SIMULATION MODELS TO OPTIMIZE THE ENERGY CONSUMPTION OF BUILDINGS

Sebastian Burhenne
Fraunhofer-Institute for Solar Energy Systems
Freiburg, Germany

Dirk Jacob
Fraunhofer-Institute for Solar Energy Systems
Freiburg, Germany

ABSTRACT

In practice, building operation systems are only adjusted during commissioning. This is done manually and leads to failure-free but often inefficient operation. This work deals with the development of simulation models to describe and optimize the building operation. Therefore a sufficiently correct representation of the building envelope, plant equipment, controls, occupancy and use of the building needs to be implemented in the simulation model. The aim of this work is to find the best compromise between accuracy and simplicity of the models to improve the usability for optimization and reduce the computing time. Models for the building and plant equipment of different complexity are developed and compared. Hourly building data is used to validate and calibrate the models. For this study the equation based simulation software IDA-ICE was used. With the simulation models simple optimizations of the building operation are conducted.
Key words: non-residential buildings, optimization, white box models, equation-based-simulation.

INTRODUCTION

In the non-residential building sector the potential energy savings for optimising the building operation ranges between 15- 30 % [Katipamula/ Brambley 2005, p. 3] and these can be implemented with minimal investment. There is a lack of practical tools to analyse and optimize the building operation. The Fraunhofer ISE is developing appropriate building energy analysis tools within the project ModBen (Model- Based Benchmarking, www.modben.org, sponsored by BMWi). In all six demonstration buildings of the ModBen project a monitoring system is installed and the data is transferred to the Fraunhofer ISE. One approach is to use physical models (so called white box models) to apply optimization algorithms (Figure 1). These models are equation- based and have physically meaningful parameters. For optimizations the computing time plays an important role, because the simulations have to run until the optimum is found.

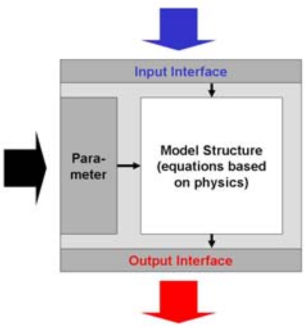

Figure 1. General set-up of a model

DETAILED SIMULATION MODELS

Approach

The shape of the building is defined in the graphical user interfaces (GUI) of IDA-ICE and the parameters for the plant equipment, controls and occupancy have to be set to obtain a mathematical model. In IDA-ICE the building geometry information can be imported via Industry Foundation Classes (IFC). In the ModBen project all demonstration buildings are modelled with the EnEV+ software from the project partner ennovatis for energy certification according to DIN V 18599. It is possible to export the building geometry from EnEV+ via IFC. The detailed models were manually calibrated.

Simulation Example

The building that is simulated is a typical small German office building with a net floor area of 436 m². There is no VAC-System in the building and the heating demand is supplied by a gas boiler. The heat is emitted by radiators with thermostatic valves to the rooms. 16 people are working in the building, 5 kW of lighting and technical equipment with a power of 5 kW is installed. The main building parameters are shown in Table 1.

Table 1. Building parameters

Parameter	Value	Dimension
$\frac{A}{V}$ (area to volume ratio)	0.38	m^{-1}
$\bar{U}$ – value (mean U-value)	0.53	$\frac{W}{m^2K}$
A_{win} (total window area)	106	m^2
Building class (thermal capacity)	medium	-

The first step is to define the building envelope and to create a 3D Plan in IDA-ICE (Figure 2).

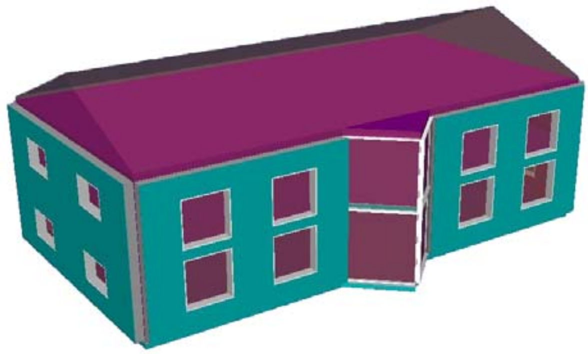

Figure 2. 3D-Plan

After this is done it is necessary to set the parameters of the plant equipment, controls, occupancy and use of the building. Measured weather data of the year 2007 is used for the simulation.

Results

Whole year simulations with measured climate data were performed. Figure 3 shows the temperature data between the 1st and the 31st of December 2007 (recording started 22nd of November). The model is capable of describing the trend of the air temperatures. By using various schedules it is possible to take holidays into account (e.g. Christmas holiday at the end of the year). The coefficient of determination (R^2) is 0.54. Some differences between the temperatures occur because of the occupants' behaviour which is not constant over time.

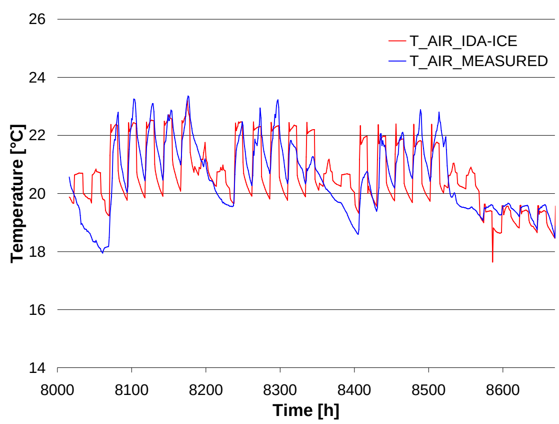

Figure 3. Air temperature IDA-ICE model versus measured data (hourly means)

A comparison of the heating power is shown in Figure 4. The coefficient of determination (R^2) is 0.69. The measured total heating energy for December is 5453 kWh and the simulated energy demand is 5613 kWh. The peak heating load in the simulation is 26.8 kW, measured 24.8 kW.

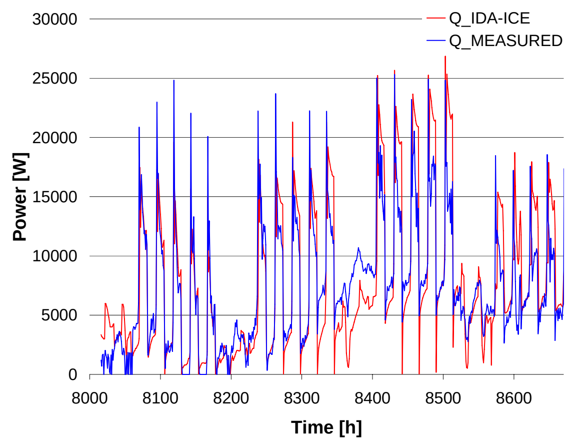

Figure 4. Heating power IDA-ICE model versus measured data

SIMPLE SIMULATION MODELS

Approach

In order to reduce the computing time it was necessary to find an appropriate simple model for thermal building simulation. Furthermore a model with many parameters is often not better than one with just a few parameters [Déqué, Ollivier et al. 2000]. In this context it is important to determine the parameters with the most influence. In the case of building simulation important parameters are the occupancy and the control parameters. For a simple zone model the simple hourly method (SHM) according to ISO 13790 is used. This zone model is based on a five resistances and one capacitance (5R1C) model (Figure 5).

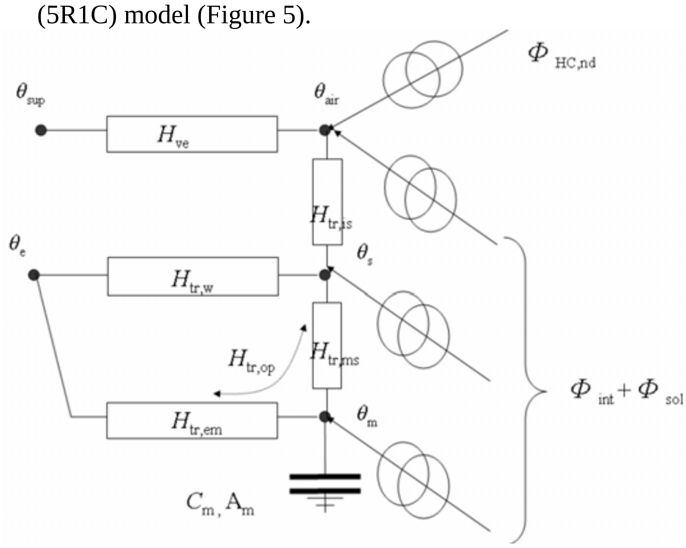

Figure 5. Five resistances, one capacitance (5R1C) model [ISO 13790:2007, p. 29]

According to ISO 13790 the intention of the simple hourly method is to have a transparent, reproducible and robust model with a limited amount of input data. This power limited model distinguishes between five operation modes which are shown in Figure 6 and described in Table 2.

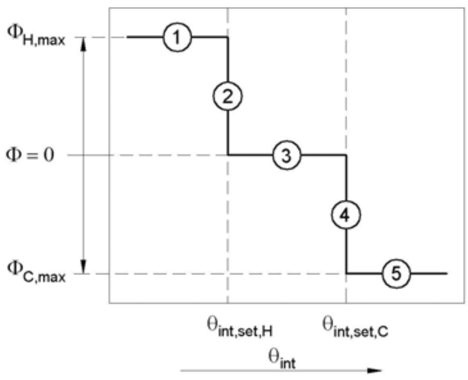

Figure 6. Operation modes of simple hourly method

Table 2. Description of operation modes

Mode	Explanation
1	Heating is required and not sufficient
2	Heating is required and sufficient
3	Neither heating nor cooling is needed
4	Cooling is required and sufficient
5	Cooling is required and not sufficient

Simulation Example

The same constraints as for the detailed model are applied in the simple model and IDA-ICE is used for the simulation. The simple hourly method had to be implemented in IDA-ICE. In this particular case the rules of ISO 13790 allow the definition of just one zone for the entire building. The Neutral Model Format (NMF) is used to write the model. NMF is a language to write models for variable time step differential-algebraic equations (DAE) solvers [Sahlin, P., Eriksson, L. et al. 2004]. A wider usability of NMF models is possible as they can be translated into Modelica-code.

Optimization algorithms were used to calibrate the model. The general structure of the calibration process is shown in (Figure 7).

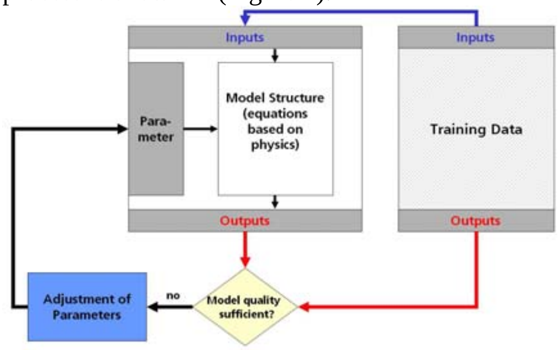

Figure 7. Calibration process

Ideally, one year of measured data should be used for calibration. However, only measured data from the 22nd of November 2007 to 1st of August 2008 was available. For this reason the air temperatures and the heating power of the detailed, validated IDA-ICE model was used for the calibration. The parameters which were changed during the calibration process were the shading control settings, the internal heat capacity of the building, the thermal transmission coefficient ($H_{tr,ms}$) and the coupling conductance ($H_{tr,is}$).

Results

Figure 8 shows the data between the 1st and 31st of December 2007. The temperature trend over time can also be described with the simple model. The temperature variations of the model are faster because the air capacity is not modelled explicitly but shifted to the one effective heat capacity. The coefficient of determination (R^2) is 0.54. This low value results from the short time period and the small temperature variation.

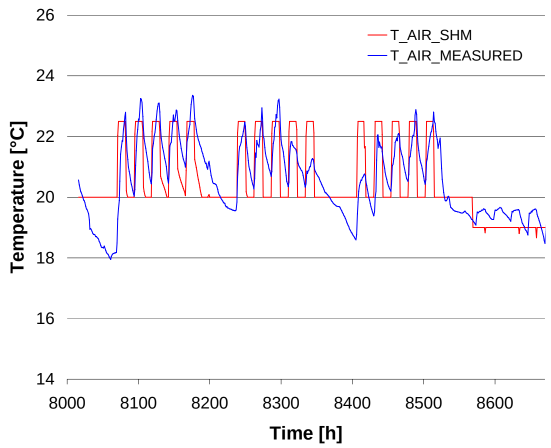

Figure 8. Air temperature SHM model versus measured data

Figure 9 shows the heating power of the SHM model versus the measured heating power. It can be seen that the model is capable of describing the real building behavior. In this case R^2 is 0.67 and the simulated heating energy demand is 5452 kWh. This value is very close to the measured value of 5453 kWh. This demonstrates that while the absolute value for one particular hour is not always the same, the sum over one month or one day provides a close match to the measured data.

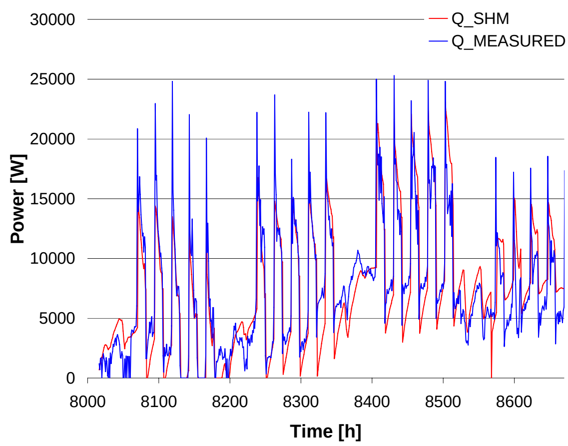

Figure 9. Heating power SHM model versus measured data

COMPARISON BETWEEN SIMPLE AND DETAILED MODELS

The level of detail between the models varies significantly. Nevertheless it is possible to describe the building behavior with both models. The temperature trend over the summer is similar in both approaches (Figure 10). The coefficient of determination (R^2) between the air temperature of the IDA-ICE model and the SHM model is 0.97.

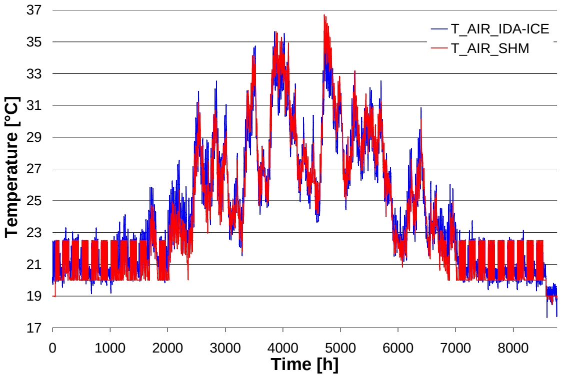

Figure 10. Comparison SHM with IDA-ICE model

In this case the most important advantage of the simple simulation model is the computing time. The SHM model is 50 times faster than the detailed IDA-ICE model.

OPTIMIZATION

Our general intention is to use the simulation models to optimize the building operation. This can be done by applying optimization algorithms to the models. Before these algorithms can be applied boundary conditions (e.g. weather, comfort requirements or the presence of people) and the parameters which are changeable during the optimization process (e.g. system operating time and set points) have to be defined.

Methods

The generic optimization program GenOpt [Wetter 2008] was used for the optimization. GenOpt can minimize an objective function by coupling it with a simulation program (e.g. IDA-ICE). For the coupling of GenOpt it is important that the simulation software has input and output text files and is executable in batch mode. This criterion is fulfilled by IDA-ICE. Figure 11 shows the interaction between GenOpt and IDA-ICE.

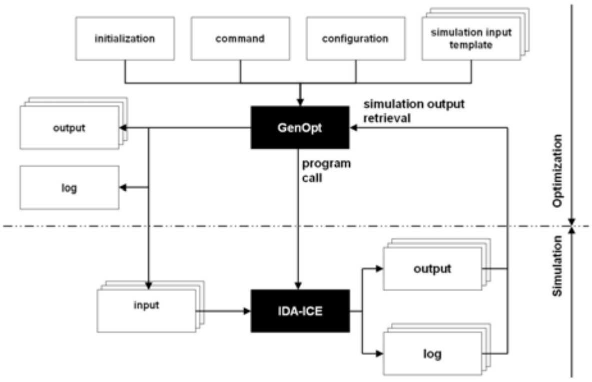

Figure 11. Interaction between IDA-ICE and GenOpt [Wetter 2008, p. 73]

There are various optimization algorithms which are supported by GenOpt. Depending on the optimization problem the appropriate method has to be selected. The decision about the method is influenced by:

- Structure of the objective function
- Number of independent parameters
- Restriction of boundary conditions

The hybrid generalized pattern search algorithm with particle swarm optimization algorithm was the most appropriate algorithm for the purpose of this paper.

Optimization Example

As an optimization example the pump schedule of the heating circuit is optimized. In the real building the pump runs 24 hours per day. The aim of the optimization is to reach the set point room temperature during the building operation hours despite of switching off the pump during the night (discrete optimization, time step 0.5 h).

In this case the objective function is the energy demand of the building during one year. The constraint is to reach the desired set point room temperature in the presence of occupants. Therefore a so called penalty function has been defined. This function adds up a penalty to the total energy consumption if the set point temperature is not reached while occupants are present. Equation (1) is used to calculate the penalty.

$$penalty = \begin{cases} 2500 \cdot \Delta\Theta; \text{ for } \Delta\Theta > 0 \text{ and } oc > 0 \\ 0; \quad \text{else} \end{cases} \qquad (1)$$

with:

$\Delta\Theta = \Theta_{int,set,H} - \Theta_{int}$

$\Theta_{int,set,H}$ ... heating set point temperature

Θ_{int} ... air temperature in the zone

oc … occupancy (0=absence; 1=presence)

Optimization Result

The minimum of the defined objective function is reached when the pump operation time is between 7:00 h and 16:30 h while the people work between 8:00 h and 18:00 h. Figure 12 shows the air temperature before and after the optimization (January). It can be seen that there is a temperature drop during the night while the set point temperature during the day is reached.

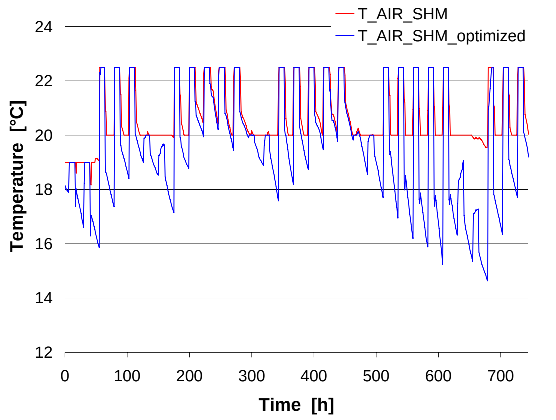

Figure 12. Comparison air temperature before and after optimization

The simulated total heating demand during the year 2007 is 20663 kWh. After the optimization the heating demand is 19112 kWh. Beside this 7.5 % saving less energy is needed to operate the pump (up to approx. 2 % source energy reduction). Figure 13 shows that after the optimization the energy consumption during the night is zero whereas the demand is higher in the morning.

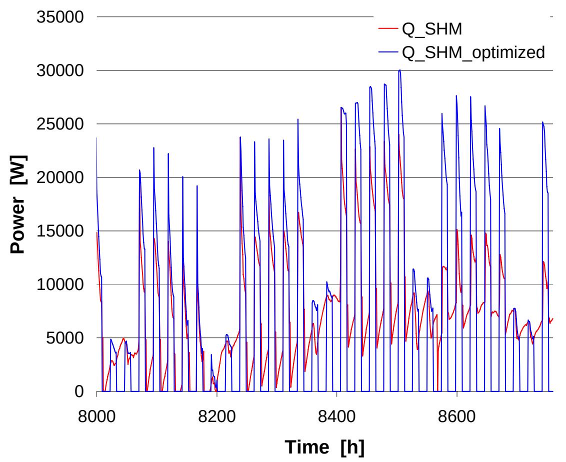

Figure 13. Comparison heating demand before and after optimization

CONCLUSIONS

It is possible to use simple simulation models to describe the thermal behaviour of buildings with sufficient accuracy for first optimizations. In order to apply optimization algorithms the primary advantage of simple models is the low computing time. Tools to perform this work already exist and the aim should be to establish a procedure which makes it applicable to model and optimize the building operation in practice. Research will be conducted if the resulting optimized building operation parameters can be implemented into the real building.

REFERENCES

Déqué, F., F. Ollivier, et al. (2000). *Grey boxes used to represent buildings with a minimum number of geometric and thermal parameters*. Energy and Buildings 31: 29 – 35.

DIN V 18599 (2005). *Energetische Bewertung von Gebäuden- Berechnung des Nutz-, End- und Primärenergiebedarfs für Heizung, Lüftung, Trinkwarmwasser und Beleuchtung*. Berlin: Deutsches Institut für Normung e.V..

ISO 13790 (2007). *Energy performance of buildings- Calculation of energy use for space heating and cooling*. Geneva: International Organization for Standardization.

Katipamula, S., M. R. Brambley (2005). *Methods for Fault Detection, Diagnostics, and Prognostics for Building Systems- A Review, Part I*. HVAC&R RESEARCH Volume 11/ Number 1.

Sahlin, P., L. Eriksson et al. 2004. *Whole-building simulation with symbolic DAE equations and general purpose solvers*. Building and Environment 39: 949 – 958.

Wetter, M. 2008. *GenOpt® Generic Optimization Program User Manual*. Berkeley: Ernest Orlando Lawrence Berkley National Labratory.