Aggregation of Residential Buildings for Thermal Building Simulations on an Urban District Scale

Abstract

In order to simulate the space heating demand of a residential building stock, often an aggregation is carried out. Aggregation in this context implies reducing the total number of building models by representing several buildings with one model. This paper explores the effect of the aggregation method on model accuracy when applying a first-order building model for the space heating demand of an urban residential district. The results show that aggregation leads to inaccuracies when the district includes buildings with varying values for their properties such as U-values and thermal capacitance. The errors are higher if the district is highly polarized and lower for more diverse districts. Aggregating buildings with identical properties diminishes the error compared to a total aggregation – aggregating the building stock as a whole. Aggregation with respect to certain building properties yields better results than others.

Keywords: building stock aggregation; thermal building simulation; low-order model; urban residential districts, model reduction

Nomenclature

Acronyms

CVRMSE	coefficient of variation of root mean square error
NMBE	normalized mean bias error
TRY	test reference years

Symbols

A	area in m^2
B	building
C	heat capacity in J/K
H	heat transfer coefficient in W/K
h	hours
P	building parameter
Q	space heating demand in kWh
s	stories
U	U-value in $W/(m^2K)$
V	volume in m^3
Θ	temperature in K
Φ	thermal power in W
ϕ	space heating demand in kW

Subscripts

A	aggregated model
air	internal/zone air
b	bottom plate
d	decreased value
D	detailed model

e	outside air
f	floor
G	ground
HC	heating and cooling
i	increased value
int	internal gains
m	building mass
op	opaque
s	internal surface
sol	solar gains
sup	supply air
tr	transmission
ve	ventilation
w	windows
wr	outer walls and roof

1. Introduction

Urbanization, the process of demographic displacement from rural to urban areas, has recently reached a tipping point. During this decade it can be seen for the first time that more than half of the global population is living in cities (UN 2014). Parallel to this, the United Nations (2004) predicts that the world's population will continue to increase until it hits a maximum of 9.22 billion inhabitants by 2075. Ergo, it can be expected that urban development will be a primary concern in the near future, as not only will there be more people on the planet, but a larger percentage of them will live in cities. Awareness of these and/or similar forecasts have nourished the interest of science in understanding the nature of cities, and how to make them resilient to these changes. This involves analyzing their morphology and growing need for resources, as well as identifying the size-scales which allow the observation of these urban reactions.

Neighborhoods, or urban districts, are a common study unit of social sciences due to the processes that take place within them, and the remarkable effects they have on their inhabitants (Hipp, Farris, and Boessen 2011). They are of great interest for the engineering sciences as well: their scale matches that of small or medium-sized energy supply and distribution systems, thus becoming a reasonable unit for urban development plans (Koch 2010). Knowing the energy demand at the scale of neighborhoods allows the conception of efficient energy administration systems, which have gained relevance with the increasing market penetration of decentralized, fluctuating renewable energy systems, such as photovoltaic modules, solar-thermal systems and small scale cogeneration. Some studies look at even higher levels where they model building stocks at national levels in order to analyze the effects of certain policy measures concerning the energy sector or built environment (Swan and Ugursal 2009; Kavgic et al. 2010). These models can be very powerful tools for policy makers in order to predict the effectiveness of certain measures – such as determining new building codes or offering incentives for retrofits – which address reducing energy consumption or greenhouse gas emissions.

There are many different methods for modelling the energy use of building stocks. They can be categorized into two fundamental classes: *top-down* and *bottom-up*. Swan and Ugursal (2009) provide a review on many of the applied top-down and bottom-up methods used for modelling the residential sector.

Top-down methods are based on the relationship between energy use and economic variables (e.g. gross domestic product, income and fuel prices) and use other factors such as saturation effects and structural changes (Kavgic et al. 2010). These methods are applied in various studies (Zhang 2004; Canyurt et al. 2005; Balaras et al. 2007). One of the advantages of this approach is, that the aggregate data used for these models is widely available, since several national and international institutions exist for the purpose of collecting this information, such as the *Bureau of Economic Analysis* in the USA, an official agency that provides economic statistics; or the *Federal Statistical Office* in Germany, where statistics regarding economy, society, and environment can be accessed. One of the disadvantages of top-down models is that they do not allow for the detection of key areas for reducing energy consumption, since the energy consumption of individual end-uses are not modelled (Swan and Ugursal 2009).

Bottom-up methods are used to model a building stock in a higher resolution such as individual end-uses or individual houses (Swan and Ugursal 2009). This offers a deeper insight into the building stocks and enables the evaluation of individual technological options. However, this high resolution approach comes with two challenges:

(1) Detailed models commonly require detailed data and obtaining these can be difficult compared to data for top-down models, as described above.

(2) Building and simulating bottom-up models for large building stocks can be very costly in terms of time, workforce and computationally.

In order to overcome the second challenge, researchers have come up with different methods to reduce the resources needed to perform simulations with bottom-up models for larger scales.

One method is: carrying out an *aggregation*. Aggregation in this context means reducing the model by representing several buildings as one building model, instead of modelling each building individually. This can either mean that the entire building stock considered is represented by a single building (total aggregation) or that the building stock is represented by a set of buildings, where each building of the set represents buildings of a certain type (categorization). Moffat (2001) suggests that if the categorization is carried out incorrectly, 'the aggregation process can lead to gross errors'. However he does not provide any results that could substantiate this statement, let alone quantify these potential errors. Others have addressed the quantification of errors due to aggregation. Gianniou et al. (2015) have studied the heat demand of a district with 16 single-family houses. Two methods are used in order to simulate the district's total heat demand. First, they simulate the buildings individually and take the sum as the total heat demand. With this method six different scenarios are carried out. The scenarios differ in regard to the parameters for the building models, which are obtained by using different sources (TABULA database; Google Maps; on site measurements etc.). In the second method, they categorize the 16 buildings regarding their construction age into five building types (aggregation), simulate these, multiply the results according to the building types' proportion in the district and take the sum as the total heat demand. For this method only one scenario is simulated taking the parameters from the TABULA database. Finally, the results of these two methods are compared with measured data of the buildings on a monthly and yearly base. When considering the results from the first method – taking the results of the scenario where the building parameters used are comparable to the ones used in the second method (TABULA database) – and the results from the second method, it can be seen that, contrary to what one would expect, using building types instead of simulating the buildings individually proves to perform better (monthly and yearly). However, by comparing the two methods with 'measured data', one includes a series of uncertainties and thus it cannot be excluded that the results are a coincidence. The results could have been distorted due to highly uncertain occupation behavior in the real buildings, the deviation of the assumed building parameters from the real building parameters or just the inaccuracy of the utilized building model. Most other studies found in literature, where the methods applied can be indicated as aggregation, compare their results also with measured data and hence include all the aforementioned uncertainties or possible errors. In order to answer the question what effect the 'aggregation method' – which is essentially a reduction of the model – has by itself, the aggregation method has to be evaluated separately by excluding or fixing other influences.

Why is it important to understand the inaccuracy or error that possibly comes with reducing a model with the aggregation method? Models of building stocks existing today always include uncertainty, whether representing the building stock of an entire nation with millions of buildings or smaller districts with the number of buildings in double figures. Some potential sources for uncertainty are:

(1) Values describing the buildings' properties such as geometries and thermal characteristics of walls, roof, windows etc. are unknown.

(2) User behavior and occupancy is unknown.

(3) The microclimate around the buildings is unknown.

(4) Samples (archetypes) are simulated and the results extrapolated to the population (entire building stock). (These methods are often used due to the three preceding unknowns.)

(5) When applying numerical methods to solve building models numerical errors are introduced.

(6) Building models describe the thermal processes in buildings but usually include simplifications.

(7) Building models are further simplified when modelling several buildings as a single building (aggregation method).

In future, with technological progresses such as the application of building information modelling (BIM) in the entire built environment, unlimited computational power and techniques that allow simulating very accurate models in very large quantities, inexpensive sensors measuring the conditions in all buildings and its surroundings and big data technologies that enable the handling of such large data, it might be possible to avoid or at least significantly reduce the above mentioned uncertainties. However, until then, it is suggested to apply stochastic models that quantify the uncertainty in the results of building stock simulations. The stochastic approach is a more insightful and thus useful method for decision makers and pursued in various studies (Booth, Choudhary, and Spiegelhalter 2011; Choudhary 2011; Tian and Choudhary 2012; Yamaguchi 2013; Zhao, Lee, and Augenbroe 2015). For robust stochastic models it is important to understand all sources of uncertainty in a building stock model. While there are already many studies regarding the first six sources of uncertainty listed above, literature review has shown that there is a lack of studies on the seventh source, the discrepancy that is caused by reducing the building model with an aggregation – modelling several buildings as a single building. Those studies that apply methods to reduce the number of buildings to be simulated for a building stock, generally address the above mentioned parameter uncertainty and extrapolation uncertainty (Booth, Choudhary, and Spiegelhalter 2011; Tian and Choudhary 2012; Yamaguchi 2013) – this is why the evaluation in these studies is based on measured data – without examining the discrepancy caused by the reduced building models specifically. Therefore, in this work we want to answer the question: *what if we had all information of a building stock (U-values, user behavior, microclimates etc.) and the building model used was absolutely accurate,* *would there still be an inaccuracy caused by modelling several buildings as a single building?* Our approach to clarify this is to exclude the other uncertainties, by assuming that:

(1) the exact building properties are known,
(2) the exact user behavior is known,
(3) the climate data used represents the microclimate around the buildings, and
(4) the results of the building model used are absolutely accurate when simulating individual buildings and the numerical errors are negligible.

The specific questions that are addressed in this work are:

(1) *Does the aggregation method affect the results, and if so, is the magnitude of inaccuracy significant?*
(2) *Does the structure of the district, which is to be aggregated, have an influence?*
(3) *Is it possible to reduce the inaccuracy by aggregating the buildings in specific groups with respect to their properties?*
(4) *Which properties should be used to conduct the grouping?*

2. Methodology

The aforementioned questions are investigated by using several simulation studies. For all simulations, a low-order building model is used, which is favorable for building stock simulations due to its reasonable data requirement and reasonable modelling and computational effort. The results of this work are only valid for this type of building model, since other models, e.g. a more detailed one, could not only lead to different results generally – when simulating an individual building – but also the aggregation method could affect the model differently and lead to higher or lower discrepancies. The model used is described in the next section. For all modelling and simulations required in this work, *Dymola*/*Modelica* (Elmqvist and Mattsson 1997; Brück et al. 2002) is used. The simulation study *Basic*, described in Section 3, investigates whether aggregation affects the results in general and whether the emerging discrepancy is significant. The simulation study *Structure*, described in Section 4, investigates whether the structure of the district influences the inaccuracy derived by aggregation. The simulation study *Criteria*, described in Section 5, investigates whether it is possible to reduce the discrepancy by aggregating the buildings in specific groups due to their properties and, if so, which properties should be used to conduct the grouping.

In order to perform the first two simulation studies *Basic* and *Structure*, the urban district *Gutleutmatten* in Freiburg, Germany, has been adopted as a reference building stock. Figure 1 shows a site plan of the district. It consists of two main sections. The West section is to include 22 buildings, and the East section is to include 13 buildings, giving a total of 35 buildings and 510 households. The buildings in the studies *Basic* and *Structure* have identical geometrical properties to the buildings in the district, though the rest of their properties have been modified as required for each study. For all simulations, weather data *TRY 12* (Test Reference Years) from the *German Meteorological Service* are used (DWD 2016). These data give a representative set of climate parameters for the climate region 12, to which Freiburg belongs. *TRY* data are hourly mean values over a 19-year period (1988 – 2007) of particular climate regions.

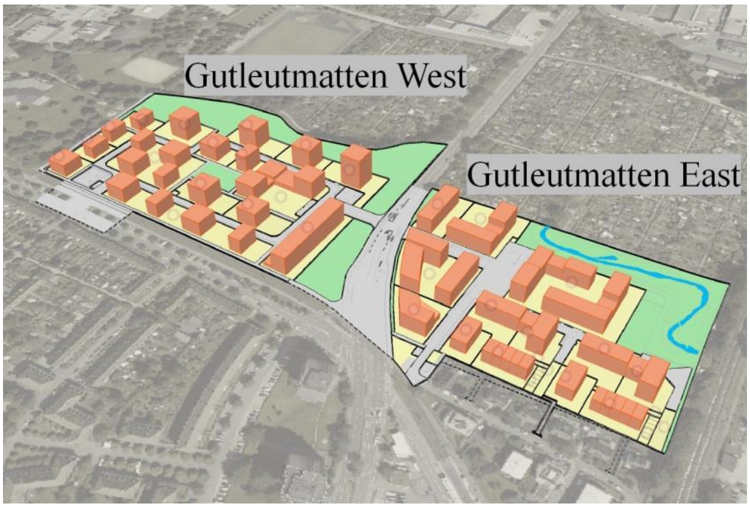

Figure 1: Site plan of the urban development project *Gutleutmatten* in Freiburg (source: town planning office Freiburg).

Simulation Study *Criteria* has been based on a reference building where random variations of its properties have been analyzed to ascertain to what extent aggregation based on certain properties, has an effect on the error.

The general approach in all three studies is the comparison of detailed simulations with aggregated ones. *Detailed simulation* involves simulating the space heating demand of each building individually and summing up the results to obtain the total demand. Since the building properties, the user behavior, the climate data and the building model for the individual buildings are assumed to be absolutely accurate, these simulation results are considered to be absolutely correct. *Aggregated simulation*, in turn, involves simulating the space heating demand of one building (aggregated building), which was designed by assigning average and, where necessary, weighted average values for each property based on each individual building that is represented by that one building. Average values for instance, are used in the case of floor areas, where the value for each building is added up and then divided by the number of buildings. Area-weighted average values are used in the case of distributed building properties such as total thermal transmittance (U-values), since they are strongly linked to the respective surface areas. Therefore, the calculation of this kind of property is as following:

$$P_{\mathrm{A}} = \frac{\sum_{\mathrm{k}=1}^{\mathrm{n}} P_{\mathrm{k}} \times A_{\mathrm{k}}}{\sum_{\mathrm{k}=1}^{\mathrm{n}} A_{\mathrm{k}}} \tag{1}$$

where P_{A} is the property calculated for the aggregated building, P_{k} is the property of building *k* and A_{k} is the area of building *k* to which P_{k} is linked to.

We assume superposition holds true, i.e., it makes no difference if the aggregated model represents an average building, as described above, whose result is afterwards multiplied by the number of buildings or if the model is an unrealistically large building which is obtained by adding up all properties of the individual buildings. (In the course of this work, both methods were tested and yielded the same results.) However, this statement refers only to the building model used in this work. It is known that for various other building models superposition does not hold true.

The comparison of detailed simulations with aggregated ones is carried out on an hourly basis with the *coefficient of variation of root mean square error* (CVRMSE) and the *normalized mean bias error* (NMBE). However, only the heating period is considered (September 1 through – May 31) since heating demand in the summer period is zero for all simulations. Taking the summer period into account would lead to lower errors. The CVRMSE is calculated as given by Equation (2):

$$\mathrm{CVRMSE} = \frac{\sqrt{\frac{\sum_{\mathrm{i}=1}^{\mathrm{h}} \left(\phi_{\mathrm{A,i}} - \sum_{\mathrm{k}=1}^{\mathrm{n}} \phi_{\mathrm{D,k,i}}\right)^2}{h}}}{\overline{\sum_{\mathrm{k}=1}^{\mathrm{n}} \phi_{\mathrm{D,k}}}} \tag{2}$$

where h is the number of hours in the heating period, $\phi_{\mathrm{A,i}}$ is the space heating demand of the aggregated model at time-step i, $\sum_{\mathrm{k=1}}^{\mathrm{n}} \phi_{\mathrm{D,k,i}}$ is the sum of the space heating demands of the detailed models k at time-step i, and $\overline{\sum_{\mathrm{k=1}}^{\mathrm{n}} \phi_{\mathrm{D,k}}}$ is the average space heating demand of the sum of the detailed models *k* during the simulated year.

The NMBE is calculated by Equation (3):

$$\mathrm{NMBE} = \frac{\sum_{\mathrm{i=1}}^{\mathrm{h}} (\phi_{\mathrm{A,i}} - \sum_{\mathrm{k=1}}^{\mathrm{n}} \phi_{\mathrm{D,k,i}})}{h \times \overline{\sum_{\mathrm{k=1}}^{\mathrm{n}} \phi_{\mathrm{D,k}}}} \tag{3}$$

The NMBE could also be viewed as the error when comparing the yearly results of the space heating demand.

2.1. Dynamic Building Model

The building model adopted is based on the equivalent resistance-capacitance model described in ISO 13790 (2008). All resistance-capacitance building models are essentially based on the *Beuken-Model* (Beuken 1936) and lend themselves to the modelling of the transient heat transfer processes encountered in buildings. A number of building simulation programs adopt such representation. The building model used in this study consists of five resistors and one capacitor. Figure 2 shows a schematic representation of the model. Its variables are listed and briefly described in Table 1. The model distinguishes between the internal air temperature and the mean temperature of the internal surfaces, to consider radiative and convective components of solar and internal heat gains separately. (Figure 3 shows the distribution of internal heat gains that is proposed by Feist [1994] and adopted in this work. The same profile applies for every day of the year.) The heat losses due to transmission through opaque components, transmission through windows and heat losses due to ventilation are considered separately. The entire building mass is represented by one capacitor yielding a first-order model according to the definition in (Lin, Middelkoop, and Barooah 2012). This model has a simpler structure than most other models and is favorable due to its reasonable data requirement and reasonable modelling and computational effort, hence making it favorable for simulations on a district scale. For more information on this model see (ISO 13790).

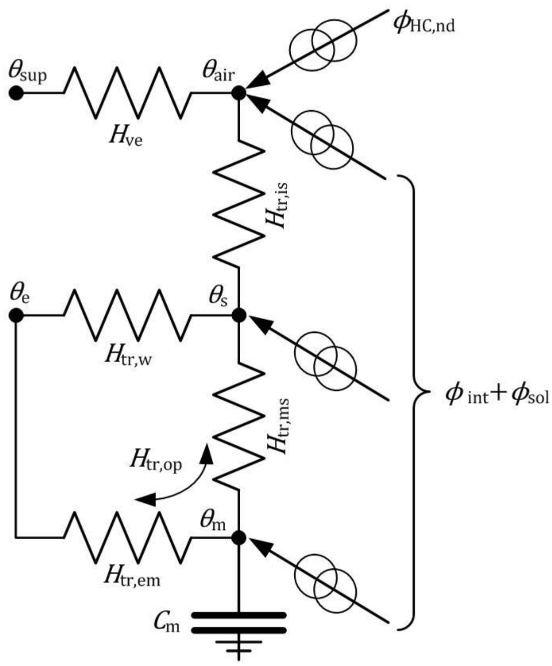

Figure 2: The first-order building model consisting of five resistors and one capacitor.

Table 1: Variables of the first-order building model illustrated in Figure 2.

Variable	**Description**	**Unit**
$\Phi_{HC,nd}$	calculated heating power	W
Θ_{air}	internal air temperature node	K
H_{ve}	heat transfer coefficient by ventilation	W/K
Θ_{sup}	supply air temperature node	K
$H_{tr,w}$	heat transfer coefficient by transmission (window part)	W/K
$H_{tr,op}$	heat transfer coefficient by transmission (opaque part)	W/K
Θ_s	mean temperature of internal surfaces node	K
Θ_m	building mass node	K
C_m	internal heat capacity	J/K
Φ_{int}	internal heat gains	W
Φ_{sol}	solar heat gains	W
$H_{tr,is}$	coupling conductance	W/K
Θ_e	outside air temperature	K

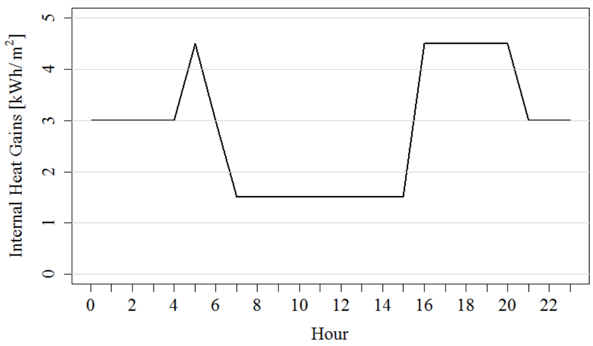

Figure 3: Daily schedule for the internal heat gains adopted from Feist (1994).

3. Simulation Scenario: Basic

To answer the questions whether aggregation affects the results, and whether the emerging error is significant, an experimental scenario has been designed, which represents an urban district composed of a heterogeneous group of buildings. The building sizes and geometries are based on the real buildings in the district as mentioned above. To emulate variations in construction year, renovations, and insulation levels, the buildings have been given different properties. Three construction characteristics have been set as distinguishing parameters, namely:

- thermal capacitance,
- U-values of opaque building surfaces, and
- window area fraction on each outer wall.

Two possible values have been assigned to each parameter, resulting in 8 different building types, as seen in Figure 4. The 35 buildings have been relatively evenly distributed according to heated floor area among the eight types. Figure 5 shows the allocation of the building types in the district.

The given parameter values are based on building data for Germany and expert knowledge. Figure 6 shows different U-values for large multi-family houses in Germany available from the TABULA database (Loga, Diefenbach, and Born 2011). Table 2 shows the units and values used for the parameters in this scenario. The assigned values are polarized, to ensure a high degree of heterogeneity in the district.

After having designed the district, the space heating demand of the 35 buildings has been simulated individually and summed up (detailed simulation), thus obtaining the total demand of the district. Subsequently, the 35 buildings are aggregated into one building model as described in Section 2, and the space heating demand of this aggregated model has been simulated too (aggregated simulation).

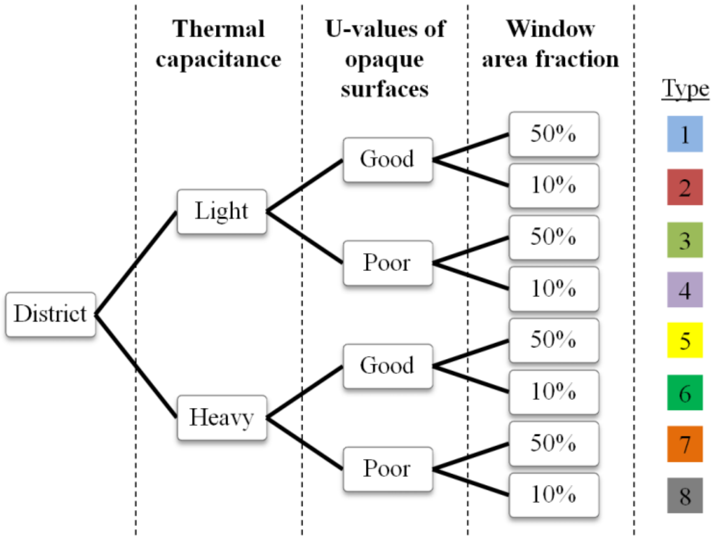

Figure 4: Building typology of simulation scenario *Basic*.

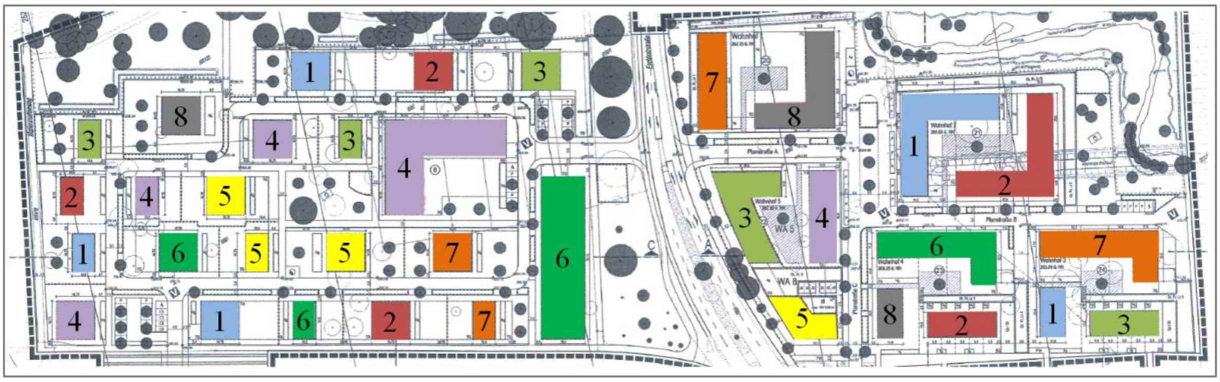

Figure 5: Site plan of the district: Allocation of the eight building types.

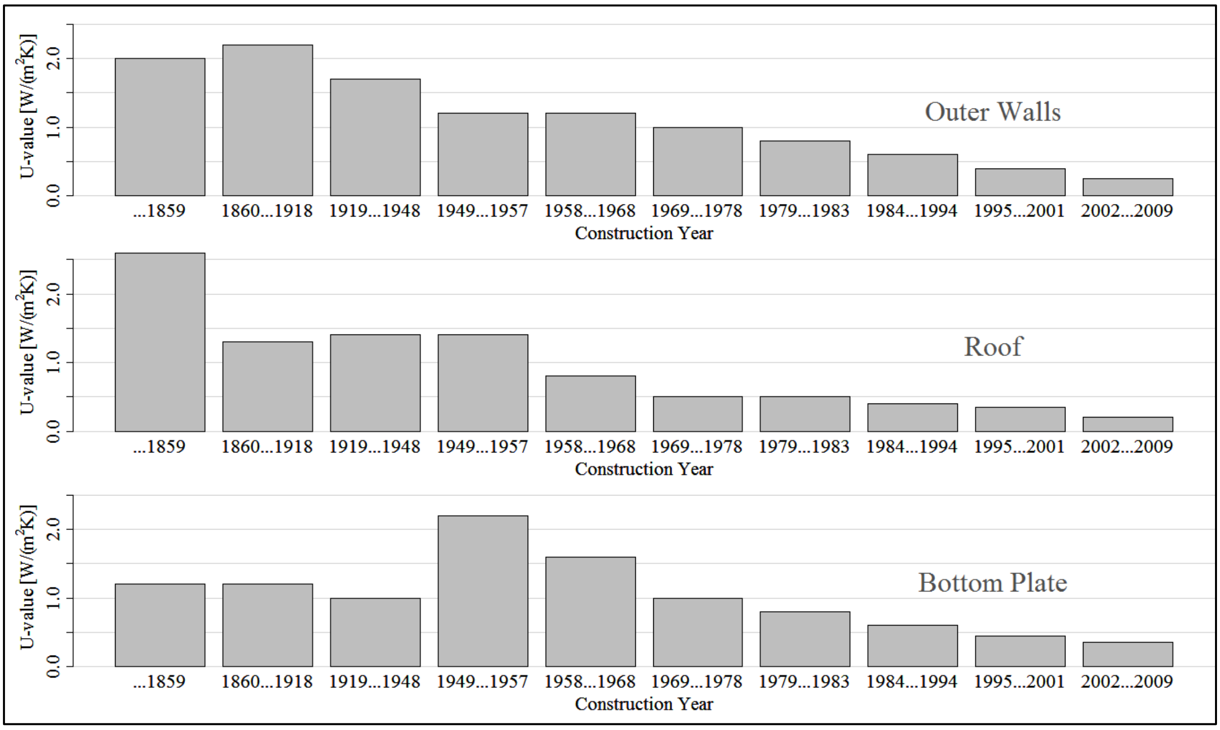

Figure 6: U-values for *outer walls*, *roof* and *bottom plate* as given in the TABULA database for multi-family houses (Loga, Diefenbach, and Born 2011).

Table 2: Units and values of building parameters evaluated in simulation scenario *Basic* (U_{wr} for outer walls and roof; U_b for bottom plate).

Parameter	Decreased Value	Increased Value	Unit
Thermal capacitance	Light 65,000	Heavy 195,000	J/(m^{2}K)
U-values of opaque surfaces	Good U_{wr} = 0.5 U_b = 0.3	Poor U_{wr} = 2.0 U_b = 1.2	W/(m^{2}K)
Window area fraction	10	50	%

Figure 7 illustrates the space heating load curve of the detailed and aggregated simulation for three days in the transition season (above) and the heating season (below). These results are representative for the days in the rest of the year. From these results two findings can be derived. First, the results from the aggregated model clearly differ from the results of the detailed model. Secondly, when the heating load is low, a relatively small discrepancy between the detailed and the aggregated results can suddenly become larger. This is triggered by thresholds implemented in building models, determining whether the building requires heat or not. For instance, if the zone temperature of several buildings is slightly higher than 20°C, it is likely that the zone temperature of other buildings in the district is slightly lower than 20°C – due to lower solar gains for example. Hence, if 20°C is the threshold, some buildings have zero heat demand and others still have a low heat demand, resulting in a low heat demand for the district. However, the state (zone temperature) of the aggregated building that represents all these buildings, is likely to be somewhere between slightly higher and slightly lower than 20°C but when it exceeds the 20°C, it results in zero heat demand for the entire district. Thus, the aggregated model fails to recognize the low heat demand that is still required in the district by some of the buildings.

In order to quantify the discrepancy between the detailed and the aggregated simulations, the CVRMSE and NMBE are calculated and the results are 7.3% for CVRMSE and 0.1% for NMBE. If we compare these values with the model uncertainty commonly encountered in the field of dynamic building simulations, we can see that they are not very significant. For instance, in the ANSI/ASHRAE Standard 140 (2011) simulation results of different building models, which are generally accepted as state of the art such as TRNSYS or ESP-r, are compared for several test cases. The example results of annual heating loads for *Case 600* (Base Case) for instance, show that when comparing the maximum and minimum values they differ by 27.8%, based on the total average.

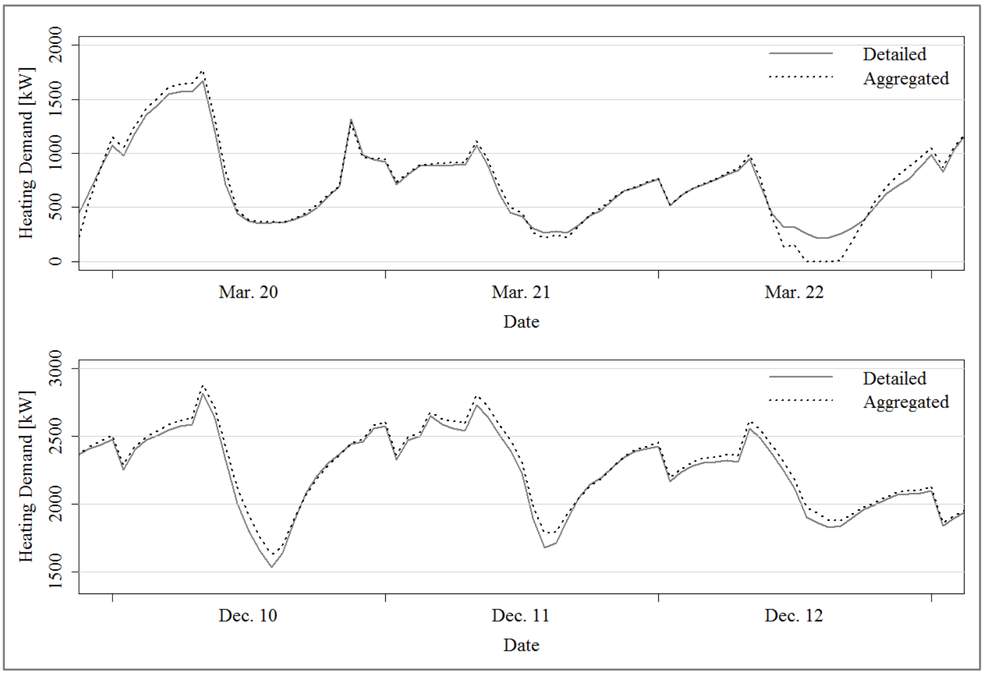

Figure 7: Space heating demand in the transition season (above) and the heating season (below) for the detailed (black) and aggregated (grey) simulations in simulation scenario *Basic*.

4. Simulation Scenario: Structure

To clarify whether the structure of a district affects the results derived by aggregation, two additional variations of the district have been developed. The results of these two variations and the results from the scenario *Basic* are then compared.

In one of the variations, the buildings have been distributed among only *two types*. This variation with only two types is classified as highly 'polarized' as the building typologies, which characterize the district, share few common properties, as seen in Figure 8. Figure 9 shows the allocation of the two building types in the district.

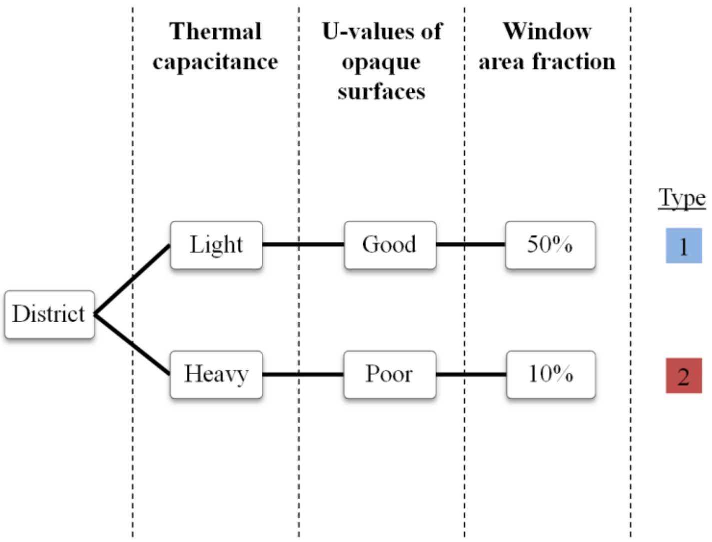

Figure 8: Building typology of variation with two types.

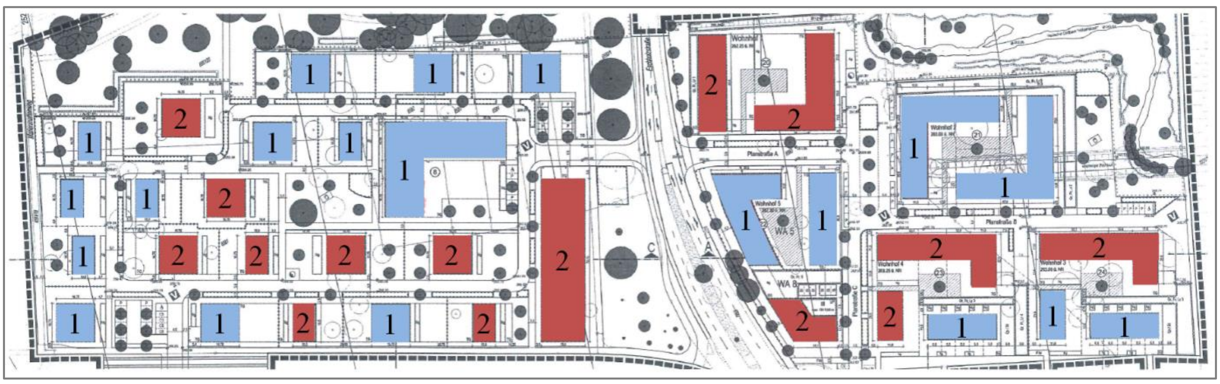

Figure 9: Site plan of the district: Allocation of the two building types.

In the other variation, the buildings have been distributed among *four types*. They consist of the two building types shown in Figure 8, further differentiated by the window area fraction.

Figure 10 shows the building typology for this variation. Figure 11 shows the allocation of the four building types in the district.

After having designed both variations of the district (*two types* & *four types*), for both variations/districts the detailed simulation (simulating all 35 buildings individually and summing up the results) and the aggregated simulation (simulating one building that represents all 35 buildings) are performed and the results evaluated.

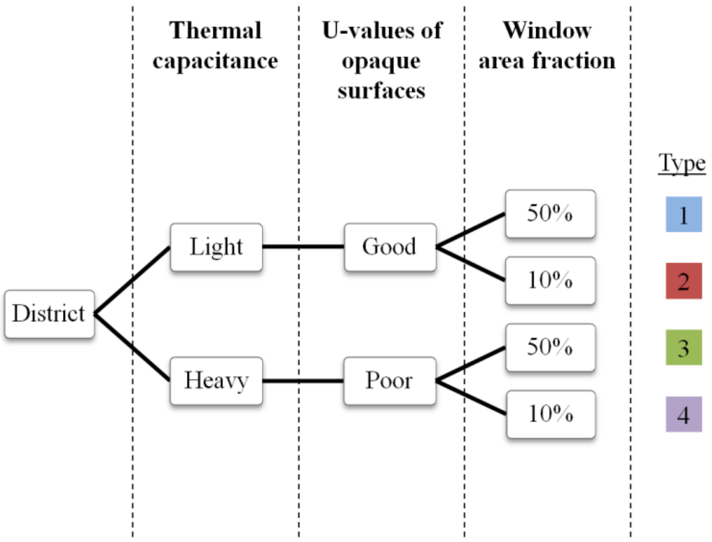

Figure 10: Building typology of variation with four types.

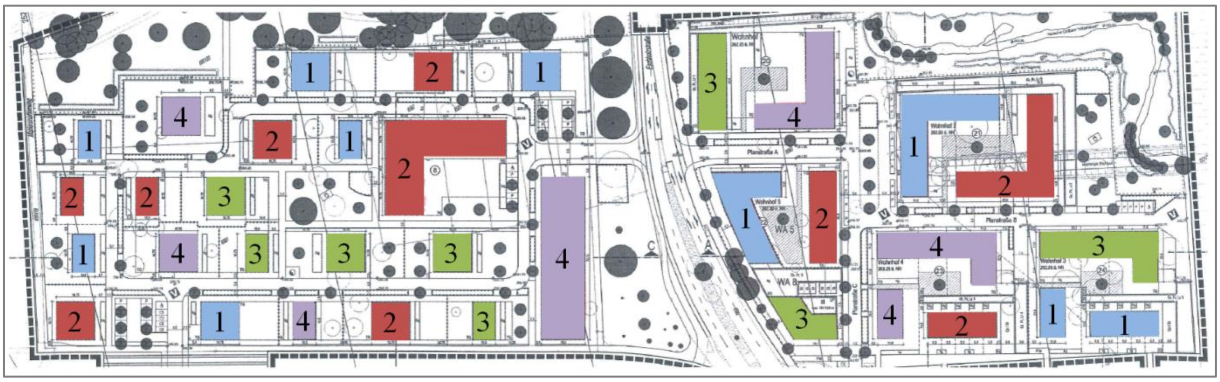

Figure 11: Site plan of the district: Allocation of the four building types.

The errors resulting from aggregation, for the two variations (*two types* & *four types*) and the variation from Section 3 (*eight types*), are shown in Figure 12. It can be seen that the structure of the district clearly has an influence on the error due to aggregation. While the CVRMSE of the variation with eight types is 7.3% and the NMBE is 0.1%, it increases for the variations with four types and with two types, to 8.1% / -1.1% and 13.8% / -8.1% respectively. This shows that there is a tendency that more polarized district structures result in increased model inaccuracy due to aggregation.

The structure of a residential district or group of residential buildings usually depends on the size of the sample. When looking at a small sample of recently erected buildings, closely located to one another, it is likely that the year of construction of these buildings do not vary significantly and they therefore tend to have similar properties leading to a homogeneous structure. This is due to the nature of late urban developments, which are usually the result of carefully considered masterplans to develop entire districts in stages rather than to construct each individual building sporadically. If we increase the sample size and include a 'few' districts which are developed in different time periods, the structure of the sample becomes polarized. If we further increase the sample and include 'many' districts which are developed in different time periods, the structure becomes more heterogeneous. When considering these structural changes by the sample size and the obtained results above, it can be suggested that the inaccuracy due to aggregation is slight for small samples, increases for mid-sized samples and decreases again for large samples.

As mentioned above, this assumption can only be made for recently erected buildings. There are still numerous buildings in urban areas that are not results of developments with masterplans. However, if we look at e.g. Germany's residential building stock with 18.26 million buildings in total, and define the boundary year for 'recent' and 'not recent' buildings as 1919, we can see that 87% of the residential buildings can be classified as recently built. If we define the boundary year as 1949, we can see that 74% of the residential buildings can still be classified as recently built, for which the assumption holds (Zensus 2011, 2016).

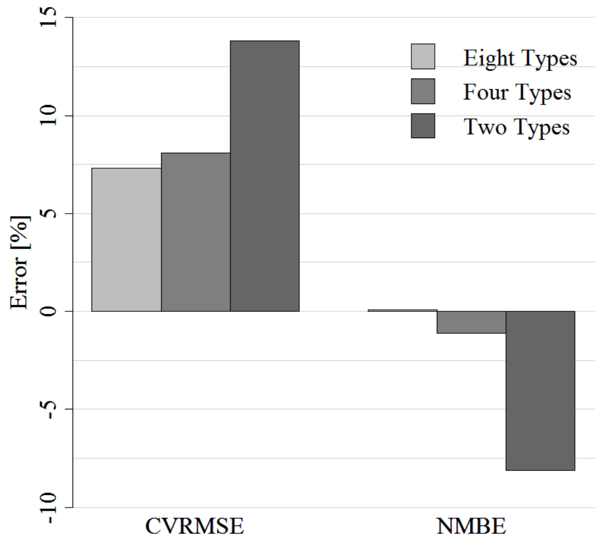

Figure 12: CVRMSE and NMBE derived from aggregation of scenarios with different structures.

5. Simulation Scenario: Criteria

The purpose of the simulations in this section is to investigate whether it is possible to reduce the error by aggregating buildings in specific groups based on their properties, and if so, which properties/criteria should be used to conduct the grouping.

The methodology applied is as following: a reference building has been designed based on existing housing characteristics in Germany (Loga, Diefenbach, and Born 2011) and expert knowledge. The properties of this reference building are shown in Table 3 in column *Reference value*. Subsequently, several variations based on the reference building are created. This process is explained by Equation (4), where $\boldsymbol{B}_{\mathrm{r}}$ is the reference building with its property values $P_{1,\mathrm{r}}$, $P_{2,\mathrm{r}}$ etc. for its ten properties. $\boldsymbol{B}_{\mathbf{1},\mathrm{d}}$ and $\boldsymbol{B}_{\mathbf{1},\mathrm{i}}$ are two building variations, where the value of their first property is changed to a lower value (see Table 3 column *Decreased Value*) and a higher value (see Table 3 column *Increased Value*), respectively. The remaining nine properties of $\boldsymbol{B}_{\mathbf{1},\mathrm{d}}$ and $\boldsymbol{B}_{\mathbf{1},\mathrm{i}}$ (properties 2 to 10) are the same as the reference building's. $\boldsymbol{B}_{\mathbf{2},\mathrm{d}}$ and $\boldsymbol{B}_{\mathbf{2},\mathrm{i}}$ are two additional building variations, where the value of their second property is changed to a lower and a higher value, respectively, and where the remaining nine properties (property 1 and properties 3 to 10) are the same as the reference building's. (This can be called a local method, since the parameters are varied one at a time.) This is carried out for all ten properties resulting in a total of 20[1] additional buildings, where the two buildings with variations in the same property can be seen as a pair ($\boldsymbol{B}_{\mathbf{1,d}}$ & $\boldsymbol{B}_{\mathbf{1,i}}$ / $\boldsymbol{B}_{\mathbf{2,d}}$ & $\boldsymbol{B}_{\mathbf{2,i}}$ etc.). Subsequently, for each pair, an aggregated building is created that represents the two buildings, resulting in a total of 10 aggregated buildings.

$$\begin{array}{cccccccc} \boldsymbol{B}_{\mathbf{r}} & \boldsymbol{B}_{\mathbf{1,d}} & \boldsymbol{B}_{\mathbf{1,i}} & \boldsymbol{B}_{\mathbf{2,d}} & \boldsymbol{B}_{\mathbf{2,i}} & \ldots & \boldsymbol{B}_{\mathbf{10,d}} & \boldsymbol{B}_{\mathbf{10,i}} \\ \begin{bmatrix} P_{1,\mathrm{r}} \\ P_{2,\mathrm{r}} \\ \vdots \\ P_{10,\mathrm{r}} \end{bmatrix} & \begin{bmatrix} P_{1,\mathrm{d}} \\ P_{2,\mathrm{r}} \\ \vdots \\ P_{10,\mathrm{r}} \end{bmatrix} & \begin{bmatrix} P_{1,\mathrm{i}} \\ P_{2,\mathrm{r}} \\ \vdots \\ P_{10,\mathrm{r}} \end{bmatrix} & \begin{bmatrix} P_{1,\mathrm{r}} \\ P_{2,\mathrm{d}} \\ \vdots \\ P_{10,\mathrm{r}} \end{bmatrix} & \begin{bmatrix} P_{1,\mathrm{r}} \\ P_{2,\mathrm{i}} \\ \vdots \\ P_{10,\mathrm{r}} \end{bmatrix} & \ldots & \begin{bmatrix} P_{1,\mathrm{r}} \\ P_{2,\mathrm{r}} \\ \vdots \\ P_{10,\mathrm{d}} \end{bmatrix} & \begin{bmatrix} P_{1,\mathrm{r}} \\ P_{2,\mathrm{r}} \\ \vdots \\ P_{10,\mathrm{i}} \end{bmatrix} \end{array} \tag{4}$$

The detailed simulations in this scenario are carried out by simulating the two individual buildings of a pair separately and adding the two outcomes to give the correct result. This result is then compared with the outcome of the aggregated building representing the pair. This is carried out with each pair and their corresponding aggregated building and the discrepancies calculated with CVRMSE and NMBE. The reference building's purpose is to serve as a base case, enabling the 20 variations, and is not simulated. The list of properties investigated in this scenario is a choice of the authors and does not claim comprehensiveness. Only building parameters are considered that are able to be obtained if building plans exist or on-site building examinations are carried out. A brief description of the tested building parameters is as follows:

(1) *U-value of opaque surfaces* refers to the overall heat transfer coefficient attributed to the opaque surface elements (outer walls, roof and bottom plate).

(2) *U-value of transparent surfaces* corresponds to the heat transfer coefficient of transparent surface elements (windows).

(3) *Window percentage* represents the fraction of window surfaces on the north, east, south and west walls of the building, with the frame accounting for thirty percent of the window surface.

(4) *Window orientation* is changed by locating the total area of windows of the reference building on different outer walls: North / East / South / West.

[1] Since one of the parameters (*window orientation*) has four instead of two variations, it actually results in 22 buildings. However, this is neglected in the description of the method in order to make it easier to understand.

(5) *Floor area* refers to the ground surface that is occupied by the building. Thus, it also defines the area in square meters through which the building exchanges heat with the soil.

(6) *Outer wall surface* consists of the area in square meters of the four outer walls of the building, including transparent surfaces.

(7) *Conditioned volume* refers to the air volume enclosed within the four walls, the roof and the ground. This parameter, in turn, defines two other quantities:

- *Air exchange* is the amount of air that flows through the building. It is commonly calculated as the product of the air exchange ratio, in h^{-1}, and the volume, in m^3.
- *Conditioned floor area* is the surface in m^2 within the boundary of the building that is subject to heating, calculated in accordance to EnEv (2009) as given by Equation (5):

$$A_\mathrm{f} = 0.32\ \mathrm{m}^{-1} \cdot V_\mathrm{e} \tag{5}$$

where V_e is the conditioned volume.

(8) *Conditioned floor area* may also be calculated as given by Equation (6):

$$A_\mathrm{f} = b_\mathrm{f} A_\mathrm{G} s \tag{6}$$

where b_f is a factor indicating the ratio between ground area and conditioned area, A_G is the ground area, and s is the number of stories, with $s = 3$ for this study.

(9) *Building Orientation* is portrayed by means of a different building configuration. While the remaining cases are based on a building with a square ground surface, the simulations for this parameter are based on a building with a rectangular ground surface: the orientation of the main axis of this rectangle is North-South in one case and West-East in the other case.

(10) *Internal heat capacity* is calculated with the thermal characteristics and volume of the construction materials of the opaque elements in the building. In this study, the variation is based on substituting the materials while keeping the same transmission coefficient values as the reference building.

Table 3: Building parameters evaluated for aggregation error in simulation scenario *Criteria*.

Properties	**Unit**	**Reference Value**	**Decreased Value**	**Increased Value**
U-value of opaque surfaces	W/(m^{2}K)	U_{wr} = 1.25 U_b = 0.75	U_{wr} = 0.5 U_b = 0.3	U_{wr} = 2.0 U_b = 1.2
U-value of transparent surfaces	W/(m^{2}K)	1.75	0.7	2.8
Window area fraction	%	30	10	50
Window orientation[a]	-	-	N E	S W
Floor area	m²	200	100	300
Outer wall surface	m²	460	230	690
Conditioned volume	m^3	1626	813	2439
Conditioned floor area	%	85	75	95
Building orientation[a]	-	Squared floor	Rectangular floor, main axis N-S	Rectangular floor, main axis E-W
Thermal Capacitance	J/(m^{2}K)	130,000	65,000	195,000

[a]For these properties there are no 'decreased' or 'increased' values, but different variations as required.

Figure 13 and Figure 14 show the CVRMSE and NMBE for the simulation results. It can be seen that the criteria *window area fraction* leads to the most significant error (CVRMSE: 8.18% / NMBE: -1.53%), followed by *U-value of opaque surfaces* (CVRMSE: 6.46% / NMBE: 1.25%) and *thermal capacitance* (CVRMSE: 4.84% / NMBE: -0.79%). Table 4 lists the three criteria leading to the highest errors. The ranking of the three most influential criteria is the same for CVRMSE and NMBE.

It should be noted here, that the parameter study carried out in this work, is not to be confused with a direct sensitivity analysis, where, for a building model, the sensitivity of its simulation output to its input parameters is evaluated. Nevertheless, intuitively one would expect that there is a clear relationship between the influential parameters and the criteria to aggregate after. However, the result of the significance of *thermal capacitance* when carrying out aggregation shows that this assumption does not necessarily hold.

The results obtained in this section are based on a local method where the interaction between the criteria is not considered. For instance, the importance of the criteria *thermal capacitance* could be sensitive to the internal heat gain schedule used in this study, thus the ranking of important parameters could change for other schedules. In order to reveal these kinds of relationships, for the purpose of considering these for aggregations, a regression analysis can be carried out. Another solution is to directly apply a global method, where the variables are varied simultaneously. This would provide an understanding of the importance of the individual criteria beyond the reference building used in this study. Saltelli et al. (2008) give a comprehensive overview of global methods and Burhenne (2013) shows more specifically the application of global methods in building performance simulations.

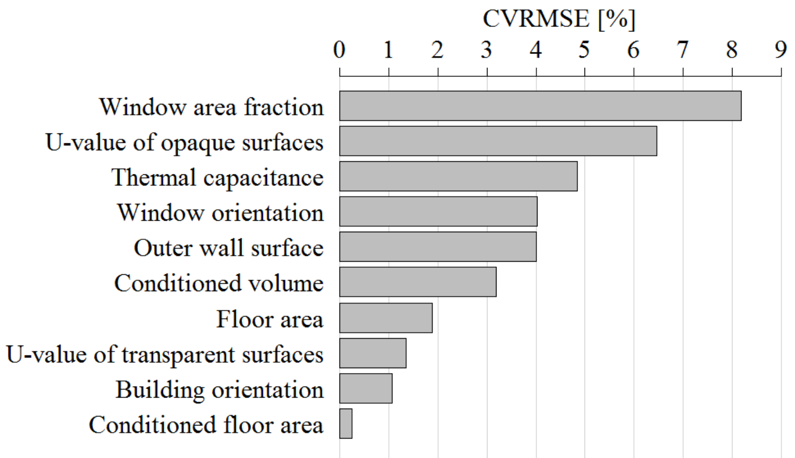

Figure 13: CVRMSE derived from aggregation in simulation scenario *Criteria*.

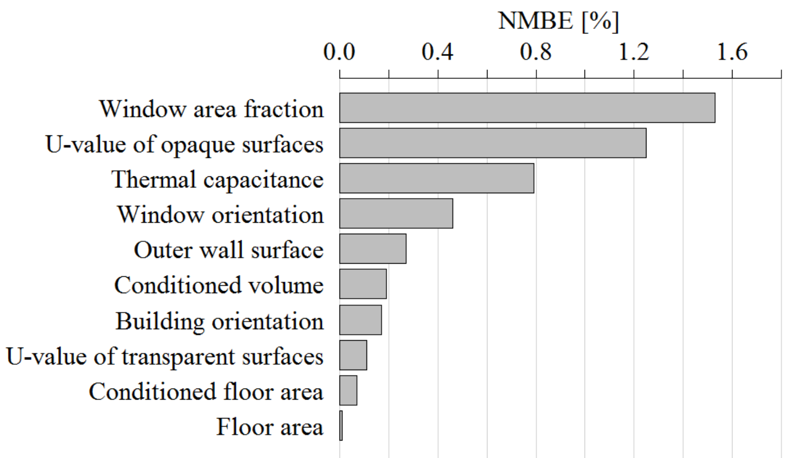

Figure 14: NMBE derived from aggregation in simulation scenario *Criteria* (all error values are depicted as absolute values).

Table 4: Criteria leading to the highest aggregation errors.

Ranking	CVRMSE	NMBE
1.	<u>Window area fraction</u> 8.18%	<u>Window area fraction</u> -1.53%
2.	<u>U-value of opaque surfaces</u> 6.46%	<u>U-value of opaque surfaces</u> 1.25%
3.	<u>Thermal capacitance</u> 4.84%	<u>Thermal capacitance</u> -0.79%

From the results above one can derive that aggregating buildings in specific groups according to *window area fraction* should lead to the smallest error, followed by *U-value of opaque surfaces* and *thermal capacitance*. In order to further evaluate this conclusion a complementary simulation study is carried out, in which the conclusions are tested on a district where the buildings vary in geometry and size. For this, the district described in Section 3 (*eight types*) is used. In this test, instead of aggregating the district into a single building (total aggregation), as done in Section 3 and 4, the district is aggregated according to each of the criteria in Table 4, resulting each time in 'two' aggregated buildings. Table 5 shows how in each simulation study the buildings in the district have been aggregated according to the criteria. For instance, for the first test, all buildings in the district are aggregated according to *thermal capacitance*. Meaning all *light* buildings, which are of type 1, 2, 3 and 4 (see Figure 4 and Figure 5), are aggregated to one building, and all *heavy* buildings, which are of type 5, 6, 7 and 8 (see Figure 4 and Figure 5), are aggregated to another building, resulting in two aggregated buildings (one represents all *light* buildings and one all *heavy* buildings). These two aggregated buildings are then simulated individually and the results summed. The result of this aggregated simulation is then compared with the detailed simulation (all 35 buildings individually) as described in the previous sections. This is carried out for all three criteria listed in Table 5, resulting in three different simulation studies.

Table 5: Aggregations performed in the complementary simulation study.

Aggregation Criteria	**Assignment of Buildings / Types**	
	Aggregated Building 1	**Aggregated Building 2**
Thermal capacitance	Light 1;2;3;4	Heavy 5;6;7;8
U-value of opaque surfaces	Good 1;2;5;6	Poor 3;4;7;8
Window area fraction	10% 1;3;5;7	50% 2;4;6;8

The errors resulting from each complementary simulation study can be seen in Figure 15, next to the result of Section 3 (total aggregation). As expected, the new results show a smaller error compared to the error due to a total aggregation. It can also be seen that the ranking resulting from the simulations above (see Table 4) also apply to the district simulation. Aggregating in specific groups according to *window area fraction* leads to the lowest error while aggregating according to *U-values of opaque surfaces* and *thermal capacitance* lead to the second and third lowest errors respectively.

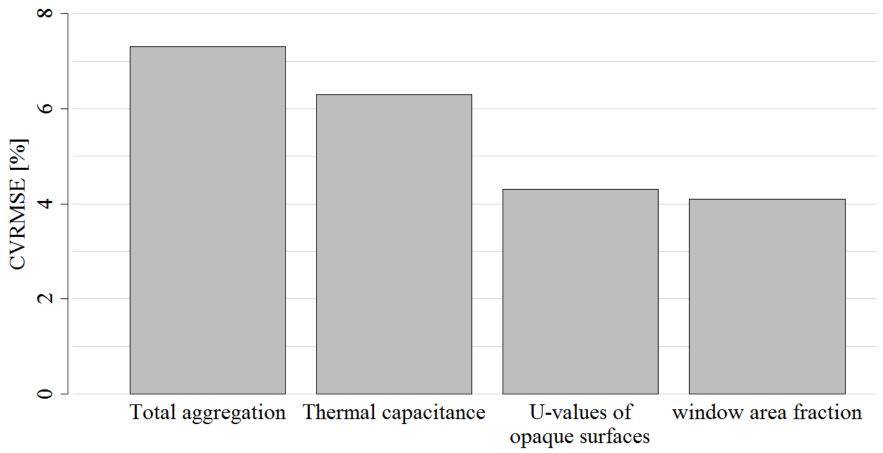

Figure 15: CVRMSE derived from aggregation in the complementary simulation study of a district.

However, it must be mentioned, that the error also depends on the range of the parameter values. The values used in the scenarios in this work are based on real data (Loga, Diefenbach, and Born 2011) and hence are realistic. Nevertheless, the parameter values can be very different for other cases. The range of values could be smaller or larger. Therefore, the effect of the range of values on the error derived from aggregation is also investigated in this section.

To do so, a subset of buildings has been created by a similar process as shown with Equation (4). However, this time, instead of varying a different parameter for each pair of buildings, only the parameter *window area fraction* is repeatedly varied (while all other parameters remain fixed), resulting in five pairs with different value ranges for the parameter *window area fraction*. The values for the variations are shown in Table 6. It can be seen that the buildings of the first pair have the same values as in Table 3, while the range of values decreases from the second pair onwards until both values are the same, as seen in pair five. For each pair of buildings an aggregated building is created and the results obtained from the aggregated simulations compared with the results of the detailed simulations.

Table 6: Variations of window area fraction.

Pairs	**Window Area Fraction in %**		
	Decreased Value	**Increased Value**	**Value Range**
1.	10	50	20
2.	15	45	15
3.	20	40	10
4.	25	35	5
5.	30	30	0

Figure 16 shows the results of this study. It can be seen that the larger the range of values, the greater the error due to aggregation, with an almost linear correlation. Where there is only one single parameter value, and hence no range of values, no errors are incurred through aggregation. This result shows that the ranking of parameters shown in Table 4 cannot be used as a general template, even if the here utilized building model is used. The magnitude of error also depends on the range of the parameter values and hence must also be considered when applying the aggregation method.

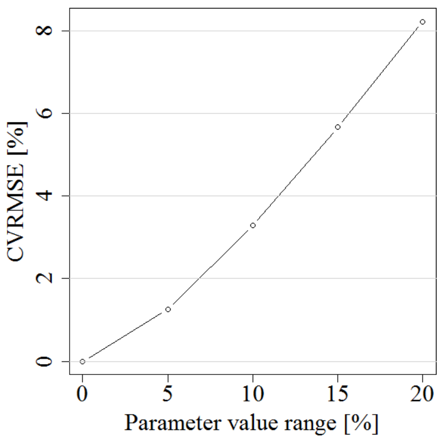

Figure 16: CVRMSE vs. parameter value range (window area fraction).

6. Conclusions

In this paper the aggregation method regarding building stocks has been evaluated. The following questions have been investigated: First, to what extent does aggregation affect the accuracy of results? Second, does the structure of the investigated district (i.e., the distribution of buildings with different properties within the district) have an effect on the magnitude of error? Third, is it possible to reduce aggregation error by aggregating the buildings by specific groups with respect to their properties, and finally, if this is so, which properties should be used to conduct the grouping? In order to answer these questions several simulation studies were carried out. For all simulations a first-order building model was utilized and the results therefore valid only for this particular type of model and are based on the reference building used.

The results in Section 3 show that an aggregated simulation of a district that includes buildings with varying values for their properties such as U-values, leads to errors. The results in Section 4 show that errors due to aggregation also depend on the structure of the aggregated district. Aggregation of a highly polarized district results in larger errors (CVRMSE: 13.8%) than one of more diverse districts (CVRMSE: 8.1% and 7.3%). It could also be seen that aggregating according to specific properties diminishes the error compared to a total aggregation. In the investigated scenario in Section 5, an aggregation according to the parameters *window area fraction, U-value of opaque surfaces* and *thermal capacitance* led to the lowest errors. However, we could also see in Section 5 that the error depends on the range of the parameter values. This means, if the aggregation method is to be applied without introducing large errors, the ranking in this paper can be used as an orientation, however the value range of the parameters should always be taken into account.

In order to overcome the limitations of this work, the following future research is recommended. First, additional parameters which are not examined in this study (e.g. g-values) should also be investigated regarding their importance for grouping. Second, the parameters should be assessed by applying a global method, where the interactions between the parameters are considered, and the results compared with the local method applied in this paper. Third, the study should be extended to non-residential buildings and to cooling load. Fourth, the aggregation method should be assessed for various district sizes in order to fully understand the relationship between the district or sample size and the inaccuracy incurred by a total aggregation. Finally, the aggregation method should be evaluated for other building models as well. The building models should vary in detail and also include building-to-building effects (shading and wind protection from neighboring buildings), since these effects are not considered in this study.

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