Urban Energy Computing: An Hourglass Model

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Abstract

This contribution describes an urban energy modelling method that enables the use of dynamic performance simulation for urban-scale energy inquiries. The associated framework involves 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 recovers part of the lost diversity (due to the reductive procedure) via stochastic variation of selected model parameters such as thermal properties of building components and occupancy-related factors.

1. Introduction

The development of energy performance improvement strategies for the built environment requires reliable data on the spatial and temporal distribution of energy demand and supply. This implies the need for modelling environments that can facilitate energy-related district-level inquiries (pertaining, for example, to candidate intervention scenarios) beyond the scope of individual buildings. The bottom-up modelling approach (Swan and Ugursal, 2009) has the potential to support the impact investigation of energy-relevant change and intervention scenarios (Kavgic et al., 2010). Thereby, results from thermal models of a number of sample buildings are up-scaled to the neighbourhood or even whole-city level. The effectiveness of this approach depends not only on the underlying performance assessment routines, but also on the nature of the reductive procedure adopted to reduce computational loads.

Past efforts have frequently adopted simplified and reduced order algorithms in order to meet massive data requirements and extensive computational loads. This may yield a broad urban-scale energy view, but is unlikely to capture the temporal dynamics of building thermal states given transient internal and external (occupants and climate). On the other hand, most current reductive procedures follow stock segmentation methods that ignore a number of relevant morphological aspects of the urban stock such as adjacency relations and the effect of mutual shading. In our implementation of the reductive method, such issues were addressed in the adopted classification criteria, together with measures to include the building operational properties beyond function-related assumptions (Ghiassi et al., 2015).

In this context, we have developed a reductive bottom-up urban stock heating demand model, which relies on a Building Performance Simulation (BPS) tool to assess the performance of the buildings, such that scenario modelling capabilities and resolution are enhanced. To enable the large-scale adoption of BPS tools a two-module framework (an hourglass model) was conceived. The first (reductive) module uses data-mining methods to reduce the computational load via representative sampling. As this inadvertently results in some loss of diversity, a second module was designed to partially recover lost diversity. The resulting urban energy decision support environment has thus the potential to comparatively analyse and evaluate various change and intervention scenarios pertaining to macro and microclimate conditions, inhabitants' demography and behaviour, physical and technical aspects of the buildings, and urban morphology.

2. Approach

The framework architecture is depicted in Fig. 1. To accommodate the high informational and computational requirements of BPS as the framework's computational engine, the first module involves the

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Pernigotto, G., Patuzzi, F., Prada, A., Corrado, V., & Gasparella, A. (Eds.). 2018. Building simulation applications BSA 2017. bu,press.
https://doi.org/10.13124/9788860461360

selection of a sample of buildings representative of the energy diversity of the stock. The second module aims to recover part of the building diversity lost through the reductive process. The initial reduction and subsequent re-diversification steps explain the authors' choice of the "hourglass model" to characterise their approach.

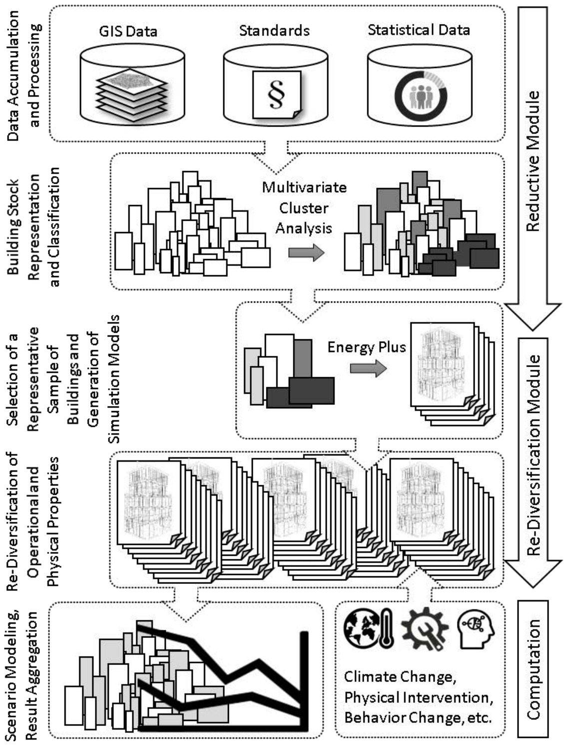

Fig. 1 – The proposed urban energy computing framework

3. The Reductive Module

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), uses the available GIS data of an urban area, as well as relevant standards and statistical data to reach an energy-relevant sample of buildings. The prerequisite urban stock representation includes the geometry and adjacency status of the building enclosures; area, orientation and shading condition of transparent building components; various usages present in each building, and relevant standard operational parameters; age-dependent thermal properties of building components; floor area, etc. (for more details, Ghiassi et al., 2015; Ghiassi and Mahdavi, 2016a; 2016b, 2016c).

Once the representation is created, key energy-relevant features of the buildings are aggregated into descriptive indicators (Table 1) that constitute the criteria adopted for the segmentation of the building stock. The resulting matrix of indicator values for all buildings is subjected to Multivariate Cluster Analysis, MCA (Hair et al., 2010), to identify groups of buildings with similar properties. 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. Preliminary performance tests, carried out using the results of steady state heating demand calculations on the neighbourhood 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 heating energy demand of the neighbourhood (according to ÖNORM, 2014).

4. The Re-Diversification Module

The re-diversification module was developed to reintroduce part of the diversity lost due to the reductive step and to obtain more realistic representations of energy demand's spatial and temporal distribution. Once the reductive module selects the representative buildings, reference simulation models are developed using EnergyPlus (2016) and detailed building plans. In reference models, operational parameters are represented through standard schedules.

Constructions are specified according to available plans or the common practice of the construction period of the buildings. Ventilation is modelled as dependent on the occupants' presence. The re-diversification module, also developed in Python programming language, requires these reference models as an input.

Given the extensive time and effort required for the acquisition of building information and generation of the geometric building models (Mahdavi and El-Bellahy, 2005), the reductive module limits the modelling domain to a manageable (user-defined) number of buildings. The re-diversification module readjusts a number of non-geometric parameters of the reference simulation models. For this purpose, for all buildings within the study domain, permutations of the relevant reference simulation models are created with the modified parameters. Building parameters subjected to diversification include:

- Schedules of the occupants' presence and activity, lighting, and equipment use;
- Thermal properties of building envelope;
- Internal loads (inhabitants, equipment and lighting power);
- Ventilation (air change) rates.

This diversification process is guided by the information contained in the initially generated building stock representation. The reference simulation model is modified based on descriptive indicators defined in Table 2. Simulation models generated by the re-diversification module are subjected to computations with hourly resolution.

Table 1 – Descriptive energy-related indicators of buildings' characteristics 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	$V_n=\Sigma(A_{feat,I} \,.\, h_{feat,i}) \,.\, f_n$	$A_{feat,i}$ $h_{feat,i}$ f_n	Area of footprint feature [m] Height of foot print feature [m] Net to gross volume ratio
Geometry	h_e	Effective floor height [m] Ratio of the building volume to the floor area	$h_e=V_n / (A_{f,I} \,.\, n_f)$	$A_{f,i}$ n_f	Total floor area [m] Number of floors
Geometry	C_t	Thermal compactness [m] Ratio of the net building volume to the thermally effective envelope area	$C_t=V_n / A_e$ $A_e =\Sigma(A_i \,.\, f_{t,i})$	A_e A_i $f_{t,i}$	Thermally effective envelope area [m] Area of element [m] 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	$GR_e=WWR \,.\, GWR \,.\, g \,.\, \Sigma(A_{ow,i} \,.\, f_{o,i} \,.\, SVF_i)/ \Sigma A_{ow,i}$	WWR GWR $A_{ow,i}$ $f_{o,i}$ g SVF_i	Window to wall ratio Glass to window ratio Area of outside wall [m] Corresponding orientation correction factor Solar factor of glazing Sky View Factor near 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	$U_e = \Sigma(U_i \,.\, A_i \,.\, f_{t,i}) / A_e$	U_i	U-value of element [W.m⁻².K⁻¹]
Operation Parameters	O_u	Fraction of time the building is used annually	$O_u = t_{use,a} / t_a$	$t_{use,a}$ t_a	Annual use hours [h] Total hours in a year[h]
Operation Parameters	Ig_d	Daily area related internal gains [Wh.m⁻².d⁻¹]	$Ig_d = \Sigma\ (q_{i,h} \,.\, t_{use,d} \,.\, f_i)$	$q_{i,h}$ $t_{use,d}$ f_i	Usage-based internal gains rate [W.m⁻²] Daily use hours [h] Share of the usage in the overall building volume
Operation Parameters	Ac_d	Daily air-change rate [d⁻¹]	$Ac_d = \Sigma(n_v \,.\, t_{use,d} .\, f_i)$	n_v	Usage-based hourly air-change rate [h⁻¹]

4.1 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 on a large scale, however, will result in unrealistically monotonous internal load profiles and identical peak hours across the computation domain. To achieve a more realistic 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. 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. A default Coefficient of Variance (CV) is used along with the mean value to generate this distribution (Mahdavi and Tahmasebi, 2015). Based on the generated distribution for each time step, a value is randomly selected for the schedule.

Table 2 – Descriptive indicators for the re-diversification process

Abbr.	Variable Description	Formula	Parameters	
$U_{e,r}$	Effective roof/ceiling U-value [W.m-2.K-1]	$U_{e,r} = \Sigma(U_{i,r} . A_{i,r} . f_{i,r}) / A_e$	$U_{i,r}$ $A_{i,r}$ $f_{i,r}$ A_e	U-value of roof/ceiling element [W.m-2.K-1] Area of roof/ceiling element [m] Corresponding temperature correction factor Effective envelope area [m] (Table 1)
$U_{e,f}$	Effective floor U-value [W.m-2.K-1]	$U_{e,f} = \Sigma(U_{i,f} . A_{i,f} . f_{i,f}) / A_e$	$U_{i,f}$ $A_{i,f}$ $f_{i,f}$	U-value of floor element [W.m-2.K-1] Area of floor element [m] Corresponding temperature correction factor
$U_{e,w}$	Effective wall U-value [W.m-2 .K-1]	$U_{e,f} = \Sigma(U_{i,w} . A_{i,w} . f_{i,w}) / A_e$	$U_{i,f}$ $A_{i,f}$ $f_{i,f}$	U-value of wall element [W.m-2.K-1] Area of wall element [m] Corresponding temperature correction factor
I_{gd}	Daily area related internal gains [Wh.m-2.d-1]	See Table 1		
A_{cd}	Daily air-change rate [d-1]			

4.2 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, 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 (e.g. Kemna and Moreno Acedo, 2014).

4.3 Readjustment of thermal properties

The readjustment of the thermal properties of the main building elements is informed by the respective effective element U-values. The buildings that belong to the same construction period, with different geometries and adjacency situations, have different effective component U-values.

This diversification step modifies each simulation model, so 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. Subsequently, the thermal properties of the main constructions in the new model (external walls, uppermost and lowermost enclosures) are determined so that they reflect the deviation in effective U-values from those of the reference model. Since a modification of the thermal mass of the building was not intended, only the thermal conductivity of the main layer (massive load bearing element or insulating element) is readjusted.

5. Illustrative Example

5.1 Case Study

The utility of the developed computational framework was tested via a case study in the city of Vienna, Austria (located in the centre of the city, featuring over 740 buildings of various usages and construction periods). Following data was incorporated:

- Land Use Plan (ViennaGIS, 2015)
- Digital Elevation Model (ViennaGIS, 2015)
- Building Inventory (ViennaGIS, 2015)
- Building Usage (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)

5.2 Modelled Scenarios

To assess the impact of the diversification process, predictions of the non-diversified model were compared with the predictions resulting from models with two levels of diversification. The non-diversified model is based on the reference simulation files. The first level of diversification involves only operational schedules. The second level includes all diversification steps introduced in the method (Table 3).

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

Three simple illustrative scenarios pertaining to changes in the operational parameters of buildings (occupant behaviour) were designed. The first scenario follows the standard assumptions for internal temperature and HVAC availability hours. The second scenario assumes a setback heating setpoint for the vacant hours in non-residential spaces, which is closer to the actual building operation tendencies. The third scenario, emulating the behaviour of a more energy-aware population, maintains the setback threshold, and modifies the internal heating setpoint temperatures in proportion to the occupancy rate of the building in every time step. These scenarios were simulated with the NDS and DS-2 models. Table 4 provides an overview of the modelled scenarios.

6. Results and Discussion

6.1 Reductive Module

The implementation of the reductive method for the case study area resulted in 7 clusters. The buildings representing these clusters include three residential buildings, two office buildings, as well as two mixed use residential and gastronomy building (Fig. 2).

As mentioned before, the representational performance of the reductive module 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 shown in Fig. 3. Buildings grouped together in each cluster, feature similar performances. The most representative building performance is close to the cluster mean, however, the representatives of Clusters 3 and 6 underestimate their respective categories demand.

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 used to predict the heating demand of the represented buildings. These predictions were compared to the standard-based values (Fig. 4), suggesting an acceptable building-level predictive performance.

Table 4 – An overview of the modelled behaviour change scenarios

		Residential		Non-Residential	
S0	Setpoint 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	Night hours	14	Not working hours
		16	Occupancy rate <25 %	16	Occupancy rate <25 %
		20	Occupancy rate >55 %	20	Occupancy rate >75 %
		Interpolate	Other times	Interpolate	Other times
	HVAC Availability	24 hours a day		24 ours a day	

6.2 Re-Diversification Module

The impact of the diversification process is illustrated for an office building in Fig. 5, where reference schedules are compared to a one-week data generated for one building. The generated schedules maintain the overall tendencies of the reference schedules, but provide, due to their probabilistic nature, unique profiles for various buildings. The diversification of the schedules results in minor modifications in the annual peak load (+1 %) and the aggregated annual demand of the neighbourhood (-1 %). The additional readjustment of the building thermal properties, internal loads, and ventilation rates causes more significant changes in model predictions (-3.4 %).

The impact of the diversification process is magnified when the observation scale is reduced. At a building level, the annual volume-related heating demand of the buildings computed by DM-2 can deviate by as much as 30 % from 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 (Fig. 6). Although unnoticeable at aggregate scale, such variations can have significant implications (e.g. for the design of small scale distributed generation schemes).

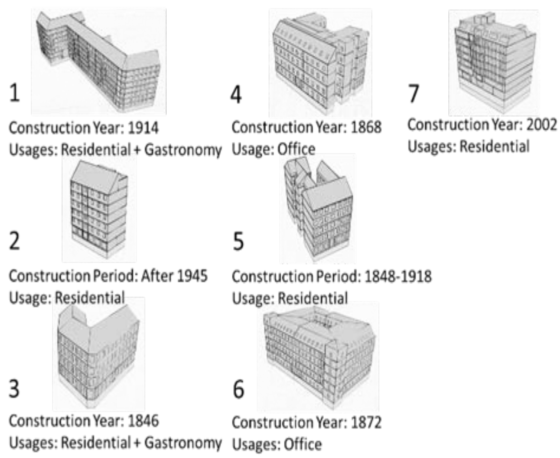

Fig. 2 – Buildings representing the clusters emerged from applying the reductive module to the case study

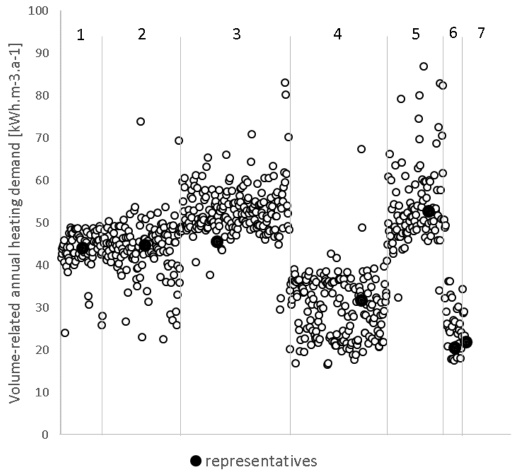

Fig. 3 – Volume related heating demand of buildings in each cluster and the cluster representative

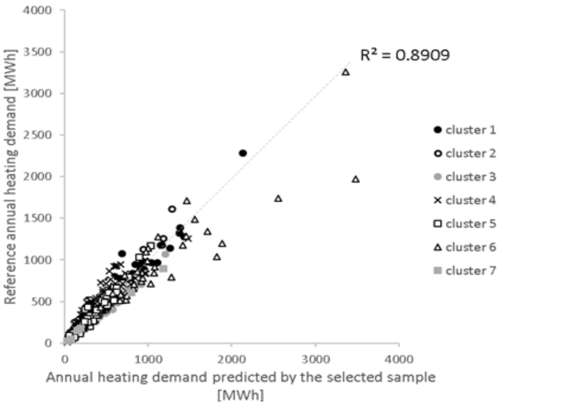

Fig. 4 – Sample-based prediction of heating demand compared to the computed heating demand

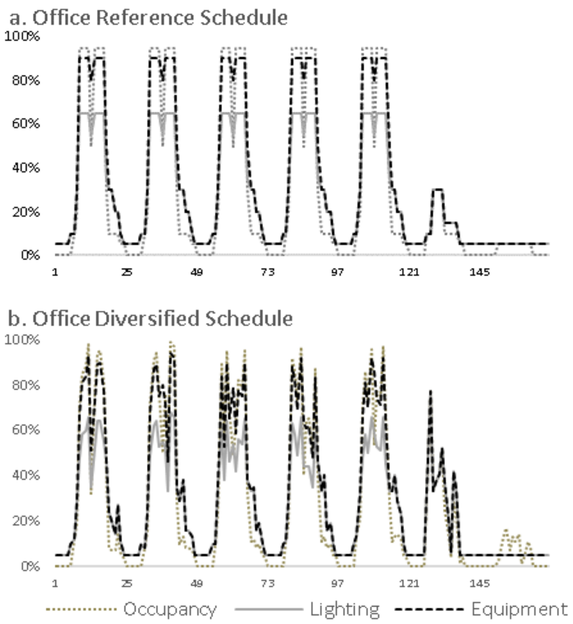

Fig. 5 – a. Office reference schedules according to ASHRAE
b: One-week data of the diversified schedules generated for an office building

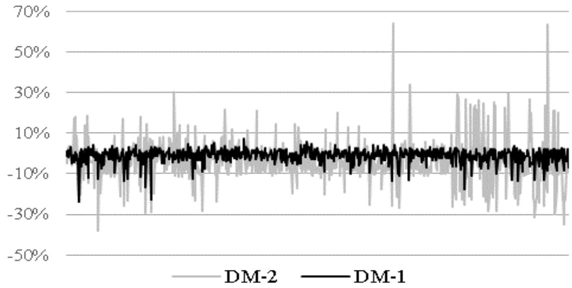

Fig. 6 – Relative deviation of hourly demand results of all buildings as predicted by the DM-1 and DM-2 from NDM predictions for a single time step in heating period

6.3 Scenario Modelling Results

The results of modelled scenarios are summarised in Table 5. At the aggregated level, peak, mean, and total heating demand simulated for the base case assumptions (S0) change little due to the inclusion of a re-diversification in the modelling procedure. The application of the first behaviour change scenario does not result in the divergence of the tendencies of non-diversified and the diversified model. This is to be expected, as the modifications applied in this scenario are somewhat independent from the occupancy-related aspects (they apply only to non-residential spaces in non-occupied hours).

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

The differences become more visible in case of the second scenario. The comparison of the second scenario predictions of both models (NDM-S2, DM-2-S2) with the respective base case predictions of the same models (NDM-S0, DM-2-S0) shows that in the non-diversified model, the application of the occupant-sensitive HVAC control scenario has led to a much larger decrease in demand than in the diversified model (14.7 % compared to 11.1 %). Moreover, the peak load predicted by the non-diversified model is much higher than the predictions of the diversified model, which provides a more realistic representation of the people's presence and actions. The non-diversified model appears to overestimate annual demand reduction due to occupant behaviour change, while failing to realistically predict the impact of these improvements on the peak loads. This can have major implications for the design of energy infrastructure and sizing of distributed generation systems.

7. Conclusion

This contribution described an urban energy-computing environment for urban-level change and intervention scenario modelling. The proposed "hourglass" framework entails a reductive module toward a sampling-based reduction of the computational domain via cluster analysis. Thus, detailed transient numeric simulation can be deployed to analyse the building thermal behaviour. Thereby, to more systematically capture the dynamic nature of the urban building stock and its transformations through retrofitting and densification, as well as operative changes, an original set of energetically relevant indicators was assembled for stock segmentation. The computational framework involves a second (re-diversification) module to partially reintroduce to the model diversity lost through the reductive procedure as well as the adoption of standard-based reference schedules. The utility of the diversification was illustrated via simple behaviour change scenarios. The non-diversified model appears to overestimate the urban-level consequences of occupancy-related changes in the system control settings, due to its unrealistic representation of the occupants' presence and behaviour. Re-diversification has the potential to ameliorate this circumstance, supporting thus, amongst other things, a more effective approach to the design and deployment process of urban-scale distributed energy networks.

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