Joint Peak Clipping and Load Scheduling Based on User Behavior Monitoring in an IoT Platform

Mahshid Mehr Nezhad, *Student Member, IEEE*,
Mohammad Hossein Yaghmaee Moghaddam, *Senior Member, IEEE*, and Mohsen Asadi

***Abstract*—This article proposes a demand-side management (DSM) mechanism for energy management based on user behavior monitoring in a smart home. In the proposed mechanism, first through an analytic hierarchy process, the most influential factors related to power consumption are extracted. Next, by employing the K-means algorithm on the extracted factors, users are clustered. The user's clusters, the power grid state, and the user's real-time power consumption are inputs for a control unit. We present an interactive algorithm for the control unit, which causes peak reduction using peak clipping techniques. We also develop a day-ahead scheduling mechanism, which optimizes the load based on load shifting techniques. The proposed system is implemented in an Internet of Things (IoT) testbed consisting of four tiers—sensors, home gateways, server, and web portal. The central server is based on the Kaa IoT platform, an open-source platform widely used in the IoT domain. The performance of the proposed system is evaluated through simulation and a case study. Results confirm that the proposed system reduces the power consumption and costs for users and improves power grid performance in terms of the peak-to-average ratio.**

***Index Terms*—Demand response (DR), demand-side management (DSM), Internet of Energy (IoE), Internet of Things (IoT), optimization, smart home.**

I. Introduction

In RECENT years, by the growth of the Internet of Things (IoT) and digital technologies, the smart grid has been becoming more mature. The smart grid is involved in the electric power system of power generation, transmission, substation, and power distribution or utilization [1]. Internet of Energy (IoE) is a subset of IoT, which covers all aspects of the electrical energy system to provide secure connectivity and interoperability between the smart grid and the Internet [2]. Concerning power consumption, demand and supply are important issues that should be considered. To utilize the total demand with the amount of supply, demand response (DR) has emerged. DR refers controlling loads and embedded generation as a response to electricity prices [3]. In DR programs, utility companies offer customers credit for reducing electricity consumption for specified periods. DR applications control the load, therefore, not only do they make customers reduce their power consumption depending on the energy price, but also help power supply authorities to manage the smart grid better.

By utilizing DR approaches, it is possible to reduce or shift energy consumption from peak hours to nonpeak hours (i.e., the period of less demand). To achieve this goal, customers can decide to disconnect nonessential loads at peak hours [3]. To ensure the supply and demand balance in real time, demand-side management (DSM) approaches are utilized. DSM encompasses mechanisms to optimize consumers' demand for electrical energy by encouraging the customer to use less energy [4]. Applying DSM increases financial benefits and boosts the quality of energy services [5]. For efficient DR programs, especially DSM programs, energy consumption and generation information should be tracked in real time. Therefore, we need to measure and monitor the required information remotely. As described in [6], IoT can be used to furnish the intelligent management of energy distribution and consumption under different circumstances. Hence, the power grid needs to be implemented in a distributed topology that can dynamically absorb various energy sources [2]. There has been extensive research focusing on developing smart environments equipped with smart meters and smart plugs [7]. In the current study, we have used these smart meters, sensors, and actuators to make smart homes. Time-of-use (ToU) pricing is usually applied by utility companies, which means electricity during peak hours costs more than off-peak hours. During peak hours, the demands of the customers rise, and the utility companies may have to supply additional power. Providing extra power has higher operating costs and greenhouse gas (GHG) emission rates. Therefore, we need some strategies to reduce the power consumption of the network during peak hours based on the current power supplies. Reducing peak load decreases the energy generation expenses and the GHG emissions [8].

Regarding energy consumption during peak hours, occupant energy consumption behavior is the major contributor to the variance in domestic energy consumption [9]. There has been extensive research on energy behavior, with the main concentration on the residential sector, aiming at establishing behavior determinants and the best strategies to promote more efficient energy behaviors [10]. To this end, homes are equipped with smart meters and sensors to collect consumption behavior data. Then, data are transferred to the central IoT cloud platform to be analyzed and managed [11]. There are several open-source IoT platforms such as Kaa, DeviceHive, OpenIoT, and

Manuscript received October 30, 2019; revised April 9, 2020 and June 28, 2020; accepted July 12, 2020. Date of publication July 28, 2020; date of current version March 9, 2021. *(Corresponding author: Mohammad Hossein Yaghmaee Moghaddam.)*

The authors are with the Department of Computer Engineering, Ferdowsi University of Mashhad, Mashhad 91779, Iran (e-mail: mahshid.mehr-nezhad@warwick.ac.uk; hyaghmae@um.ac.ir; mohsen.asadi@um.ac.ir).

Digital Object Identifier 10.1109/JSYST.2020.3009699

ThingSpeak, which enable programmers to connect different devices to the Internet. For this article, we selected the Kaa platform [12] because it provides all the functionality needed to operate on large-scale data and has been used in various industries. Kaa is an open-source middleware platform for the IoT nodes, which provides software development kit (SDK) for the nodes to communicate data to the platform as well as the required cloud infrastructure for managing data.

In this article, we propose a DSM system for energy management in smart homes based on user's behavior monitoring in real time during peak hours. The proposed system consists of three major components. The first component generates a consumption model via: 1) employing analytical hierarchy process (AHP) for extracting factors that affect the amount of power consumption the most; 2) using K-means clustering algorithm to cluster users based on the significant factors; and 3) finally describing a set of thresholds as well as a permissible amount of energy for each class of users. The second component includes an optimization module to find the optimal mal day-ahead schedule for each user to shift the shiftable loads during a day. Finally, the third component of the proposed system is a control algorithm, which is based on the traditional random early detection (RED) algorithm [13] used in the Internet congestion control. The control unit utilizes the outputs of the first component, the real-time power consumption of the user (knowing the optimal schedule), and the power grid state to efficiently decrease the amount of load during peak hours in real time. The real-time power consumption of the user is collected through an IoT platform. We have implemented a testbed containing four levels, including sensors, gateways, server, and web portal. Gateway and server are implemented based on the Kaa IoT platform, which guarantees load balancing and high availability.

A. Contributions

Knowing that IoT can be utilized for different applications of smart homes and various areas of energy management, this article is an aggregation of IoT and an energy management system that reduces the power consumption during peak hours in real time. The contributions of the current study are summarized as follows.

1) Developing a model based on AHP, which finds out the factors that affect the power consumption the most.
2) Presenting a DR program with a convex optimization function for minimizing both customer and utility company costs.
3) Proposing an innovative control algorithm based on the RED algorithm for energy management in smart homes, which works in real time and reduces the amount of consuming power during peak hours.
4) Implementing an IoT testbed for the smart home scenario.
5) Employing the Kaa platform for supporting DSM use cases by implementing gateway and server of the mentioned IoT testbed.
6) Improving users' behaviors in terms of power consumption via a graphical web portal that visualizes their power consumption. The reports on minimum, maximum, and average of the community help users to change their behaviors.
7) Evaluating the performance of the proposed system based on the real implemented testbed and simulation.

The rest of the article is organized as follows. Section II discusses related work in this scope. Section III presents the proposed model, which consists of the learning model and the control unit. Section IV presents the implementation and simulation results and confirms the performance of the proposed model in addition to comparison to related work. Finally, Section V concludes the article.

II. Related Work

DR and DSM are critical applications of IoT that are divided into different categories. In [14], the authors propose a pricing policy framework for DR in smart grid machine-to-machine (M2M) networks based on the provider's price announcements. It also controls the appliances remotely during peak hours according to the price schedule set by each user. In this system, individual users adapt to the price signals to maximize their benefits. In [15], a real-time DR algorithm is proposed, which can be used to allocate resources among heterogeneous devices efficiently. This can be determined by choosing an optimal strategy that maximizes a utility function for a specific solution. This system also has the potential to not only reduce peak demand but also increase the overall efficiency of the system. As mentioned in [16], DR applications may be based on web services that use IoT protocol stack rather than classic Internet protocol stack, which reduces web service traffic overhead by over 10%. A web of things architecture also is presented in [17] that manages households' consumption and programs the power grid state. DR applications can be based on social media. In [18], the authors developed a system that takes information from appliances and posts information to the Twitter social network. The proposed gateway makes decisions based on the received data and sends notifications to Twitter.

In the smart grid, typical applications are distributor centric rather than customer centric. These applications usually have issues of scalability and user acceptance. To solve such problems, customer-centric DR applications, called DSM applications, recently emerged that fit customers' needs. In [19], a new method named home energy management as a service (HEMaaS) is proposed, which is based on an advanced neural fitted Q-learning algorithm to reduce peak load that is self-learning and adaptive. HEMaaS provides a flexible and energy-efficient decision-making system for home energy management. Authors in [20] also emphasize on the importance of DSM by investigating a smart home equipped with IoT sensors. Besides, a game theory algorithm is proposed that manages daily power consumption of households by the proposed DSM framework.

In IoT applications, many devices are connected, which produces a large amount of data. Issues related to data transmission, process, and storage force IoE to be integrated by cloud computing. Furthermore, to enhance the performance and reduce the volume of transmitted data and process information in an acceptable time, fog computing is suggested as a layer between

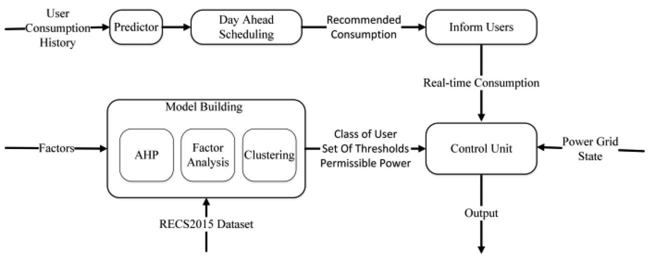

Fig. 1. Proposed system components.

the IoE layer and the cloud layer. In [21], a cloud-based DR (CDR) model is proposed, which is implemented as a two-tier cloud computing platform. Authors in [2] also present a fog-based IoE architecture for transactive energy (TE) management systems that consists of three different layers, including gateways, local fog nodes, and cloud servers. Another category of DR application includes models that work in a combination of different domains. For example, in [22], based on a combination of time-based programs and incentive-based DR programs, a real-time incentive DR program is proposed, which reduces the peak load through energy management at the customers' side.

Inhabitants' behavior is a significant factor that influences energy consumption. The ultimate goal of all research focusing on user's behavior is to reduce the energy consumption in buildings while maintaining a maximum comfort level for occupants [7]. In [23], it is shown that consumption relates to unconscious habits, and technological structures are the most useful when analyzing households' energy consumption. In the mentioned article, practice theory is introduced as an approach that better includes both unconscious habits and technological structures, which is the best way to conceptualize energy-consuming practices in everyday life. Much research has been done in the scope of user behavior pattern prediction. The authors in [7] try to develop algorithms for sensor-based modeling and prediction of user behavior in intelligent buildings and connect the behavioral patterns to building energy consumption by event-based pattern detection. The results of the dynamic schedule show significant energy savings with minimal comfort sacrifice. Some research focus on building equipment, especially office equipment. For example, in [24], the energy consumption patterns observed across two U.K. workstations are presented. In this article, the potential effect of using feedback to encourage energy reduction through behavior change is explored. Energy consumption was monitored for four months. The results revealed a significant variation in consumption patterns between workstations providing the same function in comparable locations. The study establishes that it is possible to reduce energy use up to 20% through behavior change in typical U.K. office spaces.

III. Proposed Model

Fig. 1 shows the elements of the proposed model, which introduces a DSM system based on user behavior monitoring. As shown in this figure, the following functions are applied to make the proposed model.

1) Model building: During this stage, based on experts' knowledge and a dataset, a model is generated, which is one of the inputs of the control unit. RECS2015 dataset has been used to determine the factors that affect the power consumption the most. This is done through an AHP analysis based on experts' knowledge. The selected factors are then analyzed to check their validity, and the data are clustered based on the final factors into five clusters. A permissible amount of power consumption is determined based on the average amount of power consumption in the dataset and experts' inputs. A set of thresholds for consumption is also assigned to each class. The class of user, a set of thresholds, and permissible amount of power consumption is the output of the model and the input of the control unit. Details about this model are presented in Section II-A.
2) Prediction: As the proposed scheduling mechanism is based on the day-ahead approach, the predictor is used to predict the future day power consumption. Power consumption history is used to predict the power consumption of the users for the next day.
3) Day-ahead scheduling: The day-ahead scheduling module is used to optimize the shiftable load of users and schedule power consumption. Load scheduling is done through a convex optimization problem. The output of the scheduler is recommended to the user, which optimizes the load during the day. Users may or may not follow the recommended scheduling. Therefore, knowing the recommended power consumption, users may consume power differently. Next, real-time power consumption is monitored through an IoT testbed and is considered as an input for the control unit. Section III-B explains how the day-ahead scheduler works.
4) Control: The control unit uses the class of users, some set of thresholds, the permissible amount of power consumption, real-time power consumption, and power grid state to execute different actions to reduce power consumption during peak hours. Section III-C explains how the control unit works.

A. Model Building

1) Analytical Hierarchy Process: Information about the network power consumption can lead us to efficiency and better management. Therefore, we need to know which factors influence power consumption the most. For this purpose, we follow the following steps.

a) Dataset selection: There are different datasets that collect energy-related data for housing units. We selected the Residential Energy Consumption Survey (RECS) [25] version 2015, which is a periodic study conducted by the U.S. Energy Information Administration (EIA) that provides detailed information about energy usage in U.S. homes. More than 500 factors are involved in this dataset. The housing characteristics data and the billing data are the basis for individual energy consumption.

b) AHP analysis: This section is to examine the factors that affect power consumption. Due to a large number of characteristics for each home in the RECS2015 dataset, we need to find the most effective factors. To solve this issue, we have used the

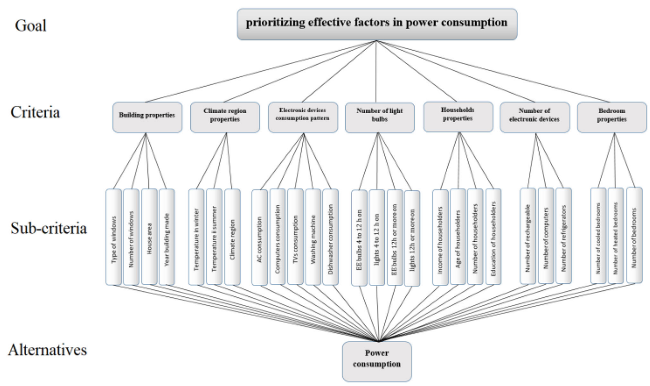

Fig. 2. Decision hierarchy.

AHP, which belongs to the multicriteria decision-making methods (MCDM). The basic idea of AHP is to capture the expert's knowledge of complex decision-making problems under study. The core of AHP is the comparison of pairs instead of sorting (ranking), voting (e.g., assigning points), or the free assignment of priorities. In AHP, the decision-maker first breaks down the problem into a hierarchy of goals, criteria, and alternatives. The goal of the decision is placed at the top, criteria in the middle, and alternatives at the bottom of the hierarchy. Fig. 2 shows the proposed decision hierarchy. As it illustrates, prioritizing effective factors in power consumption is placed at the top, which is our goal. Criteria (bedroom properties, number of electronic devices, etc.) and subcriteria are placed in the middle. And finally, at the bottom of the hierarchy, the amount of power consumption is placed as an alternative. In the AHP analysis, the consistency ratio (CR) of 0.10 or less is acceptable to continue the analysis. In this article, we have calculated all IR for experts' judgments, and all were consistent.

c) Ratio threshold: In the previous section, final weights obtained from the AHP analysis output show the factors' priority to the goal. Factors with more final weights affect power consumption more. The number of selected factors depends on a threshold that is applied to the weights. Due to the sensitivity of the scope, developers can choose a different ratio (weights) threshold with a different number of factors. Here, first, we have multiplied all final weights by ten and then set the ratio threshold to α so that L factors are chosen as the characteristics that affect the most the amount of power consumption. By setting $\alpha = 0.4$, $L = 9$ factors are selected. Table I shows the sorted effective factors in power consumption. As it is mentioned, air conditioner power consumption mostly affects the amount of power that has been consumed.

2) Factor Analysis: To check the relationship between each selected factor and the power consumption, we have used the John's Macintosh project (JMP) tool for analysis. By using a prediction model of the mentioned dataset and its validation, a fit model is created. We fit the models with constant parameters that are functions of effects. The model is valid to be used since its probability of $\mathcal{F}$ ratio is less than 0.05. To test whether the linear relationship in the sample data is strong enough to be used, we perform a hypothesis test of the significance of the correlation coefficient. To this end, we calculate the *P*-value significance test. This test tells how unlikely a given correlation coefficient r will occur given no relationship. The hypothesis test lets us decide whether the value of the population correlation coefficient ρ is close to zero or significantly different from zero. We decide this based on the sample correlation coefficient r and the sample size m. The results from the effect of parameters show that all parameters are significant to use, except the ninth one, the "income of householders," which represents the aggregation amount of salary each home's householders earn. The *P*-value for each of these parameters should be less than 0.05 to be significant. The *P*-value for "income of householders" factor is equal to 0.05006, which is not less than 0.05; hence, it is not valid to be used in the next step, clustering. Finally, with $L = 8$ number of factors, we calculate the correlation coefficients of the relationship that indicate the strength and direction of the linear relationship. In this model, all parameters have been tested and have a positive effect on the amount of power consumed.

TABLE I
EFFECTIVE FACTORS IN POWER CONSUMPTION

	Factor name	Experts' ratio	Normalized ratio
1	AC Consumption	0.0996	0.177
2	Temperature in summer	0.0871	0.155
3	Number of refrigerators	0.0740	0.131
4	Number of householders	0.0604	0.107
5	Number of windows	0.0553	0.098
6	House area	0.0477	0.086
7	Lights turned on 12h or more	0.0468	0.083
8	Number of computers	0.0467	0.082
9	Income of householders	0.0457	0.081

Before we start to cluster the data, we assume that we have L number of factors (which is eight here) in the system. Let $F = \{f_1, f_2, f_3, . \ \ldots, f_L\}$ show the vector of factors where f_j represents the jth factor ($j = 1, 2, \ldots, L$). Each of these factors has different weights that are obtained from the correlation in the previous step, shown as vector $R = \{r_1, r_2, r_3, \ \ldots, r_L\}$. End users also have different input values for each factor. Suppose vector $\mathrm{IN} = \{\mathrm{in}_1, \mathrm{in}_2, \mathrm{in}_3, \ldots, \mathrm{in}_L\}$ indicates the input values of the user for L factors. Let vector $U = \{u_1, u_2, u_3, \ldots, u_L\}$ be defined as a normalized user input vector which is calculated as follows:

$$u_j = \frac{\mathrm{in}_j \cdot r_j}{\sum_{j=1}^{L} \mathrm{in}_j \cdot r_j}. \tag{1}$$

U is applied as the input vector for the clustering process, which is described in the next subsection.

3) Clustering: In terms of power consumption, we divide users into five different classes of A, B, C, D, and E which represent groups of "very energy efficient," "energy-efficient," "power-saving," "power consuming," and "very power-consuming," respectively. For this division, we need to cluster users into these five groups that indicate their level of power consumption. RECS2015 dataset has been used to cluster users. We followed the steps from the previous section and clustered users by the K-means algorithm [26]. K-means is one of the learning algorithms that solve the well-known clustering problem. It is one of the most popular centroid-based (where objects closer to the cluster center are grouped together) clustering methods due to its computational efficiency and low-complexity implementation [27]. The procedure follows a simple way to classify a given dataset through a certain number of clusters (five clusters here). We have used 5686 rows of input data from the RECS2015 dataset. Of the data, 70% (4000 rows) is used for training the algorithm, and the rest (1686 rows) is used for testing. The input matrix dimension equals $L = 8$ as we selected eight factors. We have also used the city-block distance vector. For newly registered users, the classification algorithm also runs. The error rate in the classification phase is about 0.01 (2 out of 1686), which is an acceptable rate. For each of these classes, based on the average amount of power consumed in the dataset and according to experts' knowledge, the permissible consumption is determined.

For real-time feedback and automation, we need some thresholds that can control power consumption in real time. Real-time analysis is an approach to produce useful information from massive raw data [27]. These thresholds are used for the control unit, which reacts if the amount of power consumed exceeds the thresholds. We should consider that these thresholds should not be bothering users. If individuals feel that their freedom is threatened, they act to restore that freedom. If people believe that this process of the smart home is prohibiting them from living the way they wish, they may respond by consuming power even more than before [28]. Hence, it is essential to set the thresholds accurately for each class of users. For each class i, a set of action thresholds TH_i are specified as $\mathrm{TH}_i = \{\mathrm{th}_1, \mathrm{th}_2, \ldots, \mathrm{th}_{z_i}\}$ where z_i represents the number of action thresholds of classi, which are determined by experts' knowledge of the system for each class and may vary due to its needs. By specifying these thresholds, the permissible consumption in each action threshold is also determined.

B. Day-Ahead Scheduler

The prediction module is used to predict the load. We use power consumption history to predict the power consumption of the users for the next day. The day-ahead scheduling module is also used to optimize the shiftable load of users and schedule power consumption. Load scheduling is done through a convex optimization problem. The final recommended power consumption schedule for the next day is informed to the user. However, knowing the optimal load schedule, users may still consume power differently. Hence, real-time power consumption of the user is considered as an input for the control unit. In the proposed system, the real power consumption of the user is collected through an IoT testbed, which contains sensors, gateways, and server, which will be explained in Section IV. The following describes how the day-ahead scheduler works.

By using the predicted consumption for the next day, a day-ahead schedule is provided to the end-users. Optimizing the energy is known as an essential issue in the literature that seeks to achieve an efficient tradeoff between low costs and energy usage. We aim to minimize the cost of energy both for customers and utility companies. For this purpose, first, we need to model the cost function of both customers and utility companies. Suppose C_C^t and C_U^t represent the power consumption cost for customers and utility company at time $t \in \mathbb{T}$, respectively, where $\mathbb{T}$ represents the day time set and is split to high-load time H, midload time M, and low-load time L. Let C_T^t represents the total hourly cost of both customers and the utility company. C_T^t is defined as follows:

$$C_T^t = C_C^t + C_U^t. \tag{2}$$

1) Cost Function of Customers: Suppose each customer is equipped with two types of appliances, including shiftable and nonshiftable ones. Let D_i, D_i^{sh}, and D_i^{nsh} denote the total, shiftable, and nonshiftable appliances sets of each customer $i \in \mathbb{N}$ where $D_i^{sh} \cup D_i^{nsh} = D_i$, and $\mathbb{N}$ represents the customer set.

Let $P_{d,i}^t$ represent the power consumption of appliances $d \in D_i$ of customer $i \in \mathbb{N}$ at time slot $t \in \mathbb{T}$. The power load of shiftable and nonshiftable appliances of customers i at time slot t are calculated as $\overleftrightarrow{P_i^t} = \sum_{d \in D_i^{sh}} P_{d,i}^t$ and $\widehat{P_i^t} = \sum_{d \in D_i^{nsh}} P_{d,i}^t$, respectively. The total power consumption of customer i at time slot t is computed as

$$P_i^t = \overleftrightarrow{P_i^t} + \widehat{P_i^t}. \tag{3}$$

Let $p_{d,i}^{\min}$, $p_{d,i}^{\max}$, $[S\_\mathrm{time}_i^d, E\_\mathrm{time}_i^d]$, and $E_{d,i}$ represent the minimum power level, the maximum power level, the operation time which is between the start time and end time, and the total energy needed for shiftable appliances $d \in D_i^{sh}$, respectively. Note that for each customer $i \in \mathbb{N}$, the total power consumption of shiftable appliances during a day $\overleftrightarrow{P_i}$ is always fixed and calculated as

$$\overleftrightarrow{P_i} = \sum_{t=1}^{24} \sum_{d \in D_i^{sh}} P_{d,i}^t, \quad i \in \mathbb{N} \tag{4}$$

Let (L_i^L, L_i^M, L_i^H) and (pr_L, pr_M, pr_H) indicate the total load of customer $i \in \mathbb{N}$ and the ToU price at low-load, midload, and high-load, respectively, where $L_i^H = \sum_{t \in H} P_i^t$, $L_i^M = \sum_{t \in M} P_i^t$, and $L_i^L = \sum_{t \in L} P_i^t$. There are two high-load periods in the day, including 11 A.M.–3 P.M. and 7 P.M.–10 P.M. Between these two periods, it considered being midload. The rest of the day is also considered as low load.

The overall daily cost for customers $i \in \mathbb{N}$, C_i, is computed as follows:

$$C_i = (L_i^H * pr_H) + (L_i^M * pr_M) - (L_i^L * pr_L). \tag{5}$$

Since the overall load of nonshiftable appliances is not scheduled, we consider the total nonshiftable load of each customer i as a constant S_i as follows:

$$S_i = pr_H \sum_{t \in H} \widehat{P_i^t} + pr_M \sum_{t \in M} \widehat{P_i^t} - pr_L \sum_{t \in L} \widehat{P_i^t} \,. \tag{6}$$

The final overall daily cost for customers i is calculated as follows:

$$C_i = \ S_i + \ pr_H \sum_{t \in H} \overleftrightarrow{P_i^t} + pr_M \sum_{t \in M} \overleftrightarrow{P_i^t} - pr_L \sum_{t \in L} \overleftrightarrow{P_i^t}. \tag{7}$$

2) Cost Function of Utility Companies: The quadratic cost function has been widely used to model the hourly cost of energy provided by utility companies at time t as follows:

$$C_U^t = a_t {L_t}^2 \tag{8}$$

where a_t is the cost coefficient at time $t \in \mathbb{T}$ which is determined by some elements, such as operating costs, facility construction, and ownership cost [29], and L_t is the overall load of all customers and is calculated as $L_t = \sum_{i=1}^{\mathbb{N}} P_i^t$. As mentioned earlier, P_i^t is the sum of both shiftable and nonshiftable load of customer i at time t. L_t can be computed as follows:

$$L_t = \sum_{i=1}^{\mathbb{N}} \sum_{t=1}^{24} \left(\overleftrightarrow{P_i^t} + \widehat{P_i^t} \right), \ \ i \in \mathbb{N}. \tag{9}$$

Finally, the overall cost of power consumption for the utility company is as follows:

$$C_U^t = a_t \left(\sum_{i=1}^{\mathbb{N}} \sum_{t=1}^{24} \left(\overleftrightarrow{P_i^t} + \widehat{P_i^t} \right) \right)^2. \tag{10}$$

3) Optimization Problem: By setting the values of C_U^t and C_C^t in (2), the final cost C_T^t is calculated. We need to minimize the total cost by scheduling the energy consumption of each customer i at time slot t. The day-ahead scheduling problem is formulated as a convex optimization problem as discussed as follows, which minimizes the total daily cost of both customers and utility company:

$$\text{Minimize } \ C_T^t = C_U^t + C_C^t$$
$$= \text{Minimize } \left(\sum_{i \in \mathbb{N}} C_i + a_t \left(\sum_{i=1}^{\mathbb{N}} \sum_{t=1}^{24} \left(\overleftrightarrow{P_i^t} + \widehat{P_i^t} \right) \right)^2 \right) \tag{11}$$

subject to:

$$C_i^t = \overleftrightarrow{C_i} + \widehat{C_i}, \ i \in \mathbb{N}, t \in \mathbb{T} \tag{11a}$$

$$\overleftrightarrow{P_i^t} = \sum_{d \in D_i^{sh}} P_{d,i}^t \ \ i \in \mathbb{N}, t \in \mathbb{T} \tag{11b}$$

$$\widehat{P_i^t} = \sum_{d \in D_i^{nsh}} P_{d,i}^t, \ i \in \mathbb{N}, t \in \mathbb{T} \tag{11c}$$

$$p_{d,i}^{\min} \leq P_{d,i}^t \leq p_{d,i}^{\max}, \ d \in D_i^{sh}, \ i \in \mathbb{N}, \in \mathbb{T} \tag{11d}$$

$$\sum_{t=S\_\text{time}_i^d}^{E\_\text{time}_i^d} P_{d,i}^t = E_{d,i} \ , \ d \in D_i^{sh}, \ i \in \mathbb{N}, t \in \mathbb{T} \ . \tag{11e}$$

The proposed quadratic and convex optimization problem (11) can be solved by a well-known and highly efficient algorithm, interior-point-convex. As it has been proven in [30], the most important advantage of convex optimization is that the locally optimal solution is the optimal global solution.

The optimal power consumption schedule is informed to the user. The presented schedule is based on the historical data of power consumption. In addition to the diversity of the devices and objectives to consider, there is also a significant degree of uncertainty pertinent to households. These uncertainties include photovoltaics (PV)/wind power production, energy consumption behavior, and weather conditions [31]. Therefore, based on these uncertainties, the optimal presented schedule may not happen for all users of the community for all days. Hence, considering the real consumption behavior of users, a control system is presented in the control unit to control the load in peak hours.

C. Control Algorithm

This section explains the proposed control algorithm, which receives the following inputs:

1) class of user;
2) set of thresholds;
3) permissible amount of power consumption from the model building phase;
4) real-time power consumption;
5) power grid state;

The control algorithm is implemented with the initial idea of the RED algorithm. RED is a congestion avoidance mechanism that takes advantage of transmission control protocol (TCP)'s congestion control mechanism. When it comes to DSM, there are different approaches to the RED algorithm. If the real consumption of the user exceeds the permissible amount of energy at a specific threshold, the relevant action for that threshold runs. There are different actions for different thresholds. Soft notification action includes sending a notification to the user and notifying that the amount of real consumption is exceeding a certain minimum threshold. Users can analyze the data through the central point and make informed decisions about power management [32]. Hard notification action is also used to warn users again and ask them to turn OFF some of their appliances. These notifications can be sent on the web portal or the mobile application. At this point, the feedback from the user's behavior is sent to the system for recalculation. If the user does not pay attention to each of the notifications, nothing will happen after the user reaches the next threshold. Before the occurrence of high power consumption during peak hours, when the user's real consumption exceeds the permissible consumption at the next threshold, compared to the permissible amount of power consumption, another action occurs after soft and hard notification, which is the reaction system. This reaction system turns OFF the shiftable appliances of the user's smart home that the user already has given the system the privilege of switching ON and OFF. These appliances are the ones that the user permits the system to be turned OFF/ON. The flowchart of this decision-making is shown in Fig. 3. As can be seen, based on the user's input values for L selected factors and the created model from the previous step, a class is assigned to the user. Then, the set of thresholds and an amount of permissible power consumption for that class are retrieved based on the expert's knowledge. Knowing the power grid state, in a loop, the real-time consumption and permissible consumption

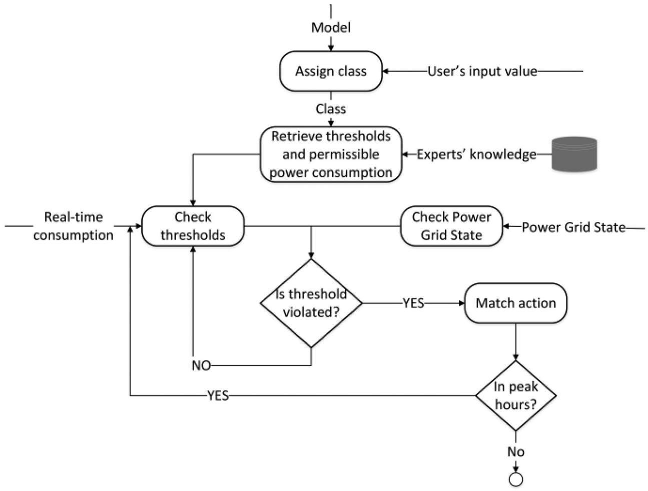

Fig. 3. Decision-making flowchart.

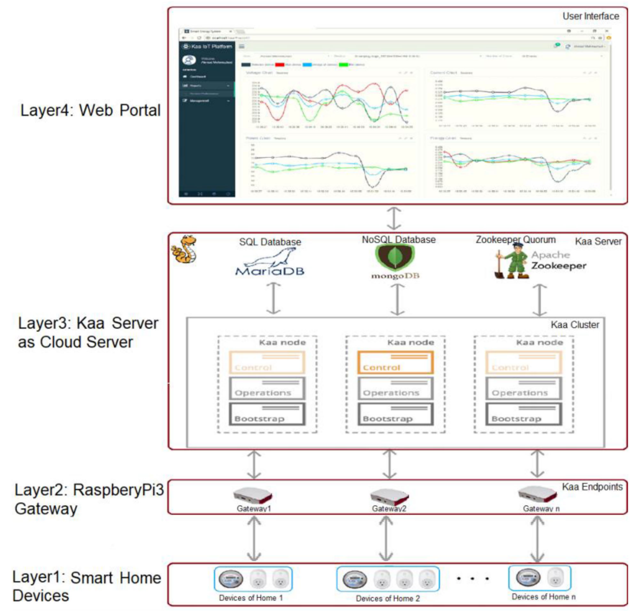

Fig. 4. Testbed architecture.

of the user are compared in real time. Once the action threshold is violated, the matched action is called. Otherwise, the next threshold is checked. It continues until peak hours end.

The day-ahead scheduler acts as the load shifting unit that suggests the users how to shift their consuming power from peak hours to nonpeak hours based on their history of power consumption. The control algorithm is the peak clipping technique that takes action and turns OFF the appliances whenever it is required. The proposed peak clipping, along with load scheduling, controls the consuming power of customers during peak hours.

IV. Implementation and Simulation Results

In this section, using the implementation and simulation results, we evaluate the performance of the proposed system in terms of peak load reduction. To this end, we have developed a testbed as presented in Fig. 4, consisting of four levels, including smart home devices and sensors, IoT gateway, Kaa server, and web portal.

To collect householders' home data, smart meters and smart plugs are used. Smart meters identify energy consumption precisely and in much more detail rather than other conventional meters. A smart meter collects accurate and real-time energy consumption data and gives specific analysis on it [1]. We have used our already developed smart meter to measure the amount of electric energy consumed by a residence [33]. Smart plugs are connected to home appliances as well. Each smart home can have several smart plugs that are used with home appliances. Smart plugs and smart meters communicate with the gateway and send the collected data to the related gateway through a Wi-Fi connection.

The IoT gateway and server are implemented through the Kaa IoT platform. We have implemented the home gateway on Raspberry Pi3 with Raspbian operating system. We have programmed the gateway by Java programming language, using Java SDK from the Kaa server. The gateway collects data from connected sensors and sends them to the Kaa server. It also receives commands from the Kaa server and notifies actuators (smart plugs only) about the received command. The main server is implemented on the Kaa platform. Kaa is a highly flexible, multipurpose, and open-source middleware platform for implementing complete end-to-end IoT solutions, connected applications, and smart products, which claims to have essential middleware for industrial IoT application, by having a set of methods that can be used to predict future failures and simplify troubleshooting errors. Kaa can manage data in back-end infrastructure through a server and endpoint SDK components. Kaa nodes in a cluster run a combination of control, operations, and bootstrap services. They use Apache ZooKeeper to coordinate services. Interconnected nodes make up a Kaa cluster associated with a particular Kaa instance. Kaa cluster requires NoSQL and structured query language (SQL) database instances to store endpoint data and metadata, accordingly. We have used Maria DB as the SQL database and MongoDB as the NoSQL database. The data that are collected from the first layer (sensors at home) are stored in the MongoDB database. MongoDB is an operational NoSQL database. It relaxes many of the relational databases' properties such as ACID transactional properties to allow for greater querying flexibility, operational scalability and simplicity, higher availability, and faster read/write operations [27]. Kaa platform provides many features, including high availability and scalability, active load balancing, hybrid encryption system for security that is based on RSA with 2048-bit key pair, and AES with 256(512)-bit key.

Finally, on the fourth level, a web portal is designed to visualize the collected data. It fetches the data from MongoDB database, containing sensors' power consumption data, and visualizes them. Feedbacks sent from the visualization system vary according to their type. They can be factual (showing real-time consumption, average, a maximum and minimum load of the network), social (e.g., using smiling/frowning faces), or comparative (e.g., current versus historical consumption data).

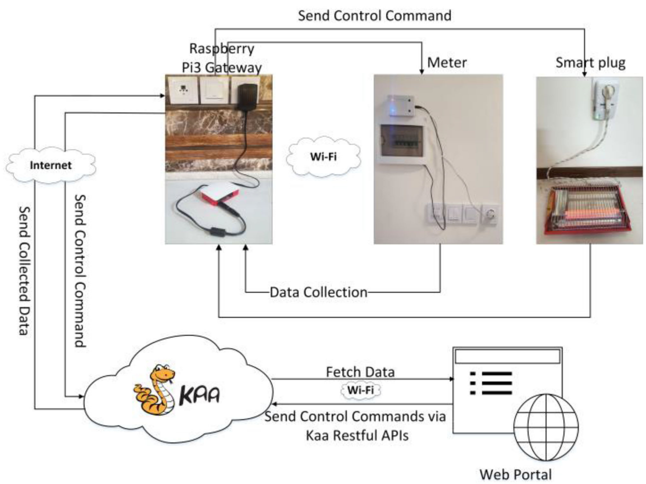

Fig. 5. Implementation testbed.

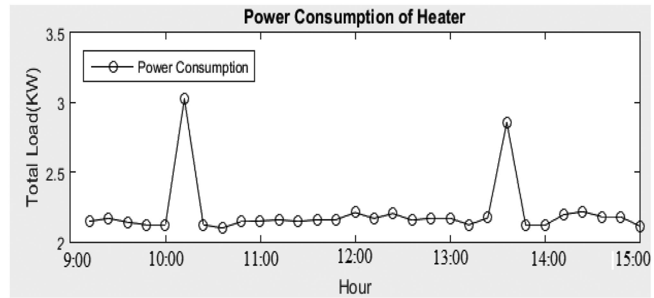

Fig. 6. Power consumption of the heater.

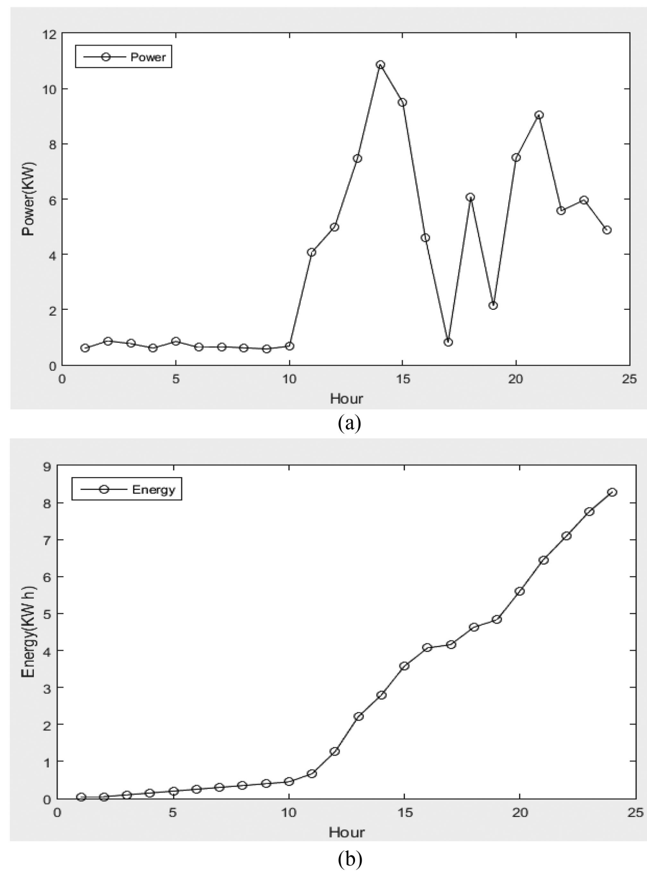

Fig. 7. (a) Power consumption. (b) Energy of the residential home.

Factual and comparative feedbacks are combined in the designed web portal. Real-time daily and monthly consumption are provided. A comparison between consumers in society is also provided, which contains users' real-time consumption, average, minimum, and maximum load of the society. Therefore, users can compare themselves to others and find out their place. Since the comparison of real-time consumption and permissible consumption (based on the set of thresholds) in the algorithm is made in the web portal, to send control commands, restful application programming interface (APIs) of Kaa are used to send unicast notifications from web portal to the Kaa server. The Kaa server receives this notification and passes the control command to the selected endpoint (gateway) specified in the notification message. The gateway also sends the control command to the sensors to be applied.

A. Single Home Monitoring Results

The real implementation of the testbed is shown in Fig. 5. We have implemented the proposed mechanism in a single home during a whole day on December 29, 2018, which is gathered by IoT sensors from the previous section. These data are captured via IoT nodes and then are sent to the Kaa home gateway implemented on Raspberry pi3. The home gateway communicates with IoT sensors every 10 min. According to the user's input, this home belongs to class D, a power-consuming group. A heater, as a shiftable appliance, is connected to the smart plug. The power consumption of the heater from 9 A.M. to 3 P.M. is shown in Fig. 6. Fig. 7 also shows the hourly power consumption and cumulative energy. All these data are gathered through our testbed every 10 min and have been available and plotted in the portal of the user during the day. The plots on the user's web portal are live and change whenever new data are received on the server.

A day-ahead schedule is recommended to the user based on the history of the user's power consumption. The control algorithm is also applied in real time. For this scenario, the permissible amount of power for each peak period is assigned due to the expert's knowledge. According to the power grid state, the first peak load happens from 11 A.M. to 3 P.M. (4 h), and the second one happens from 7 P.M. to 10 P.M. (3 h). As shown in Fig. 8, we have set two thresholds for the real scenario, occurring at 70% and 90% for each class. The action for the first threshold is a soft notification, and the action for the second one is turning OFF devices. When the amount of real-time power consumption reaches almost 70% of permissible consumption, a notification is sent to the user that notifies the user about their consumption. If the user does not pay attention to the notification and reaches the second threshold at 90%, the shiftable allowed appliances to turn OFF. Fig. 9 shows the total load of "unoptimized," "optimized," and "optimized-controlled" at a different time of the day. The results confirm that the power consumption during peak hours in

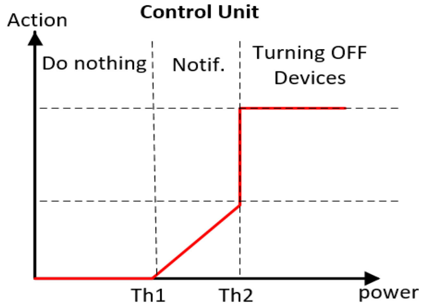

Fig. 8. Implemented control algorithm.

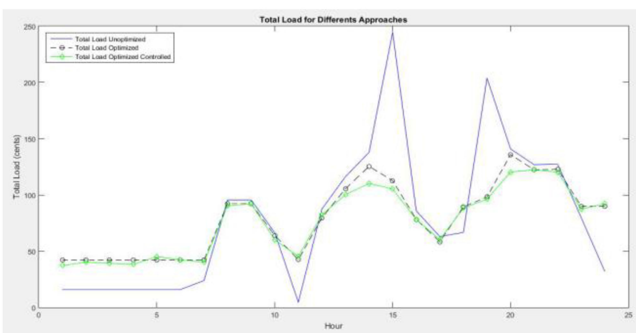

Fig. 9. Peak reduction in the implementation results.

the "optimized-controlled" graph has been reduced by 31.34% compared to the "unoptimized" data, which is about 21.76 KW for the user.

The results of this implementation prove that this system works appropriately in the real-world scenario and can be extended to a big scale. Since we have difficulties with providing the required hardware (such as smart plugs, smart meters), we tested our algorithm on a community where the power consumption data of residential homes have been simulated. The results of this simulation are presented in the next section.

B. Community Monitoring Results

In this section, we evaluate the performance of the proposed system by simulating a community containing 100 different users in five different classes, A, B, C, D, and E. Different numbers of appliances have been considered for each class. Each user has a random number of appliances in selected ranges from 0 to 23. These ranges vary for different classes (e.g., class E has more appliances than class B). For each class, there is a limited number of appliances that users will have for sure (e.g., refrigerator). Some of these devices are shiftable, while others are not. Peak hours are the same as the single home scenario. The permissible amount of power consumption for each peak period is set for each class of users as follows:

$$H_1^{cl} = \frac{\sum_{j=1}^{n_j} \widetilde{X_i}\,(t)}{n_j n_{p1}} \tag{12}$$

TABLE II
PEAK REDUCTION FOR DIFFERENT NOTIFICATION LISTENER RATES

P Values	PAR		Peak 1 reduction	Peak 2 reduction	Overall peak reduction
	No Control	With Control			
10%	2.3	1.99	8.12%	1.65%	5.70%
30%	2.3	1.97	12.84%	4.86%	9.87%
50%	2.3	1.95	18.85%	12.05%	16.31%

$$H_2^{cl} = \frac{\sum_{j=1}^{n_j} \widetilde{X_i}\,(t)}{n_j n_{p2}} \tag{13}$$

where n_j represents the number of customers in each class. $\widetilde{X_i}(t)$ also shows the real-time power consumption in time slot t. $n_{p1} = 4$ and $n_{p2} = 3$ represent the two periods of peak load hours as the first peak load lasts for 4 h, and the second one lasts for 3 h.

A set of thresholds with different actions is set for each class. For performance evaluation, we have set three thresholds with three different actions for all classes. The first action threshold happens when real-time consumption reaches 80% of permissible energy consumption during peak hours. The selected action for the first threshold is a hard notification that asks users to turn OFF some of their devices by themselves. In the simulation application, we have considered p as the percentage of users who pay attention to the notification and will turn OFF some of their devices randomly. Different values of p are tested in the simulation. As it is shown in Table II, 10%, 30%, and 50% values for p are considered. Each of these users who pay attention to the notification turns OFF 20% of their shiftable appliances randomly. We have set different values for p as we are aware that in different societies, the percentage of people that really pay attention to these notifications differ. As can be seen, the higher the p value is, the less power is consumed during peak hours. The peak-to-average ratio (PAR) is a critical power network metric that is defined as the maximum daily load divided by the average load. Results confirm that the proposed control algorithm has less PAR compared to the traditional algorithm without any control. As a result, more p causes less PAR. It means that if this system can motivate users to pay attention to the first notification more, the overall peak reduction will increase, which results in less power consumption.

The second and third thresholds happen when real-time consumption reaches 90% and 95% of the permissible energy in peak hours, respectively. Turning OFF appliances is chosen as actions for both the second and third thresholds. When it comes to peak load reduction, user convenience (UC) must be considered as well. As mentioned in [19], UC level for 5% and 10% load reduction is maintained at and above 80%, whereas more percentage of peak power reduction causes more discomfort for users. Therefore, by using the results from this article, when the second action threshold happens, 5% of shiftable appliances are turned OFF, while we turn OFF 10% of shiftable appliances for the third threshold. Due to the sensitivity of the system, the permissible amount of energy for each class can be set with more restrictions. The results of the algorithm for 100 users based on three thresholds are shown in Fig. 10. The diagram labeled as "total load unoptimized uncontrolled" shows the historical data

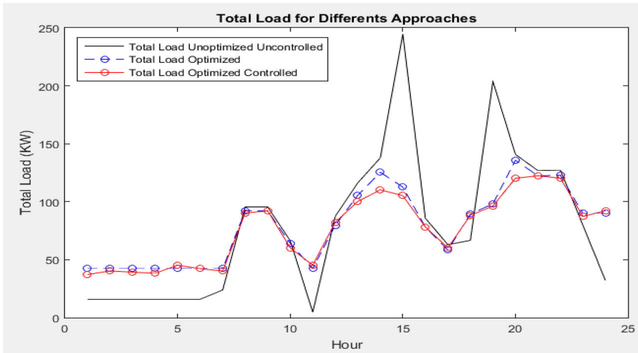

Fig. 10. Total power consumption before and after the proposed algorithm.

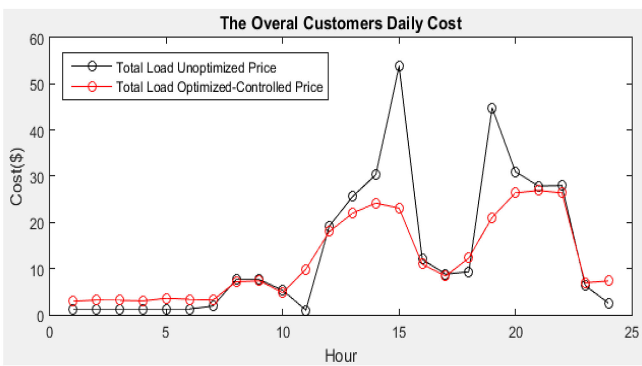

Fig. 11. Overall customer daily cost.

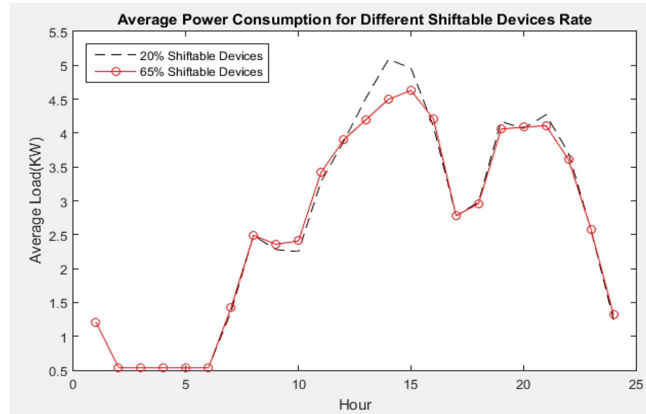

Fig. 12. Peak reduction for different number of shiftable devices.

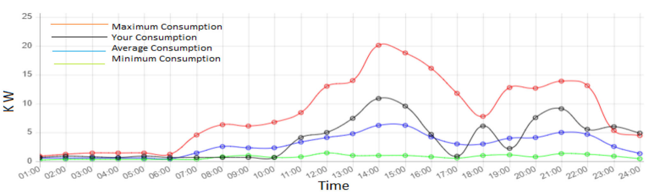

Fig. 13. Comparison of the power consumption.

of users in the community. By applying the proposed day-ahead scheduling, it can be seen that some unnecessary loads can be shifted from peak hours to off-peak hours to decrease power consumption and cost. The results from the optimization problem are plotted in the diagram labeled as "total load optimized." The control unit works only during peak hours. The control algorithm is applied to the optimized load. As it can be seen in the "total load optimized controlled" diagram, the total load during peak hours has reduced. By looking at these graphs and comparing the total "unoptimized uncontrolled" load with the total "optimized controlled" load, we conclude that during two intervals of peak hours, the total load has shifted down by the rate of 22.42%, which is about 220.22 KW for the community. It significantly benefits both customers and utility companies in terms of power consumption. As the consumed power decreases, it affects the cost as well. To calculate the costs for customers, we have used the ToU pricing model. Twenty-two cents/kWh energy price is used for two intervals of high-load hours, known as peak hours. For midload and low-load hours, grid energy price is equal to 15 and 8 cents/kWh, respectively. These numbers are hypothetical to show the cost reduction and may vary in different countries for different utility companies. We have calculated the electricity cost of customers with the ToU pricing model based on the cost function of customers, presented in (7). The overall customers' daily cost using the proposed algorithm and power grid pricing is shown in Fig. 11. Results confirm that customers benefit from the proposed system financially. Customers can reduce their daily costs at a rate of 13.5%, about $45 per day. As we have assumed, there are 100 customers in the power grid; the average daily benefit for customers is almost 45 cents per customer.

The number of shiftable appliances also affects the performance of the proposed algorithm. During the registration phase in the portal, users will specify which appliances are shiftable and can be turned OFF during peak hours. It is obvious that if users set more appliances as shiftable and let the system turn them OFF automatically during peak hours, the algorithm will perform better, and the power consumed during peak hours will reduce. Fig. 12 shows the effect of this fact with different number of shiftable appliances. We can see that the algorithm reduces power consumption during peak hours more when 65% of appliances are set to be shiftable compared to the situation when only 20% of appliances are allowed to be turned OFF by the algorithm. Hence, the more users set their appliances as shiftable, the better the control algorithm works.

With big data, energy information can be extracted, and corresponding energy strategies can be made. Operational inefficiencies, such as always turning ON lights, may waste plenty of energy, which may be diagnosed and solved via big data technologies [32]. In Fig. 13, the comparison between users of the community and the mentioned single home in the previous section is shown on the web portal of the "single home scenario." The user interface plots the average, maximum, and minimum of the society compared to the actual user consumption. As can be seen, the consumption of the mentioned home is almost more than the average of the community. Each customer uses this information to evaluate his/her consumption. This kind of visual

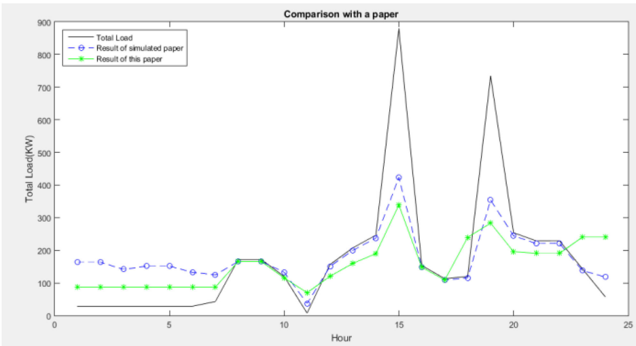

Fig. 14. Comparison of our approach and paper [34]'s approach.

representation of data can show how the average of the community is behaving, and proper policies could be set for different communities with different levels of electricity consumption. We also believe that these visualized data affect customers as well. It can notify users about the amount of their power consumption and motivate them to behave better in a community in terms of electricity usage by comparing themselves to others. Some people reported that the comparison between their own home power consumption with the community would help them to modify their behavioral patterns when it comes to consuming energy.

C. Comparing With the Existing Approaches

In this subsection, we compare the performance of the proposed system with that of existing work, which presents a multiobjective demand response optimization model for scheduling loads in a home energy management system [34]. The results are shown in Fig. 14. As can be seen, the proposed system can reduce power consumption more than the existing work.

V. Conclusion

In this article, we proposed a DSM system for smart home energy management, which monitors users' behavior based on real-time feedback. The proposed system consists of an optimization module that presents a day-ahead schedule to the user and a real-time control algorithm that reduces the amount of power consumption during peak hours. The power grid state, the real-time power consumption of the user, and the expert-based model are the inputs of the control unit. The expert-based model contains three different parts. First, effective factors in terms of power consumption in residential homes are extracted through the AHP, which is based on experts' knowledge. Second, a threshold is set in order to select a specific number of effective factors according to their priority. Selected factors are validated through the JMP tool to pass the significant test. Final significant factors are inputs for the last part, which clusters users based on the amount of power consumed with the K-means algorithm. It assigns a set of thresholds and permissible amount of power consumption for each class. Based on the output of the model for each user, the control unit has different outputs for different users, which leads to peak reduction. Real-time power consumption of the residential homes is collected through an IoT testbed. The implemented testbed includes sensors, home gateways, server, and web portal. The home gateway and server have been implemented on the Kaa IoT platform. The information provided in the web portal helps customers make intelligent decisions for their power consumption. We have used the deployed testbed to run the algorithm. We evaluated the proposed model through simulation and real implementation. Results confirm that the proposed system decreases the total power consumption during peak hours. Presenting an online classifier and linear programming for thresholds' extraction are our future works.

References

[1] K. Wang *et al.*, "A survey on energy Internet: Architecture, approach, and emerging technologies," *IEEE Syst. J.*, vol. 12, no. 3, pp. 2403–2416, Sep. 2018.

[2] M. Y. Moghaddam and A. Leon-Garcia, "A fog-based Internet of energy architecture for transactive energy management systems," *IEEE Internet Things J.*, vol. 5, no. 2, pp. 1055–1069, Apr. 2018.

[3] P. Koponen *et al.*, "Definition of smart metering and applications and identification of benefits," Deliverable D3 of the European Smart Metering Alliance ESMA, London, U.K., Ver. 1.1, 2008.

[4] S. V. Kadu, D. S. Bhosale, and J. Bsiotr, "Energy meters using Internet of Things platform," *Int. Res. J. Eng. Technol.*, vol. 4, no. 6, pp. 1516–1519, Jun. 2017.

[5] E. Et-Tolba, M. Maaroufi, and M. Ouassaid, "Demand side management algorithms and modeling in smart grids: A customer's behavior based study," in *Proc. Int. Renewable Sustain. Energy Conf.*, 2013, pp. 531–536.

[6] N. Ruiz, I. Cobelo, and J. Oyarzabal, "A direct load control model for virtual power plant management," *IEEE Trans. Power Syst.*, vol. 24, no. 2, pp. 959–966, May 2009.

[7] B. Dong and B. Andrews, "Sensor-based occupancy behavioral pattern recognition for energy and comfort management in intelligent buildings," in *Proc. Building Simul.*, Jul. 2009, pp. 1444–1451.

[8] M. Erol-Kantarci and H. Mouftah, "TOU-aware energy management and wireless sensor networks for reducing peak load in smart grids," in *Proc. IEEE 72nd Veh. Technol. Conf. - Fall*, 2010, pp. 1–5.

[9] S. van Dam, C. Bakker, and J. van Hal, "Home energy monitors: Impact over the medium-term," *Building Res. Inf.*, vol. 38, no. 5, pp. 458–469, 2010.

[10] M., Lopes, C., Antunes, and N., Martins, "Energy behaviours as promoters of energy efficiency: A 21st century review," *Renewable Sustain. Energy Rev.*, vol. 16, no. 6, pp. 4095–4104, 2012.

[11] T. Malche and P. Maheshwary, "Harnessing the Internet of things (IoT): A review," *Int. J. Adv. Res. Comput. Sci. Softw. Eng.*, vol. 5, no. 8, pp. 320–323, 2015.

[12] Kaa IoT Platform Documentation. Accessed: Dec. 3, 2017. [Online]. Available: https://kaaproject.github.io/kaa/docs/v0.10.0/Welcome/

[13] S. Floyd and V. Jacobson, "Random early detection gateways for congestion avoidance," *IEEE/ACM Trans. Netw.*, vol. 1, no. 4, pp. 397–413, Aug. 1993.

[14] S. Ali, R. Ahmad, and D. Kim, "A study of pricing policy for demand response of home appliances in smart grid based on M2M," in *Proc. 10th Int. Conf. Frontiers Inf. Technol.*, 2012, pp. 231–236.

[15] S. Hong, M. Yu, and X. Huang, "A real-time demand response algorithm for heterogeneous devices in buildings and homes," *Energy*, vol. 80, pp. 123–132, 2015.

[16] V. Altmann, J. Skodzik, F. Golatowski, and D. Timmermann, "Investigation of the use of embedded web services in smart metering applications," in *Proc. 38th Annu. Conf. IEEE Ind. Electron. Soc.*, 2012, pp. 6172–6177.

[17] S. Mohanty, B. Panda, and B. Pattnaik, "Implementation of a web of things based smart grid to remotely monitor and control renewable energy sources," in *Proc. IEEE Students' Conf. Elect., Electron. Comput. Sci.*, 2014, pp. 1–5.

[18] J. Lloret, E. Macías, A. Suárez, and R. Lacuesta, "Ubiquitous monitoring of electrical household appliances," *Sensors*, vol. 12, no. 11, pp. 15159–15191, 2012.

[19] C. Mahapatra, A. Moharana, and V. Leung, "Energy management in smart cities based on Internet of Things: Peak demand reduction and energy savings," *Sensors*, vol. 17, no. 12, 2017, Art. no. 2812.
[20] M. S. Hoosain, S. Rimer, and B. S. Paul, "Smart homes: Energy efficiency based on demand side management and game theoretic algorithm," in *Proc. 5th IASTED Int. Conf.*, 2016, pp. 1–7.
[21] M. Yaghmaee, A. Leon-Garcia, and M. Moghaddassian, "On the performance of distributed and cloud-based demand response in smart grid," *IEEE Trans. Smart Grid*, vol. 9, no. 5, pp. 5403–5417, Sep. 2018.
[22] M. Eissa, "First time real time incentive demand response program in smart grid with "i-Energy" management system with different resources," *Appl. Energy*, vol. 212, pp. 607–621, 2018.
[23] K. Gram-Hanssen, "New needs for better understanding of household's energy consumption—Behaviour, lifestyle or practices," *Architectural Eng. Des. Manage.*, vol. 10, no. 1/2, pp. 91–107, 2013.
[24] M. Mulville, K. Jones, and G. Huebner, "The potential for energy reduction in UK commercial offices through effective management and behaviour change," *Architectural Eng. Des. Manage.*, vol. 10, no. 1/2, pp. 79–90, 2013.
[25] "*Residential energy consumption survey (RECS) - Data*," U.S. Energy Inf. Admin., Washington, DC, USA. Accessed: May 15, 2018. [Online]. Available: https://www.eia.gov/consumption/residential/data/2015/
[26] G. Wilkin and X. Huang, "K-means clustering algorithms: Implementation and comparison," in *Proc. 2nd Int. Multi-Symp. Comput. Comput. Sci.*, 2007, pp. 133–136.
[27] R. Atat, L. Liu, J. Wu, G. Li, C. Ye, and Y. Yang, "Big data meet cyber-physical systems: A panoramic survey," *IEEE Access*, vol. 6, pp. 73603–73636, 2018.
[28] A. Zipperer *et al.*, "Electric energy management in the smart home: Perspectives on enabling technologies and consumer behavior," *Proc. IEEE*, vol. 101, no. 11, pp. 2397–2408, Nov. 2013.
[29] A. Mohsenian-Rad, V. Wong, J. Jatskevich, R. Schober, and A. Leon-Garcia, "Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid," *IEEE Trans. Smart Grid*, vol. 1, no. 3, pp. 320–331, Dec. 2010.
[30] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge, U.K.: Cambridge Univ. Press, 2009.
[31] M. Beaudin, H. Zareipour, and A. Schellenberg, "Residential energy management using a moving window algorithm," in *Proc. 3rd IEEE PES Innov. Smart Grid Technol. Europe*, 2012, pp. 1–8.
[32] J. Wu, S. Guo, J. Li, and D. Zeng, "Big data meet green challenges: Big data toward green applications," *IEEE Syst. J.*, vol. 10, no. 3, pp. 888–900, Sep. 2016.
[33] M. Yaghmaee and H. Hejazi, "Design and implementation of an Internet of Things based smart energy metering," in *Proc. IEEE Int. Conf. Smart Energy Grid Eng.*, 2018, pp. 191–194.
[34] J. Veras *et al.*, "A multi-objective demand response optimization model for scheduling loads in a home energy management system," *Sensors*, vol. 18, no. 10, 2018, Art. no. 3207.

Mahshid Mehr Nezhad (Student Member, IEEE) received the B.S. degree in software engineering from Semnan University, Semnan, Iran, in 2016, and M.S. degree in software engineering from the Ferdowsi University of Mashhad, Mashhad, Iran, in 2018. She is currently working toward the Ph.D. degree in computer science with the University of Warwick, Coventry, U.K.

Her research interests include Internet of Things (IoT), network security, and payment security.

Mohammad Hossein Yaghmaee Moghaddam (Senior Member, IEEE) received the B.S. degree from the Sharif University of Technology, Tehran, Iran, in 1993, and the M.S. and Ph.D. degrees in communication engineering from the Amirkabir University of Technology (formerly Tehran Polytechnic), Tehran, Iran, in 1995 and 2000, respectively.

From November 1998 to July1999, he was a Visiting Research Scholar with Network Technology Group, C&C Media Research Labs, NEC Corporation, Tokyo, Japan. From September 2007 to August 2008, he was a Visiting Associate Professor with the Lane Department of Computer Science and Electrical Engineering, West Virginia University, Morgantown, WV, USA. From July 2015 to September 2016, he was a Visiting Professor with the Electrical and Computer Engineering Department, University of Toronto (UoT), Toronto, ON, Canada. He is currently a Full Professor with the Computer Engineering Department, Ferdowsi University of Mashhad (FUM), Mashhad, Iran. His research interests include smart grid communication, software defined networking, and network function virtualization.

Mohsen Asadi received the M.Sc. degree from the Sharif University of Technology, Tehran, Iran, in 2009, and the Ph.D. degree from Simon Fraser University, Burnaby, BC, Canada in 2014.

He is an Assistant Professor with Ferdowsi University of Mashhad, Mashhad, Iran. Previously, he was a Senior Research and Software Engineer with SAP Canada, Toronto, ON, Canada, where he obtained seven U.S. patents with his colleague on data analytics. He is the author or coauthor of more than ten journal papers and more than 20 conference papers in reputed venues in computer science. His research interests include cloud computing, big data systems, and Internet of Things platforms.