DYNAMIC UNCERTAINTY ANALYSIS OF THE BUILDING ENERGY PERFORMANCE IN CITY DISTRICTS

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ABSTRACT

This paper shows the application of uncertainty analysis methods in building performance simulation to a city district. In the energetic evaluation of city districts, every house has its own uncertainties concerning user behavior and building physics. When analyzing an existing city district with very low information about the building structure, uncertainties concerning the state of renovation add to the uncertainties which already exist if the building itself is well known.

The central point of this paper is the analysis of these uncertainties for a generic city district. The detailed analysis of a city district requires a great deal of computation capacity. Therefore, a Quasi-Monte-Carlo (QMC) approach is used to keep the computational effort in reasonable limits.

The necessary number of simulations to ensure a sufficient result is analyzed. It is figured out that at least 64 simulations are necessary to have a sufficient reproducibility of the dynamics in heat demand. The uncertainty in the total heat demand is quite low, while the uncertainty in the dynamics varies during the year. The relative uncertainty is much higher in summer times when the heat demand is very low.

INTRODUCTION

Building performance simulation has become increasingly important for the design and operation of buildings' energy systems. The used tools are getting more sophisticated. To model the different physical effects affecting the energetic performance of buildings, many parameters have to be set. Mostly, designers choose one parameter set with standard parameters. If these standard parameters do not fit with the real application, a discrepancy between the calculated demand and measured consumption can be observed. To overcome this discrepancy, methods for uncertainty analysis can be used. During the last years, some methods were developed to analyze uncertainties in building simulation (Lomas and Eppel, 1992) (de Wit and Augenbroe, 2002) (Hopfe and Hensen, 2011). However, still many designers do not use this possibility of improving the quality of the simulation results (Lee et al., 2013). Additionally, the object under consideration was up to now mostly only a single building.

During the last years, the object under consideration is exceeding from one building to whole city districts. One reason for this are decentralized energy concepts for the integration of bigger amounts of renewable energies especially into the electrical grid. (Molitor et al., 2012) On the low-voltage-level, increasing feed-in from photovoltaics is observed. As buildings are also located in the low-voltage-grid, one option for decentralized storage capacity could be the building stock with its thermal water storages. Heat pumps could be used to transform the energy from electricity to heat if there is too much energy in the grid (Arteconi et al., 2013). Additionally, combined heat and power plants can be used to generate electricity when there is too little renewable energy in the grid (Stinner et al., 2014). In both cases, heat storages can be used to decouple the heat generation from the demand of the building. One water storage alone cannot deliver enough storage capacity to balance the grid. This leads to the idea to couple all storages in one city district to get a noticeable storage capacity for the integration of renewable energies. To determine the amount of storage capacity that the buildings can provide over time, a detailed dynamic analysis of the heat demand is necessary. As there are uncertainties in the input parameters as stated before, these uncertainties will also influence the possible usable storage capacity. For this reason, we analyze the uncertainties in the heat demand on the city district level.

In this paper, we use a Quasi-Monte-Carlo (QMC) method to consider the uncertainties in the input parameters. These methods are presented in different studies concerning the uncertainties for single buildings (Burhenne et al., 2011)(Hopfe and Hensen, 2011)(Macdonald, 2002). For the different parameters, probability distributions instead of single values are chosen. As a result, the calculated demand is as well not a single value, but a probability distribution. With this, it is possible to get a more realistic insight into the possible heat demand of the buildings. In most cases, especially the user behavior is uncertain and has to be considered. Additionally, the parameters of the used materials are not known exactly.

In this paper, we show a methodology to consider uncertainties not only in single buildings but in city districts. This means that we have to consider the uncertainties in the user behavior as well as in the building structure. Besides that, statistical data for the composition of the city district is used as input to have a realistic distribution of building ages in the regarded system. By now, if a city district should be evaluated, every house has to be analyzed in terms of its thermal behavior. This is a big effort, because someone has analyze each building in detail. As it is more important how the overal performance of the district is and not how buildings are located, top-down statistics can be used to characterize the structure of the buildings. In other studies, local sensitivity analysis for city districts were already applied (Kavgic et al., 2013). We are not interested in the influence of the single parameters but in the overall performance of the city district. Additionally, (Booth et al., 2013) presented a study that calibrates a housing stock model with macro-level data for energy consumption. As far as we do not know a distribution for energy consumption by now as the work should be applied to a generic city district, we cannot use this method in our case. Additionally, we want to focus on the dynamic behavior of the energy demand which is not considered in (Booth et al., 2013).

In the following, we will present the methodology basics and their transformation to the city district scale. Here, we will also focus on the statistical data and the statistical methods we use. Furthermore, we will present the simulation environment and the results. At the end, a conclusion and an outlook finish this paper.

METHODOLOGY

Modelling

As we want to model buildings on a city district level, it is very important to have a simulation model which has short simulation times. Additionally, it has to model the physical behavior of the system as well as possible. For this reason, we decided to use a simplified building model which is built up based on components known from electrical circuits. Heat transfer processes can be modelled by resistances and heat storage phenomena are represented by capacities. The model we use for this application consists of three resistances and two capacities (Lauster et al., 2014). This model fits well our requirement for fast calculation times as well as for a high accuracy. The air exchange is calculated with an energetic balance of the air entering the system from the outside and the air leaving the room through leakage, windows and doors. For a first analysis, the air exchange rate is left constant for the whole year. All buildings are simulated separately.

The influence of the weather to the building is modelled by radiaton and outdoor air temperature. This data is taken from the test reference year of the German weather service (Deutscher Wetterdienst DWD, 2011). The data base provides weather profiles with an hourly solution. All values in between are interpolated linearly.

In this paper, no technical equipment for the buildings like heat generators or heat storages is considered. The focus is only on the demand side of the buildings. Thus, an ideal heater is implemented which supplies the building with heat if the temperature falls below the heating threshold temperature. As we are analyzing a German case, the indoor temperature can fall below this temperature even in summer times. This results sometimes in a heat demand for summer times. Normally, the space heating applications are not used during summer, but as we want to ensure the prescribed temperatures in the rooms, we accept the heating demand in summer.

Basics of Uncertainty Analysis for Building Simulation

Uncertainty analysis methods were developed and applied in the building simulation area during the last years (Kotek et al., 2007)(Hopfe, 2009)(Burhenne et al., 2011)(Lee et al., 2013). To get a better insight to the uncertainties, basically two options are available. On the one hand, it is possible to modify the existing model to directly use the differential equations to calculate the borders that can be reached if the parameter values are uncertain (Macdonald and Clarke, 2007). This would require a change in the model equations for every model which is not desirable in our application, as this would require a high modelling effort if the models are extended or changed. For this reason, this method is not used in this paper. On the other hand, it is possible to use the standard model and apply a systematic variation of the input parameters. In other scientific fields like economics, these analyses are performed with a Monte-Carlo-Method (Breuer, 2001). Here, the probability distributions of the uncertain parameters are given or derived from measured data. Then random numbers are drawn from these distributions for every uncertain parameter, combined to one parameter set and many (mostly thousands of) simulations are operated. Due to the simulation times that can be reached in building simulation applications, this is not the best way to analyze the uncertainties, as the total simulation time could grow to non-acceptable amounts. This is even more important if we look at city districts like in our case, where we have to simulate larger numbers of buildings. We have to multiply the number of buildings with the number of simulations that we need to analyze the uncertainties.

To overcome the problem of increasing simulation effort while still getting better insights to the considered uncertainties in the city district, methods of the so-called quasi-Monte-Carlo(QMC)-method were developed. In literature, the number of simulations needed to get good results is given with about 80, independent from the number of varied parameters (Macdonald, 2002). In this paper, we will analyze this number with statistical methods. The basic idea is to draw the random number not randomly anymore, but systematically. For this, a method is needed to cover the space of the distribution with less steps. Here, the Latin Hypercube and the Sobol method are used in the literature. As the Sobol method promises a better performance with a lower number of simulations (Burhenne et al., 2011), we will perform our analysis with the Sobol sequence. Here, a uniform distribution is taken and covered best with the Sobol sequence. As this sequence uses a system to cover the uniform distribution, a high accordance to the real distribution can be reached with a lower number of drawings.

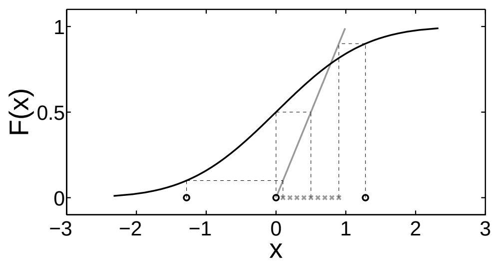

Figure 1: Cumulative density function for a uniform distribution (grey) and a normal distribution (black) and transformation process.

With this, it is possible to get a high accuracy of other types of distributions (for example normal distribution or lognormal distribution). This procedure is shown in figure 1. From every point of the uniform distribution between 0 and 1 (grey function), the point in the cumulative distribution function (CDF) with the same cumulative probability has to be searched in a different distribution (normal distribution with mean 0 and standard deviation 1 in black). After this, the corresponding x value has to be calculated. The calculation of the single parameter sets using the Sobol sequences is performed in Matlab which is very helpful because it can also be used to parameterize the simulation models and evaluate the simulation results.

Application to City Districts

For the sensitivity or uncertainty analysis of bigger building clusters like city districts, only few approaches are made in the literature. The quasi-Monte-Carlo-Method was up to now only used to evaluate the uncertainty of single buildings. As we want to investigate city districts, some other parameters play a role which are uncertain. In most cases, we do not know the thermal state of the single buildings in a city district. Instead of this, we can use statistical data. Ideally, at least the distribution of houses according to their building age are known. If not, we can use data of higher instances as regional data about the shares of single house types or, if this is also not available, of the national housing stock. The accuracy of the prediction depends highly on the quality of the input data at this step, so that it is recommended to try to figure out good data. In the second step, knowledge about the ac tual insulation standard of the buildings is mostly also not available. Thus, refurbishment statistics have to be considered to approximate the actual status. This means that a share of the regarded buildings is equipped with insulation according to the actual status of renovation in its building age. Additionally to the question whether the houses have an insulation or not, it is important to analyze the thickness of insulation material (or the new U-value). For this purpose, it is possible to use data from refurbishment projects in which different thicknesses of insulation were applied. Besides the physics of the single buildings, the user behavior in the single buildings is very important. Here, similar approaches as in the single building simulations can be chosen for every house. Especially the air exchange rates and the indoor temperatures are important figures which influence the heating demand of the building. In this paper, we calculate a sequence for every household according to the preset distributions. If there are multiple households in one dwelling, the values (for example indoor air temperature) are averaged. Since it is not realistic that all households in one house have extremely high or low temperatures in their dwellings, this reduces the variations for these buildings in advance. The averaging of the values might include some mistakes as the heat demand could vary, but in this study, we use it as a first approach.

Uncertain Parameters

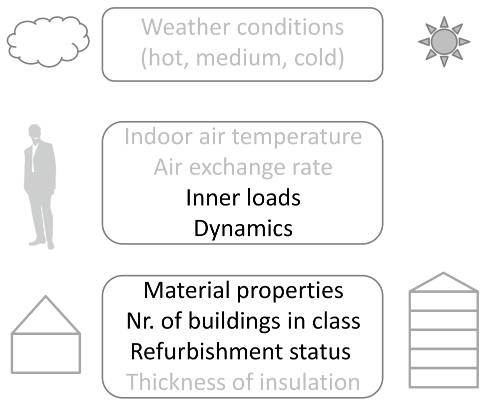

Figure 2: Regarded uncertain (grey) and known (black) parameters.

Figure 2 shows the considered certain and uncertain parameters. As stated before, especially the actual renovation status and the user behavior in the buildings is important to determine the total energy demand of the buildings. For the user behavior, many parameters influence the thermal behavior of the buildings. As we only analyze the space heating demand of the buildings in this paper, the two main user behavior parameters that influence the energy balance of the building, are the indoor air temperature and the air exchange rate. The air exchange rate is composed of the infiltration caused by leakages in the building envelope and the opening of windows and doors. The infiltration is not influenced by the user, but the two effects are not completely separable as they are very heavy to measure. For the air exchange rate, mostly just figures for the total amount of air exchanged between the inner and the ambient space are named. The second user parameter we are analyzing in the presented study is the indoor air temperature. Especially in building refurbishment or new-built projects, higher temperatures than in the building standards are seen. In contrast to this, the temperatures in older buildings are lower than in the codes. Here, it cannot be separated between two effects. On the one hand, the users could set the temperatures to a lower value, because they want to lower their energy bills. On the other hand, it is possible, that the users would choose a higher temperature, but their heating system is for several possible reasons not able to deliver enough heat to the room. Nonetheless, the indoor air temperatures in the different houses are not fixed on the values written down in the standard which means that this difference has to be mentioned. Additionally, in both cases the temperatures differ across the different houses and dwellings. This means that a probability distribution for the different types of buildings has to be applied. Additionally to the uncertainties which are observed in every single building concerning building physics and user behavior, the weather plays an important role, as especially solar radiation and outdoor temperatures influence the heat demand of buildings.

In this paper, we will analyze a city district where the composition of buildings is known. This means, that the building age classes and the types of buildings are known. Building types could be multi-family dwellings or one-family dwellings. For each building class (combination of building type with building age), the average status of renovation is additionally known. In the model, for every house of the building class a sequence of zeros and ones is generated according to the renovation status. This vector shows whether there is a refurbishment or not. It is multiplied elementwise with the sequence of the distributions for the thickness of the insulation. With this, we ensure that the uncertainty about the refurbishment for every building is included. All types of walls (outer walls, ground floor, top-floor ceiling) are assumed to have the same type of refurbishment, which means that either all types are refurbished or none. However, for every wall type, there is a different distribution of the thickness of insulation.

Weather data is also a source of uncertainty, as the weather is never the same in two subsequent years and never the same as in the used standardized data set. As the uncertainties in the weather influence the energetic behavior of all buildings at once, we use a first approach to include weather uncertainties into the work. For this, we use three different kinds of weather data files ("normal", hot summer, cold winter) and calculate a mixture between three weather files.

SIMULATION

Case Study

To test the used methods in a real application, we build up a generic city district constisting of 200 buildings. One family dwellings (OFD) and multi-family dwellings (MFD) are represented equally in the city district. All MFD are assumed to have ten flats. Both for OFD and MFD, three types of buildings according to their building age are considered. The first one is an old building according to the 1960s. The second is built up according to the German Heat Insulation Ordinance 1984 which is a medium refurbishment status while the third one is modeled acoording to the German Energy Saving Ordinance 2009 which is a quite new status. All six building classes are assumed to have a different refurbishment status while the newest buildings (both in OFD and MFD case) are not refurbished as they are quite new. All buildings are modeled according to the models described in (Constantin et al., 2014). For our purpose, we just modeled all buildings as one zone models. The weather data is taken from the TRY zone 5 out of (Deutscher Wetterdienst DWD, 2011). Here, the data for an average year is given as well as the data for a hot summer year and the data for a cold winter year.
An overview about the composition of the city district and the assumed refurbishment rates for each building type can be found in table 1. The data for the refurbishment rate is just a guess for a generic city district, but not a representation of a real city district or the total German refurbishment status.

Table 1: Composition of the city district

Type	Building Age	Number of Houses	Refurbishment in %
OFD	1960	50	100
OFD	1984	40	50
OFD	2009	10	0
MFD	1960	50	50
MFD	1984	40	20
MFD	2009	10	0

As the refurbishment alone does not provide enough information about the energetic status of the building, the thickness of the installed insulation is also important. For this purpose, we use a statistics which analyzes the used amount of insulation material in refurbishment projects (IWU, 2009). For different types of walls, there are different data extracted. Outer walls, lowest floors and top-floor ceilings show different amounts of insulation material. For the outer wall, a lognormal distribution with mean -1.95 and standard deviation 0.25 is assumed. The thickness of the insulation additionally installed at the ground floor is supposed to have a lognormal distribution with mean -2.33 and standard deviation 0.33. Additionally, the thickness of the upper ceiling insulation thickness is

assumed to have a normal distribution with mean 0.2 and a standard deviation of 0.05.
For the indoor air temperature, a study found out that the distribution is different for buildings built in different ages (Schröder et al., 2010). In this work, a separation was conducted between buildings built before 1995 and for buildings built after 1995. According to this, the buildings built before 1995 are assumed to have normal distributed indoor air temperatures with a mean of 18.25 °C and a standard deviation of 4 °C. For the newer buildings, a mean temperature of 20 °C and a standard deviation of 2.5 °C is assumed. This data is extracted from measurements in MFD. This limits the applicability in the OFD case, but in absence of better input data, we take this as a first assumption. As stated before, the temperature distribution for the MFD is calculated as the mean of all flats.
The second user behavior parameter which is varied is the air exchange rate. As this parameter is not easy to measure, not many studies have measured this data. Nonetheless, we try to model this parameter and take a study into account which already draws out a probability density function for the air exchange rate (Corrado, 2003). According to this, we chose a Nakagami distribution with shape parameter 1.5 and scale parameter 0.3.
As a weather data set, we use data for the region 5 in Germany (Deutscher Wetterdienst DWD, 2011). The center of this region is located in Essen. The data is split up into three different kinds of weather data files. For the important data in simulation (direct and diffuse radiation, outdoor air temperature), we interpolate between the three cases (normal, hot summer, cold winter). In (Rodriguez et al., 2013), a discrete variation between the three cases is proposed. As the cold winter and the hot summer are the extreme cases and we are not interested in a local but in a global sensitivity analysis, this assumption cannot be transferred to the analysis in this paper. Instead of this, we assume that the normal weather file is the most probable and the hot summer and the cold winter case are much less likely. Thus, these files should not be used regularly. Because of this, we assume a normal distribution with a mean of 0. Additionally, if the cold winter should be chosen, the distribution should delive a value of -1 and for the hot summer a value of 1. Therefore, a standard deviation of 1/2.57 is used, which means that the extreme values lie at a 99 % level of the distribution. If a value between 0 and the extreme values is chosen, the values are interpolated between the normal and the extreme weather conditions. For values above zero, we interpolate between the medium and hot conditions. Obviously, we interpolate between the medium and cold conditions if the values are below 0.

Analysis - Number of Simulations

To reduce the simulation effort as much as possible, the number of needed simulations to get a good aproximation of the distributions in heat demand and heat flows has to be analyzed. As we do not know the real distribution, we can only analyze the reproducibility of the results of the thermal simulation. For the total heat demand, we get a distribution for every new simulation run which is shown in figure 3 as an example with a sample size of 32.

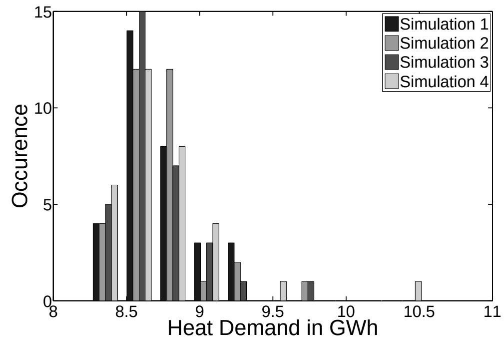

Figure 3: Distribution for the heat demand of the city district for different simulation runs.

As we can see, the distributions look similar, but they are not equal. For this reason, we have to evaluate if the distributions are close enough to each other that we can observe a reproducibility of the results.
The same evaluation is necessary for the dynamic behavior of the energy demand. In figure and 4, we can see the dynamics in the heat demand for an exemplary summer day. To get a reasonable measure for the dynamics and have a good performance of the storage capacity of the used computer, we use a resolution of an hour to characterize the dynamic heat demand. To avoid inaccuracies in the dynamics due to peaks or valleys in the heat flow rate at the regarded time steps, we choose the heat demand during the hour instead of the heat flow rate. In the figure, we can see the median of the dynamic heat demand for two cases (each with 32 samples) and additionally the 5 and 95 per cent quantiles which show the spread of the results in both variants. As stated in the case of the total heat demand, we can obtain a variation of the results between the two variants. This means that we have to analyze the reproducibility of the dynamic behavior.

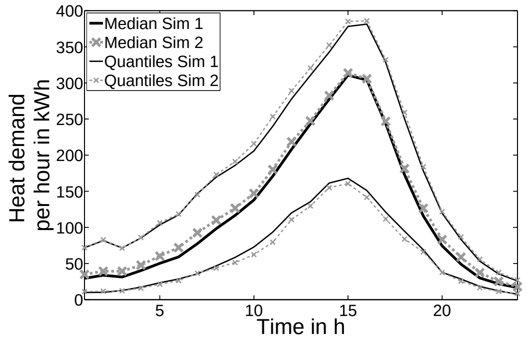

Figure 4: Dynamic behavior of the heat demand during a summer day.

To analyze the reproducibility of the results, we performed the uncertainty analysis with a maximum number of 128 simulations. For reasons of comparability, for all different numbers of simulations, four variants are compared to each other. 128 is chosen because it is the first number of simulations (calculated as a power of 2) which is higher than the 80 simulations named in (Macdonald, 2002).

For the goodness of fit, we use the Kolmogorov-Smirnov test (Massey, 1951). The first figure we want to examine is the total heat demand. For all buildings and for the total city district, the distributions of the total heat demand are compared for four, eight, 16, 32, 64 and 128 simulations. We performed the two-sided Kolmogorov-Smirnov test with a significance level of 5 per cent. The test evaluates the probability that two vectors can be from the same distribution. This probability is called p.

Figure 5 shows the minimum and mean values of p for the different numbers of simulations for the total heat demand of the building. As we can see, there is a trend that the values increase with the number of simulations. However, with a number of 16 simulations, the number decreases slightly. For all regarded cases, the calculated distribution of the total heat demand can be regarded as the same as the minimum observed values are higher than 0.05 which would imply a rejection of the hypothesis that the distributions are the same.

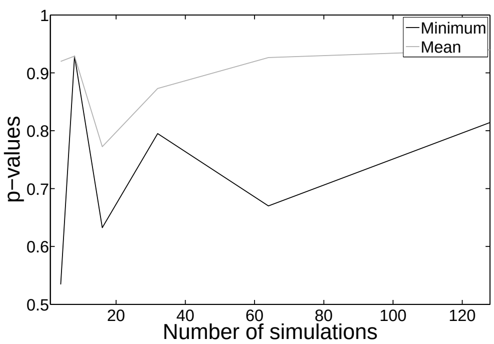

Figure 5: Values of p for different numbers of simulations for the total heat demand.

In addition to the total heat demand, we want to investigate the dynamic behavior of the energy demand. In this case, we see rejections of the hypothesis for all regarded cases. Figure 6 shows the highest number of rejections in one comparison from one distribution over time to the other. Additionally, we can see the mean value of rejections for all compared variants.

The values of rejections generally decrease with the number of simulations. Two exceptions of this rule can be observed. The number of rejections is higher for the number of simulations of eight and it increases slightly for the number of simulations of 32 which was already observed in the heat demand case. For 64 or 128 simulations, we can assume the calculated distribution time series as equal. For the 64 simulations case, only eight time steps in one combination pair are not consistent and for the 128 simulations case, even only three rejections can be observed in one combination. For all other combinations, no rejections of the hypothesis that the single distributions are equal could be observed.

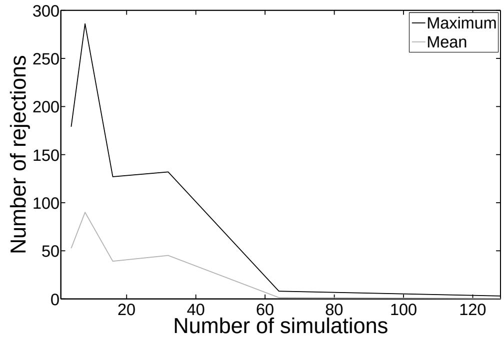

Figure 6: Maximum and mean number of rejections for different numbers of simulations for the dynamic heat demand.

Analysis - Total and Dynamic Heat Demand

As we want to analyze the uncertainties in the dynamics of the simulations, we have to choose some figures that can describe the statistical nature of the results. As we do not get a normal distribution as result (at least we cannot guarantee it), we will choose the median of the data and additionally the relative interquartile range:

$$RIQR = \frac{p_{75} - p_{25}}{p_{50}} = \frac{IQR}{median} \quad (1)$$

It is calculated as the difference of the 75 per cent quantile and the 25 per cent quantile as a measure of the deviation of the data divided by the 50 per cent quantile (median) which is a measure for the center of the data.

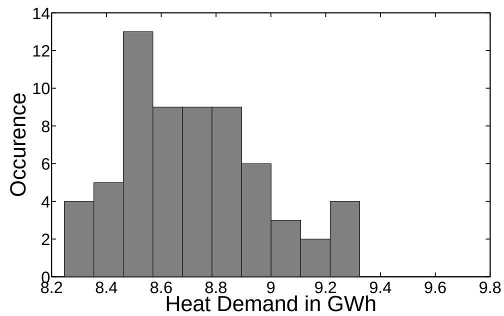

Figure 7: Distribution of heat demand in the total city district.

For the presented results, we chose a number of 64 simulations based on the results of the previous section. Figure 7 shows the distribution of the heat demand in the regarded city district. The RIQR for the total heat demand is about 0.04 which is a quite low value. This means that the total heat demand is well predictable.

Figure 8 shows the characteristics of the median of the dynamic heat demand for the analyzed city district. The seasonal differences can be seen and some spikes in the summer which indicate that the weather can be so cold that a heat demand would be present if the set point temperature should be reached.

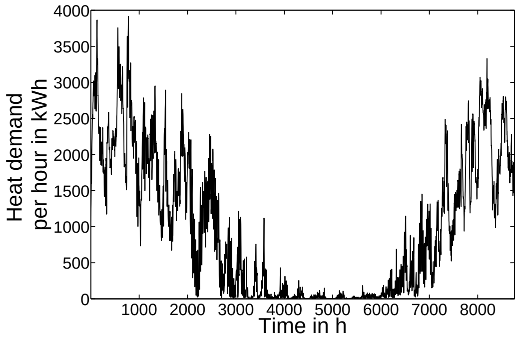

Figure 8: Median of the dynamic heat demand in the city district.

Additionally to the median, figure 9 shows the RIQR of the total city district. The values especially in winter times with high heat demand are quite low while the relative deviation is much higher in times when the heat demand is already low. Values where the median is zero are excluded from the figure as there is no value calculable. Additionally, we excluded all values for heat demands lower than 0.5 kWh/h for reasons of clearness.

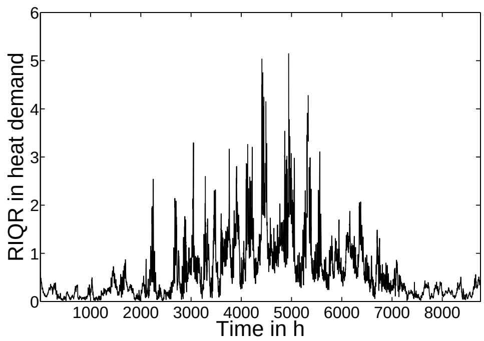

Figure 9: RIQR of the dynamic heat demand in the city district.

CONCLUSION AND OUTLOOK

This paper shows a methodology to evaluate uncertainties in building simulation on city district level based on a quasi-Monte-Carlo approach. As the most important result, the amount of simulations to get a sufficient reproducibility was analyzed. For this, a Kolmogorov-Smirnov test was performed both for the total heat demand and for the dynamic behavior. The number of simulations needed to get reasonable results is at least 64.

It can be concluded that the uncertainties in heat demand are noticeably low if the heat supply of several buildings is coupled. The relative interquartile range of the total heat demand in the regarded city district is about 0.04. Besides that, we can see, that the uncertainties in the dynamic behavior can be reproduced quite well. The RIQR in the dynamic heat demand increases with lower heat demands per hour.

With the low uncertainty in the total heat demand, it could be more convenient from the perspective of an energy provider to handle billing with the heat customers with a flatrate model as the total amount of heat demand can be calculated very good. Especially if a district heating system is installed, the knowledge of the total heat demand could provide improvements in this area. On the other hand, this could lead to a changing user behavior as a result. Most probably, it would lead to an increasing heat demand.

In the dynamic behavior of the heat demand, still some uncertainties can be observed. For a demand side management, this is not very helpful as the status of flexibility is unclear. The usable storage capacity is highly dependent on the heat demand in each point. Here, the influence of the used time step will be under investigation in future research.

Additionally, we will analyze the influence of the dynamics in the input parameters (especially the user behavior) on the uncertainties in the heat demand. In addition to the already mentioned user behavior parameters, the domestic hot water demand will be investigated. Moreover, uncertainties in the composition of the district and/or refurbishment status will be investigated. Potentially, the number of simulations needed should be increased to get a reasonable result. Additionally, the effect of dynamic heat demands considering the storage potential will be analyzed.

A very important point to investigate in future applications is the determination of authoritative input data for the user behavior. Especially for existing buildings, the data base is not sufficient at the moment. Besides the values itsself, the averaging of the values for multifamily dwellings will be under investigation.

NOMENCLATURE

IQR	interquartile range
RIQR	relative interquartile range
p_{25}	25th percentile of data
p_{50}	50th percentile of data (median)
p_{75}	75th percentile of data

ACKNOWLEDGEMENT

We gratefully acknowledge the financial support for this project by BMWi (German Federal Ministry of Economics and Energy) under promotional reference 03ET1111B.

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