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ESTIMATING WINDOW DIMENSIONS OF RESIDENTIAL BUILDINGS IN DISTRICT ENERGY MODELS

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ABSTRACT

This work focuses on the impact of the window-to-wall ratio (WWR) on the energy demand for space heating and the building overheating through the evaluation of three WWR acquisition methods and four WWR allocation levels for a virtual district, containing 174 single-family dwellings. A new WWR acquisition method, based on a database, is proposed and evaluated. The impact of the WWR on the energy demand for space heating is limited (root mean square percentage errors up to 0.07), whereas the impact on the overheating is significantly higher (root mean square percentage errors up to 12.4). Both errors are higher for newer buildings compared to older buildings.

INTRODUCTION

Since the evaluation of individual buildings typically neglects synergy effects that result from the heterogeneity of the existing building stock, it is essential to assess renewable energy integration as well as energy efficiency measures at district level, e.g. by using district energy models. Through their rising popularity, geographic information systems (GIS) and geospatial data models are considered as a convenient source for building input data, resulting in more accurate building energy models on district level. Geospatial data models often contain valuable information on roof surfaces, wall surfaces and ground floor surfaces, but window surfaces are seldom included (Cerezo Davila et al., 2016), although automated methods for the estimation of window areas based on aerial photographs have been developed (Cao et al., 2015). Windows do not only affect the transmission heat losses but also the solar heat gains and seem therefore to be important to quantify the energy demand of a building.

Since window surfaces are often not modelled within geospatial data models, often a window-to-wall ratio, which is equal to the ratio of window area to the total façade area, is used as a measure. There are several options to define the WWR for a building stock. Firstly, in its most elaborate form, a different WWR can be defined per building and per orientation, as the orientation of windows strongly influences the calculation of the solar heat gains. Secondly, a different WWR can be defined per building. Thirdly, a different WWR can be defined per group of buildings (e.g. buildings from before 2000 have a WWR of 0.25 and buildings from 2000 onwards have a WWR of 0.35 (Perez, Kämpf, & Scartezzini, 2013)). Finally, in its most rough form, a WWR can be defined for a whole district. The required WWR allocation level depends on the focus of the study (e.g. to determine the local heat demand or to estimate specific overheating issues, a WWR per building per orientation might be required, whereas a WWR on district level might suffice to calculate the district heat demand). The WWR allocation level also depends on the deployed method to obtain the WWR.

Multiple approaches to obtain the WWR are found in literature and can be divided into two categories: survey-based methods and experience-based methods. Within the survey-based methods, the WWR is carefully collected on-site, such as in the study of Nouvel et al. (Nouvel et al., 2014) or from drive pass surveys, such as in the work of Jones et al. (Jones et al., 2001), or through photography analysis, such as in the study of Cerezo Davila et al. (Cerezo Davila et al., 2017) or through other visual surveys, such as in the work of Perez et al. (Perez et al., 2013). These survey-based methods allow to allocate a WWR on all four levels, but are all time- and resource-consuming, especially if they are performed for every building within the considered district. Nevertheless, they result in the most detailed description and thus in the most reliable district energy simulations. The survey can also only be performed for a representative sample of buildings, which decreases the effort but also the accuracy (e.g. based on a survey of 500 buildings of Zürich (Perez et al., 2013)).

Within the experience-based methods, the WWR is often defined as a fixed value on district level or per group of buildings, due to the lack of more detailed input data and/or resources to conduct a more in-depth analysis. This fixed value can be obtained by either using an empirical value, such as in the study of Agugiaro (Agugiaro, 2016), or using values from standards, such as in the work of Ghiassi and Mahdavi (Ghiassi & Mahdavi, 2017), or using an empirical range and random sampling, such as in the study of Talebi et al. (Talebi et al., 2017). These experience-based methods are cheap and universally applicable, but they may introduce a significant uncertainty and also only allow the WWR to be allocated per district or per group of buildings.

Efforts are made to reduce the uncertainty on the WWR within district energy simulations, which suggests that significant errors on the WWR result in a significant error on the heat demand quantification. However, Nouvel et al. (Nouvel et al., 2014) performed a parametric study of the WWR on district level and found that the uncertainty on the WWR led to a mean percentage error of less than ± 5% on the annual heating demand, but they also conclude that this result cannot be generalized as it depends on the climate amongst others factors. Strzalka et al. (2015) did a similar exercise, but they studied the impact of an unknown window type and an unknown WWR for only one building.

Within this context, while focusing on single-family dwellings, the goal of this paper is twofold. Firstly, a new, data-based method to obtain the WWRs of buildings within district energy simulations is presented. This new method results from a clustering analysis based on an extract from the Flemish Energy Performance Certificates (EPC) database and intends to decrease the data collection effort compared to survey-based methods but to increase the accuracy compared to experience-based methods. Secondly, the performance of this method is compared to the performance of both survey-based and experience-based methods, based on a virtual district of 174 buildings through the evaluation of the energy demand for space heating and the overheating risk (evaluated as exceeding time above 25°C). This comparison establishes the uncertainty that can be expected as a result of a particular WWR acquisition method and a particular allocation level.

In the next Section, the workflow for this study is discussed. Subsequently, the accuracy of the data-based method is presented and the comparison of all acquisition methods and their performance on the different allocation levels is introduced. Lastly, the conclusions are drawn.

METHODOLOGY

In this Section, the construction of the new data-based method is discussed first. Subsequently, the case to study all acquisition methods and all allocation levels is presented.

Construction of the data-based method

A data-based method is proposed to decrease the data acquisition effort compared to survey-based methods but to increase the accuracy compared to experience-based methods. Within the data-based method, the WWR is obtained through analyzing a dataset, containing detailed building geometry. For this study, the data-based method is based on the Flemish EPC database. Energy Performance Certificates inform consumers of the energy efficiency of buildings they plan to purchase or rent. The Flemish EPC database contains therefore all energy performance-related data of buildings (i.e. building type, construction year, building geometry, thermal performance of the building envelope, information on the heating, ventilation and air-conditioning systems, etc.). Within this work, ± 360000 residential buildings in Flanders were considered. The proposed data-based method is conducted as follows,

Step 1: Pre-processing of the database;
Step 2: Cluster analysis on the database;
Step 3: Statistical analysis on the clusters;
Step 4: Quality check of the clusters;
Step 5: Allocation of the sample buildings with the clustered results.

The first step is to standardize the data of the related variables and prepare for the clustering analysis. The *k*-means method is one of the most commonly used clustering methods (Hartigan & Wong, 1979). The *k*-means method iteratively refines the clusters and finally converges to a clustering result. It assigns *N* data observations in a space of dimension *i* to *k* separate clusters. The assignment of data points to a certain cluster *k* is based on the nearest mean using the Euclidean distance:

$$d(p,q) = \sqrt{\sum_{i=1}^{n} (q_i - p_i)^2}$$

The *k*-means method first randomly initializes *k* cluster centroids, and each point is assigned to the cluster with the closest centroid to the point, while the centroid is re-calculated in each cluster and the loop is repeated until the assignments no longer change clusters between two consecutive iterations.

As the *k*-means method requires the user to predefine the number of clusters *k,* the Elbow method is used for

determining the optimal number of clusters in the EPC database. The Elbow method looks at the total intra-cluster distance as a function of the number of clusters. The total intra-cluster distance in this analysis is defined as the sum of the distances between the centroid and all points in the cluster. The optimal number of clusters can be defined as follows:
Step 1: Compute clustering algorithm for different values of k;
Step 2: For each *k*, calculate the total intra-cluster distance;
Step 3: Plot the total intra-cluster distance as a function of the number of clusters, the optimal number of clusters is indicated by the bend or "elbow" in the plot - illustrating that the marginal reduction in total intra-cluster distance would significantly decrease by adding another cluster.
The cluster analysis and the corresponding statistical analysis of the clusters are performed by using STATISTICA software, and the detailed results are presented in the next Section.
In order to verify the quality of the clustering results, some additional numbers of clusters are assigned to re-calculate the total intra-cluster distance, and it is then plotted and checked visually by the Elbow method. Thereafter, sample buildings can be assigned to specific clusters based on the building type, construction year and protected volume, in order to obtain the average WWR for each building.

Introduction to the virtual district

To compare the survey-based, the experience-based and the data-based methods and their performance on the four allocation levels, a virtual district, composed of single-family dwellings in three virtual streets, was considered (Table 1). The first street consists of 51 terraced buildings that were constructed in the 1960s or 1970s and is referred to as TER_6070. The second street consists of 90 detached dwellings that were constructed in the 1980s and is referred to as DET_80. The third street consists of 33 buildings that were constructed between 2005 and 2011 and is referred to as ALL_05. All buildings are existing buildings in the City of Genk, as they originate from the Flemish EPC database. All required input data to perform dynamic energy simulations were taken from this database, except for the thermal properties which originate from the TABULA-project (TABULA, 2016) and are based on the construction year (the exact assumptions are given in the work of Protopapadaki et al. (2014)). To compare the different methods, the WWR was calculated with the survey-based, the experience-based and the data-based method and subsequently allocated to the virtual district. The exact workflow is now discussed more elaborately.
Within the survey-based methods, the WWR is normally surveyed carefully for the considered buildings. However, as the buildings for this study were taken from the EPC database for the City of Genk, the WWRs were not collected on-site, but they were calculated based on the geometrical information that is included in the EPC database. Within the survey-based methods, the WWR can be allocated on all four allocation levels (Table 2). In the most detailed case, the WWR is allocated per building and per orientation, which is considered to be the ground truth within this study. The WWR can also be specified on building level, by calculating the area-weighted average of the WWRs towards all orientations. The WWR can also be allocated per group of buildings (or per street in this virtual district), by averaging the WWR of all buildings within the group. In the least detailed case, the WWR is specified on district level, by averaging the WWR of all buildings within the district.

Table 1 Characteristics of the virtual district

<table>
<tr><th>VIRTUAL STREET</th><th>BUILD-ING TYPE</th><th>NO.</th><th>CONSTRUC-TION YEAR</th><th>U-VALUE WINDOW [W/m²K]</th><th>G-VALUE WINDOW [-]</th><th>U-VALUE WALL [W/m²K]</th><th>U-VALUE ROOF [W/m²K]</th><th>U-VALUE FLOOR [W/m²K]</th><th>AVERAGE U-VALUE [W/m²K]</th></tr>
<tr><td rowspan="2">TER_6070</td><td rowspan="2">Terraced</td><td>39</td><td>1960 ≤ year ≤1970</td><td>5.2</td><td>0.88</td><td>1.7</td><td>1.55</td><td>2.5</td><td rowspan="2">1.93</td></tr>
<tr><td>12</td><td>1971 ≤ year ≤1979</td><td>3.5</td><td>0.78</td><td>1.07</td><td>0.71</td><td>0.81</td></tr>
<tr><td>DET_80</td><td>Detached</td><td>90</td><td>1980 ≤ year ≤1989</td><td>3.5</td><td>0.78</td><td>1.07</td><td>0.71</td><td>0.81</td><td>1.01</td></tr>
<tr><td rowspan="5">ALL_05</td><td>Terraced</td><td>2</td><td rowspan="3">year = 2005</td><td rowspan="3">3.5</td><td rowspan="3">0.78</td><td rowspan="3">0.61</td><td rowspan="3">0.63</td><td rowspan="3">0.65</td><td rowspan="5">0.61</td></tr>
<tr><td>Semi-det.</td><td>3</td></tr>
<tr><td>Detached</td><td>6</td></tr>
<tr><td>Semi-det.</td><td>8</td><td rowspan="2">2006 ≤ year ≤2011</td><td rowspan="2">2</td><td rowspan="2">0.589</td><td rowspan="2">0.40</td><td rowspan="2">0.32</td><td rowspan="2">0.52</td></tr>
<tr><td>Detached</td><td>14</td></tr>
</table>

Table 2 Overview of the allocated WWRs to the virtual district, depending on the deployed acquisition method and allocation level. Mean WWR (μ) is allocated. Standard deviation (σ) is reported as additional information.

ALLOCATION LEVEL	GROUP OF BUILDINGS / STREET	ACQUISITION METHOD OF WWR					
		SURVEY-BASED *(In this study, based on EPC data for Genk)*		EXPERIENCE-BASED		DATA-BASED *(In this study, based on EPC data for Flanders)*	
		μ	σ	μ	σ	μ	σ
WWR per building per orientation		Ground truth		/		Possible extension of the proposed method	
WWR per building		Area-weighted average per building		/		Proposed method	
WWR per group of buildings	TER_6070	0.2224	0.0950	0.3000	0.0000	0.2495	0.0826
	DET_80	0.1453	0.0465	0.2000	0.0000	0.1631	0.0522
	ALL_05	0.1771	0.0980	0.2000	0.0000	0.1877	0.0739
WWR per district		0.1745	0.0823	0.2500	0.0000	0.1747	0.0682

Within the experience-based methods, an overall WWR is known from either experience or standards and no further in-depth analysis is performed. Therefore, the WWR cannot be specified per building nor per building per orientation (Table 2). The WWR can be allocated per group of buildings. In this study, the dwellings constructed before 1980 are considered to have a WWR of 0.3, whereas all other dwellings are considered to have a WWR of 0.2. These values are estimated based on knowledge of the Flemish building stock and the difference between these groups was confirmed by the Flemish EPC database. The WWR can also be allocated on district level (Table 2).

Within the data-based method, the WWR is allocated based on the analysis of a database containing detailed building geometry, in this study the Flemish EPC database is used, as discussed in the previous subsection. Depending on the depth of the data analysis, the WWR can be allocated on all four levels. To allocate a different WWR per building, the data-based method, as presented in the previous subsection, is used. To allocate the WWR per group of buildings, the average for this group within the Flemish EPC database was calculated (no. of TER_6070: 13816, of DET_80: 11422, of ALL_05: 6816). To allocate the WWR for the district, the average WWR of all single-family dwellings within the Flemish EPC database was calculated (no. of single-family dwellings: 215532).

All approaches are compared with a view to the energy demand for space heating and the overheating risk of the day zone (evaluated as exceeding time above 25°C) as key performance indicators (KPIs). Within this comparison, the WWR allocated per building per orientation and obtained through a survey-based method is considered as the reference (ref).

Subsequently, the root mean square percentage errors (RMSPE) for all other approaches are calculated as:

$$RMSPE_{KPI,appr} = \sqrt{\frac{\sum_{b=1}^{n}\left(\frac{KPI_{appr}^{b} - KPI_{ref}^{b}}{KPI_{ref}^{b}}\right)^2}{n}}$$

Description of the simulation model

To compare all WWR allocation methods and assess their influence on the energy demand for space heating and overheating, the different approaches were modelled in the IDEAS Modelica library (Jorissen et al., 2018), using detailed IDEAS building models to simulate the energy demand of the district.

The Integrated District Energy Assessment Simulations (IDEAS) library allows simultaneous transient simulation of thermal, control and electric systems at both building and district level. The IDEAS library supports detailed building energy simulations modelling transient thermal phenomena within the building using a zonal modelling approach, assuming perfect mixture of the air inside the zone. A detailed description of the IDEAS library is given in (Jorissen et al., 2018). An adapted version of TEASER (Remmen et al., 2017) is used to generate two-zone IDEAS building models, assuming that the ground floor represents the day zone while all the upper floors belong to the night zone. As this paper intends to assess the impact of different WWR allocation methods on the energy demand for space heating, each building is implemented with an ideal radiator heating system (Reynders, 2015) and no cooling nor a ventilation system. To calculate the ventilation losses, air infiltration is included (ACH for all buildings is set to 0.4). Opening of windows is however not considered. Occupant behavior is modelled following the ISO

13790 standard with an indoor air temperature set point for day zone and night zone respectively of 21°C/18°C in the occupied period, 18°C/20°C at night and 16°C/16°C in unoccupied periods and internal gains for day zone and night zone respectively 20W/m² / 1.857W/m² in the occupied period, 2W/m² / 6W/m² at night and 8 W/m² / 1.286 W/m² in unoccupied periods. The simulations are conducted for the heating dominated climate of Uccle (Belgium) for a period of 1 year. An initialization period of 1 month is used. Dymola is used to simulate the Modelica models using the Dassl solver with an output interval of 10 min.

DISCUSSION AND RESULT ANALYSIS

In this Section, first the accuracy of the proposed data-based method is discussed as a reference. Subsequently, the performance of all acquisition methods on the different allocations is compared.

Accuracy of data-based method

In the data-based method, the *k*-means clustering is performed for each building type separately, while considering 3 dimensions (building construction year, building protected volume and building average WWR) for each building type.
The Elbow method with *k*-means clustering has been used to determine the number of clusters for different building types. As a result, 6 clusters for terraced buildings, 8 clusters for semi-detached buildings and 8 clusters for detached buildings have been obtained. The statistics of the results of the clustering are presented in Table 3. Analysis of the results shows that newer and older buildings are usually clustered into separated clusters in all three different building types. Even though a few clusters in each building type have the similar range of construction year, the protected volume generally varies in different clusters. WWRs, therefore, can be assigned to different clusters based on the building type, construction year and protected volume. In the virtual district, the newer buildings, ALL_05, are clustered into cluster 6 of terraced building, cluster 7 of semi-detached building and cluster 2 of detached building. TER_6070, according to the protected volume, are assigned to cluster 1, cluster 5 and cluster 6 in terraced buildings. DET_80, according to the protected volume, are assigned to cluster 1, cluster 4 and cluster 6. The corresponding WWR for each building is then assigned.
It should be noted that, although additional tests using the Elbow method were conducted, the clustering results still might be improved. It is not always possible to identify the “elbow” unambiguously and future analysis is highly recommended for the presented data-based method to allocate the WWR on building level.

Table 3 Descriptive statistics of the clusters (number of buildings (No.), mean (μ) and standard deviation (σ))

	CLUSTER	SEMI-DETACHED			DETACHED			TERRACED		
		No.	μ	σ	No.	μ	σ	No.	μ	σ
WWR	1	9914	0.1765	0.0282	6663	0.2759	0.0477	13987	0.2523	0.0374
	2	13120	0.1168	0.0255	11206	0.1443	0.0301	8085	0.1990	0.0485
	3	11750	0.1910	0.0255	16520	0.1900	0.0239	12561	0.1953	0.0456
	4	5485	0.1190	0.0325	5976	0.1769	0.0472	13204	0.1408	0.0354
	5	8500	0.1141	0.0339	15278	0.1104	0.0261	7396	0.3474	0.0576
	6	9196	0.1557	0.0362	11320	0.1283	0.0288	6330	0.2083	0.0592
	7	3002	0.1731	0.0489	10524	0.1640	0.0328	/	/	/
	8	5933	0.2746	0.0456	7918	0.1021	0.0336	/	/	/
Protected Volume	1	9914	561.2	74.11	6663	612.1	181.64	13987	372.5	96.26
	2	13120	379.6	83.87	11206	745.6	110.52	8085	433.6	119.7
	3	11750	349.8	75.00	16520	466.3	104.22	12561	361.8	99.79
	4	5485	628.3	105.0	5976	1141.8	147.53	13204	416.2	102.9
	5	8500	355.3	83.60	15278	429.2	104.20	7396	484.3	121.5
	6	9196	489.1	109.9	11320	434.0	122.31	6330	782.3	174.6
	7	3002	927.9	167.9	10524	730.6	116.13	/	/	/
	8	5933	477.6	116.1	7918	502.3	194.25	/	/	/
Construction Year	1	9914	1963	11	6663	1979	14	13987	1952	12
	2	13120	1959	10	11206	1966	11	8085	1990	13
	3	11750	1966	12	16520	1970	10	12561	1920	12
	4	5485	1934	16	5976	1978	18	13204	1946	13
	5	8500	1925	12	15278	1957	8	7396	1973	18
	6	9196	1997	9	11320	1989	9	6330	1942	22
	7	3002	1972	25	10524	1994	8	/	/	/
	8	5933	1978	17	7918	1923	13	/	/	/

Table 4 RMSPE for all approaches compared to the ground truth (obtaining the WWR through a survey-based method and allocating the WWR per building per orientation)

ALLOCATION LEVEL	STREET	ACQUISITION METHOD OF WWR					
		SURVEY-BASED		EXPERIENCE-BASED		DATA-BASED	
		Energy demand for space heating [-]	Overheating of day zone [-]	Energy demand for space heating [-]	Overheating of day zone [-]	Energy demand for space heating [-]	Overheating of day zone [-]
WWR per building	TER_6070	0.0136	0.5094	/		0.0249	12.4040
	DET_80	0.0188	0.2337	/		0.0278	2.8143
	ALL_05	0.0437	0.2363	/		0.0675	0.8754
WWR per group of buildings	TER_6070	0.0180	2.8723	0.0250	8.3267	0.0191	4.4727
	DET_80	0.0236	0.6974	0.0244	1.7586	0.0231	1.0090
	ALL_05	0.0641	1.0471	0.0646	1.3557	0.0639	1.1851
WWR per district	TER_6070	0.0200	1.1316	0.0191	4.5054	0.0200	1.1358
	DET_80	0.0233	1.2227	0.0275	2.9760	0.0233	1.2266
	ALL_05	0.0643	1.0151	0.0745	2.1226	0.0643	1.0176

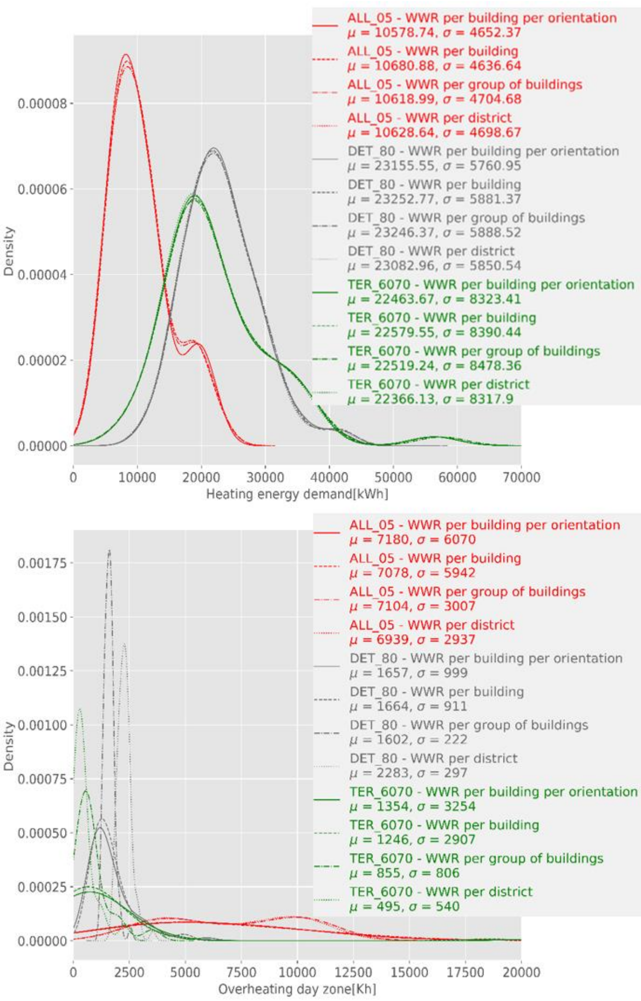

Figure 1 Kernel density plots for the three streets and the four allocation levels of the survey-based method

Comparison of survey-based, experience-based and data-based methods

In order to compare all survey-based, experience-based and data-based methods, they were applied to the virtual district on all possible allocation levels. Table 4 shows the resulting RMSPE for all approaches compared to the approach in which the WWR is obtained through a survey and allocated per building per orientation. In general, the impact of the WWR on the energy demand for space heating is found to be low (less than 0.07, which is in accordance with previous literature), whereas the impact of the WWR on the overheating risk of the day zone is substantial (up to 12.4) for this district. No cooling systems were considered within the simulations, since most Belgian houses do not have a cooling system. It should be noted that implementing shadings would reduce solar gains and therefore reduce the impact of the WWR on the energy demand for space heating. This was however not considered in this study, nor was night ventilation. Nevertheless, these measures could reduce the overheating substantially. Considering the high impact of the WWR on the overheating, the impact of the WWR on the energy demand for space cooling is likely to be significantly higher than the impact on the energy demand for space heating.

The mean percentage error is always lower than the RMSPE and is more representative for the average on district level, whereas the RMSPE represents the error on building level. The mean percentage error on the energy demand for space heating was limited to 2.4% in all cases, whereas the mean percentage error on the overheating was maximum 397% in all cases. The small deviations can also be explained by the small differences in allocated WWRs (Table 2), which are nevertheless representative for realistic estimation errors in Flanders.

When comparing the three acquisition methods, the data-based method generally deviates more from the reference than the survey-based method, but less than the experience-based method for all allocation levels except when the WWR is allocated per building. The risk of using a data-based method is the representability of the database (in this study: Flanders) for the considered district (in this study: the city of Genk). This issue in combination with the overall low impact of the WWR on the energy demand for space heating explains the increased errors for the WWR per building in the data-based method. Additionally, as previously discussed, the data-based method might be improved through further analysis.

Furthermore, as the WWR allocation level becomes less detailed, the RMSPE increases for both the energy demand for space heating and for the overheating of the day zone. This trend is more visible for newer buildings. Newer buildings are thus stronger influenced by both the WWR and the WWR allocation level. This can be partly explained since new buildings have higher insulation levels and are more sensitive to solar gains. In this study, extremely well insulated passive house buildings that are even more sensitive to solar gains were not considered. It is expected that the impact becomes more prominent when including them.

While focusing on the survey-based methods that are considered most truthful, Figure 1 compares the energy demand for space heating and the overheating risk of the day zone for the three streets and the four WWR allocation levels and allows to assess the influence of the different allocation levels. The most recent and thus best insulated houses (ALL_05) demand the least energy for space heating and overheat most. Although the detached houses of the 1980s (DET_80) have a better insulation quality than the terraced houses of the 1960s and 1970s (TER_6070), they demand more energy for space heating, not only because they do not have shared facades, but also because they are on average significantly larger than the terraced houses of the 1960s and 1970s. In general, the better the insulation level, the higher the overheating. Figure 1 illustrates that the impact of the WWR allocation level on the energy demand for space heating is low for all three streets. However, a significant error in the overheating is introduced by allocating the WWR in less detail for all three streets. The influence of the WWR allocation level on the overheating risk is thus important.

CONCLUSION

This work addresses the issue of allocating WWRs within district energy simulations. A literature review shows that both survey-based and experience-based methods are used to obtain the WWR and to allocate it on four different allocation levels (different WWRs per building per orientation, different WWRs per building, different WWRs per group of buildings and one WWR per district). This work presents a new method to obtain the WWR, more in particular a data-based method, based on the Flemish EPC database. All acquisition methods and their performance on the different allocation levels have been compared with a view to the energy demand for space heating and the overheating risk, based on a virtual district of 174 buildings.

In general, the impact of the WWR is found to be low for the energy demand for space heating (RMSPE of less than 0.07), but high for the overheating risk (RMSPE up to 12.4) for this district. The low impact of the WWR on the energy demand for space heating can be justified by the heating dominated climate of Uccle (representative for Belgium, the Netherlands and Germany) and the bad to moderate thermal performance of the buildings.

When comparing the three acquisition methods, the data-based method generally performs worse than the survey-based method, but better than the experience-based method. The data-based method can be a useful alternative thanks to its lower acquisition effort, but users should be aware of the risk that the database is possibly not representative for the considered district. The overall limited impact of the WWR acquisition method can also be justified by the small differences in allocated WWRs. Nevertheless, these differences are representative for realistic estimation errors in Flanders.

When comparing the four WWR allocation levels, the RMSPE increases for both the energy demand for space heating and for the overheating of the day zone as the allocation level becomes less detailed. Nevertheless, with a view to the energy demand for space heating, the impact of the WWR allocation level remains small, due to both the low influence of the WWR on the energy demand and the low standard deviation on the WWR within the considered district.

Based on this analysis, considering the heating dominated climate, the influence of the WWR on the energy demand for space heating appears to be low and the significant efforts of survey-based methods to obtain the actual WWR can be questioned. As the influence of the WWR is related to the specific climate and other factors, a case-specific sensitivity analysis is recommended before conducting a survey or analyzing a representative database.

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