Re-diversification of Predictions of a Reductive Urban Energy Modeling Method

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Abstract

The present contribution reports on the development of an urban energy modelling method, which enables the utilization of dynamic performance simulation for urban scale energy inquiries. The developed framework is composed of two components. The first component is tasked with the systematic reduction of the computation domain through clustering based sampling of the urban building stock. The second component, the focus of this paper, is concerned with the recovery of part of the lost diversity, due to the reductive procedure. This is achieved through readjustment of model parameters in multiple simulation runs. In this regard, data-oriented parametric modification of thermal properties of the building components and occupant related aspects has been attempted.

Introduction

The interest in the domain of urban energy computing has been steadily increasing in the past years. This is mainly attributable to the realization that the development of effective strategies aimed towards improving the energy performance of the built environment depends on reliable data on the spatial and temporal distribution of energy demand and supply. As such, the requirement for modeling environments, which address energy inquiries beyond the scope of individual buildings (e.g., impact of district-level change and intervention scenarios) has increased. In this regard, the bottom-up engineering modeling approach (Swan and Ugursal 2009) is deemed most suitable for the investigation of the energy implications of various change and intervention scenarios, Kavgic et al. 2010). This approach relies on heat transfer equations to arrive at the energy performance of a number of prototypical or sample buildings, and aggregates and extrapolates the results to the level of an entire city or neighborhood. The versatility of the model in emulating different scenarios depends on the capabilities of the underlying performance assessment routines. The predictive performance of the model, on the other hand, is not only affected by the reliability of the underlying assessment process, but also on the reductive procedure adopted for the limitation of the computational domain.

In most previous efforts, the informational and computational challenges of large scale energy assessments have led to the adoption of simplified and reduced order computational routines. These methods, although beneficial in providing a general overview of the urban energy aspects, fail to capture the temporal dynamics of load patterns and their dependency on transient phenomena (occupants and climate) with appropriate resolution. In a recent review of some bottom-up urban building energy models, Reinhart and Cerezo Davila (2016) provide an overview of the application domain, building representation process and computational methods adopted in previous efforts.

The thus far implemented reductive procedures, mainly following a stock segmentation and sampling or archetyping method, rarely consider all energy-relevant aspects of the urban stock in their classification schemes. For instance, the variance in contextual parameters such as adjacency relations and the effect of mutual shading is only sporadically considered in the selection of the representative buildings, even though the significance of the urban morphology for building energy performance has been emphasized by the research community (Page et al. 2014). Moreover, operational specificities of buildings are reflected through the building's main usage, which may not be effectively representative in the case of multi-use buildings. A more extensive review of some former urban stock segmentation and energy modeling schemas, and the adopted classification criteria is provided in Ghiassi et al. (2015).

In this context, the authors have developed a reductive bottom-up urban stock heating demand model, which seeks to address the above-mentioned issues of stock representation and performance modeling. This development relies on a Building Performance Simulation (BPS) tool to assess the performance of the buildings, thereby drastically enhancing scenario modeling capabilities and resolution. To enable the large-scale adoption of BPS tools a two-module framework was designed. The first module, integrated in a Geographic Information Systems (GIS) environment, employs well-known data-mining methods to effectively reduce the computation domain. The second module, the focus of the current contribution, is aimed at recovering part of the diversity lost through implementation of the reductive procedure. The developed energy model is intended as the core computational engine of an integrative urban energy decision support environment. The envisaged environment is geared towards evaluation and comparative analysis of various change and intervention scenarios pertaining to macro and microclimate conditions, occupants' demography and behavior, physical and technical aspects of the buildings, and urban morphology. The present contribution briefly introduces the overall framework of the model and its first module, and focuses more specifically on the methodology and outcomes of the second step. For illustration purposes, the method has been applied to a case study. The results of this implementation are presented and discussed.

Approach

The overall structure of the developed framework is demonstrated in Figure 1. The first module, addresses the challenge of high informational and computational demand of BPS tools through a systematic reduction of the extent of the required computations. This is achieved by way of selecting a sample of buildings representative of the energy diversity of the stock. The second module, is concerned with the recovery of part of the building diversity lost through the reductive process as well as the incorporation of standard operation profiles. Since the described computational method reduces the computational space in a first step and enhances it through re-diversification in a second step, the term “hourglass model” has been adopted by the authors to describe the method. The following sections introduce the above-mentioned modules and discuss the implications of the re-diversification process in detail.

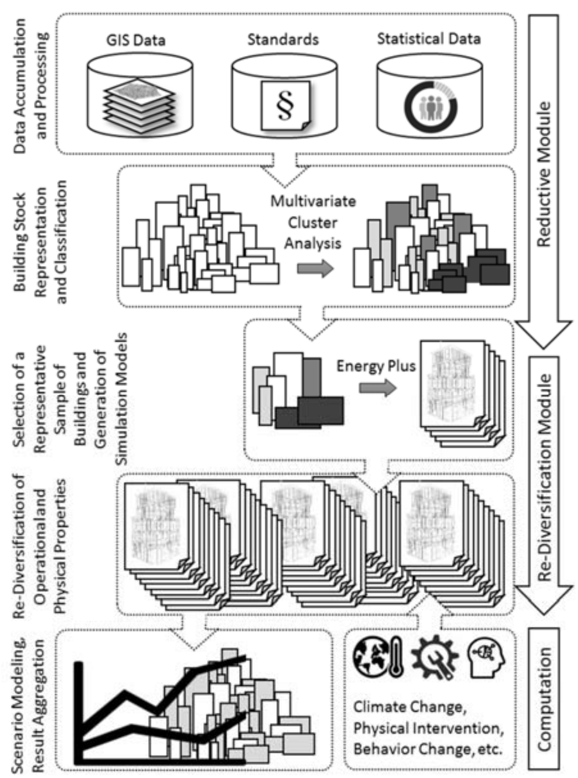

Figure 1: The overall structure of the developed computational framework

The Reductive Module

Building stock representation

The reductive module is designed and implemented as a plug-in for the open source GIS environment QGIS (2015). The plug-in, written in Python programming language (2016), utilizes the available GIS data of an urban area, as well as relevant standards and statistical data to arrive at a sample of buildings, optimally representing the area under investigation, in terms of energy performance. For this purpose, it first generates an energy-relevant representation of the urban stock in an automated procedure. This representation includes the geometry and adjacency status of the buildings’ thermally effective enclosures; area, orientation and shading condition of transparent building components; various usages present in each building, their share of the total building volume, and relevant standard operational parameters; age-dependent thermal properties of various building components; useful floor area; etc.

The geometric and contextual representation is created through analysis of the official land-use GIS plans and digital elevation models, which include building foot print geometries and height information. Official building inventory data, and crowd sourced GIS data (e.g., Open Street Map 2015) are used along with a simple rule-based logic to determine various functionalities existing in the building, and to distribute the building’s volume among them. Standards are used to associate operational parameters with various building usages. Buildings’ age or construction period is extracted from official inventory data. According to this information, thermal properties of various building components is approximated by the standard-provided values. The shading effect of the surrounding urban environment, is captured through a Sky View Factor map of the area is generated using an open source QGIS plug-in (Hammerberg 2014).

Building stock classification

Once the representation is created, key energy-relevant features of the buildings are aggregated into descriptive indicators, the values of which are computationally extracted from the generated representation. These descriptive indicators constitute the criteria adopted for the segmentation of the building stock. The list of the considered set of indicators as well as their computational method is provided in Table 1. This list has been selected from a larger set of indicators based on the performance of the emergent set of representatives in emulating the thermal behavior of the neighborhood. Note that contextual parameters (adjacency relations and mutual shading effect) have been involved in the definition of the effective glazing ratio, thermal compactness, as well as the effective envelope U-value. The resulting matrix of the values of indicators for all buildings is subjected to Multivariate Cluster Analysis, MCA (Hair et al. 2010), to identify groups of buildings with similar properties. MCA is a well-known data mining techniques that can be used for unsupervised data classification. Three different MCA techniques, K-means (MacQueen 1967), model-based

(Fraley and Raftery 2002), and hierarchical agglomerative (Hair et al. 2010), were examined towards their efficiency for the segmentation of building stock. For the purpose of MCA analysis, several packages of the R project for statistics software (R Project 2015) were integrated within the plug-in. In each resulting segmentation, the most typical building in each cluster (buildings closest to the cluster centroid) was selected to represent the cluster. Preliminary performance tests, carried out using the results of steady state heating demand calculations on the neighborhood based on the previously derived stock representation, suggest that the representatives emerging from the application of the k-means method on the presented set of classification criteria, performs best in predicting the monthly demand of the neighborhood. The heating demand for this test was computed for the entire data space following the method provided by (ÖNORM 2014) with minor simplifications. The authors, however, are aware that the temporal distribution of demand is not captured by this method and requires further validation. The number of classes identified, can be controlled by providing upper and lower thresholds in the developed plug-in's source code. In the current study a range of 6 to 30 clusters were considered. The plug-in incorporates a method to identify the optimal number of clusters or classes, by computing the values of several clustering performance indicators for the provided range (see Charrad et al. 2014). The investigated clustering schemas (resulting from various clustering algorithms and sets of descriptive indicators) varied in the number of identified clusters (within the specified range). However, no correlation was observed between the number of emerging clusters and the predictive performance of the model in view of annual heating demand. The plug-in can be operated through the QGIS interface by a simple click, provided that the required data layers pertaining to the area under study are open in the GIS environment. The standard-driven information as well as all logical and analytical procedures are integrated in the code. For more information on the reductive procedure see Ghiassi et al. 2015, Ghiassi and Mahdavi 2016a, 2016b, 2016c.

Table 1: Descriptive indicators reflecting the main energy-influential characteristics of buildings. These indicators have been adopted as the classification criteria by the reductive module.

	Abbr.	**Variable Description**	**Formula**	**Parameters**	
Geometry	V_n	Net Volume [m³] An indicator of the size of the building	$V_n = \sum(A_{feat,i} \cdot h_{feat,i}) \cdot f_n$	$A_{feat,i}$ $h_{feat,i}$ f_n	Area of footprint feature [m²] Height of footprint feature [m] Net to gross volume ratio
	h_e	Effective floor height [m] Ratio of the building volume to the floor area	$h_e = \frac{V_n}{A_f \cdot n_f}$	A_f n_f	Total floor area [m²] Number of floors
	C_t	Thermal compactness [m] Ratio of the net building volume to the thermally effective envelope area	$C_t = \frac{V_n}{A_e}$ $A_e = \sum(A_i \cdot f_{t,i})$	A_e A_i $f_{t,i}$	the thermally effective envelope area [m²] Area of element [m²] Corresponding temperature correction factor
Solar gains	GR_e	Effective glazing ratio Average glazing to wall ratio weighted by orientation and corrected for the shading effect of the surroundings Weights associated with orientations were based on reference climate data	$GR_e = \frac{WWR.GWR.g.\sum(A_{ow,i} \cdot f_{o,i} \cdot SVF_i)}{\sum A_{ow,i}}$	WWR GWR $A_{ow,i}$ $f_{o,i}$ g SVF_i	Window to wall ratio Glass to window ratio Area of external wall element [m²] Corresponding orientation correction factor Solar factor of glazing Sky View Factor in the vicinity of the wall
Thermal Quality	U_e	Effective average envelope U-value [W.m⁻².K⁻¹] Average u-value of the envelope corrected for adjacency relations and weighted by the corresponding areas	$U_e = \frac{\sum(U_i . A_i . f_{t,i})}{A_e}$	U_i	U-value of element [W.m⁻².K⁻¹]
Operation Parameters	O_u	Fraction of time the building is used annually [a⁻¹]	$O_u = \frac{t_{use,a}}{t_a}$	$t_{use,a}$ t_a	Annual use hours [h.a⁻¹] Total hours in a year [h]
	Ig_d	Daily area related internal gains [Wh.m⁻².d⁻¹]	$Ig_d = \sum(q_{i,h,i} \cdot t_{use,d} \cdot f_{v,i})$	$q_{i,h,i}$ $t_{use,d}$ $f_{v,i}$	Usage-based internal gains rate [W.m⁻²] Daily use hours [h.d⁻¹] Share of the usage in the overall building volume
	Ac_d	Daily air-change rate [d⁻¹]	$Ac_d = \sum(n_{v,i} \cdot t_{use,d} \cdot f_{v,i})$	$n_{v,i}$	Usage-based hourly air-change rate [h⁻¹]

The Re-Diversification Module

Loss of diversity is a natural consequence of a reductive process. The re-diversification module has been developed to reintroduce part of the lost diversity back to the computational model, and to obtain more realistic representations of the spatial and temporal distribution of demand. Once the representative buildings are selected by the reductive module, reference simulation models are developed for these buildings in the Energy Plus (2016) performance simulation software based on the detailed plans of the buildings. In the reference models, operational parameters are represented through standard schedules. Layered constructions are defined according to the available plans or the common practice of the construction period of buildings. Ventilation is modeled as dependent on occupants' presence. The temporal distribution of ventilation follows the occupancy schedule, whereas its magnitude is determined by a given air change rate. The re-diversification module, also developed in Python programming language requires these reference models as input.

Previous studies have shown that the acquisition of pertinent building information and generation of the geometric model of a building are the most time and effort intensive activities in building performance simulation (Mahdavi and El-Bellahy 2005). The developed reductive module, reduces this effort by way of limiting the modeling scope to a manageable number of buildings (the limits of which can be set by the user through definition of an acceptable range of cluster numbers).

Assuming that the identified sample of buildings represents the geometric features of the stock with acceptable fidelity, the re-diversification module attempts to readjust some of the non-geometric parameters of the reference simulation models, such that they emulate the characteristics of the represented buildings more closely.

The building parameters currently subjected to diversification are the following:

- Schedules of occupants' presence and metabolic rates, lighting and equipment use
- Thermal properties of the main components of the building envelope: uppermost and lowermost enclosures, external walls
- Internal loads represented by number of occupants, equipment and lighting power
- Ventilation rates represented by air change rate

As such, other operational, and contextual building parameters can be subjected to diversification. HVAC operation schedules, for instance, can be stochastically diversified to capture behavioral diversity. In the current effort, fairly constant physical contextual parameters such as adjacency relations and mutual shading have been considered in the clustering process. The contribution of other urban features such as traffic or trees to microclimate variations or user behaviour alteration can be captured the re-diversification process. This can be achieved through readjustment of standard climate data used in the simulation or operational parameters, based on location dependent variables.

However, the present effort focuses only on the diversification of those parameters, for which some source of background information concerning pertinent distribution patterns was available.

For the purpose of re-diversification, for all buildings within the study domain, permutations of the relevant reference simulation models are created with modified or readjusted parameters.

The diversification process is guided by the information contained in the initially generated building stock representation. To facilitate the data-oriented modification of the reference simulation models, descriptive indicators defined in Table 2 are extracted.

The simulation models generated by the re-diversification module are subjected to computations with hourly resolution. To compute the hourly heating demand of each building, the hourly volume-related heating demand of the corresponding simulation model is multiplied by the volume of the building.

Diversification of schedules

Reference schedules suggested by standards (e.g., ASHRAE 2013), represent the temporal distribution of internal gains in aggregate terms. Use of these average profiles for detailed demand assessments at large scale, however, will result in unrealistically monotonous internal load profiles and identical peak hours across the computation domain. To prevent this, and to achieve a more realistic stochastic representation of occupancy-related factors, for each building, a set of randomized schedule files are created, based on the reference schedules for various days of the week. Each schedule file is a matrix of 8760 rows (for every hour of the year) by 5 columns corresponding to occupants' presence, lighting use, equipment use, HVAC operation and metabolic rate. HVAC schedules are not diversified.

To diversify each schedule, for every time step, the value provided by the reference schedule is considered as the mean of a Gaussian probability distribution, representing that time step. A default Coefficient of Variance (CV) is used along with the mean value to generate this distribution. Former studies suggest that for certain applications for instance pertaining to the stochastic generation of presence patterns, CV displays a distinct value range (Mahdavi and Tahmasebi 2015). Accordingly, in the current implementation, a CV value of 0.2 was deployed. The identification of specifically appropriate CV values however, is an open research topic. Based on the generated distribution for each time step, a value is randomly selected for the schedule. Rules are defined to ensure the values remain within the acceptable range. As such, the generated schedules maintain the overall tendencies of the reference schedules, while featuring unique characteristics, which better emulate the diverse nature of occupant behavior.

Readjustment of internal loads and ventilation rates

The diversified operational parameters (i.e., reference values for equipment and lighting power, number of occupants, and air change rate) are computed for each building such that the aggregated internal gains and ventilation rates, match the values of the daily area-related internal gains and daily air change rate computed for the building. For this purpose, for every building, the annual area-related internal gains are computed based on the average daily values and the number of annual use days provided by standards (e.g., ÖNORM 2011). Similarly, the average hourly air change rate across the year is calculated. The annual value of internal gains is disaggregated into occupants, lighting and equipment gains, based on the share of these items in contributing to the internal gains according to literature. For instance, for residential spaces, 58%, 19%, and 23% were assumed for gains pertaining to equipment, lighting and people respectively (Kemna and Moreno Acedo 2014).

Energy plus computes the values of lighting and equipment gains in each time step, by multiplying the applicable usage rate provided by the schedule, by the reference power value. Since the aggregate annual internal gains from equipment and lighting, as well as the distribution schedules are known, the reference power can be calculated for each building. The same logic can provide the reference value for air change rate, based on the average annual value, and the ventilation schedule.

For determination of the number of occupants, the same logic applies. However, the metabolic rate in every time step must also be considered. In energy plus, in every time step, the value of internal gains from occupants is calculated based on the reference number of occupants, the occupant presence rate provided by the occupancy schedule, and the value of the metabolic rate of the occupants (also provided by a schedule) in that time step. If the aggregate occupant-related gains and the schedules pertaining to metabolic rate and occupants' presence are provided the reference number of occupants can be calculated for each building.

Table 2: Descriptive indicators utilized to guide the re-diversification process.

Abbr.	Variable Description	Formula	Parameters	
$\mathrm{U}_{c,e}$	Effective roof/ceiling U-value [W.m^{-2}.K^{-1}]	$\mathrm{U}_{c,e}=\frac{\sum(\mathrm{U}_{c,i}.\mathrm{A}_{c,i}.\mathrm{f}_{t,i})}{\mathrm{A}_e}$	$\mathrm{U}_{c,i}$ $\mathrm{A}_{c,i}$ $\mathrm{f}_{t,i}$ A_e	U-value of roof/ceiling element [W.m^{-2}.K^{-1}] Area of roof/ceiling element [m^2] Corresponding temperature correction factor Effective envelope area [m^2] (Table 1)
$\mathrm{U}_{f,e}$	Effective floor U-value [W.m^{-2}.K^{-1}]	$\mathrm{U}_{f,e}=\frac{\sum(\mathrm{U}_{f,i}.\mathrm{A}_{f,i}.\mathrm{f}_{t,i})}{\mathrm{A}_e}$	$\mathrm{U}_{f,i}$ $\mathrm{A}_{f,i}$ A_e	U-value of floor element [W.m^{-2}.K^{-1}] Area of floor element [m^2] Effective envelope area [m^2] (Table 1)
$\mathrm{U}_{w,e}$	Effective wall U-value [W.m^{-2}.K^{-1}]	$\mathrm{U}_{w,e}=\frac{\sum(\mathrm{U}_{w,i}.\mathrm{A}_{w,i}.\mathrm{f}_{t,i})}{\mathrm{A}_e}$	$\mathrm{U}_{w,i}$ $\mathrm{A}_{w,i}$ A_e	U-value of wall element [W.m^{-2}.K^{-1}] Area of wall element [m^2] Effective envelope area [m^2] (Table 1)
Ig_d	Daily area related internal gains [Wh.m^{-2}.d^{-1}]	See Table 1		
Ac_d	Daily air-change rate [d^{-1}]			

Readjustment of thermal properties

The readjustment of the thermal properties of the main building elements is informed by the respective effective element U-values. As mentioned before, the U-values of various building components in the initial stock representation are determined by the construction period of the buildings. As such, components of buildings constructed in the same period, feature similar thermal quality. The effective component U-value however, is not only a measure of the thermal quality of the component's construction, but also a function of the significance of the said construction for the thermal performance of the envelope. This is determined by the share of the elements associated with a particular construction in the total thermally effective area of the envelope. As such, building belonging to the same construction period, with different geometries and adjacency situations, have different effective component U-values. This diversification step, attempts to modify the properties of each simulation model, such that the resulting effective U-values of the major envelope components match the expected values calculated for every building. Since the geometry of the simulation model associated with every building is identical to that of the corresponding reference model, any deviations from the effective U-values of the reference building must be accounted for by modifying the U-values of the constructions in the new model. For this purpose, the differences between the effective U-values of the elements of the reference building and the building undergoing diversification are calculated. Then the thermal properties of the main constructions in the new model (external walls, uppermost and lowermost enclosures) are determined such that they reflect the deviation in effective U-values from those of the reference model. For simplification reasons, only the most thermally effective layers of the construction (i.e, thermal insulation layer, or the massive loadbearing layer in the absence of insulation) are subjected to modifications. Since a modification of the thermal mass of the building was not intended, only the thermal conductivity of the layer is readjusted.

Illustrative Example

Case Study

To demonstrate the utility of the developed computational framework, it has been applied to a case study in the city of Vienna, Austria. The selected urban neighborhood is located in the center of the city, featuring over 740 buildings of various usages and construction periods (Figure 2). The current implementation of the plug-in is tailored for the Austrian context. However, it can be modified with minor effort for other geographical locations. The data incorporated in the present development is listed below:

- Land Use Plan (ViennaGIS 2015)
- Digital Elevation Model (ViennaGIS 2015)
- Building Inventory Data (ViennaGIS 2015)
- Building Usage Data (Open Street Map 2015)
- Sky View Factor map generated by DEMTools plug-in for QGIS (Hammerberg 2014)
- Austrian standard: Model of climate and user profiles (ÖNorm 2011)
- Austrian standard:Principles and verification methods, heating demand and cooling demand (ÖNorm 2014)
- Guidelines: Energy-technical behaviour of buildings (OIB 2015)

The data sources available for the study contained no information on former retrofit interventions applied to the buildings. As such, buildings were considered to have maintained the original characteristics in view of component constructions. Should such information become available, however, the proposed framework is capable of incorporating the changes into the model: The construction period is only used to associate buildings with sets of component U-values and not explicitly as a classification criterion.

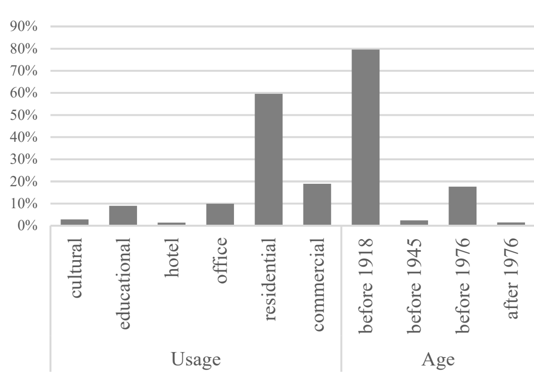

Figure 2: Distribution of buildings in the study neighbourhood by age and usage

Modelled Scenarios

To assess the impact of the diversification process on the model predictions, the predictions of the non-diversified model were compared to the predictions resulting from models with two levels of diversification. The non-diversified model is based on the reference simulation files. In this case, the volume related hourly demand values of the reference simulation models are multiplied by the volume of the represented buildings to yield the hourly heating demand of these buildings. The first level of diversification involves only the diversification of the operational schedules. The second level includes all diversification steps introduced in the method (Table 3).

To demonstrate the advantages of the developed computational model for the investigation of various change and intervention scenarios, three simple illustrative scenarios pertaining to changes in the operational parameters of buildings (occupant behavior) were designed. The first scenario follows the standard assumptions for internal temperature and HVAC availability hours. The second scenario assumes a set-back heating set point for the vacant hours in non-residential spaces, which is closer to the actual building operation tendencies. The third scenario, emulating the behavior of a more energy-aware population, maintains the set-back threshold, and modifies the internal heating set point temperatures in proportion to the occupancy rate of the building in every time step. This scenario is based on the simple assumption that if the occupancy rate is lower, fewer spaces are heated, thereby reducing the average internal temperature of the building. These scenarios were simulated with the NDS and DS-2 models. Table 4 provides an overview of the modeled scenarios.

Table 3: Overview of the investigated models with various levels of diversification. (D: Diversified, ND: Not Diversified)

Abbr.	Schedules	Thermal properties	Internal gains	Number of simulations
NDM	ND	ND	ND	7
DM-1	D	ND	ND	744
DM-2	D	D	D	744

Table 4: An overview of the modelled behaviour change scenarios.

		Residential		Non-Residential	
S0	Set point assumptions [°C]	20		20	
	HVAC Availability	24 hours a day		14 hours on weekdays	
S1	Set point assumptions [°C]	20		20 during work hours 14 other times	
	HVAC Availability	24 hours a day		24 hours a day	
S2	Set point assumptions [°C]	16 16 20 Interpolate	Night hours Occupancy rate <25% Occupancy rate > 55% Other times	14 16 20 Interpolate	Not working hours occupancy rate <25% Occupancy rate > 75% Other times
	HVAC Availability	24 hours a day		24 hours a day	

Results and Discussion

Reductive Module Outcome

The implementation of the reductive method on the case study area, resulted in the identification of 7 clusters. The buildings representing these clusters include three strictly residential buildings, two office buildings, as well as two mixed use residential and gastronomy buildings. These representatives are visually presented in Figure 3.

As mentioned before the performance of the reductive module towards efficient representation of the neighborhood was tested using the results of simplified steady state demand calculations (ÖNORM 2014). The volume related heating demand of the buildings in every cluster as well as that of the representing building is presented in Figure 4. Buildings grouped together in each cluster, feature similar performance in terms of annual volume-related heating demand. Most representative buildings demonstrate a performance close to the mean of the cluster, however, the representatives of clusters 3 and 6 underestimate the demand of their respective categories.

To investigate the representativeness of the selected sample, the volume-related demand of the representative buildings along with the volume of buildings in every cluster were utilized to predict the heating demand of the represented buildings. These predictions were compared to the expected values (computed based on the standard). Figure 5 visualizes the results of this investigation. As seen in the graph, the building level predictions present an acceptable accord with the expected values.

Re-Diversification Module Outcome

The impact of the diversification process is illustrated for an office building in Figure 6. In this graph, the reference schedules are compared to a week's data generated for one building. The generated schedules maintain the overall tendencies of the reference schedules. However, due to their stochastic representation of occupancy-related aspects, provide unique profiles for various buildings, resulting in a more realistic representation of the diversity in occupant behavior.

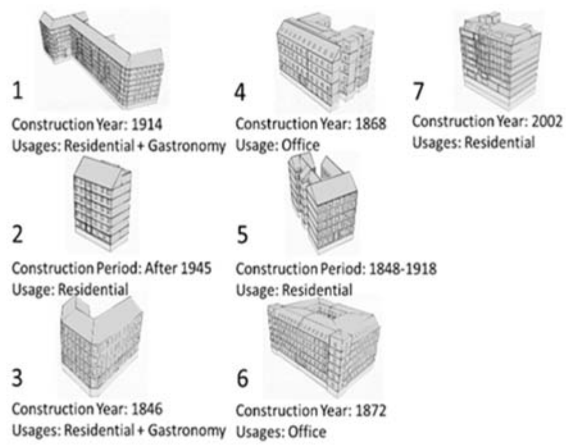

Figure 3: Buildings representing the clusters emerged from applying the reductive module to the case study

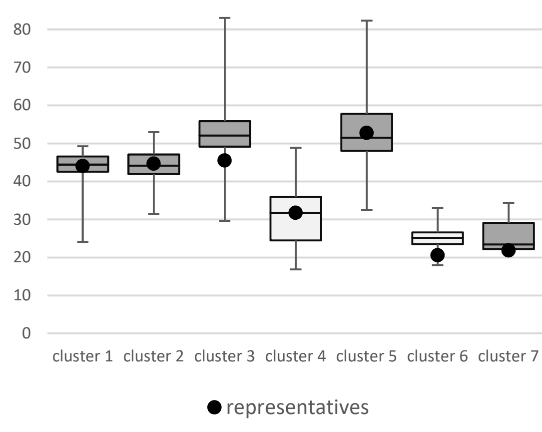

Figure4: Volume related heating demand of buildings in each cluster and the cluster representative. The lighter coloured columns pertain to non-residential buildings

The diversification of the schedules results in minor modifications in the annual peak load (+1%) and the aggregated annual demand of the neighborhood (-1%). The additional readjustment of the buildings' thermal properties, internal loads and ventilation rates causes more significant changes in the overall predictions of the model (-3.4%). However, the deviation at the aggregated level is not so substantial as to compromise the representativeness of the model.

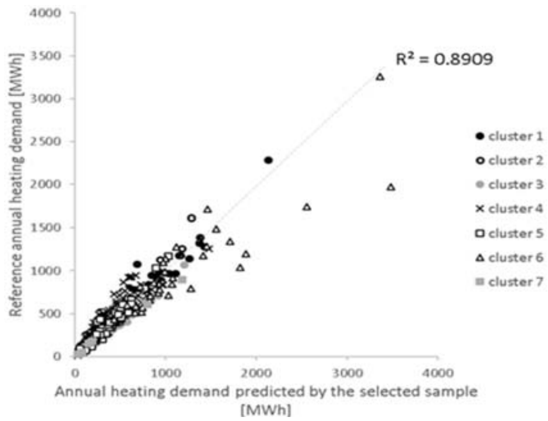

Figure 5: Sample-based prediction of heating demand compared to the computed heating demand

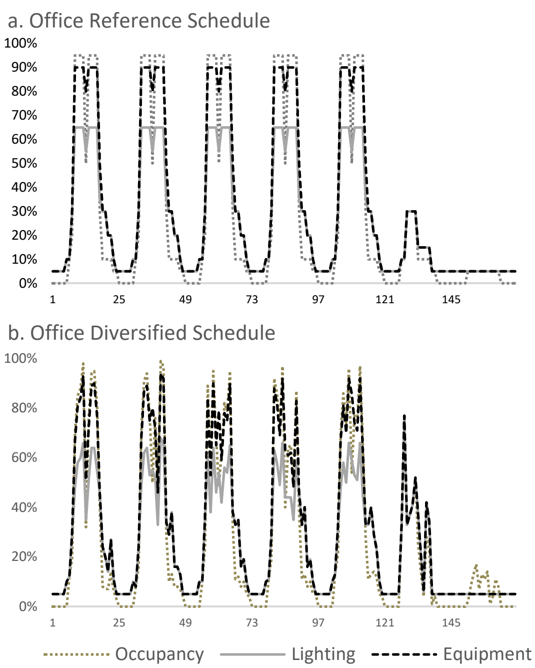

Figure 6: a. Office reference schedules according to ASHRAE (2013) b: A week's data of the diversified schedules generated for an office building

Nonetheless, the impact of the diversification process is magnified when the scale of observation reduces. At building level, the annual volume-related heating demand of the buildings computed by DM-2 can deviate by as much as 30% from the volume-related demand of the reference buildings, but the values predicted by DM-1 do not vary significantly from the reference values. If the observation scale is further reduced to a single time step, both DM-1 and DM-2 result in noticeable deviations from the non-diversified hourly predictions (Figure 7). These variations, although unnoticeable at aggregate scale, can have significant implications for instance for the design and deployment of small scale distributed generation schemes.

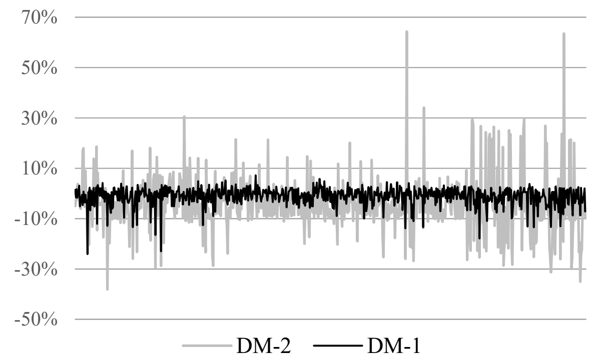

Figure 7: Relative deviation of hourly demand results of all buildings as predicted by the DM-1 and DM-2 from NDM predictions for a single time step in heating period

Scenario Modeling Results

The results of the modeled scenarios are presented in Table 5. As evident in the table, at the aggregated level, the peak, mean, and total heating demand simulated for the base case assumptions (S0) varies little when including the re-diversification step in the modeling procedure. When applying the first behavior change scenario, the tendencies of non-diversified and the diversified model are also very similar. Peak load, annual demand and mean hourly demand demonstrate little changes after the diversification process. This was to be expected since the modifications applied in this scenario are somewhat independent of the occupancy-related aspects as they only apply to non-residential spaces during vacant hours. However, the differences between the models become more visible, when the second scenario is simulated. Here again, the both model are consistent in their predictions of the annual, and mean hourly demand. However, if the second scenario (NDM-S2, DM-2-S2) predictions of both models are compared with the respective base case predictions of the same models (NDM-S0, DM-2-S0), it shows that in the non-diversified model the application of the occupant-sensitive HVAC control scenario has led to a much larger decrease, than in the diversified model (14.7% compared to 11.1%). Moreover, due to the monotonous representation of the operational parameters in the non-diversified model (the stacking of peak loads across the neighborhood), the peak load predicted by this model is much higher than the predictions of the diversified model, which provides a more realistic representation of people's presence and actions.

Table 5: Results of the behaviour change scenarios as simulated by the diversified and non-diversified computational models

Scenarios		Annual Peak load [MWh]	Relative deviation from NDM-S0 [%]	Total annual space heating load [GWh]	Relative deviation from NDM-S0 [%]
Non- Diversified Model (NDM)	S0	153.1	0	198.35	0
	S1	128.2	-16.3	200.70	1.2
	S2	122.6	-19.9	169.14	-14.7
Diversified Model (DM-2)	S0	151.4	-1.1	191.66	-3.4
	S1	124.5	-18.7	195.22	-1.6
	S2	111.7	-27.0	170.30	-14.1

It appears as though the non-diversified model overestimates the improvements to annual demand in the face of occupant behavior change, but fails to realistically predict the impact of these improvements on the peak loads. This potential misrepresentation can have major implications for the design of energy infrastructure and sizing of distributed generation systems.

Conclusion

The present contribution reported on the developmental efforts towards generation of a computational routine for an energy management decision support environment tailored for urban-level change and intervention scenario modeling. The developed “hourglass” framework relies on a reductive module to systematically reduce the computational domain through cluster analysis-based sampling. This facilitates the incorporation of full-fledged simulations for the representation of the energy behavior of the buildings. The deployed reductive method relies on meaningful energetically relevant descriptive indicators for stock segmentation rather than commonly used building properties such as age and main usage. In view of the dynamic nature of the urban building stock and its transformations through retrofit and densification, as well as operative changes, this may provide a more generic stock segmentation and sampling possibility. Preliminary tests carried out on a case study, based on simplified normative procedures suggest that the sampling schema can reliably represent the aggregate annual energy performance of an urban neighborhood.

In a second step, this computational framework employs a re-diversification process to partially reintroduce back to the model diversity lost through the reductive procedure as well as the adoption of standard-based reference schedules. The impact of the diversification process on the model predictions have been demonstrated with simple illustrative examples pertaining to behavior change scenarios. Due to its unrealistic representation of the occupants’ presence and behavior, the non-diversified model appears to overestimate the urban-level consequences of occupancy-driven changes in the settings of system controls. Amongst other things, this may be misleading in the design and deployment process of renewable distributed energy generation schemes.

Future research involves further investigation of the potential of the re-diversification routine for the data-oriented calibration of urban simulation models, as well as model evaluation with monitored energy data. In this regard lack of georeferenced information on retrofit and densification activities, as well as the diversity and distribution of HVAC systems present major sources of uncertainty. Moreover, the underlying assumptions (constant CV values) for the stochastic generation of schedules require further refinement and evaluation through empirical studies, to insure realistic representation of operational parameters.

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