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A Novel Load Scheduling Mechanism Using Artificial Neural Network Based Customer Profiles in Smart Grid

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Abstract: In most demand response (DR) based residential load management systems, shifting a considerable amount of load in low price intervals reduces end user cost, however, it may create rebound peaks and user dissatisfaction. To overcome these problems, this work presents a novel approach to optimizing load demand and storage management in response to dynamic pricing using machine learning and optimization algorithms. Unlike traditional load scheduling mechanisms, the proposed algorithm is based on finding suggested low tariff area using artificial neural network (ANN). Where the historical load demand individualized power consumption profiles of all users and real time pricing (RTP) signal are used as input parameters for a forecasting module for training and validating the network. In a response, the ANN module provides a suggested low tariff area to all users such that the electricity tariff below the low tariff area is market based. While the users are charged high prices on the basis of a proposed load based pricing policy (LBPP) if they violate low tariff area, which is based on RTP and inclining block rate (IBR). However, we first developed the mathematical models of load, pricing and energy storage systems (ESS), which are an integral part of the optimization problem. Then, based on suggested low tariff area, the problem is formulated as a linear programming (LP) optimization problem and is solved by using both deterministic and heuristic algorithms. The proposed mechanism is validated via extensive simulations and results show the effectiveness in terms of minimizing the electricity bill as well as intercepting the creation of minimal-price peaks. Therefore, the proposed energy management scheme is beneficial to both end user and utility company.

Keywords: demand side management; mixed integer linear programming; artificial neural network; Inclining block rate; rebound peaks

1. Introduction and Motivation

The demand of electricity continues to rise due to a rapid increase in consumption trends. The future predictions with the current demand of electricity are very alarming because of the immense increase in the power demand. It is therefore observed that current energy resources seem insufficient to fulfill the sustainable energy goals with reduced CO_2 emissions. According to the report of the International Energy Agency (IEA), the power demand rises by 1.3% per year to 2040 [1].

Furthermore, it is also observed that by 2050, the world's power demand is expected to increase 50% [2,3]. In the meantime, due to the large depletion of conventional energy resources and existence of older control technologies, it is difficult to manage distributed and variable energy resources (VERs). Thus, it is desirable to utilize and implement energy management and control technologies to efficiently manage residential load with the integration of VER to alleviate burden on conventional energy resources. On the other hand, to protect the environment and climate change from heavy CO_2 emissions due to massive utilization of conventional energy resources, it is required to either optimize the energy consumption trends or to integrate VER or the combination of both [4]. Because, studies show that it is more beneficial to develop hybrid energy management solutions [5]. In doing so, the load management problem can also be solved at the micro-grid level by investigating the energy consumption of individual residential consumers rather than aggregated demand.

A new electricity grid called Smart Grid (SG) has introduced market based DR programs to facilitate a home energy management system, with the help of two way communication between utility and consumer [6]. Electricity generation companies as well as the regulatory agencies in a day-ahead market in an interconnected fashion are constantly making investments in developing smart electricity structures that will decrease power consumption with flattening of the demand peaks [7]. Flattening of demand, which is also known as peak shaving, implies the reducing or shifting of the load during on-peak to off-peak hours [8]. For this purpose, different DR programs including price (i.e., real time pricing, day-ahead pricing, time of user pricing, critical peak pricing) and incentive based are being adopted by numerous researchers to help in managing the power demand by taking into consideration user welfare objective. In literature, different types of dynamic pricing mechanisms have been discussed, for example, References [9–13]. In Reference [11], an incentive-based pricing algorithm is proposed to motivate consumers to shift their demand from on-peak to off-peak hours with the objective of cost reduction. Another work reported in Reference [13] used a history based pricing algorithm that takes optimal pricing decision by learning the user demand behaviors. Other works [14–18] discussed different game-theoretic algorithms for demand side management in smart grids. By taking data sets of moderate sizes, the effectiveness of proposed works have discussed. Recently, several pricing models based on a user's optimal demand as a function of price are also discussed in References [19–21]. In some previous studies, several control techniques have been discussed to schedule the power demand for peak reduction in the distribution system [12]. These include RTP based on a simulated annealing algorithm [12], load shaping using energy storage system [10] and multi-unit auction algorithm [22], and so forth. Other researchers have worked on the peak shaving without providing any pricing incentives to the customers [23–26]. Another work provides a solution to load management problem [25,26] using an incentives based threshold policy. Furthermore, some pricing algorithms [27,28] focus on revenue maximization rather than peak shaving. In conclusion, the most of the literature [2–28] discussed the load management problems using optimization based control mechanisms by taking into consideration user and utility objectives. Some works focused on the consumer side through providing various incentives to encourage them to participate in DR programs. Others focused on the utility side to flatten the high peaks through the involvement of end users. However, due to dynamic power consumption trends and lack of motivation to adopt on-site solar powered energy sources, the residential load management problem still needs to be considered in such a way to facilitate both utility and end users. Furthermore, ANNs have been large-scale implemented in power system [29]. Many works have been reviewed on advantages and drawbacks of using of ANNs applications in power system in contrast with the other conventional methods. Major aspects of the ANN is of planning, expansion, development and load forecasting of the power system. ANNs are very fast and capable of direct coupling with electrical system to data acquisition without time constraints. A recent study shows that short-term load forecasting makes up a greater percentage (62%) of the research work. Another problem related to lack of participation of end users in DR, which is identified from the literature, is the homogeneous electricity tariff. Because the customers who receive services from single distributed system operators are assumed to receive a specific price signal rather than different for each user. Technically, it is also impossible to provide a separate electricity price signal to each individual user, depending on consumption level. In a response, the end users maintaining a balanced load consumption profile would be effected. In the contract, the other users would be charged unfairly without considering other objectives. So, there needs to be a mechanism to provide fair electricity pricing tariffs to all participating customers without disturbing the objectives of other customers. Thus, by keeping in view the aforementioned problems and limitations, we have developed a novel load management and pricing mechanism to facilitate utility and end users, particularly. The proposed work is based on a DSM mechanism to manage the residential energy demand with the twofold objective; providing a customized price to each residential user and to flatten the peaks in the overall system. This objective is carried out by making use of "*demand awareness*" as acquired from smart metering. The deterministic and heuristic algorithms to optimally devise the electricity price signal are used and their performance is analysed. The key contributions of this work are as follows:

1. A household user flexibility model based on utility and user objectives is presented. Then based on this model, a mathematical framework for calculating LBPP is provided for scheduling. The LBPP works on the basis of a historical load demand profile (suggested load profile) which is calculated by ANN using historical data of load. The suggested load profile acts as a low tariff area beyond which the load will be charged high prices and vice versa. We also proposed a load predictor which calculates the mean absolute percentage error for the controller's suggested low tariff area for a particular user (comfort).
2. However, before using LBPP to calculate energy consumption and prices, a combination of RTP and IBR is used to schedule the load with respect to the time and demand of all users.
3. To manage the load demand for customized electricity tariff, energy storage system of capacity Q is formulated and used in such a way to incentivise user and to reduced the rebound peaks.
4. The final optimization problem is formulated and solved by using different optimization algorithms (heuristic and deterministic). The results are compared in order to analyse the performance in terms of cost and PAR reduction. As the proposed model is based on the user's flexibility, depending upon which, each user gets a different price signal; therefore, the cost and rebound peaks are significantly reduced.

2. Background Literature

Many researchers have considered the application of energy storage to make demand patterns smooth [30], considering the impact of storage and solar photovoltaic (PV) systems. The limitation of survey study has been observed [2–28]—that the storage was used to increase individual-consumption, instead of focusing on rebound peak shaving. In other contributions, peak is shaved with some control algorithms including incentivised mechanism. In Reference [31], the authors used a Con Edison demand tariff for the energy dispatch for peak reduction in residential consumers' demand. Customers are charged according to the maximum demand during a period of one month with some building-based energy storage system. This study also discussed different storage techniques regarding economic point of view. The storage system used to limit the peak demand under a threshold policy can help minimize the electricity bill of end users. The work reported in Reference [32] gives a detailed overview of optimal sizing the energy storage system for the distribution system peak shaving. The results show that 5 kWh/2.6 kW for low consumption houses, and 22 kWh/5.2 kW for high power consumer are adopted. The authors also found that few cycles are needed for peak flattening. Furthermore, the system has a small life time due to limited battery backup. For the distribution system, energy storage is also considered within transmission network [33], in which control algorithms were used to optimize the size and placement of storage batteries for the electrical system enhancement. This required a new design of transmission system and storage system for the whole network. The result shows how the deferral of construction of new transmission line is suitable in a market-driven environment if storage systems are connected to certain nodes. In References [34,35], the authors examined the response of residential consumers against the time of use pricing scheme and results show that a considerable amount of consumers could be shifted from peak to off-peak hours if some incentives (i.e., reduction in bill) are applied. For this purpose, coordinating DSM actions from highly distributed electricity users are required. The work reported in References [36,37] incorporates ANNs fixed by genetic algorithm to implement a DSM controller for residential users. A distributed home automation system in which the controller comprises of scheduler and neural network system that coordinates with the utility and local PV generation having a storage system to maximize the local energy performance. In this system, individual appliances equipped with a neural controller, that is, ANN and local generation in a distributed manner, and are free to self-organize their output on the basis of preference and predicted generation. The authors of Reference [38] uses the ANNs to facilitate the implementation of DSM programs. The classification feature of the ANN is used in an intelligent environment to classify the load curves of each user from pool of load data generated by dynamic networks. With the prior greater knowledge of consumer habits, the optimization of the electrical system is carried out with the classified load data and by implementing DSM policies to each class to make it more sustainable and efficient. ANN is used to assist service providers to discover the future rates to purchase energy from its customers to balance energy fluctuations in the power system. To cope with the future uncertainties in a power system due to its inherent nature, a supervised learning in deep neural networks (DNNs) is used to predict the real time unknown load demand and wholesale market prices instead of day-ahead to incentivize the active subscribed consumer [39].

The work reported in Reference [40] discussed the individualized demand aware price policy, using MILP to incentivise the consumer to follow the suggested power profile with a storage system of particular capacity. Here, each user receives a different price signal in order to reduce high and rebound peaks in the electrical distribution system where demand awareness is exploited with advance metering infrastructure. Using the case study of residential power consumer along with ESS, the individualized approach is shown the advantage that load factor of the system is improved, even some users with the same price policy are present. The mentioned price policy has more efficient results over the global price schemes with some advantages including improved voltage and reduced network losses. There exist DSM approaches which use a direct load control (DLC) technique, which is basically the user privacy invasion schemes. In that program, market operator directly actuates the industrial as well as residential loads based on network state [33,34]. This type of control required a heavy investment for the communication and control technologies for each user. The work in References [41,42], suggested another decentralized game theoretic approach to minimize the PAR and cost of consumer, and through blockchain energy trading is made transparent with smart contracts to overcome the stress on overall system. The PV system with storage elements is incorporated in the proposed model to facilitate a DSM program, so that the consumers can schedule their demands with a higher degree of freedom to maximize their comfort. Unlike other approaches, Reference [43] presented a hopping DR scheme which is actually a heuristic optimization technique that has low time complexity and improved consumer's privacy by notably reducing communication between loads and grid. The proposed scheme significantly reduces the average PAR, energy prices and required frequency bandwidth for communication purposes as compared with DLC approach. The authors of Reference [44] showed the effectiveness of the proposed Markov decision (MDP) process based profit maximizing DR approach in which power supply demand imbalance is tackled in each hour by rescheduling the energy demand. High time complexity of the algorithm due to continuous state, is improved by transforming MDP problem into LP problem. The proposed algorithm significantly maximizes the energy profit compromising performance compared to the greedy algorithm without taking PAR into consideration. A DAP based DR methodology minimizes the cost of large residential users. A load aggregator for scheduling is proposed which classifies each demand block of specific operation time, expected delay and required consumption level by aggregating the residential appliances. The proposed scheme comprises multi-class queuing system in which consumers have to experience some waiting time [45]. Many previous studies include the peak shaving algorithms, which took more processing time like deterministic methods and LP. Here we investigate the different solvers with their default and user defined algorithms to compare the cost reduction, PAR and the processing time of the controller. This study used a meta-heuristic technique, that is, a genetic algorithm in consideration for the comparison as mentioned earlier. Short-term load forecasting by the neural network is also done to describe the user's comfort which was previously compromised. In the proposed work, we do not include the appliance categorization and optimal sizing of the storage system, which has been previously investigated by others, for example, in References [46,47].

3. System Model

We consider a hybrid energy management system model with U users, such that users are powered by a power grid and energy storage system (Figure 1). We assume that the entire operation is carried in discrete and finite time slots with $0 \leq t \leq T, \forall t \in \mathbb{Z}^{+}$. Furthermore, all operations are supposed to be completed in t slots. It is also understood that communication technologies play a vital role in transmitting and receiving messages in a secured way. Thus, it is assumed that all the messages are securely and timely exchanged between end users and utility premises. Regarding load management, home energy management controllers are normally used to schedule the appliances in such a way to reduce the cost and PAR. For the better results in optimization of the power demand of respective loads, the considered appliances are categorized mainly into shiftable and non-shiftable classes. In this way, the operational time of some loads can be shifted from on-peak hours to off-peak hours. While, some loads can not be interrupted during their operation time due to their critical nature. The further details of appliances are discussed in Section 5. However, prior to discussing the inputs and outputs control parameters, we first define the user flexibility as follow:

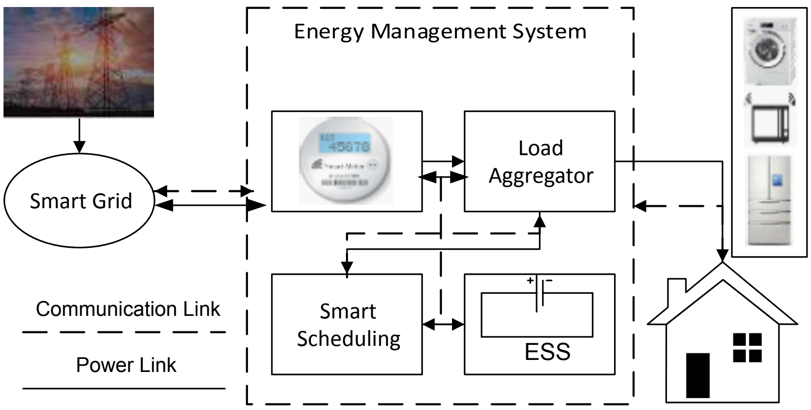


Figure 1. Architecture of Smart Home.

3.1. *Household User Flexibility Model*

This section discusses the user flexibility model based on proposed load based pricing policy (LBPP). Because the suggested individualized power profile (defined as the baseline power of each user beyond which the power consumption cost would be charged on the basis of RTP+IBR policy [40]) from LBPP is applied to all users with a periodicity (every day). Such a pricing policy is comprised on individualized electrical power profiles, confined by region ($\mathrm{P}_{u,l}$, $\mathrm{P}_{u,h}$), which are also referred to as low tariff areas. The resulted electricity tariff for a user u, which is basically an LBPP pricing policy, is obtained based on lower b_l and higher b_h price factors, respectively. In a response, if any user u consumes power by strictly following LBPP whose suggested output in time-slot t is P_u, then that particular user will pay a lower price b_l for $P_u \in [\mathrm{P}_{u,l}(t), \mathrm{P}_{u,h}(t)]$. Otherwise, that user will be charged a higher price b_h. It is worth noting here that the proposed tariff is based on the combination of two prices; IBR—which depends on used power—and ToU—which varies with time—defined as a low tariff area for each user participating in the DSM program, such that $\mathrm{P}_{u,l}(t)$, $\mathrm{P}_{u,h}(t)$ where the individualized price (i.e., the upper bound of the low tariff varies with the consumption limit). Figure 2 shows the suggested upper bound of the low tariff area $P_{u,h}(t)$ for a user u in contrast with the actual demand of the user $d_u(t)$ and the historical power $d_u^{\sim}$(t), in the reference scenario that we will use in our experimental evaluation. As depicted in Figure 2, during the time-slot t_1 from 1 a.m. to 2 a.m., the consumer's demand is inside the low tariff area ($P_{u,h}(t) > d_u(t)$) so the low price will be applied. In contrast, during time-slot t_2 from 5 a.m. to 6 a.m., when the user's demand violates the upper bound of the low tariff area. Thus, the high price will be charged to that particular user. To be remain in low tariff area even in time t_2, the user should be flexible in order to get low price, that is, user must be capable of moving at least 1 kW of the power demand ($d_u(t) - P_{u,h}(t)$), from t_2 to t_1 (flexibility).

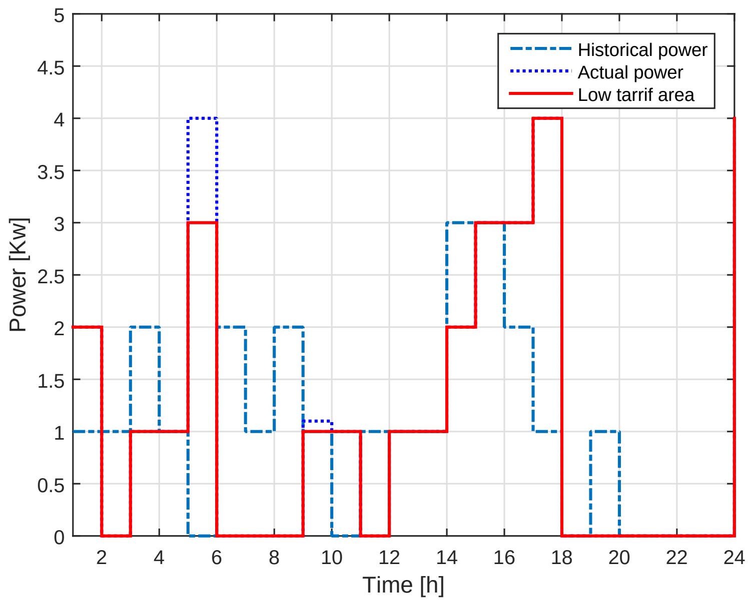


Figure 2. Historical power demand compared to power profile output by MILP solver for a single dwelling on a given day.

Now, we model the user flexibility in order to have all users inside their low tariff area by following the suggested pricing policy. For this purpose, the user flexibility can be model in conjunction with ESS which is actually a "physical" load shifting capability of user u [12]. Let a pair (Q_u,R_u) describes the user flexibility, in which Q_u defines the storage capacity (in kWh) of the ESS and R_u defines the power rate (in kW), that is the maximum power which can be delivered or stored to ESS in a particular time t. In Figure 2, to satisfy the user demand in t_2 without shifting load to t_1, it is required to have $Q_u = 1$ kWh and $R_u = 1$ kW. If user u desires to remain in low tariff area just for the first 5 h of the day, then $Q_u = 2$ kWh with $R_u = 1$ kW will be required. During the time-slot of 2 a.m. to 3 a.m., where the low tariff area is more than the user's demand, the surplus energy can be stored in ESS. This energy can be used to compensate for the exceeding demand, which is outside the low tariff area (collaborated power). In this situation, a charging and discharging value α_u of a user will be Q_u and R_u over the given time slot. In this way, there will be states for α_u, for example, for $\alpha_u^t \leq 0$, the ESS will be charged by α_u^t kW (in Figure 2 during time-slot t_1), and for $\alpha_u^t \geq 0$, discharged by α_u^t kW from ESS. Thus the $\alpha_u(t) \in [-R_u, R_u]$ denotes the limits for $t \in T$. And for $\alpha_u^t = 0$, there will be no load shifting needed (e.g., from 11 a.m. to 12 p.m.). In the next sections, we discuss the respective input and expected output parameters of the proposed system model.

3.2. Inputs

This work has certain input parameters, based on which the desired output(s) are obtained. These parameters are discussed as follows:

3.2.1. Aggregated Power

We assume that each user u has different power demand requirements of respective loads, which arrive over the time interval t with temporal variability. Each load has specific power demand P_t for a given duration Ψ. We also assume $0 \leq \phi \leq T, \forall t \in \mathbb{Z}^+$. Let τ_t be the scheduling delay experienced by load ℓ_t, with the $\overline{\tau_t}$, the upper bound of waiting time then;

$$1 \leq \tau_t \leq \overline{\tau_t}, \forall t \in T. \tag{1}$$

Thus, $[t, t+\tau_t]$ and $[t+\overline{\tau_t}, t+\tau_t+\overline{\tau_t}]$ are the earliest and latest serving time of all loads. We define;

$$\tau_t = \begin{cases} \overline{\tau_t} \geq \tau_t \geq 1; & If\ \ell \geq 0 \\ 0; & If\ \ell = 0. \end{cases} \tag{2}$$

Similarly, the average delay τ_{avg} of $\ell_t \geq 0$ can be written as;

$$\tau_{avg} = \frac{1}{T}\{\sum_{t=1}^{T} \overline{\tau_t}\}. \tag{3}$$

We use the aggregated power $P_{i,t}$ as an input in our model which ensures the base load requirements for each appliance's length of operation Ψ_i. The daily load profile of a user is computed on the historical basis considering the upper bound of the power in a certain period of time for all appliances using an aggregator.

$$P_{i,t} = E_g,\ \forall t \in T, i \in N. \tag{4}$$

3.2.2. Peak Power

For each user u over the time-slot t, the $P_{i,t}$ must be below the upper bound of power L_g set by the utility/scheduler, and may be different for each user depending on the flexibility shown by users. This constraint ensures the smoothness of power throughout the day and avoid rebound peaks in the system.

$$P_{i,t} \leq L_g,\ \forall t \in T, i \in N \tag{5}$$

3.2.3. Upper and Lower Bounds

It is required for scheduler to have lower and upper bounds on each decision variable, i.e., power must be non-negative and must be in pre-defined power limit L and must have at least d_{min} kWh on whole time T. The power rate and storage capacity of ESS is also the part of this section by keeping the state of charge, which must be equal to $1/Q$ of total capacity.

$$0 \leq (P_i) \leq L \tag{6}$$

$$0 \leq (P_i) \leq d_{min} \tag{7}$$

$$\overline{Q} \leq Q \leq \frac{b_u}{2}, \tag{8}$$

where (6) denotes the limit of maximum per hour load consumption of any user, (7) depicts minimum power required to fulfill the ongoing scheduling task, and (8) elucidates that the energy stored in backup storage units must maintain 50% of total capacity to meet the demand in a certain time period when a user violates the suggested low tariff area, respectively.

3.2.4. Electricity Tariff

We assume that if aggregated power demand d_u of user u is below the power threshold P_{th}, then the market price b_l is applied. Otherwise, a higher electricity price b_h is applied when demand exceeds this threshold. This cost factor is also known as a penalty to prevent the scheduler from shifting most power demand to least electricity price intervals. The modified tariff $\sqcap$ used in the proposed work is written as;

$$\sqcap = \begin{cases} b_l; & if \rightarrow \quad d_u \leq P_{th} \\ b_h; & if \rightarrow \quad d_u \geq P_{th}. \end{cases} \tag{9}$$

The proposed work introduces a penalty function ϕ_u for user u, which will force the user to stay under prescribed threshold of power to minimize the exceeding demand Δ^t = $d_u - P_{th}$, i.e.,

$$\phi^t = \Big\{ [d_u - P_{th}], \sqcap \Big\}. \tag{10}$$

Therefore, the cost minimization objective function subject to load balancing for user u can written as:

$$\begin{aligned} \text{P1} \qquad & = \min \Big\{ \sum_{i=1}^{N} \sum_{t=1}^{24} [P_{i,t}, f_s] + \phi^t \Big\}, \\ \text{subject to:} \quad & (1) - (10). \end{aligned} \tag{11}$$

The parameter ϕ^t is designed to encourage customers to consume energy within the suggested low tariff area, so as to minimize the total cost and, as a consequence, the overall power system stability in terms of rebound peaks is improved. To further improve the comfort level of a user in terms of cost reduction, a back-up energy storage management system is used, which supports the utility as well as the user in achieving their aforementioned goals.

3.2.5. ESS Parameters

We compute the capacity Q of ESS for a user u from historical demand data such that the power variation between consecutive time-slots on average basis over all time T. On the behalf of historical demand data $d_u^{\sim}$, the capacity Q and power rate R of ESS for user u is defined as follows:

$$(Q_u, R_u) = (\tau(avg)|d_{u,t}^{\sim} - d_{u,t-1}^{\sim}|, 2), \tag{12}$$

where the expression $(d_{u,t}^{\sim} - d_{u,t-1}^{\sim})$ in (12) shows the historical load demand of a user in two consecutive hours, in order to take information about variation in demand, R_u depicts the hourly rate of power charge of a battery unit, τ is the charging rate, and the expression Q_u, R_u gives the user flexibility in terms of load shifting capability of a particular user u. The (12) ensures the user has a suggested low tariff, so that the RTP signal remains unchanged in that time slot for the user. The collaborated power, as a result of ESS in that time slot by applying charge/discharge schedule α_u^t to the input, forecasted electrical demand $\mathrm{d}_u(t)$ for all T, satisfying respective constraints. Now, the next expression (13) denotes that the exceeding power would be fulfilled through a battery storage system.

$$c_u(t) = d_u^t + \alpha_u^t \tag{13}$$

subject to:

$$c_u^t \leq P_{th}^t, \tag{14}$$

where (14) represents that user demand must be within threshold limit P_{th}^t, provided by the utility in order to avoid peaks or rebound peaks. Generally, users do not bound to consume power over the given time. Finally, the welfare function of a user for $\alpha_u^t > 0$, can be written as:

$$\begin{aligned} \text{P2} \qquad & = \min \Big\{ \sum_{i=1}^{N} \sum_{t=1}^{24} [P_{i,t}, f_s] + [\Delta^t - \alpha_u^t] + \tau_{avg} \Big\} \\ \text{subject to:} \quad & (1) - (10), (12), (13), (14). \end{aligned} \tag{15}$$

where (15) denotes the final objective function minimizing the power consumption by encouraging customers to stay in the low tariff area. In doing so, the participating customers would be charged a low price using (9), while the customers violating the low tariff area would be penalized using (10) and (11). The expression $P_{i,t}, f_s$ in (15) gives the actual energy consumption prices using the market clearing price and the expression $\Delta^t - \alpha_u^t$ gives the exceeding demand compensation function for those customers who consumed more power, and τ_{avg} provides the average load delay during the scheduling process, respectively. For the case when $\alpha_u^t < 0$, the storage unit is charged to its capacity $\overline{Q}$ by satisfying (8). Assume that user u has the opportunity to violate the P_u for the hourly demand of u. Then we fix the power rate R_u of ESS, that is, for 2 kW, in order to meet the demand capacity without purchasing costlier power from the grid source. This parameter ensures that the user's power demand remains within the upper boundary of the low tariff area. Eventually, the market price signal remains unchanged over specific time slot for that particular user.

3.3. Modeling Methodology

The proposed scheme works on the basis of two actions, which play a key role in minimizing the daily electricity cost of u. In the meantime, the proposed mechanism facilitates distribution system operator (DSO) in managing the demand and supply without heavily relying on fuel based back-up generation facilities. The first service is introduced to control the user power demand through scheduling the load or reducing the demand capacity so that the limitation from retailer can be fulfilled. The second service is the integration of the ESS system, which would provide the load shifting capability (flexibility) to the users. The estimation of ESS system capacity is done on the basis of a user's historical power profile. It, therefore, causes the greater upper bound of a suggested low tariff power profile of a user. Therefore, the output of this algorithm is in the form of individualized power profile p (i.e., different user may receive separate power profile), if they follow their suggested power over a given time. Then the operational constraints imposed or suggested by the power system are fulfilled. Furthermore, the LBPP scheme avoids the rebound peaks generated due to load shifting in traditional schemes. This is done by following the suggested load profiles which is the major contribution of this work. It is understood that load consumption trends are dynamic and difficult to predict, accurately. Therefore, finding a low tariff area for all or individualized users on the basis of historical demand data may be applicable for a specific time duration. Moreover, it is also noticed that some users can violate this constraint and their power demand may increase causing serious concerns from the users who have maintained a balanced load profile by participating in DR programs. To handle this situation, we use ANN to predict the suggested load profile in order to have users scheduling their load, accordingly. Meanwhile, they also provided the information beyond the suggested low tariff area; they will be charged a high tariff.

4. Proposed LBPP Algorithm

In the literature, different load optimization and scheduling algorithms have been proposed by numerous researchers and are being widely used [13]. Some are based on electricity cost reduction, thus facilitating the end users. Others focused on utility in providing the balanced load profile for power system stability and optimized control. There are also some works that considered both end user and utility at the same time. However, there might be trade-offs in managing the resources of both sides. In Reference [14], heuristic techniques, for example, particle swarm optimization (PSO) and genetic algorithm (GA) have been used. Although the obtained results are optimal, these algorithms took more processing time due to complexity in terms of population size and tuning parameters. This is the basic reason for selecting a mathematical programming approach in solving the proposed model, because in LP the piecewise linear nature of objective function and constrains exist in our model. On the other hand, an MILP approach can also be used in contrast with the heuristic and hybrid algorithm to make the solution more robust [13,14]. However, it is a relatively complex task to handle the variables in MILP approaches. The results presented in Section 5.1 revealed that there is not a significant change and variations in cost and other parameters, except for computational time and constraint handling mechanism. A detailed comparison among the used solver and algorithms is presented in Table 1. The optimal solution for our problem may be obtained by using a deterministic method, that is, a MILP based MATLAB solver—that is, intlinprog—which is actually a solver based approach used to optimize the results. MILP is basically an LP-based solver with branch-and-bound algorithm. The optimal solution for the main problem is obtained by dividing the master optimization problem in sub-problems and evaluated by using divide and conquer approach which is in the form of a subtree. Bounds on each nodes are evaluated linearly and are selected to maximize/minimize our function and the remaining are ignored. The robustness and improved performance of the proposed algorithm are shown in Table 1. The flowchart in Figure 3 gives a detailed mechanism of the proposed algorithm, while the general mechanism works based on the following steps:

1. Set the optimization problem as a multi-objective LP problem, minimizing high power consumption and scheduling delay subject to respective constraints
2. Get solution from LP solver (MILP e.g., Intlinprog using Matlab software)
3. Take out the the desired output from the solution of LP and analyze the cost results.

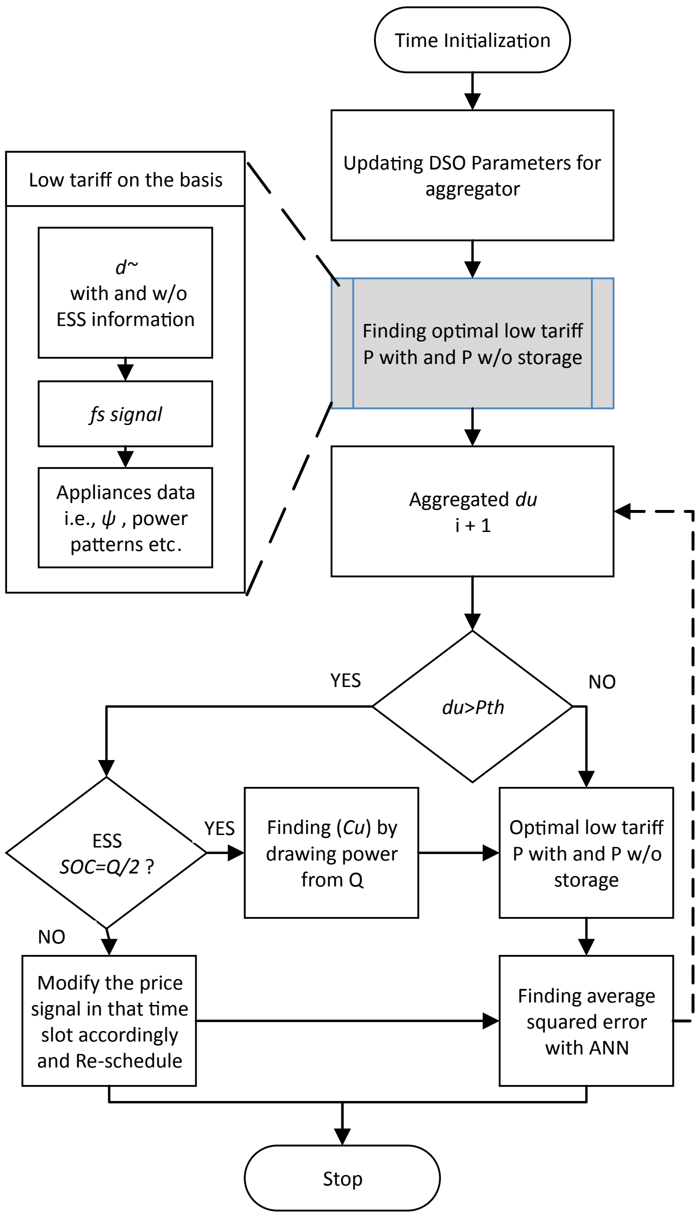


Figure 3. Flow-chart of the proposed system.

Table 1. Training Data Composition.

Parameter	Configuration
$x_1, x_2, \ldots, x_{24}$	Load profile of 24 h
$y_1, y_2, \ldots, y_{24n}$	past n pricing data
$a1, a2, \ldots, a24$	24 h load forecast

Based on the proposed algorithm, the following outputs are obtained:

- For each residential user u and time t, the P_u^t is the upper bound limit for low tariff area where F is a set of prices for each user, considered as a decision variable (in kW and \$/kW, respectively).
- For each residential user u and time t, the α_u^t denotes the charge of a battery. For example, if $\alpha_u^t > 0$, the storage unit is charging, otherwise, it would be in discharging mode where the variable b_u^t denotes the state of charge or discharge.
- For each residential user u and time t, h^t is a decision variable, which calculates the aggregated load demand for those customers who violate the upper bound of low tariff area (in kW).

The complete working detail of the proposed algorithm is explained (Algorithm 1) by assuming that the available power from the storage having capacity Q_u is α_u at time t for a particular user u where P_{th} and $\mathrm{d}_u(t)$ are the thresholds of power and user demand, respectively. We have the following cases:

Case 1. *When $d_u(t) = P_{th}$, then in this time slot, all appliances are scheduled:*
Theorem: In this case, it is expected that load demand of a particular or all users u *is within ($P_{u_{,l}}$,$P_{u_{,h}}$), such that the condition {$0 \leq d_u^t \leq P_{u_{,l}}, P_{u_{,h}}$ } is fulfilled. It is hence proved from Figure 2 that historical demand is insufficient to obtain an actual low tariff area for all users as demand trends are dynamic in nature. So, we have used ANN to predict actual low tariff area and obtained output is compared with P_u. Otherwise, if {$d_u^t \geq P_{u_{,l}}, P_{u_{,h}}$}, then ϕ^t price would be charged to* u.
Case 2. *If $d_u(t) > P_{th}$:*
Theorem: Then scheduling of appliances are done by drawing required power (i.e., $d_u(t) - ESS$) from the storage system. Otherwise by modifying pricing signal in that time slot, rescheduling is done for battery SOC≠Q/2.
Case 3. *If $d_u(t) < P_{th}$:*
Theorem: In this condition, the surplus power is stored in ESS at the cost of ζ as given in (16), which later on can be used when {$d_u^t \geq P_{u_{,l}}, P_{u_{,h}}$}. In this case, the f_s will be given to that particular user.

$$\zeta = \frac{\Theta(t-1) - \theta(t-1)}{\alpha_u(t)}, \tag{16}$$

where $\Theta(t-1)$ is the cost of charging ESS in slot $(t-1)$ and the cost of remaining energy in ESS after discharging is represented by $\theta(t-1)$ in $(t-1)$ time duration.

Algorithm 1 Proposed (LBPP) Algorithm

Require: Price signal, LOT' and power ratings of appliances, capacity of storage system
for $i \leftarrow 1$ to N_a **do**
  Schedule load using LOTs and using (1)
  for $k \leftarrow 1$ to N_b **do**
    if $\sum_{t=1}^{24} P_{i,t} \leq P_{th}$ **then**
      find P_u^t & h_t=$\sum_{t=1}^{24}(P_{i,t}$-$P_{th})$
      if b_t=Q_u **then**
        b_{t+1}=b_t
      else
        b_{t+1}=b_t
      end if
      if $b_t \geq Q_u/2$ **then**
        h_t=$\sum_{t=1}^{24} P_{i,t}$-P_{th}
        if $h_t \geq 0$ **then**
          compensate the exceeding power
          Update state of charge
        else
          Update b_t
        end if
        Modify RTEP signal in (6)
        Reschedule the load for P_u^t
      end if
    end if
  end for
end for

4.1. Outputs

The output of the proposed algorithms is the power profile p_u for all respective users u, which actually defines the low tariff area. The upper bound of the low tariff area depends on the amount of flexibility in terms of power usage by the user. This will eventually lead to different power profiles of every user, which is different over the given time t. Then based on p_u, the retailer decides whether the electricity price is low or high, irrespective to market price signal only. As a consequence, each user gets different price signal depending on (Q_u,R_u) as illustrated in Figure 4. For each user, the charge/discharge plan α_u will be the output of the algorithm, which defines the flexibility (Q_u,R_u) for that user. It is therefore sufficient for each user to schedule their load once the suggested power demand profile is obtained. Thus, the collaborated power, that is, $d_u(t) + \alpha_u(t)$ is returned to that particular user, who strives to remain in low tariff area $P_{u,l}(t) \leq P_u(t) + \alpha_u(t) \leq P_{u,h}(t)$ based on collaborative power profile, as shown in Figure 5.

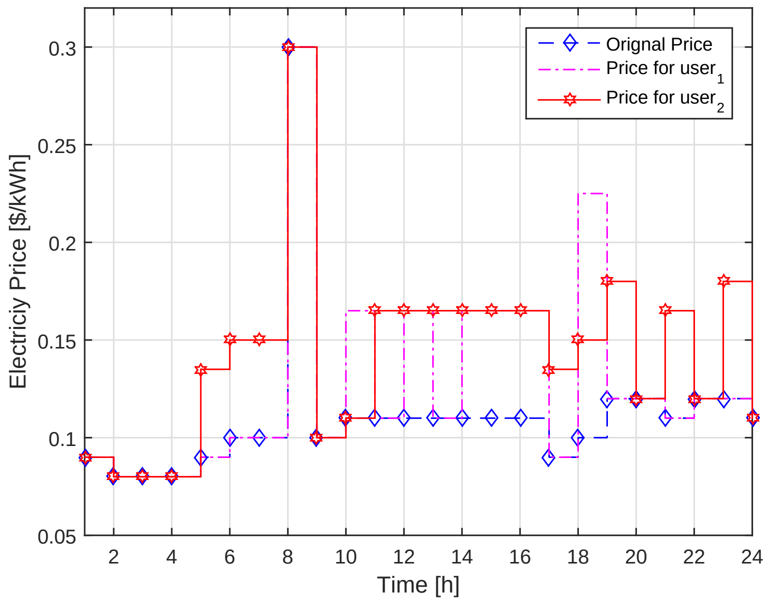


Figure 4. Pricing signal for each individualized user obtained by LBPP.

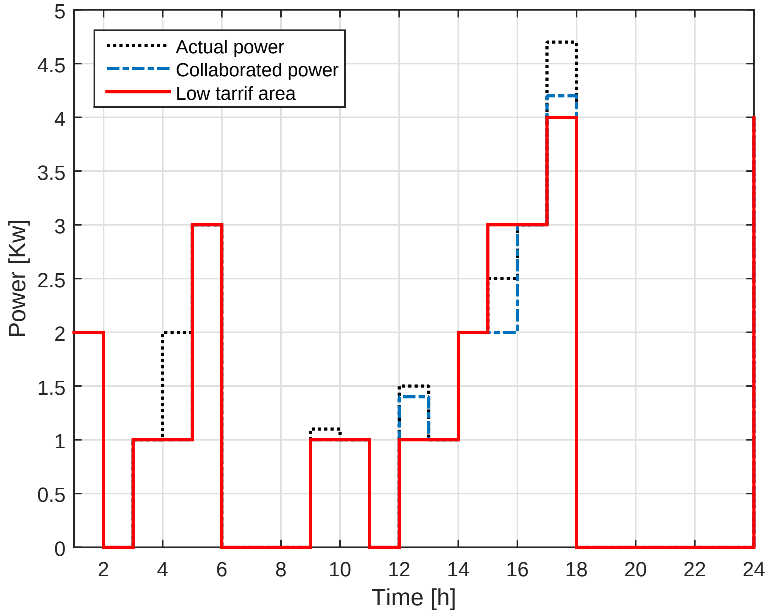


Figure 5. Collaborated power after discharge action of ESS.

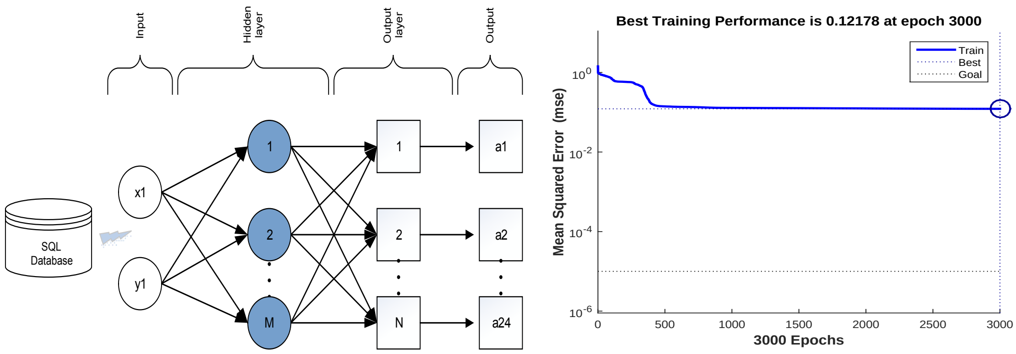
4.2. Time Complexity

We also analyze the time complexity of our proposed problem, as discussed in Section 3. The affirmation of problem can be done in polynomial time for all cases.

Case 4. *Considering shiftable appliances in scheduling problem P2, time complexity will be* $O(n^c)$*, where n and c are the number of tasks and variants, respectively. Furthermore, by reduction from the 0-1 knapsack problem, we can argue that with reduction in polynomial, the problem P2 is* $NP - hard$*.*
Case 5. *In P2, for non-shiftable appliances, the scheduling problem has polynomial time* $O(n)$ *and for power threshold* P_{th}*, will be* $\{O(P_{th}), |P \subseteq NP\}$*. We have previously discussed that objective function P2 can also be solved by using deterministic algorithms. Hence, the problem with MILP is* $NP - complete$ *with the complexity* $O(n.P_{th})$*.*

4.3. Training and Forecasting Using ANN

Due to its adaptive nature, ANN is used when a mathematical system model is unavailable for predictive results. Furthermore, ANN is also widely used for problems which are related to data classification and clustering due to its high robustness and fault tolerant nature. It has high stability inside the face of a big quantity of records and is also recommended for sorting, mathematical modeling, analyzing, and interpolating information [48]. Regarding classification, an output pattern can be obtained by providing the input data which is first split into training and test modules. In order to reduce the mean absolute error for high accuracy, **W** are multiplied in each layer, which are adjusted dynamically during training process. The algorithm works based on the considered model (Figure 6) until the best fit results are achieved or the algorithm converges with minimum squared error as shown in Figure 6b and Equation (18). The complete steps of ANN working are shown in Algorithm 2.



(**a**) Multi-layered ANN architecture (**b**) Performance of ANN architecture under given conditions

Figure 6. The considered architecture of the artificial neural network (ANN) and its performance in terms of error and convergence.

In this work, we aim at finding the low tariff area based on power profiles of each user, consumption preferences and market prices. An input matrix is multiplied by the weight matrix **W**, which has $n \in n$ element containing weights corresponding to inputs. Furthermore, a bias matrix **b** is sent to summer function. The output obtained from the summer function (forecasted demand) goes to the activation function f, which produces the output matrix **a**. The activation function f can be a linear or non-linear function, which depends on spatial frequency of the input/output relations. We have used the Tan-hyperbolic and Purelin activation functions for the fast training speed and convergence and the results are shown in Figure 6b. For simulation, Mathworks Matlab ANN toolbox is used to analyse the performance of different algorithms. It is observed that conjugate gradient with Polak-ribiere function considering (20-38-1) hidden layers performs better in given scenario. This algorithm converged to a mean squared error of at steps as shown in Figure 6b. Results show a better performance as compared to the other algorithms used in the literature. Figure 7 shows the validation of test results using test data. The error between forecasted and suggested power is basically the comfort of user in terms of electricity cost reduction.

Figure 7 gives the output of the LBPP algorithm using ANN. The actual power is the total amount of required power that a particular user is using without any load shifting. Where, the suggested power defines the power profile obtained based on a historical power demand data, and the forecasted power profile is obtained from ANN. After testing and validating the network, high error in hours is due to the low diversity in training data, and average error is also calculated which is 3.763. We proposed that the error is basically the user compromised comfort in terms of reduction in electricity cost. The (17) is a general form of ANN training and forecasting procedure (Algorithm 2).

$$a = w^T x + b, \tag{17}$$

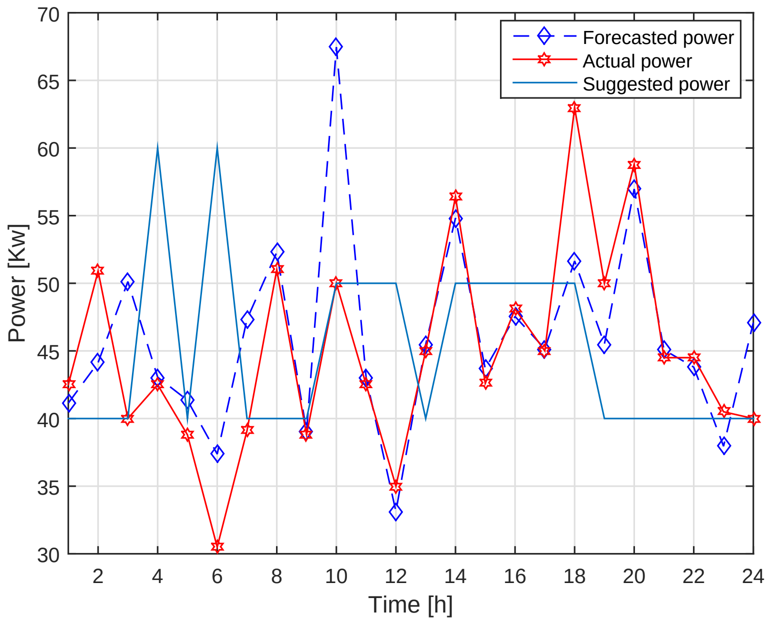


Figure 7. 24-h load forecast in comparison with output by LBPP.

The relative error between forecasted and actual low tariff area for a user is computed by mean squared error (MSE) as follows:

$$MSE = \frac{1}{N}\sum_{i=1}^{n}(Power_{actual} - Power_{forecasted})^2 \quad (18)$$

Algorithm 2 Steps Involved in Predicting Low Tariff Area using ANN

Require: Monthly measurement of Price signal, previous hours od days, load data i.e., y_1,x_{1n},x_1
 for $i \leftarrow 1$ to N_a **do**
  Format network input and output
  Pre-process the data
  Division of data into 3-steps
  Select ANN Architecture
  Calculate the error e using (18)
  Apply the first load pattern and train the network
  for $k \leftarrow 1$ to N_b **do**
   if Pattern == last **then**
    if $e < p$ **then**
     Obtained and save the output
    else
     (e = 0) by updating **W**
    end if
   else
    Measure error and update e
   end if
  end for
 end for

---

5. Simulation Setup

In this section, we present the results and discuss the performance of the proposed model in terms of cost reduction, peak shaving through a balanced supply-demand profile. We evaluate a smart grid system with two different types of users, that is, with and without the ESS system. Each user is equipped with time shiftable and non-shiftable appliances, that is, refrigerator, microwave oven, heater and dishwasher and washing machine, respectively. Then depending on the daily power usage pattern, an aggregated demand is used in encourage the user to consume power in suggested low tariff area, in order to reduce energy consumption cost. In this work, the daily energy consumption pattern of shiftable appliances is considered as: dishwashers-80 kWh; washing machines-40 kWh; and nonshiftable appliances such as refrigerator-96 kWh; lighting-1 kWh. It is working noting here that these values are assumed in order to test the applicability of the proposed LBPP algorithms. However, any value can be used on the basis of user requirements. Based on the actual data, the energy consumption pattern is managed in such a way that the dishwasher must finish working before meal time. It is also assumed that each user has a battery backup with some initial level such that its capacity must not be below half of the rated capacity.

5.1. Results and Discussion

In Figure 8, the aggregated power profile of two users for the 24 h time duration is shown with different schemes: (i) user equipped with ESS system and (ii) user without ESS. For the first scenario, the output profile of a user with ESS is generated based on the proposed model. In situations when ESS is unavailable, peak demand occurs during 16:00 to 17:00, while minimum power demand is reported during 09:00 to 10:00. For the case when load scheduling is performed in accordance with ESS, it is observed that the overall shape of the load curve has improved to flatten the demand as shown in Figure 8. Moreover, it is also observed that when a consumer is equipped with ESS, it is likely to obtain a more flattened load curve leading to a reduced consumption cost and system stability (Figure 9). Also, the SOC of local storage for that particular user in conjunction with the RTP signal is shown in Figure 10c. The storage system is mostly charged during the off-peak intervals, when the electricity price is low and discharge at peak hours. The cost profile of the users has been shown in Figure 9. The proposed algorithm has the ability to reduce the cost over the given time of 24 h. As with the aforementioned scenarios, with and without the energy management system, the comparison of electricity cost is provided. Figure 10b reveals that with consideration of ESS, the total electricity cost of the user-1 is 109.20 $, where the cost reduction is done due to load shifting which can also be considered as physical load shifting. When the optimal solution is obtained without incorporating ESS, the overall cost is obtained 154.25 $, which is approximately 30% more than other case when ESS is integrated). LBPP algorithm also incorporates the demand of user-2 that is willing to to participate in DSM program without local storage system. Figure 10a,b illustrates the ability of different LP-solvers for the same objective function. Results obtained from these deterministic techniques lead to more similarities where typical peak demand occurs from 4:00 a.m. to 6:00 a.m. All algorithms have almost the same results in comparison with cost and PAR, although the efficiency in terms of processing time is required where the size of the system increases, also shown in Table 2. Figure 10d shows the overall results obtained from the LBPP scheme. The total cost and aggregated PAR for the two aforementioned scenarios, that is, a user with and without ESS is shown, and we see that the proposed algorithm leads to a lower cost and PAR even in cases where the user is not equipped with the ESS.

Table 2. Solvers Performance for single dwelling.

Solver	Algorithm	Processing Time (s)	Cost ($)	PAR
Intlinprog	Branch and Bound	1.32	119.430	1.776
linprog	interior-point	1.425	119.650	1.766
linprog	active-set	1.930	119.430	1.767
linprog	simplex	1.653	119.100	1.777
linprog	dual-simplex	1.777	119.100	1.77
fmincon	Default	1.80	119.100	1.778

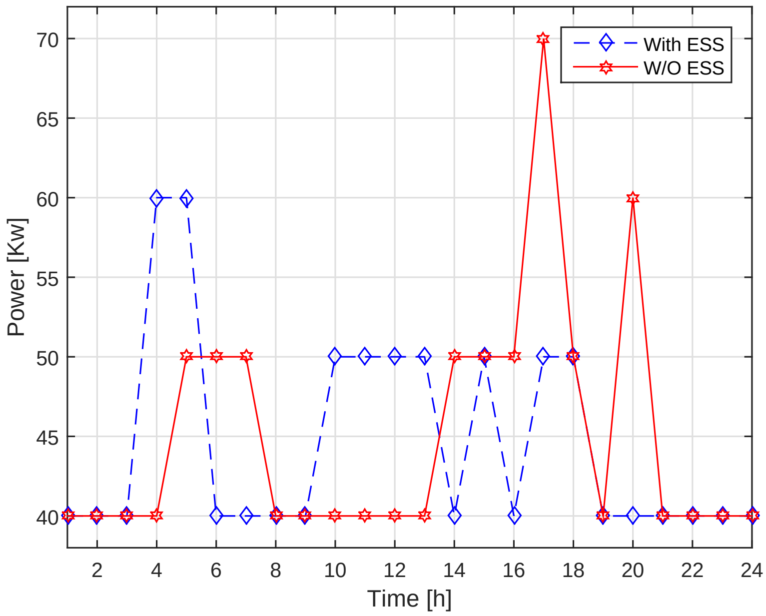


Figure 8. Aggregated power with and without ESS of user1 and user2 respectively.

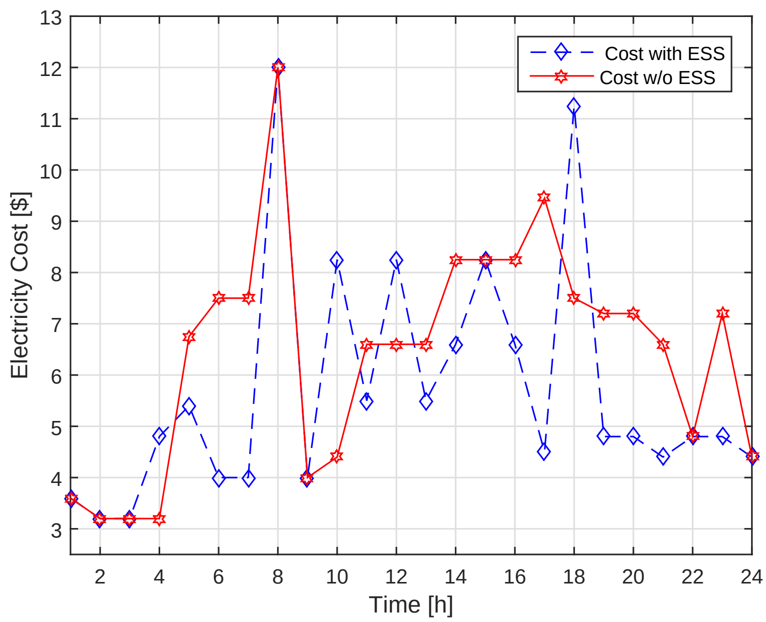


Figure 9. Aggregated cost with and without ESS of user1 and user2 respectively.

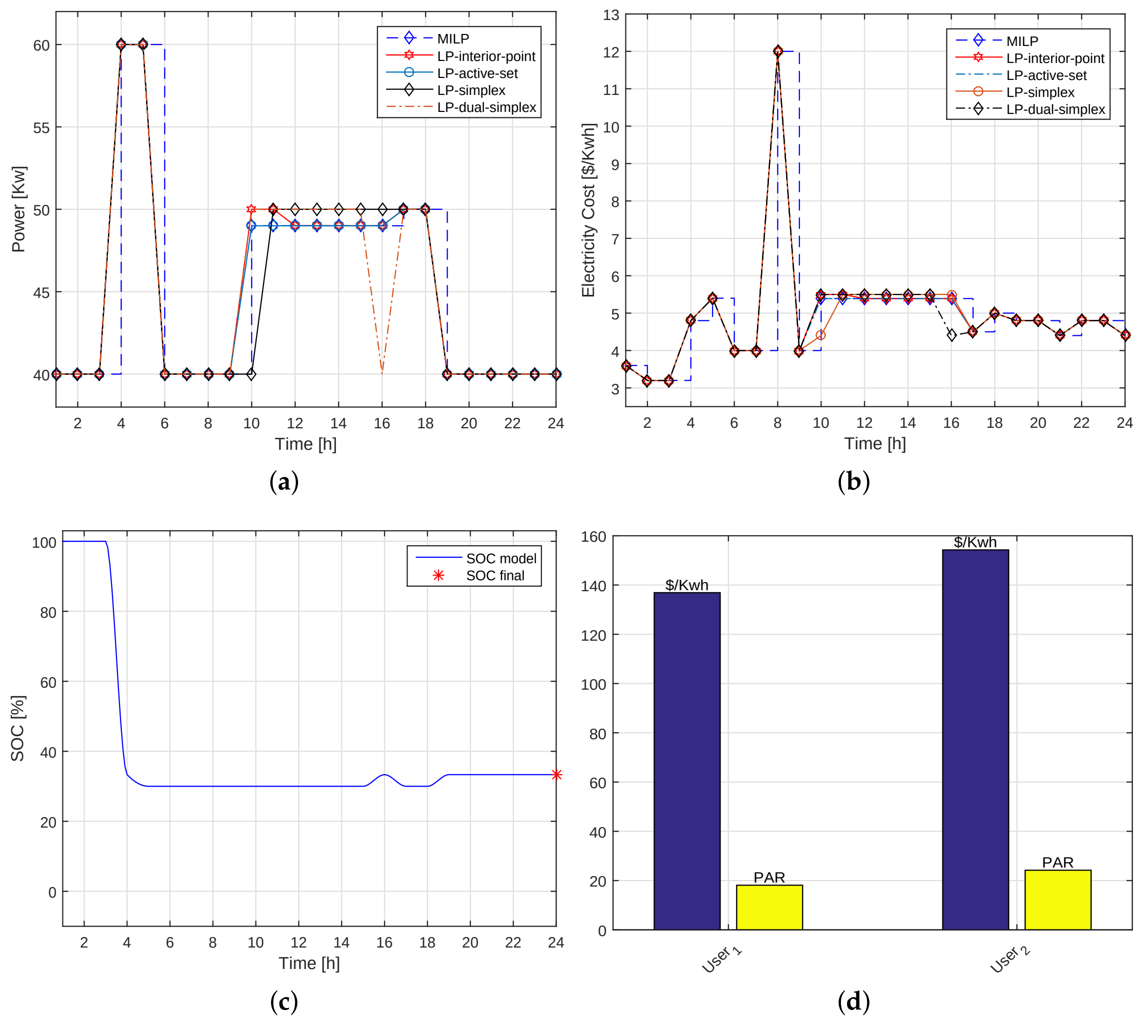


Figure 10. Comparison with power demand output by MILP solver for a single home on a day (**a**) Power analysis with different solvers (**b**) Cost analysis (**c**) State of charge output by LBPP (**d**) Overall Cost and PAR .

The proposed algorithm is basically an encouragement policy for the users to participate in demand management program. As shown in the Figure 4, the users with ESS have been offered a minimum electricity tariff. Similarly, each user would be provided the price signal in accordance with their consumption level and the conditions whether they are below or above low tariff area. On the other hand, for the worse case scenario, if a particular user does not want to participate in DSM program. Then that particular user will utilize the power in such that it violates the suggested power profile over the give time. As a consequence, that customer will be provided the modified price signal, showing increased tariff rate. Eventually, this may warn the customer that resultant electricity cost would be more in case if suggested low tariff area is violated. Because, the proposed mechanism is based on a combined tariff system using RTP with IBR tariff to facilitate the customers through attractive tariffs and benefits. Table 3 shows the PAR results of the base scenario reflecting the benefits of LBPP mechanism. When a user consumes power without ESS, the average PAR is 0.0242. While the PAR is reduced to 0.0242 when combined IBR without ESS is used, and the proposed algorithms achieved the 0.0150 which is 41% less as compared to other cases. it can also be observed that if ESS has more capacity, the user can consume less power from grid source and eventually contribute towards reduction in rebound peaks. A comparison is made with MILP solver without ESS with different algorithms of LP solver as shown in followings.

Table 3. PAR comparison.

	Using RTEP	IBR without ESS	LBPP
PAR	0.0310	0.0242	0.0150

5.2. Performance Based Analysis

In this section, we investigate the important performance parameter of the optimization algorithms, i.e., processing time in terms of optimal energy consumption cost and PAR of a single home. The results are compared against various solvers, available in MATLAB software.

5.2.1. Deterministic Techniques

Initially, deterministic optimization methods have been used and results are compared in terms of processing time, electricity cost and PAR, as shown in Tables 2 and 3. Furthermore, these results are also provided in a graphical form (Figure 10a,b). While the power and cost profiles obtained by using heuristic and deterministic algorithms have been shown in Figure 11.

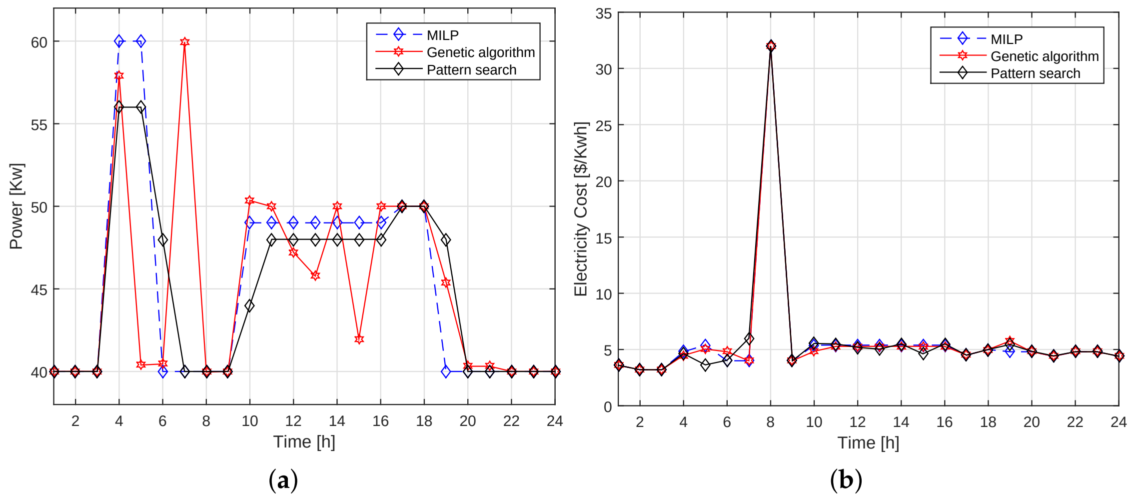


Figure 11. Comparison with power demand output by MILP solver for a single home on a day (**a**) genetic algorithm and pattern search (**b**) Cost output by MILP solver for a single home on a day (**b**) genetic algorithm and pattern search.

5.2.2. Meta-Heuristic Techniques

We also solve the proposed model using a heuristic based GA with an initial population of 150. The roulette wheel selection criteria is applied to the same problem and an analytical comparison is made with the counterpart techniques. Furthermore, the other control parameters of GA are selected. The results are shown in Table 4 and in Figure 10a.

Table 4. Solvers performance for a single dwelling.

Solver	Algorithm	Processing Time (s)	Cost ($)	PAR
GA	Default	370	119.299	1.765
Pattern Search	Default	3.2	119.401	1.54

6. Conclusions

This work has provided a novel load scheduling and pricing mechanism on the basis of individualized energy consumption profiles, historical load demand, market price signal and suggested load profile, where the suggested energy consumption profile is initially obtained from historical demand data, which later on is validated by an ANN based low tariff area. The low tariff area and RTP are then provided to each user as an input parameter, based on which the potential user can reschedule their consumption patterns with the objective of cost and rebound peak minimization. Firstly, the mathematical models of all loads and ESS have been presented along with a two step pricing mechanism, which is based on RTP and CPP. Secondly, the optimization problem is formulated as a constraint optimization problem which is solved by using the proposed LBPP algorithm. Furthermore, heuristic and deterministic algorithms have also been used to solve the problem in order to analyse the performance in terms of rebound peak minimization, cost reduction and time complexity assessment. It is also observed that the multi-objective optimization problem is NP-hard. Based on the suggested low tariff area, obtained from ANN, the users have been provided the flexibility to utilize their loads. Then the market price signal, which is fixed for given time interval changes according to user load consumption trend. As a result, each respective user gets a different price signal which helps to normalize the high peaks in the distribution system. This approach is also compared with some traditional algorithms discussed earlier. The investigation of this paper shows the benefits of proposed algorithm through simulations. The actual behavior of the customers in response to the proposed pricing policy is very difficult and unpredictable. So, the results presented by extensive simulations for the proposed scenario, are very useful to illustrate the issues, that is, rebound, in previous DSM techniques, and signify that the proposed algorithm is able to resolve that issues and incentivise the users. It is also assessed in this paper that, in the current scenario, users are encouraged to enhance their flexibility to install more capacity of ESS for economic compensation, this also clearly provides operational benefits to the utility to limit network cost (PAR reduction). With the help of ANN, the effects on user comfort are measured along with cost reduction. It can be seen in the simulation results that the effectiveness of the proposed solution is different, unlike the other counterpart techniques, which were designed to reduce cost as a primary objective. Finally, a comparison regarding processing time is also provided to check the robustness of selected algorithms.

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Abbreviations

ANN	Artificial Neural Networks	LP	Linear Programming
DSO	Distribution System Operator	LBPP	Load Based Pricing Policy
DSM	Demand Side Management	MILP	mixed integer linear programming
DR	Demand Response	MSE	Mean Squared Error
DLC	Direct Load Control	PAR	Peak to Average Ratio
ESS	Energy Storage System	RTP	Real Time Pricing
GA	Genetic Algorithm	SOC	State of Charge
HEM	Home Energy Management	SG	Smart Grid
IBR	Inclining Block Rate	VER	Variable Energy Resources
IEA	International Energy Agency		

Nomenclature

Symbols	Description	Symbols	Description
Δ^t	Exceeding demand from threshold	f	Indices of pricing signals
E_g	Total energy consumption	b_l	Lower price for energy consumption
b_h	Higher price for energy consumption	d_u	Actual demand of residential user
D_u	Forecasted demand of residential user u	L	Upper bound on residential power u
d_{min}	Minimum load demand	$d_u^{\sim}$	Historical demand of residential user u
Q_u	Total capacity of storage system for u	R_u	Rate of power in storage system for user u
α_u^t	charging/discharge plan for u in t	b_u^t	Charging state of storage for user u in t
c_u	User power after storage discharging	Ψ_i	Length of operation time of appliance i
$\sqcap$	Inclining block rate tariff	ζ	Cost for charging ESS
f_s	RTP signal from utility company	P_{th}	Threshold power for u
T	Set of time slots	ϕ	Penalty function for user u
P_u	Upper bound of suggested low tariff	U	Set of residential users
u	Indices of residential users U	t	Indexes of time slot T
F	Set of residential users pricing signal	$P_{i,t}$	Power demand of i^{th} user over t
ℓ_t	Load over time t	τ_t	Scheduling delay experienced over t
$\overline{\tau_t}$	Maximum scheduling delay over t	$\overline{Q}$	Total power capacity
e	Total forecasting error	p	Final target error

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