

3D City Modelling for Urban Scale Heating Energy Demand Forecasting

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An urban energy management tool was developed, which is able to predict the heating energy demand of urban districts and analyse strategies for improving building standards. Building models of different Levels of Detail are investigated and analysed according to their suitability for forecasting energy demand. Based on the specific 3D city model an input file is generated, which can be read by the Building Simulation Model. Special focus is put on a method for modeling the heating energy demand of the buildings with the least input parameters possible, but which gives reliable forecast results. A simple transmission heat loss method and an energy balance method were tested. In both cases, there was a good correlation between the measured and calculated annual values for a case study area of over 700 buildings in Ostfildern, Germany. The results also show that a 3D city model (with low geometrical detail) can be used for energy demand forecasting on an urban scale.

INTRODUCTION

There are many modeling techniques available that can be used to model the energy consumption of an urban area, [Swan et al. 2009]. City-scale prediction of the heating energy demand relies on the accuracy of input data (Level of Detail), which can vary significantly. The Level of Detail of the input data for simulations depends on data availability and can strongly influence the type of modeling technique that is chosen. The easiest modeling technique for the heating energy demand of an entire city is based on typification of districts, where the prediction of the heating energy demand is based on the district type, its size and number of buildings in it. This method does not consider the buildings separately, but the size of the district type in square kilometers as well as the age of the buildings, [Blesl 2002]. A very similar method was introduced by Firth et al. (2009), in which the energy prediction is made for each category of

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dwelling rather than for each individual dwelling in the community in the study. The energy prediction is made for an average national dwelling and the results are then multiplied by the number of dwellings of this type of buildings in the community. A more detailed method also described by Blesl (2002), considers each building separately, whereby the heated gross area is estimated by the multiplication of the building ground area with the number of floors. A higher precision in determining the building geometry is reached using laser scanning data. Blesl combines the obtained building volumes with the building typology in order to estimate the thermal parameters such as heat transfer coefficients (U-values), [Blesl 2010]. To verify the estimated U-values for the appropriate building type, simultaneously taken infrared images of the city quarter are used. The data is then used to calculate the heating energy demand according to the European Directive [DIN EN 12831]. Assumptions are made for the window area and the user behaviour is defined with a standard load curve. Heat-up times are not taken into account.

A rather new method, called Rapid Energy Modeling [Autodesk White Paper 2011], presents a way to identify buildings that have the greatest potential for achieving energy savings with minimal effort and cost. This method is a process of energy demand prediction involving very few data and makes use of the image capture of building exteriors and simplified simulation. This method uses simple digital pictures of the buildings to extract buildings exteriors. Hereby, the 2D images are calibrated in a special software in order to create 3D building models. These 3D CAD files are then converted to a building information model. Finally, the building information models are used as an input for a web-based simulation of the whole-building energy demand, including electricity. The main goal was to show, how effectively this method could be used to estimate the energy usage of existing buildings. To compare the calculated electricity demand values, the actual energy usage of the buildings from the utility bills was used. The deviations between the measured and calculated values by analysis of several buildings was at most 25%.

The calculation models used to predict the heating energy demand vary from very easy static energy balance, or degree-day based calculations to more complex dynamic building simulation models. The simple degree-day method estimates the heating energy demand using as inputs the difference between a constant room temperature and the ambient temperature and as parameters the overall heat transfer coefficient [Jaffal et al. 2009]. As mentioned in [Mavrogianni et al. 2009], most of the building simulation models that are available on the market, require a large amount of data input, which can lead to the

problem of being able to acquire sufficient data to model the heating energy demand of an entire city. Therefore, an important aspect of this research was to find a solution that makes it possible to forecast the heating energy demand of the buildings while using the least amount of input parameters possible, while still giving reliable results. This also involves a study of the detail of available models and how reliable the simulation results of these models are.

The weak point in the design of most of the available city-scale heating energy demand prediction methods, is the lack of the validation process. According to [Mathews, 1997], the success of the model development process depends on its validation, but this is very often neglected due to the difficulty in obtaining good data sets. In a building energy performance study by [Diamond et al. 1992], the actual energy use is compared to the predicted use, but this is only done for a few buildings. [Shimoda et al. 2004] presents a model that simulates city-level energy consumption in the residential sector, but these results are only compared with statistical data. The limited validation work on a city scale does not allow for the assessment of the developed methods regarding their accuracy. Considering city scale heating energy modeling, the sensitivity analysis of the models on changes in their parameters, which is an important stage of model development, can not really be done [Ravalico et al. 2005].

There is still a lack of study of the impact of user behavior on urban energy performance, although as a consequence of the improved quality of thermal properties of buildings the role of the occupants becomes more and more important [Santin et al. 2009]. According to [Shimoda et al. 2004], a city-scale effect of user behaviour is not really known. The work of [Branco 2004] also points out that occupant behavior is the major factor, which causes variation in the energy consumption of different households. A “standard household”, as mentioned by [Shimoda et al. 2004], is not applicable for realistic city scale simulation. Here again, the importance of validation of the models using real measured data is apparent, as it can provide information as to, how much the occupant behavior differs from that of the “standard household”, [Caldera et al. 2008]. In most of the available models, the influence of occupants on energy use is very poorly represented, [Shipworth 2010]. Current approaches put standard user behavior parameters into the energy models or use so called “occupancy schedules”.

In order to calculate the energy demand on entire district or city, it is necessary to have the required geometrical information as well as the user behavior data of the buildings in the area of interest. On this

large scale it is difficult to find geometrical information with a high Level of Detail [Mavrogianni et al. 2009]. Geometric data is available for most major cities in form of digital 3D city models. These models are mainly used for tourist applications, urban planning and various other fields in the urban domain. Many of the models used in these fields are geometrical models that represent the visual appearance of the real world with very little or no additional information or numeric data. Models for such scenarios tend to focus on the realistic visual representation that can be used to superimpose additional information, e.g. for planning purposes. For simulation models such as the one presented in this paper, a purely geometrical model is not sufficient. [Metral et al. 2009] also described the need for semantically enriched 3D city models, which do not solely focus on the geometrical/visual aspect of the real world environment. Especially for simulations, additional semantics and attributes are necessary. A growing trend from the purely visual models towards a semantically modeled urban information space can be observed. Data formats such as CityGML (Open Geospatial Consortium 2008) are good examples for the actual modeling of urban space beyond the visual appearance. These models include information about objects and their interrelationships as well as attributes, which can also be linked from other information systems. In this way the 3D city model can act as a 'base map', which can be enhanced by all kind of data. For energy demand calculations, especially attributes such as building type, heat transfer coefficient or year of construction are important input parameters for the simulation. These 3D city models also need more sophisticated management systems, often called 3D-GIS (3 Dimensional Geoinformation Systems), which can extract visual 3D models, but also datasets with more information attached in order to be entered into a simulation, for example. A prototype implementation for flexible management of these 'semantically enriched' models that was used in the energy demand forecast scenario will be presented in this paper.

Nevertheless, the effect of urban geometry on energy consumption still requires study. The reason is the difficulty of modeling complex urban geometry [Ratti et al. 2009]. For the purposes of urban scale simulation, it is important to achieve a good compromise between modeling accuracy, computational overheads and data availability, [Robinson et al. 2009]. Especially in case of 3D city models the maximum Level of Detail is mainly restricted to the outer building boundary and the detailed roof structure. Modeling of façade elements and interiors is mostly limited to small areas in the city centre or to specific project sides. The compromise in the described scenario is that the 'low detailed' information in terms of geometry

is available for the whole city. Therefore, city wide energy demand estimation is possible, though certain assumptions need to be made due to the low level of detail of the available information.

THE CASE STUDY DISTRICT

Scharnhäuser Park (SHP) is a mixed residential-commercial area that is located on the southern border of Stuttgart, Germany. The area is a former military area, in which office space, residential areas and parks have been integrated. The area of Scharnhäuser Park (Figure 1) covers 150 hectares and currently houses 7.000 inhabitants. About 80% of the heating energy demand of the whole area of SHP is supplied by renewable energies. The main portion of heating and electrical energy is delivered to the buildings in SHP from a 6.3 MW thermal and 1 MW electric wood fired co-generation plant.

METHODS

Data acquisition.

The annual heating energy consumption data for all buildings was obtained from the archive of the municipal utility company. The data was provided in the form of either Excel data or printouts and was then organized in an Access Database.

In three case study buildings an automatic monitoring system was installed to measure the heating energy consumption of the whole building and the separate apartments within it. A GSM-modem with an M-Bus interface and integrated data logger enables the data to be recorded at one hour increment. These data are then automatically transferred using a mobile phone interface, which sends the data via E-mail to the central simulation server every day.

The main thermal data needed for the simulation model are the heat transfer coefficients (U-values). Scharnhäuser Park is a modern residential area with low energy buildings. As the buildings were all constructed within the last decade, in which similar legal requirements applied for thermal standards, the thermal values needed for the simulation model are comparable for all of the buildings. Therefore in a first simplification step, these values have been assumed as averages for two building groups (row houses and multi-family houses), as shown in Table 1.

Hourly air temperature and global radiation data was provided for 2008, 2009 and 2010 from the weather station placed on the roof of the biomass power station in Scharnhäuser Park.

Data framework.

In the presented approach it is necessary to extract information from the 3D city model, which is not explicitly stored in the model itself. One example is the overall area of the outer envelope of the building. This value needs to be extracted from the available data, as well as the volume, orientation of walls, etc.

It is also necessary to find walls that are shared between buildings and therefore are not exposed to wind and irradiance. Building objects in 3D city models are mainly modelled as single objects with no information about adjacent objects. This information needs to be extracted and provided to the simulation tool in an appropriate way. In order to extract this additional data we use a 3D data management framework that is capable of reading 3D city models and additional data from different/distributed sources and convert the external information into an internal data representation. Based on the internal data format the framework is capable of extracting the required information and linking data from other sources. We have developed a software tool on top of the 3D framework that manages queries of the 3D model for the area of interest, the extraction of the required information and the creation of the output data, which can be read by the simulation tool.

GIS-interface providing input for simulation model.

The given building footprints, combined with the measured building heights are used to generate a topologically consistent 3D city model (see Figure 2). This topologically correct model created according to the method of [Ledoux and Meijers 2009], is not just an extrusion of each individual footprint by the given height, but it also takes into account buildings that share walls. The resulting dataset of the topologically correct model included a geometrical dataset of the model encoded in CityGML (Open Geospatial Consortium 2008) and a text file with information as to which wall is an outer/inner wall, as well as identifiers for roof and floor faces.

In the presented approach it is essential for calculations to know which of the faces are inner/outer walls, roofs and floors. This kind of classification can only be done if the model is generated according to specific semantics or a specific ontology, [Metral et al. 2009]. Additional information such as the year of construction, building type, etc. can also be useful and can be integrated into the model as part of a future study.

Based on this topologically correct 3D city model (block or detailed), the total area of outer walls, walls between buildings, ground floor and roof (Figure 3) can be calculated for each building as shown in Table 2 for the above example.

In order to calculate the required values an integration of several data streams was necessary. The framework architecture is highly modular and applications can use specific components that are suitable for the task at hand. The framework provides modules for three major areas: data input (connectors), data manipulation (data mapping) and data output (creators) (see Figure 4).

The interface that generates the output for the simulation tool is developed on top of this framework using several components. The framework is used to connect to the ESRI shape-file that included the original building footprints and heights of the buildings (used for extrusion) and to connect to the CityGML file, which houses the semantic 3D city model. The data mapping components are used to analyze the 3D city model geometry, connect the wall classification information and to calculate the overall inner/outer wall area of each building. The interface component writes this information into a CSV text file that can be read by the simulation model, which makes it possible to adjust the output format to possible requirements of specific simulation tools.

The window area in this case was obtained with a very simplified assumption as a part of the outer wall area: 12% for the row houses and 20% for multi-family houses. The so prepared geometry data for each building was put in one data file and serves as the input for the simulation model, according to the workflow seen in Figure 5.

Calculation and simulation model.

The 'GIS-interface-file', which includes building dimensions, was then entered into the Building Simulation Model. In order to achieve reliable results regarding the heating energy demand with as little input as possible, two versions of models were tested. The first one (Model 1) calculated the heating energy demand by taking into consideration only the transmission losses through the outer envelope of the building. The second model (Model 2) considered the entire energy balance with transmission and ventilation losses as well as solar and internal gains following the well established energy balance method described for example in the German standard [DIN V 18599].

In both models some assumptions were made; in Model 1, the heating set-point temperature was set to a constant value of 20°C and in Model 2, the heating set-point temperature was 20°C, the air exchange rate was 0,5 1/h and internal heat gains were 5 W/m². Both models were used to calculate the annual heating energy consumption for all residential buildings in Scharnhauser Park. The results of heating energy demand were validated by the measured annual heating energy consumption values for all buildings.

RESULTS

Comparison between measured and calculated values

Case study multi-family house. The case study building is a 12 apartment multi-family house with a gross heated area of 1688 m². The annual measured heating energy consumption for the year 2009 was 56 kWh/m²/a and for the year 2010 was 57 kWh/m²/a. The deviation between these values and the calculated demand using the energy balance method (Model 2) was 5-10% when using the real dimensions (including the real window orientation) and thermal properties of the building taken from the building certificate. When the geometry determination is simplified or when average U-Values are used, the error increases.

Table 3 shows how the precision of the dimensions and the thermal properties influence the annual heating energy demand calculations. Due to the fact that all buildings are calculated using Procedure 1 (dimensions from laser scanning and average U-values), a deviation of 10-22% can be expected for Model 2. The calculation that uses the very simple transmission losses model can even have an error of 34-39%.

The results depicted in Table 3 show that not only the precision of dimensions (geometry), and more importantly the U-values, influences the results of the heating energy demand, but also the modelling technique used. The results of the steady state energy balance of the building (Model 2) are significantly more accurate than those from the very simple calculation using Model 1. Model 1, which considers only the transmission losses, results in an error of 13-20%, even when the real dimensions and U-values are used in the calculation.

When the time step of the calculation is reduced from a year to a month, good correlation between the measured and calculated values can be observed in case of the energy balance method (Model 2), see Figure 6. By summing up the monthly values for the winter and summer period a reasonable accuracy (error <10%) for Model 2 can be observed (see Table 4).

When a time resolution of one day is used in the calculation, which is seen in the Figure 7, the deviation between the demand and measurement increases for both the degree-day method and the energy balance method, even when the correct dimensions and U-values are used. This can be mainly attributed to user dependent ventilation strategies, changing heating set-points with thermostatic valves, use of shading systems etc.

Figure 8 shows the annual heating energy consumption values for 10 of 12 individual apartments within the analyzed multi-family building. Although the apartments have very similar energy characteristics, the heating energy consumption values vary quite significantly. It is quite clear that these deviations are due to difference in user behavior, which should be taken into account in the energy balance Model 2.

All multi-family houses: The residential sector of SHP is divided into two residential building categories: the one- and two-family row houses (RH) and the multi-family houses (MFH). The Figure 9 shows a comparison of the measured and calculated annual values for each individual multi-family house.

In Figure 9, we can see a reasonable correlation between the measured and calculated values for many of the buildings, but the analysis also indicates some extreme deviations. The extreme deviations, which will be discussed in the next chapter lead to the quite high average deviations between the measured and calculated values of about 35-40% by both Models. Only a few buildings with deviations greater 100% were excluded from this average.

All row houses: The comparison of the measured and calculated annual values for the heating energy consumption/demand of row houses, which is seen in the Figure 10, also indicates many extreme deviations. Both models had a quite high average deviation of over 30%. The shape of the measured values fluctuates very strongly in comparison with the calculated values, which have a rather flat shape. The rather similar heating energy demand values for all row houses are due to the fact that the calculation depends mainly on the rather similar surface to volume ratios of the buildings; the measured values on the other hand are strongly influenced by user behavior. This effect becomes more important, the smaller the buildings are.

Therefore, actual user and occupancy behavior of the buildings (exact time of occupancy start or reduced daily use of a building) needs to be examined in greater detail. The construction types of the row

houses are also quite different, meaning that the use of one average U-value does not represent the actual situation very well. This can be seen in the comparison of the average heating energy consumption data for different types of row houses in Figure 11. The average consumption varies from about 55 to 90 kWh/m²/a and the standard deviation for each building type is as high as 30%.

Firth et al. (2010) mentioned in their analysis of the sensitivity of their Community Domestic Energy Model, that “The heating demand temperature (which in most cases is the thermostat set-point temperature used in the dwelling to control the heating system) results in the most sensitivity”. According to [Shipworth 2010], internal temperature is one of the most influential factors concerning the domestic energy use. Therefore, an attempt to analyze in detail the influence of user behavior related parameters, like heating set-point temperature was performed in this analysis. By generating random numbers, that have a Gaussian distribution with a mean value of 20°C, a strong correlation between the measured and calculated values for one type of the row houses could be achieved. Figure 12 shows two types of calculations; the first one was done using a fixed heating temperature set-point of 20°C, and the second one by varying the temperature set-points. The variation of the temperature set-points made it possible to achieve a good correlation between the calculated and the measured values.

The work of [Shipworth 2010] analyzed houses built to identical technical specifications and observed that their energy consumption can vary by a factor of three once occupied. This observation was also made in the research work presented here (see Figure 12).

All residential sectors of SHP. Figure 13 shows the annual sum of the calculated heating energy for all row houses and multi-family houses, which is in a quite good agreement with the measured data, especially with that from the row houses. Here the user dependent factors relevant for an individual building calculation average out.

By summing up the values of all of the buildings in SHP for each hour of the year, a total demand profile of this area could be calculated, divided into demand only for heating, demand for heating and warm water and demand for heating, warm water and heat losses from the district heating system (the average annual value in 2008 for heat losses is 17%). The comparison of the last demand profile and the measured profile of the heating energy supply from the biomass co-generations plant in SHP shows a reasonable

correlation, which can be seen in Figure 14. The total difference between the measured annual energy supply and the calculated demand without heat losses is about 20%.

DISCUSSION

Explanation of the uncertainties. The reason for the discrepancies between measured and calculated values can be seen in the Level of Detail of the 3D city model that was used. 80% of the buildings in SHP have a flat roof; therefore in this case the block model (Level of Detail 1 – LOD1) seemed sufficient for the extraction of the building heating volume. For the remaining 20% of buildings with sloped roofs, LOD1 is not precise enough for our purpose. For the buildings built after 2002 no laser scanner data are available and therefore the height value was set to 7,5 m. This could lead to building heating volumes that are too low. Furthermore, in many cases the heating energy consumption value is not measured for each building individually, but for a group of buildings (with shared energy meters) and then divided by the building group area. This fact results in inaccurate values for individual buildings. The approximation of the heating consumption for warm water, which was set at a constant value of 12,5 kWh/m²/a and subtracted from the total annual heating energy consumption values, also causes deviations between the measured and calculated values.

Comparison with other available methods. The heating energy demand of residential areas can be estimated using several methods. The method presented here considers not only the city-scale, like it is done in district typification methods, but also the building scale. Here, the heating energy demand is calculated for each building separately and then the heating energy demand of the entire district is obtained by adding up all of these individual values.

As the buildings in the SHP study area all have a very high energy standard, it was expected that their annual heating energy consumption would not be greater than 70 kWh/m²/a. In reality, the analysis showed that although the heating energy consumption of most of the residential buildings was within the range of 40-80 kWh/m²/a, there are also many buildings with much greater energy consumption.

Although the method presented in this paper is very similar to the method of [Blesl 2010], we were able to confirm the results of the heating energy demand values with monitored heating energy consumption values. The validation process of the calculated values made it possible to identify deviations between the measured and calculated values. The analysis of one case study multi-family house has proven

that the Level of Detail of the input data regarding dimensions and U-values influences the results greatly. The further deviations are due to different user behavior; analysis of similar buildings and apartments showed significant differences between the heating energy consumption of the analyzed objects. The works of [Robinson et al. 2009] and [Page 2007] indicate that the occupant's behavior is one of the key sources of the accuracy of building and urban simulation.

These deviations will be further investigated in the future. Due to the fact that the modeling technique plays an important role, when the correct dimensions and thermal data are known, a fully dynamic simulation will be done. The results of this model will be compared to the results of the energy balance model, in order to show, whether or not Model 2 (less input data) will be sufficiently accurate for predicting the heating energy demand, if user behavior is taken into account.

SUMMARY

The paper presents a method of forecasting the heating energy demand of a whole city quarter and validates the models with measured data. Two models were tested and validated by comparing their results with the actual heating energy consumption of the buildings as given in actual utility bills. One primary goal was to test how effectively a 3D model could estimate the heating energy use. The presented approach shows that 3D city models are useful for urban scale simulations. However the models need to be generated in a semantically enriched way and according to a specific ontology (e.g. CityGML). Purely geometric models do not suffice to satisfy the information demand of simulation tools. In the authors view, the geometrical models are widely available as many municipalities have already produced them. These were indeed not created with the main intention of using them for simulation, but they might be used as a basis for a semantically enriched model. Some municipalities already have semantically built models based on CityGML and the integration of additional information in these cases is much easier. The presented approach outlines the feasibility of connecting 3D city models/3D GIS with simulation tools and shows that further research into this field would be beneficial.

Depending on the assumptions that are made as to the input data (U-values and geometrical information), there are varying levels of agreement between the measured and calculated annual heating values. When the calculation was performed using real U-values and dimensions, the deviation between the measured and calculated values was about 10% with an energy balance model (Model 2) and about 20%

with a transmission loss model (Model 1). When average U-values and general dimensions (ground floor multiplied by building height) were used for the calculation, the deviation increased to 22% with Model 2 and to 39% with Model 1. As most of the buildings were calculated by simplifying the dimensions and using average U-values, the average deviation between the measured and calculated values was about 35-40%.

The analysis showed that both of the tested models were suitable for forecasting the city-scale heating energy demand, but the energy balance model was better, because it also considers the ventilation losses and solar and internal gains. Regarding the data inputs, both models require the same Level of Detail regarding the building dimensions and thermal parameters. The only additional information that is needed by Model 2 is the orientation of the windows as this model also takes the solar gains into consideration. Another advantage of Model 2 is the possibility of varying the user behavior related parameters such as the set-point temperature, internal heat gains, air exchange rate and duration of heating. It could be shown that statistical variations of heating set-point temperatures strongly improves the accuracy of the building modeling, the more so, the smaller the building is.

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FIGURES

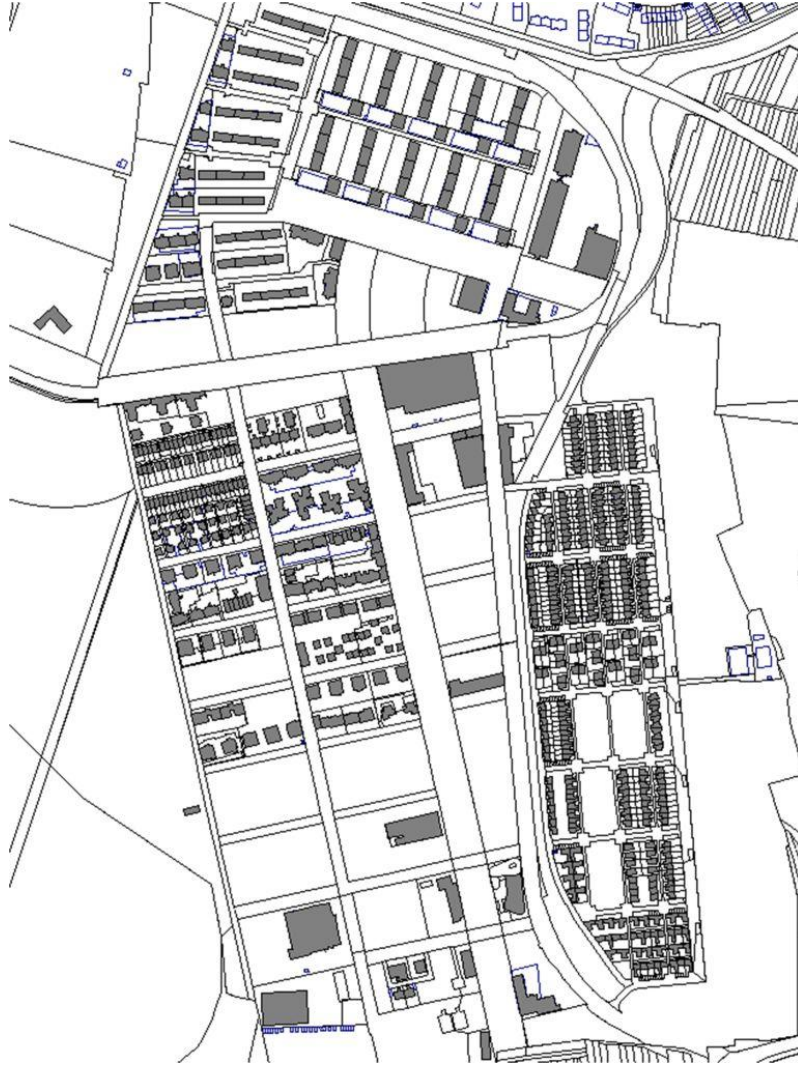


Figure 1: GIS thematic map of the case study district with building footprints

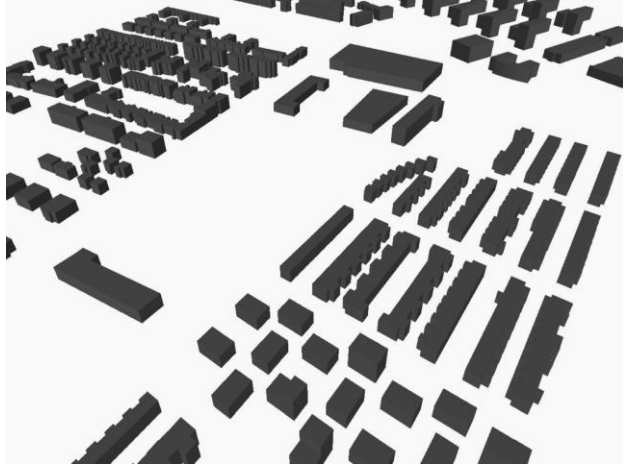


Figure 2. Topologically consistent 3D block model of Scharnhäuser Park

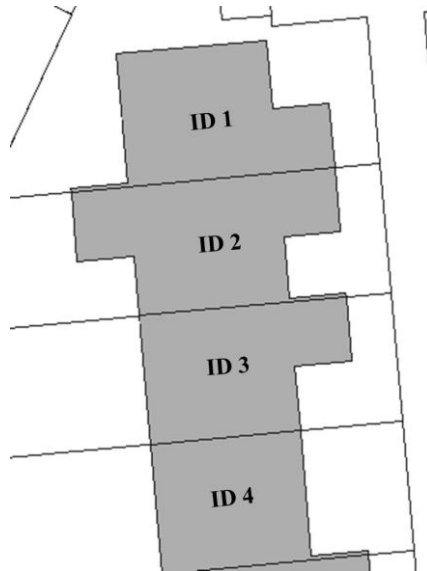


Figure 3. Example of the extraction

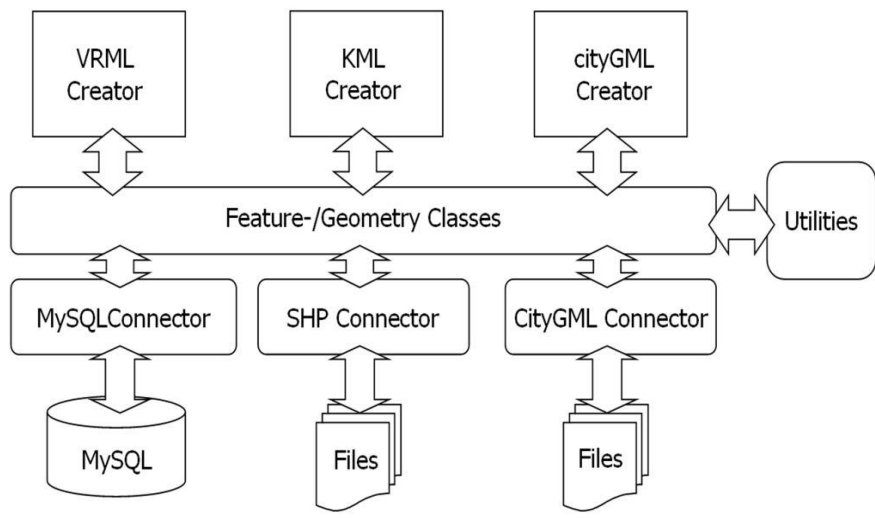


Figure 4. The 3D data management framework

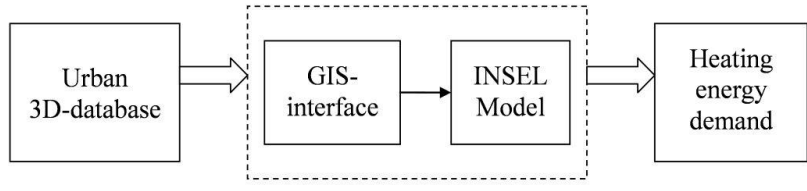


Figure 5. The workflow of data exchange

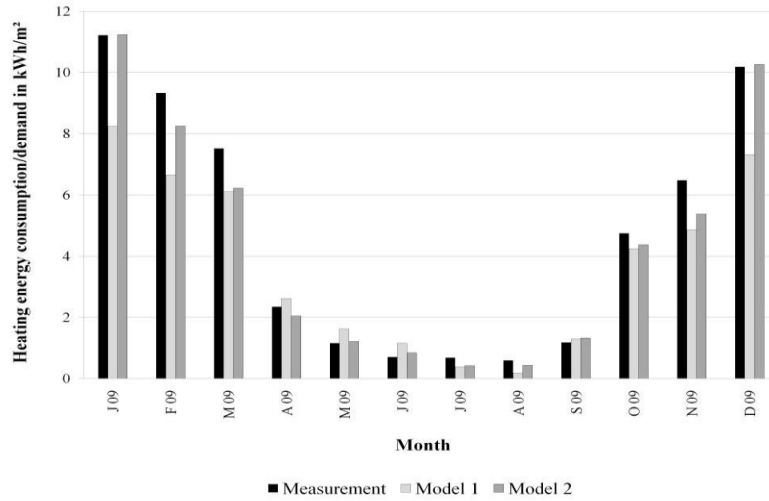


Figure 6. Comparison between measured and calculated monthly values for a case study multi-family building (2009)

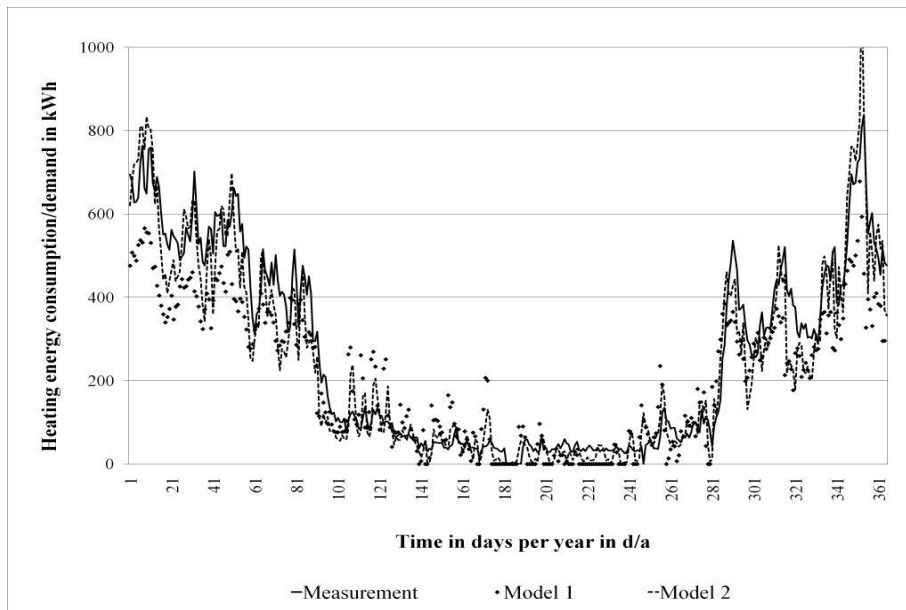


Figure 7. Daily measured and simulated profiles for the case study building

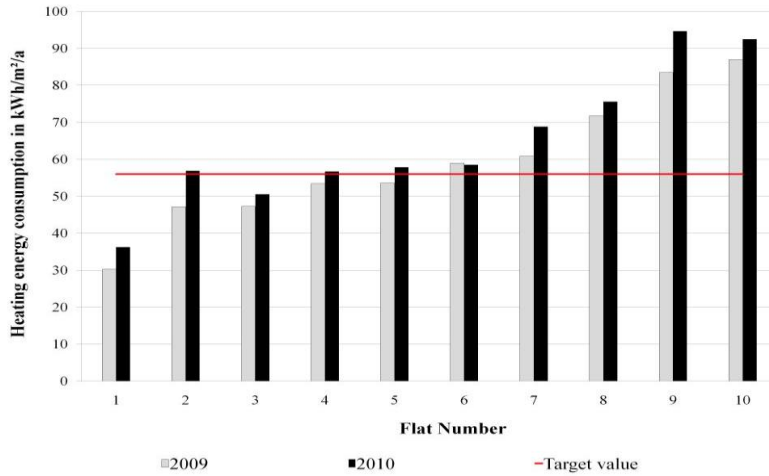


Figure 8: Annual heating energy consumption of similar apartments in the multi-family case study building

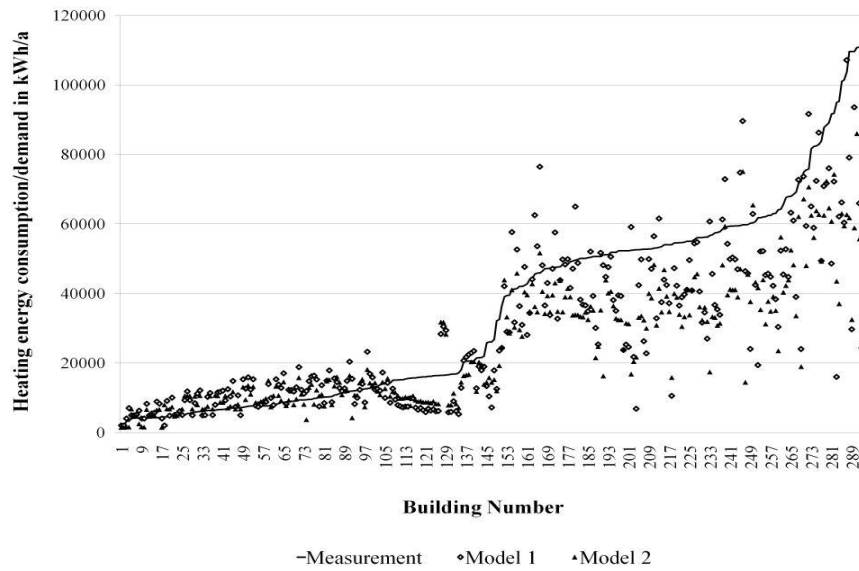


Figure 9. Comparison of the calculated and measured annual values for all multi-family houses in the district (2008)

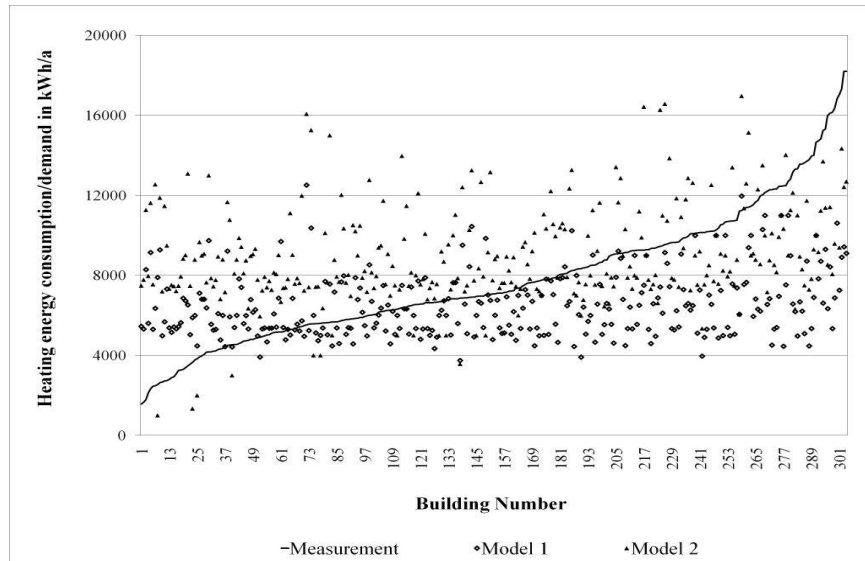


Figure 10. Comparison of the measured and calculated annual values for all row houses (2008)

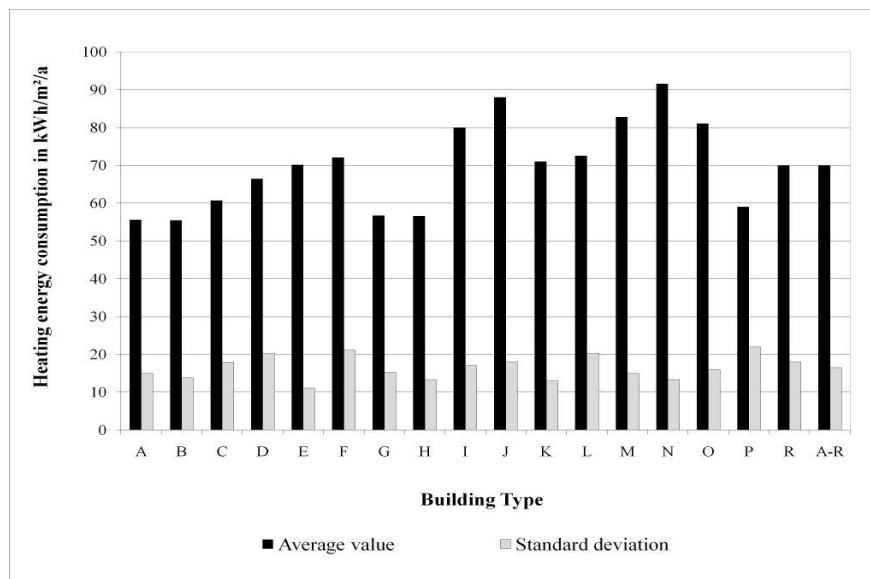


Figure 11. Average heating consumption values and standard deviation for different types of row houses (2009)

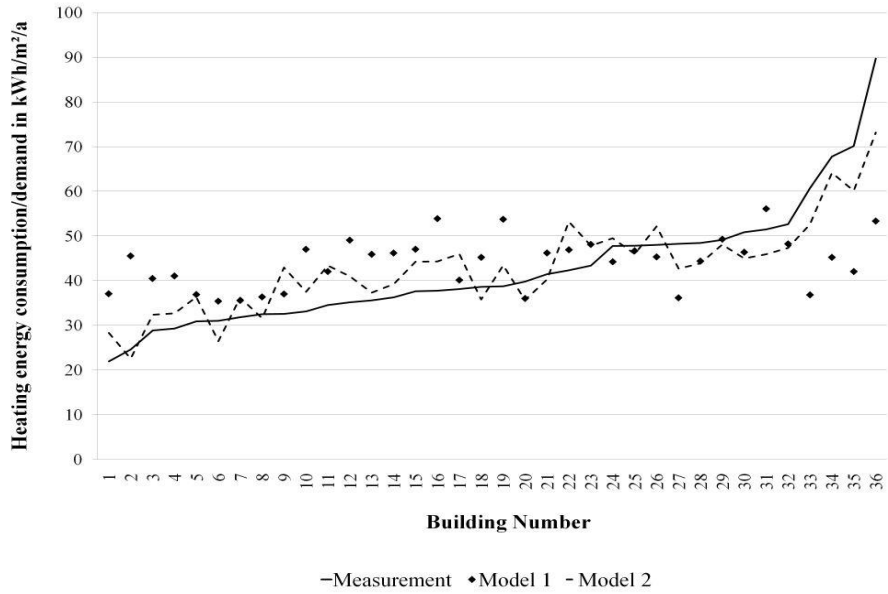


Figure 12. Comparison of the measured and calculated values for one type of row houses. The points use a fixed heating temperature set-point of 20°C, the dotted curve has variable temperature set-points.

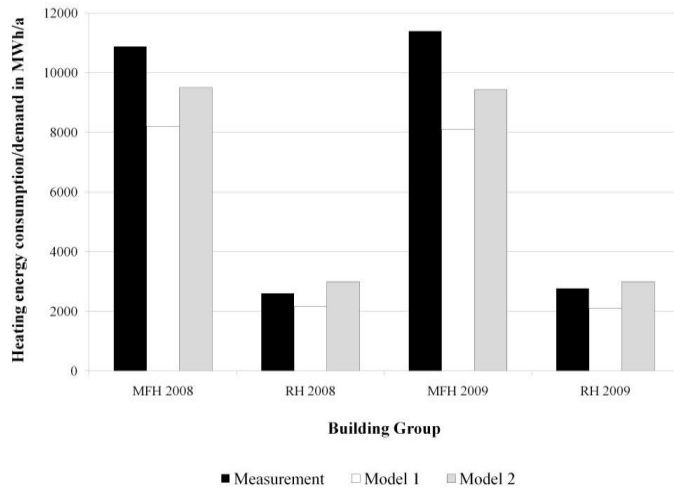


Figure 13. Overall annual comparison of measurement and demand for two building groups: multi-family houses (MFH) and row houses (RH).

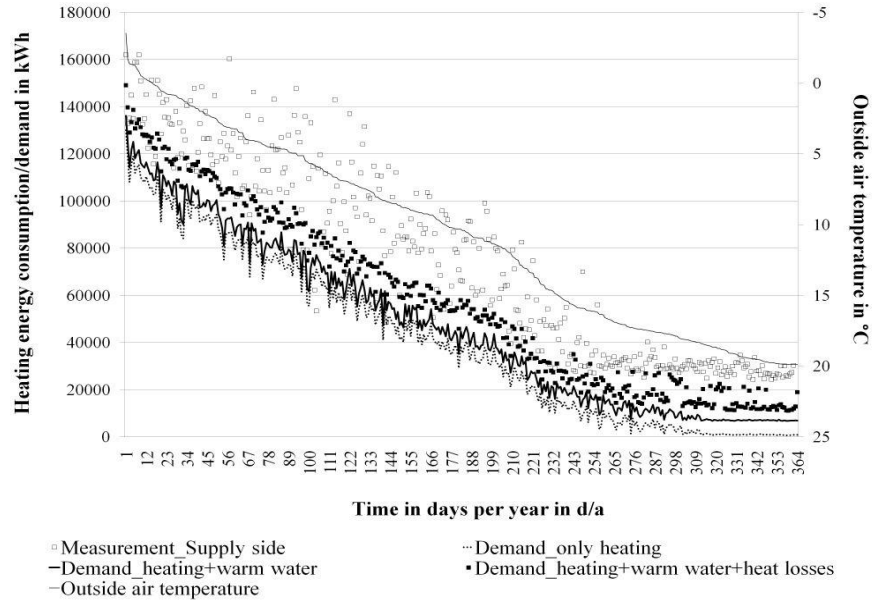


Figure 14. Annual measured and calculated load duration curves for the whole district (2008)

TABLES

Table 1: Average U-values for the buildings constructed between 2000 -2008.				
Building element	Outer wall	Roof	Floor	Window
Building category	Row houses			
<i>Avg U-Value [W/m²K]</i>	0.22	0.165	0.21	1.3
Building category	Multi-family houses			
<i>Avg U-Value [W/m²K]</i>	0.241	0.214	0.556	1.2

Table 2. Example of data calculation of the building data				
Building element	Ground Floor Area	Internal Wall Area	Outer Wall Area	Roof Area
Building ID	m ²	m ²	m ²	m ²
ID1	64	80	177	64
ID2	73	138	162	73
ID3	62	115	141	62
ID 4	53	115	96	53

Table 3. Errors in demand calculation as a function of geometry and U-value precision					
Year		2009		2010	
Nr	Calculation procedure	Deviation Model 1 [%]	Deviation Model 2 [%]	Deviation Model 1 [%]	Deviation Model 2 [%]
1	Dimensions from laser scanning and average U-values	-39	-22	-34	-10
2	Dimensions from laser scanning and real U-values	-29	-13	-23	-1
3	Real dimensions and average U-values	-29	-19	-23	-5
4	Real dimensions (incl. real window orientation) and real U-values	-20	-10	-13	+5

Table 4. Deviation between measured and calculated values for heating periods								
Year	2009				2010			
Model type	Model 1		Model 2		Model 1		Model 2	
Time period	Heating period	Summer	Heating period	Summer	Heating period	Summer	Heating period	Summer
Deviation in %	24	9	8	6	26	24	3	10