature between the CAO controlled rooms and the neighboring rooms.

DISCUSSION AND RESULT ANALYSIS

Offline experiments

The summer offline experiments were done for the 24th and 25th July, a couple of warm summer days for the Aachen region, with a maximum of 27°C for the ambient temperature on both days. Controllers for all three towers were generated starting from the C1 rule-based controller. For all three towers we have a reduction in the energy demand, for the Towers NW and NE up to 75% (Figure 8). Neither the initialization nor the optimization results had violations of the comfort constraint.

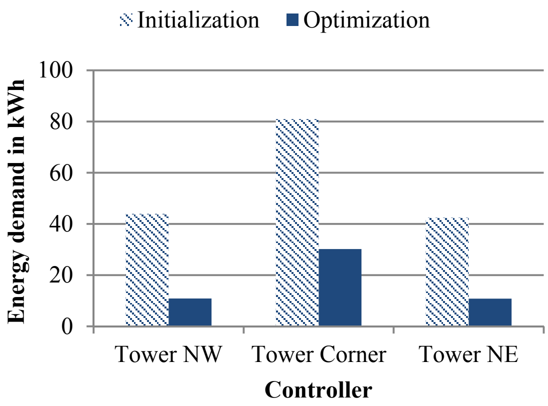

Figure 8 Results for the CAO algorithm for each tower for the summer test case

The Tower Corner has three times the energy demand of the other two towers after the optimization, although its floor area is less than twice the floor area of the other two. It does however have two outer walls and respectively a larger window area, which leads to higher gains through the solar radiation. The energy savings come partly from the dependence of the control parameters on more than just the ambient temperature, as is the case of the C1-controller. Furthermore, the rule-based controller does not explicitly consider the comfort in terms of a constraint that has to be respected. In some cases in summer the rule-based controllers lead to better comfort values, which explain the higher energy demand. CAO however considers the comfort as a constraint and not as a part of the cost function.

The winter cases were simulated for the 5th and 6th January, which are particularly cold days for Aachen, with a minimum ambient temperature of -6 °C. For all three towers we have a reduction in the energy demand (Figure 9). However the improvements are lower than in the summer case: for the Towers NW and NE 10%, and for the Tower Corner 17%. Neither the initialization nor the optimization results had violations of the comfort constraint.

The comfort levels for both controller types are similar. The energy savings come from using the weather and occupancy prediction and reducing the heating power because the gains through solar radiation or humans and machines can compensate for it.

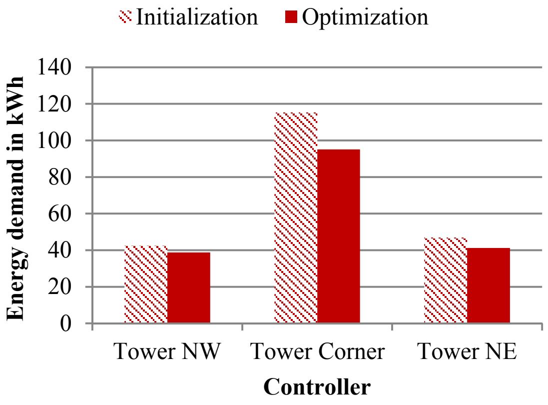

Figure 9 Results for the CAO algorithm for each tower for the winter test case

Online experiments

The online experiments presented ran between 14th and 20th December 2012, which were typical winter days for the region Aachen with mean ambient temperatures of 0 °C.

Figure 10 presents the set temperatures for four offices: the reference room on the 1st floor in the simulated tower (CAO), the office on its left (Left), the office on its right (Right) and the other reference room on the 1st floor (Reference). The latter belongs to another CCA area and has a south-east orientation.

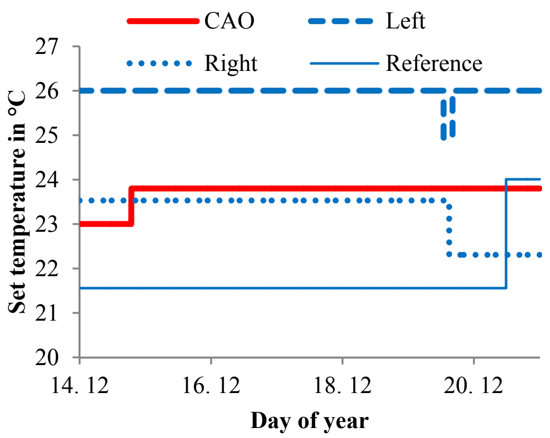

Figure 10 Set temperatures from the CAO algorithm and three not controlled rooms

The set temperature from CAO is a combination of the results from the algorithm and the adjustment of the user in the room. CAO suggested temperatures of around 23 °C for the duration of the experiment, but the user decided on higher temperatures (23.7 °C). The set temperatures in the other offices are all determined by the users' preferences. CAO leads to the lowest adjustment on the part of the user, combined also with a somewhat realistic level of the temperature. According to the indoor comfort requirements of the building, the temperature should not rise above 26 °C (as it does for the left office) or sink under 22 °C (as it does for the reference office).

The set temperature does not actually reflect what happens in the office. Figure 11 shows the comparison between the set temperature in the reference room from the Tower NW (Set CAO) and the actual room air temperature (Measured). As the 14th December was a Friday, the two lower peaks correspond to the weekend; the following are the working days in the week after, with peaks around noon according to the solar radiation and presence in the room. The drop at the end is due to natural ventilation through window opening.

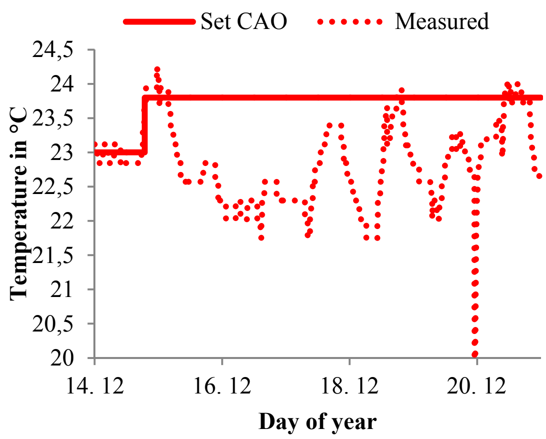

Figure 11 Comparison between the set temperature and the actual temperature in the room

The figure shows how the technical equipment was not capable of reaching the set temperature. This has often been the case last winter, as the BAS-system and some FVU do not work properly. Further online experiments were suspended for this matter and will be restarted once the system works.

These first online experiments were however useful in understanding how CAO reacts to a real case and how user reacts to the set temperatures generated by CAO.

CONCLUSION

We presented in this paper the implementation in a real building of a model-assisted fine-tuning methodology for control parameters. All the stages from building up the model for the building and technical equipment, to formulating the control problem and setting up the co-simulation were briefly discussed. The configuration of the method according to the building's particularities was presented in more detail.

Offline experiments meant to show the theoretical energy saving potential of the building were presented and offered promising results, of energy savings up to 75% in some cases in summer and 17% in winter, even when compared to very good rule-based controllers (temperature setback for night mode, set temperatures depending on the ambient temperature). The real innovations of CAO when compared to rule-based controllers is the consideration of the indoor comfort, along with the dependence of set temperatures on more than just the ambient temperature.

Online experiments were theoretically possible, as the connection between building and co-simulation worked and actual data from the building as well as weather prediction data could be incorporated into the simulation. However because the BAS-system was not fully operational, not enough energy was made available to be distributed by the FVU and the CCA to the rooms. Furthermore not all FVU worked properly. A comparison between the measured and the set air temperature shows a difference of up to 1 K during office hours.

When comparing the set temperature calculated by CAO with the set temperatures from other neighboring offices, the CAO algorithm offers sensible set temperatures. Online experiments will be restarted as soon as the BAS-system is reliably working and will be extended to the whole CCA zone north. As future work the mediation of the discussed challenges regarding the evaluation process for the CAO controllers is planned; for example by comparing the results of a day when the CAO algorithm was used with a simulation of the same day using a rule based-controller.

NOMENCLATURE

BAS = building automation system
CAO = cognitive adaptive optimization
CCA = concrete core activation
FVU = façade ventilation unit
MPC = model predictive control
$Nr_{Ini.It.}$ = number of initial iterations
$Nr_{Max.It.}$ = maximal number of iterations
Nr_{States} = number of states
$Nr_{Ctr.Par.}$ = number of control parameters
PPD = Fanger PPD index
U = vector of the control parameters
X = vector of the building states
θ = matrix for the gains of the building states

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REFERENCES

Bishop, C. M., 2006. Pattern recognition and machine learning, Volume 4, Springer New York, USA.

Constantin, A., Fütterer, J., Müller, D., Rovas, D.V., Kontes, G., 2012. Implementation of a model based predictive control for a non-residential building with a complex energy system – Simulation results. Proceedings of the 4th German-Austrian IBPSA Conceference, Berlin, Germany.

DWD, 2010. Deutscher Wetterdienst.

European Union 2012. Directive 2012/27/EU, Brüssel, Belgium.

Fanger, P. O. 1970. Thermal Comfort, Danish Technical Press, Copenhagen, Denmark.

Giannakis, G.I., Kontes, G.D., Kosmatopoulos, E.B. and Rovas, D.V. 2011. A model-assisted adaptive controller fine-tuning methodology for efficient energy use in buildings, Proceedings of the 19th Mediterranean Conference on Control and Automation, Corfu, Greece.

Green, S. 1991. How many subjects does it take to do a regression analysis? Multivariant Behavioral Research, Volume 26, Pages 499-510..

Kosmatopoulos, E. B., 2009. An adaptive optimization scheme with satisfactory transient performance, Automatica, Volume 45, Pages 716-723.

Müller, D., Hosseini Badakhshani, A. 2010. Gekoppelte Gebäude- und Anlagesimulation mit Modelica, BauSim Conference, Vienna, Austria.

Seppanen, O., Fisk, W., Faulkner, D. 2004. Control of Temperature for Health and Productivity in Offices, Lawrence Berkley National Laboratory, Berkley, USA.

Široký, J., Oldewurtel, F., Cigler., J., Prívara, S., 2011. Experimental analysis of model predictive control for an energy efficient building heating system, Applied Energy, Volume 88, Pages 3079-3087.

VDI 2078 1996. Calculation of cooling load and room temperatures of rooms and buildings (VDI Cooling Load Code of Practice) Düsseldorf, Germany.

Wetter, M., Haves, P. 2008. A modular Building Controls Virtual Test Bed for the integration of heterogeneous systems, Proceedings of the 3rd SimBuild Conference, Berkeley, USA.