AN ENHANCED SAMPLING-BASED APPROACH TO URBAN ENERGY MODELLING

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ABSTRACT

The building energy performance simulation community is increasingly concerned with the assessment and evaluation of not only single buildings, but large assemblies of built structures in the urban context. Thereby, a fundamental challenge involves the identification of a proper balance between the spatial scope of the modelling domain and the resolution of the individually represented entities in the model. For high resolution assessments, the modelling domain extent needs to be reduced. In this context, the present contribution explores the potential of a systematic modelling approach that relies on sampling, supported by cluster analysis and based on energy relevant building charachteristics.

INTRODUCTION

More than half of the world’s population lives in urban areas; this ratio is nearly 75% in the European Union (World bank 2015), as such, cities must now be considered the principle human habitat. The sustainability discourse has been increasingly focused on the idea of sustainable urban environments and portraying the city as more than just the sum of its various elements. The concept of the Smart City as a web of intertwined and interacting sub-systems and elements has emerged from this paradigm shift. Accordingly, the building energy performance community is more and more concerned with the assessment and evaluation of not only single buildings, but large assemblies of built structures in the urban context and their potential interactions. Such large-scale urban/neighborhood energy models are required, for instance, in inquiries pertaining to urban energy grids involving distributed energy generation and delivery.

Toward this end, multiple approaches are being developed and implemented. Comprehensive analyses of urban energy modeling techniques and methods for various purposes has been done by Swan and Ugursal (2009), Kavgic et al. (2010), and Yeo et al. (2013). In this context, bottom-up Engineering Models (EM) (Swan and Ugursal 2009), which rely on information on buildings and use characteristics to calculate the energy consumption based on heat transfer and thermo-dynamic principles, are the most promising. EMs are relatively independent from historical data, highly flexible and capable of investigating unprecedented technological advances and climatic or behavioral changes.

The present research effort, focuses on the development of a framework for a building performance simulation-supported EM. Thereby, due to the high informational and computational demand of building performance simulation, a fundamental challenge involves the identification of a proper balance between the spatial scope (extent) of the modelling domain (i.e. the size of the urban segment considered) and the resolution (level of detail) of the individually represented entities in the model. In other words, a very large spatial scope may render the deployment of detailed dynamic building simulation codes infeasible. Hence, if high-resolution and dynamic simulation is required (as in the case of Smart Grids), the modelling domain extent needs to be reduced, either by focusing on smaller areas, or by conducting a proper sampling.

Representation of the urban building stock through sample buildings or archetypes is not a new venture. However, a review of some contemporary sampling-based energy assessment methods and their adopted sampling criteria (the set of building attributes intended to characterize the energy-relevant features of the building population) revealed a frequent lack of explicitly stated arguments, evidence, or reasoning in support of the selected criteria. Moreover, in most previous classification and sampling schemes, buildings are treated as isolated entities and their urban context is ignored. Due to the significant implications of the immediate boundary conditions on the building’s performance and the high sensitivity of energy demand to aspects such as available solar gains, such approaches may not lead to a realistic representation of the urban building stock. The present contribution explores the potential of a systematic modeling approach that relies on multivariate cluster analysis, MCA, (Hair et al. 2010) for the selection of a representative sample from a typical neighborhood in the city of Vienna, Austria. Using available GIS data, Austrian norms and standards, and relevant literature, buildings are represented by a set of attributes that have a large impact on heating energy demand. An agglomerative clustering method is then used to group buildings into homogeneous clusters or types based on the assumption that similarity in the selected attributes leads to similar energy behaviour. Representative buildings are then selected from each of the resulting building clusters to create a representative sample of the neighborhood in terms of heating energy demand.

The following sections include a review of previous research efforts towards sample-based urban energy modeling, cover details of the implemented method and offer a discussion on the results and future research intentions.

BACKGROUND

As mentioned before, various research efforts have been made to address the challenge of building classification and sample-based energy modeling.

At the European level, the TABULA project (Tabula 2015) has identified residential building typologies across 13 European countries involved in the project. These types are defined based on the construction period and building size ("single family houses", "terraced houses", "multifamily houses" and "apartment blocks"). In Austria, 28 types are defined based on four size categories and seven construction periods (Amtmann 2010). However, these types are neither intended nor suitable for urban-scale design or intervention oriented inquiries, as they fail to capture the diversity of urban building stock with an acceptable precision.

In Orehounig et al. (2011) two approaches have been adopted to estimate the energy consumption of a village (of about 100 dwellings). In a first attempt, buildings are categorized based on usage and vintage. Generic archetypes representing these types are modeled and simulated and the results extrapolated to the entire village. In a second attempt, all buildings were modeled in detail and simulated. Results of both models were compared to measured data. The simplified archetype-based results deviated from the actual values by 25%, whereas the detailed model showed an error of approximately 8%. However, due to the high computational and informational demand of the latter procedure, its scalability for urban-scale studies is doubtful.

Jones et al. (2001) employ a cluster analysis method to identify building classes according to variables such as exposed surfaces, glazing ratio, and built form. In this effort, construction period is used, not as an implicit classification criterion, but to determine certain variables such as component U-values, which are in turn used as clustering criteria. In Sansregret and Millette (2009) basic information including the year of construction, main building usage and floor area, location and main heating energy carrier are used to define archetypes. Other characteristics of these archetypes (e.g., glazing ratio, systems, etc.) are statistically determined and automatically supplied to a simulation engine for assessments.

In an attempt to develop a GIS-based, simulation supported energy model of a small town, Page et al. (2014) also, propose a typology of buildings based on vintage and usage. The relevance and significance of these criteria are then examined through sensitivity analysis. In the analysis, however, each construction period is associated with a "unique total U-value of the building envelope". Although U-values of various components of buildings of the same construction period may be reasonably assumed to be similar, the effective average U-value of the thermal envelope depends on component areas and adjacencies (relative to neighboring buildings). In other words, this analysis demonstrates the relevance of the average envelope U-value in the definition of types, and not necessarily that of the construction period. The same study points out the importance of the building's urban context, adjacencies and obstructions in the thermal performance of the building, but does not include such factors in the development of building types.

Table 1 offers an overview of the consulted models and the various characteristics used to describe and categorize buildings into types. Although a variety of factors have been considered in these approaches, not all energy-relevant aspects of a building have been included. Construction period appears often as a major categorization criterion. Geometry is often expressed in terms of built form (detached, semi-detached, row house, etc.) in combination with floor area and some indication of façade area, height and/or glazing ratio. In some instances, surface to volume ratio replaces built form to express the geometry of the building. Building use is considered as the main indicator of operational characteristics of a building. The urban context's implications for the solar gains are frequently ignored and the effect of surrounding buildings in the reduction of heat emitting envelope area is only sporadically considered.

APPROACH

Study neighborhood

The neighborhood selected for the study is located in central Vienna, covering parts of the 1st, 4th, 5th and 6th districts. It includes around 750 buildings of various vintage, use, and shape. Varied orientation and width of streets and presence of parks and squares account for diverse urban morphologies.

Data Acquisition and validation

In order to ensure the scalability of the adopted method, and to facilitate future use by urban domain experts, Vienna GIS (2015) data was selected as the primary source of information. The following are the acquired GIS data types for the selected neighbourhood:

Table 1 Comparative analysis of some previously developed sample-based urban energy models

				Geometry															Thermal quality of envelope			Systems		Operational parameters		boundary conditions		
	scale	scope	construction period	Geometry	Built form	Footprint Shape	Surface to volume	Heated volume	Footprint	Floor area	Exposed end area	Number of levels	Number of units	Height/Floor height	Window to wall ratio	Window area	Roof shape	Type of lowest floor	Uvalues of elements	Construction Method	Maintenance state	HVAC	Fuel type	Use	Occupancy	Location	Climate zone	Density of urban area
Huang, Y. J., & Brodrick, J. (2000)	National	residential commecial office	✓		✓																			✓			✓	
Snäkin, J. (2000)	Natoinal	various	✓		✓																	✓	✓	✓				
Jones, P., et al.(2001).	City	various			✓				✓	✓	✓			✓	✓				✓			✓		✓		✓		
Hens, H., et al.(2001).	Natoinal	residential			✓					✓												✓	✓					
Parekh, A. (2005).	City	residential	✓		✓	✓			✓			✓					✓	✓									✓	
Boardman, B., et al.(2005)	National	residential	✓		✓							✓							✓								✓	
Yamaguchi, Y.,et al. (2007)	City	districts								✓		✓			✓								✓					
Heiple, S., & Sailor, D. J. (2008).	National	residential commercial	✓							✓												✓		✓	✓		✓	
Sansregret, S., & Millette, J. (2009).	State	various	✓							✓														✓				
Amtmann, M. (2010).	National	residential	✓		✓																						✓	
Girardin, L., et al. (2010)	City	various	✓																					✓				
Firth, S., Lomas, K., & Wright, A. (2010	National	residential	✓		✓																							
Theodoridou, I., et al.(2011)	National	residential mixed	✓		✓							✓						✓						✓		✓	✓	✓
Orehounig, K., et al. (2011)	City	various	✓																	✓	✓	✓	✓	✓		✓		
Benejam, G. M. (2011)	National	various	✓																					✓			✓	
Dall'O', G., et al. (2012)	National	various					✓			✓						✓			✓			✓		✓			✓	
Ribas Portella, J. M. (2012).	National	various	✓		✓																		✓	✓			✓	
Caputo, P., et al. (2013).	National	residential office	✓				✓	✓		✓		✓				✓								✓				
Yeo, I.-A., et al. (2013).	National	various		✓						✓				✓	✓				✓					✓			✓	
Page, J., et al. (2014)	City	various	✓																					✓				

- Polygons constituting the foot print of every legal entity (a single building or multiple building on the same property)
- Height of each polygon
- Elevation of polygons from ground level
- Building use
- Period and/or year of construction
- Number of floors

In order to improve data precision, using Google axonometric images (Google maps 2015), distinct buildings were separated, where several buildings within one property were identified with the same reference number. Since roof geometry is not included in the 2.5D Vienna GIS data, roof type (sloped or flat), as well as attic condition (heated/unheated based on presence of windows) were derived (manually) from Google images.

Selection of clustering parameters

A fundamental prerequisite of a performance oriented urban building sampling is the identification of groups of buildings with similar energy behavior, from which representative buildings can then be selected. In this work, MCA is used to identify groups based on a robust set of energy-relevant criteria. The energy-relevant building characteristics fall under three main categories: 1) physical properties of the building (geometry and thermal properties), 2) use profiles (schedules, set points, user behavior), and 3) urban contextual parameters (adjacencies, obstructions). As mentioned above, most previous efforts have focused on the vintage, usage and size of the building as the main classification criteria. These parameters partially cover the first two categories, but ignore the third. In the present research effort, the heating demand of a building has been selected as the main indicator of energy behavior. Building systems, household appliances, lighting and Domestic Hot Water demand, although constituting an important share of the overall building energy requirements, are for the moment set aside for simplification purposes.

In order to identify the most relevant factors for classification, as well as relying on former sensitivity analyses performed by Page et al. (2014) and the authors, the main terms in the building's heat balance were considered:

1. Transmission losses: calculated based on the area of heat emitting surfaces (dependent on geometry and adjacencies), their thermal quality (U-values), as well as the inside/outside temperature difference at every time step.
2. Ventilation losses: dependent on the type of ventilation (natural/mechanical), required air change rate and volume of the space, as well as inside/outside temperature difference.
3. Solar gains: function of the available solar potential, area and orientation of transparent building elements, and their solar energy transmittance (g-value). The reductive impact of external obstructions on solar gains, due to shading, has been demonstrated to be very significant (Page et al. 2014).
4. Internal gains: dependent on occupancy profiles and activity types, as well as use of appliances and lighting.

Since the buildings in the study are not geographically scattered, climate conditions are assumed to be similar across the entire neighborhood. Although orientation of streets and vicinity of water bodies or green spaces may cause variation in microclimate (Maleki et al. 2014), such minor changes have been ignored in the present treatment.

Operational parameters such as occupancy profiles, user behavior, and desired internal conditions (temperature set points and fresh air requirements) can be expressed in terms of numerical indicators, for cluster analysis purposes. However, in the current stage of the project, buildings have been categorized based on their dominant use prior to the cluster analysis. In other words, similar to previous research efforts, operational parameters have been represented through building use and the clustering is done within each use category, based on physical and contextual properties of buildings. To account for the physical and contextual properties, the following indicators are proposed and computed for all buildings within the neighborhood:

- Effective average envelope U-value (Equation 1), defined as the average U-value of heat emitting building enclosures weighted by area of the respective building components and corrected for adjacency relationships.

$$U_e = (\Sigma(U_i \cdot A_i \cdot f_i))/(\Sigma A_i) \qquad (1)$$

U_e: Effective average envelope U-value

U_i: U-value of a building component of a certain construction period based on OIB guidelines (OIB 2007)

A_i: Area of heat emitting building components extracted from the GIS data using a PLPGSQL function (Postgresql 2015) developed for the purpose. In the case of heated attics, the foot print polygon area was multiplied by 150% to account for the area of the steep roof. A better approximation could be made by using height values provided in Digital Surface Models.

f_i: Temperature correction factor based on the position of the heat emitting enclosure relative to ground, outdoor space and adjacent unheated spaces (OIB 2007)

- Effective window to wall ratio (Equation 2), defined as the average window to external wall ratio, corrected for orientation, shading and g-value. The variance in frame to window ratio among buildings of different vintages has not been included in the study so far, but is intended for future consideration.

$$WWR_e=(\Sigma(WWR_i \cdot A_{wi} \cdot f_{oi} \cdot g_i \cdot SVF_i))/(\Sigma A_{wi}) \qquad (2)$$

WWR_e: Effective window to wall ratio

WWR: Window to wall ratio of the building according to construction period (based on an internal survey on a random sample of buildings in the neighborhood)

A_{wi}: Area of the external wall facing a certain orientation (12 orientations were considered)

f_{oi}: Correction factor for the orientation (with a maximum of 1 for south and a minimum of 0.5 for north oriented windows)

g_i: g-value of window based on construction period according to OIB guidelines (OIB 2007)

SVF_i: Value of the Sky View Factor on a point on the ground close to the building's facade. This value is used as an approximation of the shading factor, to account for the impact of the surrounding obstructions in reducing solar gains.

- Thermal compactness (Equation 3), defined as the ratio of heated volume to thermally effective envelope area, which is the sum of areas of heat emitting building elements, corrected for adjacencies.

$$C_t=(\Sigma(A_{fi} \cdot h_i) \cdot f_h)/(\Sigma A_i \cdot f_i) \qquad (3)$$

C_t: Thermal compactness

A_{fi}: Area of the foot print polygon

h_i: Height of the polygon

f_h: Ratio of heated volume to total volume based on building usage. This value was determined for various usages based on the analysis of a random sample of buildings in the area.

- Heated volume (Equation 4)

$$V_h=\Sigma(A_{fi} \cdot h_i) \cdot f_h \qquad (4)$$

V_h: Heated volume

- Effective floor height as an indicator of the ratio of building volume to floor area (Equation 5)

$$h_e=\Sigma(A_{fi}\cdot h_i)/(A_{fi}\cdot n_f) \quad (5)$$

h_e: Effective floor height

n_f: number of floors as given by Vienna GIS data

Due to the relatively small number of buildings in other categories, only residential and office buildings were included in this study.

Cluster analysis

The extracted matrix of building data was then subjected to cluster analysis using the statistical analysis software R (2015). In hierarchical agglomerative cluster analysis, each object starts as its own cluster. The two most similar clusters are joined consecutively until only a single cluster (containing all objects) remains. The hierarchical agglomerative clustering method, with "Euclidean distance" as the distance function and "Ward's method" as the similarity measure between clusters were used. The distance function determines distances between individual objects, whereas the similarity function determines which clusters should merge at every step. "In the Ward's procedure, the selection of which two clusters to combine is based on which combination of clusters minimizes the within cluster sum of squares across the complete set of disjoint clusters" (Hair et al. 2010). Once the analysis performed, the desired number of clusters is selected in the identified clustering scheme. Prior to the analysis, the data was standardized to reduce the impact of magnitude variations among variables on the clustering. Without standardization, larger values such as heated volume would dominate the clustering process, working as an unintentional weighting. Additionally, since hierarchical clustering methods are vulnerable to outliers, outliers in each dimension were removed from the matrix to insure non-skewed clusters. After elimination of outliers, 476 residential and 159 office buildings were analysed.

RESULTS AND DISCUSSION

Once the cluster analysis is performed, clusters can be defined by application of a so-called stopping rule, which determines how many steps to go back in the clustering scheme to arrive at the optimal number of clusters. One of the most critical issues in cluster analysis is determining a number of clusters that will produce relatively distinct, yet compact groups. Various indicators have been proposed by statisticians to evaluate the quality of the clustering scheme. Charrad et al. (2014) have developed an R function, NbClust, that extracts the value of over 25 such indicators for a range of clustering schemes, determining the number of clusters suggested by the majority of clustering evaluation indicators. This number is assumed to insure high intra-cluster homogeneity and high inter-cluster heterogeneity (well separated, yet compact clusters).According to this function, the optimal number of clusters among the residential buildings is eight. For the office buildings, three clusters were suggested. Interestingly, the identified clusters are also intuitively and visually distinguishable. For instance, buildings of similar shapes and sizes, or similar settings are often clustered together (e.g., most small compact buildings sandwiched between two adjacent buildings are in the same cluster).

Figure 1 illustrates the dendrogram of the residential buildings. Clusters are shown in various shades.

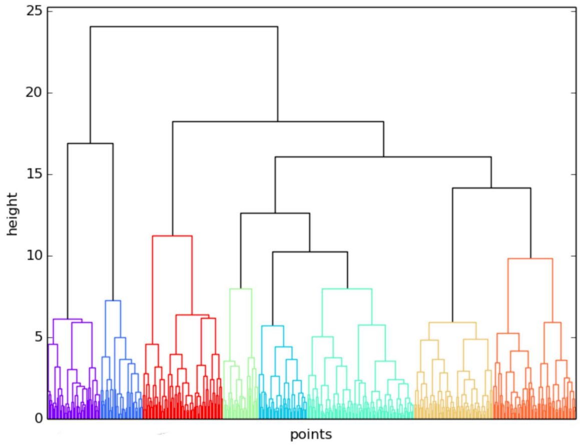

Figure 1 Dendrogram of the cluster analysis of residential buildings

A comparison between the data summary of the five descriptive variables among construction period categories ('before 1900' and '1900-1918') and that of the same variables in the first cluster containing mainly buildings of these two periods, is offered in Table 2. Note that the calculations involve buildings of the selected study area and not the entire Viennese building stock. The results confirm that a multivariate cluster analysis (MCA), removing the bias of building vintage, can reduce the variance of single dimensions within each category, thereby improving the performance of samples.

Table 2 Data summary of variables of the neighborhood's residential stock across two vintage groups and a cluster containing both vintages

INDICATOR	H_F	V_H	U_E	C_T	WWR_E
Before 1900					
MEAN	4.57	8882.03	1.36	3.28	0.0246
STDEV	0.66	4856.01	0.09	0.45	0.0052
1900-1919					
MEAN	4.77	9472.20	1.36	3.26	0.0371
STDEV	0.54	4700.01	0.07	0.39	0.0073
Cluster 1					
MEAN	4.63	7908	1.41	3.20	0.02
STDEV	0.44	3572.78	0.05	0.31	0.004

In order to determine the best representative for each cluster, the cluster centroid (a virtual object with average dimensions) was identified. Then, the Euclidean distance between the centroid and every building within the cluster was computed and the building closest to the centroid was selected as the cluster representative for energy evaluation purposes. The energy evaluation results of the representatives were scaled up (according to heated volume) to yield the overall heating demand of the neighborhood. Detailed numeric simulations and an empirical validation of the model are deferred to future phases of the project, due to difficulties in procuring measured energy demand values. However, a simpler experiment performed by a group of students highlights the promise of the above method. As a preliminary validation step, groups of students implemented the above-mentioned sampling procedure on a neighbourhood, calculated the heating demand of the representative sample using a steady-state code-based performance assessment software (Archiphysik 2015), and extrapolated the results of their assessments to a larger randomly selected subset of the neighbourhood. Subsequently, they computed the heating demand of every building in the larger sample using detailed building information and compared the results. Due to discrepancies in the computation of volumes, the absolute values of heating demand varied significantly between the two cases. However, the average heating demand per unit of volume within the larger sample was estimated with a precision of over 95%.

CONCLUSION

The proposed method incorporates a widely used statistical data analysis approach, hierarchical agglomerative cluster analysis, to identify a sample of buildings representing the energy behavior of an urban neighborhood. As mentioned before, partitioning resulted from the computed values of the relevant indicators of clustering performance. While this approach resulted in plausible solutions, we currently explore other clustering methods (e.g., model-based clustering) for their potential to deliver cluster solutions with a more explicit underlying reasoning. The sampling process was aimed at reducing the computational time and effort required for high-resolution urban energy assessments. Unlike most previous efforts, the suggested procedure does not rely on building age as a main sampling criterion. Rather, this property is used to determine other characteristics, which better relate to a building's thermal behavior (U-value of components, overall window to wall ratio, etc.). The reduction in the variance of the selected thermally relevant building attributes, when switching from age-based categories to clusters, supports the assumption that the removal of the construction period bias in the definition of types can lead to a better performing sampling. The present contribution incorporates the impact of the urban context on the thermal behavior of buildings through an automated evaluation of adjacency relationships, façade orientation and shading effects caused by surrounding buildings. Shading is approximated by the sky view factor in the vicinity of the building's facades. Due to the reliance on GIS data, the entire process (aside from data validation) down to the selection of representative buildings can be fully automated. If use of actual buildings as representatives is not particularly desired, the generation of virtual archetypes can also be computationally achieved for a fully automatic energy modeling process (see Sansregret & Millette 2009).

As is common in energy modeling efforts, the precision of the input information is of critical importance in determining the overall model performance. Unfortunately, the Vienna GIS data varies in precision and resolution in different districts of the city. Moreover, thermally significant information such as thermal retrofit dates, condition of attic and basement spaces, or a thorough description of building use are lacking. Thus far, the operational parameters of buildings are represented through building usage. However, future research by the authors involves the identification of appropriate operational indicators to capture the diversity of operational profiles even within one use category. A refinement of the calculation of volume, using Digital Surface Models is also planned. An empirical validation of the model with measured data represents the next key step in this ongoing project. Thereby, the potential and implications of more extensive data sets will be explored.

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