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A Fair Pricing Mechanism in Smart Grids for Low Energy Consumption Users

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ABSTRACT Based on energy demand, consumers can be broadly categorized into low energy consumers (LECs) and high energy consumers (HECs). HECs use heavy load appliances, e.g., electric heaters and air conditioners, and LECs do not use heavy load appliances. Thus, HECs demand more energy compared to LECs. The usage of high energy consumption appliances by HECs leads to peak formation in various time intervals. Different pricing schemes, i.e., time of use (ToU), real time pricing (RTP), inclined block rate (IBR), and critical peak pricing (CPP), have been proposed previously. In ToU, an energy tariff is divided into three blocks, i.e., on-peak (high rates), off-peak (low rates), and mid-peak (between on-peak and off-peak rates) hours, and these rates are applied to all electricity users without distinction. The high energy demand by HECs causes the high peak formation; thus, higher rates should be applied to only HECs rather than all consumers, which is not the case in existing billing mechanisms. LECs are also charged higher rates in on-peak intervals and this billing mechanisms are unjustified. Thus, in this paper, a fair pricing scheme (FPS) based on power demand forecasting is developed to reduce extra bills of LECs. First, we developed a machine learning-based electricity load forecasting method, i.e., an extreme learning machine (ELM), in order to differentiate LECs and HECs. With the proposed FPS, electricity cost calculations for LECs and HECs are based on the actual energy consumption; thus, LECs do not subsidize HECs. Simulations were conducted for performance evaluation of our proposed FPS mechanism, and the results demonstrate LECs can reduce electricity cost up to 11.0075%, and HECs are charged relatively higher than previous pricing schemes as a penalty for their contribution to the on-peak formation. As a result, a fairer system is realized, and the total revenue of the utility company is assured.

INDEX TERMS Smart grid, low energy consumers, pricing tariff, load forecasting, extreme learning machines, time of use, fair pricing scheme.

I. INTRODUCTION

A report by the International Energy Agency (published in 2016) stated that power demand is increasing daily due to an increasing number of electrical appliances, and a large portion (40 %) of the total demand is utilized in residential buildings [1]. Power demand is increasing compared to energy supply; thus, traditional power grid systems are facing various challenges, e.g., energy production, energy distribution, energy transmission, and price calculation. Thus, new technologies that can convert traditional grids to smart grids are required. In the smart grid era, the above-mentioned challenges can be solved by employing various programs, i.e., demand response (DR), demand-side management (DSM), and supply-side management. DSM strategies [2]–[4] play an important role in reducing energy bills of residential consumers and minimizing peak creation, which helps utility companies avoid blackouts or other dangers. In addition, power grid operators also offer several pricing mechanisms to address power-related challenges. These energy pricing strategies are separated into two major classes: quantity-differ and time-differ energy tariffs [5], [6]. Real-time pricing (RTP) and time of use (ToU) tariffs refer to time-differ pricing, where prices are reduced or increased based

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on predefined time periods. In the RTP tariff, energy rates vary dynamically based on real-time power consumption. The literature [7] states that a dynamic pricing strategy is an efficient mechanism to optimize the energy utilization of residential consumers. Inclined block rate (IBR) tariff belongs to quantity-differ tariffs, where the energy price increases after passing a specific energy consumption threshold during specific time slots. Energy users can avoid power consumption in these time slots to avoid higher costs. Consequently, the power grid avoids peak creation in these time slots.

The ToU pricing scheme has fixed prices in various time slots, e.g., off-peak (low price), mid-peak (medium price), and on-peak (high price) hours [2]. The primary goal of the ToU pricing scheme is to motivate energy consumers to consume power intelligently by incentivizing (in terms of low cost) end users to shift their load to off-peak hours. A large number of recent studies have focused on ToU from economic perspectives in various power sectors, i.e., Taiwan [8], Brazil [9], China [10], and Australia [6]. There are three types of electricity users: high-energy consumers (HECs), low-energy consumers (LECs), and medium-energy consumers (MECs). LECs are those consumers who consume too low energy, while the consumers with high energy consumption are called HECs and the consumers that they have load demand between LECs and HECs are called MECs.

However, state-of-the-art studies have either failed to adequately incentivize LECs or just focused on DR programs. They propose financial incentives only to participating (in DR programs) consumers and ignore LECs while proposing energy tariffs. Therefore, this study focuses on LECs by providing a novel extreme learning machine (ELM)-based fair pricing scheme (FPS). Since, LECs do not cause peak generations; thus, why do LECs pay higher costs during on-peak hours? The high peak in any time interval is only generated by HECs; thus, in the proposed FPS mechanism, they are proposed to pay higher costs during on-peak hours compared to LECs. Day-ahead load demand is required to distinguish LECs and HECs; thus, this work extends our previous study [6] and develops an ELM-based day-ahead load forecasting model to predict the load demand of various consumers. Then, based on the predicted load demand, a FPS tariff is proposed for LECs and HECs.

Our primary contributions are summarized as follows.

- We develop a novel pricing model that benefits LECs.
- We formulate the proposed pricing model as a two-stage optimization model, where power load is predicted to differentiate LECs and HECs at the first and then at the second stage, a novel FPS is developed based on forecasted load.
- We develop an ELM-based day-ahead load forecasting model.

The remainder of this paper is organized as follows. Next section discusses literature review. Section III discloses the proposed system model (including the pricing and load forecasting models) and the problem formulation. Simulation settings and results are discussed in Section IV. Finally, Section V concludes the paper.

II. LITERATURE REVIEW

Over the last decade, several studies have considered the economic perspective of ToU pricing scheme in various electricity markets, e.g., Brazil [9], China [10], Australia [6], and Taiwan [8]. Many studies have investigated energy cost minimization for residential consumers and peak load shaving for utility companies by proposing various pricing tariffs. This section introduces some recent studies that focused on the above-mentioned issue.

A previous study [11] developed a load shaping policy, which relies on a dynamic pricing (DP) model in order to mitigate energy cost and balance user demands and energy supply. In addition, an incentive-based dynamic pricing strategy has been developed in [12]. This strategy motivates energy users to shift their maximum energy consumption to low-peak slots. Sibo Nan *et. al.,* in [13] have developed and implemented a demand response program considering residential community as smart in which residential loads are grouped into various classes and then scheduling is performed for consumer's cost minimization. Results prove effectiveness of the proposed pricing strategy in terms of cost reduction, decrease in peak valley and peak load difference and the user's comfort. Another paper [14] also investigated dynamic pricing problems, where energy providers offer day-ahead energy tariffs and users can schedule their power load that increases user benefits in terms of reduced cost. In [15], a reinforcement learning-based DP mechanism was proposed, through which utility companies can make an optimal decisions about tariffs by knowing the consumers' energy consumption behaviors. Another study [16] proposed a cost-efficient energy management system by employing dynamic pricing to balance energy demand and supply. This study also exploited heuristic algorithms, i.e., the enhanced differential evolution and harmony search algorithms, to shift load demand from on-peak to off-peak slots. In addition, Babar *et al.* [17] developed a multi-agent-based energy management system to mitigate peaks in smart buildings. Here, the ToU pricing method was implemented to encourage end-users to schedule energy consumption from high price to low price hours, which realized alleviation of peak generations.

One study [18] proposed a RTP mechanism for energy cost alleviation, where several energy consumers and multiple retailers were considered for implementation. They modeled the decision process of RTP as a Stackelberg game framework. Further, coordination among all energy consumers was formulated as an evolutionary game. In contrast, price competition among energy providers was modeled as a non-cooperative game. Simulation results demonstrated that the price was minimized by employing the RTP mechanism, and, as a result, energy consumers incurred minimum cost. Authors of [19] have focused on electricity consumer's preferences and utility's profit. They have proposed a dynamic pricing algorithm using reinforcement learning for decision making. Evaluation results proved the proposed study equally beneficial for utility and consumers. Another cost minimization study [20] developed a cost reduction mechanism using dynamic pricing signals. This study proposed a cost-oriented and comfort-oriented pricing tariff to facilitate energy consumers, and extensive simulations were performed to demonstrate the performance of proposed cost-oriented and comfort-oriented pricing tariffs over standard day-ahead real-time prices. The results validated that consumers could enjoy maximum comfort with affordable cost over counterparts.

Faza *et al* [21] evaluated two intelligent dynamic pricing schemes, i.e., clipping and percentage reduction schemes, by employing a particle swarm optimization algorithm. They performed a large number of experiments with the real-time load demand data for Amman city, Jordan, where various DR strategies were implemented with these two pricing schemes. The experimental results provided evidence for reasonable behavior of clipping and percentage reduction schemes in terms of cost reduction (up to 12%). Urooj *et. al.,* have implemented genetic algorithm (GA) for scheduling of consumer's electricity load to decrease electricity cost in [22]. They have used renewable energy data, user's preferences, and energy demand as input parameters to GA, while employing real time pricing scheme. Evaluation results validate the effectiveness of proposed scheme in terms of cost alleviation and grid stability. Another study [23] developed a behavioral real-time pricing (B-RTP) mechanism based on energy consumers' behaviors. They claimed that no pricing scheme fairly rewards demand responsive consumers, who are more interested in adopting energy-efficient habits than other users. Thus, existing pricing tariffs do not motivate behavior change because they do not provide sufficient incentives. To address this issue in existing pricing models, the proposed B-RTP mechanism provides incentives to energy consumers who are actively involved in DR strategies. Based on simulation results, they performed a comparative analysis, and it was proven that the proposed B-RTP mechanism is beneficial for energy consumers in terms of energy bills reduction. Another behavioral RTP strategy, namely Fair RTP (FRTP) [24], has been proposed. This scheme fairly and dynamically adjusts incentives offered to participating energy consumers. This pricing mechanism offers a high level of fairness relative to distributing financial incentives among consumers based on the level of involvement in DR programs. Furthermore, their proposed FRTP can be adjusted dynamically based on conditions in the wholesale market, the level of competition among retailers (utility companies), and the flexibility level of energy consumers. A comparative analysis was performed to validate the effectiveness of the proposed FRTP, and the results indicated that the proposed scheme was more suitable for consumers compared to a benchmark scheme, i.e., standard RTP.

Another previous study [25] developed a data-driven pricing strategy to reduce peak load for utility companies. This strategy coordinates with demand side aggregators, and the primary goal is to achieve peak shavings in different hours. They performed extensive simulations to validate their proposed data-driven pricing strategy over existing pricing schemes, i.e., ToU and flat pricing. The results confirmed that the proposed pricing strategy can alleviate peaks by encouraging energy users to schedule energy usage in different time slots. In [26] authors have stated that it is challenging task to maintain a balance between user comfort and energy cost. Therefore, they have proposed and implemented a hybrid genetic algorithm-particle swarm optimization (GAPSO) algorithm for effective and efficient management of residential load. Results of the proposed scheme were compared with genetic algorithm and binary particle swarm optimization algorithm. Proposed scheme was proved more efficient and effective for minimization of cost and peak power consumption.

Based on this brief literature review, we conclude that researchers from academia and industry are working to find a uniform, comprehensive, and justified pricing mechanism for energy consumers in smart grids. However, to the best of our knowledge, none of the reviewed studies considered LECs while proposing their pricing tariffs. For example, [11], [12], [14]–[18], [20], [21] treated HECs and LECs at the same place without considering the fact that peak is only created due to LECs. Several previous studies [23], [24] proposed behavioral pricing strategy that can benefit consumers who actively participate in DR strategies even they cause peaks in different hours, and another study [25] proposed a pricing mechanism that only benefits utility companies in terms of peak alleviation. *However, the peaks are only generated by HECs; thus, why are the LECs charged higher during peak hours?* To the best of our knowledge, the current study is the first to consider LECs in the development of energy tariffs, i.e., LECs are not charged high rates. As high-peaks is generated because of HECs so, different rates are offered for all energy users based on their energy consumption, and HECs have to pay high prices during on-peak hours. Accordingly, the cost burden due to the high price in peak hours on LECs is minimized significantly.

III. PROPOSED SYSTEM MODEL

This section unfolds proposed system model, the requisite mathematical formulations, and the ELM-based load forecasting model.

In modern era, electricity services are being changed from traditional grid system to smart grid system in which two way flow of communication data and electricity between utility and customer is possible. Electricity consumers can participate in electricity management thus can affect the grid stability, demand response program and electricity cost. A win-win pricing scheme has always remained a dream and various pricing schemes have been proposed by research community in this regard. Primary goal of this study is to propose a fair pricing scheme that reduces energy costs for LECs. Energy users are broadly categorized based on their power consumption, i.e., HECs and LECs, which are denoted by *hec* and *lec*,

TABLE 1. Residential energy tariff offered by Multan Electric Power Company (MEPCO), Pakistan [28].

Category	Load		Price (PKR/kWh)	
	Upto 50 kW		4	
Sanctioned load <5kW	Beyond 50 KW	1-100 kwh	9.52	
		101–300 kwh	12	
		301–700 kwh	15	
		>700	16	
Sanctioned load =>5kW	ToU		ON-peak	OFF-peak
			16	10.50

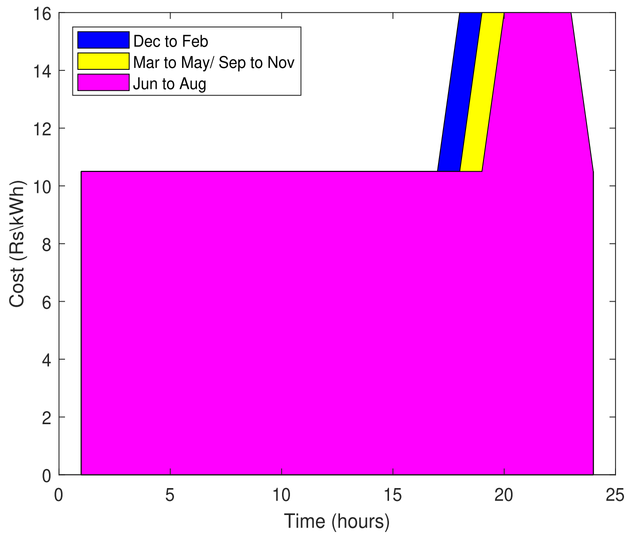


FIGURE 1. Season-based TOU in Pakistan [31].

respectively. We denoted a single home as h and $h \epsilon [H] = \{1, 2, 3, \ldots, H\}$. Here, each individual house has n different electrical appliances $app = \{1, 2, 3, \ldots, \mathrm{n}\}$. In time period t, each smart home has a specific energy demand, where one time slot is represented by $t \epsilon [T] = \{1, 2, 3, \ldots, T\}$. In this study, we consider 24 hours (single day). We assume a similar energy tariff is offered to all houses in any hour [27], which is presented by $\lambda(t)$. Here, we consider the ToU pricing tariff from MEPCO Pakistan [28], which is shown in Table 1 and Fig. 1. The target problem and mathematical modeling are described in the following section.

A. PROBLEM DESCRIPTION

The authors of [29] and [7] explored different threshold-based policies to alleviate peak power consumption. The authors of [29] employed a strategy for smart homes where energy consumers consume energy only when the tariff is less than the desired threshold. In [7], the authors extended the exploration in [29] by adopting a policy (threshold) demanded by the user. Here, if a user demands a specific amount of energy υ at specific time t, the request is satisfied if and only if it is less than the desired threshold. Furthermore, the energy demand exceeding the desired threshold is delayed to future time slots. However, such a strategy is impractical because it compromises user comfort [30]. Energy users demand access to energy as required and do not want to compromise comfort.

The main concern in our exploration is *"If LECs are not the cause of peak creation, why should they bear high energy costs for their small power consumption even in peak hours"*. Thus, we propose a novel FPS that benefits LECs in terms of minimum cost and does not disturb the interests of utility companies.

B. PROBLEM FORMULATION

The demand of the electricity of each user in time interval t is denoted by d. Energy price λ at any time instance t affects electricity demand d, calculated as:

$$d(h) = (app \sum_{app=1}^{n} (\alpha) \ \times \tau), \tag{1}$$

where $d(h)$ represents the electricity demand of a smart home. Consider that the $app(\alpha)$ indicates appliances that are "ON," and τ represents the power ratings of these appliances.

The aggregated demand of the electric load for all high and low electricity users at a specific time instance $t$is expressed as follows:

$$\gamma(t, \lambda) = \{dh1(t, \lambda),\ dh2(t, \lambda),\ dh3(t, \lambda), \ldots,\ dH(t, \lambda)\}, \tag{2}$$

where $\gamma(t, \lambda)$ represents the total electricity demand at time slot t with price λ for all considered smart homes. Here, $\{dh1, dh2, \ldots, dH\}$ represents the electricity demand of smart homes $\{h1, h2, \ldots, H\}$, respectively.

Based on the electricity demand of the residential area, the utility company advertises the 24 prices for the next 24 hours (a day) $\lambda = \{1, 2, 3, \ldots, 24\}$. The prices for 24 hours are divided into 3 major blocks $\{b1, b2, b3\}$. The $b1$ indicates on-peak (high price) intervals and $b2$ indicates off-peak (low price) slots. Whereas, the mid-peak intervals are indicated by $b3$, in which the energy price is lower than on-peak and higher than $off - peak$ hours. Normally, the utility advertises three different prices $\lambda 1$, $\lambda 2$ and $\lambda 3$ for the different blocks $b1$, $b2$ and $b3$, respectively. Nonetheless, in Pakistan, the ToU consists of only 2 blocks which are $b1$ (on-peak) and $b2$ (off-peak), as presented in Figure 1 [31]. Since, this study employs case study of Pakistan, therefore, two blocks of ToU, on-peak and mid-peak, are considered for implementations. For each peak block, the energy demand can be modeled as follows:

$$X_b(t) = \mu b + \varepsilon b(t), \quad b = \{1, \ldots, B\} \tag{3}$$

where μb is the average value during the b^{th} block, and $\varepsilon b(t)$ indicates time-dependent error. We know that the ToU scheme in Pakistan only two blocks, i.e., off-peak (00:00 to 19:00 and 23:00 to 24:00) and on-peak (20:00 to 23:00), as shown in Figure 2. The electricity demand of various residential users is shown in Figure 4.

The electricity cost that is paid by each energy user is calculated as,

$$bill(h) = \left\{ \sum_{t=1}^{T} \sum_{dh=1}^{dH} \times \lambda(t) \right\} \tag{4}$$

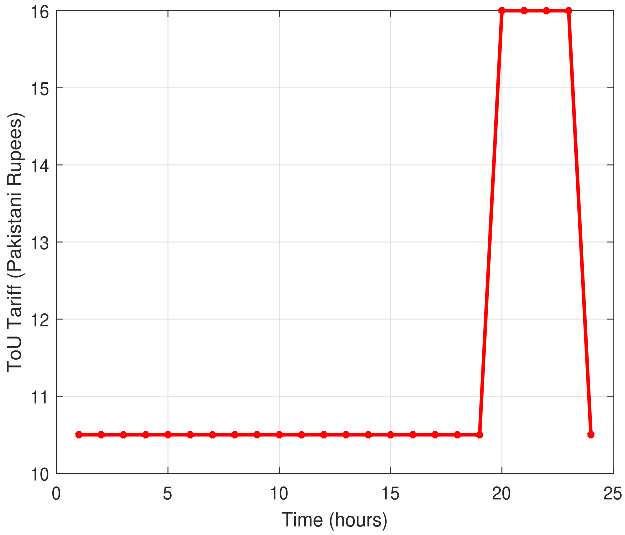


FIGURE 2. Standard ToU (July, 2019 [6]).

In this equation, the $bill(h)$ indicates the energy cost of every smart home and $\lambda(t)$ indicates electricity price at any time interval t. The price λ is applied for whole day except the intervlas belong to block $b1$. In the equation below, a fair pricing scheme (FPS) is presented. The FPS helps in the cost reduction for the LECs in equation 5.

$$FPS - lec = \{b_0 + (\lambda 1 - 0.5 \times (\lambda 2)) + \lambda 2\} \tag{5}$$

In the above equation 5, the $FPS - lec$ indicates the pricing scheme for LECs in the smart community. The term b_0 indicates the basic price, which is paid by every electricity user for tax and service cost. that is also dependent on total electricity demand. Consider that the $\lambda 1$ and $\lambda 2$ indicate the cost for on-peak and off-peak intervals, respectively. In our proposed FPS, the electricity cost in on-peak slots for the low electricity user is determined as $\{\lambda 1 - 0.5(\lambda 2)\}$, to compensate the LECs.

The new FPS for HECs is defined in equation 6.

$$FPS - hec = \{b_0 + (\lambda 1 + 0.5 \times (\lambda 2)) + \lambda 2\}. \tag{6}$$

Here, 6, $FPS - hec$ is the HEC price. Additionally, a penalty cost $\{\lambda 1 + 0.5(\lambda 2)\}$ for HEC is included in on-peak hours as they contribute more in peak generation.

According to the new fair pricing scheme adopted in this work, in $on - peak$ hours, the higher prices will be charged from high energy consumers only, instead of the whole community. Since the peaks are created because of the high consumption of HECs so, in our study aims to minimize energy cost for LECs using the below equation.

$$Min \left\{ \sum_{h=1}^{H} \sum_{t=b1=1}^{bn} \sum_{dh=1}^{dH} \times (\lambda(t)) \right\}$$
$$s.t: \ \forall\, t \in [b1], \ h \in LECs, \tag{7}$$

In above equation, the $b1$ indicates the $on - peak$ block in a given day. The factor bn indicates the last hour of the block $b1$. The application of these equations leads to cost reduction for LECs. The high energy consumers will pay a higher price in the peak hours since the peaks are generated because of their higher energy consumption. Alternatively, We can express our objective function of Equation 5 in the following way.

$$Min \left\{ \sum_{h=1}^{H} \sum_{t=b1=1}^{bn} \sum_{dh=1}^{dH} \times (\lambda 1 - 0.5(\lambda 2)) \right\}$$
$$s.t: \ \forall\, t \in [b1], \ h \in LECs, \tag{8}$$

where, new pricing scheme is employed as presented in equation 5. By applying our proposed new FPS, it is guaranteed that time interval t is within the range of $b1$ block and the home h is the LECs. It is also guaranteed that the penalty is added for HECs for maximizing their total cost. The energy cost of HECs can be determined using equation 9.

$$bill - hec = \left\{ \sum_{h=1}^{H} \sum_{t=b1=1}^{bn} \sum_{dh=1}^{dH} \times (\lambda 1 + 0.5(\lambda 2)) \right\}$$
$$s.t: \ \forall\, t \in [b1], \ h \in HECs. \tag{9}$$

A penalty cost is added in the above equation for HECs in on-peak duration by applying equation 6. We should note that energy price in off-peak intervals is determined in a similar way for both the low and high energy consumers using equation 4.

C. FORECASTING MODEL

Many forecasting models have been used in various studies [32]–[34] for load prediction. In this study, we have used an ELM forecasting model for time-series load prediction and further, segregation of LECs and HECs on the basis of a reliable load prediction. This section explains the ELM in a sufficient detail. In addition, this section describes the parameters of the load forecasting model. ELM belongs to the feed-forward neural network (FNN) family, which is adopted for regression, classification, compression, clustering, sparse approximation, and feature learning tasks with a single hidden layer, whereas a hidden node's parameters do not need to be tuned. The ELM is a three-layer NN that can approximate the complex non-linearity of data [35], [36]. ELM is a new learning method having higher performance. Implementation of generalized single hidden layer FNN with ELM has gained huge attention of research community. The ELM completes the learning procedure in two steps, where the input weights and hidden biases are initialized randomly as the first step. Then, the output weights are computed via an inverse operation on the hidden-layer output matrix. The basic idea of ELM is that NN learning is transformed to a least-squares problem that can be solved easily and quickly [37]. Based on a training set of N samples (xi, di), the single hidden-layer FNN (Figure 3) can be formed as mentioned in [37]:

$$\sum_{j=1}^{n} \beta_j g(w_j.x_i + b_j) = o_i, \quad i = 1, \ldots, N. \tag{10}$$

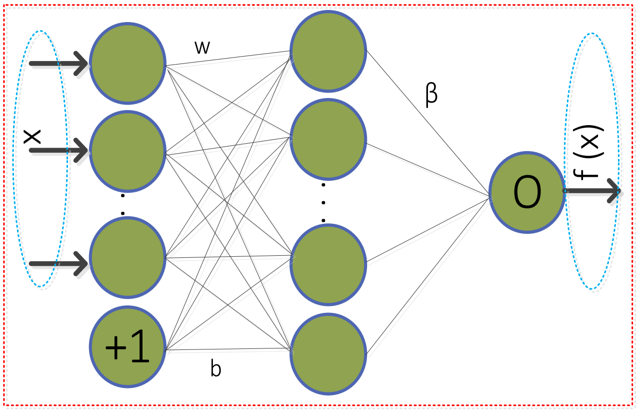


FIGURE 3. Single hidden-layer FNN.

TABLE 2. Parameters of ELM.

Parameters	Value
Function name	XGB Classifier
No of hidden layers	70
Activation function	Tan h
Propagation	Back propagation
Number of jobs per Iteration	1
Learning Rate	0.1
Random state	0

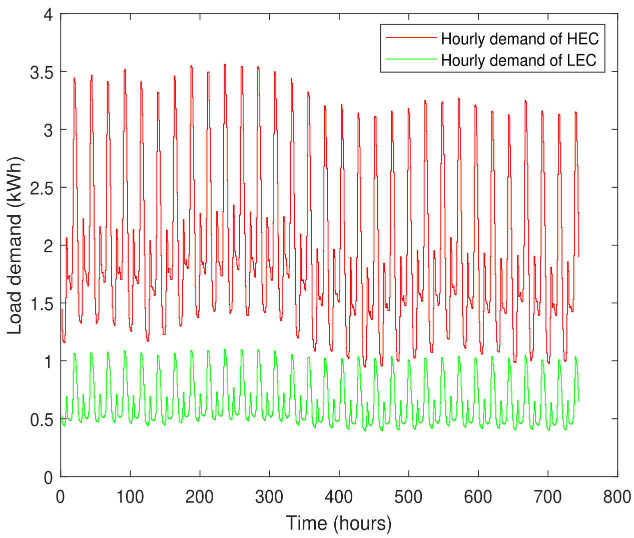


FIGURE 4. Power consumption of HEC and LEC for the month of July.

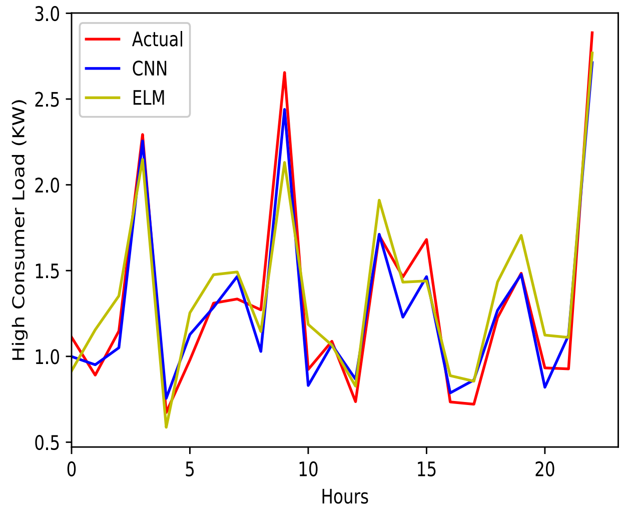
where, x_i and d_i denotes input pattern and desired output, respectively. On the contrary, $g(.)$ denotes activation function, n shows number of hidden layers, and actual output is denoted by o_i. Furthermore, w_j, β_j, and b_j show input weight, output weight, and hidden bias, respectively.

If the training error is 0, we can say in this way:

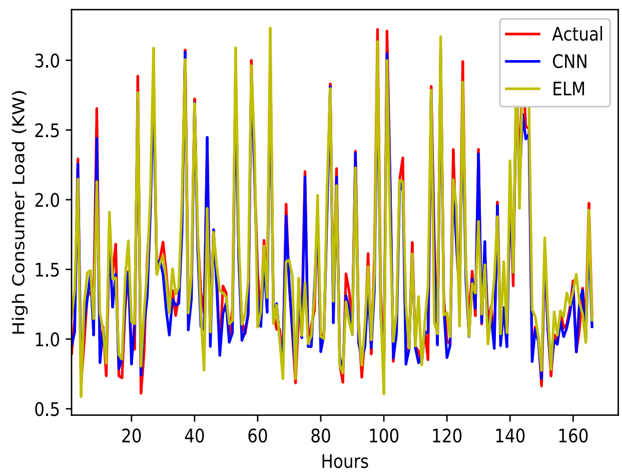
$$\sum_{j=1}^{n} \beta_j g(w_j.x_i + b_j) = d_i, \quad i = 1, \ldots, N. \tag{11}$$

IV. SIMULATION SETTING AND RESULTS

Extensive simulations have been carried out on Computer System Core i7 using MATLAB 2019b for FPS mechanism



(a) Predicted load of HEC for one day

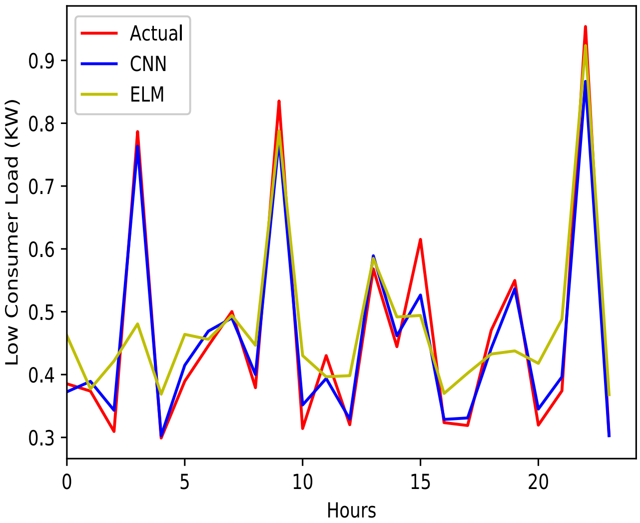


(b) Predicted load of HEC for one week

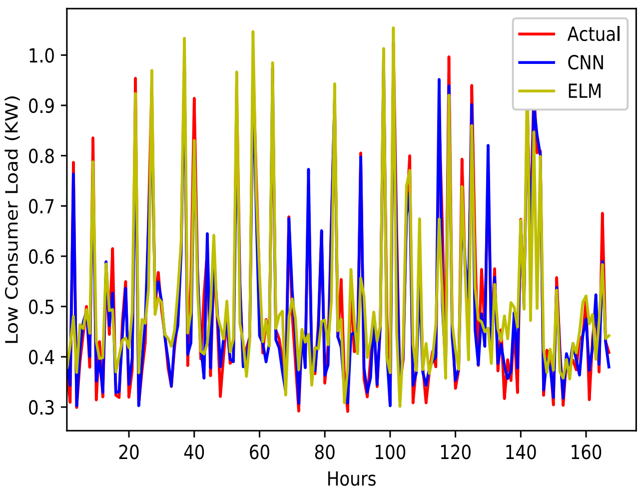
FIGURE 5. Electricity load forecasting for high energy consumers using ELM and CNN.

and Python version 3.6 is used to develop load forecasting model. This section will discuss in detail simulation results along with achievements of the study.

In this study, to confirm the performance of the proposed FPS mechanism, it is assumed that there is a single energy provider and two types of energy consumers, i.e., HECs and LECs. Unlike a previous study [6], here, we first perform load forecasting to categorize homes as HECs or LECs by using ELM and then its forecasting results are compared with the forecasting results of convolution neural network (CNN) to prove its supremacy, as shown in Figures 5, 6 and 9. Here, it is important to note that we have performed time-series load forecasting and we have ignored other parameters, i.e., indoor temperature, outdoor temperature, humidity, wind speed, etc. Then, a novel FPS is developed based on the load demand. For simulations, datasets were taken from HEC and LEC homes [38]. We implemented the proposed load forecasting



(a) Predicted load of LEC for one day



(b) Predicted load of LEC for one week

FIGURE 6. **Load forecasting for LEC using CNN and ELM.**

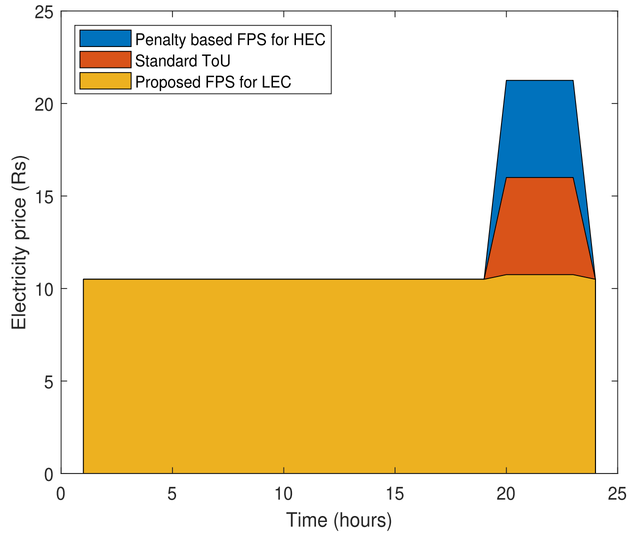


FIGURE 7. **ToU tariff and our fair pricing scheme for both types of consumers, i.e., LECs and HECs.**

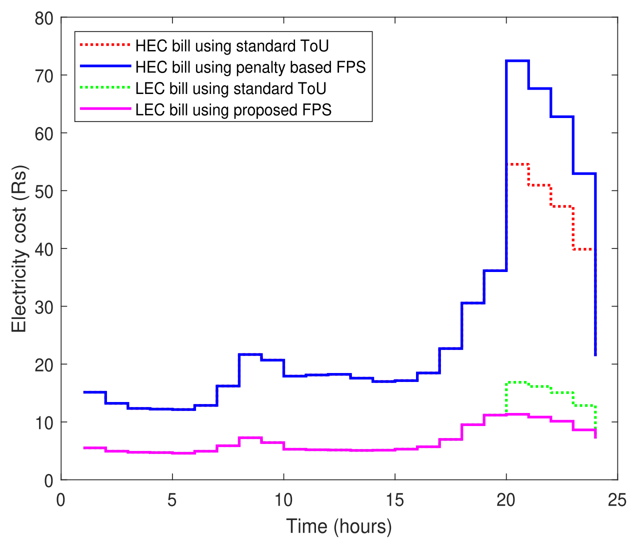
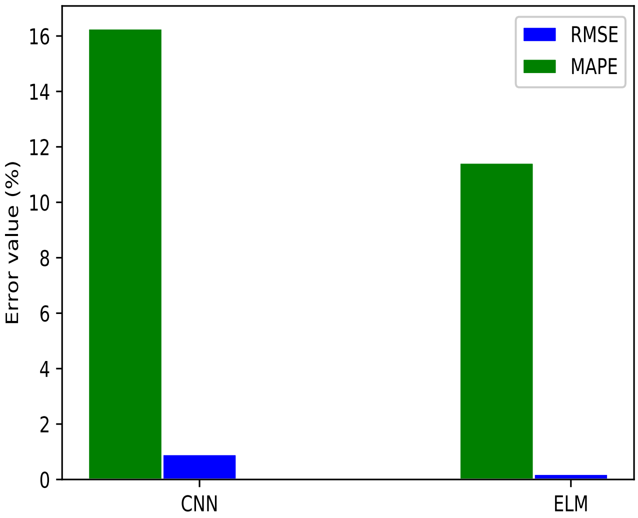


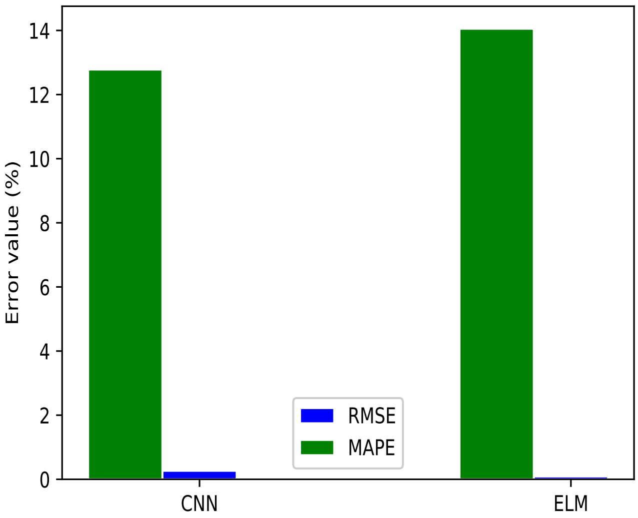
FIGURE 8. **Per hour cost paid by LEC and HEC by employing ToU and our proposed FPS.**

model for a single day and a week to evaluate its performance. Then, the FPS mechanism for LECs and HECs is developed based on the load forecasting. In addition, we employed the ToU tariff [31], which only has two blocks, i.e., off-peak and on-peak blocks. Note that the adopted ToU varies seasonably (Figure 1).

Here, the primary goal is to minimize the electricity bills of LECs because they do not contribute to high-peak creation. The energy consumption of LECs is less than that of HECs (Figure4). Figure 4 shows the load demand for LECs and HECs for the month of July [38]. According to the ToU pricing mechanism, energy providers announce a single rate in any time interval for all consumers; however, the same price for on-peak (high price) hours is charged to LECs; thus, the pricing distribution is not equitable. To address this drawback of the current ToU pricing mechanism, we first perform load forecasting, and then we apply the proposed FPS mechanism to provide financial benefit to LECs. Figure 5 shows the load forecasting of HECs for a single day (5a) and one week (5b). Figure 5 shows that the proposed ELM-based load forecasting method provides higher accuracy. Accordingly, Figure 6 shows the load forecasting for LECs. Based on the load forecasting, we have proposed a novel fair pricing scheme that is shown in Figure 7, which presents three various prices, i.e., ToU for LECs, penalty-based ToU for HECs, and standard ToU. As can be seen, the standard ToU does not differentiate between HECs and LECs because the energy rates are equal for both types of energy users. Nonetheless, the proposed FPS mechanism distinguishes between LECs and HECs, where the energy rate is high for HECs, i.e., 16.00 (Rs/kWh) compared to LECs that is 10.75 (Rs/kWh) in on-peak times (proposed ToU for LECs is shown in yellow). In contrast, a penalty cost is incurred in HECs' price during on-peak hours, which is shown in



(a) Error value of lod forecasting models for high energy consumers



(b) Error value of lod forecasting models for low energy consumers

FIGURE 9. MAPE and RMSE using CNN and ELM.

Figure 7. Accordingly, HECs must pay additional costs during on-peak hours because these users cause peak creation.

Note that the proposed FPS mechanism is based on consumer energy demands. If a consumer demands low energy, then incentive-based FPS (low price) is applied; otherwise, a penalty-based energy price (high cost) is charged to specific consumers. In this study, we have categorized LECs and HECs based power load forecasting, as shown in Figures 5 and 6. Figure 8 shows the hourly energy cost paid by both LECs and HECs using both energy tariffs, i.e., the standard ToU and the proposed FPS mechanism. As can be seen, the HECs pay a higher price in on-peak times (20:00 to 23:00), and, in contrast, LECs are charger lower rates in on-peak hours (energy cost of LEC while using proposed FPS is lesser than using standard ToU). Accordingly, LECs can save 11.0075%, and HECs will pay more. Table 3 compares energy bills for both LECs and HECs.

TABLE 3. Comparative analysis.

Pricing Scheme	HEC bill (PKR)	LEC bill (PKR)	Savings by LEC
Standard ToU	564.3206	181.5322	0
Proposed FPS	627.5313	161.55	11.0075%

Eventually, to validate the proposed load forecasting model, we performed RMSE and MAPE tests to evaluate the error value of both algorithms, i.e., the CNN and ELM. Figure 9 shows the error values of the ELM-based algorithms. Figure9a shows the error value for the forecasting load of LECs. As can be seen, the ELM has lower error values in terms of RMSE and MAPE, as compared to the CNN technique. Accordingly, the ELM also shows high performance in load forecasting of HECs, as shown in Figure9b. As shown, the RMSE of ELM is lower than its counterparts; however, MAPE is a little bit higher than that of the CNN while load forecasting for HECs.

V. CONCLUSION

In this paper, we have discussed the inequitable ToU energy pricing mechanism, where high prices are charged during on-peak times to all electricity users, i.e., both LECs and HECs. However, peaks are only created by HECs; thus, such users should pay higher costs. Therefore, we have developed an ELM-based load forecasting model to ensure day-ahead load demand. Then, based on the load forecasting results, we developed an FPS mechanism for electricity consumers that charges customers exactly based on their actual energy consumption, especially low rates in on-peak times for LECs and high rates with a penalty for HECs. Simulations have demonstrated that the proposed load forecasting model has higher accuracy over counterparts, and HECs are charged higher costs relative to their contribution to on-peak formation. In contrast, LECs receive a financial benefit of up to 11.0075%. Finally, using the proposed FPS mechanism, the total revenue of the utility company remains unchanged.

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