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QUANTIFYING THE IMPACT OF EXTERNAL AND INTERNAL FACTORS AND THEIR INTERACTIONS ON THERMAL LOAD BEHAVIOUR OF A BUILDING

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Abstract. For the energy-efficient design of district heating networks, knowledge about the neighborhood heat load behavior, through heating load profiles in high temporal and spatial resolution, is crucial. Due to the high effort required for transient calculations, a less complex method is needed at the neighborhood level. For this reason, a method is developed, which identifies the relevant parameters influencing the building heating load behavior. Taking these parameters into account, a simple method for heating load profiling is developed using a machine learning algorithm. For this purpose, a parameter study is conducted using dynamic thermal building simulation software. Different parameters influencing the building heating load behavior are varied. To determine the strength of the influence of the individual parameters on the building heating load, to check whether the influence of the parameters is constant or varies over the year and whether parameters are missing here, the results of the parameter study are evaluated statistically. First results show promising results in the detection of the significant parameters, for the creation of a model based on a machine learning algorithm, and the possibility of quantifying their impact on building heating load behaviour.

Keywords: Energy-efficient building design, sector coupling, thermal load behaviour, standardised and parameterised thermal load curves.

1. Introduction

Globally, the building sector accounts for a large share of total energy demand and greenhouse gas emissions. In the EU, the building sector is estimated to be responsible for 40 % of total energy demand and about 36 % of greenhouse gas emissions [1]. In the United States, the building sector accounts for 38.9 % of energy demand, with heating, cooling, and ventilation of buildings already accounting for 34.8 % [2].

These facts highlight the great potential for energy and greenhouse gas savings in the building sector. In order to exploit this potential, not only an energetically optimized building envelope and an optimization of energy generation and transmission technology are required, but also a targeted establishment of technical building equipment, since local and district heating networks are being expanded more and more worldwide. Most research on the optimization of local and district heating networks is still based on energy generation and only a few consider the consumer side [3].

However, a suitable prediction of the load behavior on the load side is a fundamental prerequisite for the development and optimization of local and district heating networks. In particular, for an energy-efficient design of the networks and their components, the knowledge of the temporally high-resolution course of the load as well as the simultaneity of the heat demand is of central importance.

These parameters, the coincidence factor and the heat load curve, are currently determined using static methods and assigned safety factors due to the resulting uncertainties [4].

As a result, systems are not operated in terms of optimal energy efficiency. In practice, local and district heating networks are designed and optimized on the basis of previous findings. Historical data from other local and district heating networks are used to predict the load behavior of an area supplied. Since different areas may differ greatly in their underlying conditions, the inherent data characteristics must be adapted for the new area. How well this transfer fits, depends heavily on the experience of the planner [5].

In order to enable a differentiated and quantitative prediction of the heat load demand for the planning and optimization of local and district heating networks, some research has been done in the last years [3]. On the one hand, so-called top-down models have been developed, which are based on historical data of existing local and district heating networks. However, these models have proven to be too coarse and too general for network planning and optimization. Bottom-up models, on the other hand, which consider individual nodes in detail as a basis for operation, for example, can be divided into four categories: empirical models, statistical models, physical-statistical hybrid models, and engineering models. While models in the first three categories have a high level of detail,

	Stage experimental plan			
Climate	TRY 2	TRY 4	TRY 14	
Wind	city centre	in the countryside	sea	
Building tightness	tight	medium tight	leaky	
Window size	10 %	100 %	200 %	
Orientation	north	south	west	east

Table 1. Experimental plan.

compared to top-down models, they still have disadvantages, especially in the early stages of planning, because they are also based on historical data and are therefore not transferable. It is not possible to implement effects that are not included in the observed data in these models. The engineering models allow the implementation of all required physical effects and user behavior and are based on thermal building simulations. This makes them highly adaptive and also quite accurate in predicting heat demand. However, this approach is very complex and thus expensive to create, since each unit of a neighborhood to be supplied must be simulated individually. To facilitate this, general load profiles can be developed for specific building types, e.g. office buildings, residential buildings, etc. While this simplification speeds up the development of the heat load profiles, it comes at the expense of accuracy as it relates to average building data. For a more detailed overview of heat load profile modeling, the reader is referred to [3], where the authors provide a comprehensive review of current assessment methods.

Following the latter approach, the goal of this research is to produce heat demand profiles with reasonable accuracy and the advantage of a less time-consuming setup, compared to methods, where all units are assessed individually.

For this purpose, a method is developed to identify the relevant parameters that influence the heating load of a building. On the basis of these identified influencing factors, a simple method for the creation of heating load profiles will be developed with the help of a machine learning algorithm.

In this work, the method for identifying the influencing variables is tested.

2. Method

According to the need to gain insight into the load behavior of the building without a complex transient simulation, the method aims at reducing the building analysis to the crucial parameters of the heat load profiles. In contrast to a coarse simulation for the whole building with only one node, in this work a method is developed and tested making an identification of the most important parameters is possible. With the help of these identified parameters, a method will be developed at a later stage which, with the help of machine learning algorithms, can quickly generate precise heating load profiles.

The approach is induced by the task to provide profiles for a long-term simulation and a linear optimization of a district heating network and its heat generators and to develop its future-oriented energy concept.

2.1. Principle procedure

The individual simulations of the test series for this work are very time-consuming. For this reason, only one building and only one user profile are used to test the method. The basis of the investigations is the small residential building (EFH_klein) from the research report "Entwicklung einer Datenbank mit Modellgebäuden für energiebezogene Untersuchungen, insbesondere der Wirtschaftlichkeit" [6]. Using this building, the variables generally considered as relevant, such as storage mass, window size, building orientation, etc., are varied and simulated with the help of a parameter study. Subsequently, the simulation results from the parameter study are statistically evaluated with the help of an ANOVA (analysis of variance).

In order to find out which parameters have a significant influence on the heating load behavior of a building, the small residential building from the research report "Entwicklung einer Datenbank mit Modellgebäuden für energiebezogene Untersuchungen, insbesondere der Wirtschaftlichkeit" [6] was first implemented in the dynamic thermal building simulation software IDA ICE [7]. In this first step, a residential use from DIN V 18599-10 [8] was assumed as the user profile and user behavior and was not varied further. Thus, the results are based on a small residential building and may differ for a large building and/or a different use to these.

The varying parameters were changed in a two to four step experimental design.

The parameters climate, taken from DIN 4710 [9], wind, building tightness and window size were varied in a three-stage test plan. The parameter building orientation was varied in a four-stage test plan, see Table 1.

The building insulation and storage mass were varied in a two-stage experimental design. For the building insulation, the TABULA database [10] was used as a basis for the varying component structures. The U-values and the corresponding storage mass are shown in Table 2. All parameters are varied and simulated using the experimental plan Table 1.

	U-value [W/m²K]	Heavy Storage [kJ/m²K]	Light mass [kJ/m²K]
Exterior wall new construction	0.136	484	24
Exterior wall not refurbished	1.52	352	16.6
Interior wall		74	16.1
False ceiling		370	176
Base plate new construction	0.21	531	348
Base plate not refurbished	0.95	495	215
Roof new construction	0.14	393	29
Roof not refurbished	1.81	281	18.1

Table 2. Characteristic values of the building components.

For these investigations, as mentioned above, ANOVAs were performed to find out to what extent the influencing parameters and their interaction have an influence on the building heating load. For this purpose, the average heating load was determined for each month of the year and used as a dependent variable. The varied influence parameters from the test plan form the independent / explanatory variables in the analysis. Thus, 12 ANOVAs were performed, one for each month. Subsequently, for each independent variable and interaction among the variables, the partial η^2 was used to determine the influence strength on the building heating load within the ANOVA. In a further step it was examined whether the influence strength changes over the year. Finally, it was examined, whether the coefficient of determination R^2 of the individual ANOVAs changes over the year.

2.2. Model set up

The software "IDA ICE" of the software manufacturer EQUA provides the possibility of parameterized simulations. This makes it comparatively easy to carry out parameter studies with several varying parameters. Following the parameterized simulations, the generated data can be relatively easily merged in Excel for further analysis.

At the beginning of a series of tests, the parameters within this series are permanently set according to the experimental setup in Table 1. For example, before a parameter simulation, it is determined whether it is a heavy or light building. Furthermore, the quality of the building envelope is defined. Here it is distinguished, whether it is a "not refurbished" building envelope or whether it is a "new" building. The components for the category "not refurbished" would correspond to buildings of the age class 1816 to 1918, the components of the category "new construction" to the age classes 2016 to today. The characteristic values of the building components are shown in Table 2.

The parameters to be varied are defined in the IDA ICE software at the beginning and automatically varied during the parameter simulations.

For the climate, the test reference years TRY 2, TRY 4 and TRY 14 of DIN 4710 [9] were used. The test reference years contain hourly values of, for example, outdoor temperature, solar radiation, etc. For more detailed information see DIN 4710 [9]. For the wind profiles (wind), the ASHRAE profiles "In the countryside", "Sea" as well as "City centre" stored in the software IDA ICE were used. The n_{50} air change rate was used to characterize the building tightness. This defines how often the air exchanges in one hour at a pressure difference of 50 Pa. In the "tight" category, an n_{50} value of 0.35/h was assumed, in the "medium tightness" category an n_{50} value of 3.675/h was assumed, and in the "leaky" category an n_{50} value of 7/h was assumed. Window sizes were simulated at 10 %, 100 % and 200 % starting from the initial model. From the research report "Entwicklung einer Datenbank mit Modellgebäuden für energiebezogene Untersuchungen, insbesondere der Wirtschaftlichkeit" [6], the small residential building has a volume of 465 m^3 in its basic configuration and has 26.5 m^2 of window area, a usable floor area of 148.8 m^2 and an A/V ratio of 0.98. The building orientation was varied in four steps starting from a south orientation to a west, north and east orientation.

3. Results

The following section presents the results for testing the method of quantifying the effects of external and internal factors and their interactions on the thermal load behavior of a building and interprets the results Statistical analysis on the parameter studies of selected influencing factors and their interactions, as well as the change in model quality over the course of the year.

3.1. Difference in the strength of influence of individual parameters and their interactions over the course of the year

The first step was to investigate the extent to which the influence of the individual independent variables and their interactions change over the year. Due to the abundance of independent variables and especially

Data series	ANOVA-model parameter (Variable and interaction)
1	Wind
2	Building tightness
3	Climate * Building tightness
4	Window size * Wind
5	Wind * Building tightness
6	Wind * Average U-value building
7	Climate * Window size * Wind
8	Climate * Wind * Building tightness
9	Window size * Orientation * Average U-value building
10	Climate * Window size * Wind * Building tightness

Table 3. Selected data series with model parameters.

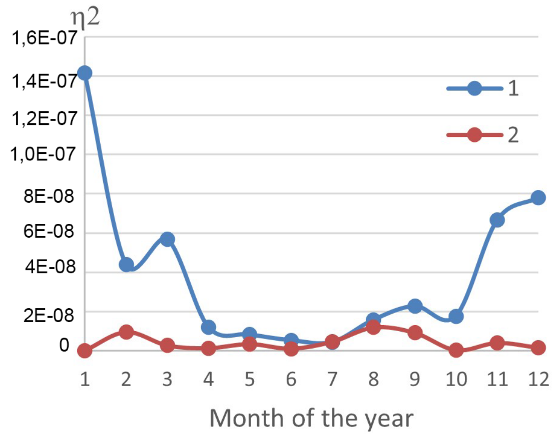

Figure 1. Influence of data series 1 and 2 over the year.

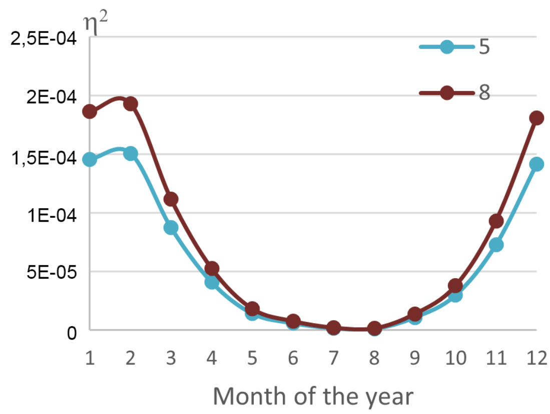

Figure 3. Influence of data series 5 and 8 over the year.

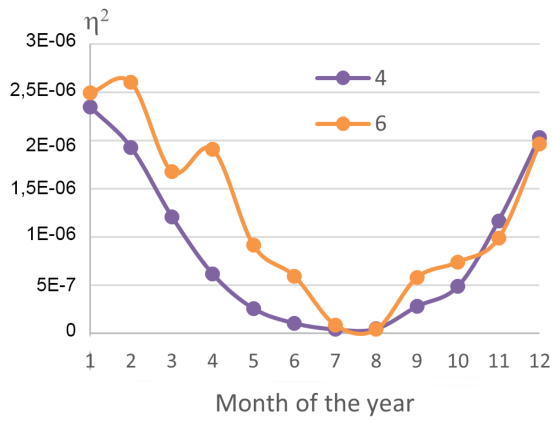

Figure 2. Influence of data series 4 and 6 over the year.

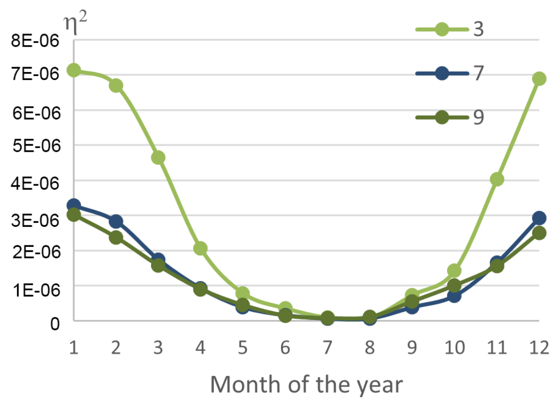

Figure 4. Influence of data series 3, 7 and 9 over the year.

their interactions, which leads to a total of 1585 model parameters (variables and their interactions) within an ANOVA, the 10 most important data series are shown as examples. The presented data series with their model parameters are listed in Table 3.

In order to quantify the strength of influence or effect of the individual variables and their interactions on the overall model, the partial Eta-squared η^2, which results from the quotient of the explainable sum of squares to the total sum of squares, was calculated for each data series. According to Cohen [11], a η^2 of 0.01 indicates a small effect, whereas a η^2 of 0.14 and higher indicates a large effect.

The following figures show the influence of the individual variables and their interactions over the year.

As shown in Figures 1, 2, 3 and 4, the influence of the individual variables and their interactions change over the year, except for data series 2, where the influence on the heating load behavior remains relatively constant over the year. With the data series and the variables and interactions contained therein 1 as well

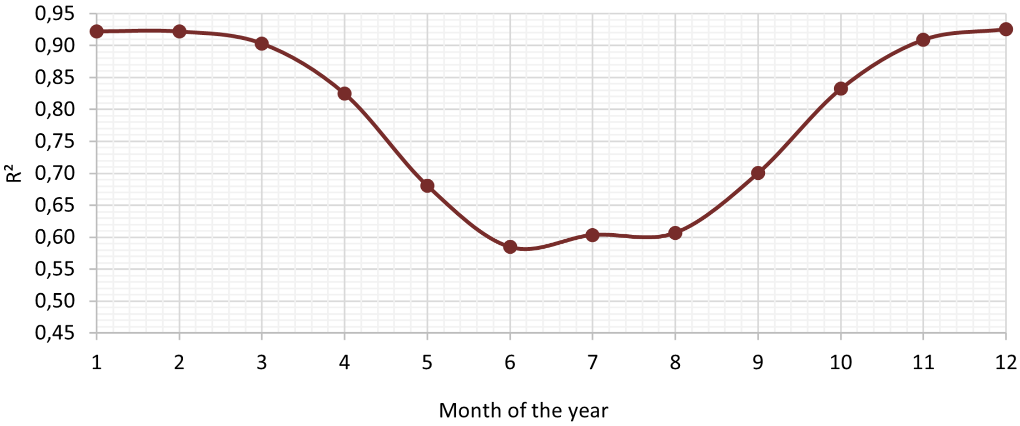

Figure 5. Coefficient of determination of the ANOVAs over one year.

as 3 to 10 it is to be recognized that their influence of the winter months to the summer months decreases and in the connection again rises. If we look at the variable in data series 2 in combination with the variable climate, which corresponds to data series 3, we can see that the building tightness, which corresponds to the variable in data series 2, also loses importance from the winter months to the summer months and vice versa gains importance again.

It seems to be possible to determine the influence of individual parameters and their interactions with the help of this method. In addition, this analysis indicates that the significance of the influencing variables and their interactions change over the year.

3.2. Coefficient of determination of the ANOVAs

Next, it was checked whether the coefficient of determination R^2 of the ANOVAs remains constant over the year or whether there are differences. For this purpose, the coefficient of determination R^2 was calculated for each ANOVA and compared with each other.

As shown in Figure 5, the quality R^2 of the ANOVAs decreases from the winter months to the summer months and then increases again. In the winter months the R^2 is about 0.91 which indicates a very good predictability of the building heating load by the ANOVA. In the summer months, the R^2 decreases to about 0.6, indicating only moderate predictability.

Overall, this decrease in R^2 from the winter months to the summer months indicates that explanatory variables are missing here to be able to predict the building heating load well in summer. This means that more variables have to be included and not all explanatory variables are included in the regression model to predict the building heating load behavior in summer. This means that not all variables that have an influence on the heating load behavior of a building have been identified yet.

4. Discussion

The results from Section 3 show that it is possible to determine the strength of influence of individual parameters and their interactions. Furthermore, the analyses show that these vary strongly over the year. Also, it seems to be possible to determine with this method whether all important parameters for the prediction of the heating load behavior of buildings have been found. As shown in Section 3.2, the decrease of R^2 from winter to summer and vice versa indicates that not all important parameters have been included in the analysis yet.

In a next step, further analyses will be performed to determine the last missing parameters that have an influence on the building heating load behavior. Afterwards a principal component analysis will be performed to check if variables can be combined. This should reduce the input effort for a later heat load prediction model. With the principal component analysis, the influence of the individual parameters on the building heating load model can be determined and quantified even more precisely.

The influential parameters will ultimately serve as input variables for a machine learning algorithm, which will then be used to predict the building heating load behavior with similar precision as with a dynamic thermal building simulation, but with considerably less effort. With this algorithm, the heating load behavior of entire neighborhoods should also be precisely presentable without great effort.

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