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PARAMETER IDENTIFICATION FOR LOW-ORDER BUILDING MODELS USING OPTIMIZATION STRATEGIES

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ABSTRACT

The simulation of entire city districts asks for a large number of descriptive parameters for all considered buildings. These buildings are often represented by models using only one thermal zone and few subcomponents in general. This is why parameter sets that describe a district are as dependent on the model being used as on the actual building.

This article proposes an approach to identify parameter sets for existing buildings based on low-order building models and optimization strategies.

Comparing to a generic, higher order simulation reference and, subsequently, referring to a case study on an existing building the feasibility of this approach is demonstrated.

INTRODUCTION

Besides the simulation of single buildings, simulating the energy performance of entire city districts in order to yield detailed information about their energy-related behaviour gains importance. Commonly, models used for building performance simulation range from simple one-zone models that might be based on indoor/outdoor temperature differences only, to multi-zone models of great detail, which attempt to describe physical effects with high fidelity. Generally speaking, simple one-zone models require fewer parameters and compute faster but also neglect some of the accuracy inherent to detailed multi-zone models.

Maintaining acceptably short computation times is of great interest when dealing with city districts that might include energy supply and grid models in addition to numerous buildings. Therefore, fast, simplified models are often the tool of choice for the simulation of city districts.

Furthermore, city districts display a near infinite parameter space (Kämpf and Robinson, 2009) to describe each building's constructions, installations and related user behaviour. Here parameter acquisition and management can be challenging - especially regarding existing building setups where detailed parameter sets of construction materials are often not available. Hence, using simplified models with a reduced parameter count give the additional benefit of a smaller parameterisation effort in district simulations.

In this article the term low-order model is used to describe simplified building models that comprise only a small number of variables dependent on time-derivatives of temperatures, i.e. thermal capacities in the case of building simulations.

Low-order models, which focus on simplification, require presumably different parameter sets than more detailed models. That is because, firstly, in most cases more simplified models require fewer parameters altogether. And, secondly, these fewer parameters combined with a model described by an inherently smaller underlying set of equations still need to represent the thermal characteristics of a certain building. Consequently, parameter sets can only provoke optimum results when they are fitted to the model they are actually simulated with. On that account, low-order models described in this article are grey-box models for their reliance on parameter fitting. They contrast with white-box models that are solely based on first principles. Optimization strategies appear to be suitable to fit parameter sets to these low-order models.

This article proposes a strategy that adapts parameter sets to low-order simulation models in order to represent the thermal characteristics of buildings with known monthly energy consumption and measured weather data. In this context, all modelling is done with the object-oriented modelling language Modelica and simulation with Dymola. The BuildingSystems Modelica library (Nytsch-Geusen et al., 2012) for building performance simulation is used. The GenOpt optimization tool provides various optimization algorithms as well as a profound framework for optimization problems (Wetter, 2001).

The parameter identification strategy is tested against a higher-order reference model, which is also created using Modelica. Comparison with a simulation based reference with known properties and thermal behaviour allows for an assessment of the proposed strategy's feasibility.

Furthermore, the method is demonstrated on an existing non-residential building located at university campus Berlin-Charlottenburg with known monthly energy consumption, roughly known building geometry and measured weather data.

PARAMETER IDENTIFICATION USING OPTIMIZATION STRATEGIES

For the parameter identification strategy, a low-order building model is simulated with an initial parameter set that describes all relevant thermal characteristics of a building. The building's ambient conditions are generated using measured weather data for a specific location and time. To ensure meaningful start values in all components, a period of 12 month is simulated before an evaluation period of $n = 12$ months begins.

After simulation the resulting monthly energy consumption is compared to measured energy consumption data of the same time frame as the measured weather data. For comparison a cost function f_c, defined as follows, is evaluated.

$$f_c = \frac{1}{\sum_i^n Q_{con,i}} \cdot \sum_i^n \left| Q_{sim,i} - Q_{con,i} \right| \qquad (1)$$

It describes the sum of the n positive differences of simulated and measured monthly heating energy consumption - $Q_{sim,i}$ and $Q_{con,i}$ respectively - divided by the entire heat consumption in the evaluation period. In other words, an optimally fitted parameter set is achieved when simulated and measured monthly heating energies are equal, resulting in $f_c = 0$.

After evaluating the cost function, the parameter set is adjusted and simulation is engaged again. A framework for this optimization process is provided by GenOpt optimization tool, which is developed at Lawrence Berkeley National Laboratory, USA (Wetter, 2011). The Jeeves-Hooke general pattern search algorithm, as described in the GenOpt manual, is used for the parameter identification. In numerous iterations the algorithm minimizes the cost function f_c.

The optimization process is stopped when a defined accuracy is reached. The parameter set that yields a minimum for f_c is the result of the parameter identification process.

Low-order building model

The used low-order model defines the parameters that need to be identified, the occurring computation time per iteration as well as the process' adaptability to various usage scenarios. The experiments described in this article make use of the simplified building model whose inner structure is depicted in figure 1. It is assembled from components provided by the BuildingSystems Modelica library (Nytsch-Geusen et al., 2014).

The model is designed to represent a rectangular building. It features three wall constructions in total, representing (1) external walls, (2) intermediate walls, ceilings as well as other internal thermal capacities and (3) the building's base plate, which has a constant 10 °C boundary condition. The three thermal capacities are defined with their respective volumetric heat capacity (VHC) in J/K per m³ of construction volume. This ensures that start values and identified parameters can be derived more easily from or compared to material databases.

Geometry related parameters, i.e. dimensions and orientations of facades and windows are set according to the examined building. Four window models are used to account for solar irradiation. Their normal vectors are offset by 90° each. The model building's azimuth can be set according to the

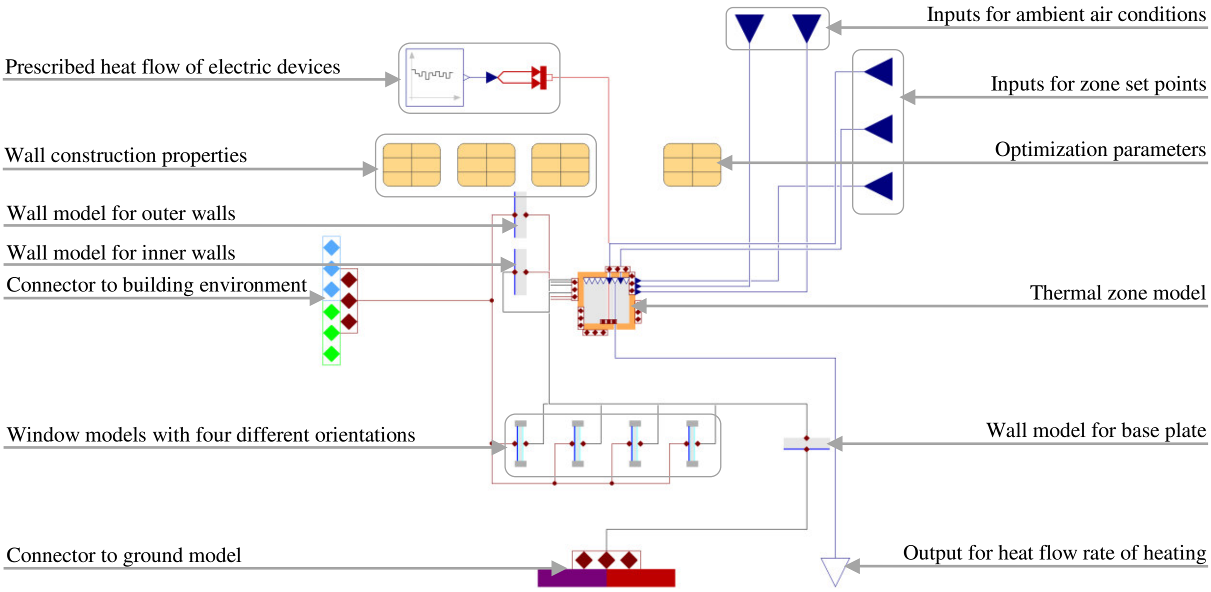

Figure 1: Low-order building model implemented in Modelica using the BuildingSystems library

building that is being represented by the model.

Furthermore the model contains one air volume that is connected via two air paths with constant air change rates to the building's environment. Heat gains from electrical loads are reproduced through a prescribed heat flow that might be different for each month. Finally, an ideal heating and cooling system calculates ideal loads - within specified limits - according to a set air temperature range.

According to this table 1 shows those parameters that need to be adjusted in order to match the model's thermal behaviour to the actual building's behaviour. This is also the parameter set, which is identified using the proposed method. Simulation time for a one-year simulation with this low-order model is about 25 sec.

1D-REFERENCE MODEL

To show the feasibility of the proposed parameter identification strategy, it is applied to a higher order, one-dimensionally discretised reference model with weather boundary conditions of three consecutive years. The identified parameter set resulting from the proposed strategy is compared to a parameter set that is derived from the reference model through weighted averaging.

The 1D-reference model depicts a flat-roofed two story building with a floor area of 128 m² evenly spread over 8 rooms. A basement is not included. The building characteristics are adapted from building DE.N.SFH.06.Gen.ReEx.001 as described in TABULA Building Typology Germany (IWU, 2015). Figure 2 shows the corresponding Modelica model, which is also based on the BuildingSystems Modelica library. Within the model each room is represented by one thermal zone. Each thermal zone is connected to two air paths, which ensure the zone's air connection to the building's ambient. Additional

Table 1

Parameters of low-order building model

PARAMETER	UNIT
Set temperature heating	*°C*
Set temperature cooling	*°C*
Set air change rate	
Window-to-wall ratio	
Volumetric heat capacity external wall	J/m^3K
Volumetric heat capacity internal walls, etc.	J/m^3K
Volumetric heat capacity base plate	J/m^3K
Thermal transmittance external wall	W/m^2K
Thermal transmittance internal wall, etc.	W/m^2K
Thermal transmittance base plate	W/m^2K
Thermal transmittance windows	W/m^2K

heat gains through internal electrical consumption are represented by one prescribed heat flow per zone with monthly varying loads. Values for air change rates and heat loads are different for each zone to emulate different user behaviour. Cooling of the thermal zones is not enabled in this model.

The building envelope includes 12 windows in total with three different orientations. Different constructions are simulated for external and internal walls as well as ceilings, intermediate ceilings and the base plate. Constructions are composed from 3 respectively 4 layers of different materials (e.g. brick, insulation, etc.). Each layer is discretised into 5 thermal nodes. Simulation of the described reference model takes 40 to 50 minutes for a two-year simulation depending on the used weather data. The first 12 months of simulation are regarded as run-in time to ensure meaningful start values for the second year of simulation. The model is simulated with

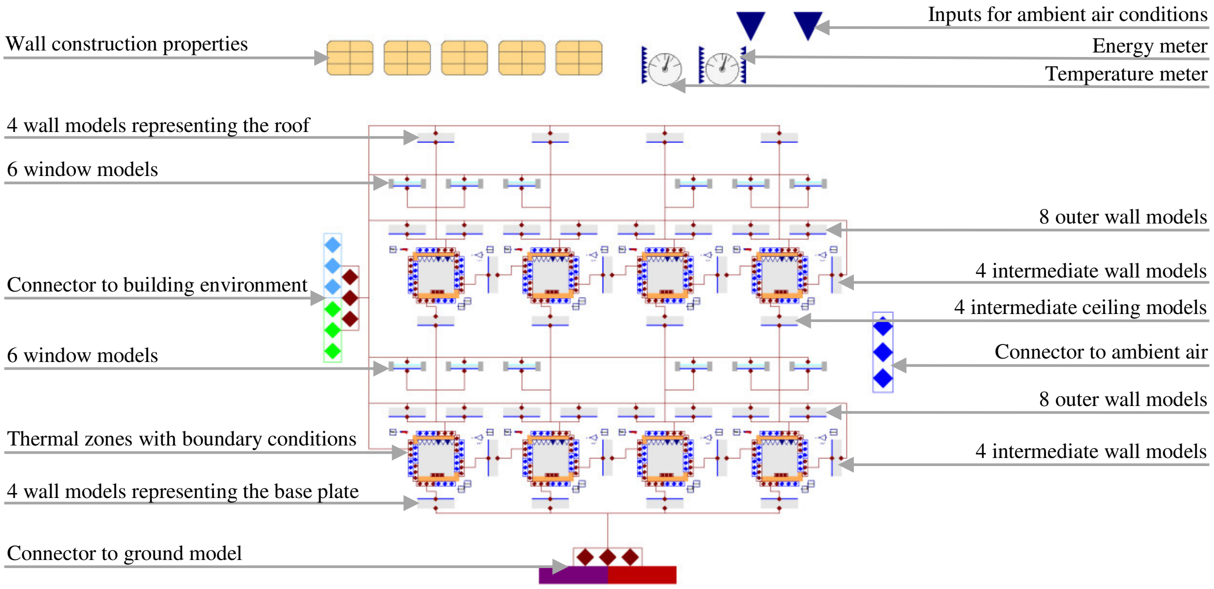

Figure 2: 1D-reference model with 8 thermal zones (not all connections are visually represented)

actual weather data from Potsdam, Germany for 2011, 2012 and 2013. The computed monthly energy consumption data is saved for further reference.

Parameter identification

The parameter identification process is conducted separately for the years of 2011, 2012 and 2013. Firstly, the low-order building model is provided with basic geometric information of the reference building - excluding window-to-wall area ratio. Secondly, start values and limits for all parameters are set within the GenOpt command file. Limiting values for material parameters are theoretical limits obtained from construction material databases, start values are their respective mean values. Finally, the optimization process is started.

For this specific 1D-reference model and 2013 weather data the optimization algorithm finds its optimum result after 503 iteration steps or roughly 10 hours of computation time. The identification process results in a cost function $f_c = 0.018$. That means, the positive, monthly deviations between reference and low-order model amount to 1.8 % of the yearly energy consumption. Figure 3 depicts the monthly heat energy consumption of the reference model as well as the low-order model after parameter identification for 2013. Only small deviations in monthly energy usage can be observed. Figure 4 shows a comparison of heating loads for the 1D-reference as well as the low-order model, the ambient temperature is also plotted. The heat load of the low-order model follows the reference load rather good, although with more jitter.

Table 2 shows identified parameters for the low-order model for the years 2011 to 2013 in comparison to parameters that have been derived from the 8-zone reference model through weighted averaging. The last two rows quantify the cost function f_c, firstly, for the low-order model with identified parameter sets, and secondly, for the same low-order model but with a parameter set derived from the reference model, which is constant for all three years and is simulated with all three weather data sets.

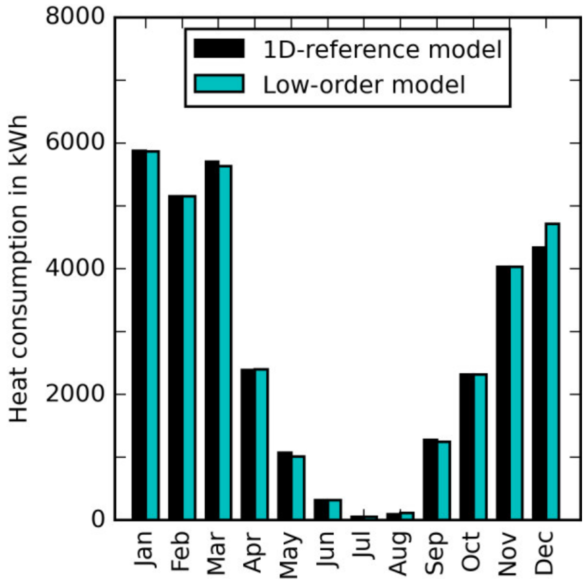

Figure 3: Monthly heat energy consumption in low-order model and 1D-reference model for a generic building with 128 m² heated floor space

Generally, values for f_c are far smaller for the identified parameter sets, being as low as 1.8 %, than for the derived parameter set, reaching 16.3 % and above. Subsequently, the identified parameter sets show a better ability to reproduce the thermal behaviour of the reference model than the derived set.

However, it can be observed that the identified

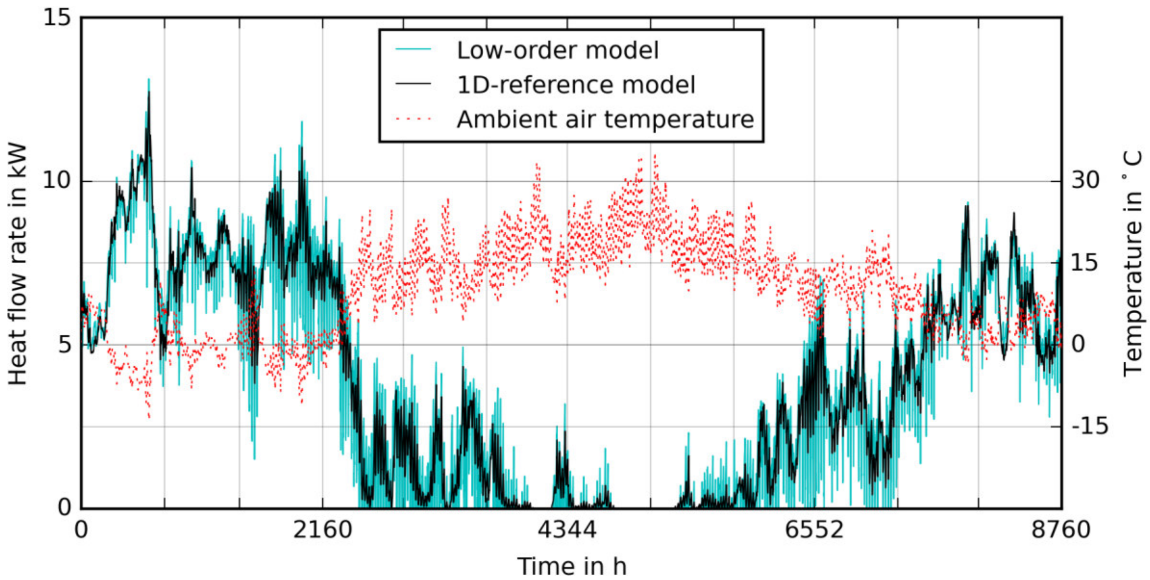

Figure 4: Heating load from low-order model after parameter identification compared to heating load from 1D-reference model and ambient air temperature

Table 2

Parameters of low-order building model after parameter identification compared to parameters derived from 1D-reference

	REFERENCE	**LOW-ORDER MODEL**		
Measured weather ambient condition from year	(*)	2011	2012	2013
Set temperature heating in *°C*	20.25	20.50	20.13	20.38
Set air change rate	0.50	0.75	0.91	0.81
Window-to-wall ratio	0.18	0.50	0.42	0.39
Volumetric heat capacity external wall in J/m^3K	465,050	625,000	1,562,500	896,875
Volumetric heat capacity internal walls, etc. in J/m^3K	265,120	565,000	1,236,250	788,125
Volumetric heat capacity base plate in J/m^3K	425,000	310,000	895,000	551,875
Thermal transmittance external wall in W/m^2K	1.50	1.79	1.44	1.67
Thermal transmittance internal wall, etc. in W/m^2K	3.16	2.39	2.39	2.36
Thermal transmittance base plate in W/m^2K	0.69	0.60	1.05	0.60
Thermal transmittance windows in W/m^2K	4.66	4.50	4.50	4.50
f_c from identified parameters	-	2.5 %	2.0 %	1.8 %
f_c from derived parameters	-	16.3 %	16.6 %	16.5 %

(*) parameters are derived through weighted averaging of properties of the 1D-reference model

parameter sets vary greatly from year to year. Especially parameters for thermal capacities are subject to huge variations. In lesser manner air change rates, window-wall-ratios and thermal transmittances do also differ from the derived values. This suggests that more than one combination of parameters can reflect the thermal behaviour of a given building reference.

In order to explore this conjecture in more detail, table 3 shows cost function values when simulating identified parameter sets with different weather data. Each row represents simulations with consistent parameters, whereas each column indicates f_c-values with consistent weather data.

It is apparent that identified parameter sets yield the best f_c-values (shaded in grey) for the weather data and consumption data - both from the same year - the set was optimized for. Simulating the model with a different combination of weather data and parameter set yields less than optimal results.

Table 3

Cost function f_c for combinations of parameter sets and weather boundary conditions

COST FUNCTION f_c		Weather data from... 2011	2012	2013
Parameters identified with optimization strategy for consumption in...	2011	2.5 %	19.7 %	18.8 %
	2012	16.1 %	2.0 %	19.6 %
	2013	16.4 %	21.7 %	1.8 %

CASE STUDY: EXISTING BUILDING

The following paragraphs describe a case study on an existing building of Berlin University of the Arts in order to illustrate the practical feasibility of the proposed strategy. The building from 1898, located at university campus Berlin-Charlottenburg, Germany is depicted in figure 5. It has a heated floor space of approx. 12,349 m² spread over 4 floors. For this university building with its ateliers, seminar rooms, lecture halls and offices only rudimentary construction information can be obtained. However, monthly heat and electricity consumption data of several past years as well as geometric information is available.

The low-order model is prepared for parameter identification by providing basic geometry information, electricity consumption data as well as weather data from 2013. To evaluate the cost function f_c the monthly heat energy consumption data of 2013 is inserted.

Figure 5: Building of University of the Arts Berlin

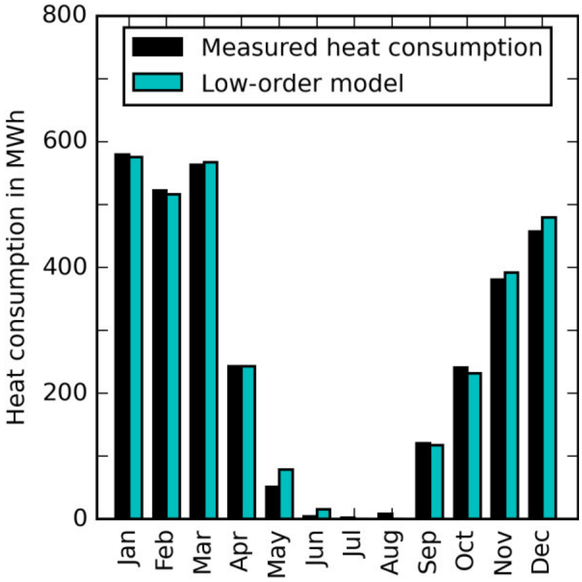

Figure 6: Simulated monthly heat consumption from low-order model and measured heat consumption of existing building with approx. 12,349 m² heated floor space for 2013

The parameter identification process takes 457 iterations for this configuration or a computation time of 7.5 hours respectively and results in a cost function value of $f_c = 3.4$ % for the found optimum. Figure 6 shows the resulting monthly heat energy profile, comparing simulated data and measured data.

The identified parameter set, table 4, can now be used to simulate the same low-order model in another context to represent this existing building's thermal behavior, for example in a district simulation along with other buildings as well as energy production and distribution components. Representing the building with a model, which contains a fitted parameter set leads to more accurate results when simulating than estimated parameters would.

DISCUSSION

The presented experiments done on the 1D-reference model demonstrate the general feasibility of the proposed parameter identification method. Especially when simulating the identified parameter sets with the weather data they are optimized for, the identification process yields parameter sets, which together with the low-order model mirror the reference consumption correctly. This is true for all three years the process is performed for.

However, it can be observed that considerably different combinations of parameters can reproduce the thermal behaviour of a given reference building model with reasonable accuracy for different years (see table 2).

When repeating the simulation with different combinations of weather boundary conditions and parameter sets (table 3), it is apparent that only the original combination of parameters, weather data and

Table 4

Parameters after identification for actual building

IDENTIFIED PARAMETERS	
Set temperature heating	18.00 *°C*
Set air change rate	0.35
Window-to-wall ratio	0.25
VHC external wall	835,000 J/m^3K
VHC internal walls, etc.	160,000 J/m^3K
VHC base plate	415,000 J/m^3K
Thermal transmittance external wall	0.84 W/m^2K
Thermal transmittance internal wall	2.15 W/m^2K
Thermal transmittance base plate	1.08 W/m^2K
Thermal transmittance windows	4.66 W/m^2K

low-order model yields vastly better results than using parameters, which are derived from the reference model. Simulating different combinations of weather data and parameters yields results of the cost function that are similar to results of simulations with derived parameters.

At this point it is important to remember that in most cases the derivation of parameters for actually existing buildings is just not possible or at least extremely time- and labour-intensive, particularly when the derivation had to be performed for a vast number of buildings in a city district.

Testing the identification process on an actual building shows that the process can yield a parameter set to describe an actual building's thermal behaviour, though in this case with a slightly higher error margin as is found with generic testing.

CONCLUSION

This article demonstrates an optimization-based approach to identify parameter sets for low-order building models, which are required to mirror the thermal behaviour of a given building. The used low-order model is composed using Modelica component models from the BuildingSystems Modelica library. The GenOpt optimization tool provides a framework for the optimization process.

The experiments show that it is feasible to identify parameter sets with optimization strategies that accurately reproduce the energy consumption and heating loads by comparing to a generic 1D-reference model, which is also modelled and simulated using Modelica.

In next steps, besides enhancing the structure of the low-order model to ensure its adaptability to various types of existing buildings, the optimization process will be improved to result in parameter sets that represent the building's thermal behaviour correctly over several years. Further work will be done on reducing the number of parameters that need to be identified in the optimization process in order to reduce the number of iterations and consequently speed up the entire process.

NOMENCLATURE

f_c : Cost function

n : Number of months in evaluation period

$Q_{con,i}$: Measured heating energy consumption

$Q_{sim,i}$: Simulated heating energy consumption

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