Development of Dynamic Pricing Algorithm in a Smart Grid

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Abstract. Conventional grid has limited power generation resources. Therefore, we need an architecture which fulfil the power demand of the users and can restricts the excess use of power beyond the limit. Since the past few years, smart grid has become a better architecture as it can manage the crucial part of the IoT (Internet of Things). Due to its compatible results along with great performance and the new outlook in the computer intelligence for managing the grid to self-monitoring power consumption, the smart grids have started to replace the conventional grids. Even if we are using the smart grid it may lead to the operator incurring a loss; while satisfying the user's power demand. Hence, we are designing a system which will trade-off the users' satisfaction and profit earned by the Smart Grid Operator (SGO). Second goal of the system is to achieve a dynamic pricing scheme for the power consumption, along with maximum power generation. The simulation is carried out by using practical power usage data from ISO (Independent System Operator) New England in Python 3 environment to validate the proposed algorithm's effectiveness towards maximizing the profit of the SGO without compromising user's satisfaction.

Keywords: Smart Grid · Optimal Dynamic Pricing · Demand Response Management · User Utility · Neural Network

1 Introduction

The contemporary civilization in large parts relies upon electricity furnished by means of a large infrastructure along with energy, transmission lines & power distribution management tools. The increasing variety of the customers, electrical gadgets, application-based diversity (in terms of power quality and sufficiency), the prolonged and luxurious manner of exploiting new electricity assets and the restricted energy assets have put the reliability of the traditional electricity structures within challenging levels. Subsequently, there is an increasing need for implementing new technologies to boost the distribution energy efficiency and to fulfill the various customers' electricity requirements [1]. For generation of extra power to cater to the expanded consumer base, extra proportion of conventional resources including gas, oil, etc. have to be utilized [2]. According to the

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information at the Department of Energy and Climate Change (DECC) of United Kingdom, the energy output in 2018 became 12.5 percentages exorbitant than that in 2017 due to which production of oil and gasoline were expanded via 12.8% and 8.8%, respectively, within the year 2017–2018. With the expanded manufacturing, the availability of conventional sources is becoming narrower and hence their costs are rapid growing [3, 4]. Due to this limitation of the conventional grid, there is a need to design a smart grid architecture. The smart grid allows efficient allotment of the power generated from the utility to the users which complete their power demand with the help of IoT (Internet of Things). SGO (Smart Grid Operator) tries to achieve the optimal utilization of power resources. Hence its aim is to gain more profit and it can fulfill the user's power demand in a better way. The conventional power grids cannot satisfy the requirements as there is absence of effective communication between the supply and demand side, and flexibility in the system. The reliability of conventional systems is less in comparison which may lead to blackouts [5]. Through restructuring of the power system, a conventional grid can be transformed into a responsive and reliable system. A smart grid also provides solutions to some of the problems associated with conventional grid [6].

The authors in [7] studied the electricity cost. According to the customer's load level demand service provider will decide the electricity cost. To achieve this aim, they used two different types of algorithms. First is Energy Consumption-based appropriate State (EAS) definition, and the second one is the adoption of virtual experience updation in the conventional Q-learning algorithm. Results of this system are divided into two approaches: 1. Straightforward approach is the reasonable and conventional approach as not all the customers are to be necessarily strategic. The main aim is to find out the dynamic events of the system. As per this approach, system performance is better in terms of both cost and convergence; 2. Transmission probability of cost function is known. Due to this approach, they found out some errors in real time applications. Hence for the future work they will be considering various types of models of energy resources such as solar power, electric vehicle, and impact on bidirectional energy delivery. Compared to this study, our proposed system is capable of studying the impact of different types of energy resources. In [8] and [9], the authors have proposed a method using which we can figure out the optimal amount of power that is to be purchased by the SGO in the absence of any future information regarding the price of power or the user's power requirement. The existing method is depending on the offline and online algorithm, where offline algorithm will provide only the present analysis of the energy demand. The proposed approach allows deriving the function of actual instantaneous system parameters i.e. to derive the resource allocation and closed form of instantaneous energy procurement. Authors studied different parameters and the energy cost of the system is minimized effectively. According to their result, the system works effectively even during critical problems. In [10], the authors had studied the charging/discharging schedules of Electric Vehicles (EV) and the energy management of the building based on the decentralized sort of Cloud-SDN communication architecture, in real-time energy demand application. For changing and discharging of the EVs, they have derived two different algorithms and a separate algorithm to manage the overall system's operation. Using large-scale simulations and several comparisons with past research works, the objective is to prove that the pricing model which has been proposed in this paper optimizes the power load at some point during the peak hours. It will also help in maintaining the microgrid stability. For this simulation, they used dataset of one thousand EVs. For future work, they are planning to increase the size of their dataset. In [11] and [12], the authors suggested a system considering day-ahead energy planning and designed a retail pricing model. So, one can similarly limit the average appliance's value and rebound peaks through electricity acquisition charge, load scheduling and integration of renewable energy source (RES). End results were acquired after simulation accomplished for the parameters along with aggregated load and market rate, individualized load, marketplace rate, proposed rate. The mechanism proposed here can charge the fee to every user with 23.77% lower energy cost or 5.12% increased cost depending on appliance's requirement. In future, they are planning to lessen the power consumption cost, use multi agent approach for real-time coordination and management. In [13] and [14], consumers are managing their electricity consumptions according to the electricity price and time varying loads.

In this paper, we have proposed a smart grid layout and implemented a simulation that gather information from electricity utilities such as approximate electricity charges, environmental conditions, and information regarding various renewable technologies that have been implemented. It can simulate dynamic pricing of energy from more than one energy providers. The main objectives of this research work are:

- Develop an effective power management model for a smart grid.
- Modelling of utility function to capture user satisfaction.
- Modelling of smart grid operator's profit.
- Determine an optimal selling price to maximize user utility and smart grid operator's profit.
- Development of user demand estimation model based on varying price.
- Comparison of the proposed algorithms with state-of-the-art algorithms

The organization of different sections of this paper as follows: Section 1 discusses the literature review and motivation from different research works that have been carried out in this field. In Sect. 2, the proposed model which describes the machine model as well as formulate an application function and a pricing function is discussed. Utility function, profit function and optimal power allocation algorithm and their working is discussed here. In Sect. 3, the performance of the algorithm is assessed with various performance criteria like average user utility, profit per day and power utilization efficiency for number of days and number of users. An optimization characteristic based on the utility characteristic and fee feature has also been presented here. Numerical consequences are shown. Section 4 draw conclusions from the research work and scope of future work has been discussed briefly.

2 System Modeling and Proposed Method

2.1 User Preference and SGO Profit

Three key components of a smart grid framework are: Smart Grid Operator (SGO), Energy Producer (EP) and User. From Fig. 1, we can see that EPs are in charge of

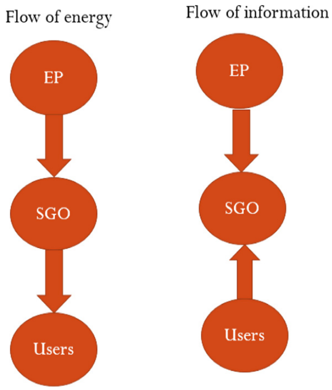


Fig. 1. Schematic diagram illustrating power and information flow among various components of a smart grid.

production of power and the power is distributed from SGOs to users. Exchange of information between the users and EP is carried out by the SGO.

In our proposed system, we have tried to maximize the user's utility demand and SGO profit. To achieve this goal, we formulate SGO profit and user's satisfaction. Satisfaction of the consumers of power demand and allocation can be designed through theory of utility function. In this research work, the corresponding utility function has been represented as U x_it, ω_it; where, x_it is the allocated power to user i at time slot t, and it is the preference of user i at time slot t. User preference it is user i's weight of power consumption at time t. It is defined as:

$$\omega_i t = \frac{d_i t}{Dt} \tag{1}$$

Where d_it is the power demand of user i at time slot t and Dt is the total demand from users at time slot t which can be expressed as $Dt = \sum_{i=1}^{n} d_i t$

A variety of utility functions choices are available in the literature which perfectly satisfy the utility demand. Here, the following function has been used as the linearly decreasing managerial profit.

$$U_i t(x_i t, \omega_i t) = \{\frac{(x_i t, \omega_i t) - \frac{1}{2}\frac{x_i t}{D_t} x_i t}{\frac{1}{2}(x_i t, \omega_i t)} 1 \frac{if \;\; x_i t < d_i t}{if \;\; x_i t \geq d_i t} \tag{2}$$

When user demand corresponds to the forecast of the SGO, then its profit gets maximized. Since according to the forecasted power generation, demand selling price is determined even though it is impossible to forecast exact price in real time. Even then we can forecast the model which will give us minimum error over the real time forecasting model. We get the profit by subtracting the cost from the income. Hence SGO profit can be formulated as expressed below:

$$P_{SGO}^{t} = \sum\nolimits_{i=1}^{n} .x_{i,t}, S_t - \sum\nolimits_{j=1}^{m} .y_{i,t}, C_{j,t} \tag{3}$$

Where, S_t = per unit optimal selling price to users, $C_{j,t}$ = per unit purchase price from EP j at time slot t, $x_{i,t}$ = allocated power to user i at time slot t, and $y_{i,t}$ = indicates purchased power from EP j at time slot t.

2.2 Power Allocation Algorithm

Now a days, power demand is varying dynamically. One such system is named as ODPT (Optimal Dynamic Pricing with Trade-offs) in the literature. It is able to make tradeoff within the user utility's value and operator profit. An ODPT between the user and operator is a smart power congestion management policy. For maximizing the profit of SGO and user utility demand, the proposed ODPT has been formulated here. In the initial stage of the system, it is assumed that SGO has knowledge about the price according to varying load demand of the user.

$$0 = \sum\nolimits_{i=1}^{n} .\left(U\left(x_{i,t}, \omega_{i,t}\right) + x_{i,t}, S_t\right) - \sum\nolimits_{j=1}^{m} .\left(C_{j,t}, y_{j,t} + A_j^t - y_{i,t}\right) \tag{4}$$

$$0 \le x_{i,t} \le d_{i,t} \tag{5}$$

$$\sum\nolimits_{i=1}^{n} .x_{i,t} \le \sum\nolimits_{j=1}^{m} .y_{j,t} \tag{6}$$

$$S_t > 0 \tag{7}$$

$$0 \le y_{j,t} \le A_j^t \tag{8}$$

Allocated power is in Eq. (4) and the first constraint Eq. (5) conveys that this power should not exceed the demand of the user. The second constraint Eq. (6) conveys that the power demanded by the user is limited by the power purchased by SGO at time t. The third constraint Eq. (7) conveys that selling price of the SGO is limited to low. Fourth constraint in (8) shows that, in each time slot t, the SGO can't purchase more power from the EP than available resources.

User power demand structure is varying with the price and it is confidential and independent. It is not possible for SGO to go through each user in the real time application. Hence SGO needs to evaluate the requirement of the user. Some techniques have been developed to optimize this problem. In this paper, a feedforward ANN (Artificial Neural Network) Multilayer Perceptron has been used which is coupled with the Back-Propagation training algorithm. Optimization problem is now estimated through the ANN model. Hence SGO will purchase the estimated amount of power from the EP, announce the selling price as per time slot to the user. When SGO get demand from the user, two cases might occur:

Case 1. Over-provision: $D_t \le \sum\limits_{j=1}^{m} .y_{j,t}$.

In this case, SGO will allocate power to the user as per their requirement.

Case 2. Under-provision:

$$D_t > \sum\nolimits_{j=1}^{m} .y_{j,t}$$

In this case, SGO will try to maximize the total amount of utility by solving the sub optimization problem.

In under provision, two different cases can be observed:

1. Zero power is allocated to few users so that other user can be satisfied.
2. Minimum power is allocated than compared to the power demand to all user

In this proposed system, these two cases are being focused on.

In this paper, the feedforward ANN Multiplayer Perceptron which is coupled with the Back Propagation is called FF-BP-ANN. This FF-BP-ANN model is popular, having three layers namely: input layer, hidden layer, and output layer. Node value in the hidden layer is calculated as shown:

$$h_1 = (1 + exp\, exp((-1)(tw_{11} + S_{tw21})))^{-1} \tag{9}$$

$$h_2 = (1 + exp\, exp((-1)(tw_{12} + S_{tw22})))^{-1} \tag{10}$$

Where 'h_1' and $'h_2'$ are the nodes in the hidden layer, 't' and $'s_t'$ are the nodes in the input layers. The weight between the node in input (a) layer and hidden layer (b) is shown as w_{ab}.

Similarly, output layer is defined as:

$$d_{i,t} = (1 + exp\, exp((-1)(h_1 v_1 + h_2 v_2)))^{-1} \tag{11}$$

Node of the output layer is $d_{i,t}$. Hidden layer and output layer create an error and these can be calculated using the formula:

$$\partial_{d_{i,t}} = \left(d - d_{i,t}\right) d_{i,t} \left(1 - d_{i,t}\right) \tag{12}$$

Where, d is observed data.

Weight of the input layer and hidden layer is given as:

$$w_{1i}^t = w_{1i}^{t-1} + \Delta w_{1i}^t \tag{13}$$

$$w_{2i}^t = w_{2i}^{t-1} + \Delta w_{2i}^t \tag{14}$$

Where, $\Delta w_{1i}^t = \alpha \partial_{h_i} t + \beta \Delta w_{1i}^{t-1}$, $\Delta w_{2i}^t = \alpha \partial_{h_i} t + \beta \Delta w_{2i}^{t-1}$, α = learning rate and β = momentum rate and $i = 1{,}2$.

The overall operation of optimization in SGO is summarized in the following algorithm. In each time slot, SGO receives the purchase price and the available power amount from EP.

The power allocation algorithm for SGO is as follows:

Input: $C_{j,t}$, A_j^t, $d_{i,t}$
Output: $y_{j,t}$, S_t, $x_{i,t}$

1. Start loop
2. For every time interval t, SGO will collect ($C_{j,t}$, A_j^t) from every producer j.
3. Run the optimization function specified in (4)
4. Declares the optimal energy price S_t to every user i.
5. Input the net actual power demand $d_{i,t}$ from every user i.
6. Calculates D_t through (1).
7. if $D_t < \sum_{j=1}^{m} . y_{j,t}$ then
8. SGO allocates $d_{i,t}$ power to every user i.
   else
   SGO solves the sub-optimization function in (15) and it allocates $x_{i,t}$ power to each user i
9. end if
10. updates ANN model parameters specified in (9) to (14).
11. end loop

$$O_1 = \sum_{i=1}^{n} .\left(U\left(x_{i,t}, \omega_{i,t}\right)\right) \tag{15}$$

This is how the optimized power using the ANN model is obtained. To get the optimal price of this power SGO will run optimization function of Eq. (4). This function will focus on how to maximize the profit of user utility and SGO. Then the selling price of the power will be announced by the SGO. According to this price smart meter at the user's end will consider the power to be purchased. Now the SGO will run the sub-optimization function from Eq. (15) to optimize the optimal power to each user's end meanwhile trying to maximize the utility of the user. In the algorithm, we consider input to the system as, $C_{j,t}$ (purchase price), A_j^t (available power) and $d_{i,t}$ (actual demand of user). The outputs of the system are $y_{j,t}$ (purchase price) of the power with S_t (slot time) and $x_{i,t}$ (allocated power to user).

3 Performance Evaluation

The results were compared with the DOA (Distributed Optimal Algorithm) in two categories: first without considering model as ANN based i.e. ODPT (W/ANN); and the second is fixed rage profit i. e. ODPT (FRP). To forecast the user demand in the model ODPT (W/ANN) and ODPT (FRP) we are using EWMA (Exponentially Weighted Average) formula. Here we are considering profit range of the SGO as the limit whereas the remaining constraints are constant. For proper result, we are assuming that DOA is purchasing the power from numerous EPs. In the beginning each EP will declare its own selling price at the time slot. We are using the dataset which contains the per hour power usage. This dataset is collected from the ISO New England. The proposed system is solved using the K-nitro optimization API.

In this simulation process, 500 users have been considered along with 11 Eps with one hour of updating time. One hour is an ample time to gain information of the user

Table 1. Data parameters for simulation.

Parameters	Value
Users	500
EP	10
Demand of single user in one slot	0–4 kW
Capacity of EP	0–60 kW
Per unit purchase price	2.0–4.0
Per unit selling price	4.0–8.0

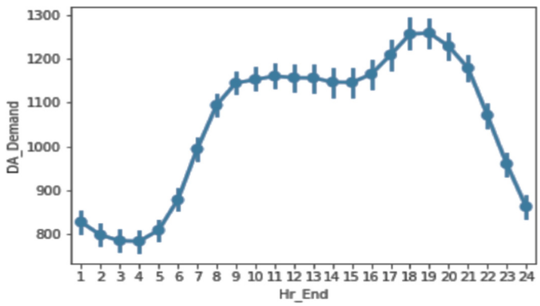


Fig. 2. Day ahead demand of users.

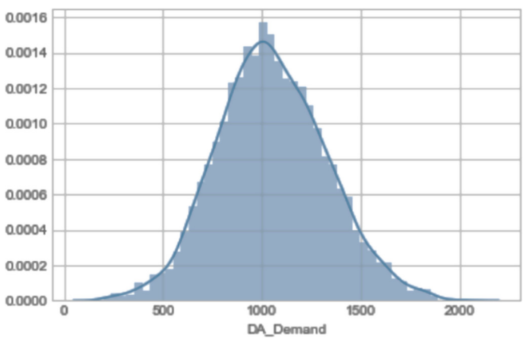
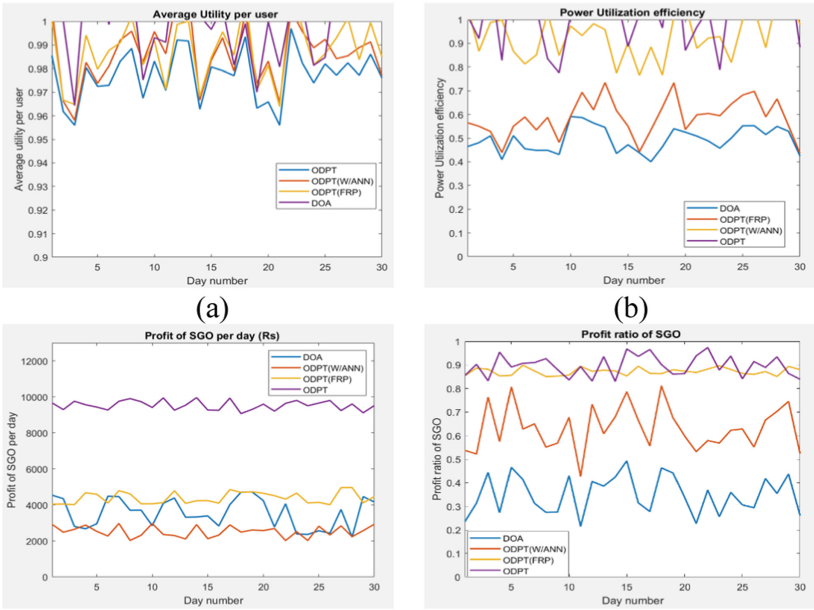


Fig. 3. Probability distribution of Demand.

and to execute the SGO trade-off operation. When we have to evaluate the daily power operation, 24 h of power utilization is used to markup the results. Capacity C = [0, 60] KW and declared price P = [2.0, 4.0] Rs has been considered. Actual power demand of the user varies between D = [0, 4] KW. Selling price of power to the user is determined according to the per unit Pu = [4.0, 8.0] BDT. Table 1 lists out all the parameters related to simulation along with their values.



(c) (d)

Fig. 4. Figure showing (a) Average User Utility, (b) Power Utilization Efficiency, (c) Per day profit of SGO, and (d) Profit ratio of SGO.

Figure 2 describes the day ahead demand of users for 24 h from 00:00 to 24:00 it tells us about the consumption behavior of the users. From Fig. 3 we can observe the probability distribution of the demand of users. This plot helps us to understand the distribution of the values and to detect the outliers.

Figure 4 (a) shows the graph for ODPT, ODPT (W/ANN), ODPT (FRP). As per the graph, fluctuation within the user utility is less (0.96 to 1). This indicates that our system results into a constant output. From the results, we can state that our system gives steady (constant) utility values and When user demand is unsatisfied, utility get decreased (when SGO purchase less power compared to user's demand).

This leads to increase in the power utilization efficiency of SGO. This has been shown in Fig. 4 (b). From Fig. 4 (b), it is clear that the power utilization efficiency of ODPT is normally greater than the previous ODPT version and DOA. This represents the balance within the sold power and purchased power. As observed from others graph, utilization efficiency of the DOA is less.

The plot in Fig. 4 (c) depicts the benefit of ODPT, ODPT (W/ANN), ODPT (FRP) and DOA over a time of 30 days. We can see that the benefit of ODPT is quite higher than different variants. Note that the benefit of an SGO relies upon the usage effectiveness. Since the ODPT has a higher usage proficiency, it can help in realizing higher benefit (practically 125%) than the others. The DOA plot in Fig. 4 (c) shows a lower benefit in contrast to ODPT on the grounds that the DOA SGO is purchasing more power than user demands. The profit plot of ODPT (W/ANN) in Fig. 4 (c) shows a lower scope of profit

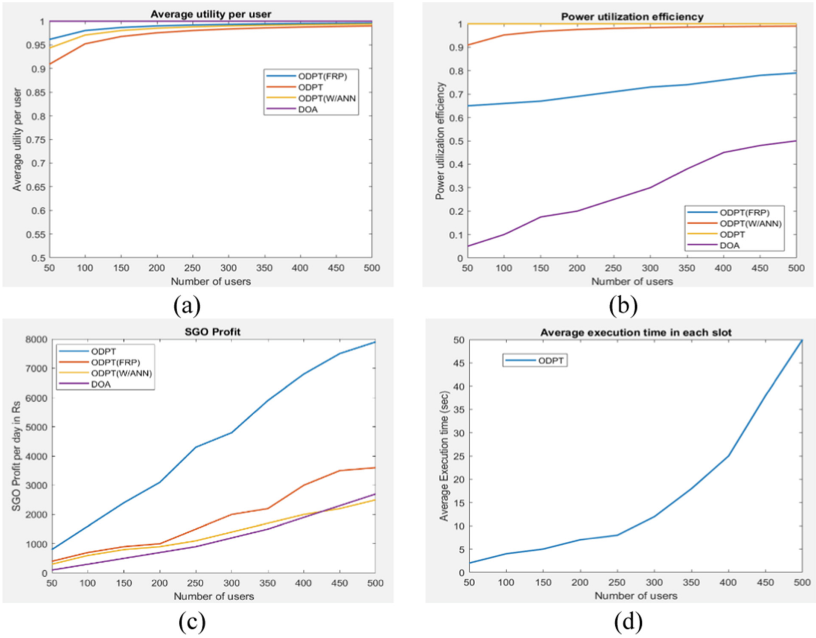


Fig. 5. Figure showing (a) Average user utility for 500 users, (b) Power utilization efficiency for 500 users, (c) SGO Profit per day for 500 users, and (d) Average execution time for each slot.

in contrast to other methods. The ODPT (W/ANN) gives good outcome on forecasting user demand for each time interval. However, it cannot choose the ideal profit value and utility. Along these lines, the scope of profit has been set in ODPT (W/ANN) multiple times for buying value, hence keeping the plot to remain at low level. In Fig. 4 (d), the profit ratio plots of ODPT, ODPT (W/ANN), ODPT (FRP) and DOA over a time interval of 30 days are introduced. The normal profit of our proposed ODPT framework is practically equivalent to the genuine profit due to utilizing less error inclined expectation in view of ANN-model. Subsequently, it gives a higher profit ratio than others. Once again, there is no interest forecast model utilized in DOA for which DOA buys all the accessible assets from EPs. Subsequently, its profit ratio is at lower level in the plot.

Figure 5 (a) shows the graph of user utility verses number of users. This graph states that average utility of ODPT, DOA, ODPT (FRP), ODPT (W/ANN) is steadily increasing as number of users increases within the range from 0.96 to 1. Average utility graph of ODPT (FRP) and ODPT (W/ANN) increases significantly as compared to the average utility of ODPT. As the ODPT (FRP) and ODPT (W/ANN) have got the fixed rate of profit, this result into the steadily increasing graph with increase in the number of users. Therefore, operator of SG will buy more power from the EPs for satisfying the user demand and this results in an increase in the profit of SGO.

Figure 5 (b) exhibits the SGO's power utilization efficiency versus the number of users. In the figure, the ODPT and ODPT (W/ANN) plots show a higher utilization efficiency than the other two. They result in the most increased efficiency. This is caused due the way that the assessment models of ODPT and ODPT (W/ANN) give nearly accurate estimation of user's demand over the increasing number of users. It follows that the SGO of the two frameworks buy precisely the quantity of power that they are going to sell, which isn't more than the power demanded. Hence, the efficiency of ODPT, and ODPT (W/ANN) get enhanced. The plots of ODPT (FRP) and DOA stay at low levels due to similar reasons, that is, their SGOs buy more power than the user's demand.

Figure 5 (c) shows the SGO's total profit versus the number of users. The normal utilization efficiency of each framework increases with the number of users. As observed in Fig. 5 (c), the related profit likewise gets maximized. Since the power utilization efficiency of ODPT is the highest among all, its profit additionally stays higher. Once again, the power utilization efficiency of ODPT (W/ANN) is relatively higher than that of ODPT (FRP). Be that as it may, because of its fixed selling value (multiple times of buying value), its profit remains lower than that of ODPT (FRP). The normal time taken for executing the proposed calculation versus the total number of consumers can be observed from Fig. 5 (d). It is obvious from this plot that the ODPT framework presented in this paper can be tackled in polynomial time.

If the time taken to run an algorithm is upper bounded by a polynomial expression which is the input size of that particular algorithm, then it is supposed to be of polynomial time i.e., T(n) = O (nk). k represents a positive constant here. Those real-world problems whose algorithm is a polynomial time type and deterministic in nature are said to be of P complexity category.

4 Conclusion

In this paper, the system was modelled with variable dynamic power demand depending on the dynamic price of the supply power. The ANN model was adapted with respect to price and time. The main objective was to formulate and achieve the optimal profit and optimal price for the dynamic power demand by the user. To meet this objective, an optimization function was formulated which provided the utility operators an optimal solution to the problem. Considering the number of energy providers in the system, the power failure possibility tends to null or zero. Proposed ODPT system offered a dynamic way to utilize all the resources in the SGO over the time slot. The proposed system facilitates an analysis from the users' utility demand with preferences and then helps in maximizing the utility's profit, providing better solution. According to the results obtained from the system it can said that the proposed system delivered efficient performance in comparison to other studies. After the model has been designed, the system's feasibility and performance were tested in the real-world using optimization and modelling tools. Comparing this system model with ODPT (O/W ANN), DOA and ODPT (FRP), significant improvements were observed. Thus, the proposed system gave better solution to the existing issues and can perform more efficiently.

This research work deals with linear cost function and quadratic user utility. Other machine learning and deep learning methods can be used for forecasting the demand. Nonlinear regression models can perform better compared to linear models because they capture the complexity better than the linear models.

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