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PROFILING OCCUPANCY PATTERNS IN COMMUNITY-SCALE RESIDENTIAL BUILDINGS USING MEASURED ENERGY USE DATA CLUSTERING

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ABSTRACT

Uncertainty in predicting occupancy patterns leads to discrepancies in simulated building energy compared to measured data. Typical simulation models represent occupants through identical schedules and repetitive behavior. However, users' activity patterns comprise numerous variations, especially when focusing on occupants' interactions on neighborhood scale. This paper presents a framework for modeling occupancy and consequent energy loads in residential buildings using measured data for calibration; it employs a clustering approach to profile energy use which generates inputs for Urban Energy Models (UBEMs). The framework is demonstrated on a residential neighborhood and reveals that the generated inputs can more accurately predict energy load patterns.

INTRODUCTION

Buildings are responsible for the largest share of energy consumption in the US, accounting for up to 40% of the US energy consumption (EIA 2010). Consequently, energy conservation in buildings has been receiving attention in recent years due to its significant impact on global climate change. Energy use has also influenced urban planning and the development of energy policies at an urban scale. Therefore, the roles urban planners and designers play in reducing the negative impacts on the built environment are critical. Urban-scale building modeling was developed as a way to represent the state of urban energy consumption and predict its future evolution (Reinhart and Davila 2016).

Urban Building Energy Models (UBEMs) simulate various performance measures, including operational energy use, in order to inform designers, urban planners and policy-makers in their evaluation of energy demand and supply strategies, or to assess design decisions and performance of urban energy systems. Similar to building models, the generation of a UBEM requires the definition of data inputs for building geometries in addition to a large set of non-geometric parameters that include usage schedules and behaviors, which affect internal loads. These non-geometric inputs are usually reduced by deterministically simplifying the real diversity of occupant behavior into defined architypes (Wilke et al. 2013). This results in simulations where all occupants perform identical actions, which leads to erroneous hourly demand peaks (He et al. 2015) and ultimately to the misrepresentation of urban energy demands. Therefore, uncertainty in defining occupancy pattern and behavior is a major cause of discrepancies in simulated building energy when compared to real measured data.

Human behavior entails the occupants' interaction with building equipment, lighting, heating, and cooling systems. These systems determine the energy use of a building, therefore the behavioral factor in building performance simulation is of significant value (Zhang et al. 2014). In brief, occupancy schedules and behavior are a necessary input for simulation models to accurately predict energy use, and models should be able to generate simulations of temporal behavioral patterns in order to better inform users regarding their energy use behaviors.

Previous literature that has been devoted to this issue focused on energy load prediction and pattern profiling to represent occupant behavior. Profiling energy load of occupants has been applied qualitatively and quantitatively to improve load prediction. When attempting to profile energy, data clustering was utilized to classify and analyze the energy consumption behavior in buildings. Common clustering methods in determining energy load vs time are: K-means, the self-organizing map, the minimum variance criterion, as well as the fuzzy C-means and combinations of these methods can also be found in some literatures (Panapakidis et al. 2014, Tsekouras et al. 2007). Other more robust approaches are model-based, including cluster-wise regressions and mixture models (Hsu 2015). The effectiveness of clustering method varies when applied to different data sets and there is an inherent tradeoff when comparing clustering methods. Therefore, clustering methods should be chosen appropriately for particular cases depending on the conflicting goals of application (Hsu 2015).

Identifying patterns of occupant presence and predicting occupancy schedules allow modeling occupancy energy use behaviors more accurately. Three typical methods were used in previous literature that model occupant presence. The first method consists of representing occupants as groups with fixed schedules (Zhang et al. 2011). These groups are combined afterwards to represent the schedule of the whole building. In the second method, occupant schedules are represented as a probability distribution (Zhou et al. 2015). The third method consists of analyzing practical observation data (D'Oca et al. 2015). While these methods improved occupant schedules modeling, they are limited in presenting accurate schedules because: (1) Occupant schedules are highly stochastic, therefore it is inappropriate to simply label occupants to belong to a certain schedule or certain distribution. (2) Results are not practical, as they only conclude with summarizing rules of occupant presence rather than workflows that can present occupancy schedules in future-case scenarios. (3) The results lack validation with measured data and (4) Observed data attained just from a specific building part cannot be generalized to represent the whole building.

In order to represent occupants' behavior and operational energy use accurately simulation models should be calibrated. Calibration is widely used at a building scale and has proven to be successful in improving simulation accuracy. In an attempt to define the improvement level of calibration; Samuelson and Reinhart analyzed each of the standard calibration tasks systematically. These tasks included inputting actual weather data, adding unregulated loads, revising process loads, and updating a small number of inputs. The results showed that the bulk of this improvement came from revising process loads using sub-metered data (Samuelson and Reinhart 2016). Unfortunately, such calibration tasks are challenging to apply to UBEMs due to the time and computational power associated with the modeling and calibration process. In UBEMs, profiling energy use and behaviors could be represented in various ways. In previous limited literature, researchers associated energy use with household income. Filogamo et al. estimated several occupancy parameters from national statistics as a function of average income (Filogamo et al. 2014). However, this deterministic approach does not represent the variety of behaviors accurately.

Occupant behavior parameters are among the most uncertain in energy modeling, yet behavior is one of the main drivers of energy use in the residential sector (Branco et al. 2004). Urban models only validate their averaged results on an annual basis, therefore discrepancies in occupant schedules might not be apparent due to the aggregation of results. However, when generating hourly energy use at a neighborhood scale, representing every building with identical behavior is expected to be erroneous. Modeling techniques that deal with unknown parameters has been extensively used to address individual building energy simulation (Hopfe et al. 2013). However, it is unclear how to apply these methods at an urban scale, where the process is constrained by the over-parameterized and high-computational cost of simulation. As a result, most UBEMs have so far used deterministic characterization, at a detail level supported with the available data.

This paper focuses on addressing the research gap of load profiling in residential urban neighborhoods, by connecting occupants' schedules to behavioral profiles and creating a practical workflow to represent patterns of energy loads in a systematic way. This methodology allows results to be applied as input data to calibrate UBEMs. A framework is presented for modeling occupancy presence and consequent energy loads in residential buildings on the urban scale. The work employs a computational clustering approach to data from the Mueller community in Austin, TX, USA, where energy is continuously measured using smart meters. The paper's goal is to determine energy use profiles that represent occupants' presence, as well as activity patterns, by clustering available hourly energy use data. First, energy use behaviors are defined using functional clustering of hourly data for each of the building energy use variables (lighting, equipment, cooling and heating). The resultant energy use behavior for all the variables are then utilized to derive occupancy presence profiles. Profiles from the twofold process are then matched to associate occupancy presence with behavioral patterns on a daily basis. Finally, the outcome is translated for use as an input for UBEM simulation software. The clustering and input generation process is automated using R, a code-driven application (Ross and Gentleman 1996), and a UBEM for the residential community is developed using the Urban Modeling Interface (UMI) plugin (Reinhart et al. 2013) for Rhino3D CAD software. The UBEM is constructed with initial inputs from existing construction and presence/behavioral inputs that are generated from the clustering process. The study concludes by defining the effect of occupancy on energy consumption and illustrating the importance of hourly changes in simulation tools to enhance the accuracy of outcomes.

RESEARCH METHOD

The proposed framework is illustrated in Figure 1.

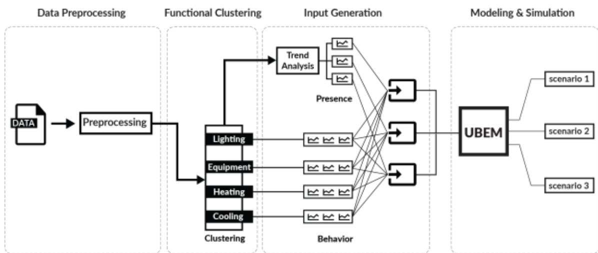

Figure 1- Research framework for the generation of inputs to calibrate UBEM simulation

Data Pre-processing

Firstly, the data is processed in 3 steps: 1) Restructuring the data and cleaning the dataset from corrupt and missing data. 2) Energy use measures collected from sensors are restructured into hourly energy consumption from 0:00 till 23:00 for each component of a household to reduce data dimensions. 3) Hourly data of each household is grouped in to four categories (lighting, Equipment, Heating and Cooling).

Functional Data Clustering

If collecting sensor energy use readings from N different households, for the ith household, the history of the observed energy use pattern is denoted as $\boldsymbol{y}_i = \{y_i(t_{i1}), \dots, y_i(t_{ip_i})\}^{\mathrm{T}}$ where T denotes a transpose, p_i represents the number of observations, i.e. sensor measurements, for unit $i \in \{1, \dots, N\}$ and $\{t_{iq}, q = 1, \dots, p_i\} \subset \mathcal{R}$ (The real line) represents the observation time points for unit i, the time at which energy use is measured. For instance, $t \in \{0{:}00, 1{:}00, .., 23{:}00\}$ may represent the daily energy consumption structured into hourly use for each household. We note that the measurements represent accumulated readings of a sensor value over an hour. Based on the energy use profiles collected from N different households functional clustering is utilized to define energy use behavior patterns. To address the functional nature of the data and identify common energy use patterns, our analytical approach utilizes model-based clustering, which was proposed by Bouveyron et al. (Bouveyron et al. 2015).

Let $\{y_1(t), \dots, y_N(t)\}$ denote the function that needs clustering. The first steps are based on recovering the functional nature of the data through a finite basis expansion, as shown in equation (1).

$$y_i(t) = \sum_{j=1}^{z} \omega_{ij} \varphi_j(t), \tag{1}$$

Where $\varphi_j(t)$ are a set of basis functions with coefficients ω_{ij}. The coefficients $\omega_i = (\omega_{i1}, .., \omega_{iz})$ for function $y_i(t)$ are then assumed to belong to a mixture of gaussian distribution, where clustering of the time series data is performed in a discriminative functional subspace (2).

$$P(\omega) = \sum_{k=1}^{K} \pi_k \phi(\omega; \eta\mu_k, \eta^t \Sigma_k \eta + \Lambda), \tag{2}$$

Where P denotes probability, π_k is the mixing probability, ϕ is the standard Gaussian density function, μ_k and Σ_k are the mean and covariance matrix of the k^{th} cluster for the mapping of ω into the discriminative subspace, where η is a matrix representing the mapping to the discriminative subspace, also, Λ denotes the covariance matrix related to measurement noise. Then the optimal number of clusters K is selected using a Bayesian Information Criterion (BIC).

In this clustering analysis, hourly data of each building is plotted over 24 hours. Continuous functions of 365 days are plotted for each building as repetitive measures. To simplify the clustering analysis, the 365 functions of each building are presented by a mean profile. Afterwards building profiles are clustered into K number of groups (Figure 2), then a mean behavioral profile with a confidence interval is plotted as a representation of each cluster. The user can visually follow up with this functional clustering approach and can identify the group in which each building belongs and determine the number of building in every clustered group.

The benefit of the method used is that it takes advantage of the temporal dynamic of the data and graphically models it. In addition, the low computational complexity and efficient visualization of the clustered systems adds practicality to real applications. In this process, clustering errors can be distinguished by the user who can sometimes identify meaningful patterns that computers cannot, subsequently reinterpreting according to human reasoning. The functional data clustering is applied to define usage schedules (behavior).

Generation of Usage Schedules and Behavior Inputs

The translation of behavioral energy use profiles is achieved using the formula below. Let $F_c(t_1, t_2)$ be the fraction to be applied to a load between time instances t_1 and t_2 for a specific variable cluster vc, where $v \in$

$\{l, e, c, h\}$ where l, e, c, h are lighting, equipment, cooling, and heating respectively.

$$F_c(t_1, t_2) = \int_{t_1}^{t_2} y_{vc}(t).dt / Max\ Load \qquad (3)$$

Deduced schedules from weekdays and weekends are combined to form weekly and annual schedules of occupancy presence and usage behaviors.

While modifying schedules settings aims to more accurately represent the energy use behaviors on an hourly basis; illuminance targets and heating/cooling setpoints also have a significant effect on defining the overall intensity of the lighting, cooling, and heating energy use. The authors defined a range of setpoints based on ASHRAE 90.1 (ASHRAE 1989) as a standard, then parametrized for energy efficiency. Using this range of setpoints, each behavioral profile will be assigned a setpoint or illuminance target that correspond to its energy use intensity.

Occupancy Presence Input Generation

The use of lighting, equipment and conditioning appliances are typically linked to the presence of the users. While most researchers have mainly focused on studying the importance of occupant interaction with lighting appliances to model the randomness of occupancy presence (Hunt 1980, Newsham et al. 1995, Reinhart 2004); the relationship of lighting energy use and occupancy schedules is more likely dominated by daylighting effects. Therefore, all energy variables are considered as a proxy for occupancy presence in our framework, and occupant's schedules are represented by defining different behaviors of heating, cooling, equipment and lighting energy use. For this reason, clustering analysis results are analyzed to determine presence schedules. The process is applied by conducting several trend analyses to group different occupancy presence variations. In this study, only one identified trend was translated empirically into a schedule of occupancy (Figure 5). While the community population was represented with only one dominating trend, others may exist that would help to deduce more presence profiles. Future research should review and further develop this approach.

Template Generation

In this phase, occupancy presence schedules are matched with all possible variations of behavioral/usage schedules along with the associated illuminance targets and heating/cooling setpoints to create an input for a UBEM; this input is characteristic of the whole population.

UBEM inputs, in the form of template libraries, are used to include the schedules and behaviors. Therefore, the matching process is achieved by customizing a template to include a specific presence schedules and its corresponding usage behaviors. The templates are then assigned to the corresponding building ID's or cluster of buildings in the UBEM. The use of the template contributes the following:

(1) Occupancy schedules represent occupancy density and presence.

(2) Heating behavioral profiles represent the conditioning use schedules for heating and are used to specify heating set points.

(3) Cooling behavioral profiles represent the conditioning use schedules for cooling and are used to specify cooling set points.

(4) Lighting behavioral profiles represent lighting usage schedules and are used to specify illuminance target values.

(5) Equipment behavioral profiles represent plug load usage schedules.

Model calibration is achieved by using the generated inputs that represent the behavior of the neighborhood more accurately. This calibration process is more effective in comparison to previous calibration methods that require high computational power and time.

UBEM Development and Simulation

In this final phase, building and developing a UBEM is achieved through three steps: characterization, generation and simulation. First weather information, buildings and context geometry, and non-geometric properties should be specified. Data inputs for building geometry, construction, material properties, and Window to Wall Ratio (WWR) are usually provided from a survey of existing construction or from the municipality archives. The building and context geometries information are used to build a 3-dimensional model in Rhino3D. This digital massing model provides volumetric information of the built environment and is used to calculate orientations and areas. The inputs of occupancy schedules, behavioral schedules, heating/cooling setpoints and illuminance targets along with material properties and WWR information, should be used to detail the templates' geometrical and nongeometric settings. After assigning the 3D massing with all the templates, simulations are performed. Users can simulate different scenarios and iterations of their proposals. These can be design proposals in which the user adjusts geometric and non-geometric parameters, or the user can study load shifting strategies by comparing the effect of new occupancy and usage schedules to the base parameters defined by the clustering method.

RESULTS

The Mueller community in Austin, TX, where energy is continuously measured using smart meters, is used as a case study to demonstrate this methodology. Following the methodology steps, the authors initiated the preprocessing phase with 66 building data sets. After data cleaning, 17 buildings were removed due to data corruption and absence of data points, leaving 49 houses suitable for further analysis. After pre-processing the data, behavioral/usage profiles are determined by applying functional clustering analysis to each variables on weekdays and weekends separately. Figure 2 shows the clustering process of cooling energy; the optimal number of clusters K is determined to be 3 according to the BIC vs K graph.

The three mean profiles that represent behavioral patterns are translated into schedules that represent the fraction of energy use for every hour of the day. The inputs for weekdays and weekends are then matched and combined to create an annual schedule for every possible combination. This process is illustrated in Figure 3, which presents the generation of inputs from profiling equipment energy use data. Usage schedules are generated by separately profiling lighting, heating, cooling, and equipment energy. Lighting and HVAC behavioral profiles are then characterized by illuminance target or heating/cooling setpoint. Figure 4 shows the generated inputs in response to their mean profiles.

In the next step, an occupancy schedule is deduced from a trend analysis of the profiled behavioral patterns. After analyzing the clustered profiles of equipment and lighting energy use, the authors identified peak hours of energy use to be in the morning from 7AM till 10AM, and in the afternoon from 6PM till 11PM. Most of the occupants are inferred to be workers and students that leave the house in the morning and return in the evening. Therefore, weekday and weekend schedules are constructed representing this trend (Figure 5). Daily schedules are combines into an annual schedule that represent the occupancy of the whole neighborhood.

Next, occupancy presence schedules are combined with each of the usage behavior inputs into several input templates, where each template corresponds to a cluster of buildings. It is important to note that the number of behavioral and presence profiles one generates will determine the number of combinations that can be included in the general template library. This methodology characterizes the urban built environment more accurately since the average usage patterns and occupancy schedules summarize the behavior of the whole population.

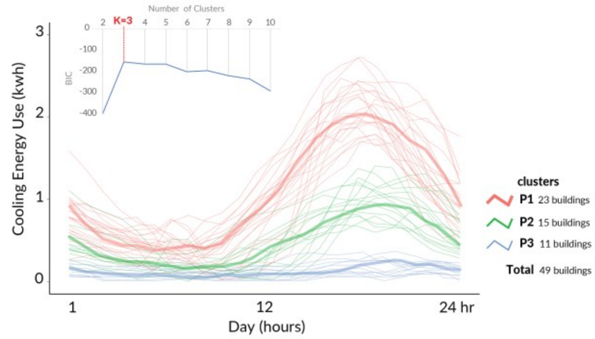

Figure 2- Clustering analysis using cooling energy use data

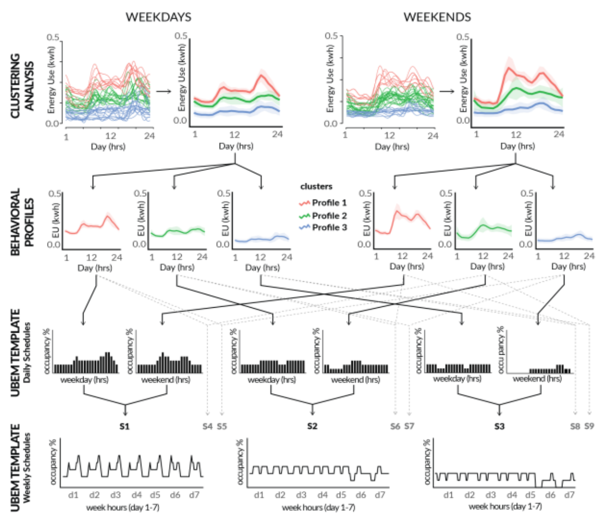

Figure 3- Generating usage schedule inputs from profiling equipment energy use.

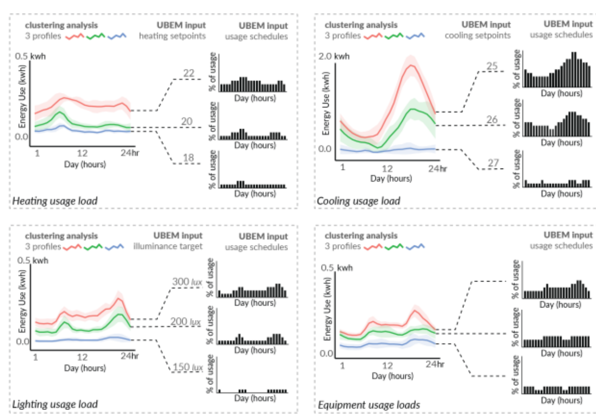

Figure 4- Mean behavioral profiles deduced from clustering analysis then translated into usage schedules

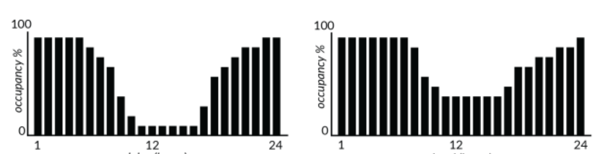

Figure 5- Generated presence schedules

Finally, a baseline UBEM for this case study is developed using the Urban Modeling Interface (UMI) plugin for Rhino3D CAD software. UMI's operational energy simulation is based on an algorithm that abstracts an arbitrarily shaped set of building volumes into a group of simplified 'shoebox' building energy models (Dogan and Reinhart 2017) and uses EnergyPlus (Crawley et al. 2001) as an underlying simulation engine. The Austin camp-Mabry Actual Meteorological Year (AMY) weather file with historical data from 2014 was used for the study. Inputs for building geometric data, constructions and material are defined by extracting information from the existing community construction.

Starting with this baseline UBEM, two files are created: The first is a default file in which all the buildings are assigned the same template that include default occupancy and usage schedules of UMI residential template and default setpoints and illuminance targets. These selected defaults are based on ASHRAE and IESNA: a heating setpoint is set to 20°C, cooling setpoint is set to 25°C, illuminance target is set to 200 lux, while the selected schedules are based on the Swiss Society of Engineers and Architects (SIA) (Merkblatt 2006). The second file is calibrated so that buildings are grouped according to the clustering analysis. Each cluster of buildings is assigned with a generated template that corresponds to its occupancy, behavioral energy use patterns and intensity.

To test our designed inputs, simulations from each file are generated and compared. Figure 6 shows false-color simulation results for total operational energy use in Energy Use Intensity (EUI) from the default and calibrated models compared with a false-colored 3D model that shows a real representation of the EUI obtained from measured data.

DISCUSSION

Hourly results of cooling, equipment and lighting energy use as well as total energy use were extracted from the simulated models and plotted as averaged profiles over a day. To test the validity of the model, the simulation results of one building are plotted (Figure 7). These results include both the UBEM simulated results from the default and calibrated files, and compared with plots from the measured data.

Based on outcomes illustrated in Figure 7, the relevance of using measured data in calibrating UBEMs can be discussed. First and most importantly, the model based on functional clustering significantly improved the performance of the simulation model to match real performance. As shown in Figure 7, the simulated patterns (denoted as y_{sim}) in cooling, equipment and lighting energy use are notably closer to the measured data (denoted as y_{mea}), within a 10% margin of error, as compared to the default model results.

These results are validated through the Root Mean Square Error (RMSE), which is a statistical measure to describe the similarity of two data sets. It characterizes the average variance of the elements of the simulated profile with respect to the measured profile. A small RMSE indicates smaller variance between the compared data series, defined as:

$$rel.RMSE = \frac{1}{24}\sqrt{\sum_{i=1}^{n=24}\left(\frac{(y_{sim,i} - y_{mea,i})}{y_{mea.i}}\right)^2} \quad (4)$$

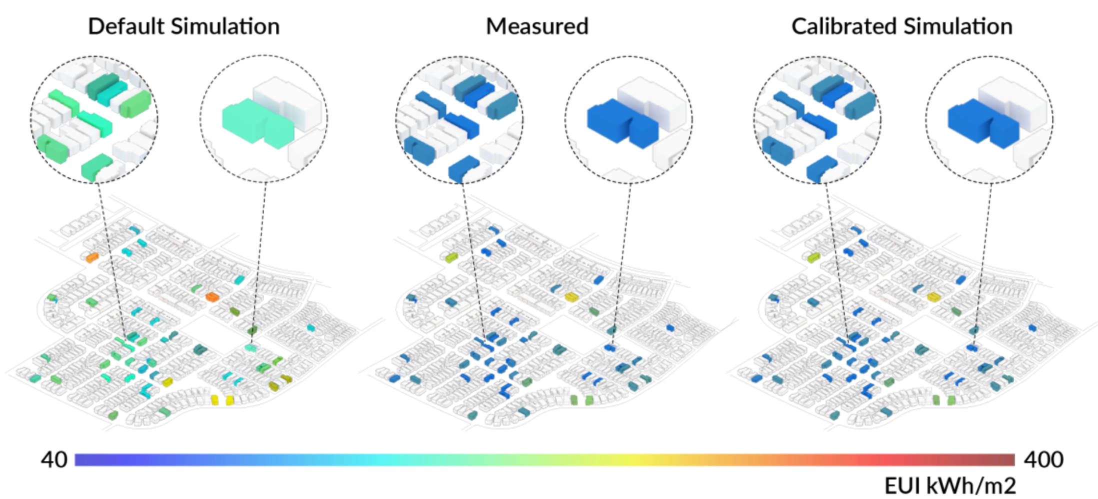

Figure 6- Comparing measured data with default simulation and calibrated simulation models

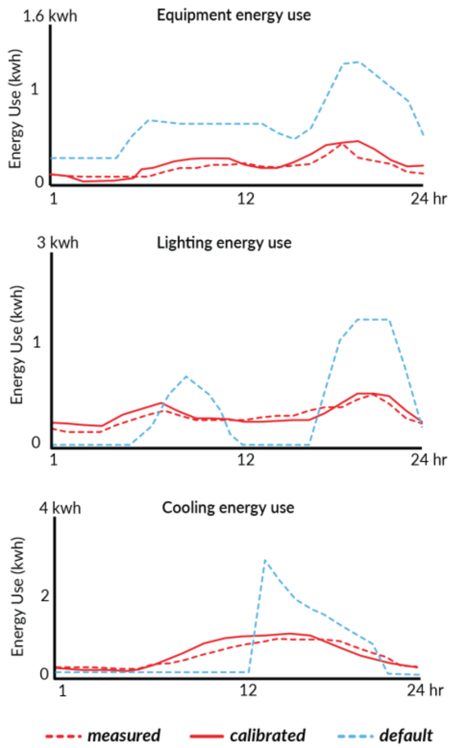

Figure 7- Comparing calibrated simulation results with measured data and default simulation

According to the RMSE and through comparison with the measured data, the authors identified the following improvements resulting from the calibration method:

- In lighting energy, the error decreased from 32% to 4%.
- In equipment, the error decreased from 60% to 8%.
- In cooling energy, the error decreased from 30% to 7%.

In the results, heating energy use was disregarded since the use of heating is negligible in the warm climate of Austin, TX. As this example demonstrates, the performance of the clustering approach is dependent on data availability, the size of the sample data from the community, as well as observations of contextual issues. The observation of our study validates that the accuracy of simulation models can be improved by identifying behavioral patterns using a measured-data driven approach. Second, the results confirm that the proposed modeling framework is able to scale to an urban level due to the prediction accuracy provided through summarizing the population behavior into a small number of clusters. The resulting daily (24-hr) profiles of occupants' energy use behavior are the main outcomes of this study. At an urban scale, these simulated hourly profiles allow users to more accurately inform occupants about their hourly energy use behavior in relation to the community energy performance, and consequently inform load shifting strategies. The simulated results more accurately visualized the building energy demand peaks and primary energy load patterns. Thus, urban designers and policy makers can more accurately test the performance of potential future-case scenarios, in relationship to existing condition.

CONCLUSION

Occupancy behavior and presence have a significant impact on building energy consumption. With growing use of simulation tools to support built environment research and practice, misrepresentation of people's presence and behavior can misinform design decisions. The field of UBEMs is still emerging, and simulation errors at the multiple-buildings scale can be momentous. In this study, we demonstrated how the use of measured data can develop more accurate UBEMs that especially help in creating design cases. The method's robustness is shown through the scenario-based approach, which is accessible for researchers exploring speculative designs based on numerous inputs that follow community trends without relying on excessive computational power, an extraordinary level of expertise or substantial labor time. The impact of the proposed framework is demonstrated through the use of functional data clustering that creates occupancy-based inputs, which calibrated UBEMs within a 10% maximum margin of error. The vision for this work is to aid in developing UBEMs that are calibrated in real-time to inform users, designers, utilities and others how to make informed decisions that reduce the environmental impact of communities, neighborhoods and cities using measured data.

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