User Behavior Modeling for Estimating Residential Energy Consumption

Baris Aksanli(✉), Alper Sinan Akyurek, and Tajana Simunic Rosing

University of California San Diego, La Jolla, CA 92093, USA
{baksanli,aakyurek,tajana}@ucsd.edu

Abstract. Residential energy constitutes a significant portion of the total US energy consumption. Several researchers proposed energy-aware solutions for houses, promising significant energy and cost savings. However, it is important to evaluate the outcomes of these methods on larger scale, with hundreds of houses. This paper presents a human-activity based residential energy modeling framework, that can create power demand profiles considering the characteristics of household members. It constructs a mathematical model to show the detailed relationships between human activities and house power consumption. It can be used to create various house profiles with different energy demand characteristics in a reproducible manner. Comparison with real data shows that our model captures the power demand differences between different family types and accurately follows the trends seen in real data. We also show a case study that evaluates voltage deviation in a neighborhood, which requires accurate estimation of the trends in power consumption.

Keywords: Residential energy · Modeling · Appliance · User activity

1 Introduction

Residential energy accounts for 38 % of the total energy consumption in the US, with millions of individual consumers [10]. Although the other components, such as commercial or industrial, are well-investigated, residential energy has not been studied extensively until recently. Due to high potential of savings, many researchers have started to focus on methods to minimize the residential energy consumption. These studies target heating, air conditioning and ventilation (HVAC) units, appliances, and electric vehicles (EVs). The new technologies, such as home automation kits, smart meters, controllable appliances, provide constant monitoring and detailed energy usage breakdown in the houses, making it easy to deploy energy-aware solutions. The studies show that it is possible to obtain significant savings by cleverly adjusting the power demand, and these savings can easily add up to correspond millions of dollars savings.

Despite the effectiveness of energy-aware residential solutions, it is not easy to test them on a larger scale. Residential buildings have a dominant human factor. Many of the energy-aware mechanisms are designed to perform uniformly

A. Leon-Garcia et al. (Eds.): Smart City 2015, LNICST 166, pp. 348–361, 2016.
DOI: 10.1007/978-3-319-33681-7_29

regardless of different compositions of families leading to variations in habits and energy usage. Thus, we cannot expect that the outcomes (e.g. savings) will be the same for different households. It is also important to see the overall effect of these mechanisms on the electrical grid, when several houses are applying them simultaneously. This aspect is important for utilities, that want to predict the energy demand ahead of time to match supply and demand. To reflect the human element, the differences across the demand profiles of individual houses should be considered. Previous studies use either real [3] or generated traces [15] for this purpose. The former requires equipment installation across many houses, which has high cost. It is not generalizable and the traces cannot be used to create statistically correlated, new traces. The latter increases the scalability of representing houses, but requires careful modeling for the human element.

This paper presents a user-behavior model to estimate the energy consumption of a house. Our model is based on detailed activity sequences of household members and the connections between these activities and appliances. We use two publicly available data sets, American Time Use Survey (ATUS) and Residential Energy Consumption Survey (RECS) to account for user activity and appliance usage habits. ATUS contains detailed activity responds from more than 10000 individuals over one year and RECS has statistics from more than 110 million households, both from entire US. Our model develops hierarchical activity graphs for each individual and probabilistically determines the appliance usage events. When creating power profiles for the houses, we consider the characteristics of the inhabitants and show the relationships between these and the house power demand. We compare our model against real house traces from Pecan Street database [11]. The power profiles we generate follow the trends in real traces, e.g. matching the peak demand times and frequencies. We show the importance of this with a case study, where we evaluate voltage deviation in a neighborhood. We use a grid simulator [2] to compute the deviation values and show that our model captures the high deviation events with high accuracy.

2 Related Work

User behavior modeling studies estimate appliance and plug load energy consumption in residential houses. Previous studies construct models based on historical activities [6,12,15], using commonly available activity data sets such as ATUS [17] data. They group the activities into meaningful clusters and create user categories based on people's age, gender, employment status, and the number of other household members. Other studies use similar survey data from France [4], UK [7] and Spain [14]. These studies also use machine learning methods such as Markov chains [12], neural networks, Bayesian networks, and decision trees [4] to determine the activity chains, i.e. which activity is more likely to follow another. These models rely only on activity data, thus cannot capture the dynamic relationship between activity sequences and appliance usages.

Using these data sets, previous studies determine which activities are related to appliances either manually [12] or by using another data set [15] (RECS [8]).

After this linking, they estimate the starting time of appliances (such as washer, dryer, dishwasher) and the operating conditions of bigger units (e.g. refrigerator, HVAC, lighting, etc.). The house energy consumption is then simply aggregation of all the individual appliances and plug load units. By disaggregating the total energy consumption, previous studies can apply different mechanisms (such as appliance rescheduling, controlling HVAC and lighting parameters, etc.) to participate in demand response programs ultimately to save energy [16] and electricity cost [18]. There are also the widely-used residential energy databases, REDD [13] and Smart* [3] that show the disaggregated energy consumption of several houses over a couple of months. To get detailed user behavior models, the researchers use the disaggregated appliance consumption to deduce the user behavior or occupancy [5]. The main disadvantage of this approach is that there is no real information in the data set on what the users were actually doing and thus have to be mostly guessed. Different than previous studies, we use high granularity user activity data to represent the relationship between users and appliances. We create power profiles not just for individuals but also for families and a neighborhood with several families. We verify our model using real data from Pecan Street, and show that our traces are highly correlated with real data.

3 User Behavior Modeling with Activity Graphs

In this section, we first develop a graph-based model to represent the chain of user activities. Our main goal is to probabilistically capture the time-series nature of user behavior. These probabilities depend on several people-related and non-people-related variables. The former include the number of other household members, people's gender, age, employment status, etc. whereas the latter have time of day, day of week, etc. We use these variables to calculate the probability of an event that would follow another event at a given time.

User activities are the main events in a house that trigger energy consumption. We define user activity as a set of actions associated with one or multiple appliances over a time period. For example, cooking is an activity that includes all actions between getting into the kitchen and cleaning the dishes. During this activity, the user might use several appliances such as refrigerator, oven, microwave, etc. The exact set of appliances associated with an activity changes among different activity instances. All activities have a duration associated with them. The day of a person is divided into discrete activity blocks. The next step is determining the chain of activities for a user. We model the next activity for a given one probabilistically, which depends on a similar set of

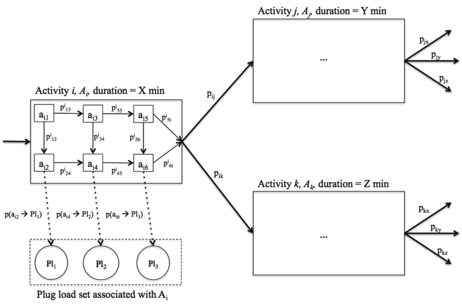


Fig. 1. Activity graph structure

variables as described earlier. Using this information, we build activity graphs, where the nodes are the activity blocks (with inner graphs as actions for a specific activity) and the edges are the activity transitions. The graph is designed to be cyclic with sleeping activity as the reference node. The formal construction of the activity graph includes the following steps (following Fig. 1):

1. The activity graph is a directed graph and with activity blocks $\{A_i|1 \leq i \leq N\}$, where N is the number of activities, as the nodes and transitions between the activities as edges. The activity blocks are shown by big rectangles and the transitions are the directed edges between them in Fig. 1.
2. Each activity, A_i, is followed by a set of activities $\{A_j|1 \leq j \leq N_i\}$ where each transition $(A_i \rightarrow A_j)$ has a probability, p_{ij}. Thus, $\sum_{j=1}^{N_i} p_{ij} = 1$. This makes sure that the activity chain never ends.
3. Each activity, A_i, consists of a sub-graph, with nodes as the actions of that activity, a_{ik}, and the edges are the transitions between the actions. The actions are shown by the smaller rectangles in the activities and the transitions are the directed edges between the smaller rectangles in Fig. 1. The transitions can result in another action but also the end of that activity. The probability of transition from a_j to a_k in A_i is denoted by p^i_{jk}. The probability of transition from a_j to the end of A_i is shown by p^i_{jt}, where the sub-index t corresponds to activity termination. Similar to 2, $\sum_{k=1}^{N_j} p^i_{jk} = 1$, where N_j is the number of transitions that can follow a_{ij} in A_i.
4. For each activity A_i, there is an appliance set associated with it $Ap_i = \{Ap_{ij}|1 \leq j \leq n_i\}$, where n_i is the number of appliances in set Ap_i. This set contains the individual appliances Ap_{ij}, whose operation can be triggered by the actions of A_i. We follow a probabilistic approach for the appliance triggering. The probability of a_{ij} triggering appliance Ap_{ik} is $p(a_{ij} \rightarrow Ap_{ik})$. These relations are shown by dotted lines in Fig. 1. For these probabilities, we do not require any probability summation to be equal to 1 because an action (or a set of actions) does not always trigger an appliance.
5. Our appliance definition suits most of the plug loads with ON/OFF states. These are discrete appliances [18]. This might now work for some appliances with continuous energy draws, e.g. refrigerator, HVAC, and lighting.

   Refrigerator: The power consumption follows a duty cyclic behavior, except when its door is opened. This is mostly observed during a cooking activity. We model the refrigerator power consumption as a constant addition to the aggregated house consumption, with higher value during cooking activities.

   Lighting: We breakdown the lighting into individual rooms and associate them with activities when performed in the relevant room. We also set time-of-day as another constraint for room lights to be ON.

   HVAC: The operation of HVAC is correlated with user preferences [18]. Since its temperature settings affect its active power consumption, we cannot assume an ON/OFF model. As developing a new HVAC manager is not

Table 1. List of activities, actions and associated appliances

Activities	Actions	Appliances
Sleeping	N/A	N/A
Personal grooming	Showering, bathing, brushing teeth, hair drying, shaving	Electric razor, electric toothbrush, hair dryer, bathroom lights
Cooking	Preparing food, eating, cleaning kitchen, washing dishes	Microwave, stove, oven, refrigerator, dishwasher,water heater, kitchen lights
Cleaning	Laundry, interior cleaning, exterior cleaning	Washer, dryer, vacuum cleaner, room lights
Entertainment	Watching TV, using computer	TV, computer, any other small entertainment device, e.g. x-box, playstation,etc., room lights
Working at home	Using computer, reading, writing	Computer, room lights
Going to work	N/A	N/A

in our paper's scope, we adopt the methodology in [18], which models the correlation with user preferences for scheduling and temperature settings.

6. We model the activity graph as cyclic. We select one activity as the starting activity of a day where at the end of the day, that activity is repeated. We choose the sleeping activity for this purpose, but another repeating activity can be used.

4 Activity Graph Construction

This section shows how we calculate the activity graph parameters. There is a separate graph for each individual, thus we estimate the parameters separately for different classes of people. To meet our classification needs, we use ATUS data [17]. It has more than 10000 participants from different parts of the society and includes their detailed activity information, which corresponds to the actions/activities in our graphs. ATUS does not have any details about appliance usages. We use another data set, RECS [8], which surveys more than 110 million households and has statistics regarding the families, the types and numbers of appliances used, and how frequently they use the appliances. We get the higher level family and appliance statistics from RECS and connect them with the lower level, individual activity data from ATUS.

Activity-Related Parameters. These parameters correspond to the physical characteristics of user actions and activities.

Table 2. Example action duration values for different groups of individuals

User group	Action	Average duration (min)	Action	Average duration (min)
< 18 y/o	Sleeping	360	Preparing food	22
≥ 18 y/o working male	Sleeping	325	Preparing food	31
≥ 18 y/o working female	Sleeping	322	Preparing food	32
≥ 18 y/o unemployed female	Sleeping	333	Preparing food	35
< 18 y/o	Eating	28	School	207
≥ 18 y/o working male	Eating	34	Work	197
≥ 18 y/o working female	Eating	33	Work	188
≥ 18 y/o unemployed female	Eating	33	Job search	96

Set of Activities: The ATUS data set does not make a distinction between actions and activities. It provides the information of what a user does. It classifies the activities hierarchically, which helps us determine the set of actions vs. activities. The first column of Table 1 shows the list of main activities we find.

Set of Actions for a Given Activity: These actions are determined manually found from ATUS. The difference between actions and activities are based on the activity tiers (1, 2, 3) reported in ATUS. The second column of Table 1 shows the actions included in different activities. We increase the granularity of user events mainly to understand and study what actions may lead to appliance usage or to another action that might result in appliance usage. Without this, the exact properties of an appliance usage event can be missed.

Durations of Actions: Since the action duration varies among individuals, we use statistical distributions to represent these durations, and sample a value from those distributions to assign an action duration. We use the activity duration information from ATUS to construct these distributions. We cannot create a separate distribution for each person or use a single distribution for everyone. Instead, we create multiple distributions to account for different user groups for each action. Table 2 shows example values for action durations for different groups. Based on the average values, each action instance samples a value from an exponential distribution with the corresponding average. We obtain these averages based on the weight values assigned to the individuals based on demographic representations by ATUS data set.

Duration of Activities: Since an activity is a composite (of individual actions) object, we compute its duration as the total duration of its individual actions.

Appliance-Related Parameters. These parameters show the list of appliances and how they are associated with specific actions and activities, determined by the statistical data from RECS. We then manually select the appliances associated with a given activity, shown in Table 1. An appliance may not be used for each instance of the activity it is associated to (probabilistic relation).

Probability-Related Parameters. These parameters determine both the possible transitions between actions and activities, forming the connections in the activity graph, and the probabilities of appliance usage events based on user actions. These parameters depend on two factors (1) user gender and age, (2) user employment status. We also consider time of day and day of week information because the activities a user performs change highly based on time of day (morning vs. evening) or day of week (weekday or weekend). In this paper, we do not make the distinction between days of week but consider time of day differences.

Action Transition Probabilities: These are based on the observed user actions and how frequently they follow each other. For each action in an activity, we count the number of actions following a given action to calculate the transition probabilities, as shown in Eq. 1. Since these probability values change for each user group and time of day, we calculate separate values accordingly. We use discrete time-of-day classification, i.e. morning, noon, and evening.

$$p(a_{ij} \rightarrow a_{ik}) = p^i_{jk} = \frac{\#\text{ action transitions from } a_{ij} \text{ to } a_{ik} \text{ in activity } A_i}{\#\text{ total transitions from } a_{ij} \text{ in activity } A_i} \tag{1}$$

The special case occurs when the activity that a specific action belongs to terminates. Equations 2 revises 1 by counting the instances where an action a_{ij} in an activity A_i is followed by an action A_{kl} in another activity A_k.

$$p^i_{jt} = \frac{\#\text{ transitions from } a_{ij} \text{ to } a_{kl} \text{ from } A_i \text{ to } A_k, i \neq k}{\#\text{ total transitions from } a_{ij} \text{ in activity } A_i} \tag{2}$$

Activity Transition Probabilities: These are computed similarly to the previous case, except we consider when an activity ends rather than single actions. The transition probabilities are computed in Eq. 3, which is calculated for each user group. To simplify and obtain a more compact model, we consider activity transitions independent of the actions finishing an activity. We compute the next activity independent of the last action of the current activity.

$$p(A_i \rightarrow A_j) = p_{ij} = \frac{\#\text{ activity transitions from } A_i \text{ to } A_j}{\#\text{ total activity transitions from } A_i} \tag{3}$$

Appliance Triggering Probabilities: We use the appliance usage frequency information from RECS to deduce the probability of using an appliance given the current action/activity. For example, assume that the *cooking* activity takes place twice in the activity graph of a user. But not all the kitchen appliances are used in all the *cooking* activity occurrences. According to RECS, 8.7 % of the households use the oven twice a day, 17.3 % use it once whereas 34.6 % use it only a few times a week. The appliances that RECS has these data stove/oven, microwave, dishwasher, washer, dryer, portable loads. We determine these probabilities based on the family size, e.g. single vs. couple, with or without children. We demonstrate how we construct families from individual people in the next section. We first calculate the average usage frequency of a given appliance and

Table 3. Example appliance triggering probabilities

Activity appliance couples	Family types				
	Single male	Single female	Couple	Couple +1 child	Couple + 2 children
p(cooking → oven)	0.13	0.15	0.21	0.25	0.28
p(cooking → microwave)	0.52	0.53	0.49	0.51	0.51
p(cooking → dishwasher)	0.12	0.13	0.27	0.31	0.39
p(cleaning → washer)	0.26	0.33	0.59	0.76	0.91
p(cleaning → dryer)	0.23	0.28	0.52	0.67	0.81

Table 4. Family distribution percentages (%) of ATUS and RECS data sets

	Single male	Single female	Couple	Couple - 1 kid	Couple - 2 kids	Couple - 3 kids	Couple - 3+ kids
RECS	9.87	13.18	33.53	17.14	14.47	7.11	4.70
ATUS	17.85	22.07	26.73	12.29	13.93	5.15	1.98

then deduce the probability based on the time frame of this average. We use one week as the time frame to compute these averages using RECS data set. Similar to ATUS, we leverage pre-computed sample weights RECS provides to calculate average values. We compute the appliance triggering probabilities for different family sizes for a given activity as follows:

$$p(A_i \rightarrow PL_j|\text{family type } t) = \frac{\text{average usage of } PL_j \text{ of family type } t}{\#\text{instances of } A_i \text{ over the time frame}} \quad (4)$$

where PL_j is a specific appliance, t is an enumeration for family types. The number of instances of A_i is counted based on the activity-appliance couples. For example, possible number of *cooking* instances in a week is 21, whereas this number is 7 for *cleaning*. Table 3 shows some examples of these values.

Combining Activity Graphs. We construct different families based on ATUS and RECS and first analyze the family statistics. We specify family types as single (male or female) and couple (no child, 1–2–3 or more children) as in Table 4. These percentages are calculated based on only the listed family types, which span more than 85 % of the survey respondents. The family types are distributed based on the numbers presented in Table 4 over all the houses. We obtain the final percentages as the average values between ATUS and RECS. We also specify the employment status of the adults in Table 5 for different family types, gathered from ATUS as the duration of *work* activity is modeled using it.

Next, we combine the the activity graphs of individuals. If each graph is mutually exclusive, we can simply add up the power profile of each person to obtain the total consumption. But multiple instances of a single appliance

Table 5. Employment percentages (%) of the adults

	Single man	Single woman	Couple	Couple - 1 kid	Couple - 2 kids	Couple - 3 kids	Couple - 3+ kids
Male	54.1	N/A	92.93	95.74	94.7	95.21	95.85
Female	N/A	42.88	84.86	97.91	82.08	65.47	55.96

can coincide. Thus, we cannot simply add up the consumption values. To solve this, we adopt a first come first serve solution. Assume that person x's activity graph leads to starting Ap_i at time t, where Ap_i has been in use by person y, which started at time $t - \delta$. If $\delta \leq \frac{d_i}{2}$, where d_i is the execution duration of Ap_i, the new instance of Ap_i is assumed as concurrent and discarded. If $\delta > \frac{d_i}{2}$, the incoming instance is scheduled to be executed after the current instance of Ap_i finishes.

5 Evaluation

This section first presents the power profiles we generate for families and then shows a case study for a neighborhood with 50 houses covering a range of families. The family types include single adults (male or female), couples without and with 1 or 2 children. The appliance power consumption values, shown in Table 7, are taken from Home Appliance Energy Use data from General Electric [9]. Profiles are generated for 5 days to observe the daily changes. We use residential power traces from Pecan Street database [11] to evaluate the effectiveness of our model. We gather these traces for corresponding family types. We match the time frames of the traces to the time frames of the generated traces. We select 5 consecutive days for each family type, randomly between 01–01–2014 and 06–01–2014. Table 6 shows the summary of our data sources and how we use the data. We incorporate multiple data sources (ATUS, RECS and GE) to build our user behavior model and compare it against the real power traces from Pecan Street database. It is difficult to directly compare the exact values in generated vs. real power traces since (1) the data we build our model on does not have direct correspondence with Pecan Street database (activities + appliance statistics vs. energy traces), (2) ATUS and RECS data spans the entire country, whereas Pecan Street has data only from Austin, TX, (3) the appliance power ratings from GE and Pecan Street do not match. Appliance power data from many houses in Pecan Street are missing. Although the exact values may not match, our model still accurately finds the peak demand times for both individual houses and a neighborhood with several houses. We scale the appliance ratings based on the peak values observed in generated vs. real traces and show that our model is more accurate if the correct appliance ratings are used.

Individual Power Profiles. Figures 2 and 3 show the power profiles of single male and female houses. The first and second figures show generated and real

Table 6. Data sources and usage purposes summary

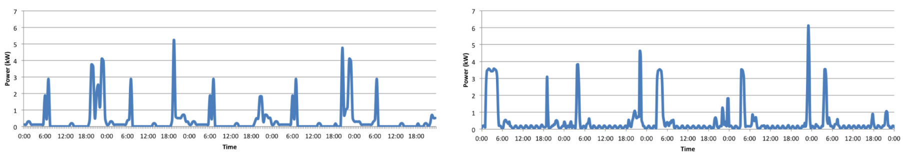
Data source	Usage purpose	Data size	Data span
ATUS [17]	Modeling activities	10000+ participants/year	Entire US
RECS [8]	Modeling appliance usage	110+ million participants	Entire US
General electric [9]	Appliance power ratings	N/A	N/A
Pecan street Inc. [11]	Verification of power profiles	778 houses	Austin, TX

Table 7. Appliance power consumption values [9]

Appliance	Power (W)	Appliance	Power (W)	Appliance	Power (W)
Central HVAC	3000–5000	Hair dryer	1500	Dryer	3400
Vacuum cleaner	500	Oven	3000	Laptop	100
Dishwasher	1500	Washer	500	LCD TV	210
Microwave	1500	Toaster	1100	Lights	50–100/room

traces. Both adults are assumed to be working full-time. The generated traces match the times of the power spikes of the real traces, where exact values do not match due to the reasons listed previously. The generated traces demonstrate more spikes and higher maximum power consumption for female adult households, which is also visible in the real traces.

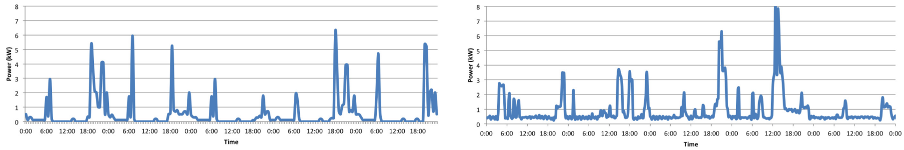
Figures 4, 5 and 6 show the power profiles of couples with 1 child, 2 children with the mother is working and stay-at-home (with and without HVAC). These profiles show similar peaks, all higher than the couples only case as the families with children use the appliances more often and spend more time at home. The difference arises in terms of the frequency of peaks. In the case with stay at home mother, we see the duty cycle behavior of HVAC spread throughout the day. The appliances are not used only in the evenings but also during the day. Most of the washer, dryer, dishwasher instances occur during the day because the appliance usage probabilities are higher for the stay at home mother during the day. The maximum power demand never exceeds 8 kW since the appliance operations do not coincide. In the case with working mother, appliances accumulate in the evenings, leading to a larger maximum power demand, around 12 kW.



(a) Generated trace

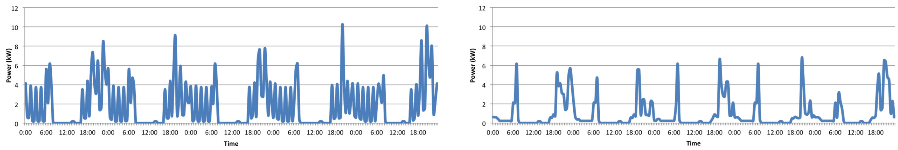
(b) Real trace [11]

Fig. 2. Single male house power profile



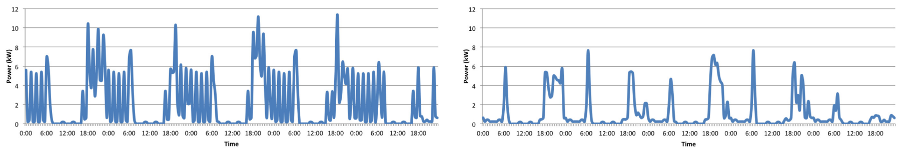
(a) Generated trace (b) Real trace [11]

Fig. 3. Single female house power profile



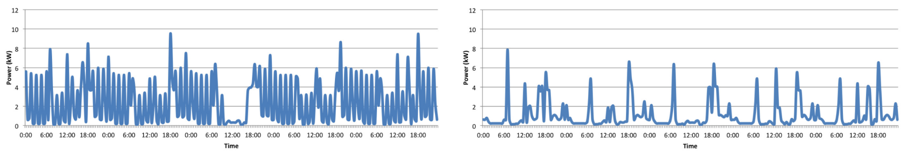
(a) with HVAC (b) without HVAC

Fig. 4. Generated power traces for couples with 1 child



(a) with HVAC (b) without HVAC

Fig. 5. Generated power traces for couples with 2 children - mother is working



(a) with HVAC (b) without HVAC

Fig. 6. Generated power traces for couples with 2 children - mother is not working

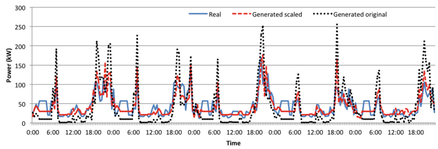


Fig. 7. Total power consumption

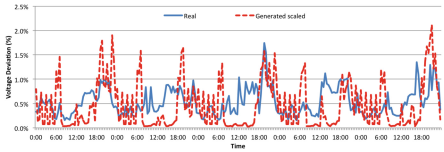


Fig. 8. Max voltage deviation

Case Study: Neighborhood Energy Analysis. One of the strengths of our model is that it can capture the nuances between the power profiles of different family types and show when the maximum power draws are likely to occur. This is an important and very useful capability when studying the effects of total power consumption during peak periods [2]. By creating several, reproducible power traces, we significantly increase the scalability of such system analyses and reduce the complexity to evaluate several cases with many homes.

Figure 7 shows the total power consumption of a neighborhood with 50 houses. The numbers of different family types are calculated based on Table 4. Comparing the real (straight) and generated (dotted) traces, we see that our model matches the times of peak spikes, but not the exact values due to (1) different appliance power ratings and (2) various small plug loads not included in our model as we either could not associate any user activity with them or did not find any usage data for them in large, long-term ATUS and RECS data sets. We scale values based on the maximum observed in generated vs. real traces and add an offset to account for the various plug loads. We show this new trace with the dashed line in Fig. 7. The scaled trace matches the peak power times and obtains 38 % absolute mean error, with minimum 0.25 % error. This shows that our model becomes more accurate once appliance power values closely match the original appliances used. We also compute the correlation coefficient between generated and real traces. This coefficient is between 0.1–0.3 for individual houses, 0.45 for the neighborhood with original generated traces and 0.62 with scaled generated traces. Our values have strong correlation with real traces for aggregate consumption, by correctly detecting the power spikes.

We use this neighborhood profile to study voltage deviation. Deviation values elevate with increased total consumption [2], thus, it is imperative to correctly estimate both the times and the magnitude of the spikes. We use the grid simulator in [2] to compute the deviation values. We get the physical circuit as a subset from one of EPRI's openly released test circuits [1]. Figure 8 shows the maximum deviations for both real and generated (scaled) traces. The deviation values show significant correlation with the spikes in Fig. 7. Our traces match these high deviation events (captures 5/5), which generally occur during the evenings. During these events, we get little or no error in voltage deviation.

6 Conclusion

Residential sector is a significant portion of the overall energy consumption in the US. Recent studies propose several energy-aware automation and scheduling solutions to address this. However, they need power profiles from a diverse set of houses to test these solutions. To achieve this, we propose a user behavior model to estimate the power demand of a house. We consider the features of both users and appliances to create diversity across neighborhoods. We can form several house profiles with different energy needs in a reproducible way. We compare the traces we generate against real data from Pecan Street. Our model matches the trends observed in real data for both individual houses and a neighborhood with 50 houses, by accurately estimating appliance usage times and thus peak power times. We also show the effects of peak power spikes with a grid simulator. Our model detects the high voltage deviation events observed with real data.

Acknowledgment. This work was supported in part by TerraSwarm, one of six centers of STARnet, a Semiconductor Research Corporation program sponsored by MARCO and DARPA.

References

1. EPRI test circuits. http://svn.code.sf.net/p/electricdss/code/trunk/Distrib/EPRITestCircuits/Readme.pdf
2. Akyurek, A.S., Aksanli, B., Rosing, T., S2Sim: smart grid swarm simulator. In: International Green and Sustainable Computing Conference (IGSC). IEEE (2015)
3. Barker, S., Mishra, A., Irwin, D., Cecchet, E., Shenoy, P., Albrecht, J.: Smart*: An open data set and tools for enabling research in sustainable homes. In: SustKDD 2012 (2012)
4. Basu, K., Hawarah, L., Arghira, N., Joumaa, H., Ploix, S.: A prediction system for home appliance usage. Energy Build. **67**, 668–679 (2013)
5. Chen, D., Barker, S., Subbaswamy, A., Irwin, D., Shenoy, P.: Non-intrusive occupancy monitoring using smart meters. In: ACM Buildsys (2013)
6. Chiou, Y.: Deriving us household energy consumption profiles from american time use survey data a bootstrap approach. In: 11th International Building Performance Simulation Association Conference and Exhibition (2009)
7. Collin, A.J., Tsagarakis, G., Kiprakis, A.E., McLaughlin, S.: Multi-scale electrical load modelling for demand-side management. In: IEEE PES ISGT Europe (2012)
8. U.S. E.I.A. Residential energy consumption survey (2009)
9. General electric. http://visualization.geblogs.com/visualization/appliances/
10. Center for climate and energy solutions. Energy and technology (2011). http://www.c2es.org/category/topic/energy-technology
11. Pecan street Inc. Dataport (2015)
12. Johnson, B.J., Starke, M.R., Abdelaziz, O., Jackson, R.K., Tolbert, L.M.: A method for modeling household occupant behavior to simulate residential energy consumption. In: Innovative Smart Grid Technologies Conference, IEEE PES (2014)
13. Kolter, Z., Johnson, M.J.: REDD: a public data set for energy disaggregation research. In: Workshop on Data Mining Applications in Sustainability (2011)

14. López-Rodríguez, M.A., Santiago, I., Trillo-Montero, D., Torriti, J., Moreno-Munoz, A.: Analysis, modeling of active occupancy of the residential sector in spain: an indicator of residential electricity consumption. Energy Policy **62**, 742–751 (2013)
15. Muratori, M., Roberts, M., Sioshansi, R., Marano, V., Rizzoni, G.: A highly resolved modeling technique to simulate residential power demand. Appl. Energy **107**, 465–473 (2013)
16. Neill, D.O., Levorato, M., Goldsmith, A., Mitra, U.: Residential demand response using reinforcement learning. In: IEEE SmartGridComm (2010)
17. Bureau of Labor Statistics. American time use survey (2014)
18. Venkatesh, J., Aksanli, B., Junqua, J., Morin, P., Rosing, T.: Homesim: comprehensive, smart, residential electrical energy simulation and scheduling. In: International Green Computing Conference (IGCC). IEEE (2013)