ON THE INFLUENCE OF PARTY WALLS FOR URBAN ENERGY MODELLING

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ABSTRACT:

In the last 15 years semantic 3D city models have seen a steady growth in terms of creation and adoption. Many cities world-wide have now at least one city model which can be used for several applications. Energy- and sustainability-related topics are among those that have experienced a noteworthy increase of interest from the Geomatics community. 3D city models have become a steady component of Urban Energy Modelling, in which bottom-up approaches are developed to assess, for example, the energy efficiency of the building stock and to explore different scenarios of building refurbishment. Within this context, this paper focuses on investigating how much party walls can contribute to the energy demand estimation of a building. For this reason, two approaches to compute party walls are described and compared. The nature and the magnitude of their differences, as well as their possible impact on downstream applications, are considered in order to shed light on whether discrepancies in the amount of computed party wall area might lead to significant differences in terms energy demand of the residential building stock. The case study area is located in the Netherlands and encompasses the municipality of Rijssen-Holten.

1. INTRODUCTION

The growing availability of country-wide spatial data for the building stock is fostering the steady development of new approaches when it comes to Urban Energy Modelling (UEM) (Keirstead *et al.*, 2012; Sousa *et al.*, 2027). Instead of the "classical" top-down approaches, the trend is now to develop multi-scale bottom-up approaches where the starting point is the building. Virtual 3D city models, ideally based on open standards, have seen a growing popularity in the last decade as they can represent an integrated source of spatial and non-spatial information, which different applications can take advantage of. For example, the energy domain has seen a growing number of studies and advances in this regard, with particular attention paid to linking 3D city models with energy simulation tools to estimate or simulate the energy demand of the (residential) building stock (Agugiaro, 2016b; Remmen *et al.*, 2018).

In the case of the Netherlands, several country-wide open datasets (spatial and non–spatial) have been available for years now and have already been used to perform some energy-related studies. A major role is played by the BAG dataset, which contains 2D footprints[1] of all circa 9.5 million buildings in the country, and a selection of other attributes (e.g. address, year of construction, building function, etc.). In recent years, the 3D BAG has been released: the first version, released in 2019 (Dukai *et al.*, 2019), contained LoD1 geometries, while the most recent release, the 3D BAG v. 2.0, released in 2021, has added multi-LoD geometries up to LoD2 (Peters *et al.*, 2022). The 3D BAG is modelled according the international standard CityGML and its improved LoD concept (Biljecki *et al.*, 2016). In particular, LoD2 geometries are reconstructed and semantically enriched, i.e. it is possible to differentiate between the different types of surfaces composing the building envelope: GroundSurfaces, WallSurfaces, and RoofSurfaces. However, party walls between adjacent buildings are either semantically not differentiated, or not part of the current 3D BAG at all. An example for the former case is given by a two adjacent building completely sharing a WallSurface: the user cannot distinguish such WallSurfaces from the outdoor adjacent walls, i.e. those in contact with the air. An example of the latter case is given by two adjacent buildings sharing only a portion of the adjacent WallSurfaces: neither geometry not semantics are available to distinguish the surface "touching" another building from the one in contact with the air. It is currently up to the user to define and implement algorithms to compute them if needed, for example when performing energy simulations based on the building envelope. The paper presents, compares and discusses two different approaches to extract the party walls from adjacent buildings to address this gap.

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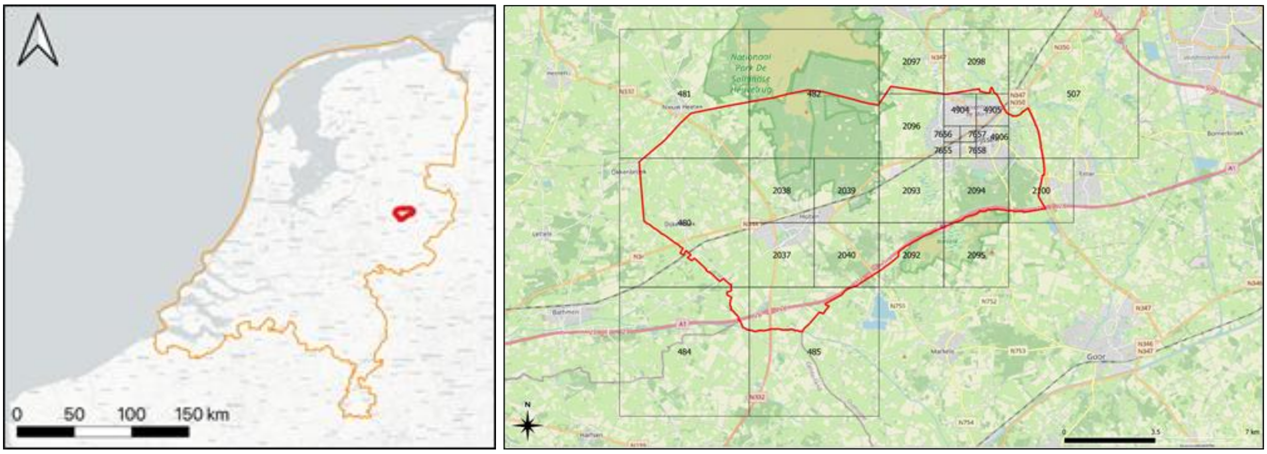

Figure 1. [Left] Overview of the study area, i.e. the municipality of Rijssen-Holten (highlighted in red), and its location in the Netherlands. [Right] Detailed view of study area and the 3D BAG tiles covering it.

1.1 Study area

Although the tests and comparisons were carried out on a dataset of circa 30.500 buildings, the aim of this research is to gain insight into the advantages and disadvantages of each method before scaling it up to the whole country. The test dataset refers to the municipality of Rijssen-Holten, in the eastern part of the Netherlands, and was obtained by integrating, enriching and further processing data from the 3D BAG, the BAG, and additional datasets. The geographical extent of the test area (divided into 25 tiles) is presented in Figure 1. It covers the whole area of the municipality of Rijssen-Holten and buildings from the nearby municipalities falling within the tiles. The data sources were harmonised and integrated to build a semantically enriched 3D city model. The dataset was previously pre-processed in terms of geometries, as described in (León-Sánchez *et al.*, 2021). Additionally, several energy-relevant properties were also computed and/or integrated (León-Sánchez *et al*., 2022):

- Following the CityGML model for buildings, building attributes are always available at building level. The only attributes available for building parts are the respective GroundSurface area and the volume of the LoD2 building envelope (if available)
- The available attributes for the buildings are:
  - The *Pand* ID (i.e. building ID, from the BAG)
  - Class of the building
  - Function(s): defined by means of the BAG *gebruiksdoel* values (in Dutch: usage function)
  - Number of floors above and below terrain (if this information is available)
  - GroundSurface area, in m^2
  - Gross volume (i.e. enclosed by the LoD2 thematic surfaces), in m^3
  - Information regarding their topology (e.g. free-standing or adjacent to other buildings), expressed by means of the number of adjacent buildings;
- For all thematic surfaces (i.e. Roof-, Wall and GroundSurfaces), attributes are extracted from the geometries and are:
  - Azimuth angle, in decimal degrees, measured counter-clockwise from North
  - Orientation, expressed as one of {N, NE, E, SE, S, SW, W, NW} values
  - Inclination (tilt) angle, in decimal degrees, measured from the horizontal plane upwards
  - Normal vector to the thematic surface, expressed by means of its 3 components (n_x, n_y, n_z)
  - Area of the thematic surface, in m^2.

Table 1 and Table 2 provide a general overview of the dataset in terms of buildings and thematic surfaces, respectively.

Buildings	Count	%
Number of buildings	30448	100.0%
of which:		
• only in LoD0	886	2.9%
• up to LoD2	29562	97.1%
- Single-part LoD2 building	29505	96.9%
- Multi-part LoD2 building	57	0.2%
• Free-standing building	17058	56.0%
• Non-free-standing building	13390	44.0%
• Residential building	14489	47.6%
• Mixed-use building	1235	4.1%
• Non-residential (single function)	9787	32.1%
• Non-residential (multi-function)	200	0.7%
• Of unknown class	4737	15.6%

Table 1. Overview statistics of the Rijssen-Holten dataset in terms of buildings.

LoD2 thematic surfaces	Count		Area	
	n	%	m^2	%
Total	672129	100.0%	15834612.46	100.0%
of which				
• GroundSurface	29624	4.4%	4484810.56	28.3%
• RoofSurface	94237	14.0%	5118210.27	32.3%
• Ext. WallSurface	548268	81.6%	6231591.64	39.4%

Table 2. Overview statistics of the Rijssen-Holten dataset in terms of thematic surfaces, before the computation of the party walls.

2. COMPUTATION OF PARTY WALLS

Two different approaches have been implemented and compared to compute of the area of the party walls, in order to get insight in the pros and cons of each method, both in terms of accuracy and computation time. For example, first, the less time-intensive 2D & 3D "hybrid" approach (in the following also called simply "Hybrid"), which in our test dataset took approximately 4 minutes to complete, might represent an acceptable solution whenever accuracy can be traded off for quicker computation time, if compared to the circa 11 minutes required for the second, fully 3D approach. More details regarding each approach will be given in the next subsections. Nevertheless, besides the differences in computational time, this research attempts to shed light on the nature and the magnitude of these differences and their possible impact on downstream applications. Furthermore, it is relevant to investigate whether discrepancies in the amount of computed party wall area might lead to significant differences in terms of results when computing the energy demand of the residential building stock. More details will be given in section 3.1.

2.1 2D & 3D "hybrid" approach

The first method uses the (LoD2) 3D BAG 3D dataset and combines a 3D approach for calculating the areas of semantic surfaces with a 2D approach to identify and assess the area of shared walls between two adjacent building units. First, the 3D BAG data are retrieved as CityJSON tiles, which contains the 3D building geometries classified as semantic surfaces. Then the area of all 3D planar polygons is computed via a Python code. Then, surface areas for all the semantic surfaces of the buildings are aggregated, resulting in the total wall, floor and roof surface for each building. The next step is to identify the party walls. This operation is carried out using the LoD1.2 building geometries of the 3D BAG to identify where the footprint of adjacent buildings touch. Combining the length of the border overlaps between two buildings with the 50 percentile height information from the LoD1.2 model, the percentage of overlap between the total wall surfaces of two neighbouring buildings is estimated. Finally, in the last step, the previously computed percentage value is applied to the wall surface areas from the LoD2 model, resulting in a rough but quick estimate of the party wall surface area between adjacent buildings. In total 12221 residential buildings were processed using this "hybrid" approach. They were further integrated with information regarding the number of dwellings (e.g. apartments) for each building, resulting in 14704 dwellings. Due to different versions (e.g. temporal misalignments) of the underlying source data of the 3D BAG, the dwelling database (CBS, 2021) and the LoD1.2 3D BAG data, coupling these data resulted in a loss of 1.1% of dwellings. However, this data loss can be considered negligible for the later analyses.

The 2D & 3D hybrid approach is expected to introduce an error in estimating the surface area of party walls due to the usage of the 50 percentile height information of the LoD1.2 version of the 3D BAG. Using the 50 percentile, height information provides a singular estimate of the vertical dimension per building, though in practice using only one value to express the height of a dwelling may in many cases may deviate greatly for the actual height profile. Furthermore, utilising just the percentage of footprint perimeter in common between two adjacent buildings provides no detailed spatial information regarding the position of party wall. Additionally, tolerance values are included in the algorithm to tackle possibly slightly overlapping or disjoint footprint polygons. Table 3 lists the tolerance parameters used for this approach.

2.2 Fully 3D approach

The second method follows a purely 3D geometrical multi-step approach and uses the 3D city model "as is", but stored in a 3D City Database (Yao *et al.*, 2018) instance. It is based on and improves the approach mentioned in (Agugiaro, 2016a). In order to reduce the number of buildings (and the respective WallSurfaces) to be tested, only those buildings that are non-free-standing, i.e. have a number of adjacent building greater than zero, are selected. This means that only circa 43% of all buildings (i.e. 13129 out of 30448) were processed, therefore speeding up the whole process.

For each building, the WallSurfaces adjacent to those of another building are selected and a geometrical intersection is carried out in 3D. The resulting polygon (or polygons) are then stored and classified as "Party WallSurface(s)". In Figure 2 they are represented in red. The remaining polygon(s) of the intersection are then stored as "(external) WallSurfaces" and, in the same Figure, are represented in blue. All newly created 3D polygons are checked for validity. Additionally, area, azimuth, direction and surface normal are also computed for all newly generated 3D polygons. Extremely small polygons with an area value smaller than 0.0001 m^2 are ignored and not stored. The same operation is then repeated tile by tile and for each selected building. Figure 2 presents a 3D visualisation of a set of buildings computed within the same tile. The colour coding is the same as mentioned before.

In order to cope with errors that may occur in fully automatically generated datasets (such as the 3D BAG), some tolerance values were included in the developed algorithm. "Typical" problems are:

- Slightly overlapping (or disjoint) polygons (in theory the footprints of adjacent houses should be perfectly adjacent)
- Footprint polygons with "spikes" or particularly irregular shapes
- Not perfectly coplanar polygon geometries
- Not perfectly vertical walls
- Wrongly oriented vertical walls (e.g. surface normal vectors wrongly pointing "inside" the building instead of outside)
- Not perfectly parallel walls between adjacent buildings.

The tolerance values listed in Table 4 were used in this work.

Once the computation of the party walls was completed, the resulting values of area for all WallSurface geometries were aggregated and compared, at building level and for the whole dataset. For each building, the total sum of WallSurface area

Parameter name	Value	UoM	Description
Min. "touch" length for perfectly adjacent buildings	>0	m	For all "perfectly" touching building footprints (no overlaps, no gaps), any segment corresponding to the intersection of the two polygons with a length greater than 0 is used for computation of party walls.
Geometry buffer for nearly adjacent footprints	0.05	m	Maximum distance between two nearby building footprints polygons to classify adjacent walls was party walls.
Min. "touch" length for nearly adjacent buildings	0.3	m	Minimal length of segment resulting from the intersection of the polygon perimeters of two nearly adjacent buildings to compute a party walls.

Table 3. List of tolerance parameters used to compute the party walls with the 2D & 3D hybrid approach.

Parameter name	Value	UoM	Description
side_reduction_epsilon	0.05	m	Distance from the footprint vertices to look for adjacent walls
side_width_epsilon	0.01	m	Max side distance to look for adjacent walls
area_tolerance	0.0001	m^2	Minimum area accepted
collinearity_angle_epsilon	4.0	° (dec. degrees)	Maximum angle in order to consider two non-collinear vectors as collinear

Table 4. List of tolerance parameters used to compute the party walls with the fully 3D approach

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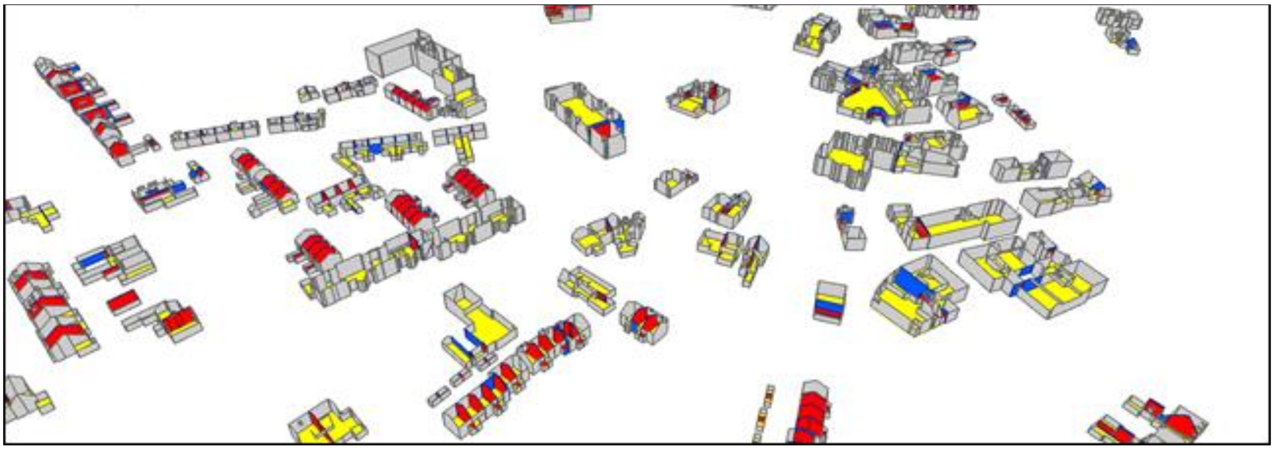

Figure 2. Example of 3D visualisation of the 3D city model after the computation of the party walls. GroundSurfaces are represented in yellow, WallSurfaces in grey. In case of adjacent buildings, the party walls are represented in red, while the non-shared part is represented in blue. RoofSurfaces are not shown.

before and *after* the computation of the party walls was compared, the difference being – ideally – always 0. Values were compared in terms of absolute differences (in m^2) and relative (in%). At building level, Table 5 contains the maximum (i.e. >0) and minimum (i.e. <0) differences, as absolute and relative area differences, respectively. The same test was carried out for the whole dataset. Results are shown in Table 6. Globally, the overall WallSurface area difference before and after the computation of the party walls yields only -0.03 m^2, which corresponds to -5.2*10^{-7}%. In both cases, it can be seen that the area differences *before* and *after* are rather negligible, at least considering the scope for which these geometries and values were computed.

	WallSurf. area [m^2]		Difference	
Building Pand ID	Before	After	[m^2]	[%]
1742100000006559	206.837	206.838	0.0012	0.0006
all other buildings	...	...	...	...
1735100000056783	189.323	189.322	-0.0006	-0.0003

Table 5. Comparison of WallSurface area before and after the computation of the party walls. Analysis at building level.

WallSurf. area	Before	After	Difference (after-before)	
	m^2	m^2	m^2	%
Total	6231591.64	6231591.61	-0.03	-5.2*10^{-7}%
of which				
Ext. WallS.	6231591.64	5413005.64	-818586.00	-13.1%
Party WallS.	0	818585.97	818585.97	N/A

Table 6. Comparison of WallSurface area before and after the computation of the party walls. Analysis at dataset level.

2.3 Comparison of the party walls results

For both approaches, once the computation of the party walls was completed, a comparison was carried out on the residential buildings within the municipality of Rijssen-Holten (i.e. 12221 out of 14489 in the whole dataset, cfr. Table 1). All other buildings (e.g. non-residential ones) were left out at this state of the work, as they are not used in the later computation of the energy demand. In particular, the resulting values of area for each class of geometries composing the building envelope were aggregated for the whole dataset and compared. Later on, major differences at building level were identified in order to better understand the pros and cons of both methods and foresee further sources of errors. Looking at the whole dataset, the first comparison was carried out in terms of number of residential buildings identified as adjacent and for which party walls were computed. The results from the fully 3D approach was used as reference. Table 7 presents the success rate as number of adjacent buildings for which party walls were computed in both approaches and, vice-versa, the cases where the process did not work (and the reasons of success or failure). Overall, the "hybrid" approach identified circa 98% of the adjacent buildings compared to the fully 3D approach. For the second comparison, the composition of the building envelope of an "average" residential building in Rijssen-Holten was computed by averaging all surface area values (according to the corresponding class: exterior walls, party walls, etc.). The same operation was carried out the with result of both methods. Table 8 contains the results and allows for comparison between the two approaches. Globally, the "hybrid" approach computes circa 5% less envelope surface. The differences in terms of average floor and roof surfaces are negligible, in both cases the relative difference is -0.16%. However, differences are larger when comparing the values of exterior and party wall surfaces. Compared to the fully 3D approach, the "hybrid" approach overestimates by circa 3% the area of the exterior walls. But of particular relevance is the underestimation of circa 40% of the party walls. This difference is considerable and is not fully compensated by the overestimation of the external wall surfaces. One of the reasons for these results might be an indication that utilising LoD1.2 average building height information to estimate the surface area of the party wall leads to such a negative bias.

Looking at the distribution of the differences in surface areas provides further information on how the two approaches differ. Figure 3 shows these differences in two histograms for external wall and party wall surface areas, respectively. This figure emphasises the earlier observation that the "hybrid" approach, on average, overestimates external wall surface areas while underestimating party wall surface areas – though for both thematic surfaces the opposite also occurs. Table 9 provides additional insights concerning the percentage of the total "hybrid" appraoch results that deviate no more than a given percentage from the fully 3D approach results. The table reveals that roughly 36% of external wall "hybrid" approach estimates differ no more than 1% from the fully 3D approach, while 94% fall within 25% deviation. Conversely, merely 2% of "hybrid" approach results differ no more than 1% from the fully 3D approach. Moreover, no more than 64% of by the "hybrid" approach computed party wall surfaces deviate less than or equal to 50% from the fully 3D approach.

Success rate	Count	%
Success: adjacent buildings, and party walls computed with both approaches	8081	66.1%
Success: Non-adjacent buildings, no party walls computed with both methodologies	3905	32.0%
Failure: Failed to identify adjacent buildings, no party walls computed with "hybrid" approach	163	1.3%
Failure: Failed to identify adjacent buildings, party walls computed with "hybrid" approach where there are actually none	72	0.6%

Table 7. Success rate of identifying adjacent buildings and computing party walls with the 2D & 3D hybrid approach.

	Surface area [m^2]				
Approach	Ext. wall	Party wall	Roof	Ground	Tot
"Hybrid"	201.43	50.15	133.37	108.49	493.44
Fully 3D	195.59	83.40	133.57	108.66	521.22
Diff. (%)	2.98%	-39.87%	-0.16%	-0.16%	-5.33

Table 8. Comparison of the building envelope composition of an average residential building in Rijssen-Holten.

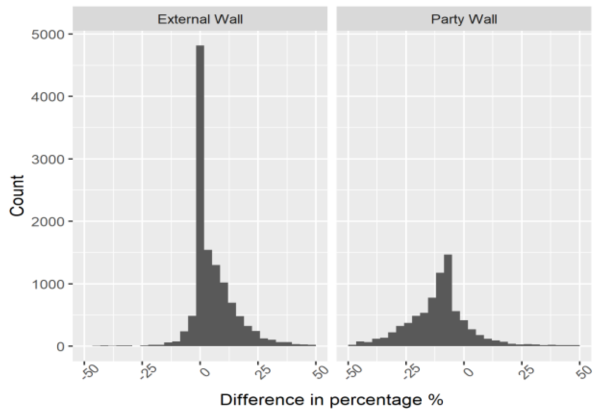

Figure 3. Distribution of the difference (in %) between the estimates of the external wall surface areas (left) and the party wall surface areas (right). Differences are between the hybrid and the fully 3D approach.

	Maximum area difference. Up to…			
	...1%	...5%	...25%	...50%
Ext. walls	36.4%	56.0%	94.0%	98.6%
Party walls	2.0%	10.1%	54.1%	64.2%
Roof	99.8%	99.8%	99.9%	99.9%
Ground	99.8%	99.8%	99.9%	99.9%

Table 9. Population percentage of the thematic surface areas computed with the hybrid approach that deviate respectively at maximum 1%, 5%, 25% and 50% from the corresponding results of the fully 3D approach.

Finally, in order to facilitate data exploration and visual analysis, building-level attributes were attached to the 3D city model geometries and visualised (e.g. in QGIS). An example of a 2D view is given in Figure 4. In this way, some outliers or particularly "critical" buildings could be identified and checked, also visually, in order to reason on and understand what the reasons for such particular large deviations might have been. An example of some of the most problematic buildings is presented in Table 10 and an example of detail view is given in Figure 5.

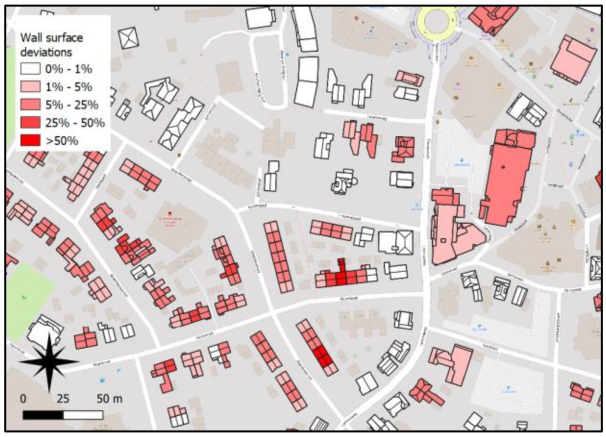

Figure 4. 2D visualisation of the wall surface deviations (in %) between hybrid and fully 3D approach.

	Roof surface area [m^2]		Ground surface area [m^2]		Exterior wall surface area [m^2]	
Building Pand ID	Hybrid	Fully 3D	Hybrid	Fully 3D	Hybrid	Fully 3D
1742100000009131	0.01	71.87	0.00	50.83	1.06	174.47
1742100000001657	**3.67**	**1708.3**	**0.00**	**1363.2**	**68.89**	**1072.6**
1742100000013944	14.01	85.43	11.45	69.91	37.41	218.7
1742100000004411	17.33	81.99	14.30	70.43	44.19	213.30
1742100000005071	18.51	71.31	15.44	61.52	49.29	177.49
1742100000006296	16.52	110.9	15.89	97.06	31.43	206.67
1742100000000588	18.83	24.73	18.83	24.65	127.7	156.32

Table 10. Some outliers in computation of thematic surface areas.

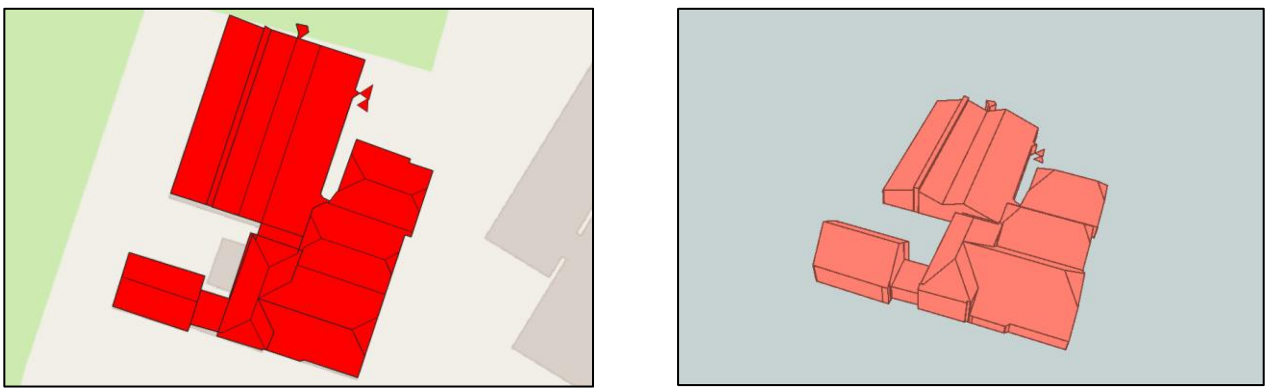

Figure 5. 2D and 3D representation of building with Pand ID 1742100000001657 (highlighted in **bold** in Table 1).

3. ENERGY DEMAND COMPUTATION

The set of results from both methods were used as input to estimate the energy demand of residential buildings in the municipality of Rijssen-Holten. For this purpose, a beta version of the energy model Hestia was used. Hestia is an energy simulation model, currently under development at the Netherlands Organisation for Applied Scientific Research (TNO) and the Netherlands Environmental Assessment Agency (PBL). It allows to evaluate effects of policy measures and other external influences on the built environment. One of the key functionalities is to calculate the energy demand of a building as a product of varying circumstances. Although, at the time of writing, there is still no documentation publicly available, its model architecture is based on the predecessor Vesta MAIS, for which its functional design is available (van der Molen *et al.*, 2021).

Hestia performs a yearly heat balance calculation, where the sum of a diversity of heat losses and heat gains result in the yearly energy demand. Herein, thermal transmittance through building unit surface areas plays a key role, which allows to compute the aggregated values of yearly energy demands for all residential buildings in Rijssen-Holten. In order to perform simulation runs in Hestia – and consequently assess the energy demand for dwellings as a result for the two approaches detailed in this study – the thematic surface areas as a result of the earlier exercise are altered in a number of ways in order to facilitate its use in the Hestia model. Firstly, wall and at places roof surface areas are further detailed by identifying additional thematic surface areas, such as window and door surface areas. These thematic surface areas have been semi-randomly processed, based either on average values or the distribution according to the relation between the total building envelope and these individual thematic surfaces, depending whether or not a trend is observable between these factors. This processing was applied for various dwelling types separately and were based on via the 2D & 3D hybrid approach computed values. Thereby, a slight bias is introduced for the fully 3D approach computed values, though we estimated this effect would be marginal. Secondly, the surface area data is disaggregated from building unit to residence unit level. This disaggregation is especially relevant for buildings that house multiple dwellings, such as apartment buildings. This disaggregation is executed by means of an algorithm that systematically divides a compound residential building into a plausible division of individual residential units, based on data available in the VBO database regarding the composition of these buildings. The resulting division details the location along vertical and horizontal axes of individual residential units, dictating the amount of adjacent dwellings above, under or next to a given residential unit. The relative location of residential types provides information regarding the relative amount of diabatic and adiabatic surface area of its building envelope. Thirdly, for each thematic surface area, a measure for its thermic resistance is assumed. The values assumed for thermic resistance is based on an analysis of the Statistics Bureau of the Netherlands' dataset "WoON 2018" – a dataset that is representative for the Netherlands as a whole (CBS, 2019). From the WoON 2018, the distribution of thermal resistance values is mapped for various dwelling building types and "energy labels" – an overarching measure of a dwelling's energy performance. This distribution is reproduced for the entire residential building sector, by randomly assigning each dwelling of a given dwelling type and energy label in such a way that it results into a plausible set of thermal resistances for each thematic surface that reflects the distribution found in the WoON 2018.

In the end, the energy demands calculated with Hestia is the theoretical energy demand for space heating as a result of heat transmittance through the sum of the diabatic thematic surface areas (i.e. roof, ground and exterior wall surfaces, in our case). Thereby, the resulting energy demand does not account for factors such as a measure of efficiency of a space heating installation. As reference year, the year 2020 was selected in Hestia to determine the theoretical energy demand. Consequently, the absolute energy demand is subject to meteorological conditions of that year, though the relative energy demand between dwellings should be mostly unaffected by this choice.

3.1 Comparison of the energy demand results

Results, this time in terms of energy demand, were compared and analysed at different levels. The goal is to understand whether (and, to which extent) the differences in terms of party wall area influence the energy estimation by an energy model such as Hestia. By default, energy demand is met in Hestia completely by gas usage, hence the two terms are used interchangeably in this results section.

Figure 6 show the differences in gas usage in GJ/a for buildings, derived from both approaches, as calculated by Hestia. Overall, the energy demand as a result of two different datasets for thematic surface areas are similar – with an overall difference of 0.05% for Rijssen-Holten as a whole. Beyond that, the graph in Figure 6 shows a tendency for the hybrid approach to estimate a higher energy demand as compared to the fully 3D methodology. This is likely a result of the on larger average estimate of the external wall surface by the hybrid approach. The on average considerably larger estimate for party walls are in this exercise inconsequential, since adiabatic surfaces are not considered at all in Hestia.

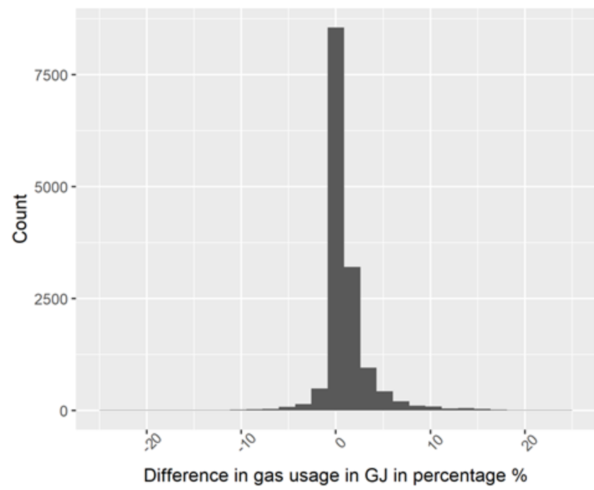

Figure 6. The distribution of the difference in percentage between the by Hestia calculated yearly energy demand in GJ, as a result of subtracting energy demand associated with the fully 3D approach results in from the energy demand associated with 2D & 3D hybrid approach results.

Looking at the difference between energy demand results for various dwelling types reveals that the error margin between the two results is not homogenous among dwelling types (Table 11). The results for semi-detached, corner and terrace houses are on average overestimated using the hybrid approach, while detached houses are on average underestimated. When the distribution of the difference in energy demand is taken into account, it becomes

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apparent that the underestimation of energy demand for detached houses by the hybrid approach is caused by a series of outliers (Figure 7). Multi-residential unit compound buildings – in this section also referred to as apartment buildings – have a very similar energy demand, regardless of which approach is used for computing thematic surface areas

At building level, a similar analysis (both quantitative and visual) was carried out in a similar way a described before in order to spot the major discrepancies in terms of energy demand between the two approaches. Figure 8 presents an excerpt of the map (obtained in QGIS) representing such differences between the two approaches.

	Energy demand (GJ/a)					
	Avg	SD-H	CH	AB	TH	DH
Hybrid	90.43	96.51	73.24	54.56	59.43	155.28
Fully 3D	90.47	95.49	72.54	54.61	57.95	157.99
Diff.	0.05%	-1.07%	-0.96%	0.09%	-2.54%	1.72%

Table 11. Comparison of the yearly energy demand values (in GJ/a) from Hestia for semi-detached houses (SDH), corner houses (CH), apartment buildings (AB), terraced houses (TC) and detached houses (DH).

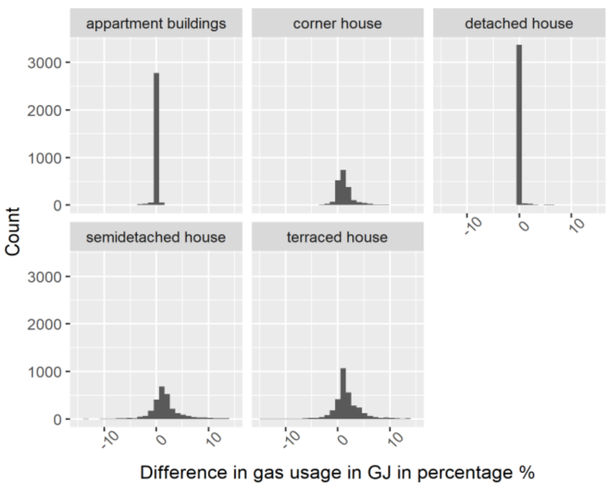

Figure 7. Distribution of the differences (in %) between yearly energy demand of the five dwelling types. Differences are between the hybrid and the fully 3D approaches.

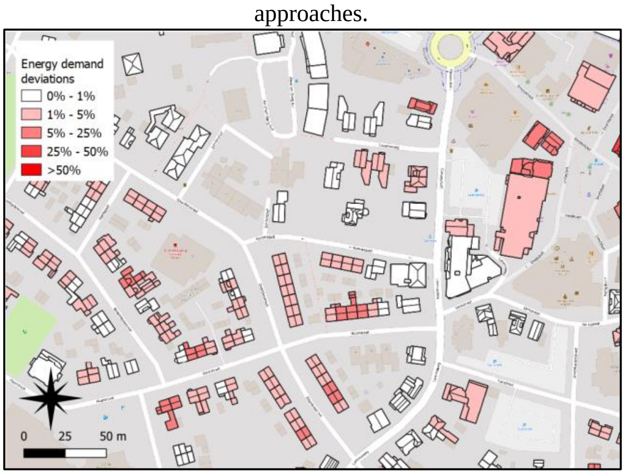

Figure 8. 2D visualisation of the energy demand deviations (in %) between hybrid and fully 3D approach.

4. CONCLUSIONS

In the context of Urban Energy Modelling (UEM), first steps were done in this paper towards a deeper understanding of the role played by party walls when performing city-wide energy demand estimations. Two methodologies to compute party walls were implemented and compared using the 3D city model of a Dutch municipality as test area. The goal was, among the rest, to gather insight in the process and the results before scaling up the methodology to the whole country.

The results so far show that:

- Both approaches result in negligible differences among floor and roof surface area estimates
- The 2D & 3D hybrid approach results in a limited overestimation of the external wall surface area, as compared to the fully 3D methodology
- The 2D & 3D hybrid approach results in a non-negligible underestimation of the party wall surface area, as compared to the fully 3D methodology
- The resulting energy demand from the Hestia model as a result of the two different approaches is highly comparable, largely due to the difference in party wall surface area not being taken into account by the model. This is however a current limitation of the Hestia model and other simulation software tools might lead to difference results.
- The differences in energy demand that can be found differ among dwelling types, where terraced houses, corner houses and semi-detached houses deviate more among the two approaches than detached houses and multi-residential unit compound buildings.

Therefore, we can say that:

- If the total exterior building envelope is the most relevant object of investigation, both approaches provide similar results. However, if the party walls are relevant, a substantial underestimation by the hybrid approach is to be expected.
- Though seemingly minimal, both approaches result in slightly different energy demand according to the Hestia model. Furthermore, this difference is heterogeneously distributed among dwelling types, with a potential bias as a result.
- The less computationally intensive 2D & 3D hybrid approach might be preferred once its limitations are clear.
- However, the fully 3D approach has the advantage of delivering more accurate results. Additionally, all results are directly integrated back into the 3D city model, therefore they can be reused more easily for other applications that might be energy-related, or not.

Given the current results from this first set of first experiments, it is clear that more tests, especially with other UEM simulation tools, need to be carried out and compared. This is also the reason why the 3D city model of Rijssen-Holten is being prepared to be released as an open-data benchmark dataset (León Sánchez *et al.*, 2022), in order to offer, also to other colleagues in the energy community, the possibility to test, compare and assess their tools in a more homogeneous way.

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