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AGGREGATION OF BUILDING ENERGY DEMANDS FOR CITY-SCALE MODELS

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ABSTRACT

Smart Cities initiatives and its focus on city level energy policy management has emphasised the need for development of aggregated energy demand models. This study models aggregated energy demand in 16 single-family houses, which are investigated on energy performance. The energy performance is modelled with Termite which uses Danish Be10 for energy performance calculations according to EN ISO 13790. Two methods of aggregating the energy demand were examined: the first method was based on modelling the individual energy performances, while the second method used building typologies and archetypes. The results highlight that the latter represents quite well the respective buildings, but deviates from the actual measured heat consumption in the buildings. However, the modelled annual aggregated heat demand was found to be very close to the measured consumption. Extensive discussion on the challenges and uncertainties of the suggested city scale energy model is presented.

INTRODUCTION

Aggregation is an important step towards estimating building energy demands, which is extensively discussed by many studies nowadays. It starts with the analysis of individual buildings' energy demands and continues with an upwards aggregation, which can be used to evaluate the performance of the whole building stock. This can be expressed as a bottom-up approach to determine the energy demand in the building stock. The observation of energy use trends and profiles for total aggregate stock also facilitates prediction of energy demand of buildings in the future (IEA, 2001).

The scale of building energy aggregation can range from small neighborhoods for single projects to national building stocks for residential, commercial or industrial sectors. Either way, the aggregation method and the structure of the data processing are the same.

Aggregating building energy demands has been studied for years especially in connection to central energy grids, electricity and district heating (Heller, 2000), (Heller, 2002). This scientific interest for aggregation has increased the last years, as the concepts of sustainable energy and smart cities have become popular topics for city administrations. This is also due to its potential to support decision-making in many urban development projects. More specifically, its contribution to decision-making can be summarized in two ways (IEA, 2001):

• It gives designers a better overview of the impact individual buildings have on the aggregated stock and adapt their design accordingly.

• Planners and policy-makers can have a holistic database including energy use data, which directly affects energy resources use, power system stability, as well as environmental emissions.

The aggregation of building energy demands can be classified with two different methods: i) the energy estimates of individual buildings can be added up to calculate the total energy use of the building stock, ii) reference buildings and building categories can be used, which are representative for the whole stock and weighting factors can be used proportionally for every category (Choudhary, 2011), (Matsuoka et al., 2013). Both methods are valid for all types of building energy demand, including space heat demand and domestic hot water (DHW) demand. They are presented analytically below.

METHODOLOGY

This paper investigates two methods to aggregate building energy demands. Method 1 uses the simplest form of aggregation, namely a sum of the measured energy consumption of the stock. Method 2 is based on an aggregation of building typologies. These typologies are generated from various information level indicators such as building age, net floor area and location. The indicators are used as input to a simulation tool, which in turn generates an estimate of the energy consumption of each individual building. The paper investigates how these two methods are applied on a small scale. This includes a qualitative investigation of selected information level indicators.

Method 1 - Aggregation of individual buildings' energy estimates

Aggregation of individual building energy demands is calculated in a plethora of studies. However, very few studies have described analytically the methodology of the aggregation. The simplest and

most common way to aggregate energy demands is to add them up. Thus, the total energy consumption of the aggregated stock Y will be a sum of the individual buildings' energy demands, as presented in the following equation.

$$Y = \sum_{i=1}^{n} X(i) \quad (1)$$

where

Y = total energy demand of the examined building stock [kWh]

n = number of individual buildings

X = energy demand per building [kWh].

It is assumed that each building's load profile is independent and normally distributed for simplification reasons.

The majority of scientific studies that deal with aggregate energy data in a variety of applications make use of this method. The advantage of it is the simplified methodology and the accuracy of the total results. On the other hand, detailed data, measurements and a load of energy simulations are required to calculate the energy demand of every building. This data-intensive approach proves to be very time-consuming and expensive. For this reason, it is mainly used at local scale, when a small neighborhood or a district is examined and access to such data is possible. However, if aggregation aims at a national level, then estimating the energy use for every building becomes even more difficult.

Method 2 - Aggregation based on reference buildings

To overcome the difficulties that arise from aggregating every individual building's energy demand, reference buildings have been introduced as a concept to stock aggregation. These represent fully the features of buildings included in every category. The process of aggregation is in this way greatly simplified, since the number of reference buildings is only a small part of the total stock. What is more, they are not so much affected by poor data quality. Databases of reference buildings enable the addition of new buildings or even existing ones, when their data become available and can be registered to them (IEA, 2001).

According to the methodology of using reference buildings as an aggregation method, the aggregation of building energy demand is made in two steps: i) multiplying the results of each building type with either the total number of buildings included or their total floor area and ii) summing the sub-totals to calculate the aggregate energy demand. These steps are indicated by the equation (2) below.

$$Y = \sum_{j=1}^{N} X(j)\, B(j) \quad (2)$$

Where

j = building type

N = total number of building types describing the stock

B = total number of buildings included in every type.

In the present study, every archetype's energy demand is estimated per floor area - also known as Energy Use Intensity (EUI) [kWh/m^2]. So, the above equation is changed as follows:

$$Y = \sum_{j=1}^{N} EUI(j)\, A(j) \quad (3)$$

where

EUI = energy demand per floor area [kWh/m^2] for each building type

A = total floor area [m^2] of all buildings included in the respective type.

These aggregating methods were applied in the present study to a real case consisting of 16 single-family houses located in Sønderborg, Denmark. The energy performance in the examined houses was modelled by Termite, a newly-developed parametric modelling tool, which uses Rhinoceros design interface, Grasshopper parametric options and Be10 for energy performance calculations according to EN ISO 13790 (Negendahl, 2014).

Information levels

One of the most significant challenges of bottom-up city simulation is data requirement. For this reason, four different information levels were investigated regarding the amount of data available for the specific examined case in Sønderborg. These data levels are summarized below:

A. Simple typological data. These data regard the type of the examined house according to building typologies. In the current study, TABULA database was used, as mentioned before.

B. Information collected by online public databases. In particular, the construction year, the floor area, a general overview of the building's design and the construction materials were collected from the Danish Building Register (BBR).

C. Information acquired by Google Maps, Street View. More specifically, these were used to acquire basic design information, such as the houses' ground plan and the houses' orientation, as well as the type and placement of windows and doors.

D. Information acquired by personal visits to the examined houses, on site measurements and distributed questionnaires to the occupants. In particular, two sources of information are included in this information level for the present study: i) the number of occupants and ii) whether the houses had undergone any refurbishments that affected their energy performance. The energy refurbishment state is indicated by the U-values of building materials and windows, which in case of renovation are significantly lowered according to TABULA

database. Personal visits to the examined houses may also determine if any additional systems (solar PV panels) have been installed.

Information levels A, B, C and D were used to model energy performance in the 16 single-family houses in Sønderborg. Six different scenarios were investigated, which are illustrated in Table 1. The scenarios represent every possible combination of the available information (A, B, C and D) that can be created. To facilitate the easy understanding and analysis of the six created scenarios, Table 2 presents a brief description of the information included in every scenario.

Table 1 Presentation of the six created scenarios based on the four different information levels

Inform. Level	S1	S2	S3	S4	S5	S6
A	X	X	X	X	X	X
B	X	X	X	X	X	X
C		X		X		X
Di				X	X	X
Dii			X		X	X

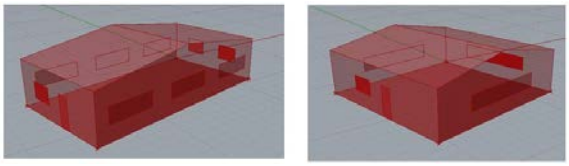

Figure 1 Design of House 1 for Scenario 1 (left) and 6 (right)

Table 2 Description of specific information contained in every Scenario

Scenario No.	Description of information included
S1	BBR
S2	BBR & Google Maps/Street View
S3	BBR & Refurbishment
S4	BBR & Google Maps/Street View & Occup. Loads
S5	BBR & Occup. Loads & Refurbishments
S6	BBR & Google Maps/StreetView & Occup. Loads & Refurbishments

The first scenario was initially constructed using only the basic information, included in information levels A and B, which are the type of the building, the age of construction, the floor area and the typical U-values of the houses according to TABULA Webtool. The design of houses was created based on generic means, aiming at an abstract representation of the actual design. Thus, the floor plan for all 16 houses was assumed to be a square area, having equal sides. The glazing area was set to be the same for all houses, and the exact orientation was not defined in Termite.

The second scenario was made by adding information level C, thus the exact design of the houses. The dimensions of the houses and windows, as well as their placement were taken into account at this stage. This design information was collected by Google Maps and Street View.

The third, fourth and fifth scenarios of the houses' model were made according to information level D: questionnaires distributed to occupants and on site observations. These scenarios' models included the actual occupancy loads based on the real number of occupants, while they also contained information about any possible energy refurbishments applied to the houses. The existence of energy refurbishments to the building envelope affects significantly the thermal characteristics of the building materials and windows (U-values, g-values). The information level

D was divided into these three scenarios (3, 4, 5) so as to separate the impact of the individual parameters. More specifically, Scenario 3 only takes the information about any energy refurbishments in the houses into account, neglecting the actual people loads and the real dimensions or design of the houses. In this scenario, a standard occupancy load of 1.5 W/m^2 for all 16 house models is considered. Scenario 4 makes use of the real design of the house, as well as the real occupancy loads, but without any information about energy renovations. Scenario 5 considers both the actual occupancy loads and the energy refurbishment state, but without including the real design of the houses. When the refurbishment state of each house was known, the adapted U-values to the renovated building envelope were collected by TABULA database.

Finally, a sixth scenario (Scenario 6) was investigated, which combined all the existing available information (information levels A, B, C, D), thus creating a realistic model of the 16 single-family houses. More specifically, the houses were modelled using their real design - both dimensions and orientation- and considering the real occupancy loads and the energy refurbishment states.

Figure 1 illustrates indicatively the design of House 1 created in Grasshopper for Scenarios 1 and 6, respectively. The building's floor area has remained constant in all cases, but the dimensions of the building envelope as well as the dimensions and placement of the windows differentiate between these two cases.

To calculate the aggregate energy demand, the first aggregating method was applied. Thus, the aggregation was made by summing up the individual buildings' energy demands for the different case-scenarios (Equation 1). This data-intensive method was possible to implement in the specific case, because only a small sample of buildings in the Sønderborg area was examined. Since the computation time of Termite remains very small even for a very large number of buildings, the main

difficulty faced in city models is the building data collection and analysis.

In cases where the number of investigated buildings increases a lot and the examined area extends to a district or city level, the second methodology as presented previously is proposed. Thus, the aggregation of building energy demand is based on archetypes of reference buildings, using Equation 3. TABULA database and Webtool were used to create the archetypes, as already described. The 16 examined houses were all of the same type (single-family house), thus, the differentiation among them was based on their construction age. All Danish building stocks are categorized into nine time periods according to Wittchen & Kragh, 2012; the examined 16 houses correspond to five of them. Based on these time periods, five building types were created covering all 16 examined houses. One example building was created for each type. The characteristics of the example buildings are presented in Table 3. The example buildings share similar technical characteristics to the buildings that they represent, such as building envelope, U-values, HVAC systems etc. The floor area, U-values and g-values were acquired by TABULA Webtool for every building type.

Table 3 Characteristics of the example buildings

Building type	Construction period	No. of incl. buildings	Total floor area [m^2]
A	1931-1950	2	238
B	1951-1960	2	180
C	1961-1972	10	1,530
D	1973-1978	1	117
E	1979-1998	1	122

Model setup

First, a building model was created for house number 0 in Grasshopper. Danish building databases, as well as the TABULA WebTool were used as information sources to collect data. The geometry of the house included the building envelope (external walls, floor, roof), as well as the glazing and external doors. To create the remaining building models (Houses 1-15) a number of lists were made in Grasshopper, which contained the input data. The main idea behind that was the parametric modelling; thus, by introducing a main controller which would be able to move from one house model to the other, all 16 house models would be simulated with just one model setup by simultaneously changing all input parameters. So, the only differentiation among the various house models was the input parameters, which are altered from house to house. These inputs' lists covered every building component and characteristic that had to be defined. Regarding geometry and design, lists of 16 different inputs were made for the dimensions of the houses, the windows' sizes and placement, as well as orientation. All lists were connected with the main controller that determined which house would be modelled every time. Therefore, the main controller could take values from 0 up to 15, corresponding to the house model number. The automatic movement of the main controller from one building model to the other via a timer enabled the modelling of an unlimited number of buildings varying from hundreds to millions. Of course, the larger number of buildings, the more complicated the model setup would be.

RESULTS

According to the collected weather data for the Sønderborg area, the lowest outdoor temperature of the examined period was -12°C, which coincided with the dimensioning outdoor temperature defined by Termite. Thus, simulation results and measurements were possible to be compared with each other.

According to the measurements of monthly heat consumption in the 16 examined single-family houses, the aggregate heat consumption was calculated based on the aggregation methodology of individual buildings.

To be able to evaluate the results of the 6 different scenarios of information levels, the results were compared with the ones acquired by the real measurements. In Table 4, the aggregated heat demand is presented as calculated by Termite for every scenario including all 16 houses, as well as the average value of the deviation between the specific scenario's monthly heat demand results and the monthly measured heat consumption. In addition, the deviation of the calculated annual heat demand for each scenario from the aggregate measured one is illustrated in Table 4.

Table 4 Results of scenarios - deviation compared to the real measurements of heat demand

Scenario	Total heat demand [kWh]	Average deviation of monthly demands	Deviation of yearly demand
1: BBR	421,295	45%	40%
2: BBR &GoogleMaps/Str. View	448,439	54%	49%
3: BBR & Refurb.	252,700	18%	16%
4: BBR & Google Maps/Str. View & Occup. Loads	445,742	53%	48%
5: BBR &Occup. Loads&Refurb.	250,658	19%	17%
6: BBR & Google Maps/Str. View & Occup. Loads & Refurb.	266,045	14%	12%

The results presented in Table 4 help the prioritization of the available building information

towards an accurate energy simulation. It is observed that the least accurate results, hence the highest deviation from the measured values, are the results of Scenarios 1, 2 and 4, which lack the information about the current energy refurbishment state of the houses. When this information is included in the modeling (Scenario 3, 5, 6), the heat demand results improve significantly and become much more realistic compared to the real measurements. In particular, just the knowledge of the energy refurbishment state of the house improves the deviation of yearly demand by 24% compared to the simplest model including just BBR information. In the scenario where BBR data, realistic design acquired by Google Maps/Street View and occupancy loads are known, the addition of information about energy refurbishment improves the deviation of annual calculated heat demand from the measured one by 36%. Scenario 6, which combines all the available information, has the lowest deviation (12%) from the aggregate measured heat consumption, as it was expected.

The knowledge of the real design of houses and windows, as obtained by Google Maps and Street View, does not seem to affect the calculated heat demand results a lot compared to the scenarios that do not include it. This is due to the fact that the dimensions of windows, as well as the total glazing area of every house, were calculated based on generic means. Thus, for some houses the generic glazing area was lower than the actual one, resulting in lower heat loss through the transparent components calculated by Termite. Therefore, heat demand was lower and more close to the measured one. When the knowledge of real occupancy loads was added, the calculated heat demand results did not improve much. This may be attributed to the fact that the default occupancy load of 1.5 W/m^2 used in Scenarios 1, 2 and 3 is not that different compared to the real occupancy loads based on the exact number of occupants in every house. However, this result would have been different if houses with more occupants were examined.

Figure 2 presents the results of the six modelling scenarios of the examined houses in Sønderborg in terms of heat demand. The results are aggregated for all 16 houses and are presented throughout one year period. All models follow the same pattern, having the highest heat demand during winter months and the lowest during summer, as expected. The graph supports the conclusions based on Table 4 above. It is clear that knowing whether a house has undergone any energy refurbishments improves the calculated heat demand results significantly. Scenario 6, which contains all available building information that can be gathered, is most closely aligned with the real measurements' curve compared to the rest scenarios. The highest deviation between Scenario 6 and measurements is observed between May and September. The explanation is that Be10 does not consider any heating in summer months, since it uses the Danish Design Reference Year (DRY) as weather data (DMI, 2013), which has very high temperatures in summer. However, according to the real measurements, there is still some demand for space heating during the summer period.

The least realistic approaches are the ones of Scenarios 1 (BBR data), 2 (BBR & GoogleMaps/Str. View) and 4 (BBR & GoogleMaps/Str. View & Occup.Loads), as already mentioned. These scenarios exclude the information of refurbishments of the investigated houses. Their highest deviation from the measured consumption values is observed in winter period. This was expected since the models created based on these scenarios contain much higher U-values of the building envelope and the windows than the actual ones. Thus, heat loss is calculated to be much higher and the heat demand is therefore significantly increased compared to the real measurements.

Figure 2 also indicates that knowing the exact occupancy loads (Scenario 4, 5) does not necessarily lead to better results, as already indicated with the sensitivity analysis. Thus, the curves of these scenarios differentiate too little compared to the ones that do not include these information. The same goes also for the knowledge of the real design of the windows and the house. Even though glazing area and its placement in terms of orientation does affect the Be10 results a lot, the way they were generated in the present Scenarios (1, 3, 5) was based on a generic pattern for all houses, thus cannot outline such difference.

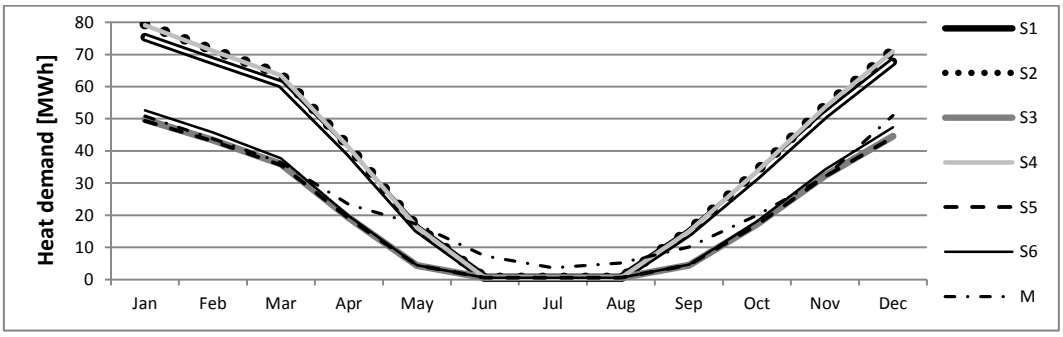

Figure 2 Aggregate heat demand results of the six different scenarios compared to real measurements conducted in the 16 single-family houses

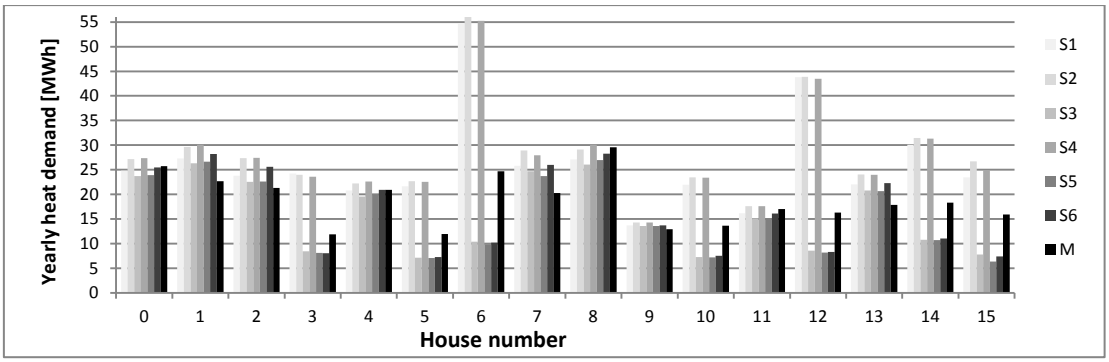

Figure 3 Yearly heat demand per house for all six examined scenarios compared with real measurements.

Figure 3 illustrates the annual heat demand results of the 16 examined houses individually for all six modelling scenarios. In addition, the consumption measurements are included in Figure 3 based on the examined year. First of all, the houses that have undergone renovations can easily be identified through the large deviations among the six models. In particular, Houses 3, 5, 6, 10, 12, 14 and 15 have undergone some kind of energy renovation as indicated by the large deviations between Scenarios 1 (BBR data), 2 (BBR & GoogleMaps/Str. View) or 4 (BBR & GoogleMaps/Str. View & Occup.Loads) and scenarios 3 (BBR & Refurb.), 5 (BBR & Occup. Loads & Refurb.) or 6 (BBR & Google Maps/Str. View & Occup. Loads & Refurb.). A similar refurbishment state was noticed for all these renovated houses. However, it was observed that benefits from energy renovations in houses were highly depended on their construction age. These benefits increased significantly for the oldest of the examined houses (Houses 6, 12) constructed in the 1930s and 1940s. In particular, House 6 and 12 reduced their heat demand significantly by 81% and 80%, respectively, between Scenario 1 (BBR data) and Scenario 3 (BBR and refurbishment data). Therefore, some usual renovation measures in old houses can lead to impressive reductions in the energy demand. Since these houses were constructed in the thirties and forties, their U-values according to TABULA database were the worst ones in terms of energy performance. Similarly, the renovated houses constructed in the 1960s (House 2, 14) had a decrease in energy demand of 65% and 64% respectively. In general, the newer a building is, the more advanced renovation measures are required to achieve high energy savings.

Moreover, it is observed that results according to Scenario 6, which represents the highest information level and the most realistic results, do not match the real measurements' results when looking into the individual house's energy performance. In particular, the highest deviations are noticed in House 6 and 15. It is also worth mentioning that the newly-built House 9 presents the lowest deviation among all models compared to the measurements. This indicates that new buildings must fulfill specific standards and requirements regarding their construction process and thus, their thermal characteristics are determined by national regulations. So, the actual U-values of their building envelope comply with the ones presented in official databases. These databases are not as representative when it came to older buildings, which did not comply with specific technical rules. Furthermore, Figure 3 validates what Figure 2 also illustrated: Scenarios 1, 2 and 4, which did not take the corrected U-values based on the energy refurbishment state into account, are far from realistic. However, the existence of actual design information and people loads slightly differentiate them from each other.

Aggregation based on reference buildings

Afterwards, the aggregate heat demands based on Equation 3 were calculated. The heat demands per floor area, thus EUI, for every building type are presented in Table 5. It has to be reminded that the presented energy demand includes heat demand for space heating, as well as DHW demand of the houses.

Table 5 Energy results of the example buildings per building type

Building type	EUI [kWh/m^2]	Total floor area [m^2]	Energy demand [kWh]
A	82	238	19,516
B	91	180	16,380
C	158	1,530	241,740
D	118	117	13,806
E	104	122	12,688

Adding up the above-presented estimations results in an aggregate heat demand of 304,130 kWh. Compared to the real aggregate consumption based on the measurements, an impressively small deviation of 1% is observed (Table 6). This outlines that even if the example buildings failed to represent the individual measured heat demands, they resulted in a very accurate result concerning the aggregate heat demand of the 16 single-family houses. However, the small range of the selected sample of

the 16 houses does not allow general conclusions on the accuracy of the followed method.

Table 6 Comparison of aggregate heat demand results between measurements and archetypes

Calculation method	Aggregate heat demand [kWh]	Deviation
Measurements	300,858	1%
Archetypes-Example buildings	303,582	

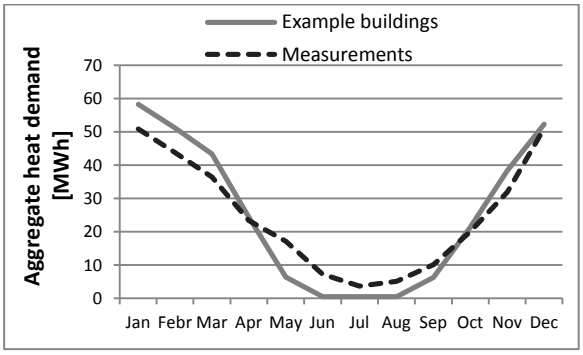

Figure 4 Aggregate heat demand results based on example buildings and measured values

Finally, Figure 4 illustrates the aggregate heat demand results on a monthly basis that were calculated based on the example buildings and the respective measured consumption. It is observed that overall, the aggregate heat demand of example buildings follows a similar trend to the real consumption in the 16 houses, as measured. The highest deviation between these two is noticed during the first three months of the year, as well as from May to August. During the summer period, this difference is attributed to the fact that Be10 does not consider any demand for space heating, based on the DRY climate data. Even though the deviation between the annual heat demand results of example buildings and measurements is infinitesimal (Table 6), it is observed that their monthly demands do not coincide throughout the year (Figure 4).

CONCLUSION

According to the **first aggregation method**, data availability was found to be crucial. Thus, six scenarios based on different information levels were constructed and examined. It was found that the information level which is necessary to conduct building energy simulations includes BBR data. However, to be able to define the real U-values of the examined houses, it has to be known whether they have undergone any refurbishments that affect their energy performance. In particular, just adding the knowledge of the energy refurbishment state of each house to the basic scenario was found to improve the model's results by 24%. In addition, it was observed that the knowledge of the real occupancy loads from people did not affect the accuracy of the model's results very much. Furthermore, it was observed that benefits of energy renovations depend highly on the building's age. In particular, a similar energy refurbishment led to higher energy savings for the oldest buildings than for the newest ones. Thus, standard renovation measures can have impressive reductions of energy demand in older buildings.

The model that was found to represent the real heat consumption of the examined houses best was the one that included the highest information level - consisting of BBR data, realistic geometry, energy refurbishment state and occupancy loads- as expected.

According to the **second aggregation method**, the examined houses were classified into five building types based on their construction age, as indicated by TABULA. One example building was defined and modelled for each building type. It was found that the specific example buildings represented the individual houses' performance as modelled based on the highest information level quite well, but did not represent the real heat consumption as measured very well. The error increased significantly when the respective houses had undergone energy renovations, but the example building representing them did not include improved U-values. Thus, a different classification strategy may have been more effective, which would differentiate between renovated and not renovated buildings. In any case, the importance of knowing the exact energy refurbishment state of every investigated house was outlined in these results, as well. Moreover, on an annual basis, the calculated aggregate heat demand was found to be almost identical to the real consumption as measured. Furthermore, when the aggregate heat demand was studied on a monthly basis, many differences were noticed between the calculated heat demand of the archetypes and the measured one.

The results of the modelled heat demand demonstrated a deviation from the measured heat consumption. The sample of the building stock examined in the current study was very limited, covering only the category of single-family houses and a restricted number of building subcategories. Thus, it would be inappropriate to draw generalized conclusions. Extensive research is proposed focusing on a larger building population case to evaluate the observed trends and patterns. However, the deviation between modelled and measured demands may have been quite smaller, if a different energy simulation tool was used or integrated in Termite. In particular, dynamic energy simulation tools, such as IDA-ICE or EnergyPlus, may give the opportunity to model the houses with higher accuracy in terms of internal gains, climate data etc. The introduction of occupancy profiles can also lead to a better representation of the actual building energy demand. Furthermore, results will be in hourly values which enable the investigation of further parameters' effect.

However, it increases data requirement both at the modelling level and at the reference of real measurements (based on hourly heat consumption data).

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