Implementation of a calibrated Urban Building Energy Model (UBEM) for the evaluation of energy efficiency scenarios in a Kuwaiti residential neighborhood

Carlos Cerezo Davila[1], Nathaniel Jones[1], Adil Al-Mumin[2], Ali Hajiah[3], Christoph Reinhart[1]
[1]Massachusetts Institute of Technology, Cambridge MA, USA
[2]Kuwait University, Kuwait City, Kuwait
[3]Kuwait Institute for Scientific Research, Kuwait City, Kuwait

Abstract

To support the implementation of urban energy efficiency strategies, a new generation of urban building energy modeling (UBEM) tools has been introduced which allows cities to simulate the expected energy demands of neighborhoods. In order to define simulation inputs, UBEM models usually use archetypes, in which occupant-related parameters like occupancy, plug loads or set point temperatures are defined deterministically. This simplification can lead to wrong predictions in savings for energy efficiency strategies. Building on previous research, this paper implements an UBEM workflow to evaluate the relevance of occupant uncertainty modeling when predicting energy efficiency savings for a neighborhood. An existing model of 172 villas in Kuwait city is used as a case study. Occupant parameters are characterized through both deterministic assumptions and calibrated uncertainty distributions. Three retrofit and two pricing scenarios are modeled and simulated using both methods. Finally, energy and cost savings are calculated, and the performance of both modeling methods is evaluated from the application perspectives of three urban decision makers. Results show that while effective for aggregate savings, deterministic UBEMs ignore uncertainties up to 30% when considering single buildings, and can misrepresent average cost savings, especially with tiered pricing.

Introduction

In response to current global environmental challenges, city governments are developing ambitious long-term greenhouse gas (GHG) emission reduction targets such as 60% by 2025 for London or 80% by 2050 for New York City. With energy consumption in buildings being a key contributor to emissions, cities are exploring the potential impact of a variety of energy retrofit strategies that apply to both the buildings (envelope and system updates) as well as occupant lifestyle choices. In this context, Kuwait City has the goal to reduce its building-related emissions by 2030 by at least a 15% (Kuwait EPA 2012). In order to understand the full gamut of measures that this goal requires, the city's leadership needs planning tools that provide an understanding of current energy demands, along with predictions of how these energy demands would change if various energy policies were to be implemented.

Urban Building Energy Models (UBEM) have recently been proposed as a bottom-up, physics based modeling technique to support the implementation of energy efficiency strategies in urban policy (Reinhart and Cerezo 2016). As opposed to more traditional top-down (Howard et al 2012) or bottom-up statistical models (Abdolhosseini 2016), UBEMs apply performance simulation methods to represent each building and its immediate surroundings as a thermal model. As with single building energy models (BEM), the generation of an UBEM requires the definition of numerous data inputs, including a large set of non-geometric parameters such as construction assemblies, usage schedules and internal loads. To define these model inputs, UBEMs usually rely on "archetypes", classifying buildings by use or age (Filogamo et al 2014), and then assigning them a common set of properties. Yet, in the absence of detailed building stock information, this process remains somewhat arbitrary, relying on deterministic estimates based on the judgement of the modeler. Such broad simplification misrepresents the real diversity of energy demands, and can lead to wrong predictions when evaluating energy strategies.

This is particularly true for occupant-related parameters such as occupancy schedules, plug loads or set point temperatures, which are unknown for the modeler at the urban scale but have a significant impact on simulated energy demands (Jones et al 2015). Providing a static value for these parameters will produce and UBEM in which all occupants behave identically, hence ignoring extreme demands and leading to unrealistic load peaks. Developing methods for their simulation and calibration against metered demands is therefore especially relevant if UBEMs are to be used for urban decision-making. In the simulation of single buildings, occupant related demands have been traditionally modelled through a combination of peak loads and hourly diversity schedules. While this approach is appropriate for the analysis of annual or monthly demands, it cannot represent the stochastic nature of loads, especially relevant at smaller time scales and for risk analysis. To address this issue, extensive research has focused on combining occupant data with probabilistic uncertainty modelling methods to improve BEM effectiveness (Yan et al 2015), using data from occupant monitoring, time use surveys (Yamaguchi and Shimoda 2015), or travel surveys (Rakha et al 2014).

In the definition of UBEM archetypes, the use of deterministic peak loads and schedules is particularly problematic, since they represent a large number of buildings, and occupant behavior related parameters are likely to vary substantially among buildings within the same archetype. When an UBEM is used to determine the overall annual demand for a district, differences in occupant behavior tend to average out. In that case, deterministic UBEMs have been shown to reproduce the overall metered energy demand with an aggregate percentage error (PE) lower than 15%. However, when comparing simulated and real energy demands on the building level for the same UBEMs, reported PEs increased up to 15 times (Reinhart and Cerezo 2016). In this context, the diversity of behaviors within an archetype makes it also impossible to perform a typical optimization based calibration, since no single set of parameter values will fit all the buildings represented.

Instead, to capture the real distribution of demands in UBEM, parameter uncertainties need to be considered through the probabilistic modeling of occupant variables. Stralzka et al (2011) showed that introducing normally distributed heating set points in an otherwise fixed/deterministic UBEM achieved a significant improvement in accuracy. Similarly, He et al (2015) employed a stochastic occupancy model to reduce the unrealistic hourly demands resulting from the use of deterministic load definitions in UBEM. Probabilistic models for occupant parameters can not only reproduce demands more accurately, but also are better suited for calibration through Bayesian methods.
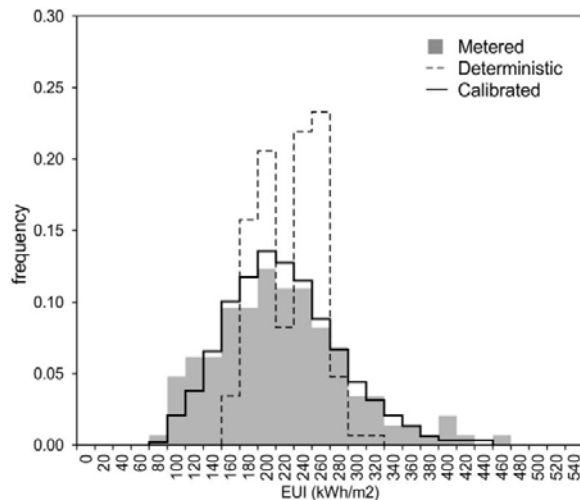

Figure 1: Metered and calibrated EUI distributions

Bayesian calibration techniques, extensively applied in individual building simulation, assume prior uncertainty distributions for select unknown parameters, which are later refined based on available metered demand data using "Bayes law" (Heo et al 2012). More recently, their use has been suggested for the calibration of large portfolios of buildings (Heo et al 2015) or apartments (Kim et al 2015), and extended to an urban context by applying it to clusters of buildings of the same type

(Booth et al 2013). In previous research, the authors validated such application at the annual (Cerezo et al 2015) and monthly scales (Sokol et al 2017) for neighborhoods in Kuwait and Cambridge (MA), achieving in both cases a significant accuracy improvement in the simulation of energy use intensities (EUI) distributions. In the Kuwaiti case study of AlQadisyah, also explored in this paper, a joint likelihood distribution for occupancy, plug loads and set points parameters was developed through Bayesian calibration using building metered demand data. Figure 1 shows how the EUI distribution from the probabilistic calibrated model compared to that of a deterministic (uncalibrated) one, as well as to the metered distribution in the case study of this paper. While performing clearly better, the calibrated model also requires access to individual building data, and it is accompanied by a substantial simulation overhead. However, it has not yet been established what are its advantages over its basic deterministic counterpart. More specifically, it remains unclear how relevant is the modeling and calibration of uncertainty in archetype occupant parameters when comparing potential energy retrofit scenarios.

To address this question, this paper lays out a modeling procedure applicable in the analysis of any other urban building stock. The procedure is tested by comparing three retrofit and two energy-pricing scenarios in the above mentioned UBEM model of a Kuwaiti residential neighborhood. As part of the case study, occupant archetype parameters are defined using two methods: Deterministic uncalibrated assumptions, referred to as the "Basic" case, and probabilistic calibrated variables, the "Stochastic" case. In the implementation of this procedure the paper fulfills two main goals: First, to compare the performances of the two methods by scenario. Second, to understand how these predictions can inform a decision about energy policy. For that purpose, results are interpreted from the perspectives of a municipal energy planner, a local utility trying to target building owners, and local policy maker defining implementation strategies.

Methodology

The data collection and simulation procedure, as applied in this study, can be broken up into the following steps:

1- Building and energy data collection
2- Archetype classification and definition
3- Calibration of occupant related parameters
4- Definition of retrofit scenarios
5- UBEM generation and simulation
6- Calculation of energy and cost savings

Building and energy data collection

The initial step is to identify and gather data about the area of study, necessary for the model and representative of the larger building stock of interest. For the present case study in Kuwait, residential building energy use is of particular relevance as it accounts for 60% of the country's electricity use. Moreover, in this cooling

dominated climate, air conditioning accounts for more than 60% of that use and 85% of annual peak loads. The latter statistic is especially important for the local utility, since cooling peaks currently exceed grid capacity during the summer, while the demand for new residences keeps increasing. The use of UBEM is therefore particularly pertinent in this residential case study.

The residential district of AlQadisyah, developed initially in the 1960s, is mostly formed by 2 to 3 stories villas or small apartment buildings. It is organized in nine distinct areas of which area 8 was chosen for this study. It comprises 172 documented buildings, which according to their year of construction (Figure 2), can be grouped into four main periods: (1) Original government villas built between the 19060s and 80s in 32% of the district. (2) Retrofitted original villas in the 1990s or 2000s (16%). (3) Villas, private or government sponsored, from the 80s and 90s under the 1983 Energy Conservation code (42%). (4) Recent structures built after the 2010 Energy Code accounting for a 10%.

Figure 2: Area 8 buildings classified by period

As part of the earlier mentioned previous research work (Cerezo et al 2015), extensive data gathering was conducted for the area, which included GIS information from the city, constructions data from local experts, and on site photographic documentation of Window to Wall Ratios (WWR) and number of stories. Regarding energy consumption data for calibration, measured annual demand for 2013 was gathered for 172 buildings. Weather data sufficient for the generation of a real year EPW file was obtained for the same period. The energy use intensity (EUI) for each building was calculated based on built floor area, resulting in a mean of 209 kWh/m2 with a global minimum of 66 kWh/m2 and a global maximum of 444 kWh/m2.

Archetype definition methods

For the characterization of the UBEM of AlQadisyah, all buildings were classified into four main archetypes according to the four construction/renovation periods: 1960s original villas, 1960s retrofitted villas, 1980s-00s villas, and those built after 2010. All building-related parameters were defined deterministically, based on

gathered data from available literature and site visits (Table 1). Constructions, glazing and shading types, coefficients of performance (COP) and infiltration levels were chosen according to expert assumptions, published energy models of Kuwaiti homes (AlAjmi and Hanby 2008; Assem and AlRagom 2009; Kuwait PAHW 2008) and requirements from the 2010 (Kuwait MEW 1983) and 1983 (Kuwait MEW 2010) Energy Codes. The authors chose to ignore uncertainties in these parameters, assuming that most of their variation is captured by the four types. The decision was based on the sensitivity analysis of an average-sized building by archetype, in which the effect in EUI of 15% variations in envelope U values, cooling COPs and infiltration rates was estimated to remain below a 10% in all cases. Further analysis will be required in future studies to incorporate those parameters as additional uncertainties.

Table 1: Building-related parameters by period

Parameter	Period	Value
Wall / Roof U (W/mK)	60s (Org.)	2.53 / 1.56
	60s (Rtr.)	2.53 / 0.53
	80s-00s	0.62 / 0.53
	10s-Now	0.32 / 0.40
Glazing U (W/mK) / SHGC	60s (Org.)	5.96 / 0.86
	60s (Rtr.)	2.89 / 0.76
	80s-00s	2.89 / 0.17
	10s-Now	2.33 / 0.65
Infiltration rate (ach)	60s (Org.)	0.8
	60s (Rtr.)	0.5
	80s-00s	0.5
	10s-Now	0.3
Cooling system COP	60s (Org.)	2.4
	60s (Rtr.)	2.4
	80s-00s	2.4
	10s-Now	2.9

As previously discussed, occupant related parameters were defined using two separate methods: (1) Basic as single values, and (2) stochastic through a calibrated distribution. Four base parameters were chosen as being critical to the variability of the archetype, to be defined probabilistically: Cooling set point temperature in °C (STP), peak installed lighting power density in W/m2 (LPD), peak average occupancy in occupants/m2 (OCC), and a multiplier factor for plug loads (MLT). Peak plug loads (PLG) and peak hourly domestic how water consumption (DHW) were derived as linear functions of those four as shown in equations 1 and 2, based on deterministic appliance modeling for a standard villa.

$$PLG(W/m2) = \begin{cases} (7.7 + 260 \times OCC) \times MLT & 1\,fl., \\ (4.7 + 260 \times OCC) \times MLT & 2\,fl., \\ (3.2 + 260 \times OCC) \times MLT & 3\,fl. \end{cases} \quad (1)$$

$$DHW(m3/h/m2) = 0.01083 \times OCC \quad (2)$$

In the basic approach, values were assigned to the four parameters based on available literature and local expertise (Table 2), while the associated diversity hourly schedules were developed by residential room type based on a survey of 50 similar residences (AlMumin et al 2003) and average room sizes for government

provided housing. Window shading operation, was not modeled, since when available it stayed closed. Given that only annual demands were available for calibration, schedules were treated deterministically in both cases.

Table 2: Occupant-related parameters by method

Parameter	Floors	Deterministic	Calibrated
Occupancy (pp/m2)	Any	0.012	Joint Dist.
Lighting Power (W/m2)	Any	12.3	Joint Dist.
Plug Multiplier (-)	Any	1.0	Joint Dist.
Plug Power (W/m2)	One	10.8	f (OCC,MLT)
	Two	7.8	f (OCC,MLT)
	Three	6.3	f (OCC,MLT)
DHW Peak (m3/m2/h)	Any	0.00013	f (OCC)
Cooling Set point (°C)	Any	22	Joint Dist.
Heating Set point (°C)	Any	18	18

Calibration of occupant related parameters

For the stochastic method, the four critical parameters were initially defined as uniform prior distributions with an acceptable min/max values, and later calibrated using the Bayesian approach described in the introduction, already applied to this UBEM (Cerezo et al 2015). As part process, each building was simulated under 625 combinations of parameters with the real weather data, and the calibration error (α) was calculated as the percentage error (PE) in the simulated EUI, with a acceptable value of 5%. Later, all combinations for all buildings where $\alpha < 5\%$ were aggregated in a joint likelihood calibrated distribution. The marginal distributions before and after are shown in Figure 3. The calibrated parameters were validated comparing the simulated and measured EUI distributions for area 8, showing a PE in the mean of 1%, PEs for the 10 and 90 percentiles below 15%, and very good fit in the distribution shape (Figure 1). While these calibrated parameters are only "true" for this especific case study, their further validation in a similar district in Kuwait rendered equally low PEs in average and percentiles.
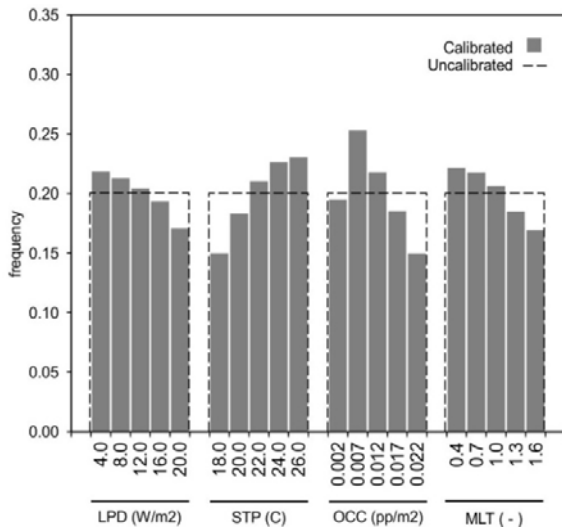

Figure 3: Calibrated parameter marginal distributions

Calibrated parameters were applied to all buildings, regardless of archetype, assuming that all residents belong to a single socioeconomic group. Further analysis of census data may allow for a finer classification.

Retrofit and pricing scenarios

Once archetype parameters have been calibrated, a suite of energy efficiency strategies (EES) can be proposed for evaluation. In AlQadsiyah, these strategies range from simple and affordable to deep retrofits, and were defined in collaboration with local institutions. Table 3 lists the EES by increasing difficulty of implementation with estimated average cost in Kuwaiti Dinars (KD). For reference, at the time of writing 1 KD = 3.28 USD.

Table 3: EES descriptions and costs

Energy Strategies	Unit	Cost (KD)
Facade weatherization	m2	0.16
LED light bulb 80% replacement	item	4
Refrigerator replacement (EnergyStar eqv.)	item	290
Washing replacement (EnergyStar eqv.)	item	240
Dryer replacement (EnergyStar eqv.)	item	140
High efficiency AC system upgrade	ton	185
Exterior XPS insulation addition	m2	3
Exterior finish paneled leaf addition	m2	18
Window replacement with low emissivity	item	145

For simulation, these strategies were grouped into three scenarios. The first includes all EES related with the upgrade of lighting, appliances and cooling equipment, which could be implemented without any construction activities. The second includes the retrofit of the building envelope to reach the 2010 code requirements, and the replacement of all windows. Finally, the third combines all EES. The archetype parameter changes used to represent these scenarios are detailed in Table 4.

Table 4: Parameter upgrades by scenario

Parameter	Lighting Equipment	Envelope Glazing	Combined
Lighting Power (W/m2)	base x 0.40	-	base x 0.4
Plug Power (W/m2)	base x 0.84	-	base x 0.84
Wall / Roof U (W/mK)	-	0.32 / 0.40	0.32 / 0.40
Glazing U (W/mK) / SHGC	-	2.33 / 0.65	2.33 / 0.65
Infiltration rate (ach)	0.4	0.4	0.4
Cooling system COP	3.3	-	3.3

In order to understand the affordability and economic feasibility of the scenarios, two energy pricing scenarios were modeled as part of the study. In the first case, the current unifrom electricity price of 0.002 KD/kWh was considered. The Kuwaiti government heavily subsidizes energy, paying for about 90% of the generation costs, and has maintained this flat rate for residential users since 1966. In the second scenario, a tiered pricing system is considered, proposed by the Kuwaiti government in 2016, and under review at the time of this research. In this model, electricity rates range between 0.005 kD/kWh and 0.015 KD/kWh depending on monthly consumption (Table 5).

Pricing	Consumption	Price
Uniform	Any consumption	0.002 KD
Tiered	kWh/month < 3,000	0.005 KD
	3,000 < kWh/month < 6,000	0.008 KD
	6,000 < kWh/month < 9,000	0.010 KD
	kWh/month > 9,000	0.015 KD

UBEM generation and simulation

For the comparison of retrofit scenarios full UBEMs need to be built, in this case using both basic and stochastic archetypes. A multi-tool workflow was set up for this purpose, using a GIS shapefile as a base input for geometry, and a database for archetype definitions (Figure 4). Each structure was described in GIS by its footprint polygon, height and number of stories, WWR, and archetype name. Based on this dataset, multi-zone energy models for all buildings and context shading were created within the CAD environment Rhino 3D (McNeel 2015) and its parametric modeling tool Grasshopper (McNeel 2016). Custom C# applications were built within Grasshopper for the generation of 3D massing, windows, thermal zoning and shading as part of the UMI modeling suite (MIT SDL 2016).
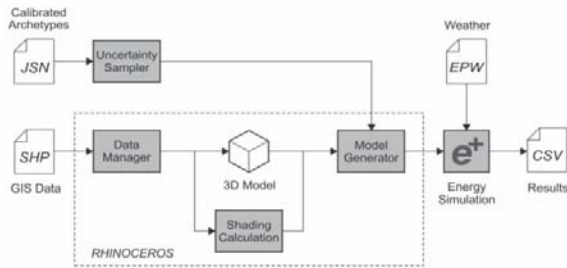

Figure 4: Urban simulation workflow

Simulation parameters for each archetype were stored and implemented in a JSON library file format proposed as a standard for UBEM model inputs exchange (Cerezo et al 2014). Finally, archetype data was associated with each building within Grasshopper, and used to generate individual energy models using the Archsim plugin tool (Dogan 2016). The underlying engine for all simulations was EnergyPlus (US DOE 2016). For stochastic cases, the calibrated joint distribution was sampled using a Latin Hyper Cube (LHC) approach, to guarantee a uniform coverage of the parametric space with a manageable run time. In the simulation of the three retrofit strategies plus the base conditions, each building was modeled using 100 samples. In addition, to calculate the distribution of total demands for the neighborhood, individual results were subsequently randomly sampled 10,000 times and added together, assuming the 100 values equally likely. A standard TMY3 weather file was used in the simulations as the authors chose to include no weather-related uncertainties. Both aggregate and individual results were then used to calculate the energy and cost savings as discussed below.

Calculation of energy and cost savings

As a final step in the methodology, simulated demands were processed, and savings calculated by scenario for both energy use and costs. The final results were analyzed at three levels of aggregation.

1- Total neighborhood demand: Annual energy use per building was aggregated for each scenario, and compared for both the basic and stochastic modeling methods.

2- Single building savings: Annual energy and cost savings were obtained by building and compared for both methods and all scenarios. In the stochastic case, the likelihood distributions of savings were obtained using 100 samples.

3- Payback time likelihood: Simple payback times (PBT) were calculated for 100 samples by building. Cumulative distributions were obtained for each one, and the likelihood of a PBT to be equal or smaller than a given value (p), expressed as $P(PBT \leq p)$ was calculated. Finally, buildings were aggregated according to this likelihood value, for all scenarios.

Results

Total neighborhood demand

The evaluation of the above described simulation results can be conducted from multiple points of view. For the local municipality or utility, overall energy reductions from all buildings are particularly relevant in order to plan for future GHG emission. In order to make results more generic, the aggregate energy use intensity per conditioned floor area unit was calculated for the neighborhood.
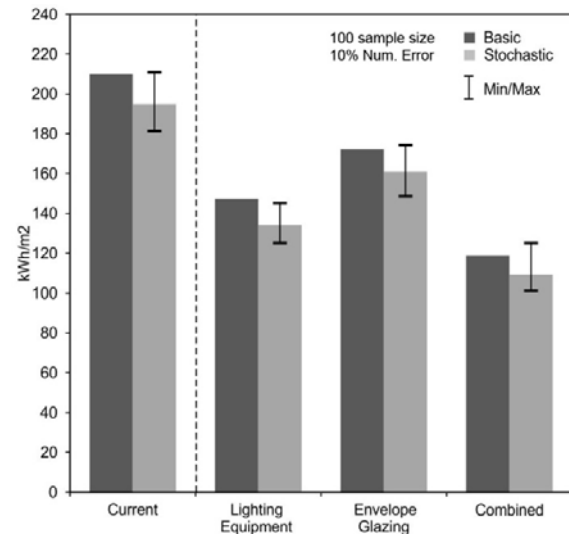

Figure 5: Total normalized energy use by scenario

Figure 5 represents that the total EUI calculated through the basic and stochastic methods, as well as the minimum and maximum values obtained from the sampling in the latter. A numerical error of a 10% is considered, given the limited sample of 100 simulations.

Figure 6: EUI and energy cost savings by scenario for sample building "42k"

Regardless of the method considered, the lowest EUI value is always achieved by the "combined" scenario, followed by "lighting/equipment". The results show that, on average, the basic model slightly over predicts energy use by a 6 to 8%, consistent in all cases when compared to the stochastic result. It also shows that the maximum variance in the total demand stays within a ± 8% in all cases, plus a 10% numerical error with the basic result lying within that uncertainty range. When the demand results were translated into relative savings compared to the current scenario, the resulting uncertainty was even smaller, within a total ± 4%.

Single building savings

The earlier discussed energy savings assume that any of the three scenarios would be adopted across all buildings in a neighborhood. Since the decision to retrofit a building remains with its owner, it is also necessary to understand the range of savings that can be expected by building from an EES, so that municipalities and utilities can consider the owner's perspective. Stochastic and basic savings were calculated by user and compared for by pricing scenarios. Figure 6 shows the energy use and cost savings for a sample building, a two story 60s villa, to illustrate the differences between calculation methods.

According to the stochastic model, the current EUI distribution (Figure 6A) of the building ranges between 140 and 380 kWh/m2, a variation of ± 45% over the deterministically predicted EUI of 270 kWh/m2. While the basic EUI values agree with the mean stochastic result in each scenario, uncertainty ranges remain comparably large. Results also show that for this building, "ligt/equ" and "env/glaz" scenarios result in almost identical EUI distributions. The large uncertainty in energy use translates to the predicted cost savings presented in figures 6B and 6C. In both cases, the largest savings according to the basic model are achieved by the "Combined" scenario, with very close savings for the "ligt/equ" and "env/glz" respectively.

With uniform pricing, the stochastic model agrees in the average (PE < 3%), but shows a 38% smaller uncertainty in "ligt/equ" compared to "env/glaz", presenting it as a less risky option. The relevance of the stochastic model becomes even more evident with tiered pricing, since lower EUIs for the same user will result in lower prices. The basic model predicts savings 30% higher than with uniform pricing in all scenarios, failing to capture the different possible pricing situations for a building. The stochastic model shows a much larger uncertainty, with the increase in savings over uniform pricing ranging
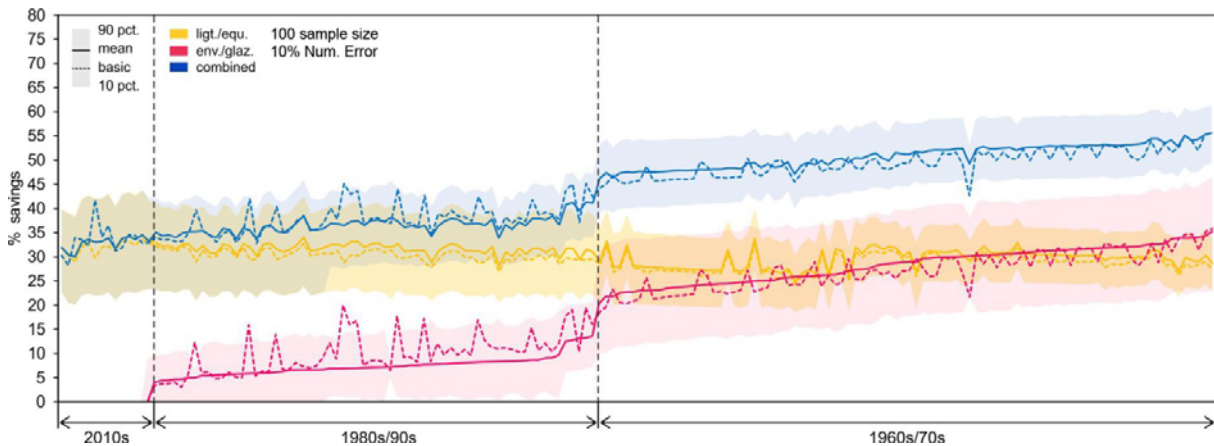

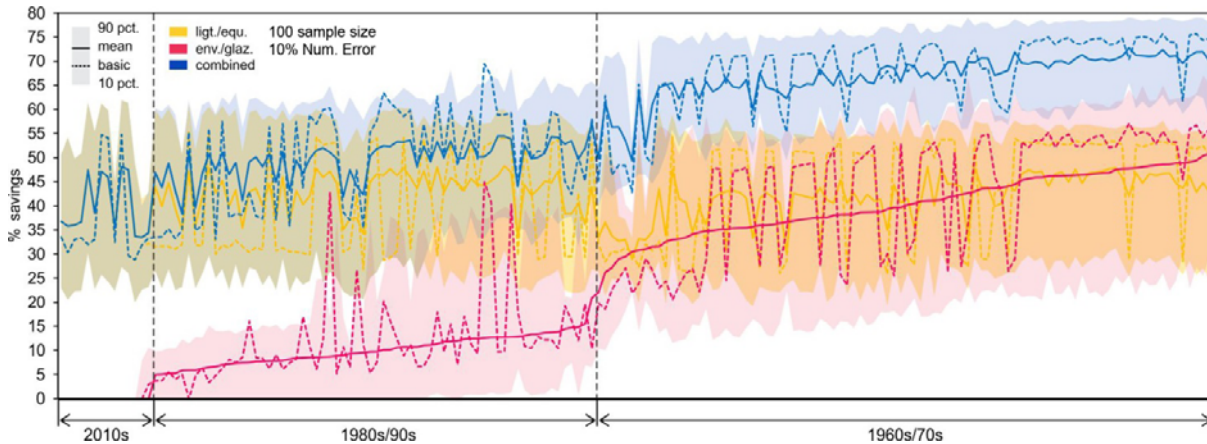*Figure 7: Energy cost savings by building with uniform pricing*

Figure 8: Energy cost savings by building with tiered pricing

from 0% for the highest EUIs, to 15-20% in the best case. This last comparison shows the need for a stochastic model by building in the analysis of tiered pricing implications, to help identify the number of buildings likely to change tier with a retrofit.

Figures 7 and 8 summarize the results from building "42k" for all buildings in the neighborhood. Figure 7 shows the mean (μ), 10 percentile (p10) and 90 percentile (p90) relative savings were calculated for each building along with the deterministic prediction for the current pricing system. Basic and mean stochastic savings are close for the majority of buildings, with differences between 1 and 13% for all scenarios. The figure also reveals that buildings from the 1960s/70s tend to have significantly estimated higher savings from envelope upgrades than more recent buildings.

Figure 8 shows corresponding results for tiered pricing. In this situation, basic and mean stochastic methods diverge between 6 and 35% for different buildings. As with the individual building example, the basic case can only consider one tier by building, misrepresenting its potential range of savings. Additionally, the stochastic model shows larger variation between the uncertainty ranges in buildings, with differences between p10 and p90 of 6-37% savings. Based on the uncertainty in savings, buildings can be classified and targeted differently. For example, for those in the right side of the graph, the "combined" scenario might be worth pursuing, while for those on the left "ligt/equ" seems like the best option.

Payback time likelihood analysis

While occupant related uncertainties can help energy providers and third parties to target buildings based on potential savings and reduced risks, owner decisions to apply the proposed EESs will depend on the implementation costs. The probabilistic results of a calibrated UBEM become especially useful in this context, since they allow those defining implementation policies to understand the likelihood of affordability for every building. To illustrate this idea simple payback times (PBT) were calculated by building and by scenario

for 100 parameter samples, using the implementation costs described previously. Then, in order to mimic a decision making process, the likelihood distribution per building was used to calculate the PBT value met in at least 80% of the parameter combinations sampled. This limit was chosen as a confidence interval allowing the decision maker to judge the viability of the retrofit scenario with one number per building. Next, based on these 80% likelihood values, the cumulative distribution for PBT was obtained for the complete neighborhood in each scenario and pricing scheme. All cases were finally compared against a maximum PBT of 10 years.
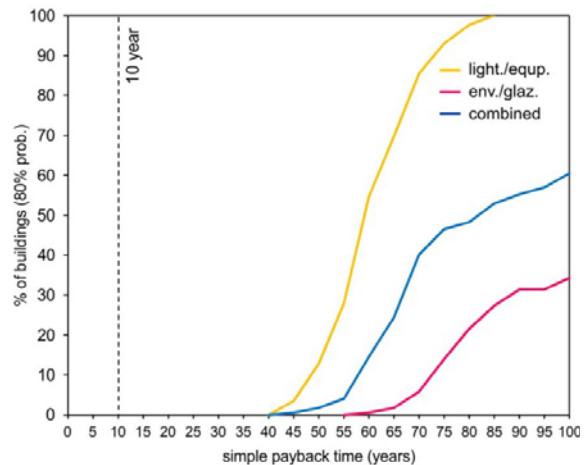

Figure 9: Cumulative PBT distribution (80% likelihood) with uniform pricing

Figure 9 compares the resulting distributions assuming uniform pricing, and clearly shows that with the current very low energy prices in Kuwait (0.002 KD/kWh) no retrofit scenario is affordable enough, with PBT values starting at almost 40 years. Putting aside the unreasonable PBTs, the graph also shows that the larger implementation costs necessary in envelope upgrades reduce their estimated implementation rates, compared to the "ligt/equ" scenario, which is the more affordable option for any chosen payback time.
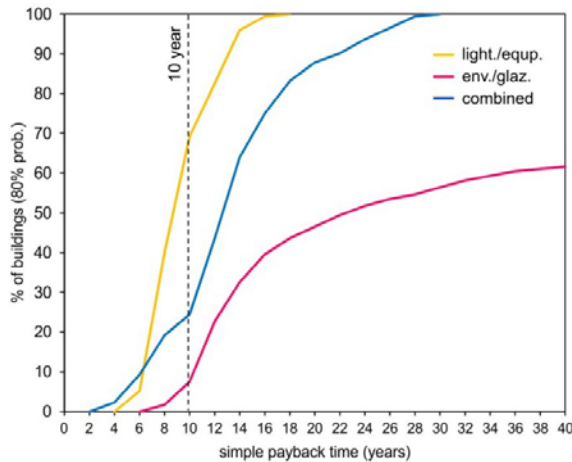
Figure 10: Cumulative PBT distribution (80% likelihood) with tiered pricing

The potential introduction of tiered pricing raises rates significantly above the uniform pricing scenario, between 2.5 and 7.5 times more depending on the tier, and hence increases the financial appeal of the retrofits. In Figure 10, PBT likelihood distributions are explored for the tiered pricing scenario. The higher prices result in much smaller PBT values in many cases under the 10 year mark, but which still do not cover all buildings. A majority of buildings (68%) can meet a PBT ≤ 10 (At least 80% of the time) in the "ligt/equ" scenario, followed by a 24% in the "combined" case and a 7% in "env/glaz". This result seems to suggest that the "ligt/equ" scenario is the most effective to pursue, unless a higher PBT is allowed. The total demand reduction in the neighborhood calculated previously seems to support this option as well, but the PBT analysis showed it would only be feasible under higher tiered rates.

Discussion

The results described above provide new insights into the relative merit of deterministic versus stochastic UBEM models as well as what roles UBEMs may play in future urban decision-making processes.

Deterministic vs. Stochastic models

The advantage of using probabilistic variables to define occupant parameters in an urban model is the capability of taking into account the modeller's large uncertainty regarding types of users and their behaviour. If such variables are calibrated, UBEMs can more effectively represent existing demand extremes and predict how they will be affected by potential retrofit policies. However, they also require extensive data about existing energy demands and building characteristics, and significantly more computational power. Are there analysis scales at which the additional complexity is not necessary? This study has shown that when considering total energy demands and savings at the scale of 100-200 buildings, the variability introduced by the uncertainty in occupant parameters is very small. Small enough that a

simpler deterministic approach in which parameter assumptions and vetted against local expert knowledge can be used to prioritize energy solutions. When moving from aggregate analysis, to a policy implementation level, the results have shown how a deterministic model can misrepresent the annual demands of individual buildings, and as a result, over predict the potential savings of tiered pricing. Such discrepancies, which would only become larger at smaller timescales of analysis, can lead decisions makers to misplace incentives in strategies with very small likelihoods of adoption. As highlighted, with the introduction of numerical errors, further analysis in building sampling and additional sources of uncertainty such as the climate will be necessary to make stochastic UBEM fully effective in decision-making.

Unfortunately, developing uncertainty distributions for occupant model parameters requires large amounts of surveyed building user data, which simply does not exist. The Bayesian calibration stochastic approach applied in this paper offers a partial solution to the problem, as it can improve the modeller's knowledge if metered energy use is available for a large enough sample of buildings. This is rarely the case, since privacy concerns make individual energy data still extremely difficult to access, especially in small temporal scales. It also relies on the assumption that the modeller accurately knows building characteristics, rarely the case unless previous surveys have been developed for the specific neighbourhood. In the application of calibrated occupant parameters to other neighbourhoods, uncertainty distributions would have to be introduced for key building parameters as well. Future research should explore the value of Energy Performance Certificates to minimize the effort of the modeller in the characterization of such model inputs. In the opinion of the authors, a strong collaboration is necessary between municipal governments and utilities to address these accessibility limitations.

Urban applications and stakeholders

As discussed in the introduction, a calibrated UBEM can provide building scale information about potential energy retrofits or technologies, helping cover the information gap that exists between long-term urban emission reduction goals and the specific implementation strategies they require. To achieve that goal, modelling workflows have to adapt to the data needs and scale of work of different urban stakeholders. Based on the simulation results for area 8 in AlQadisyah, this paper identifies three levels of UBEM application. First, the model can inform policies for *emission reduction planning* by evaluating the potential savings of different energy technologies in the mixed building stock of specific urban areas. This type of general planning, typically developed by municipal governments, can rely on simpler deterministic UBEM.

In a more detailed scale, UBEMs can be applied for *targeting buildings*, in order to identify which specific structures or blocks might gain more from a retrofit intervention. At this scale the characterization of occupant uncertainties can help quantify implementation risks or outliers. This is the perspective of energy utilities and other third parties which need to interact with specific building owners. They have the opportunity to reduce uncertainty by asking owners about conflicting data, and to offer them modelling services. Finally, UBEM can help those developing the *implementation policies* regarding energy prices, efficiency incentives, etc. The results analysis showed how occupant modelling is necessary to understand the likelihood of a retrofit being adopted under a particular pricing scheme; something deterministic models cannot address. This type of analysis can be enriched with demographic, economic and social modelling to guarantee adoption rates and affordability.

While having different objectives, all these urban actors are necessarily intertwined. For that reason, the authors believe that they would all benefit from the existence of a common energy-modelling infrastructure, which facilitates the exchange of information about model parameters, and the evaluation of policies at multiple decision scales. The effort level required to build such framework is of course significant, especially in terms of the gathering of building and energy data, which in this case study was mostly developed manually. In order to scale up UBEMs, institutional support for data collection will be fundamental, and further research need to explore basic dataset requirements and minimum sample sizes.

Conclusion

This paper has implemented an UBEM workflow to evaluate the relevance of occupant uncertainty modeling when predicting energy efficiency savings for a neighborhood. A 172 buildings Kuwaiti residential neighborhood was modeled, with occupant parameters being defined through both deterministic assumptions and calibrated uncertainty distributions. Using both methods, three retrofit and two pricing scenarios were simulated in EnergyPlus. Finally, energy and cost savings were calculated, and the performance of both modeling methods was evaluated from the application perspectives of three urban decision makers.

Results showed relevant differences in the type of information that each approach provides for decision-making, and ultimately suggested the need for stochastic occupant modeling in UBEM. While effective for the analysis of aggregate savings by scenario in the neighborhood, deterministic UBEMs ignore uncertainties up to 30% when considering single buildings, and can misrepresent average cost savings. The calibrated stochastic approach proved to be especially relevant in the analysis of tiered pricing, identifying an uncertainty range in savings by building of 6-38%. All retrofit options were shown to be unaffordable with current uniform rates. In the tiered pricing scenario, the PBT likelihood analysis showed that lighting and equipment retrofits become a best option, in which 70% of buildings achieved a PBT lower than 10 years with a likelihood of 80%.

Acknowledgements

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