A Probabilistic Approach to Modelling Home Appliances for Demand Side Management

Fatih ÇAKIL[1], İbrahim Gürsu TEKDEMİR[2]

[1,2]Bursa Technical University, Department of Electrical and Electronics Engineering, Yıldırım, Bursa, Türkiye
[1]fatih.cakil@btu.edu.tr, [2]ibrahim.tekdemir@btu.edu.tr

Abstract

Demand-Side Management is a set of various optimization techniques and/or strategies based on techno-economic factors which focuses on planning, implementation and monitoring in power systems. In this context, energy consumption behavior of residential users is focused on and electrical appliances are modelled in various studies in literature. Electrical energy usage patterns of residential consumers and consumption behaviors are intended to be modelled in this study. We conducted a survey for modelling electrical appliances in residential houses, findings of which form the basis for developing probabilistic models designed for demand-side management applications. After that, we applied Monte Carlo sampling method to make the statistical data and relevant probabilistic models enable a thorough probabilistic simulation. 300 virtual consumers are created by using this approach as part of the simulation and relevant outcomes are obtained finally. Besides that, a graphical user interface (GUI) is created in MATLAB to demonstrate results. It is concluded that results of the simulation carried out in this study are useful in demand side management context and they may be used for studying new dynamic price models or for testing some DSM functions in future.

Keywords - Demand side management, Monte Carlo Sampling method, residential energy consumption, electrical appliances

1. Introduction

There has been a significant rise in power demands and resulting power imbalances in energy consumption with the increase in industrial centers and growing population. Unpredictable factors in energy systems contribute to this issue. Therefore, addressing these problems to control escalating electricity consumption expenses and enhance power system flexibility plays a crucial role [1]. In this context, Demand-Side Management (DSM) employs various optimization techniques and/or strategies based on techno-economic factors. DSM focuses on planning, implementation, and monitoring as a service activity to enable energy consumers to utilize electrical energy in the desired manner. Moreover, it aims to influence customers/consumers in terms of the timing and quantity of load, considering the consumption characteristics [2].

DSM algorithms/strategies have diverse applications in the literature [1-10]. Demand management programs and deep learning models proposed to reduce the Peak-to-Average Ratio (PAR) and electricity tariffs, thereby increasing the economic and environmental characteristics of end-users [1]. A novel energy management system consisting of multiple microgrids was introduced [3]. The system adopts a two-level control structure and employs Fuzzy Takagi-Sugeno models to predict the production and consumption of microgrids. In smart grids, Automatic Demand-Side Management (ADSM) is proposed to find the optimal energy consumption level, low convergence rate, and significant computational volume [4]. Energy storage systems, renewable energy sources, and a genetic algorithm with a Seagull-based method is combined to model consumer demands and optimize microgrid operation [5]. A game theory-based demand-side management approach is proposed to mitigate power fluctuations caused by renewable energy sources, focusing on thermostat-controlled loads [6]. Internet of Things (IoT)-based energy management system is evaluated in smart grids and achieving real-time performance-based power and energy savings [7]. A novel algorithm was proposed, which minimized energy consumption costs considering power consumption, temperature parameters, and electricity tariffs using linear programming [8]. Also, this study suggested integrating photovoltaic battery systems and thermostat-controlled loads for residential energy management. Smart home energy management is enhanced through the support of machine learning algorithms [9]. The study minimizes energy costs and improves energy efficiency by utilizing demand and production predictions and real-time cost calculations. For user classification in demand-side management, an algorithm that integrated k-means was suggested [10].

Electrical appliances in residential houses are intended to be modelled in a thesis study [11]. Analyses are carried out so as to obtain harmonic profile of households as a result. For that purpose, relevant electrical energy usage patterns at home are modelled probabilistically and some statistical data are used as profile data in this context. Profiles regarding cooking, laundry, TV and PC, lighting, house cleaning activities and occasional events are obtained afterwards. Consequently, it has become possible to model and simulate residential usage of electrical appliances [11].

In this study, electrical energy usage patterns of residential consumers are also intended to be modelled probabilistically. A survey was prepared and administered for that purpose, outcomes of the survey were used for generating probabilistic models which is suitable for being used for demand side management applications. Following this, generated probabilistic models were utilized by using Monte Carlo sampling method, thus a probabilistic simulation approach is introduced as a result. Implemented survey, relevant results, probabilistic models and simulation results are revealed in this study.

2. Energy Consumption Behavior

2.1. Load Diversity

In the electrical energy system, all electrical and electronic devices that enable the formation of electricity consumption profiles are defined as loads. When examined within the scope of DSM, loads are basically categorized into three types; these are shiftable loads, fixed loads, and adjustable loads. In DSM studies, the aim of reducing load density and/or energy consumption can be achieved by managing these loads with different characteristics.

Flexible loads are devices that can adjust their energy consumption over time without affecting the user [12-13]. These loads are categorized into two types: Thermostat Controlled Loads and Manual Controlled Loads.

Thermostat-controlled loads provide heating and cooling by adjusting temperature settings and can shift energy consumption over time using demand-side management, leading to energy savings without compromising user comfort.

Manual flexible loads are devices whose usage times are determined by the user. Examples include charging electric vehicles and using household appliances. With smart home technology, these loads can be remotely managed, enabling more effective energy savings.

2.2. Energy Consumption Survey

In this study, consumer consumption profiles/sample sets are needed to be realized in DSM context. For this purpose, data was collected from consumers through a survey implemented by the authors. Outcomes of the survey is obtained by collecting data from 100 households in Bursa so as to generate profiles as will be explained.

A simple random sampling method and snowball technique were used to determine the sample size and the sample population so as to implement the survey, in this study. Random sampling is a method in which each member or unit has an equal chance of being selected by the researcher. In this method, the researcher generates a sample by randomly selecting individuals or units from the population. The snowball method is an effective sampling technique at uncertain starting points. The researcher takes action with the participants or information initially selected and expands the sample by adding new data and participants in this context [14]–[16].

Variables used in survey are relevant to occupancy (weekday, weekend), activity (cooking/kitchen, breakfast, TV, computer, laundry, lighting, cleaning, other) and work style (full-time, morning part-time, afternoon part-time, not working and other). In the process, household appliances are associated with activities.

Table 1 shows the parameters for household electric appliances (EA) in the literature. These parameters are activity, Nominal Power (NP), Average Daily Operating Frequency (ADOF), and Average Cycle Duration (ACD), respectively.

2.3. Occupancy Function

The presence or absence of individuals at home is directly related to their lifestyle. Therefore, processing outcomes of the survey using statistical methods is crucial. Time intervals when a full-time worker is at home will not be necessarily the same as those of a part-time worker. Probabilistically, determining the usage of household appliances during these time intervals will be highly correlated with the occupancy function. Various statistical data will be considered for weekdays and weekends so as to generate the occupancy function.

The effect of the work style on the occupancy function will be determined through grouping them. To create the occupancy function associated with the desired work style, only groups with the same work style in the survey data should be examined. Inferences may be made about the appropriate time intervals when ones in this group probabilistically stay at home. The average time during ones in this group stay at home, the average entry time and standard deviation will be determined. Consequently, grouped data will be used to determine entry time using normal distribution, and similarly, time intervals when they will be at home will be found, and the simulation will be conducted.

$$\mathrm{OF}(t) = \begin{cases} 1, & \text{If the consumer is at home at time t} \\ 0, & \text{If the consumer is not at home at time t} \end{cases} \tag{1}$$

Table 1. Parameters for home appliances [11], [17-18]

EA	Activity	NP (hours)	ADOF	ACD (min)
Microwave Oven	Cooking	1500	5	5
Refrigerator	Cooking	110	40.5	12
Blender	Cooking	350	1	5.9
Deep Fryer	Cooking	1500	1	15.8
Kettle	Cooking	1500	8	3.7
Mixer	Cooking	175	1.5	7.9
Electric Stove	Cooking	1250	0.7	39.4
Toaster	Breakfast	1200	1	7.9
Television	TV	105	1.62	90
VCR	TV	40	2	98.7
Computer	Computer	100	2.5	60
Iron	Laundry	1000	0.5	47.4
Washing Machine	Laundry	400	0.36	54
Dryer	Laundry	2500	0.72	125
Lighting	Lighting	120	10	30
Vacuum Cleaner	Cleaning	800	1	19.7
Dishwasher	Cleaning	2400	1	45
Coffee Maker	Other Activities	900	0.76	6
Air Conditioner	Other Activities	1300	1.36	120
Hair Dryer	Other Activities	1000	1.46	7

3. Simulation of Residential Energy Consumption

3.1. Probabilistic Acquisition of Household Appliances

The usage patterns of household appliances were intended to be simulated by using outcomes of the survey which contains data of consumers in Bursa, Türkiye. In this process, Monte Carlo simulation was used, and integration was performed with a computer program.

Usage statistics were plotted as occupancy functions for each activity, which depict the relationship between the number of people and time of each activity directly. After this step, the probability density function (PDF) was obtained and plotted using these data. The probability density function for an activity at home represent probability of any consumer performing an activity at any time during the day.

The equation for obtaining the probability of activity as a function of time (t) is shown in equation (2). The function Activity(t) represents the number of people performing the activity as a function of time, while the parameter N represents the total number of people participating in the survey.

$$P(t) = \frac{Activity(t)}{N} \quad (2)$$

For each moment t, the probability is expressed as the probability function (P_D). The P_D expression represents the ratio of the probability for each t (time) to the total probability at that moment.

$$\mathrm{P_D(t)} = \frac{\mathrm{P(t)}}{\mathrm{\Sigma P(t)}} \quad (3)$$

Until now, the user's presence at home has not been reflected in the activities. The probabilistic expression of each activity should be multiplied by the occupancy function (OF), which represents the occupancy status at home, without the cumulative processing. However, when multiplied by OF, the area under the graph will not be equal to 1, so the probability density function process is to be re-generated. The main goal in this process is to obtain the probabilistic representation of the area when the user is at home because the consumer can't perform any activity when he/she is not at home. Continuous operation of household appliances has been excluded in this stage.

$$\mathrm{PDF^*} = \sum_{\mathrm{t=1}}^{\mathrm{t_{end}}} \mathrm{P_D^*(t)} = \sum_{\mathrm{t=1}}^{\mathrm{t_{end}}} \mathrm{c.P_D(t).OF(t)} = 1 \quad (4)$$

$$\mathrm{c} = \frac{1}{\sum_{\mathrm{t=1}}^{\mathrm{t_{end}}} \mathrm{P_D(t).OF(t)}} \quad (5)$$

Equation (3) demonstrates the process of multiplying the probability density function (PDF) by OF and then converting to (re-generating) a new probability density function (PDF*). The parameter 'c' in equations (4) and (5) is necessary to ensure that the area under the probability density function multiplied by OF equals to 1.

In the OF, the occupancy status was determined by evaluating users which has the same working pattern according to the survey data. The integration of working patterns and the hours when the user's present at home, into the probabilistic model was performed in this way.

The cumulative distribution function (CDF*) is generated by using the probability density function (PDF*) in equation (4) as shown in equation (6).

$$\mathrm{CDF^*} = \mathrm{C^*(t)} = \sum_{\mathrm{k=1}}^{\mathrm{t}} \mathrm{P_D^*(k)} \quad (6)$$

In Fig. 1, the PDF value of lighting activity, based on survey data, is displayed along with an OF (Occupancy Function) value as an example.

The PDF* and CDF* of lighting activity are shown in Fig. 2.

A randomly obtained value between 0 and 1 will refer to a point on the graph that cumulatively converges to 1. This marking point will determine the operating hours of the home appliance.

The pseudo code for the proposed and applied residential consumption simulation is presented in Fig. 3. Here, EA_Activity_C denotes the cumulative function connected to various activities and EA_Activity refers to survey data gathered for individual activities. Electric Appliance Frequency (EA_frequency) quantifies how often household appliances operate daily. CF is an indicator of whether an Electric Appliance (EA) has a connection with the Occupancy Function (OF) or not. Starting_Hour denotes the time when home appliances start operating, and the EA_working_per_cycle signifies the time taken for each operation period. Finally, Cond. 1 indicates the possibility of assigning a particular condition.

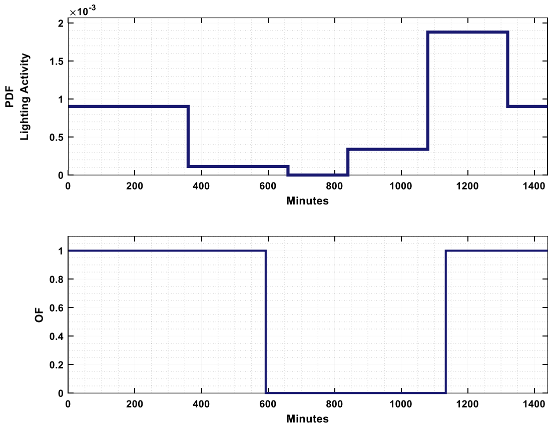

Fig. 1. PDF of lighting activity based on survey data and an OF value as an example.

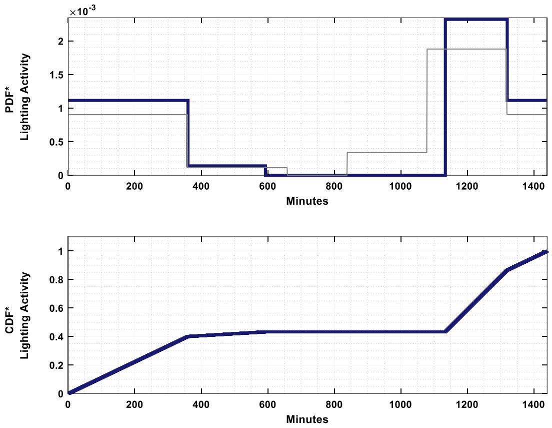

Fig. 2. PDF* and CDF* of lighting activity.

4. Analyses and Results

The MATLAB interface was developed to make it easier to run and monitor the Monte Carlo Simulation in this research. A simulation's Occupancy Function (OF) relating to consumer behavior on weekdays or weekends is obtained after all activities' PDF and CDF values are displayed. Monte Carlo sampling is used in order to allocate the temporal expressions of home appliance usage probabilistically based on these variables. Then, each home appliance is examined in detail. The simulation of daily consumption of a virtual consumer in Fig. 4 was carried out using the usage patterns of a full-time weekday employee. The utilization of home appliances has been looked at in Fig. 5.

Table 1 has been used to determine the operating frequency and duration of common household appliances using a normal distribution. A normal distribution and cumulative distribution graph for the microwave appliance's operating time is shown in Fig. 6.

According to the survey data, there are 47% full-time workers, 15% morning part-time workers, 15% afternoon part-time workers, and 23% non-workers. In a representative manner, data for 300 individuals have been generated for a month, while preserving these percentages. The usage data for each consumer, indicating when household appliances are used, has been simulated for a representative month. The monthly consumption information for 300 users is shown in Fig. 7.

Algorithm 1 Simulation

```
if DAY == WEEKDAY then
    EA_Activity ← EA_Activity_wk
    EA_Activity_C ← EA_Activity_C_wk
else
    EA_Activity ← EA_Activity_wn
    EA_Activity_C ← EA_Activity_C_wn
end if
Obtain OC function
Generate PDF using EA_Activity
Generate CDF using PDF
PDF* ← c * PDF * OC
Generate CDF* using PDF*
for EACH EA IN Number of Electric Appliances do
    Calculate N2 using σ and μ for EA
    EA_Frequency ← N2
end for
for EACH EA IN Number of Electric Appliances do
    for EACH EA_Frequency PER EA do
        if EA is independent of OC then
            CF ← CDF
        else
            CF ← CDF*
        end if
        Starting_Hour ← Lookup CF using uniform random value [0, 1]
        while cycleX = 1 do
            Calculate N3 using σ and μ for EA
            EA_Working_per_cycle ← N3
            if Cond.1 then
                Assign EA working for Day's Time Period
                cycleX ← 0
            end if
        end while
    end for
end for
```

Fig. 3. Pseudocode of the residential consumption simulation which uses Monte Carlo sampling method.

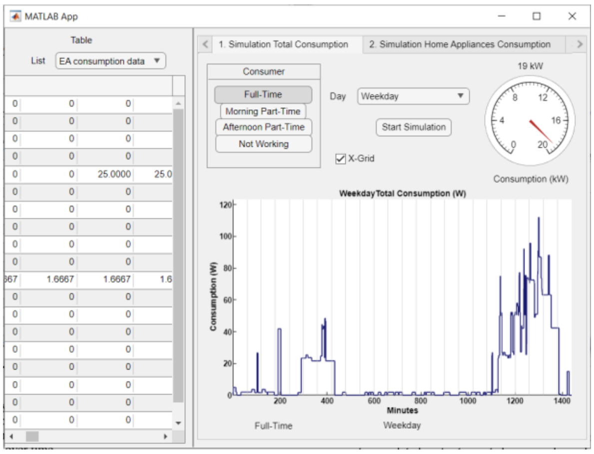

Fig. 4. Demonstration of the simulation using the generated MATLAB GUI program.

Daily usage of a household appliance is shown in Fig. 8. The introduction of Time-of-Use (TOU) pricing or the establishment of a dynamic tariff model can be facilitated by knowing the load profiles over time.

5. Conclusions

In this study, energy consumption behavior of residential users is focused on and relevant statistical models are revealed. A probabilistic simulation approach is conducted next by using statistical data which is obtained by forming and implementing a survey dealing with determining energy consumption pattern of residential users.

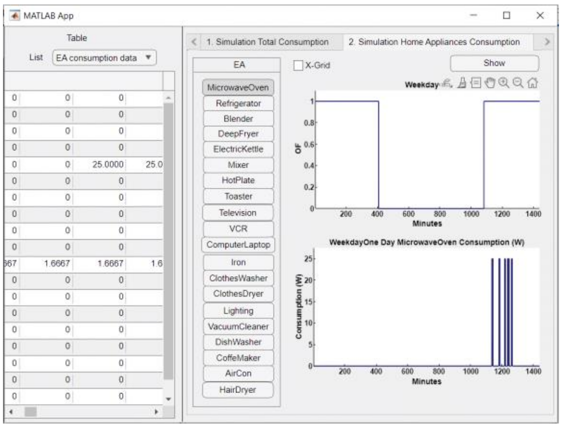

Fig. 5. Visualization of household appliance usage in MATLAB GUI.

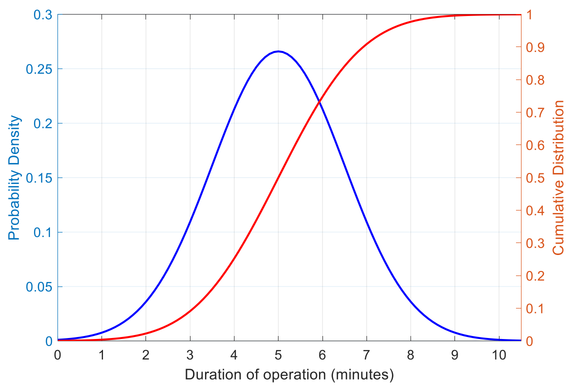

Fig. 6. PDF and CDF of normal distributed usage time variable of microwave appliance.

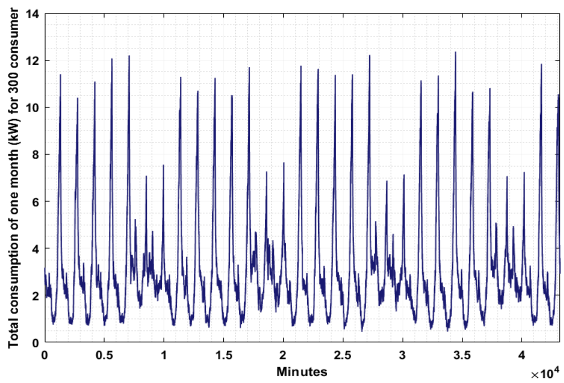

Fig. 7. Monthly consumption data.

Indicators such as occupancy of residential users, energy consumption related activities at home and work style of households are tried to be found by the conducted survey. Outcomes of the survey are used for generating probabilistic models in this study.

Appropriate probability density functions are generated by using the obtained statistical data. It is assumed that some consumption relevant parameters such as usage frequency of electrical appliances are normal distributed, and some others are uniform distributed. After generating proper probability density functions, associated cumulative distribution functions are created and Monte Carlo sampling is applied in this way.

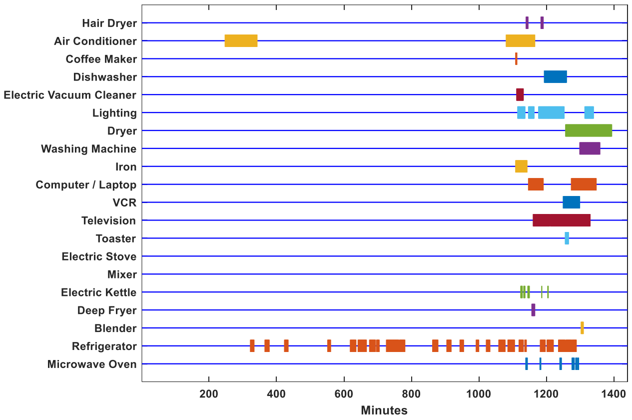

Fig. 8. Daily usage frequency of home appliances.

The statistical approach is useful in modelling and simulating energy consumption behaviors of residential users. In courtesy of obtaining statistical data by an appropriate survey, a probabilistic approach for simulating consumption of residential energy users is developed and realized in this study. 300 virtual consumers are created by using this approach at last. Besides that, a graphical user interface (GUI) is created in MATLAB to demonstrate results of energy consumption simulation carried out.

Results of the simulation are useful in demand side management context. Researchers may use these simulation data for studying new dynamic price models or for testing some DSM functions and examining effects of them from various angles. The simulation technique used in this study may also be improved by adding more statistical details in the future.

6. References

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