

THREE METHODS FOR CHARACTERIZING BUILDING ARCHETYPES IN URBAN ENERGY SIMULATION. A CASE STUDY IN KUWAIT CITY.

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ABSTRACT

Significant research effort has gone into developing urban building energy modeling (UBEM) tools, which allow evaluating district-wide energy demand and supply strategies. In order to characterize simulation inputs for UBEM, buildings are typically grouped into representative “archetypes”. This simplification reduces the real diversity of usage patterns, potentially leading to results that misrepresent energy demands. Unfortunately, very little research has focused on identifying the impact of such process in the effectiveness of an UBEM to reliably predict savings from retrofit measures.

This paper analyzes two deterministic common approaches for the definition of building archetypes in UBEM, and proposes a probabilistic third method based on the characterization of uncertain parameters related to building occupancy using measured energy data. Frequency distributions for number of occupants, lighting power and cooling set points are generated through parametric simulation of an urban sample, later used for Monte Carlo (MC) simulation of retrofit scenarios. Measured data for the yearly energy use of one hundred and forty residential buildings in Kuwait city is used as a case study for the evaluation of the three methods. Results for the proposed probabilistic method suggest a significant improvement in the fit of the model to the measured energy use distribution.

INTRODUCTION

In response to current global challenges in climate change, city governments worldwide have developed ambitious emission reduction targets for the next 20 to 60 years. With buildings being a key contributor to urban GHG emissions, considerable effort has been invested in our ability to model the energy demand of existing neighborhoods. The purpose of those simulation methods is to reliably predict the impact of new developments, building retrofit interventions and energy supply strategies on GHG emissions.

The analysis of current overall urban building energy demands can be realized via “top-down” or “bottom-up” models. Top down models (Howard et al, 2012) while useful for the understanding of larger existing stocks, necessarily extrapolate from the status quo and are hence less suitable when future energy

supply-demand scenarios are investigated, especially at the smaller scale of the neighborhood or with smaller temporal resolution. Bottom-up urban building energy models (UBEM), proposed as part of a larger field of “urban micro simulation” (Robinson et al, 2009), apply simulation methods to model individual buildings either as single (Nouvel et al, 2013) or multi zone (Reinhart et al, 2013; Sehrawat and Kensek, 2014) dynamic thermal models.

The process of generation of UBEM (Reinhart and Cerezo, 2015) requires the definition of model data inputs of buildings’ geometry, materials and usage patterns, as well as climate conditions. Weather data is largely standardized since the introduction of TMY format and EPW files (Crawley et al, 1999), and the automated generation of 3D building envelopes is readily available through the use of Geographic Information Systems (GIS), or more advanced urban information models such as CityGML (OGC, 2012). However, given the diversity of building constructions, systems and occupancy patterns in the urban environment, their characterization in UBEM typically requires the use of “building archetypes” i.e. sets of inputs representing a group of similar buildings. Archetypes have been extensively used in top-down modeling of national stocks (Tabula, 2012) classifying building by use, age and shape, and characterizing them according to average properties of a real buildings sample (Ballarini et al, 2014).

The division of a group of buildings into archetypes is typically done in a deterministic fashion and based on generic assumptions. This exact nature of this division has a crucial effect on UBEM accuracy as well as the ability of a model to predict energy savings from proposed interventions of an existing neighborhood. At the aggregate level of large groups of buildings where uncertainties in occupant behavior and operation tend to average out, previous validation works have reported acceptable errors in total energy use of 5 to 20%, especially in heating dominated climates (Dall’O et al, 2012; Caputo et al, 2013). Reported errors however increased up to 99% when results of UBEM were analyzed at the individual building level (Nouvel et al, 2013; Fonseca et al, 2015). These shortcomings, largely related to unknown occupant behavior (Robinson et al, 2011) become especially relevant in the analysis of hourly load profiles (Heiple and Sailor, 2008).

The limitations of available building specific data for usage and operation patterns suggest a need for the introduction of uncertainty modeling in UBEM. Nevertheless, very limited research has focused on identifying the impact of simplification through archetypes and related uncertainties in the effectiveness and accuracy of UBEM in informing urban intervention decisions.

Although given the existing uncertainties around occupant behavior it is unrealistic to expect individual building models to match real demand, the access to datasets of measured energy use can improve both the selection and characterization of archetypes (Aksoezen, 2015). Furthermore, if available at multiple temporal resolutions (Monthly, hourly, etc.) it can significantly improve the accuracy of dynamic simulation models through calibration (Samuelson et al, 2014). While common in single building modeling, the calibration of UBEM is an unrealistic goal, given number of uncertain parameters and the lack of data about use patterns in each building. How much do these issues limit the accuracy of the model? Does UBEM become too under defined to inform decisions about urban interventions and policies?

This paper analyzes two deterministic common approaches for the definition of archetypes for urban energy simulation, and proposes a probabilistic third method based on the characterization of uncertain parameters related to building occupancy using measured energy data. The three approaches are compared in terms of their effectiveness to reproduce the diversity in the measured EUI distribution of the case study, and their impact in the evaluation of savings for a building retrofit scenario. In the following section the three methods are described in detail, and a case study of a residential neighborhood in Kuwait City is presented as a real test case.

METHODOLOGY

Case study in Kuwait City

For the evaluation of archetype characterization methods a residential area was selected in Kuwait City. AlQadisiyah is a neighborhood formed by 2 to 3 stories villas organized in 8 blocks of 200 houses each, plus a central block for public services. Figure 1 shows block 8, the section selected for this study. It is representative of most residential areas in the city, with a majority of structures built as government provided housing between the 1960s and 80s, and is considered as a relevant sample. The residential villas in the neighborhood and in the city can be categorized in four main groups according to their age: (1) Original and (2) retrofitted government housing built before 1980s, (3) modern villas built between the 1980s and the 2000s, and (4) villas built according to code in the 2010s.



Figure 1 Al-Qadisiyah neighborhood case study

This classification based on local expertise will later be used in method B, and attends not only to the year of construction but also to the type constructive solutions and systems found in that category of buildings (See figures 2A, 2B and 2C).



Figure 2 Villa age groups examples: Original/retrofit (A), modern (B) and to code (C)

Measured yearly electricity consumption was gathered in collaboration with the Kuwait Institute for Science and Research (KISR) for 158 buildings within the area. Out of that sample, 140 data points were selected (Depicted in black in figure 1) after eliminating those in which the quality of the data was uncertain. The EUI for each building was calculated based on built floor area, resulting in a distribution with an average of 210 kWh/m², and values ranging between 73 and 597 kWh/m² (Figure 3). Although both high and low extremes of the resulting distribution are uncommon for this building type, they have been validated as real consumption values. The figure below shows how code compliant buildings concentrate in the lower part of the spectrum.

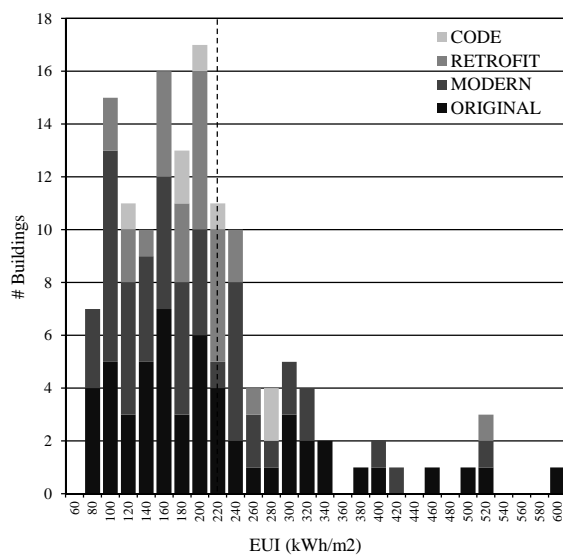


Figure 3 Measured EUI distributions

Archetype characterization methods

The definition of building archetypes for an UBEEM requires the classification of the modelled built stock in groups, and the characterization for each group of all non-geometrical data inputs necessary for an energy model. These include mainly construction and glazing assemblies, HVAC systems, occupancy patterns and internal loads. The number of archetypes and the accuracy on their characterization depends on how much information is available about the

buildings' use, age, systems, etc. The following three scenarios of increasing level of documentation were modeled and evaluated through the case study.

Method A – Available literature

In case A, all buildings sharing the same use (e.g. residential, office, etc.) are modeled with a single archetype. The characterization of building and occupancy parameters is done deterministically based only on available literature. This includes local energy and construction codes and published research. Method A is the most common approach to urban modeling, and typically the only one possible since municipal or regional governments rarely maintain any more detailed descriptions of buildings. In the case study for Kuwait construction assemblies, coefficient of performance (COP), set point temperatures and occupancy schedules (Table 1) were defined according to published residential energy simulations (Assem and Al-Ragom, 2009; Al-Ajmi and Hanby, 2008; Al-Mumin et al, 2003) and requirements from the 2010 Energy Code of Practice (MEW, 2010).

Method B – Local expertise

In case B, buildings of the same use are further divided using one or more additional classification parameters such as age or size. Method B requires a deeper knowledge of local construction and engineering practices and the documentation of a representative sample of buildings for each archetype. Simulation parameters are characterized deterministically based on these sources.

In the case study, buildings were further divided in four archetypes based on the four periods of construction presented in the previous section. The characterization of simulation parameters was developed in collaboration with the Kuwait Institute for Science and Research (KISR) and the Architecture Dept. in Kuwait University (KU), based on local expertise and two site visits in the neighborhood developed in 2014 (Table 1). The authors documented materials and systems in a group of 5 villas including already built, under construction, and in demolition structures. Window to wall ratios (WWR) for each building were individually assessed through photography analysis. In addition, detailed occupancy, plug loads, and lighting power density

Table 1 Building and occupancy simulation parameters

METHOD / AGE		Wall U W/m ² K	Roof U W/m ² K	Glazing	Infiltr. ach	Cooling COP	SetPoint C	Occupancy occ/m ²	Lighting W/m ²	PlugLoad W/m ²
A	Any	0.62	0.53	Dbl Ref	0.5	2.4	22	0.020	10.0	8
B	Original	2.50	1.56	Dbl Clr	0.8	2.2	22	0.013	6.6	7.0
	Modern	0.62	0.53	Dbl Ref	0.5	2.4	22	0.013	6.6	7.0
	Retrofit	2.50	1.56	Dbl Ref	0.5	2.2	22	0.013	6.6	7.0
	Code	0.32	0.40	Dbl LoE	0.3	2.9	22	0.013	6.6	7.0
C	Original	2.50	1.56	Dbl Clr	0.8	2.2	PROB	PROB	PROB	PROB
	Modern	0.62	0.53	Dbl Ref	0.5	2.4	PROB	PROB	PROB	PROB
	Retrofit	2.50	1.56	Dbl Ref	0.5	2.4	PROB	PROB	PROB	PROB
	Code	0.32	0.40	Dbl LoE	0.3	2.9	PROB	PROB	PROB	PROB

(LPD) schedules were developed by residential room type based on a survey of 50 similar residences (Al-Mumin et al, 2003) and average room sizes for government provided model residences (PAHW, 2014), in order to refine the generic values in method A. This resulted in lower internal loads due to lower internal gains in circulation areas.

Method C – Probabilistic occupancy parameters

While detailed expert archetype classifications as presented in method B significantly reduce the level of uncertainty related to building envelopes and systems, they are still deterministically assuming average occupant behavior, and can hardly reproduce the diversity of EUIs existing in the built environment. In case C, an additional level of detail is introduced to archetypes by assigning probability distributions to key uncertain parameters in the model such as occupancy, lighting, plug loads or set point temperatures. Since distributions for these parameters are not readily available, the following method for “probabilistic estimation” is proposed, with the initial assumption that all unknown parameters have a uniform distribution.

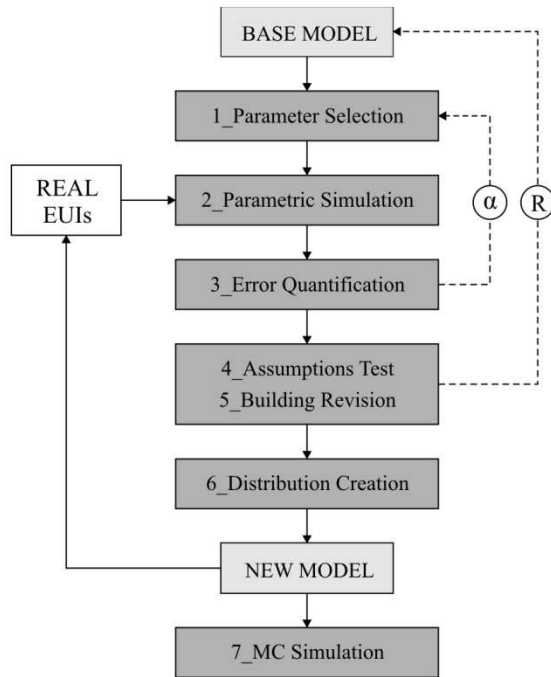


Figure 4 Probabilistic estimation method

Method C combines UBE simulation with measured energy data for a set of buildings with the same building use to estimate simulation parameters through the following steps (Figure 4):

1. *Parameter Definition:* Unknown parameters (X_i) are selected, and acceptable limits for each one's initial uniform distribution are defined. This distribution is discretized into a set of potential parameter values.
2. *Parametric Simulation:* A parametric analysis is performed for each building in the sample through UBE simulation for each combination

of parameter values $Y_i = [x_1, x_2, \dots, x_n]$. Energy use results are obtained at the same temporal resolution (Yearly, monthly, hourly, etc.) of the real energy use data.

3. *Error Quantification:* For each building result, the relative error (E) against the measured data is calculated as $(EUI_{sim} - EUI_{mes}) / EUI_{mes}$. If $E < \alpha$, with α being the maximum acceptable error in the model, the combination Y_i is selected as a solution for that building.
4. *Test of Assumptions:* The ratio of buildings (R) for which at least one solution was found within the parameter space is calculated. If R is smaller than an acceptable percentage of the sample, the general simulation model and step 1 should be revisited and refined.
5. *Building Revision:* Once R is accepted, the remaining buildings which cannot be explained are revisited in an effort to identify variables unaccounted for or irregularities in the buildings.
6. *Distribution generation:* All accepted values combinations Y_i , regardless of the building they belonged to, are treated as random vectors and put together in a multivariate joint probability mass distribution.
7. *Monte Carlo Simulation:* The UBE or a sample is simulated multiple times, picking random combinations of parameters from the created distribution (Through simple random sampling), obtaining as a result a frequency distribution of building EUIs and/or total energy use for the model.

In the case study three uncertainty occupancy related parameters (marked as “PROB” in Table 1) were chosen as critical to the variability of the UBE: Cooling set point (STP; Between 18 and 25 C), installed lighting (LPD; Between 5 and 14 W/m²) and occupancy (OCC; Between 0.005 and 0.023 occupants/m²). Plug loads (PLG) and maximum hourly domestic hot water consumption (DHW) were modelled as linear functions of occupancy as shown in equations 1 and 2:

$$PLG (W/m^2) = 560 \times OCC (occ/m^2) \quad (1)$$

$$DHW (m^3/m^2 s) = 1.68E-6 \times OCC (occ/m^2) \quad (2)$$

A parametric analysis of 640 simulations was performed for each building, in the case study. With an accepted error $\alpha = 0.05$, 105 out of 140 buildings found one or more combinations of parameters that matched the measured EUI, showing that at least 75% of the values could be explained within the proposed parameter ranges, while the rest will be revisited on the site in future research to identify shortcomings of the model. The resulting marginal probability mass distributions (PMF) are presented in the results section.

Modeling and comparison framework

For the comparison of methods full energy models were built of the urban case study. A multicomponent workflow was set up for this work to streamline the generation of UBE, using municipal GIS datasets as a base input for building geometry, ground elevation and context, as well as database for building properties such as window to wall ratios measured on site (Figure 5). Multi-zone energy models for all buildings and well as 3D context shading were generated within the CAD environment Rhino 3D (McNeel, 2012). Custom C# applications were built for the automated generation of 3D models, generic zoning and shading calculations, within the parametric Rhino plugin Grasshopper. Simulation parameters for each archetype were stored and implemented in an XML template file format developed by the authors as a standard for urban energy modeling (Cerezo et al, 2014). Energy simulations were developed in EnergyPlus (Crawley et al, 2000) and energy models were generated using the Archsim plugin tool (Archsim, 2015).

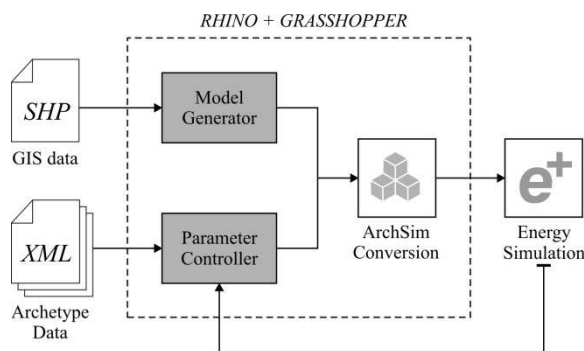


Figure 5 UBE modeling framework

The evaluation of the three methods was developed in two stages: (1) Goodness to fit against the measured distribution of EUIs, and (2) predicted absolute energy saving for the whole neighborhood:

1. *Measured EUI comparison:* The urban model was simulated using weather data gathered for the year of the measurements, for methods A, B and C. In C, each building was modelled using Monte Carlo analysis and random sampling the joint parameter distribution a hundred times. The resulting frequency of EUIs for the 10,000 EnergyPlus runs, plus the EUI distributions of methods A and B were compared with the real distribution for the 100 matched cases, in terms of average, standard deviation, and K-S statistic, defined as the maximum distance between two cumulative distributions for any value of EUI.
2. *Retrofit savings comparison:* A hypothetical intervention scenario was assumed in which all buildings from periods before the current Kuwait energy code had their envelopes upgraded in terms of insulation, infiltration rates and glazing

to modern requirements. Models A, B and C were simulated using the same procedures. In case C the distribution of total absolute savings for the model was calculated by taking 1,000 random samples from the results. Finally results were compared between the three methods in order to quantify the impact of the occupancy uncertainties in calculated savings.

RESULTS

Measured EUI comparison

The application of characterization method C resulted in a non-uniform distribution for the joint probability distribution of set points, lighting and occupancy. The resulting marginal PMFs of the three variables for the sample are depicted in figure 4, with respective average values of 22 C, 9.5 W/m², and 0.011 occ/m².

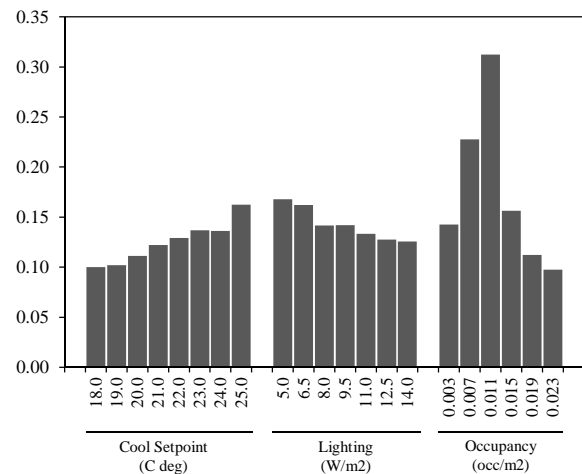


Figure 6 Marginal PMFs for cooling set point, LPD and occupancy

These results represent the uncertainty of occupancy related parameters for the whole population of residential villas and were used in method C simulation. The simulation of the case study, given the previously presented assumptions and framework, provided EUI distributions for the three methods which were compared with measured ones (See figures 7A, 7B, 7C, and table 2). In case A, the average EUI of 246 kWh/m² showed an error of 18% to the measured average of 210 kWh/m². It also showed a completely different extent of the distribution, and standard deviation of 8 kWh/m² (91% error against 90 kWh/m² in the sample) which could not reproduce the extreme energy consumption values in the sample, and a mean percentage error (MPE) of 70%. The K-S statistic obtained was 0.52.

Case B showed that the increase in detail for template characterization introduced by dividing the buildings in periods on construction was enough to match the average of the real sample (3% error). However, there was still an error of 56% in the standard deviation which showed a much more concentrated

distribution as shown in the figure 7B. Results showed an MPE of 18% and a K-S statistic of 0.21.

Method C resulted in an average EUI of 212 kWh/m² (4% error to the sample average). More importantly, it expanded the distribution spread according to the probabilistic characterization to a standard deviation of 62 kWh/m² (30% error compared to the sample). The remaining difference in variance is explained by the isolated very high real EUIs (Over 450 kWh/m²).

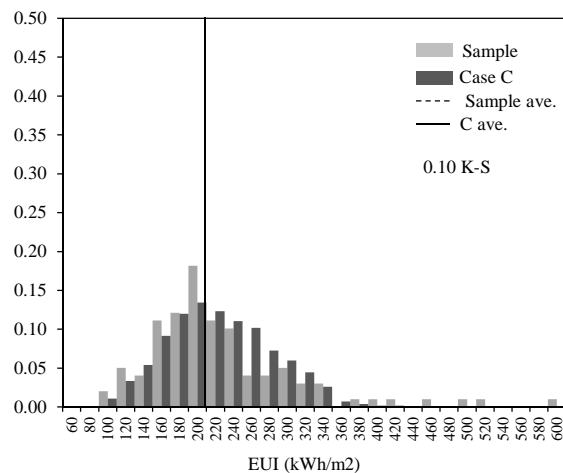
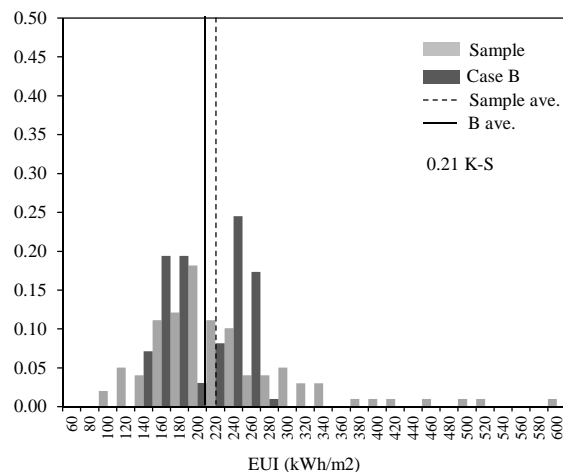
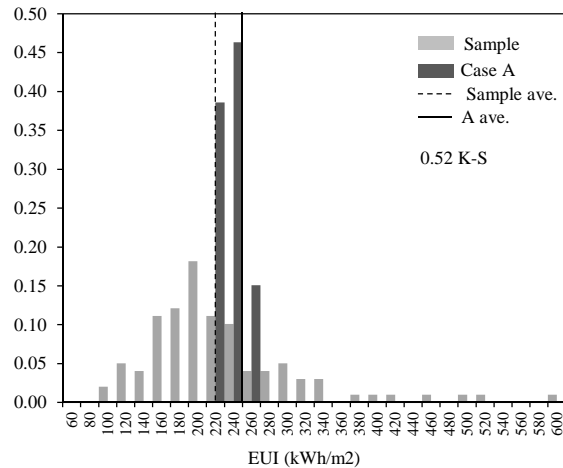


Figure 7 EUI distributions and averages for A, B and C against measured distribution

Given the probabilistic approach to the simulation in which each building has been modelled multiple times, it is not possible to calculate a MPE for case C (* in table 2). Instead the K-S statistic is used to analyze its goodness of fit against the sample, with a result of only 0.10, showing the improved reproduction obtained with the method. Therefore model C was assumed as the most accurate baseline to compare A and B for the retrofit calculation in next section.

Table 2 Comparison metrics by method

METHOD	Ave. / Std. Error	MPE	K-S
A	0.18 / 0.91	0.70	0.52
B	0.03 / 0.56	0.18	0.21
C	0.04 / 0.30	*	0.10

Retrofit savings comparison

Based on the models built following methods A, B and C simulations were developed for the retrofit scenario described in the methodology below. For each case the total absolute savings for the original 140 buildings sample were calculated, resulting in a single value for cases A and B, and a probability distribution of savings for case C (Figure 8). The deterministic result for case B of 32 kWh/m² matches the average savings for case C (31 kWh/m²), while case A slightly overestimates them.

More interestingly the uncertainty of savings associated with the occupancy parameters resulted to be relatively small (Within a 10% of the average) with a very small coefficient of variation CV = 0.02. This result coincides with that of case B and shows negligible risk caused by occupancy uncertainties.

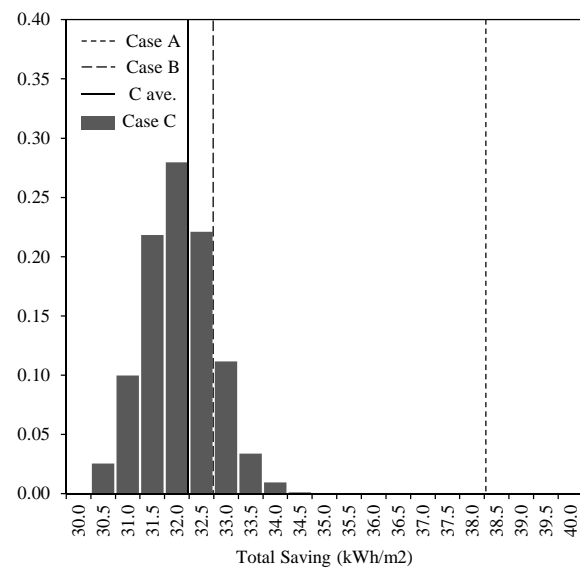


Figure 8 Total savings per m² distributions for methods A, B and C

DISCUSSION

Selecting uncertain parameters in UBEM

This work has presented a method for improving UBEM model accuracy by reproducing uncertainties in occupant behavior related parameters based on measured yearly energy data. The results have shown that for this case study the goodness of fit of the aggregate distribution of EUIs is very significantly improved, allowing the modeler to further study urban interventions taking into account the impact of these occupant uncertainties. While the approach has proven to be successful, one critical reader might question the assumption that these 3 parameters are responsible for all uncertainties in the model and enough to explain it. Although it is true than other unknown parameters such as infiltration rates or window operation are equally responsible for the discrepancy between the model and the measured data, as a proof of concept the method was limited to a computationally manageable number of variables. The further development of the method and its effective implementation will however require a previous extensive step of sensitivity analysis and uncertainty screening at the urban scale. Such procedure would help identify which parameters can be treated deterministically without significantly altering the performance of the model.

Equally important is the need for a more extensive analysis of the goodness to fit of the resulting distribution, by applying bootstrapping techniques to method C, selecting a large number of subsamples to simulate, and analyzing the resulting distributions to the remaining non sampled buildings. Such further work would be fundamental in understanding the bias of the obtained parameter distributions. Regardless the specific implementation, a new probabilistic modelling method for occupant related uncertainties needs to be streamlined in UBEM. So far though, only the CITYSIM modeling tool (Robinson et al, 2009) has implemented such a model.

The importance of measured energy data

The model of AlQadisiyah has shown the relevance of validating and improving urban energy modeling techniques with individual building yearly measured energy data. Most research in the field of UBEM has so far focused on the processes of model construction and simulation, but such models have yet to prove their capabilities to accurately represent the built environment at the building level. Particularly relevant is the validation against hourly energy data, necessary to effectively model peaks in demand of interests for both urban planners and supply utilities. Unfortunately, privacy concerns make individual energy data still extremely difficult to access for large enough samples of buildings.

In the opinion of the authors, a strong collaboration is necessary between municipal governments and utilities to address these accessibility limitations. As

part of that interaction, simulation parameter distributions could be generated through the approach here proposed, and general “archetype datasets” could be validated and refined for further analysis of urban interventions and policies. That somehow ideal scenario requires a significant effort to improve the current practices for documentation of the built environment, but it is a necessary step to produce useful urban models.

Informed urban decision making and design

Being a model’s capability to accurately represent real patterns of energy demand necessary, it is important to highlight that the main goal of any urban modeling exercise is to inform decisions about potential urban interventions. Both urban planners and policy makers wish to evaluate proposals for retrofits, energy systems and new constructions and understand their benefits and costs. In that context, occupant behavior often appears as a large uncertainty which introduces too much of a risk to justify and calculate energy savings and investment returns and for that reason characterizing those uncertainties has to be a priority in UBEM. The results for an envelope retrofit savings estimated considering method C in this work showed that, against what the wide range in EUIs suggests, aggregate yearly savings for the whole neighborhood have a very small variance and associated risk. They also suggest that aggregate savings can be predicted through the deterministic method B, as long as the average EUI obtained matches that of the real distribution. These assumptions however are only valid when aggregate savings are considered and cannot be applied to individual buildings, or smaller temporal scales such as hourly peaks. It is necessary for both modelers and decision makers to understand which level of detail and uncertainty modeling is necessary depending on the decisions under consideration.

CONCLUSION

This paper has proposed a probabilistic method for the characterization of occupancy related parameters in urban simulation archetypes, using dynamic energy simulations and yearly measured energy data. The resulting building archetypes were compared with two common deterministic methods of building archetype generation in the simulation of 140 residential buildings in Kuwait city. The results have shown that the proposed method achieved a 30% reduction in error of the standard deviation when compared with the real EUI distribution, and was used to demonstrate that the uncertainty of the model does not significantly affect the cumulative savings for a building envelope retrofit intervention.

NOMENCLATURE

EUI = Energy Use Intensity (kWh/m²)
WWR = Window to Wall Ratio
 α = Maximum simulation error

R = Ratio of buildings with acceptable α
 STP = Cooling setpoint temperature (C)
 LPD = Lighting power density peak (W/m^2)
 OCC = Occupancy density peak (occ/m^2)
 PLG = Plug load density peak (W/m^2)
 DHW = Domestic hot water peak ($m^3/m^2 s$)

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