Engineering and Technology Journal e-ISSN: 2456-3358

Volume 09 Issue 06 June-2024, Page No.- 4241-4248

DOI: 10.47191/etj/v9i06.10, I.F. – 8.227

Energy Consumption Management of Residential Appliances Based on Load Signatures Decomposition

Elias H. Ait Aissa[1], Abbas UĞURENVER[2]

[1,2] Istanbul Aydin University, Türkiye.

[1]https://orcid.org/0009-0007-1811-5876, [2]https://orcid.org/0000-0003-0989-9131

ABSTRACT: Nowadays, energy consumption management techniques in the residential side have gained significant importance due to their considerable influence on the control of power flow in distribution networks and especially the possibility of managing a huge part of domestic electrical demand during peak-load hours. Since the customer's data are recorded in an aggregated form, therefore, in order to apply control approaches, it is necessary to use load pattern evaluation techniques (load signature). These methods capable to decomposition effective features that help control approaches to implement with more accuracy. In this article, features of residential loads have been extracted by using the signature of the aggregated consumer's demand. Then these features have been evaluated by methods such as logistic regression, k-nearest neighborhood, and decision tree. By assessing the results, it was determined that among the extracted features, the first two features (consumed power and injected harmonics) covered more than 89% of the variance of the entire set, and with the help of using the principal component analysis method, it was determined that by reducing the number of features to 2, a considerable amount of computation is reduced and only about 4% of the accuracy is reduced. Also, the convolutional neural network approach was used to estimate the type of load, and by identifying controllable loads and applying remote home energy management methods, it was found that by increasing participation up to 80%, more than 41% of peak-load consumption could be shifted to off-peak hours.

KEYWORDS: Load Signature, Feature Extraction, Convolution Neural Network, Energy Management, Demand Response

INTRODUCTION

Recently, home energy consumption management is considered as one of the main principals of implementing smart distribution networks (Tostado et al. 2021). For example, in the United States, it has been estimated that the participation of household consumers can reduce up to 50% of the load during peak-load hours (Rehman, 2020). For this purpose, in (Samadi et al, 2020), a distinctive home energy management method is presented for scheduling electrical appliances by taking into account the amount of current consumption in order to minimize the operating costs. Hu et al, (2018) have used the convex programming method to manage household equipment consumption and energy storage systems. Also, the model developed by them reduces the level of consumer dissatisfaction and the cost of electricity consumption. Sedhom et al, (2021) presented a method to reduce the cost of energy supply with integration of renewable energy resources and energy storage systems to minimize the cost of consumed energy during peak-load hours. Also, reduction greenhouse gases are considered by them. Rocha et al, (2021) and Opera et al, (2019) have used bidirectional power distribution to implement household load scheduling operations and proved that the mentioned system can reduce the electricity supply costs for smart homes on a large scale.

Despite the fact that load management on the demand side can help to reduce energy bills, increase stability, reduce losses in the distribution network, and on the other side, predicting the size of controllable loads in a large set of loads reduces the uncertainty of misprediction, but processing a large amount of data for identifying the share of different categories in real-time faces serious challenges, which have not been studied comprehensively so far. For this purpose, in this project, an innovative approach for demand response management has been used, which can extract useful features from the load signature obtained by aggregating the consumption data of consumer's metering devices. Then by using the convolutional neural network (CNN), the share of controllable loads of total demand can be predicted. Among the main achievements of the proposed approach, the following contributions can be mentioned:

- Using CNN to predict the share of various categories of loads.
- Applying the principal component analysis method in order to extract the effective features in order to reduce the amount of processing requirements.
- Extracting useful features from the consumer's dataset with the help of classification algorithms

In the rest of this paper, descriptions are first presented about the concept of load decomposition, how the principal component analysis method works, and the characteristics of the logistic regression classification algorithm, then the details of the proposed approach are explained. In the following, the consumption pattern, the classification of the residential demand and the structure of the designed CNN are evaluated. After stating the details of the proposed objective function, the performance of the method has been assessed and the results obtained from managing the consumer's energy consumption have been analyzed in the form of three different scenarios.

BASIC CONCEPTS

- Features of loads

One of the most important characteristics of a distribution network's demand is the continuous variation which causes changes in operating conditions. In this state, a comprehensive understanding of the load's features could have a significant impact on the control method's performance. On the other hand, the last level of the consumption's measurements is at the residential metering devices. So, more detailed information is not available for operators. In other words, a household subscriber uses a set of household appliances, including refrigerators, electric heaters, electronic equipment, lighting systems, etc. and identifying the amount of consumed energy for every device from load signature has significant role for remote energy management systems. The main challenge in the decomposition of load signature is the definition of 'features' that have the following two characteristics:

1. It can be easily extracted from the measured data.
2. It can provide a valuable information for decomposition different loads.

- Principal Components Analysis

In today's systems, the amount of obtained information is large, and direct processing on them requires huge amount of processing capacities and takes long time. So, it is necessary to use suitable alternatives techniques such as principal components analysis (PCA) to reduce the size of the dataset while preserving the key features. In fact, such approaches, taking into account effective features and significantly reduce the information required for processing. This is implemented by extracting a set of key features from the original dataset. In order to implement the PCA approach, four steps consist of standardization, calculation of covariance matrix, extraction of eigenvalues and determination of principal components are necessary to be executed.

- Logistic Regression

The logistic regression (LR) technique is based on providing a fitting between the obtained features. If the result is more than 0.5, the output is equal to 1 and the otherwise is equal to 0. The value of LR is calculated by Equation (1). If the number of outliers is increasing, proper feature scaling should be used before applying the LR method. Indeed, LR is a machine learning classification algorithm that is used to predict the probability of a dependent variable membership to a specified classification. Although LR is similar to a linear regression model but uses a more complex cost function known as the "sigmoid function" or "logistic function". In this regard, the dependent variable is a binary variable that holds data coded as 1 (success) or 0 (failure). So, the logistic regression model predicts the probability of output as a function of X (Rahman et al, 2018).

$$S(Z) = \frac{1}{1 + e^{-Z}} \quad (1)$$

METHODOLOGY

In the proposed approach, first the measured data from smart meters are collected, then after initial sorting, with using feature extraction methods, effective features such as the amount of consumed active and reactive power, injected harmonics, current waveform, voltage waveform, current peak value, voltage peak value and power factor are calculated. Then the PCA approach will be used to extract the primary features, and with calculating of the covariance matrix, the selected eigenvectors will be used to train the convolutional neural network (CNN). It should be noted that the CNN is a type of multi-layer neural network that is used for pattern recognition and by using convolutional layers, it improves the level of accuracy for recognizing data patterns. After determination of the weight coefficients, the designed CNN is tested to confirm its performance. If the efficiency of the network is determined to be right, the share of controllable and fixed loads is estimated for the current time steps. In the proposed model, electrical appliances are divided into the categories of constant torque induction motors, quadratic-torque induction motors, resistive controllable loads, resistive uncontrollable loads, switch mode power supply and lighting which is finally the share of controllable loads in total consumption is predicted. In the ultimate step, the results of energy management of controllable devices will be investigated at distinct levels of participation.

- Residential demand modeling

To evaluate the performance of the proposed approach, the electrical equipment consumption of three households has been considered. In the following, the consumption pattern of controllable and fixed devices for the first family is presented in Table (1). It should be noted that at residential metering infrastructures, current value (I), voltage value (V), active/reactive power (P/Q) and power factor (PF) can be measured in defined time steps.

Table 1. Consumption pattern of first family (Babaei et al, 2015)

Type	Electrical appliance	Time Duration (hr)	Operating Range (hr)	Rated Power (kW)
Controllable	Washing Machine	24	2	First hr: 1 Second hr: 2
	Dish Washer	24	2	First hr: 1 Second hr: 0.8
	Water Pump	24	7	0.125 – 0.9
Fixed	Air Conditioner	10 a.m. – 8 p.m.	10	1.5
	Refrigerator	12 a.m. – 12 p.m.	24	0.104
	Electrical Oven	8 p.m. – 8:30 p.m.	0.5	0.9
	TV set	9 p.m. – 12 p.m.	3	0.16

- Classification of household appliances

Residential loads are known as a group of equipment used in homes, which are divided into two categories of controllable and fixed (uncontrollable) loads. The amount of energy consumed by the second category is fixed and it is not possible to schedule their performance, but for the controllable devices, there is possible to shift their consumption pattern from peak-load to off-peak duration. However, the controllability of some of loads is still under discussion. For example, we can mention the lighting system. This system is normally known as fixed load, but some of them can be dimmed and therefore should be considered as controllable demand. In fact, the classification made in this status is not certain for all situations. In this paper, electrical devices are divided into 6 categories. The first 3 categories are controllable loads which operation range can be changed. The classification of loads is presented as follows:

- Constant-Torque Induction Motor (CTIM)
- Quadratic-Torque Induction Motor (QTIM)
- Resistive Controllable Loads (RC)
- Resistive Uncontrollable Loads (RUC)
- Switch Mode Power Supply (SMPS)
- Lighting (L)

- Convolutional neural network

Neural networks have been widely used for load forecasting due to their nonlinear capabilities. In this paper, the convolutional neural network (CNN) has been used to estimate distinct categories of residential loads. The proposed CNN architecture is shown in Figure 1. In this structure, layers 1 to 8 are alternately composed of convolution layers and max_pooling layers. After that, layers 9 to 11 are installed for the final classification, where the number of neurons in each layer is set to 30, 14, and 2, respectively. The leaky rectifier linear unit (LReLU) function is used as the activation function for layers 1, 3, 5, 7, 9 and 10, respectively. In the last layer, the SoftMax function is used as the activation function, which can predict the load's classification type.

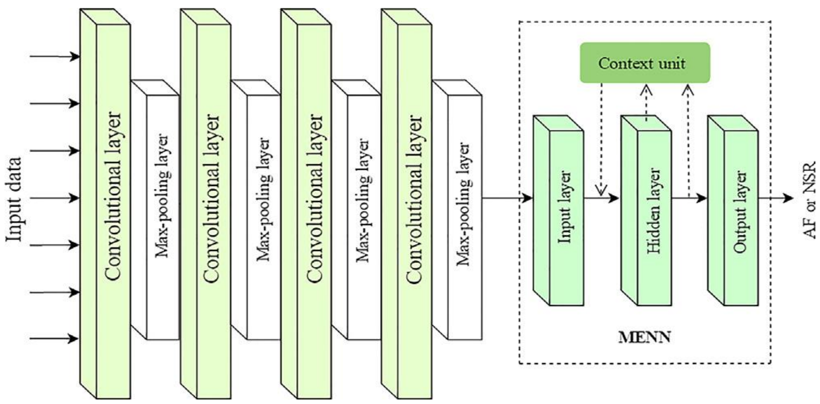

Figure 1. The structure of proposed CNN

- Objective function

As an initial, the data collected by the residential meters are preprocessed. Then, with the help of the feature extraction method, major features are extracted, and the most effective features are found using the PCA method. These obtained features are applied as input to the CNN. At this stage, the CNN is trained through the obtained data so that it can estimate the percentage of participation for each category of loads in the near future only based on the data values related to the main features. After the training phase is completed, the CNN uses the estimated load as input and adjusts the weight coefficients. Next, the weight coefficients of each category in the formation of the total load are calculated (ω) and if the active load of the j^{th} category is equal to P_{ji} in the i^{th} time period, then the weight coefficient of participation of this category is calculated by Equation 2. It is also necessary to consider the constraint which is stated by Equation 3.

$$\omega_{ji}^{p} = \frac{P_{ji}}{P_i} \tag{2}$$

$$\sum_{j=1}^{6} w_{ji}^{p} = 1 \tag{3}$$

ω_{ji}^{p} : Contribution of active power consumption of the j^{th} category in the i^{th} time step

P_i : Total active power in the i^{th} time step

The main target of the presented approach is finding the contribution of various load categories from the total load signature with a suitable convergence speed and acceptable error percentage. For this purpose, the objective function is designed as Equation 4. After figuring out the weight coefficients of CNN, the network is tested to confirm the performance. If the efficiency of the method is determined to be suitable, it is used by the operator to participate in the share of different categories of residential loads.

$$\text{Min } f = \sum_{i\in N} \frac{|P_i - P_i^0|}{P_i^0} \times 100\% \tag{4}$$

P_i : Calculated value

P_i^0 : Real value

- Feature extraction

In the proposed approach, the consumption patterns of three diverse types of families have been investigated which the first family’s consumption pattern is shown in Figure 2. Among the total 900 samples, 810 samples were used to design the model and regulate the parameters, and the rest were used to analyze the prediction accuracy. Among the 810 samples that were selected for modeling, 70% of the dataset was selected for training and the other 30% for testing. This comparison helps us to find the most suitable model with the highest accuracy among different techniques.

In the first stage, 7 features including power consumption, injected harmonics, power factor, RMS value of current, RMS value of voltage, peak value of current and peak value of voltage are defined for the main dataset. In the following, the PCA method is applied to reduce the number of features, while keeping almost all-important information about the dataset. The purpose of using this step is to reduce the dimensions of the problem without missing critical information. So, the matrix of eigenvectors and eigenvalues are calculated in the form of Equation 5 and Equation 6, respectively.

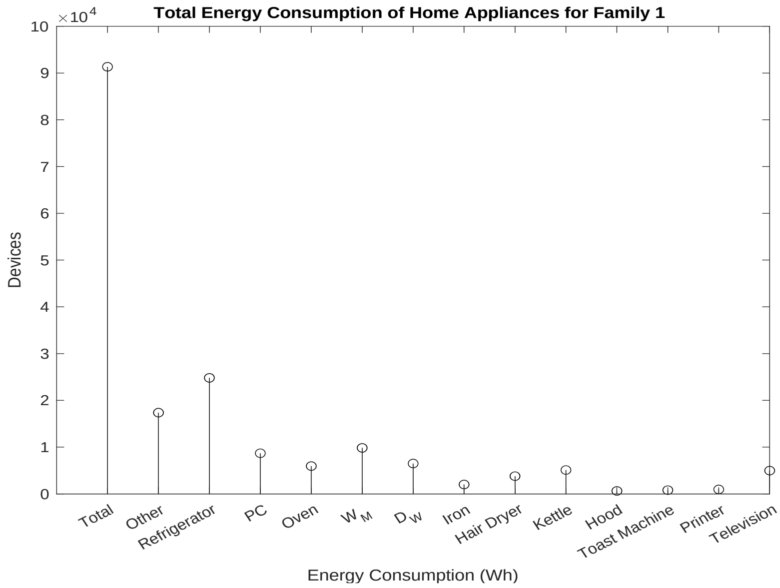

Figure 2. Consumption pattern of first family

The amount of variance for each main component (V_j) is calculated based on Equation 7. According to the obtained results by using Pareto Plot diagram, the variance of the first PC (first component) is more than 69% and the variance of the first two PCs is more than 89 % of the total variance of the original dataset (Figure 3). Indeed, by reducing the total features from 7 features to 2 features, almost 90% of the information can be saved. This significantly reduces the computation complexity and time.

$$A = \begin{bmatrix} 0.448 & -0.116 & 0.005 & -0.111 & -0.611 & -0.100 & -0.624 \\ 0.443 & 0.137 & -0.101 & 0.495 & 0.0876 & -0.686 & 0.228 \\ 0.389 & -0.375 & 0.236 & -0.656 & 0.384 & -0.240 & 0.130 \\ 0.203 & 0.611 & -0.629 & -0.426 & 0.075 & 0.054 & 0.020 \\ 0.451 & -0.0877 & 0.037 & 0.056 & -0.392 & 0.471 & 0.640 \\ -0.056 & -0.667 & -0.731 & 0.109 & 0.057 & 0.023 & -0.002 \\ 0.451 & 0.034 & 0.044 & 0.340 & 0.555 & 0.487 & -0.364 \end{bmatrix} \quad (5)$$

$$\lambda = \begin{bmatrix} 0.4.838 \\ 0.1.455 \\ .0.630 \\ .0.057 \\ .0.022 \\ .0.006 \\ .0.001 \end{bmatrix} \quad (6)$$

$$V_j = \frac{\lambda_j}{\sum_{j=1}^{p} \lambda_j} \quad , \quad j = 1,2, \dots, p \quad (7)$$

In the following, the results of applying the PCA method have been presented. Since the first two features include more than 89% of the total variance, PCA was applied only on these two features. In the next step, the classification method is applied to this part of the dataset. After applying PCA, the best accuracy belongs to k-nearest neighbor algorithm. The results obtained in this regard are shown in Table 2. If the extracted results before and after applying PCA are compared to each other, only 4% error could be seen.

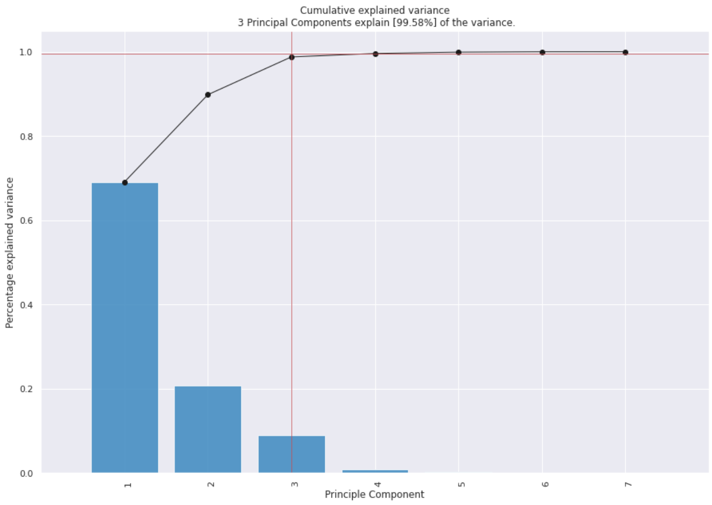

Figure 3. Pareto plot

Table 2. The results of using classified models + PCA

	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	TT (Sec)
knn	K Neighbors Classifier	0.8604	0.9060	0.8108	0.9032	0.8541	0.7211	0.7255	0.014
lr	Logistic Regression	0.8570	0.9206	0.8424	0.8748	0.8561	0.7139	0.7179	0.012
ridge	Ridge Classifier	0.8569	0.0000	0.7969	0.9102	0.8486	0.7142	0.7212	0.008
lda	Linear Discriminant Analysis	0.8569	0.9213	0.7969	0.9102	0.8486	0.7142	0.7212	0.012
lightgbm	Light Gradient Boosting Machine	0.8553	0.9056	0.8283	0.8792	0.8517	0.7107	0.7137	0.207
nb	Naive Bayes	0.8552	0.9199	0.7933	0.9089	0.8467	0.7107	0.7171	0.013
ada	Ada Boost Classifier	0.8517	0.9077	0.8145	0.8839	0.8465	0.7036	0.7076	0.079
qda	Quadratic Discriminant Analysis	0.8463	0.9112	0.7865	0.8994	0.8370	0.6930	0.7011	0.011
rf	Random Forest Classifier	0.8429	0.9069	0.8004	0.8800	0.8366	0.6859	0.6909	0.185
gbc	Gradient Boosting Classifier	0.8412	0.9094	0.8144	0.8657	0.8376	0.6824	0.6858	0.081
et	Extra Trees Classifier	0.8357	0.9171	0.8001	0.8651	0.8290	0.6716	0.6763	0.248
svm	SVM - Linear Kernel	0.8184	0.0000	0.8387	0.8202	0.8257	0.6367	0.6430	0.011
dt	Decision Tree Classifier	0.8007	0.8004	0.8107	0.8023	0.8039	0.6010	0.6052	0.011
dummy	Dummy Classifier	0.5035	0.5000	1.0000	0.5035	0.6698	0.0000	0.0000	0.013

RESULTS EVALUATION

In this project, residential electrical devices are divided into 6 different categories, including constant-torque induction motors (CTIM), quadratic-torque induction motors (QTIM), resistive controllable loads (RC), resistive uncontrollable loads (RUC), switching mode power supply (SMPS) and lighting (L). The first three categories are classified as controllable loads, and the second three categories are considered as fixed loads. By applying the CNN algorithm on the information preprocessed by PCA and classification methods, the contribution of each class of loads has been estimated. After that, the percentage of consumer’s participation in demand response programs has been modeled in the form of three scenarios of 20%, 50% and 80% participation. In other words, in the first scenario, it is assumed that only 20% of subscribers are willing to take part in demand response management programs. In order to determine the effectiveness of the proposed approach, the mean square error (MSE) index of the consumed active power was calculated and shown in Figure 4. The results of estimating the share of consumption reactive load using this proposed method is shown in Figure 5.

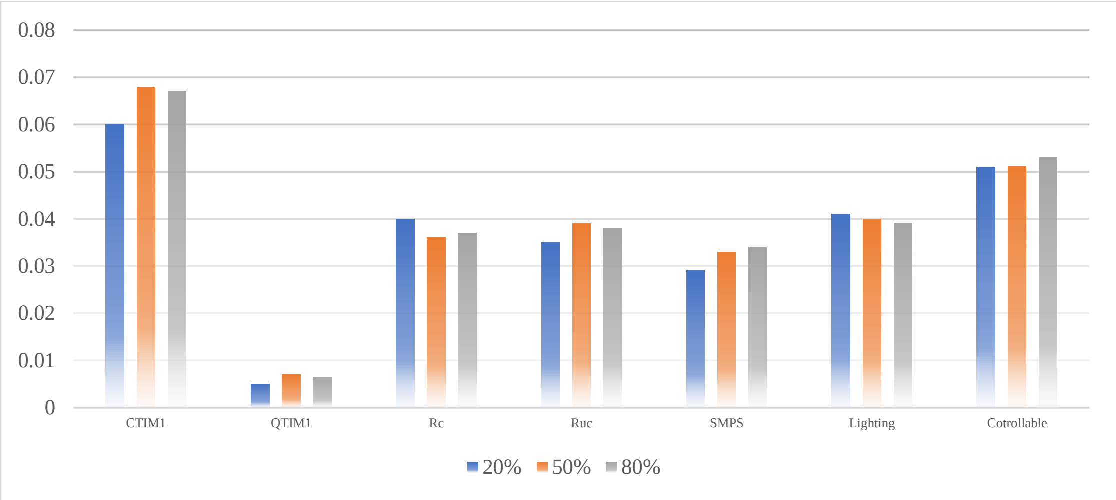

Figure 4. Calculated MSE for active power

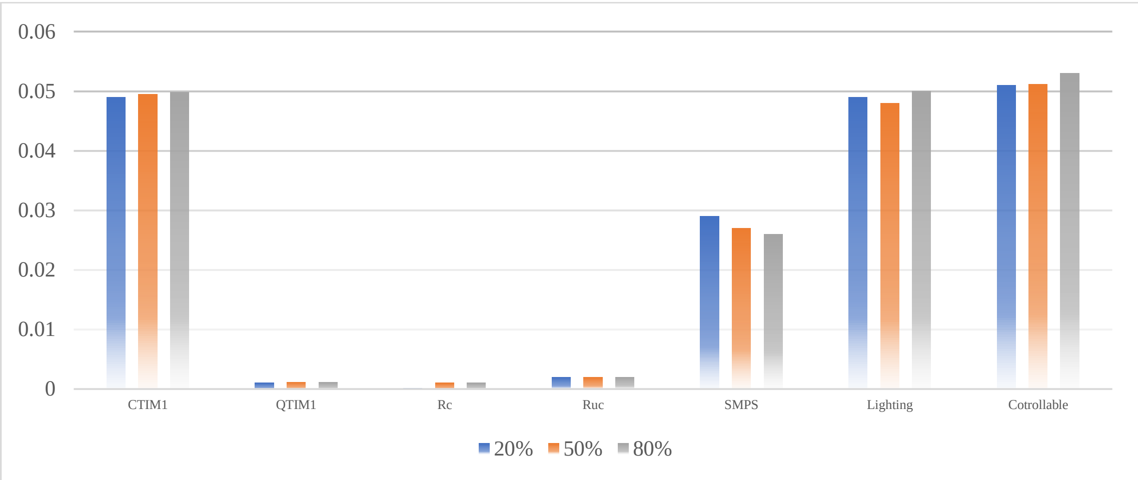

Figure 5. Calculated MSE for reactive power

- **Scenario 1: 20% Participation**

In order to calculate the amount of residential’s consumed energy from the aggregator's point of view, 300 residential houses (each category includes 100 households) have been considered, and their consumption rate has been calculated for three months (April, July and December). In the first scenario, it is assumed that 20% of 300 residential houses cooperate with the electricity utility in load management programs. According to this scenario, the total amount of monthly energy consumption during the peak-load hours is 538.5 kWh for normal status, but with applying control programs, this is reduced to 485.5 kWh (Figure 6).

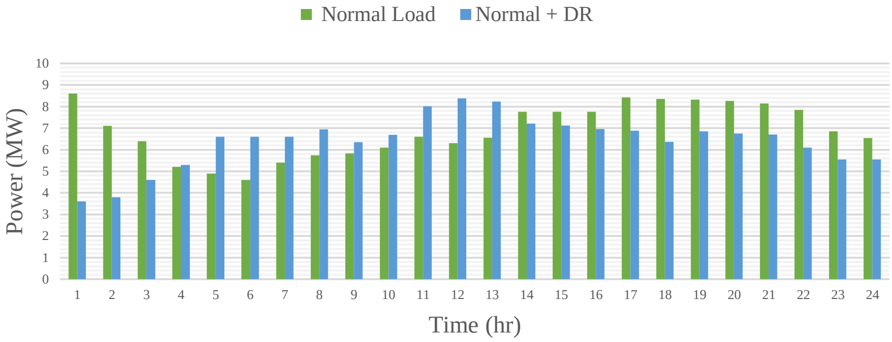

Figure 6. Comparison of normal vs. scheduled consumption (Scenario 1: 20% participation)

- **Scenario 2: 50% Participation**

In this scenario, 150 families have cooperated with the electricity utility and the rest have shown no desire. The results obtained for the amount of shifted load are shown in Figure 7. In this figure, the normal load value is displayed as a curve and the scheduled demand is displayed as a bar graph.

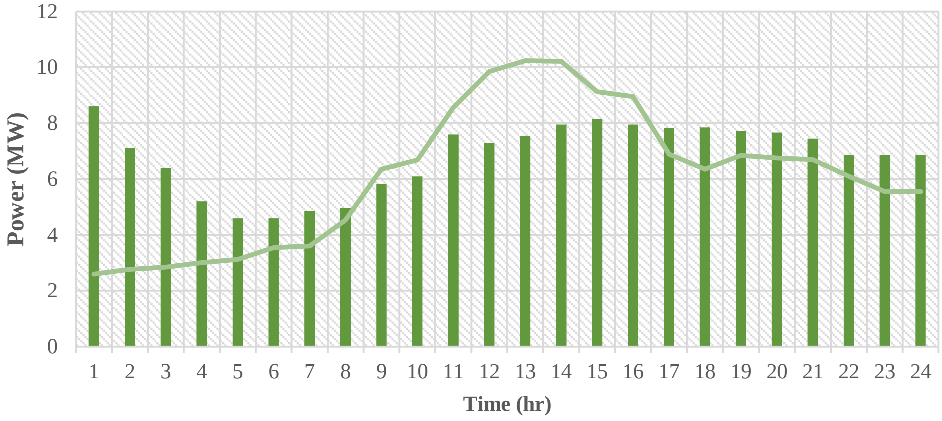

Figure 7. Comparison of normal vs. scheduled consumption (Scenario 2: 50% participation)

- **Scenario 3: 80% Participation**

In this situation, 80% of the subscribers (240 households) have taken part in DR programs. According to the obtained results, the total monthly energy consumption for peak-load hours is 538.5 kWh in the normal state, but with consumption scheduling, this is reduced to 403.5 kWh (Figure 8). The main reason is that controllable devices are turned off during peak-load hours, which is done according to consumer satisfaction. In other words, by managing the controllable equipment, 223.8 kWh of electricity consumption can be shifted from peak-load hours to off-peak load times. This amount of load is equivalent to 41% of the total consumption, so not only the consumer benefits from a significant reduction in the electricity bills, but also by increasing the stability of the distribution network and reducing the amount of power loss during peak-load hours, the utility's profit is also considered.

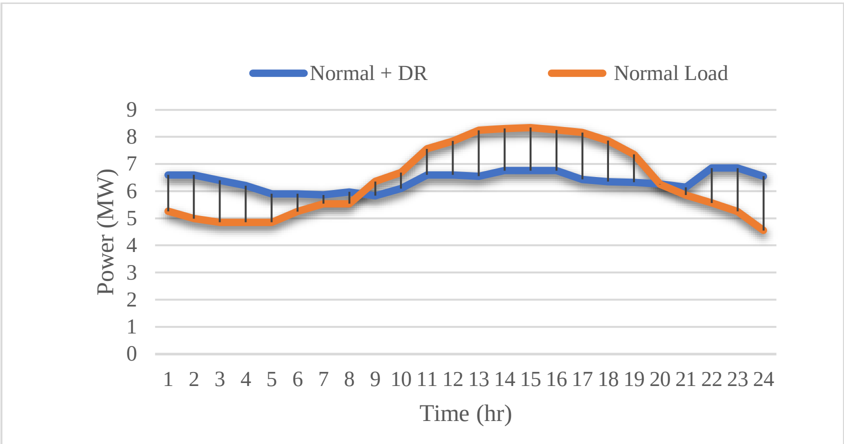

Figure 8. Comparison of normal vs. scheduled consumption (Scenario 3: 80% participation)

CONCLUSION

One of the main concerns related to power utilities is how to manage consumers in demand side management programs. The smart grid has made the interaction between the operator and the consumer to be realized in a two-side connection, which itself leads to increased reliability, better control in the presence of disturbances, reduction of environmental pollution and improvement of the efficiency. On the other hand, during the last few decades, the demand for energy consumption has grown at a significant speed, while the amount of energy generation ability has not been able to increase at a sufficient rate. So, this imbalance between supply and demand has caused serious challenges. In this regard, one of the practical solutions to overcome the above challenges is to use demand response programs. In this paper, the convolutional neural network approach is used to estimate the share of equipment found in dissimilar categories, and by classifying residential devices and identifying controllable loads, the possibility of implementing demand response programs is provided. According to the obtained results, it was obtained that by increasing participation up to 80%, more than 223.8 kWh (equivalent to 41%) of the total consumption load during peak-load hours can be shifted to off-peak hours.

REFERENCES

1. Tostado-Véliz, M., Icaza-Alvarez, D., & Jurado, F. (2021). A novel methodology for optimal sizing photovoltaic-battery systems in smart homes considering grid outages and demand response. Renewable Energy, 170, 884-896.
2. Rehman, U. U. (2020). Robust Optimization-Based Energy Pricing and Dispatching Model Using DSM for Smart Grid Aggregators to Tackle Price Uncertainty. Arabian Journal for Science and Engineering, 45, 6701-6714.
3. Samadi, Amir, Hossein Saidi, Mohammad Amin Latify, and Mehdi Mahdavi. "Home energy management system based on task classification and the resident's requirements." International Journal of Electrical Power & Energy Systems118 (2020): 105815.
4. Hu, Mian, Jiang-Wen Xiao, Shi-Chang Cui, and Yan-Wu Wang. "Distributed real-time demand response for energy management scheduling in smart grid." International Journal of Electrical Power & Energy Systems 99 (2018): 233-245.
5. Sedhom, Bishoy E., Magdi M. El-Saadawi, M. S. El Moursi, Mohamed A. Hassan, and Abdelfattah A. Eladl. "IoT-based optimal demand side management and control scheme for smart microgrid." International Journal of Electrical Power & Energy Systems 127 (2021): 106674.
6. Rocha, Helder RO, Icaro H. Honorato, Rodrigo Fiorotti, Wanderley C. Celeste, Leonardo J. Silvestre, and Jair AL Silva. "An Artificial Intelligence based scheduling algorithm for demand-side energy management in Smart Homes." Applied Energy 282 (2021): 116145.
7. Oprea, Simona Vasilica, Adela Bâra, George Adrian Ifrim, and Lucian Coroianu. "Day-ahead electricity consumption optimization algorithms for smart homes." Computers & Industrial Engineering 135 (2019): 382-401.
8. Rahman, Aowabin, Vivek Srikumar, and Amanda D. Smith. "Predicting electricity consumption for commercial and residential buildings using deep recurrent neural networks." Applied energy 212 (2018): 372-385.
9. Babaei, Toktam, Hamid Abdi, Chee Peng Lim, and Saeid Nahavandi. "A study and a directory of energy consumption data sets of buildings." Energy and Buildings 94 (2015): 91-99.