SENSITIVITY ANALYSIS WITH BUILDING SIMULATIONS TO SUPPORT THE COMMISSIONING PROCESS

Sebastian Burhenne*, Mehmet Elci, Dirk Jacob, Christian Neumann, and Sebastian Herkel
Fraunhofer Institute for Solar Energy Systems ISE
Freiburg, Germany
*Corresponding author. E-mail address: sebastian.burhenne@ise.fraunhofer.de

ABSTRACT

Building performance simulations can support the commissioning process of buildings. This paper introduces an approach to implement saving measures using sensitivity analysis with a simulation model and data analysis of measured data from the building. The building that is analyzed is a large non-residential building that was equipped with a data acquisition system. Global sensitivity analysis methods including Monte Carlo (MC) techniques are used to determine the parameters and variables for which the buildings energy consumption is most sensitive to. This information is employed for the optimization of the building operation. Furthermore, the MC simulations are used to quantify the uncertainty of the simulation results given the uncertain simulation parameters or variables. The MC simulations of the building are used to calculate the energy savings for some operational improvements and the corresponding uncertainty. One saving measure was implemented in the real building and the result of the implementation is analyzed using the measured data.

INTRODUCTION

Large scale buildings and their plant equipment are complex systems with manifold interactions between the components. Employing simulations in the analysis of the building operation has the advantage that the part load behavior as well as the interactions between plant equipment and the building can be fully examined. The results are very useful for optimizing energy systems. The analyst can calculate the effect of saving measures without a trial-and-error process on the real building and its equipment. One common question in the commissioning process is the influence of a selected parameter on the energy consumption. Sensitivity analysis is an useful tool to answer that question.

Although simulations are often used in building research and practice, the sensitivity analysis is often done with basic methods (e.g., one-at-a-time methods). These methods neglect the interactions between the input parameters. One reason that more advanced methods are hardly ever used could be the lack of simple tools and methodologies which are applicable to this specific problem.

While in other fields of science advanced sensitivity analysis is widely used (Saltelli, Ratto, Andres et al. (2008), page 5-6), Lomas et al. conducted one of the first studies about Monte Carlo analysis for building simulations (Lomas, and Eppel (1992)).

In this paper, a Monte Carlo technique is used to quantify the influence of input parameters in building simulations. The aim is to rank the parameters according to their influence on the energy consumption. In this way, influential building operation parameters can be identified and adjusted in the real building. The MC based sensitivity analysis accounts for any interaction between the input parameters as well as for any non-linearity in the model (Lomas, and Eppel (1992)). In Figure 1 the structure of the method which was developed in this paper is shown. While sensitivity and uncertainty analysis are often conducted separately, the link between both is examined in this study. Furthermore, the implementation of a saving measure and its consequence is analyzed.

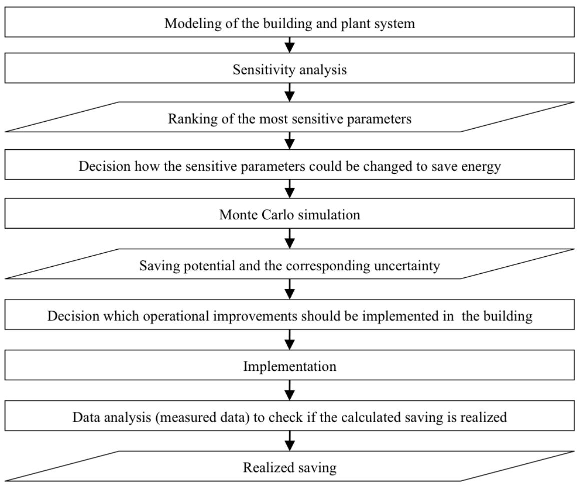

Figure 1: Process structure.

SIMULATION

Analyzed Building and Plant Equipment

The building simulated is a typical German office building of the 1980s. About 90 % of the rooms are used as office rooms, mostly single offices. The building is equipped with sensors (outside temperature, heat meter, room temperatures, control signals etc.) to allow for a validation of the simulation. The main building parameters are shown in Table 1 and Figure 2 is a floor plan of the building. The heat is emitted by radiators equipped with thermostatic valves. Some rooms are cooled by split units and one simulation zone has an air handling unit with heat recovery and heating coil.

Table 1: Building parameters.

parameter	value	unit
$\frac{A}{V}$ (area to volume ratio)	0.28	$\frac{m^2}{m^3}$
$\overline{U}$-value (mean U-value)	0.74	$\frac{W}{m^2K}$
A_{win} (total window area)	3102	m^2
NFA (net floor area)	19500	m^2

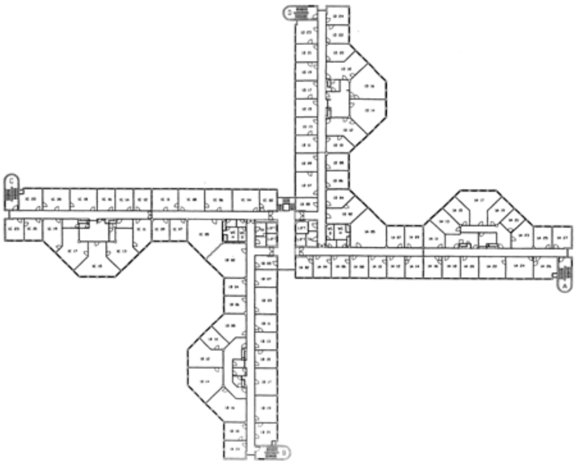

Figure 2: Floor plan of the building.

Simulation model

Monte Carlo (MC) simulations require many simulation runs and are therefore computationally expensive. In order to reduce the computing time, it is necessary to find an appropriate simple model for the thermal building simulation. For this paper a resistance-capacity-network was used to model the building. In this model a wall is represented as a three resistance-two capacity model. Heat gains (e.g., gains from appliances, people, HVAC equipment etc.) are distributed to the different temperature nodes (e.g., air temperature and surface temperature node) of the model. Figure 3 shows the graphical representation of the models and their connections between each other.

The object-oriented and equation-based modeling language Modelica is used to describe the system (Elmqvist (1997)). Components from the Modelica standard library were used instead of writing a new model whenever it was possible. The simulations are conducted using the software Dymola 6 (Dynasim AB (2004), Dynasim AB (2007)). The radiation processor is implemented according to an equation-based model (written in the modeling language Neutral Model Format; Sahlin (1996)) from the simulation software IDA-ICE (Sahlin, Eriksson, Grozman et al. (2004)). Due to the similar structure, it is straightforward to translate other equation-based modeling languages into the Modelica language.

The building was modeled in 5 different zones which are connected through internal walls. The usage of the zones and their plant equipment can be found in Table 2.

Table 2: Building zones and their plant equipment.

zone	usage	AHU	cooling
zone 1	corridors, restrooms, office-kitchens	partly	no
zone 2	offices	no	no
zone 3	offices	no	yes
zone 4	offices	yes	no
zone 5	kitchen and canteen	yes	no

Monte Carlo simulations

In a Monte Carlo analysis, a large number of evaluations of the model is performed with randomly sampled model inputs (Saltelli, Chan, and Scott (2000), p. 20-24). It contains the following main steps:

1. Selection of probability density functions (pdf) for each uncertain input (X_i).

2. Generation of a sample from each pdf.

3. Evaluation of the model for each element of the sample.

4. Result analysis.

For the MC simulations presented in this study the air change rates are implemented according to a schedule (Figure 4 and 5) and the value is multiplied with a sampled factor. The factors are ACH_{nat} (natural ventilation) for Zone 1, 2, 4 and 5, ACH_{inf} (infiltration) for Zone 3 and ACH_{AHU} (volume flow rate through the air handling unit) for Zone 3.

Furthermore, the room temperature set point (T_{set}), the efficiency of the heat exchanger of the air handling unit (η_{HX}), the shading control threshold for irradiation (I_{shad}) and the operating schedule for the pumps of the heating circuits (switch-on time (k_1) and switch-off time (k_2)) were varied during the MC simulation. In the real building the pumps were operated 24 hours per day and there was no temperature setback for the supply temperature of the heating circuits during unoccupied hours. The parameters for the distributions which were used for the sampling can be found in Table 3. The sampling (step 2) generates the input matrix (Equation 1).

Once the model is evaluated for each sample set (step 3), the result vector is obtained (Equation 2).

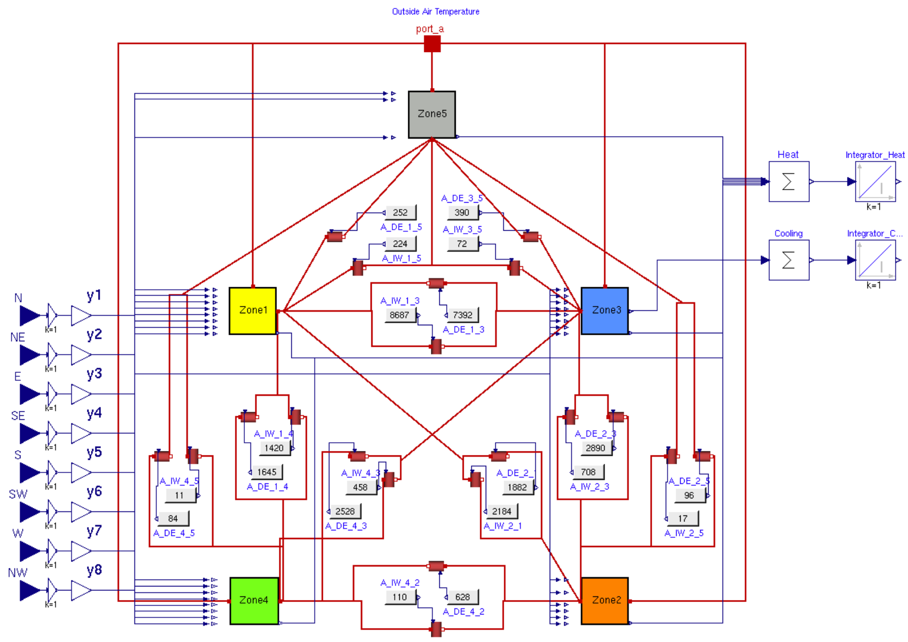

Figure 3: Graphical representation of the zone models and their connections between each other in Dymola.

$$\mathbf{M}_{\text{Input}} = \begin{bmatrix} ACH_{\text{nat}}^{(1)} & ACH_{\text{inf}}^{(1)} & ACH_{\text{AHU}}^{(1)} & T_{\text{set}}^{(1)} & \eta_{\text{HX}}^{(1)} & I_{\text{shad}}^{(1)} & k_1^{(1)} & k_2^{(1)} \\ ACH_{\text{nat}}^{(2)} & ACH_{\text{inf}}^{(2)} & ACH_{\text{AHU}}^{(2)} & T_{\text{set}}^{(2)} & \eta_{\text{HX}}^{(2)} & I_{\text{shad}}^{(2)} & k_1^{(2)} & k_2^{(2)} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ ACH_{\text{nat}}^{(n-1)} & ACH_{\text{inf}}^{(n-1)} & ACH_{\text{AHU}}^{(n-1)} & T_{\text{set}}^{(n-1)} & \eta_{\text{HX}}^{(n-1)} & I_{\text{shad}}^{(n-1)} & k_1^{(n-1)} & k_2^{(n-1)} \\ ACH_{\text{nat}}^{(n)} & ACH_{\text{inf}}^{(n)} & ACH_{\text{AHU}}^{(n)} & T_{\text{set}}^{(n)} & \eta_{\text{HX}}^{(n)} & I_{\text{shad}}^{(n)} & k_1^{(n)} & k_2^{(n)} \end{bmatrix} \quad (1)$$

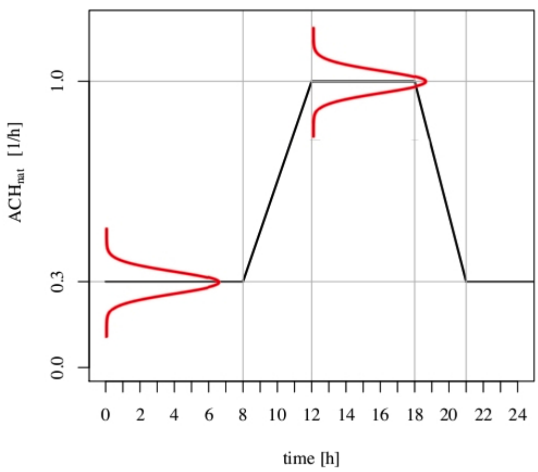

Figure 4: Schedule for the combined infiltration and ventilation in the zones without AHU. The distributions indicate which values are sampled.

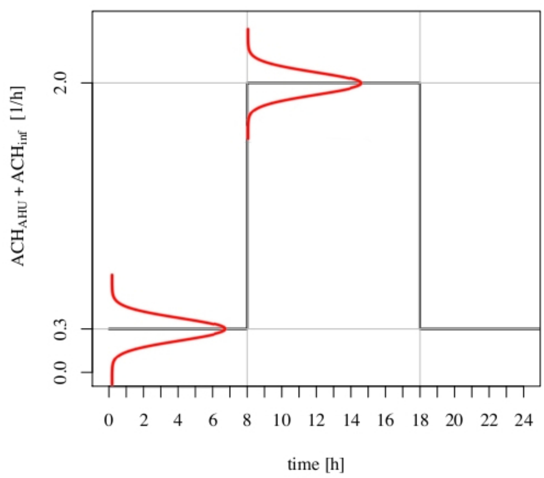

Figure 5: Schedule for the combined infiltration and ventilation of the zone supplied by the AHU. The distributions indicate which values are sampled.

$$\mathbf{Y}_{\text{Output}} = \begin{bmatrix} Q_{\text{heat}}^{(1)} \\ Q_{\text{heat}}^{(2)} \\ \vdots \\ Q_{\text{heat}}^{(n-1)} \\ Q_{\text{heat}}^{(n)} \end{bmatrix} \quad (2)$$

A crucial point in applying Monte Carlo techniques is the sample size. Macdonald analyzed this problem with respect to building simulation and stated that simple random sampling with a sample size of 100 should be used (Macdonald (2009)). However, in this paper a sample size of 1000 is used to generate the

Table 3: Distribution parameters.

parameter	distribution	μ	σ
ACH_{nat} (scaling factor)	normal	1	0.05
ACH_{inf} (scaling factor)	normal	1	0.05
ACH_{AHU} (scaling factor)	normal	1	0.05
T_{set} (scaling summand)	normal	0	0.15
η_{HX} (efficiency heat recovery AHU)	normal	0.6	0.05
I_{shad} (control threshold irradiation)	normal	200	20
parameter	**distribution**	**min.**	**max.**
k_1 (switch-on time pump)	uniform	0	6
k_2 (switch-off time pump)	uniform	20	23.99

samples. The reason for the large sample size is that it guarantees that sample values from each region of the parameter space are drawn. As long as computational limitations do not play a role a higher sample size is always preferable. The sampling is done using a simple random sampling algorithm. The language and environment *R* (R Development Core Team (2009)) for statistical computing is used to draw a sample, change the simulation input file, call the simulation program, analyze, and visualize the result.

Sensitivity Analysis

On the basis of the results from the Monte Carlo simulation the sensitivity analysis is conducted. A simple sensitivity analysis can be realized by using graphical methods such as scatter plots. Each sample value and its corresponding result (e.g. $ACH^{(1)}_{\text{nat}}$, $Q^{(1)}_{\text{heat}}$; ... ; $ACH^{(n)}_{\text{nat}}$, $Q^{(n)}_{\text{heat}}$) is plotted in a scatter plot.

To further analyze the data a ranking of parameters and variables according to their influence on the simulation result is done using a variance-based method. The method "Conditional Variances – Second Path" (Saltelli, Ratto, Andres et al. (2008), page 21-23) was the choice because the implementation is a straightforward process and it requires only one set of MC simulations.

For an illustration of the method the following generic model is introduced:

$$Q_{\text{heat}} = f(X_1, X_2, \dots, X_n). \tag{3}$$

It is essential to distinguish which factors are more influential than the others. What identifies an important factor is the existence of a shape or pattern in the points that make up a scatter plot. A uniform cloud of points is a symptom of a non-influential factor whereas a nonuniform distribution indicates an influential parameter (Saltelli, Ratto, Andres et al. (2008), p. 21-23).

The following algorithm was introduced for each parameter X_i:

1. The range of X_i is divided into 10 slices (each slice has an equal amount of points).

2. The mean value of $Q_{\text{heat}}(X_i)$ is determined in each slice.

3. The variance of the mean values of $Q_{\text{heat}}(X_i)$ over all 10 slices is calculated.

4. The calculated variance is used as a sensitivity measure of factor importance. The higher the variance the more important is the factor investigated.

After having performed the algorithm to every X_i from the factor vector X, a ranking is simply performed by ordering the sensitivity measure calculated.

Calculation of Predicted Savings

After the sensitivity analysis is performed the analyst can decide which changes should be implemented in the real building. The decision may depend on the budget, building specific requirements or realizable savings. In this paper two additional MC simulations are conducted to calculate the potential energy saving and its corresponding uncertainty. Which parameters are defined as uncertain depends on the project itself and the level of detail of the building's data and documentation.

DISCUSSION AND RESULT ANALYSIS

Simulation Result Base Case

The majority of the simulation model input data is obtained from measured data (e.g., heat gains from appliances and set point temperatures) and according to the design documentation of the building (e.g., material properties). However, there were variables and parameters which had to be estimated (e.g., infiltration air change rates). Hence, a calibration of the estimated values was necessary to fit the simulation results to the measured data. Figure 6 shows a time series plot of the total heating power of the building.

Monte Carlo simulation

In the commissioning process it is desirable to implement saving measures within a short period. Therefore the Monte Carlo simulations were conducted based on three month of measured data (September 1, 2008 – November 30, 2008). However, when a longer period of measured data is available a one year simulation should be preferred to simulate both, the winter and the summer period. Figure

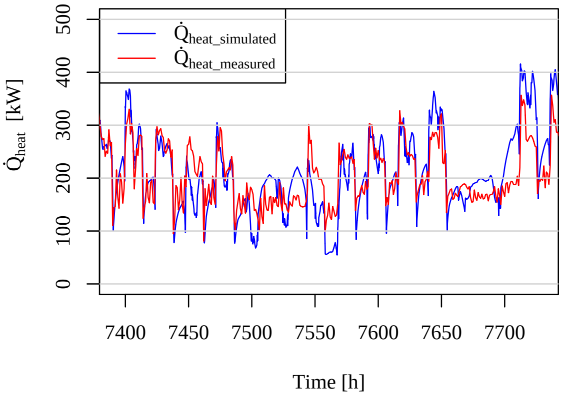

Figure 6: Heating power of the simulation versus measured data. The period is from November 3 – November 16, 2008 (hour 7393 - 7729 of the year).

7 shows the probability density function for the results of the Monte Carlo simulation. Based on the variability of the input the total energy demand varies between 301 and 394 MWh/(3 month).

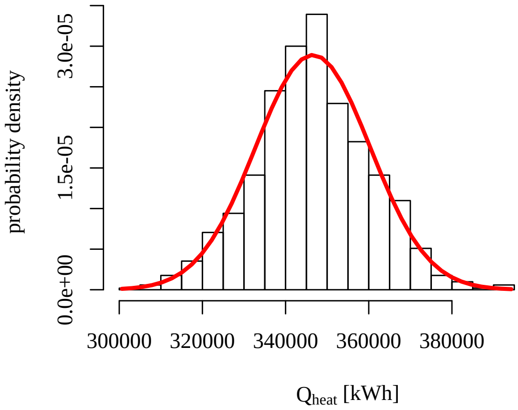

Figure 7: Probability density function of the result.

Sensitivity Analysis

Figure 8 shows scatter plots of the sampled inputs and the total energy demand of the building from September 1, 2008 – November 30, 2008. The input parameters which determine the pump schedule were combined for the sensitivity analysis (Equation 4).

$$\Delta k = k_2 - k_1 \tag{4}$$

It can be seen that the total heat consumption of the building (Q_{heat}) is very sensitive to the natural ventilation (ACH_{nat}) for Zone 1, 2, 4 and 5 as well as to the room temperature set point (T_{set}). The other pairs do not show such a strong dependency. Nonetheless, it is worthwhile to apply another sensitivity analysis method to further examine the dependencies in the model. The ranking of the inputs according to their sensitivity is shown in Table 4. It was done by calculating the variance of the mean values of $Q_{\text{heat}}(X_i)$ over all 10 slices and ordering the parameters according to it (decreasing order).

Table 4: Ranking of the parameters and variables according to their influence on the simulation result.

ranking	**parameter**
1	ACH_{nat} (scaling factor)
2	T_{set} (scaling summand)
3	Δk (hours of pump operation)
4	ACH_{inf} (scaling factor)
5	I_{shad} (control threshold irradiation)
6	ACH_{AHU} (scaling factor)
7	η_{HX} (efficiency heat recovery AHU)

The ranking shows that the pump operation schedule (Δk) is the third most influential input. The first two inputs (ACH_{nat}, T_{set}) cannot be adjusted to a certain value because they are dependent on the occupants' behavior . However, the pump schedule can be changed easily in the building automation system. The influence of ACH_{inf}, ACH_{AHU} and η_{HX} is small because they are just applied to the simulation zone with the AHU.

Calculation of Predicted Savings

For the calculation of the potential savings a pump schedule is introduced in the simulation. According to this schedule the pumps are operated from 6 a.m. till 8 p.m. on weekdays and from 6 a.m. till 4 p.m. on Saturdays. The air change rates, the temperature set point, the shading control threshold and the efficiency of the heat recovery system are considered as uncertain. Two sets of MC simulations were conducted and each simulation had a period from Dec. 1, 2008 till Nov. 30, 2009. In the first set the pump is operated 24 hours per day and in the second set the new schedule is implemented. The sampled values for both simulations were the same and Figure 9 shows the probability density functions of the results.

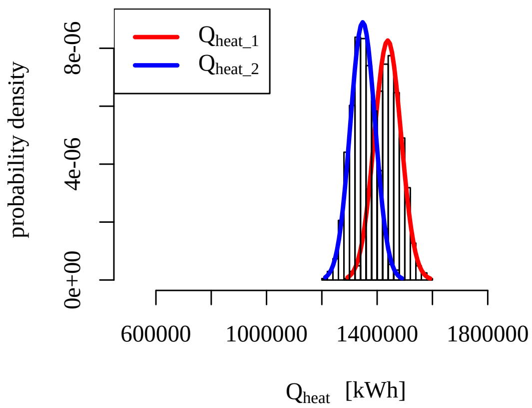

Figure 9: Probability density functions of the results. The red curve is with 24 h/d pump operation and the blue one is with the pump schedule.

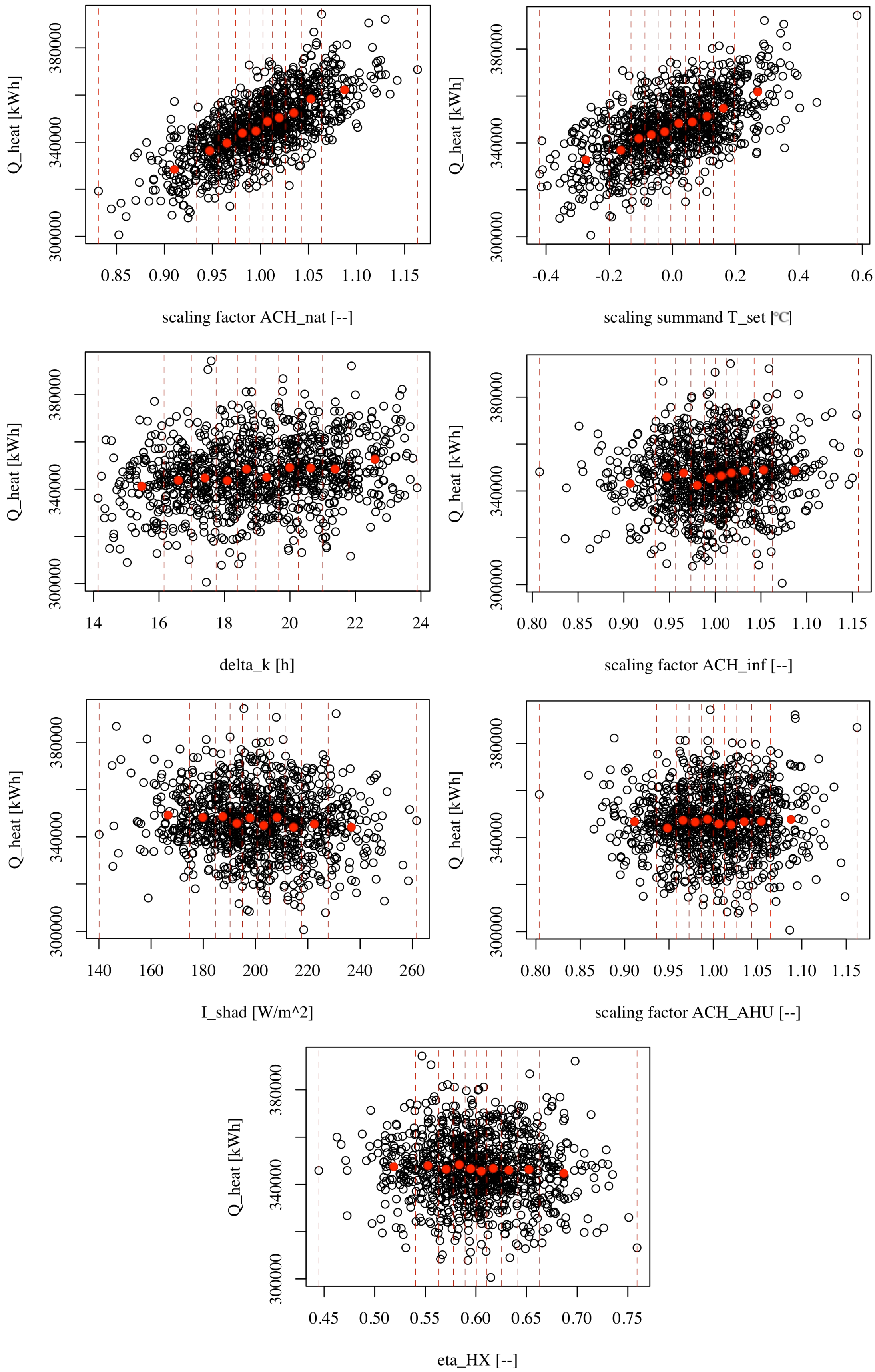

Figure 8: Scatter plots of the sampled inputs and the total energy demand of the building. The dashed vertical lines divide the scatter plots into 10 slices with 100 dots in each slice. The red dots represent the mean value of $Q_{\text{heat}}(X_{\text{i}})$ in each slice.

The potential savings are calculated according to Equation 5.

$$\mathbf{Y}_{\text{Output}} = \begin{bmatrix} Q^{(1)}_{\text{heat}_1} \\ Q^{(2)}_{\text{heat}_1} \\ \vdots \\ Q^{(n-1)}_{\text{heat}_1} \\ Q^{(n)}_{\text{heat}_1} \end{bmatrix} - \begin{bmatrix} Q^{(1)}_{\text{heat}_2} \\ Q^{(2)}_{\text{heat}_2} \\ \vdots \\ Q^{(n-1)}_{\text{heat}_2} \\ Q^{(n)}_{\text{heat}_2} \end{bmatrix} \quad (5)$$

Figure 10 shows the probability density function for the potential saving. The expected value of the result of the first MC simulation is ($E(Q_{\text{heat}_1}) =$ 1438 MWh = 73.8 kWh/m^2_{NFA} and the expected value of the potential saving $E(Q_{\text{saving}}) = 90$ MWh = 4.6 kWh/m^2_{NFA}). Taking these numbers into account a saving of 6.3 % can be reached by implementing the new schedule.

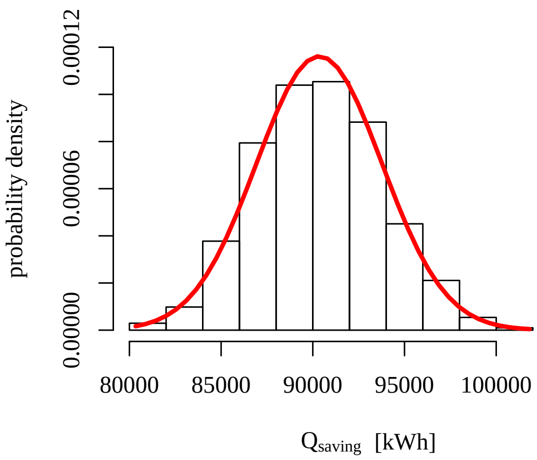

Figure 10: Probability density functions of the result.

IMPLEMENTATION OF THE SAVING MEASURES

After the decision that the pump schedules should be changed the process of implementing in the building automation system starts. Figure 11 shows a carpet plot of the measured data before and after the change of operation. From October till December the pump runs constantly (Ctrl pump; ①). In December 2008 the schedules were introduced (Ctrl pump; ②). After that the temperature difference (dT) between the supply and the return pipe is high during the nights (dT; ③). Furthermore, the supply temperature is high (T sup; ③). After further investigation it turned out that the 3 port valve of the heating circuit was in a partly open position during the night. The main distribution pump pressed the hot water through this valve which led to a high supply temperature (approx. 90° C). The valve was adjusted in April 2009 (dT and T sup; ④). The measured heat consumption from December 1, 2008 till November 30, 2009 is 1191217 kWh respectively 61 kWh/m^2_{NFA}. The measured energy consumption is less than the simulated demand which is likely to be due to other optimizations of the building operation. Furthermore, changed occupants' behavior could also be a reason.

CONCLUSION

In this paper, it was analyzed how a sensitivity analysis could fit in the commissioning process. A Monte Carlo based approach to analyze the influence of input parameters and variables was discussed. The method is applicable to provide a decision support for the optimization of the building operation. It was demonstrated that statistical methods can extend the use of classical building simulations. A sensitivity analysis offers insights into the influence of the input as well as to the model behavior under changing parameters or variables.

Future work

In this paper, the new pump schedule (pump operation from 6 a.m. till 8 p.m. on weekdays and from 6 a.m. till 4 p.m. on Saturdays) was implemented based on experience. More complex changes of the building operation may require an automated optimization based on algorithms. The process structure introduced (see Figure 1) should be extended in a way that a more sophisticated optimization would be possible.

ACKNOWLEDGMENT

This study was funded by the Reiner Lemoine Stiftung and the European Commission under the Intelligent Energy – Europe programme (EIE/06/038/SI2.448300).

REFERENCES

Dymosim AB. 2004. "Dymola Multi-Engineering Modeling and Simulation. Dymola User Manual." Dymasim AB, Lund, Sweden.

Dymosim AB. 2007. "Dymola Multi-Engineering Modeling and Simulation. Dymola User Manual. Dymola 6 Additions." Dymasim AB, Lund, Sweden.

Elmqvist, Hilding. 1997. "Modelica – A unified object-oriented language for physical systems modeling." *Simulation Practice and Theory* 5, no. 6.

Lomas, Kevin J., and Herbert Eppel. 1992. "Sensitivity analysis techniques for building thermal simulation programs." *Energy and Buildings* 19 (1992): 21–44.

Macdonald, Iain A.. 2009. "Comparison of sampling techniques on the performance of Monte-Carlo based sensitivity analysis." *Proceedings Building Simulation 2009, Glasgow, UK* (2009): 992–999.

R Development Core Team. 2009. "R: A Language and Environment for Statistical Computing." Manual. R Foundation for Statistical Computing, Vienna, Austria.

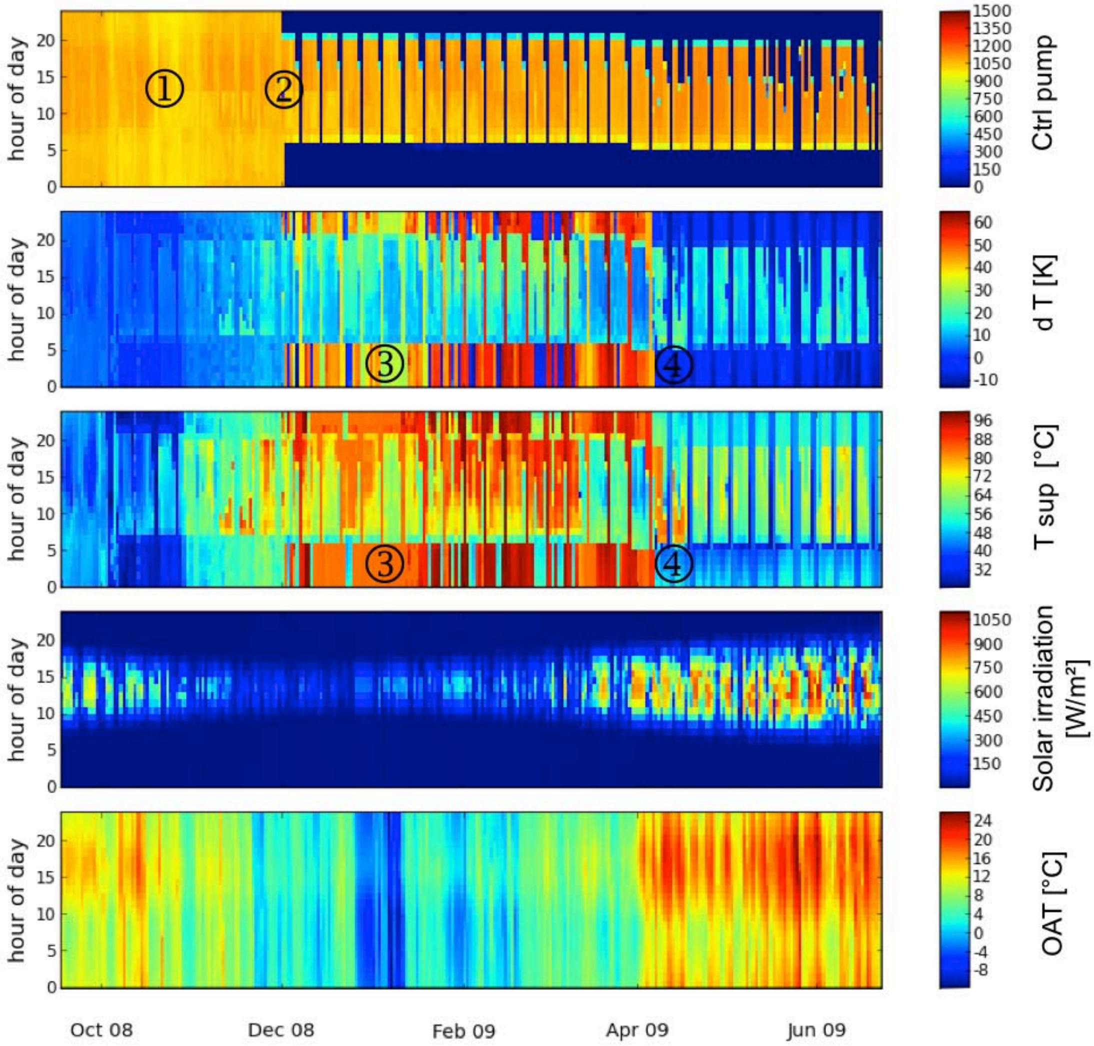

Figure 11: Carpet plot of the measured data in the building. The time of each day is shown on the y-axis from 0:00 to 24:00 and the days are plotted next to each other accordingly on the x-axis. The measurement value itself is represented by different colors corresponding to its value.

Sahlin, Per. 1996. "NMF Handbook. An Introduction to the Neutral Model Format. NMF version 3.02." Royal Institute of Technology (KTH), Stockholm, Sweden.

Sahlin, Per, Lars Eriksson, Pavel Grozman, Hans Johnsson, Alexander Shapovalov, and Mika Vuolle. 2004. "Whole-building simulation with symbolic DAE equations and general purpose solvers." *Building and Environment* 39 (2004): 949–958.

Saltelli, Andrea, Marco Ratto, Terry Andres, Francesca Campolongo, Jessica Cariboni , Debora Gatelli, Michaela Saisana, and Stefano Tarantola. 2008. "Global Sensitivity Analysis: The Primer." John Wiley and Sons, Ltd.

Saltelli, Andrea, Karen Chan, and E. Marian Scott. 2000. "Sensitivity Analysis." John Wiley and Sons, Ltd.

NOMENCLATURE

ACH	air change rate per hour
AHU	air handling unit
$\mathrm{E}(x)$	expected value of a variable x
η_{HX}	heat recovery efficiency AHU
I_{shad}	shading control threshold
$\mathbf{M}_{\mathrm{Input}}$	input matrix
n	sample size
NFA	net floor area
$P(x)$	probability of x
$p(x)$	probability desity function of x
k	sampled value for time in the pump schedule
Q	energy
$\dot{Q}$	power
T_{set}	room temperature set point
X	model parameter
$\mathbf{Y}_{\mathrm{Output}}$	result vector