Generating Manageable Electricity Demand Capacity for Residential Demand Response Studies by Activity-based Load Models

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***Abstract*—Manageable electricity demand capacity and the user activities that make up this demand is crucial for aggregators in residential demand response events. In this study, it was aimed to generate residential electricity power profiles by the enhanced activity-based load models to determine manageable demand potential. A novel method that aggregators may estimate realistic residential manageable demand capacity was presented. The method can also be used to specify which incentives that cause suitable activity changes of the consumer. Studies were performed on several home appliances associated with different activities. Using load models that are based on collected energy consumption data, consumer behaviors, behavioral adaptations, habits, and physical determinants were embedded in both activities and loads' power profiles. It was observed from simulations that deferrable loads had a significant share in total electricity consumption.**

***Index Terms*—consumer behavior, load management, power demand, power distribution, smart grids.**

I. Introduction

The lack of household's behavioral characteristics in the residential electricity consumption models that used in demand response studies makes aggregators difficult to learn about the realistic manageable demand capacity and the incentives that can be offered to customers to maintain their participation. Several energy related studies are being carried out intensively to identify and model consumer activities with consumption [1-2]. There are two most common methods preferred in these studies. Smart meters and appliances that have communication ability were used in the first method to collect each required data. The second method that focuses on the energy disaggregation and it is called Nonintrusive Appliance Load Monitoring.

Electricity demand in a household is shaped by the owned appliances. Electrical powers and usage durations are needed for owned appliances to find their consumptions [3]. Estimating the duration of use for the appliances is the most complex issue. The occupant-based appliance operating states are needed to find usage durations. If there is at least one person in a house, the house is considered occupied. There are studies in the literature that aims to link electricity consumption with the occupant behavior and behavioral adaptations. Behaviors were handled in [4] as the householders' presence in the building and the assigned activities carried out by them. Authors in [5-8] describe occupant behavior as decisions and actions given by a person that changes the use of energy in buildings. Turning on/off HVAC systems, setting the thermostats, dimming/switching lights, opening/closing windows, and pulling up/down the blinds are handled as behaviors in [5]. Clothing adjustments, the consumption of drinks, and actions that changes in the human metabolic rate are counted as behavioral adaptations in [6-7]. A relationship exists among occupant behaviors, habits, and physical determinants [8]. Habits stand out as behavioral determining factors in consumption and they are less affected by seasonal changes. They include hourly, daily, weekly information about how often the person uses appliances (e.g., washing machine). Physical determinants have factors that are highly associated with climate and building structure, but less associated with human behavior such as lighting. Studies involving different definitions for individual behavior are also available in [9-13]. The individual behavior was handled in [9-10] as the behavior of two group prosumers who consume electricity from their own generation. The authors in [11] defined individual behavior as the actions that consumers consciously did to save energy. Individual behavior was described in [12-13] as actions that lead to the peak demand and the activities that occupant can schedule their loads to defined price flexibility in [13].

Electricity energy consumption can be obtained either bottom-up or top-down modeling methods [14]. Bottom-up modeling studies are more preferred in engineering studies. Researchers in [15-17] collected lots of user data containing randomly generated consumer profiles by bottom-up modeling. Study in [18], home appliances were classified according to their power patterns. They were continuous running loads (e.g., modem), standby mode capability loads (e.g., TV), cold loads (e.g., refrigerators), and active loads (e.g., oven). Loads were grouped as basic loads and flexible loads in terms of their manageability in [19]. Basic loads were consisted of continuously running loads and cold loads. Standby mode loads and active loads were gathered into flexible loads. Authors in [8] focused on the appliances' usage requirements. Appliances were run according to the five most common scenarios for occupancy profiles of a family of three. Average energy consumption and hot water usage profiles were used in the load models. Consumers were classified in four profiles according to appliance usage by the study [20]. There were easing profile, conscious profile, cost profile, and environmental profile. In general, the models mentioned above are very complex due to containing a large number of data inputs and many assumptions.

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The researchers in [3],[21-25] aimed to create a simple electricity consumer model that can produce extremely realistic output by as little data input as possible. Artificial patterns of the nine activities were used for each household in [3]. These patterns were transformed into power. Daylight level was used in the lighting model. The activity changing parameters were the probability values of Markov chain transition. Authors in [21] interested in the user's behavior only for thermal comfort with an agent-based modeling in a commercial building. A simple model of home lighting demand was made with data collected from 100 homes in [24]. The studies in [22-23] researchers calculated lighting energy consumption in the home sector by associating it with the level of daylight coming from outside and users' activities. Active user profiles were obtained by the Markov chain transition probabilities. The authors in [25] obtained consistent family populations from heterogeneous families by statistical means. Appliances were distributed to the related families. The likelihood of performing an action during the day and its duration were taken into account. There are some issues that need to be developed in mentioned modeling studies. Generalized average consumption values were used instead of realistic appliance power in [3]. High-powered appliances with a decisive role in consumption were not addressed. Consumption has been associated with a limited number of activities. The most important issue for the method in [21] is the results may not be realistic unless a good learning structure is established. In studies [22-24], a realistic consumption profile can be failed because transition possibilities are the most determining factor in consumption. It is necessary to have up-to-date and large data for accurate identification. The study in [25] did not include data on specific devices that have a significant share on household energy consumption.

The scientific value and the major contributions of our study can be summarized as follows. A novel method was introduced that aimed to uncover the potential of the residential manageable electricity demand capacity by using activities grouped into twelve categories with enhanced behavioral load models belong to sixteen different appliances. Activity-based load models were created. We added more enhanced energy consumption modeling elements than existing studies had. Power models had energy consumption data that collected by an energy analyzer in a home. The realistic activity patterns were used in this study. They were compiled from the survey results shared by a research institution in [26]. The number of activities covered in our study is much greater than those placed in [3],[8],[15],[21], and [25]. In addition, some elements counted as activities in [3],[25] were embedded as behavioral or adaptive actions in our activities. The realistic habits of consumers were created via the study given in [27] that covers appliance penetration rates, appliance usage durations, and appliance usage frequencies. Appliance models were enhanced associating the consumer habits, behavior adaptations, and physical determinants. A great number of behavioral adaptations were incorporated into the models for different needs. For example if specified daylight value is insufficient in the house, the use of lamps is allowed. It is possible for a user to choose different washing programs. Dryer can be used after each washing. The use of hot water was triggered by needs such as cleaning, washing dishes, and showering. The use of some devices could not be performed if there was a sleep activity. The need for the use of ovens and kitchen hoods was realized in food activity. In a housework activity, the use of irons and vacuum cleaners were enabled. Activities such as television and internet have directed to run TV and computer. Worship activity prevented the use of some devices. Work, transportation, entertainment, shopping, and education activities were evaluated as a reflection of the social, cultural, and economic situation of an occupant. The number of people in the household was placed in heating/cooling and hot water consumption models. The geometry of houses and climatic conditions were added in our thermal load models. Physical determinants were forced households to use combi boilers and air conditioners due to intolerable indoor temperature.

Weekly simulations were done in twelve months with three different activity patterns for one hundred houses via our scripts written in MATLAB. Manageable demand capacity that specific to consumer activities and the interested daily time intervals were obtained. Aggregators can use the methodology offered in this study to obtain realistic load power profiles via activity-based surveys conducted by them. Manageable demand capacity and activities can be analyzed by aggregators to find convenient participants for demand response study. The rest of the paper is organized as follows: Behavioral load modeling methodology is given in section II. Problem formulation is shared in section III. Case studies are presented in section IV. Results and discussion are placed in section V. Conclusions are expressed in section VI.

II. Methodology for the Behavioral Load Models

The steps followed in the methodology for the behavioral (activity-based) load models are shown in Fig. 1. Aggregators can collect data from geographic information systems, building energy identity information, civil registration and citizenship databases, and weather forecasting servers. The developed behavioral load modeling is started by assigning activities to the number of houses. Activities requiring people to be present in the house are described. Appliances are distributed to houses according to appliance penetration rates. Appliances that need people to run are determined. Activities and appliance usage status are matched. The start times for the appliances are set in activities. The realistic energy consumption values that collected by the energy analyzer are used in the behavior embedded power profiles. Details are available in subparts of section II.

A. Assignment of Activities to Houses

The total number of houses with the same activity was obtained by the study in [26], which investigated how Turkish people use their time. Activities were named as sleep, work, food, transportation, education, housework, shopping, entertainment, television, internet, worship, and others. These activities were distributed randomly to houses to keep the total number of each activity given in one-hour time intervals. Different lifestyles were created in houses through random distributions of these activities. The type of activity carried out in each household, starting time, ending time, and the durations for each activity were obtained. Home occupation status, occupation starting time, and occupation ending time were determined for the activities that require the presence of people in houses. Activities requiring people to be present in the houses were sleep, food, housework, television, internet, worship, and activities named other.

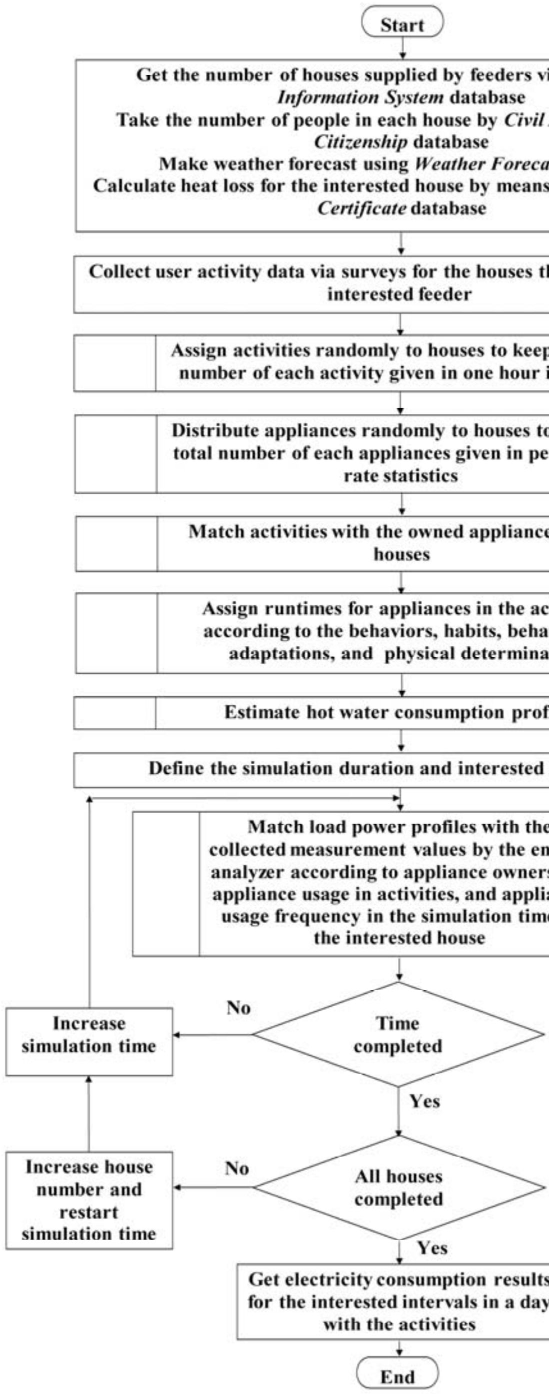

Figure 1. Flowchart for the behavioral (activity-based) load modeling methodology

B. *Distribution of Appliances to Houses*

The loads modeled in this study are television (TV), satellite receiver (SR), refrigerator (RF), freezer (FR), personal computer (PC), oven (OV), iron (IR), dishwasher (DW), washing machine (WM), additional rinsing (AR), clothes dryer (CD), air conditioner (AC), vacuum cleaner (VC), kitchen hood (KH), electric water heater (WH), combi boiler (CB), and lamps. The distribution of the devices to the houses was done randomly, providing the penetration values given in [27]. The penetration rates for RF, FR, WM, DW, CD, OV, KH, AC, CB, and WH were 106%, 52%, 95%, 42%, 34%, 77%, 70%, 8%, 70%, and 23% respectively. Penetration ratio of RF is 106% means that is found in every house and even in some homes the second one is also available. IR, VC, PC, TV, SR, and lamp were the appliances that available in all homes.

C. *Matching Activities with Appliances*

RFs and FRs were enabled to operate in all activities and there was no need an occupant to run them. Loads that require the user to be present at home were the appliances except RFs and FRs. WM, DW, CD, AC, WH, and CB were the loads used in each activity categories that require being at home and these appliances were enabled to run even if there was a sleeping activity. In addition to that it would possible to continue the running of WM, DW, CD, AC, WH, and CB in all activity categories if they were started by occupants. VC, IR, OV, PC, TV, SR, and KH were not allowed to use during a sleep activity. VC and IR were enabled in housework activity category. OV and KH were activated in food activity category. TV and SR were used in television activity category. PC could be used during an internet activity category. AC, CB, and WH were allowed to operate in all activity categories. Lamps were used in an activity category that requires an occupant in house. It was assumed that lamps were not used during sleep activity except a specified time interval such as 6 a.m. to 8 a.m.

D. Assignment of Appliance Runtimes

Each of the RFs and FRs was started to operate in a random moment of random phase to avoid cold load pick up issue. The use of WM and DW in houses was assigned at different periods of the day according to research data on how often washing was carried out during a day [27]. CD in the house was enabled to run at a random moment following each laundry stop time with a randomly assigned delay. There were 110 usages yearly for OV [27]. The probability of OV to run in a day was obtained to keep annual total usage. The probability of KH to run in a day was considered the same as the use of OV. The probability of the IR and VC to run in a day was 50%. In the house where OV, KH, IR, and VC exist, allowing interested appliance to run was enabled by random number generation and compared it to the probability value of the daily usage. OV and KH usage duration in a day was assigned randomly between the food activity start and the food activity stop time. Each IR and VC usage time in a day was assigned randomly between the housework activity start and the housework activity stop time. The watching time was randomly determined between the start and end time of each television activity. TV and SR were enabled to run during each watching intervals. Operation time intervals and usage frequency for PC in internet activity were randomly determined. AC was run in cooling mode. In cooling mode, if the room temperature was as high as the sum of the setting temperature and tolerance value, then AC was required to operate. CB was used for heating the house and the production of hot water needed for cleaning, washing dishes, and showering. A room thermostat based usage was accepted at 10% in all houses. In a house with a room thermostat, CB runs until the room temperature reaches the setting value. In a house without a room thermostat, CB runs until the water temperature circulating in the radiators reached the adjusted set temperature. If CB was used for the production of the hot water, the boiler would run until the outlet water temperature reached the setting value. The amount of hot water and the duration of use were distributed randomly to each house. WH runs until the hot water temperature reached the setting value. The use of lamps in the interested room would be possible if the solar irradiation value was below the randomly determined level in it.

E. Behavioral Load Power Profiles

Total power of an interested appliance a in the house i at time t is represented by $P^{i}_{a,total}(t)$ in (1). User behavior related power is $P^{i,j}_{a}(t)$. The total number of the same appliance in house i is represented by λ^{i}_{a}. Each appliance j activated by binary variable $f^{i,j}_{a}$. The operation of an appliance in accordance with the usage habits is ensured by binary variable $\mu^{i,j}_{a}$. The frequency of daily use of the device is $K^{i,j}_{a}$. Power on/off switch position of an appliance $S^{i,j}_{a}(k,t)$ is set to 1 during the device usage intervals otherwise its value is 0. Appliances' powers with technical specifications, physical determinants, and users' adaptive actions are embedded in $LP^{i,j}_{a}(t)$. It includes power models created by realistic consumption data collected by an energy analyzer in a house.

$$P^{i}_{a,total}(t)=\bigcup_{i=1}^{100}\bigcup_{t=1}^{T}\sum_{j=1}^{\lambda^{i}_{a}}P^{i,j}_{a}(t) \quad (1)$$

$$P^{i,j}_{a}(t)=\bigcup_{i=1}^{100}\bigcup_{j=1}^{\lambda^{i}_{a}}\bigcup_{k=1}^{K^{i,j}_{a}}\bigcup_{t=1}^{T}f^{i,j}_{a}.\mu^{i,j}_{a}.S^{i,j}_{a}(k,t).LP^{i,j}_{a}(t)$$

The sum of the standby duration, cooling duration, and defrost duration constitute the runtime period of the RF j in the house i. Power in standby, power in cooling, and power in defrosting are obtained by $LP^{i,j}_{RF}(t)$ if time spent in the related stage is taken into account. The power value of the FR can be expressed similarly to that of the refrigerator. One difference in FR is power consisted of standby power and cooling power. The values of $\mu^{i,j}_{RF}$ and $S^{i,j}_{RF}(k,t)$ are set to 1 for RFs and FRs. It means energy consumption occurs according to the state of the internal thermostat switches and running cycles. The behavior embedded powers of the interested WM, DW, CD, OV, and IR are obtained in $LP^{i,j}_{a}(t)$ by taking into account the chosen program type, the duration of each run phase, and the power in the related phases. The values of $\mu^{i,j}_{a}$ and $S^{i,j}_{a}(k,t)$ are set to 1 during the appliance daily usage habit intervals. If power switch of the interested KH, VC, TV, SR, and PC are turned on, the instantaneous power values are found during the appliance usage times. The behavior embedded load powers for AC, CB and WH are obtained the state of the thermostat set values, behavioral adaptations, usage habits and physical determinants. The total power of lamps in the house is $P^{i}_{lighting}(t)$ and it can be formulated by (2). $f^{i,r}_{l}$ is availability state of the lamp in the room r of the house i. $LP^{i,j}_{l}$ is the power of each lamp j that assigned randomly in each room of the house. The use of lamp will be possible if the solar irradiation value in the room r is below the randomly determined daylight level for the interested room. Maximum usage duration for each lamp is obtained using the total time value that the solar radiation level is below the specified level in a room. Lamp's usage durations are randomly assigned, provided they do not exceed the maximum value. $K^{i,j}_{l}$ represents the usage frequency of the lamp j in the room r of the house i. $P^{i,r}_{lamp}(t)$ is aggregated power of the lamp in the room r of the house i that is obtained according to related lamp switch position

$S_l^{i,j}(k,t)$.

$$P^{i}_{lighting}(t)=\bigcup_{i=1}^{100}\bigcup_{t=1}^{T}\sum_{r=1}^{R^i}P^{i,j}_{lamp}(t) \tag{2}$$

$$P^{i,r}_{lamp}(t)=\bigcup_{i=1}^{100}\bigcup_{j=1}^{l_l^{i,r}}\bigcup_{k=1}^{K_l^{i,j}}\bigcup_{r=1}^{R^i}\bigcup_{t=1}^{T}f_l^{i,r}.S_l^{i,j}(k,t).LP_l^{i,j}$$

F. Modeling of Hot Water Usage

The use of hot water is intended for cleaning, dishwashing, and showering in houses. In our study, the total value of hot water usage was obtained by randomly selecting a value between the consumptions found by both calculation methods given in [8], and [28]. The authors in [8] established a linear relationship between the number of people in the home and the amount of hot water needed. In [28], the amount of hot water needed was calculated according to mains water temperature, the preferred temperature for room cleaning, dishwashing, showering, and the number of bedrooms. In our study, hot water consumption profiles were obtained allocating the total hot water usage capacity in accordance with lamp usage durations for bathroom, kitchen, and toilet. The use hot water in the bathroom was possible for cleaning and/or showering purpose. As long as the kitchen is in use, random selection is provided for cleaning, dishwashing or both purposes. A random selection was provided for cleaning purposes only in the toilet.

III. PROBLEM FORMULATIONS

Loads are divided into two categories as deferrable and non-deferrable loads. If electricity demand is higher than the targeted level in the interested daily period, consumption must be balanced against current supply. Peak demand can be reduced by shifting the runtime of the deferrable loads. It is possible to interrupt the operation of some deferrable loads. The runtime of deferrable loads, which cannot be interrupted, can be delayed automatically or manually if needed. The decrease in the energy consumption of non-deferrable loads may be possible by using these appliances with less duration. Devices such as non-dimmable lamps, deep freezers and refrigerators are counted in the load group whose consumption cannot be reduced. However, the consumption of cold loads may be changed by performing the cooling process earlier, cooling process later, and changing the set values. The classification of the devices used in this study according to their manageability characteristics is given in Fig. 2.

IV. CASE STUDY

Case studies were carried out by changing twelve activities in three different ways for 100 houses. It was aimed to obtain the deferrable magnitude of the demand by the load models that include effect of individual behavior, behavior adjustment, habits, and physical decision makers on appliance usage situations. The activity pattern of Case 1 is shown in Fig. 3a for one hundred houses. It was shifted one hour towards to the left and the activity pattern of Case 2 given in Fig. 3b was obtained. The activity pattern of Case 1 was shifted one hour towards to the right and the activity pattern of Case 3 illustrated in Fig. 3c was obtained. Daily time intervals have been established to determine the time of realization of consumer habits in demand management and to adapt to electricity tariffs that will motivate the consumer. Activity durations in 100 houses were calculated for the three cases and illustrated in the daily time intervals such as night1 (00.00 - 06.00), morning (06.00 - 10.00), midday (10.00-14.00), afternoon (14.00 -18.00), evening (18.00-22.00), and night2 (22.00 - 00.00). The total durations for the same activities are equal in all three cases, but their intraday distribution differs. Fig. 4 shows the each activity duration as percentages according to the total duration of the whole activities with the cases in the interested time intervals. Appliances were distributed to houses based on device penetration rates as shared in Section II(B). The same owned appliances, behaviors, behavior adjustments, usage habits, hot water usage capacities, physical decision makers were maintained in three cases for houses. Relations between appliances and activities were established as mentioned in Section II(C). Load running times were assigned as described in Section II(D). Consumptions were obtained via the behavioral load power profiles explained in Section II(E) for each appliance. The method detailed in Section II(F) was followed for the use of hot water. Simulation was performed case by case during a week in each month via MATLAB.

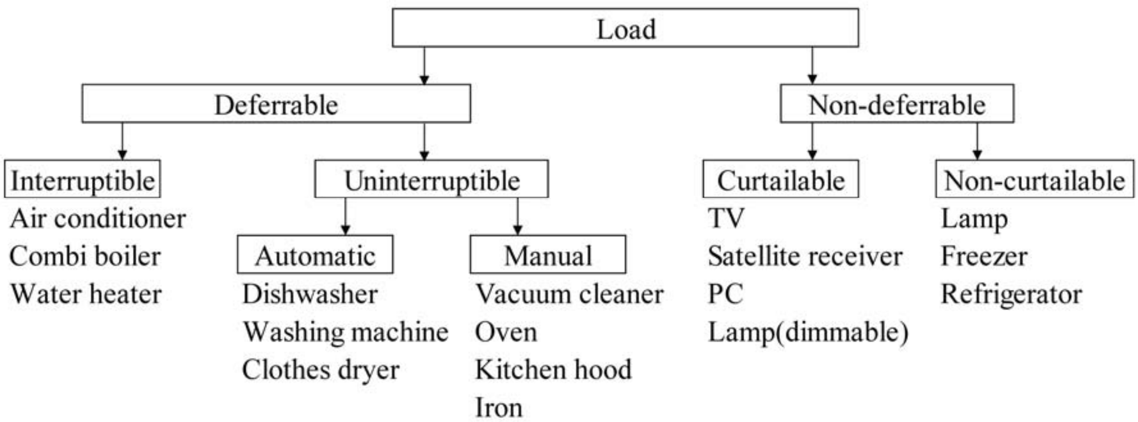

Figure 2. Classification of available appliances for demand response study

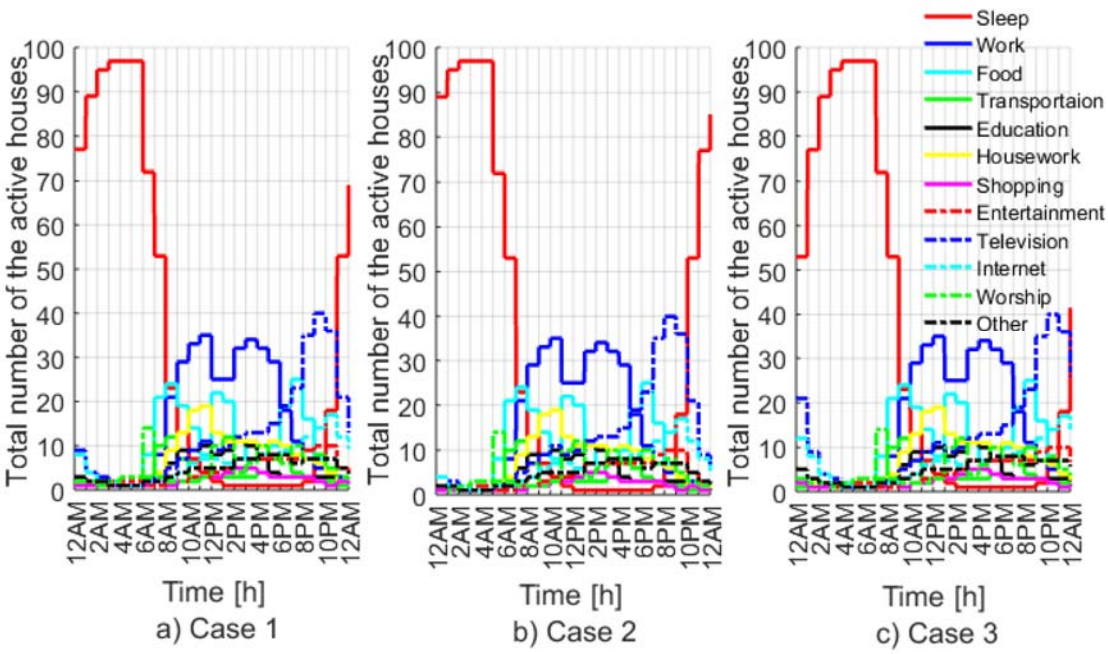

Figure 3. Distribution of the same activities for one hundred houses in cases: a) Case 1, b) Case 2, c) Case 3

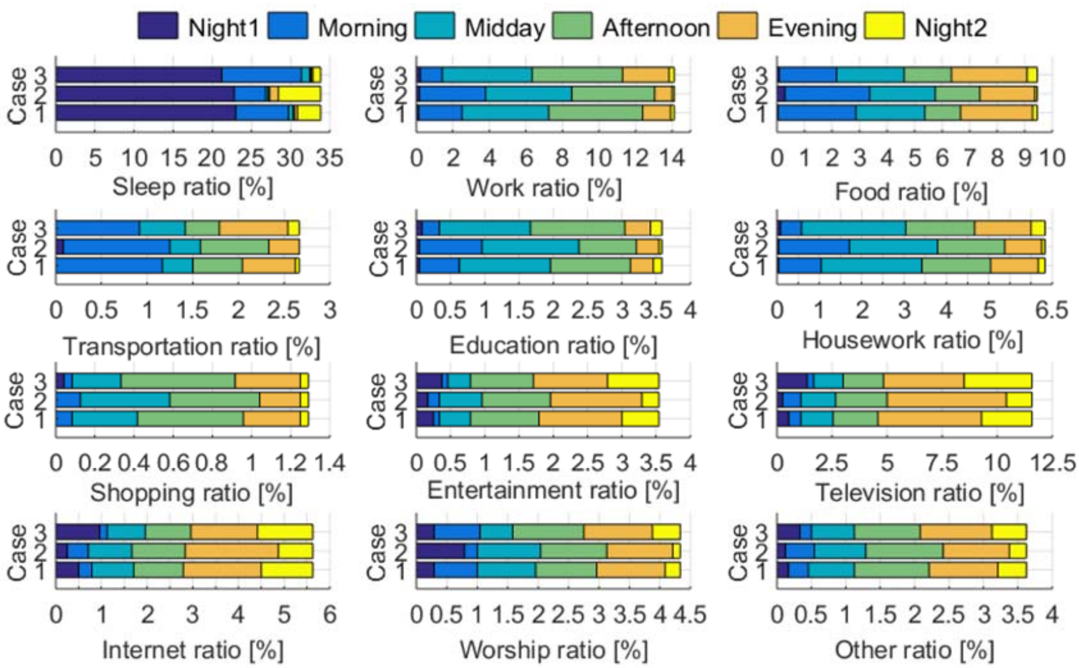

Figure 4. Percentage of activity duration in the daily time intervals for cases

V. Results and Discussions

Simulation results were obtained for the cases that have different activity distributions in a day. Electricity consumption value of each appliance in the interested time intervals are shared in Table I. The least total consumed electricity energy for 100 houses over a week for 12 months was 80534 kWh and it was obtained in the Case 3. The total electricity consumption increase was 0.84% in Case 1 and 0.54% in Case 2 compared to Case 3. This result is important. Aggregators can do demand response study in the interested time intervals without experiencing high decreasing or increasing in consumer's total consumption.

The least total electricity consumption has belonged to the interested time intervals over a week for 12 months was calculated case by case. Case 1 provided the least total consumption in night1 and afternoon by 9958 kWh and 11462 kWh respectively. Midday and night2 consumptions were the least total value in Case 2 by 13870 kWh and 7178 kWh respectively. Case 3 had the least total consumption by 13165 kWh in morning and 18777 kWh in evening. According to the daily electricity consumption reference value, 1 MWh, share of total consumed energy in each case were calculated in the interested time intervals. Case 1 provided the least mean consumed energy share in night1 and afternoon by 12.3% and 14.1% respectively. Case 2 had the least mean consumption share in midday and night2 by 17.1% and 8.9% respectively. The least mean consumed electricity share in morning and evening belonged to Case 3 by 16.4% and 23.3% respectively. The daily change in the consumed energy with the interested intervals during one week in each month for 100 houses is shown in Fig. 5.

Activity based electricity consumptions are shown case by case in Fig. 6. The least total consumption over a week for 12 months in the interested activities was calculated case by case. Case 1 provided the least total consumption in sleep and work activity by 13067 kWh and 4905 kWh respectively. Case 2 had the least total consumed energy in food, transportation, and worship activities by 20062 kWh, 1571 kWh, and 3991 kWh respectively. Education, housework, shopping, entertainment, television, internet, and other were the activities belong to the least total consumption in Case 3 by 1508 kWh, 7750 kWh, 735 kWh, 1744 kWh, 13792 kWh, 6188 kWh, and 4398 kWh respectively. Case1 had the least consumption share in total consumption in sleep and work activity by 16.1% and 6%. Food, transportation, television, and worship activities had the least mean electricity consumption share in Case 2 by 24.8%, 1.9%, 17.1%, and 4.9% respectively. Case 3 provided the least mean electricity consumption share in education, housework, shopping, entertainment, internet, and other activities by 1.9%, 9.6%, 0.9%, 2.2%, 7.7%, and 5.5% respectively.

Manageable demand capacity in Case 3 was 45696 kWh by ratio of 56.7% in total consumed electricity. Case 3 had the least consumption among the cases. Case 1 and Case 2 had 46574 kWh and 46658 kWh manageable load capacity respectively. Interruptible loads consumed the least electricity energy value in Case 2 by 22845 kWh. The least consumption for the automatic and manual deferrable loads was 12012 kWh and 10750 kWh in Case3 respectively.

Manageable demand magnitudes were analyzed in the interested time intervals using the deferrable load consumptions over a week for 12 months case by case. The least total consumption of deferrable appliances in night1 and afternoon was recorded in Case 1 by 4052 kWh and 6578 kWh respectively. Case 2 provided the least total manageable consumption in midday and night2 by 8800 kWh and 4015 kWh respectively. Morning and evening in Case 3 had the least total consumption for deferrable loads by 7927 kWh and 10897 kWh respectively.

The share of the manageable consumption was calculated case by case in the interested daily intervals according to total consumption. Case 1 had the least mean deferrable load consumption share in night1 and afternoon by 5% and 8.1% respectively. The least mean share for deferrable loads in midday and night2 was recorded in Case 2 by 10.9% and 5% respectively. 9.8% in morning and 13.5% in evening that occurred in Case 3 was the least mean consumed energy share for deferrable loads.

The least total consumption over a week for 12 months in the interested activities is analyzed case by case. Case 1 provided the least total manageable consumption in work activity by 2061 kWh. Food, transportation, and worship activities in Case 2 hit the least total consumed energy for deferrable loads by 15393 kWh, 1037 kWh, and 2024 kWh respectively. Manageable consumption in Case 3 was the least in sleep, education, housework, shopping, entertainment, television, internet, and other activity by 6293 kWh, 786 kWh, 4986 kWh, 475 kWh, 1032 kWh, 5906 kWh, 2925 kWh, and 2098 kWh respectively. Case1 had the least deferrable load consumption share in total consumption in sleep and work activity by 7.8%, and 2.5% respectively. Food, transportation, and worship activities had the least mean manageable consumption share in Case 2 by 19%, 1.3%, and 2.5% respectively. Case 3 provided the least mean manageable consumption share in education, housework, shopping, entertainment, television, internet, and other activities by 1%, 6.2%, 0.6%, 1.3%, 7.3%, 3.6%, and 2.6% respectively.

TABLE I. TOTAL ELECTRICITY CONSUMPTION OF APPLIANCES IN THE TIME INTERVALS DURING ONE WEEK IN A YEAR FOR 100 HOUSES

Load	**Case**	**Total Consumption [kWh]**					
		Night1	**Morning**	**Midday**	**Afternoon**	**Evening**	**Night2**
KH	1	4	189	115	42	163	13
PC	1	17	10	32	38	66	40
DW	1	461	517	376	381	941	276
RF	1	4062	2713	2713	2719	2707	1349
WM	1	451	1682	928	939	1514	823
FR	1	810	541	540	541	540	270
AR	1	44	20	29	22	35	26
OV	1	68	3226	1874	678	2596	259
AC	1	216	157	248	261	183	72
CB	1	1603	1161	1181	1134	1225	624
CD	1	586	181	597	546	609	492
Lamp	1	797	2489	1427	1168	4328	2353
VC	1	5	81	96	56	103	20
TV	1	88	86	214	305	692	315
WH	1	598	1861	3237	2268	4671	2496
IR	1	16	277	432	254	286	52
SR	1	132	91	104	113	152	73
KH	2	21	195	110	75	128	7
PC	2	8	16	33	43	78	26
DW	2	490	495	330	413	997	302
RF	2	4062	2712	2717	2716	2706	1350
WM	2	498	1641	841	986	1649	860
FR	2	811	540	540	541	540	270
AR	2	44	18	24	21	43	32
OV	2	355	3217	1810	1176	2005	138
AC	2	209	153	244	257	179	70
CB	2	1602	1172	1180	1144	1252	581
CD	2	900	155	570	493	603	547
Lamp	2	750	2867	1442	1299	4567	1310
VC	2	5	112	72	55	94	9
TV	2	54	126	234	348	788	152
WH	2	303	2108	3295	2178	5472	1447
IR	2	10	396	323	258	265	23
SR	2	129	95	106	117	162	56
KH	3	7	142	129	75	163	22
PC	3	33	6	29	35	56	45
DW	3	463	520	402	447	798	229
RF	3	4063	2711	2717	2714	2710	1348
WM	3	433	1625	1122	1033	1288	731
FR	3	811	541	540	541	540	270
AR	3	42	19	35	24	32	22
OV	3	130	2452	2017	1072	2627	385
AC	3	240	174	264	277	199	80
CB	3	1635	1138	1171	1138	1201	645
CD	3	509	164	651	527	519	377
Lamp	3	1566	1840	1299	1166	3892	3009
VC	3	8	50	102	41	89	37
TV	3	189	54	194	271	544	442
WH	3	1428	1520	2809	2371	3685	2959
IR	3	25	123	457	210	295	90
SR	3	143	88	102	110	137	86

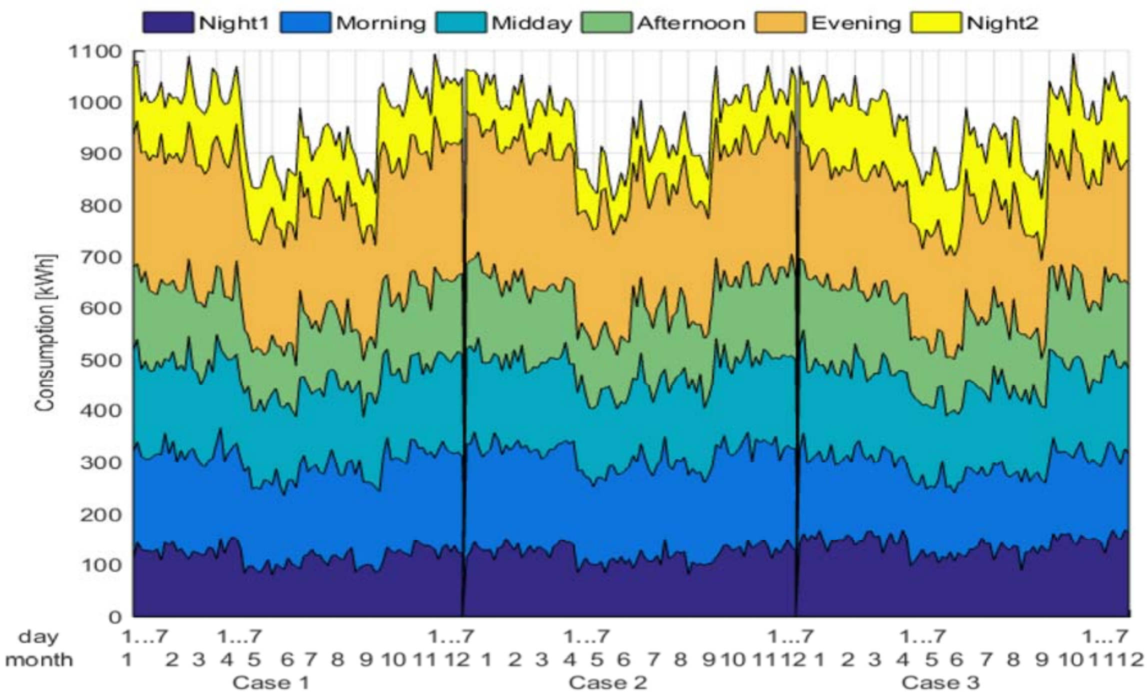

Figure 5. Consumed electricity energy in the daily time intervals during one week in each month for one hundred houses with cases

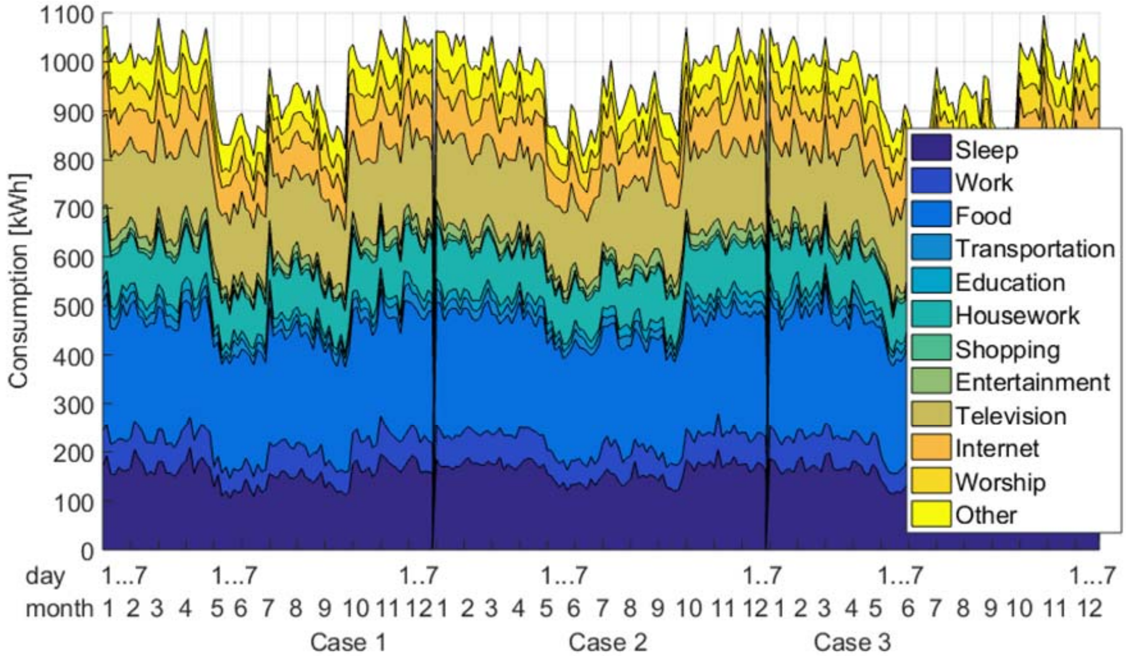

Figure 6. Activity based electricity consumptions during one week in each month for one hundred houses with cases

Manageable demand capacity percentage in each activity with the interested time intervals is shown in Fig. 7. Manageable demand capacity in food, sleep, television, housework, and internet activity were the highest share in total consumed electricity energy. Consumption emigrations for appliances were found in accordance with the interested time intervals and activities. They are illustrated in Fig. 8 and Fig. 9 respectively, for the referenced Case 1.

Consumers who wanted to maintain their behavior did not provide the use of deferrable loads in each time period because some time intervals did not correspond to their preferences (habits), thus consumers had to shape their consumption. Behavioral adaptation has been particularly effective at lighting. Since the physical conditions are kept the same in all cases during the simulation, there have been limited changes in the condition of the equipment such as air conditioner and combi boiler. There is linearity between the consumption of water heaters and the consumption of lighting in places such as bathrooms, kitchens, and toilets.

VI. Conclusion

Activity-based load models were developed to achieve manageable demand capacity in the residential demand response events. Various cases were simulated to show the importance of activities in manageable demand capacity with 100 houses. Our developed models have both more enhanced energy consumption modeling elements than existing studies and lots of home appliances associated with different activities. Consumption magnitudes specific to the daily time intervals and activities were obtained by simulation over a week for 12 months case by case. The least manageable demand capacity was 56.7% in total consumed electricity. Case 1 had the least mean deferrable load consumption share in night1 and afternoon by 5% and 8.1% respectively. The least mean share for deferrable loads in midday and night2 was recorded in Case 2 by 10.9% and 5% respectively. 9.8% in morning and 13.5% in evening that occurred in Case 3 was the least mean consumed energy share for deferrable loads. Case1 had the least deferrable load consumption share in total consumption in sleep and work activity by 7.8%, and 2.5% respectively. Food, transportation, and worship activities had the least mean manageable consumption share in Case 2 by 19%, 1.3%, and 2.5% respectively. Case 3 provided the least mean manageable consumption share in education, housework, shopping, entertainment, television, internet, and other activities by 1%, 6.2%, 0.6%, 1.3%, 7.3%, 3.6%, and 2.6% respectively. This study gives opportunity to aggregators to have manageable demand size through activity schedules collected from targeted demand response participants. Knowing the share of deferrable electricity demand capacity in various activities will increase participant satisfaction and loyalty by offering more accurate incentives. The future study is a continuation of this study that aims to shape demand with the incentives that can be given to consumers.

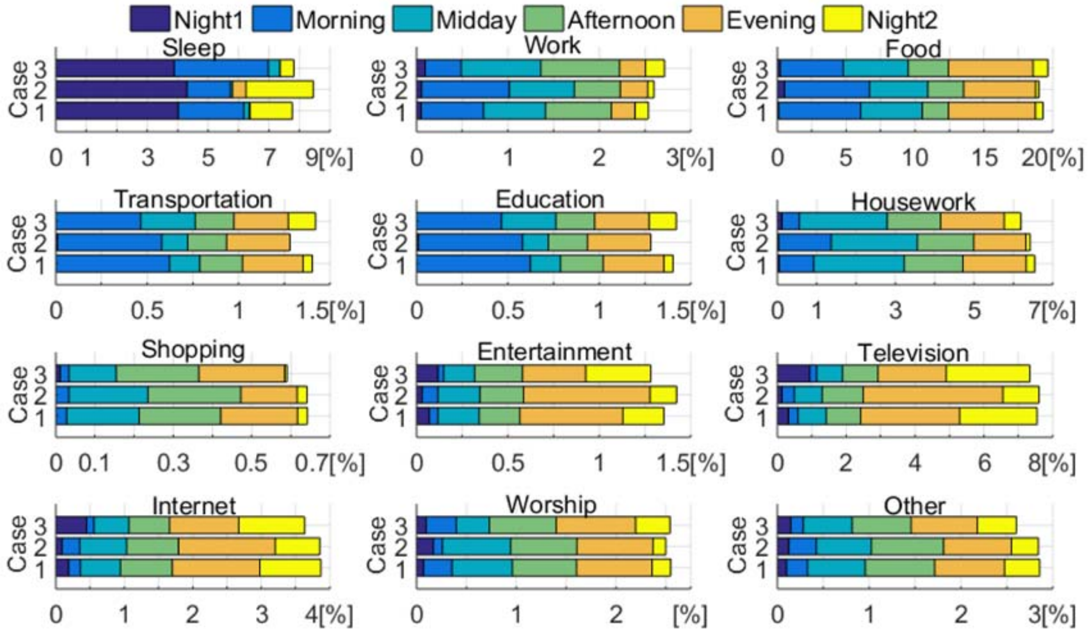

Figure 7. Manageable demand capacity percentages in activities with cases and the daily time intervals

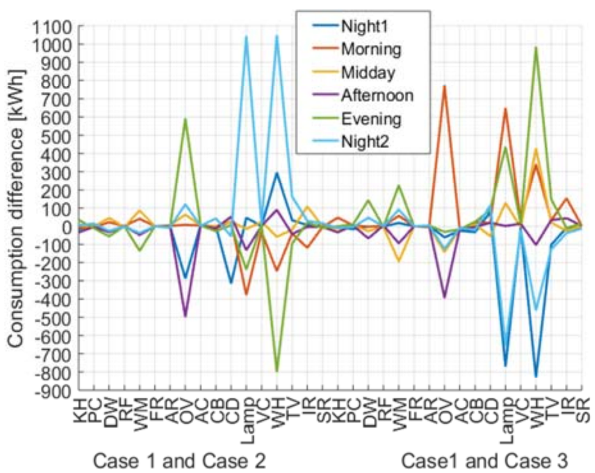

Figure 8. Change in electricity consumption value of the appliances according to Case 1 within the daily time intervals

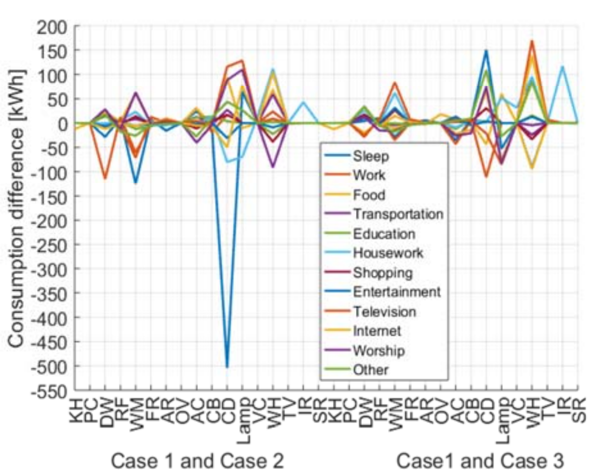

Figure 9. Change in electricity consumption value of the appliances according to Case 1 for the daily activities

REFERENCES

[1] H. Wang, G. Henri, T. Chin-Woo, and R. Rajagopal, "Activity detection and modeling using smart meter data: concept and case studies," IEEE Power & Energy Society General Meeting, August 2020

[2] T. Liu, X. Ding, and N. Gu, "A generic energy disaggregation approach: What and when electrical appliances are used," in 2015 IEEE International Conference on Data Mining Workshop (ICDMW), Nov. 2015, pp. 389–397, doi:10.1109/ICDMW.2015.28

[3] J. Widén and E. Wäckelgård, "A high-resolution stochastic model of domestic activity patterns and electricity demand," Applied Energy, vol. 87, no. 6, pp. 1880–1892, Jun. 2010, doi:10.1016/j.apenergy.2009.11.006

[4] P. Hoes, J. L. M. Hensen, M. G. L. C. Loomans, B. de Vries, and D. Bourgeois, "User behavior in whole building simulation," Energy and Buildings, vol. 41, no. 3, pp. 295–302, Mar. 2009, doi:10.1016/j.enbuild.2008.09.008

[5] L. Klein et al., "Coordinating occupant behavior for building energy and comfort management using multi-agent systems," Automation in

Construction, vol. 22, pp. 525–536, Mar. 2012, doi:10.1016/j.autcon.2011.11.012

[6] T. Hong, D. Yan, S. D'Oca, and C. Chen, "Ten questions concerning occupant behavior in buildings: The big picture," Building and Environment, vol. 114, pp. 518–530, Mar. 2017, doi:10.1016/j.buildenv.2016.12.006

[7] D. Calì, R. K. Andersen, D. Müller, and B. W. Olesen, "Analysis of occupants' behavior related to the use of windows in German households," Building and Environment, vol. 103, pp. 54–69, Jul. 2016, doi:10.1016/j.buildenv.2016.03.024

[8] R. Yao and K. Steemers, "A method of formulating energy load profile for domestic buildings in the UK," Energy and Buildings, vol. 37, no. 6, pp. 663–671, Jun. 2005, doi:10.1016/j.enbuild.2004.09.007

[9] O. Motlagh, P. Paevere, T. S. Hong, and G. Grozev, "Analysis of household electricity consumption behaviours: Impact of domestic electricity generation," Applied Mathematics and Computation, vol. 270, pp. 165–178, Nov. 2015, doi:10.1016/j.amc.2015.08.029

[10] C. Oberst and R. Madlener, "Prosumer Preferences Regarding the Adoption of Micro-Generation Technologies: Empirical Evidence for German Homeowners," Social Science Research Network, Rochester, NY, SSRN Scholarly Paper ID 2670035, Sep. 2015. doi:10.2139/ssrn.2670035

[11] A. H. McMakin, E. L. Malone, and R. E. Lundgren, "Motivating Residents to Conserve Energy without Financial Incentives," Environment and Behavior, vol. 34, no. 6, pp. 848–863, Nov. 2002, doi:10.1177/001391602237252

[12] F. McLoughlin, A. Duffy, and M. Conlon, "Characterising domestic electricity consumption patterns by dwelling and occupant socio-economic variables: An Irish case study," Energy and Buildings, vol. 48, pp. 240–248, May 2012, doi:10.1016/j.enbuild.2012.01.037

[13] H. A. Aalami, M. P. Moghaddam, and G. R. Yousefi, "Modeling and prioritizing demand response programs in power markets," Electric Power Systems Research, vol. 80, no. 4, pp. 426–435, Apr. 2010, doi:10.1016/j.epsr.2009.10.007

[14] L. G. Swan and V. I. Ugursal, "Modeling of end-use energy consumption in the residential sector: A review of modeling techniques," Renewable and Sustainable Energy Reviews, vol. 13, no. 8, pp. 1819–1835, Oct. 2009, doi:10.1016/j.rser.2008.09.033

[15] A. Capasso, W. Grattieri, R. Lamedica, and A. Prudenzi, "A bottom-up approach to residential load modeling," IEEE Transactions on Power Systems, vol. 9, no. 2, pp. 957–964, May 1994, doi:10.1109/59.317650

[16] J. V. Paatero and P. D. Lund, "A model for generating household electricity load profiles," International Journal of Energy Research, vol. 30, no. 5, pp. 273–290, 2006, doi:10.1002/er.1136

[17] M. Stokes, "Removing barriers to embedded generation: a fine-grained load model to support low voltage network performance analysis," 2005, Accessed: Sep. 06, 2020. [Online]. Available: https://dora.dmu.ac.uk/handle/2086/4134

[18] S. Firth, K. Lomas, A. Wright, and R. Wall, "Identifying trends in the use of domestic appliances from household electricity consumption measurements," Energy and Buildings, vol. 40, no. 5, pp. 926–936, Jan. 2008, doi:10.1016/j.enbuild.2007.07.005

[19] T. Zhang, P.-O. Siebers, and U. Aickelin, "Modelling electricity consumption in office buildings: An agent based approach," Energy and Buildings, vol. 43, no. 10, pp. 2882–2892, Oct. 2011, doi:10.1016/j.enbuild.2011.07.007

[20] E. de Groot, M. Spiekman, and I. Opstelten, "361: Dutch Research into User Behaviour in Relation to Energy Use of Residences," p. 5, 2008

[21] Y. S. Lee and A. M. Malkawi, "Simulating multiple occupant behaviors in buildings: An agent-based modeling approach," Energy and Buildings, vol. 69, pp. 407–416, Feb. 2014, doi:10.1016/j.enbuild.2013.11.020

[22] I. Richardson, M. Thomson, and D. Infield, "A high-resolution domestic building occupancy model for energy demand simulations," Energy and Buildings, vol. 40, no. 8, pp. 1560–1566, Jan. 2008, doi:10.1016/j.enbuild.2008.02.006

[23] I. Richardson, M. Thomson, D. Infield, and A. Delahunty, "Domestic lighting: A high-resolution energy demand model," Energy and Buildings, vol. 41, no. 7, pp. 781–789, Jul. 2009, doi:10.1016/j.enbuild.2009.02.010

[24] M. Stokes, M. Rylatt, and K. Lomas, "A simple model of domestic lighting demand," Energy and Buildings, vol. 36, no. 2, pp. 103–116, Feb. 2004, doi:10.1016/j.enbuild.2003.10.007

[25] L. Bottaccioli, S. Di Cataldo, A. Acquaviva, and E. Patti, "Realistic Multi-Scale Modeling of Household Electricity Behaviors," IEEE Access, vol. 7, pp. 2467–2489, 2019, doi:10.1109/ACCESS.2018.2886201

[26] ***, KONDA "Report on social gender in Turkey: The Life-Styles Survey," (in Turkish), 2018

[27] R. Stamminger et al., "Synergy potential of smart appliances," Nov. 2008

[28] D. S. Parker, P. Fairey, and J. D. Lutz, "Estimating daily domestic hot-water use in North American Homes," ASHRAE Transactions, vol. 121, no. 2, pp. 258–271, Jul. 2015