Optimal Dynamic Pricing for Trading-off User Utility and Operator Profit in Smart Grid

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A project submitted in partial fulfillment of the requirements for the degree of Bachelor of Science in Computer Science and Engineering

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Declaration

We, hereby, declare that the work presented in this project is the outcome of the investigation performed by us. We also declare that no part of this project has been or is being submitted elsewhere for the award of any degree or diploma.

Abstract

To meet the increasing power demand of users, conventional grid is getting infeasible due to its limited resources on power generation. For this, we are in need of a new infrastructure on power management system that will not only satisfy users demand, but also restrict the power usage within the capacity. From the realization of this necessity, the concept of smart grid has been introduced. In recent years, smart grid has managed to get the attention as a crucial part of the Internet of Things (IoT). Its consistent outperformance and new perspective in computer intelligence to control the grid for autonomous power consumption, has been gradually replacing the conventional power grid. However, providing high satisfaction to users often leads to operator's loss, even in smart grid. In this project, we propose a formula that will trade-off users satisfaction and profit of the operator in Smart Grid. Our proposal also includes dynamic pricing of power consumption, along with the maximal usage of generated power. Simulation result shows that our proposal produces a satisfactory result on balancing users satisfaction and profit of the operator in Smart Grid.

Acknowledgment

First of all, We would like to express our deepest gratitude to the Almighty Allah, who gave us patience, strength and determination to complete this work.

We owe our heartiest thanks to our supervisor for his endless support and profound guidance. His encouragement, constant supervision, valuable criticism and suggestions made the completion of the project possible.

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Jannatul Ferdous
Md. Parvez Mollah
March, 2016

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Chapter 1

Introduction

1.1 Introduction

The modern civilization largely depends on electrical energy, supplied by a huge infrastructure consisting of power generation industries, transmission lines and power distribution management units. The increased number of users, home appliances, application diversities (both in quality and quantity), the lengthy and expensive process of exploiting new power sources and the limited energy resources have put the reliability of the conventional power grid systems in danger [1]. Hence, there is a growing need to develop new methodologies to increase the power distribution efficiency to meet up the diverse power demands from users. To produce more power for the increased number of users, additional amount of natural resources such as, oil, gas, etc. are needed to be used. According to the statistics at Department of Energy and Climate Change (DECC) of UK [2], the electricity output in 2015 was 12.5 percent higher than that in 2014 for which oil and gas productions are increased by 11.9% and 9.9%, respectively, from 2014 to 2015 as shown in Fig. 1.1. With the increased production, the availability of natural resources are getting narrower and hence their prices are fast increasing. This indispensable limitation of conventional grid systems calls for a smart grid infrastructure that allows efficient allocation of power utilities to users following their demands using Internet-of-Things (IoT) devices and software-controlled real-time power allocation technologies [3], [4]. The smart grid operator (SGO) can achieve higher utilization of power resources, earn more profits and better facilitate users to satisfy their power demands [5], [6].

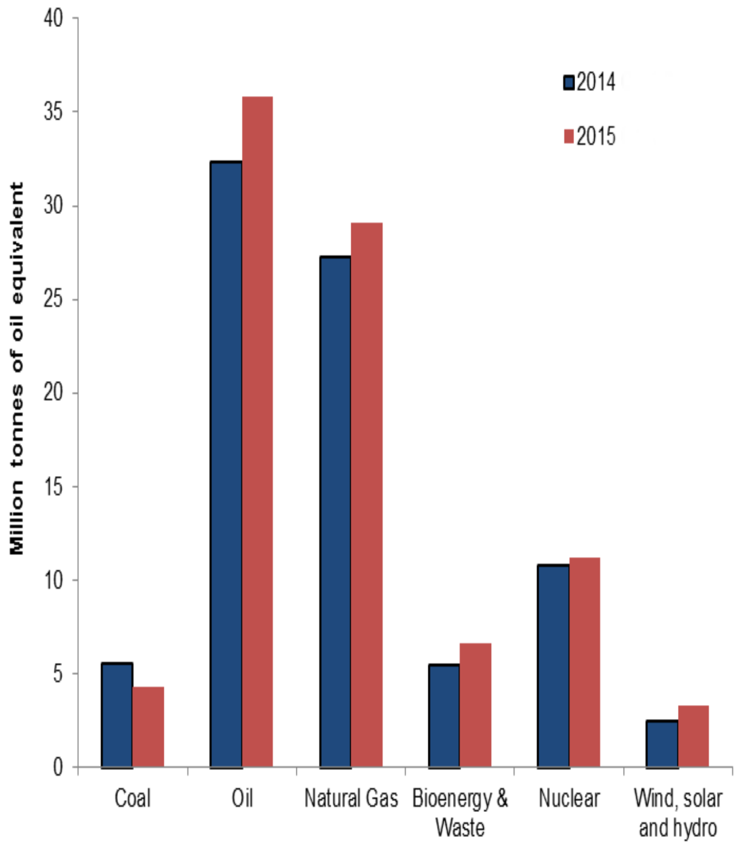

Figure 1.1: Production of indigenous primary fuels

1.2 Internet of Things

In modern wireless telecommunications, one of the novel paradigm that is rapidly gaining ground is the Internet of Things(IoT). The main driver of this concept is the widespread existence of Radio-Frequency Identification (RFID) tags, sensors, actuators, mobile phones, etc. around us which, through inimitable addressing schemes, are able to interact with each other and cooperate with their nearby devices to reach common goal. Undoubtedly, there will be a high impact on several aspects of everyday-life and behavior of potential users with the convergence of IoT. The most indisputable effects of the IoT commencement will be visible in both professional and personal arenas , with respect to an individual user. In this regard, domestics, e-health, e-learning are only a few examples of possible application scenarios in which the new paradigm will play a leading role in the near future. Similarly, from the business viewpoint, the most obvious consequences will be equally evident in areas such as, business management, machine controlled and industrial production, intelligent communication and transportation of people and goods, e-agriculture, etc. For its immense commencing in every sectors of life, the US National Intelligence Council [NIC] has included IoT in the list of six "Disruptive Civil Technologies" with potential impacts on US national power [7]. It highlights future opportunities that will arise, starting from the idea that popular demand combined with technology advances could drive widespread diffusion of an Internet of Things (IoT) that could, like the present Internet, contribute invaluably to economic development. The possible threats deriving from a widespread adoption of such a technology are also stressed.

The Internet of Things (IoT) has recently appeared as enabling technology for the smart gird, smart health, smart transportation, and smart environment as well as for smart cities. The major smart grid devices are smart home appliances, distributed renewable energy resources and power substations. The seven domains existing smart grid conceptual model was developed without the IoT concept in mind. As the smart grid evolved, many attempts started to introduce the IoT as enabling technology to the grid. Each device in the grid can be considered as an object. Utilizing the concept of IoT, each device can have a unique IP address that can upload its status and download control commands via the Internet [8]. Utilizing Internet of Things (IoT) technology in smart grid is an important approach to speed up the information of power grid system, and it is beneficial for effective management of the power grid infrastructure [8].

1.3 Smart Grid Technology

The definition and description of the smart grid are not necessarily unique, as its vision to the stakeholders and the technological complexities can be different. According to the U.S. National Institute of Standard and Technology (NIST) standard [9], the smart grid is a planned nationwide network (also known as "electricity with a brain") that uses information to deliver electricity efficiently, reliably, and securely. It is a modernized grid that enables bidirectional flows of energy using two-way communication and control capabilities that will lead to an array of new functionalities and applications. The U.S. Department of Energy (DOE) has suggested the definition of smart grid as "An automated, widely distributed energy delivery network. the Smart Grid will be characterized by a two-way flow of electricity and information and will be capable of monitoring everything from power plants to customer preferences to individual appliances. It incorporates into the grid the benefits of distributed computing and communications to deliver real-time information and enable the near-instantaneous balance of supply and demand at the device level". The smart grid concept was first built considering the seven domains as shown in 1.2.

In general, a smart grid is the combination of a traditional distribution network and a two-way communication network for sensing, monitoring, and dispersion of information on energy consumptions. An example of communication architecture in a smart grid is shown in Fig. 1.2. A typical smart grid consists of numerous power generating entities and power consuming entities, all connected through a network. The generators feed the energy into the grid and consumers draw energy from the grid. Smart grids aim is to enable an effective interaction between fluctuating renewable energy, mostly heat pumps in private households, electric vehicles and future electrical devices such as washing machine or fridges.

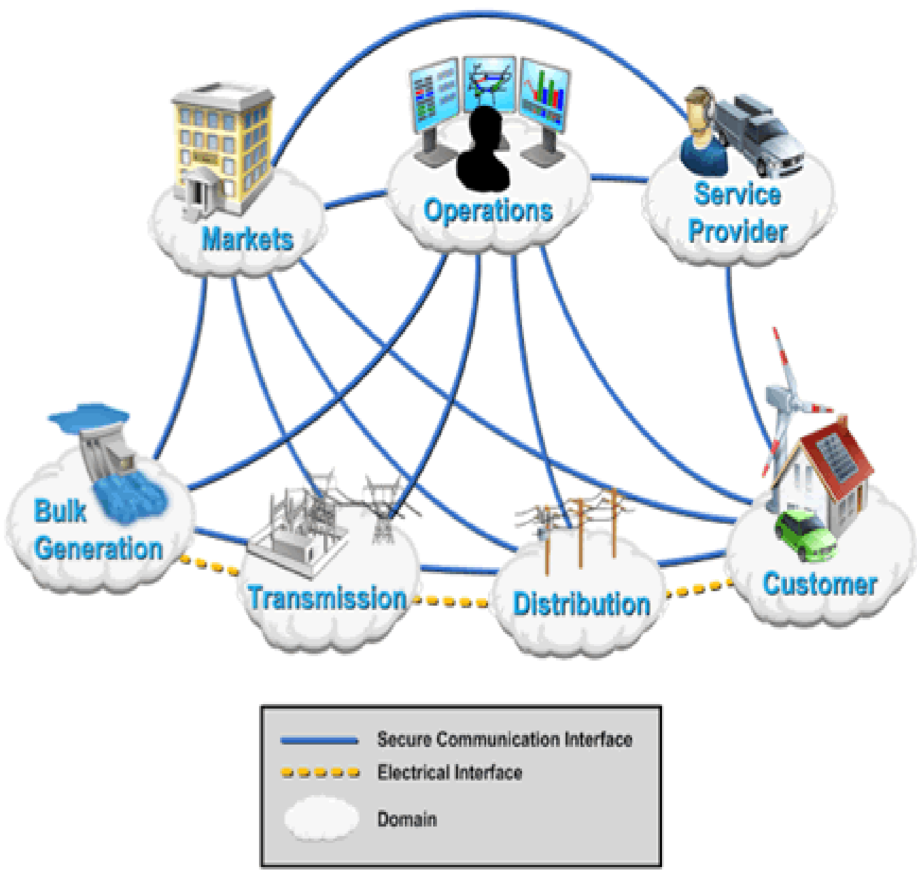

Figure 1.2: The smart grid domains

1.4 Problem Definition

The major challenges of demand side management schemes in smart grid include the need for modeling demand figure [10], [11], maximizing user's utility [12], reducing the overall cost [13] and utilizing the total production. All of these issues motivate the need for decision-theoretic tools such as game theory [14]-[4], optimization, or stochastic control [15] to properly model and analyze the various demand-response situations. In [16], a demand side management strategy is proposed for smart grid, focusing on peak shift or peak reduction for reducing grid deployment and operational costs. A heuristic based evolutionary algorithm has been developed for solving the problem. However, they consider neither the user utility nor the variable pricing of per unit power resources during off and peak hours. The authors of [17] propose a distributed online algorithm (DOA) incorporating user utility, grid load smoothing, and power usage cost. The DOA system is modeled with only one energy producer; it considers the power management operator as a joint entity with energy producer and hence, there is no clue of operator profit. Also, they don't consider dynamic variation of power prices over time. In summary, the literature studies in this domain either target to increase the user satisfaction level or to decrease the power production cost or, in some cases, to increase the operator profit. In this study, we consider an smart grid system that represents a practical business model. The smart grid operator (SGO) in the proposed model is allowed to purchase power from multiple available producers following demand-supply theory of economics [18].

1.5 Solution Methodology and Contributions

In this work, we develop an efficient demand-response management system, namely Optimal Dynamic Pricing mechanism for Trading-off (ODPT) user utility and operator profit in smart grid system. The whole operation of the proposed ODPT system is executed centrally in an SGO. The ODPT mainly focuses on to make a balance in between two contradictory parameters: user utility and SGO's profit. The profit of SGO increases when it receives significant demands from users at a certain per unit cost of power; however, a greedy SGO might loose customers and get reduced demands. Thus, following the theory of economics, the overpricing decreases the overall utility of power users. In

ODPT system, an SGO purchases power from energy producers at the start of each time slot (according to predicted user demands using ANN model) and dynamically fixes the selling price in order to allow effective changes in user demands and SGO's profit for varying purchase rates. Therefore, the SGO can make its expected profit only when it could sell full power it has purchased in the given time slot. Hence, the ODPT aims to maximize utilization of the available resources by judiciously allocating preferred amount of power to all users. The main contributions of this project are summarized as follows,

- This project proposes a practical business model for power management in smart grid that allows multiple energy producers, dynamic power prices and time-varying user demands.
- The problem of determining optimal selling price of power, that can acheive a good balance in between user utitlity and profit, has been formulated as a convex optimization problem in SGO.
- We also model user preferences from operator's perspective and develop utility function for dynamically capturing the user satisfactions.
- We employ feed-forward multilayer perceptron model coupled with an error-back-propagation technique (FFBP-ANN) in SGO to more accurately predict the power usage of users.
- Simulation results show the effectiveness of the proposed ODPT system in terms of enhancing operator profit, user utility and power utilization compared to state-of-the-art works.

1.6 Organization of the Report

The rest of the project report is organized as follows, Chapter 2 represents different related works in smart grid.In Chapter 3, we describe the system model and formulate a utility function and a pricing function. An optimization function based on the utility function and price function is also presented in this chapter. Numerical results are shown in Chapter 4. Finally, we draw conclusions in Chapter 5

Chapter 2

Background and Motivation

2.1 Introduction

The previous chapter introduces the concept of smart grid. It also describes the scopes and the challenges in the field of smart grid in details. In this chapter, we mainly focus on the background of smart grid on power distribution as well as the motivations that lead us to develop a trade-off for smart grid. With the modernized concept of power demand and supply, smart grid is gradually replacing our conventional power grid [19], [20]. To better understand the context and application of smart grid technologies the authors in [21], [22] have provided a comprehensive review. The authors of [21], systematically classify the works for the smart infrastructure system (energy, information, and communications), the smart management system, and the smart protection system along with the future research directions for each of these three major systems. Communications technologies and QoS mechanism for smart grid are introduced in [22].

Among several areas of smart grid, demand side management or demand response requires special attention. A discussion regarding demand side management is provided in [23], [3], [5]. The authors in [5], consider households that operate different appliances including PHEVs and batteries and propose a demand response approach based on utility maximization. To efficiently handle the demand side management in smart grid, predicting the user demand often appears as a necessity. A system for predicting the usage of each household appliances has been provided in [24]. Artificial Neural Network with multiplayer backpropagation model is used in [25] for forecasting the energy demand based on several economic indicator.

Demand side management is closely co-related with energy consumption. In general, the grid tries to reduce energy consumption so that the demand remains below the peak load which ultimately effects the user utility and the production cost. To reduce energy consumption and exaggerate a certain utility among a group of consumers, a constrained multi-objective optimization problem is formulated in [6]. Game theory is adopted in [26] to provide optimal energy consumption solution while maximizing user utility. In [12] authors propose an algorithm to find the optimal energy consumption levels for each subscriber to maximize the aggregate utility of all subscribers in the system in a fair and efficient fashion. In [27] a parametric time-utility model is introduced from which the price responsive behavior of aggregated loads from customers can be established. An optimal real-time pricing design under the framework of social welfare optimization and energy provisioning cost is also developed in this paper. In [28], authors focus on characterizing the structure of the optimal dynamic prices in the smart grid and the optimal demand and supply under various circumstances. The authors of [29] consider real-time energy distribution in a smart grid system by presenting first an offine algorithm. Based on that offline solution, they provide an online solution as well. Among the wide range of smart grid models and the challenge in characterizing the electricity demand and supply processes and the utility/cost/pricing functions, a general model that can accommodate various application scenarios would be highly desirable. The authors in [17], jointly consider the utilities and costs of the key components of the system to achieve optimized performance for the overall smart grid system. The authors develop a distributed online algorithm (DOA) that decomposes and solves the online problem in a distributed manner in smart grid incorporating user utility, grid load smoothing, and energy provisioning cost in a problem formulation. Our work is mainly inspired by the above aspects of power distribution in smart grid. For optimizing the performance of DOA, the authors of the paper consider the cost of the components- operator and energy producer as one single entity. Whereas we propose a practical scenario considering the operator and the energy producer as different entities. In the smart grid system, it is possible to include multiple energy producers unlike the model given in [17]. Moreover, dynamic pricing has also been associated in our project.

With the growing need of new infrastructure in power management system, intense research work have been done on smart grid technology. Several methodologies have been developed to address the limited power management, user utility and production cost in smart grid. Researchers all around the world have relentlessly given effort to solve these issues.

To ensure one of those requirements in smart grid, others have often been compromised. Such as, to ensure the limited power management and reducing the production cost, user utility is often considered as an opportunity cost. A number of methodologies are available regarding these issues. But, all these methodologies have got some limitations.

We have proposed to overcome the limitations of these existing work by introducing a trade-off in smart grid system that jointly consider user utility, operator profit and power utilization. All the approaches we have adopted are described in details in the later chapters, including the simulation results.

2.2 State-of-the-art Smart Grid

2.2.1 Demand Side Management in Smart Grid Using Heuristic Optimization

In this paper [16], operator designs an objective load curve according to the objective of the demand side management that is, maximizing the use of renewable energy resources, maximizing the economic benefit and reducing the peak load demand. The proposed optimization algorithm aims to bring the final load curve as close to the objective load curve as possible. A heuristic based evolutionary algorithm has been developed for solving the problem.

2.2.1.1 Limitations and points of improvement

The paper considers the solution based on user perspective. No such profit for the operator is described here. Moreover, for dynamic demand management no such dynamic pricing is included in this paper.

2.2.2 Multi-Objective Optimal Energy Consumption Scheduling in Smart Grids

In this paper [6], a third-party managing the energy consumption of a group of smart grid users is considered. The authors, formulate the load scheduling problem as a constrained multi-objective optimization problem (CMOP). The first objective is to minimize the total energy consumption cost, while the second is to maximize its utility measured by a certain utility function. To solve the problem, they first develop an evolutionary algorithm, called LSEA, to retrieve a set of Pareto-optimal solutions and show the trade-offs between energy consumption cost and the utility. Then, in order to further improve the algorithm efficiency, they present an ϵ approximate evolutionary algorithm, called ϵ-LSEA, to obtain ϵ-Pareto fronts of the objective space.

2.2.2.1 Limitations and points of improvement

CMOP has certain limitations. Any benefit of the third party managing energy consumption is not mentioned here. Since demand-supply are dynamic, the pricing should be dynamic as well. No such dynamic scheme is not addressed in this work.

2.2.3 Distributed Online Algorithm for Optimal Real-Time Energy Distribution in the Smart Grid

The authors of [17] propose a distributed online algorithm (DOA) incorporating user utility, grid load smoothing, and power usage cost. With a formulation that captures the key design factors of the system, they extend their prior work of a COA by decomposing the problem into many subproblems that can be solved in a distributed manner, thus protecting users' privacy and achieving scalability. they also show that the distributed online solution converges to the optimal offline solution asymptotically.

2.2.3.1 Limitations and points of improvement

The DOA system is modeled with only one energy producer; it considers the power management operator as a joint entity with energy producer and hence, there is no clue of operator profit. Also, they don't consider dynamic variation of power prices over time.

2.3 Summary

In this chapter, we have discussed about some of the recent smart grid work, their contributions and limitations. This study of the existing literature reveals a bunch of sectors, where further improvements are needed. The limitations of these state-of-the-art protocols have motivated us to develop a new methodology for smart grid. In our proposed work, we have tried to alleviate all the limitations that we have found from the study of the existing works.

Chapter 3

Proposed Model

3.1 Introduction

Smart grid is a promising technology which has been introduced to solve the problem of demand side management and limit the consumption to overall capacity. With the development of this technology, smart grids have drawn much attention because of its benefits of communications to deliver real-time information and enable the near-instantaneous balance of supply and demand at the device level. From the previous chapters, we have learned about smart grid and its architecture. Furthermore, we have studied the background and motivations behind our work. In this chapter, our proposed work, ODPT, is described in details. The optimization problem for trading off user utility and operator profit has also been formulated and analyzed for studying some performance metrics.

3.2 System Model and Assumptions

Among several components we have considered 3 of them for our work in the smart grid network- User, Smart Grid Operator (SGO), Energy Producer (EP) as shown in Figure 3.1. Users are power consumers such as, resident, industry and others. The EP is mainly responsible for the production and distribution of power. The SGO exchanges information with the User and EPs and thus it controls overall operation of the entire area to gain the objective. Each SGO is connected to multiple EPs and every user of a particular area is connected to a SGO, as shown in Fig. 3.1.

3.2.1 System Architecture

The elements in the system communicate with each other in the following manner,

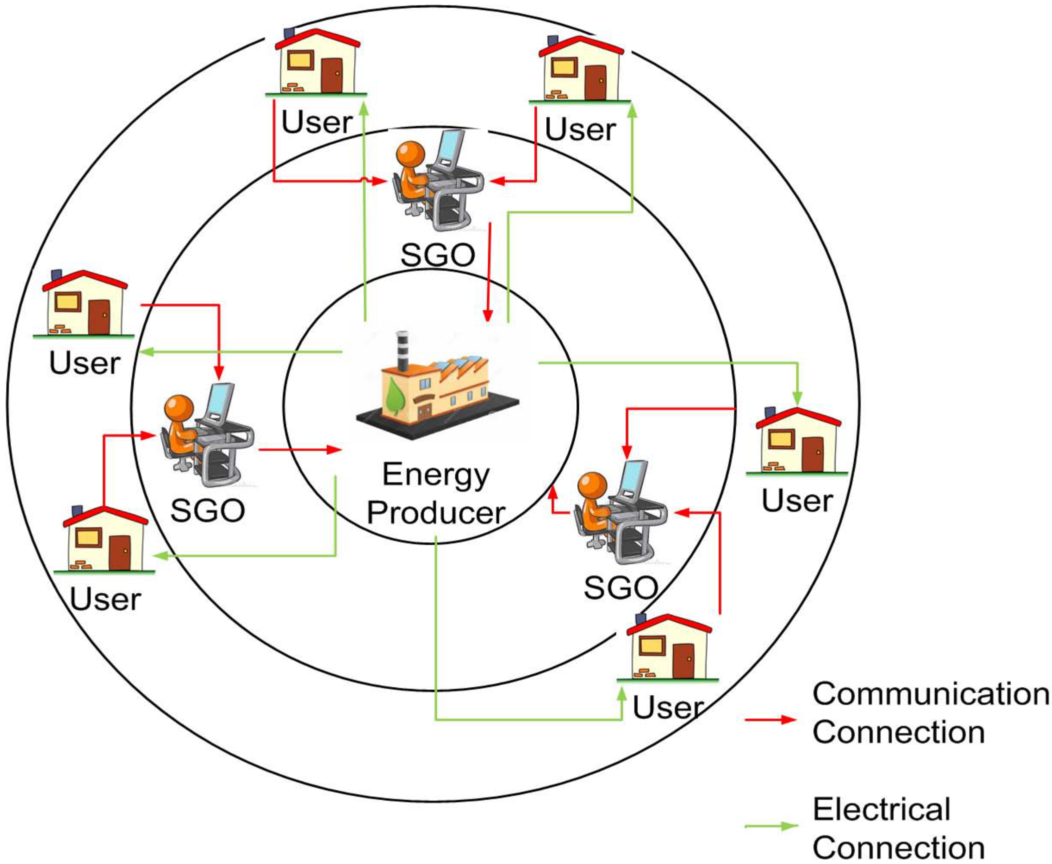

Figure 3.1: Three-tire system model

- For each user, we assume there exists a Smart Meter (SM) [30] [31]. Each SM is connected to the local SGO through a wireless or wired local area network. User demand is sent through SM to SGO.
- In each time slot, SGO purchase power from EPs. User demand is then set through SM, according to the announced dynamic selling price of SGO.
- Finally, according to the user demand the SGO handles under- and over-provisioning so that user utility gets maximized.
- We have divided the time period into T time slots and let $\mathcal{T}= \{1, 2, 3, ..., T\}$ as the set of time slots.
- We denote $\mathcal{N} = \{1, 2, 3, ..., n\}$ be the set of users and $\mathcal{M} = \{1, 2, 3, ..., m\}$ be the set of EPs.

In our project, we try to maximize user satisfaction along with the profit of SGO in smart grid system. To achieve our objective we need to formulate user satisfaction and SGO's profit which are described in subsection 3.2.2 and 3.2.3, respectively.

3.2.2 User Preference and Utility Function

We assume every user's power demand is independently set through SM based on various aspects such as- temperature of the day, price, running electrical appliances etc. There are several algorithms in literature that SM can use to predict the users power demand [30], [31]. However, this subject is not discussed here. Variation on power demand may also occur for different types of user i.e., power demand of residential user and industrial user are different even to the same price. Moreover, power demand of users of same group may not be analogous. The welfare or satisfaction of an user with respect to power demand and power allocation, can be modeled through the concept of utility function [32]. In this project, we present the corresponding utility function as $U(x_{i,t}, \omega_{i,t})$ where, $x_{i,t}$ is the allocated power to user i at time slot t and $\omega_{i,t}$ is the user i's preference at time slot t. User preference $\omega_{i,t}$ is user i's weight of power consumption at time t. It is defined as,

$$\omega_{i,t} = \frac{d_{i,t}}{D_t} \tag{3.1}$$

where, $d_{i,t}$ is the power demand of user i at time slot t and D_t is the total demand from users at time slot t which can be written as,

$$D_t = \sum_{i=1}^{n} d_{i,t}. \tag{3.2}$$

$\omega_{i,t}$ always gives a normalized value within the interval [0,1] since $d_{i,t} \leq D_t$. A higher $\omega_{i,t}$ illustrates a higher amount of power demand, i.e., user i demands more power than others when its $\omega_{i,t}$ is near to 1. In our proposed work, $\omega_{i,t}$ is defined from the SGO's perspective, unlike the user perspective defined in the literature.

Returning to utility function, we assume that the utility functions conform to the following properties.

- **Property I:** Utility functions are non-decreasing. Mathematically, this implies that we have

$$\frac{\partial U(x,\omega)}{\partial x} \geq 0 \tag{3.3}$$

- **Property II:** For notational convenience we define

$$V(x,\omega) = \frac{\partial U(x,\omega)}{\partial x} \tag{3.4}$$

  as the marginal benefit. User's marginal benefit is non-increasing. Thus we have

$$\frac{\partial V(x,\omega)}{\partial x} \leq 0 \tag{3.5}$$

  In other words, the utility functions are concave and the level of satisfaction for users can gradually get saturated.

- **Property III:** We have to be able to prioritize the user based on their utilities. In our formulation, we assume, for a fixed consumption level x, a larger ω implies a larger $U(x,\omega)$, which can be expressed as

$$\frac{\partial U(x,\omega)}{\partial \omega} > 0 \tag{3.6}$$

- **Property IV:** We assume the general expectation that no power allocation brings no satisfaction, so we have

$$U(0,\omega) = 0, \forall \omega > 0 \tag{3.7}$$

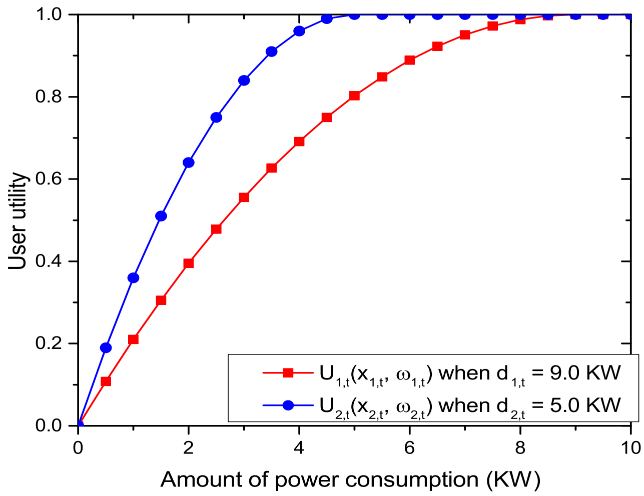

Figure 3.2: Sample utility function for two users with total demand 14KW

In literature, there are various choices of utility function to accurately model the satisfaction level of a power user. However, we use the following utility function corresponding to linear decreasing marginal benefit,

$$U_{i,t}(x_{i,t}, \omega_{i,t}) = \begin{cases} \frac{\omega_{i,t} x_{i,t} - \frac{1}{2}\frac{x_{i,t}}{D_t} x_{i,t}}{\frac{1}{2}\omega_{i,t} x_{i,t}} & \text{if } x_{i,t} < d_{i,t}. \\ 1 & \text{if } x_{i,t} \geq d_{i,t}. \end{cases} \tag{3.8}$$

An example of the behavior of utility function above is given in Fig. 3.2. The point where the utility function gets saturated and does not change corresponds to the maximum power requirement of the user. User can always perform more work if they can consume more power. Hence, they always tend to consume more power. Therefore, we can assume that utility function is non-decreasing. According to [33], the more one user consume power, the less s/he wants to have more of it. Hence, the utility derived by the user from the additional units, i.e. marginal utility goes on decreasing as the amount consumed power increases. This indicates a decreasing marginal benefit and a concave and increasing utility function for the total power consumption of users.

Table 3.1: Notations

Notation	Definition
$\omega_{i,t}$	User i's preference at time slot t
$d_{i,t}$	user i's demand at time slot t
D_t	Total power demand of all users at time slot t
$x_{i,t}$	Allocated power to user i at time slot t
$U(x_{i,t}, \omega_{i,t})$	User i's utility at time slot t
S_t	Per unit selling price of SGO to users at time slot t
$C_{j,t}$	Per unit power purchase price by SGO from EP j at t
$y_{j,t}$	Purchased power from producer j at time slot t
A_j^t	The available power of producer j at time slot t
P_{SGO}^t	Overall profit of SGO at time slot t
P_{exp}^t	Expected profit of SGO at time slot t
η	SGO's power utilization efficiency
h_1, h_2	Nodes in the hidden layer in ANN model
w_{ab}	The weight between node a in the input and node b in the hidden layer in ANN model
$\delta_{d_{i,t}}$	Error signals from the output layer to the hidden layer
d	Observed data in ANN
α	Learning rate

3.2.3 Profit of SGO

The profit SGO gets maximized when users power demand is analogous to its prediction. Because the selling price is determined through the predicted power demand. However it might not be possible to predict the exact power demand in real. Still we can minimize the error in prediction (even prone to 0) over the course of time by adopting a suitable prediction model. We know, profit can be calculated through substracting the cost from the revenue. Therefore, the overall profit of SGO at time slot t can be modeled as,

$$P_{SGO}^t = \sum_{i=1}^{n} x_{i,t} S_t - \sum_{j=1}^{m} y_{j,t} C_{j,t}, \tag{3.9}$$

where, S_t is the per unit optimal selling price to users and $C_{j,t}$ is the per unit purchase price from EP j at time slot t. $x_{i,t}$ indicates allocated power to user i at time slot t and $y_{j,t}$ indicates purchased power from EP j at time slot t. A quick search table for the abbreviations and notations used in this project is given in Table 3.1.

3.3 Proposed ODPT System

In this section, we try to maximize user utility and SGO's profit as an optimization problem. We also show an illustrative example of the proposed ODPT.

3.3.1 Optimization Problem Formulation

Selling more power leads to more profit for SGO. Hence it is desirable to utilize the overall available resources to maximize the aggregate utility of all users as well as the profit of itself. However under certain limitations we try to achieve the following goals-

- maximizing user utility
- maximizing the profit of SGO
- utilizing the overall resources

Initially we assume that SGO knows how each user demands with varying prices. Let denote $d_{i,t}$ as user i's power demand which s/he optimally decides to consume at price S_t. Optimization function maximizing user utility and profit of SGO can be formulated as,

maximize:

$$O = \sum_{i=1}^{n}(U(x_{i,t}, \omega_{i,t}) + x_{i,t}S_t) - \sum_{j=1}^{m}(C_{j,t}y_{j,t} + A_j^t - y_{j,t}), \tag{3.10}$$

s.t,

$$0 \leq x_{i,t} \leq d_{i,t} \tag{3.11}$$

$$\sum_{i=1}^{n} x_{i,t} \leq \sum_{j=1}^{m} y_{j,t} \tag{3.12}$$

$$S_t > 0 \tag{3.13}$$

$$0 \leq y_{j,t} \leq A_j^t \tag{3.14}$$

Here, $U(x_i, \omega_i)$ is defined in (3.8) and $x_{i,t}$ and $y_{j,t}$ is defined in (3.9). A_j^t indicates the available power of producer j at time slot t.

In the formulated problem in (3.10), the first constraint in (3.11) ensures that the allocated power to user i must not exceed his/her demand. The second constraint in (3.12) points that the overall power allocation to all users is limited by the amount of purchased power of SGO at time slot t. In the third constraint (3.13) the selling price of SGO is lower bounded. SGO sets the upper bound independently. Finally, the fourth constraint in (3.14) refers that in each time slot t, SGO can not purchase more power from EP j than its available resources.

Since users power demand mechanism at different prices is independent and confidential, it is not possible for SGO to endure it in real. So, the SGO needs to estimate the user demand as it is required to run the optimization problem. There are several techniques to estimate user demand. However, Artificial Neural Network(ANN) with Feed Forward Multilayer Perceptron coupled with Back Propagation training algorithm is used in this project as the prediction model [25]. This model is used to find the relationship between price and demand. A detailed description of ANN model is given in section 3.3.3. After evaluating the optimization problem with the help of ANN model, the SGO purchases the predicted amount of power from EPs and announces the optimal selling price S_t to users.

After getting the actual demand from every user two cases can occur based on total demand D_t-

- Case 1: $D_t \leq \sum_{j=1}^{m} y_{j,t}$.
  That is, when over-provision occurs, SGO allocates the amount of power to each user according to their demand.

- Case 2: $D_t > \sum_{j=1}^{m} y_{j,t}$.
  That is, in the case of under-provisioning, SGO runs the following sub-optimization problem to maximize aggregate utility,
  maximize:

$$O_1 = \sum_{i=1}^{n} (U(x_{i,t}, \omega_{i,t})), \tag{3.15}$$

s.t,

$$0 \leq x_{i,t} \leq d_{i,t}. \tag{3.16}$$

$$\sum_{i=1}^{n} x_{i,t} \leq \sum_{j=1}^{m} y_{j,t}. \tag{3.17}$$

In the case of under-provisioning, two strategies can be followed. One is to allocate no power to some users, so that others can be fully satisfied. Another is to allocate less amount of power to all the users than they have demanded. In our project, we generalize these two strategies that is, the system can follow any of these two depending on the situation to maximize user utility.

3.3.2 Optimal Power Allocation Algorithm for SGO

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

Algorithm 1 Optimal power allocation algorithm for SGO

Input: $C_{j,t}, A_{j,t}, d_{i,t}$

Output: $y_{j,t}, S_t, x_{i,t}$

loop
  For each time slot t, SGO-
  collects $(C_{j,t}, A_{j,t})$ from each producer j.
  runs the optimization function specified in (3.10)
  announces optimal price S_t to each user i.
  receives the actual demand $d_{i,t}$ from each user i.
  calculates D_t through (3.2).
  if $D_t \leq \sum_{j=1}^{m} y_{j,t}$ **then**
    SGO allocates $d_{i,t}$ power to each user i.
  else
    SGO executes sub optimization function (3.15) and alloactes $x_{i,t}$ power to each user i
  end if
  updates ANN model parameters specified in (3.18) to (3.31).
end loop

each EP. SGO then runs the optimization function specified in (3.10) to get the optimal price for the estimated power which is obtained from the help of ANN model. While doing so, the function focuses on maximizing profit of SGO and users utility. SGO then announces its optimal per unit selling price to users for sell. SMs in users end, set the amount of power the users may need considering the price announced by the SGO. According to users power demand, SGO runs the sub optimization function specified in (3.15) to get the optimal amount of power amount to be allocated to users in such a way that the overall utility gets maximized. In the above algorithm, the purchase price $C_{j,t}$ and the available power $A_{j,t}$ of each EP and the actual demand $d_{i,t}$ from each user i are considered as input. The algorithm outputs the amount of power to purchase $y_{j,t}$ from each EP j along with the optimal selling price S_t and the allocated power $x_{i,t}$ to each user i.

3.3.3 Demand Estimation Model

In this project, Artificial Neural Network (ANN) is used as demand estimation model. ANNs are programs designed to solve any problem by trying to mimic the structure and the function of our nervous system. Neural network resembles the human brain in the following two ways: A neural network acquires knowledge through learning. A neural network's knowledge is stored within the interconnection strengths known as synaptic weight. The ANN technique represents higher nonlinearity between independent and dependent variables. The ANN model adopted in this study is a feed-forward multilayer perceptron model, coupled with an error backpropagation technique (FF-BP-ANN). FF-BP-ANN is the most popular ANN model for prediction. The FF-BP-ANN model generally consists of three layers (input layer, hidden layer, and output layer). However, there may be more than one hidden layer, and the input or hidden layer may have a bias node. The node value in the hidden layer can be calculated using,

$$h_1 = (1 + \exp((-1)(tw_{11} + S_t w_{21})))^{-1}, \tag{3.18}$$

$$h_2 = (1 + \exp((-1)(tw_{12} + S_t w_{22})))^{-1}, \tag{3.19}$$

where, h_1 and h_2 are nodes in the hidden layer; t and S_t are nodes in the input layer; and w_{ab} is the weight between node a in the input and node b in the hidden layer. Likewise, the node value in the output layer can be calculated using-

$$d_{i,t} = (1 + \exp((-1)(h_1 v_1 + h_2 v_2)))^{-1}, \tag{3.20}$$

where, $d_{i,t}$ is node in the output layer. Error signals from the output layer and the hidden layer are as follows, respectively:

$$\delta_{d_{i,t}} = (d - d_{i,t})d_{i,t}(1 - d_{i,t}), \tag{3.21}$$

where, d is observed data.

$$\delta_{h_1} = h_1(1 - h_1)\delta_{d_{i,t}} v_1, \tag{3.22}$$

$$\delta_{h_2} = h_2(1 - h_2)\delta_{d_{i,t}} v_2, \tag{3.23}$$

Weights between hidden and output layers and input and hidden layer can be adjusted using the following functions respectively:

$$\Delta v_1^t = \alpha \delta_{d_{i,t}} v_1 + \beta \Delta v_1^{t-1}, \tag{3.24}$$

$$\Delta v_2^t = \alpha \delta_{d_{i,t}} v_2 + \beta \Delta v_2^{t-1}, \tag{3.25}$$

$$v_1^t = v_1^{t-1} + \Delta v_1^t, \tag{3.26}$$

$$v_2^t = v_2^{t-1} + \Delta v_2^t, \tag{3.27}$$

$$\Delta w_{1i}^t = \alpha \delta_{h_i} t + \beta \Delta w_{1i}^{t-1}, \tag{3.28}$$

$$\Delta w_{2i}^t = \alpha \delta_{h_i} t + \beta \Delta w_{2i}^{t-1}, \tag{3.29}$$

$$w_{1i}^t = w_{1i}^{t-1} + \Delta w_{1i}^t, \tag{3.30}$$

$$w_{2i}^t = w_{2i}^{t-1} + \Delta w_{2i}^t,, \tag{3.31}$$

where, α is learning rate and β is momentum constant and i=1,2. This momentum technique accelerates the training process (weight adjustment) in flat regions of the error surface and prevents fluctuations in the weights.

3.3.4 An Illustrative Example

Let there are 5 EPs with 10 users in the smart grid system.

3.3.4.1 Over-provisioning

At a particular time slot t, the selling price $C_{j,t}$ and available resources $A_{j,t}$ of each EP j are shown in Table 3.2.

Table 3.2: EP Parameters (over-provisioning)

Provider	$A_{j,t}$	$C_{j,t}$	$y_{j,t}$
1	1.0	2.562	1.0
2	3.0	3.162	1.825
3	1.0	2.75	1.0
4	5.0	3.395	0.0
5	5.0	3.375	0.0

By running the optimization function defined in Equation (3.10), SGO gets the optimal per unit selling price $S_t = 4.756$ and predicts the user demand using the equations (3.18)-(3.29), as shown in Table 3.3. It also gets the optimal amount of power to purchase $y_{j,t}$ from each EP j, as shown in Table 3.2. SGO then collects the user demand $d_{i,t}$ from each SM in the user end. Let the total power demand D_t is less than the total predicted demand as shown in Table 3.4. In this case of over-provisioning, SGO allocates power $x_{i,t}$to each user i according to their demand, that is, $x_{i,t} = d_{i,t}$. Hence the utilty of each user is 1 and a total of 10.

Table 3.3: User demand (over-provisioning)

User	Predicted demand	$d_{i,t}$	$x_{i,t}$
1	0.370	0.322	0.322
2	0.429	0.253	0.253
3	0.618	0.896	0.896
4	0.416	0.371	0.371
5	0.139	0.054	0.054
6	0.316	0.449	0.449
7	0.256	0.252	0.252
8	0.653	0.662	0.662
9	0.251	0.226	0.226
10	0.372	0.326	0.326

Table 3.4: Total calculation (over-provisioning)

Parameters	Value
Total purchased amount	3.825
Total actual demand	3.815
Total utility provided	10.0

3.3.4.2 Under-provisioning

At a particular time slot t, the purchase price $C_{j,t}$ and available resources $A_{j,t}$ of each EP j are shown in Table 3.5.

Table 3.5: EP Parameters (under-provisioning)

Provider	$A_{j,t}$	$C_{j,t}$	$y_{j,t}$
1	3.0	2.586	2.857
2	7.0	3.378	0.0
3	8.0	3.48	0.0
4	5.0	3.295	0.0
5	5.0	3.375	0.0

Through the optimization function defined in Equation (3.10), SGO gets the optimal per unit selling price $S_t = 4.805$ and predicts the user demand using the equations (3.18)-(3.29), as shown in Table 3.6 and the optimal amount of power to purchase $y_{j,t}$ from each EP j, as shown in Table 3.5. After collecting the user demand $d_{i,t}$ from each SM in the user end, if the total power demand D_t is more than the total predicted demand as shown in Table 3.7, SGO won't be able to allocate power to each user as per their demand. At this circumstance, SGO runs the sub optimization function defined in Equation 3.15 to maximize total utility. Hence the utilty of each user, in this case, may be less than 1 and a total should be lower than 10, as shown in Table 3.7.

3.4 Summary

Our proposed ODPT model is focused on trading off user utility and SGO's profit while utilizing the overall capacity of SGO. It enables the SGO to make a profit by utilizing all its available resources in a particular time slot. It also tries to maximize user util-

Table 3.6: User demand (under-provisioning)

User	Predicted amount	$d_{i,t}$	$x_{i,t}$
1	0.308	0.772	0.554
2	0.379	0.574	0.453
3	0.324	0.178	0.166
4	0.348	0.237	0.216
5	0.188	0.043	0.042
6	0.226	1.041	0.645
7	0.390	0.061	0.060
8	0.300	0.506	0.412
9	0.132	0.181	0.169
10	0.259	0.141	0.134

Table 3.7: Total calculation (under-provisioning)

Parameters	Value
Total purchased amount	2.857
Total actual demand	3.738
Total utility provided	9.678

ity through predicting the accurate user demand by running the appropriate prediction model, ANN. Since the operation is performed centrally and the time slot is large enough, there exists no delay overhead.

Chapter 4

Performance Evaluation

4.1 Introduction

The proposed Optimal Dynamic Pricing with Trade-offs (ODPT) between user utility and operator profit is a smart power management policy. In this project, the proposal is formulated as a convex optimization problem. We implement the proposed ODPT to evaluate its effectiveness compared to existing state-of-the-art works in the literature. We compare the performances of our proposed ODPT with those of Distributed Optimal Algorithm (DOA) [17], ODPT without ANN-based prediction model (ODPT(W/O ANN)), and ODPT with fixed-range profit (ODPT(FRP)). In the implementation of ODPT(W/O ANN), we use exponentially weighted average (EWMA) formula [34] [35] to predict the user demands and in ODPT(FRP), we keep the profit percentage of the operator within a range while maintaining all other constraints the same. In the original work of DOA, there exists only one EP in the system. The single EP in DOA works with the aim to minimize its production cost. It considers a quadratic cost function. In support of fair comparison, we allow DOA to purchase power from multiple EPs. Each EP declares its available power and per unit selling price at the beginning of each time slot. We set the Lagrange multiplier used in DOA as the per unit selling price to users as suggested in [12]. Each of the graph data points is corresponding to the average value of the results from 20 different simulation runs with different random seeds.

4.1.1 Simulation Environment

The simulation data and parameters used in the prosecution are collected from the measured per hour power usage of Dhaka Electricity Supply Company (DESCO) [36]. We model our proposed ODPT system using AMPL optimization modeling tool [37] and evaluate it using Knitro non-linear optimization tool [38].

In our simulation model, we consider a power distribution system in an area with 500 users, 10 EPs and 1 hr updating periods. The 1 hr time period is ample to obtain the required user information and execute our trade-off operation centrally in the SGO. To assess daily operation, power consumption within a 24-hr task epoch are used to show the results. The capacity and declared price per unit of EPs are randomly chosen from the sets $\mathcal{C}$ = [0,50] KW and $\mathcal{P}_p$ = [2.0,3.5] BDT, respectively. We assume user's actual power demand varies within the range $\mathcal{D}$ = [0,3] KW. Per unit selling price to users is determined from the set $\mathcal{P}_u$ = [4.0, 8.0] BDT. This power usage pattern of the customers is inspired by smart meter readings of the Department of Industry, Innovation and Science of Australia [39]; it is also congruent with DESCO references. The parameters and their values used in the simulation are listed in Table 4.1.

Table 4.1: Simulation Parameters

Parameter	Value
Number of Users	500
Number of EPs	10
Demand of Each User at each time slot, $d_{i,t}$	$0 \sim 3$ KW
Capacity of Each EP at each time slot	$0 \sim 50$ KW
Per Unit Purchase Price from EP at each time slot	$2.0 \sim 3.5$ BDT
Per Unit Selling Price to Users at each time slot	$4.0 \sim 8.0$ BDT

4.1.2 Performance Metrics

In this section, we describe the following performance metrics that we have used to evaluate ODPT-

- ***Utility***: In our simualtion environment, utility is measured as the average amount of utility provided to each users in each time slot. The average utility can be measured through the following equation-

$$\overline{U} = \frac{1}{T}\sum_{t=1}^{T}(\frac{1}{n}\sum_{i=1}^{n}U(x_{i,t},\omega_{i,t})). \tag{4.1}$$

  We have considered utility to understand the user satisfaction with respect to other existing work. The higher the utility is, the better the performance is.

- ***Profit***: Profit of SGO is measured as the total profit over a day, as follows-

$$P_{total} = \sum_{t=1}^{T} P_{SGO}^{t}. \tag{4.2}$$

- ***Power Utilization Efficiency***: Power utilization efficiency of SGO is measured as the ratio of average power demand of the users and the average purchased amount of power from EPs in each time slot. The utilization efficiency can be represented as follows-

$$\eta = \frac{\sum_{t=1}^{T}\sum_{i=1}^{n} d_{i,t}}{n} \times \frac{m}{\sum_{t=1}^{T}\sum_{j=1}^{m} y_{j,t}}. \tag{4.3}$$

- ***Profit Ratio***: Profit ratio of SGO is the ratio of total profit and the total expected profit in an operation cycle, as follows-

$$\phi = \frac{P_{SGO}^{t}}{P_{exp}^{t}}. \tag{4.4}$$

  where,

$$P_{exp}^{t} = \sum_{t=1}^{T}\sum_{j=1}^{m}(y_{j,t} \times (S_t - C_{j,t})). \tag{4.5}$$

  Here, P_{exp}^{t} is the expected profit of SGO at time slot t, that is, if the SGO could sell all the purchased power at time slot t then the profit it makes is known as expected profit. The SGO can make a maximum profit if it could sell all its purchased resource at that particular time slot. Hence, the profit ratio remains within the range [0,1].

4.1.3 Simulation Results

4.1.3.1 Performance study over days of a month

The graphs in Fig. 4.2, depict the utility of ODPT, ODPT (W/O ANN), ODPT (FRP) and DOA over a period of 30 days of a month based on the user demand as shown in Fig. 4.1. The graphs show that there is a fluctuation of user utility in a very small range

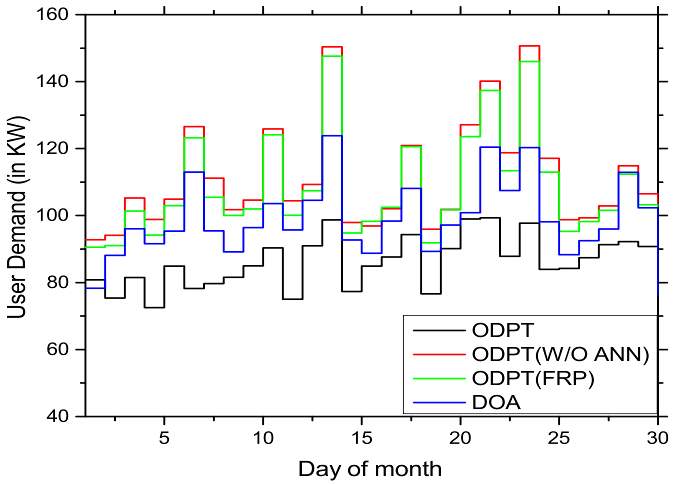

Figure 4.1: Total power demand of all users in a day

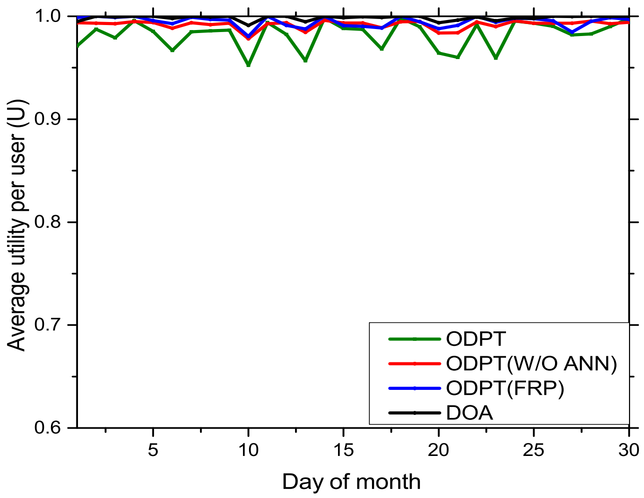

Figure 4.2: User utility performances of the studied smart grid power management system over the day of a month

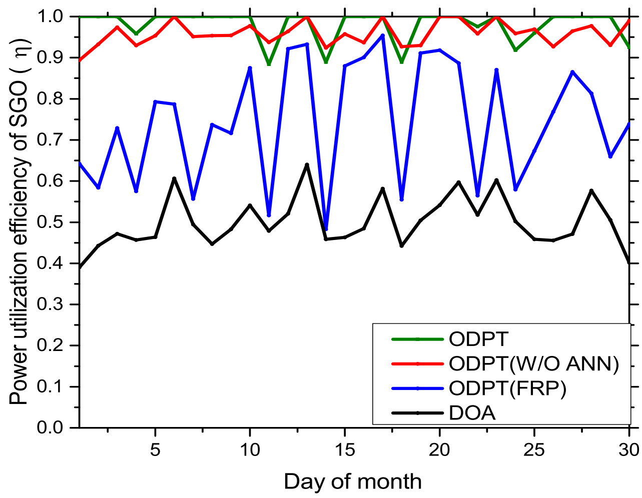

Figure 4.3: Power utilization efficiency performance of the studied smart grid power management system over the day of a month

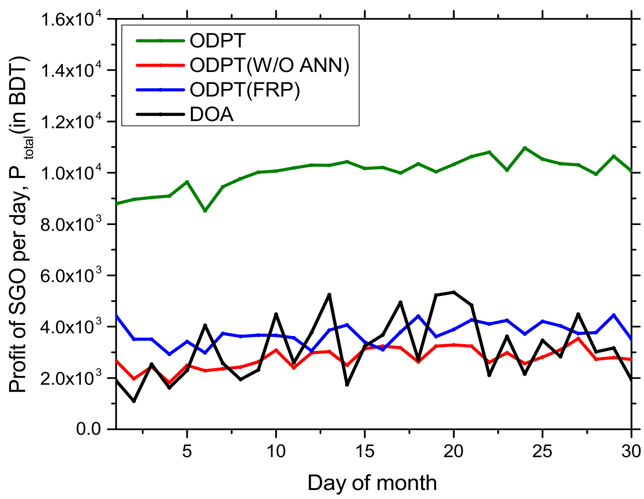

Figure 4.4: Profit of SGO of the studied smart grid power management system over the day of a month

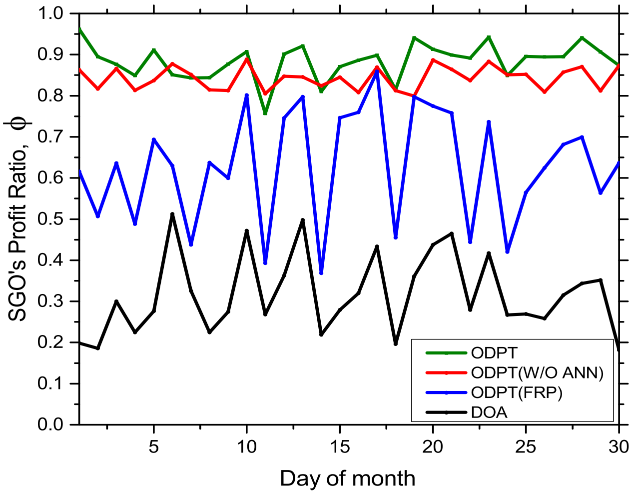

Figure 4.5: Profit ratio of SGO of the studied smart grid power management system over the day of a month

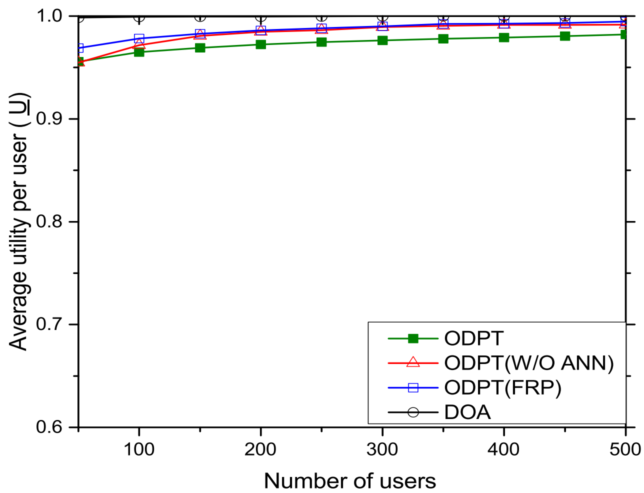

Figure 4.6: User utility performances of the studied smart grid power management system over the number of users

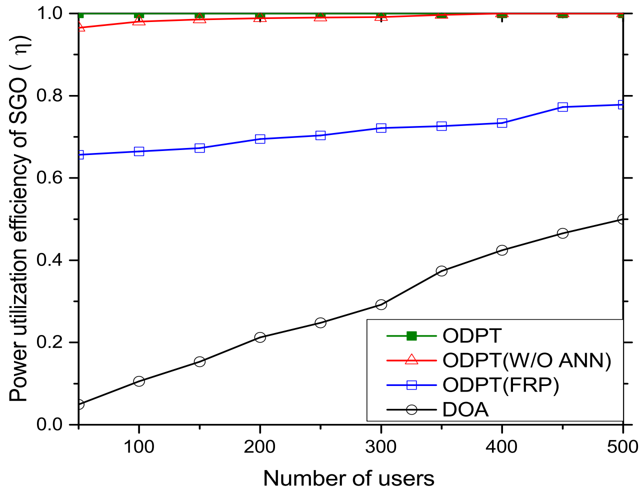

Figure 4.7: Power utilization efficiency performance of the studied smart grid power management system over the number of users

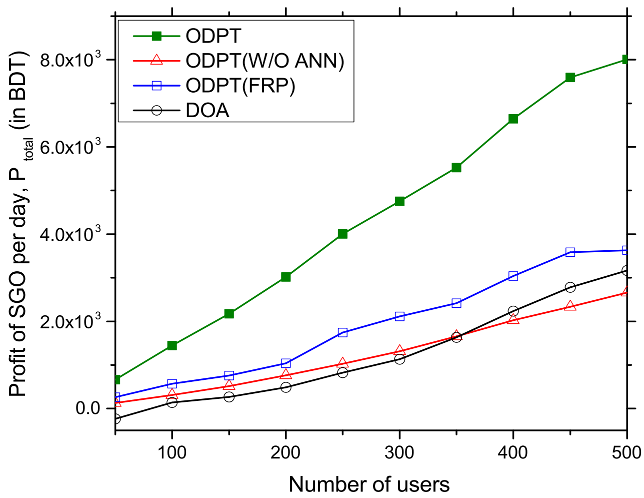

Figure 4.8: Profit of SGO of the studied smart grid power management system over over the number of users

i.e., 0.95 to 1. Hence, we can state that the studied systems provide with steady state utility values. It is also observed that the utility of proposed ODPT is slightly lower than others. The utility decreases when user demand is not fully satisfied. This could happen when SGO is purchasing less power than the user demand. In contrast, this will cause SGO's power utilization efficiency to increase. That is why, in Fig. 4.3, we can see that the power utilization efficiency of ODPT is significantly higher than the other versions of ODPT and the DOA, indicating a proper balance in between the amount of purchase and selling powers. On the other hand, the power utilization efficiency of DOA is lower than any others in the graphs. Again from Fig. 4.2, we can see the user utility of DOA is significantly higher among all. This is because in DOA, the SGO purchases more amount of power than the user demand. Hence the graph of DOA in Fig. 4.3 is below to others, indicating a lower power utilization efficiency of SGO. The utility graphs of ODPT (W/O ANN) and ODPT (FRP) in Fig. 4.2 lay in between the DOA and ODPT graphs and vary between 0.98 to 1. Again, the utilization efficiency graphs in 4.3 lay between 0.5 to 1. The ODPT (FRP) utilization efficiency graph is continuously fluctuating as shown in Fig. 4.3. This is because, the profit of ODPT (FRP) has a fixed upper limit and for which the ANN model used in this work cannot reach the optimal point. Therefore, the error rate of the ANN model gets increased. As a result, the prediction of user demand cannot be accurate causing the power utilization efficiency of SGO to fluctuate in the long range.

The graphs in Fig. 4.4 portray the profit of ODPT, ODPT (W/O ANN), ODPT (FRP) and DOA over a period of 30 days from which we can observe that the profit graph of ODPT is notably higher than the other versions. Note that the profit of an SGO depends on the utilization efficiency. Since the ODPT has a higher utilization efficiency as we can see from Fig. 4.3, it can make comparatively a higher amount of profit (almost 125%) than the others. The DOA graph in Fig. 4.4 shows a lower profit comparing to ODPT because the DOA SGO is buying more power than user demands. The profit graph of ODPT (W/O ANN) in Fig. 4.4 exhibits a lower range of profit comparing to others. Since there is no ANN model (that helps to determine the optimal selling price for profit) in ODPT (W/O ANN), we assume that the SGO will set its profit in a fixed range to determine the selling price based on purchasing price. The ODPT

(W/O ANN) gives satisfactory result on prediciting user demand on each time slot, but it can not decide the optimal price for profit and utility. Thus, we set the range of profit in ODPT (W/O ANN) upto four times of purchasing price, causing the graph to remain at low level.

In Fig. 4.5, the profit ratio graphs of ODPT, ODPT (W/O ANN), ODPT (FRP) and DOA over a period of 30 days are presented. The expected profit of our proposed ODPT system is almost equal to the actual profit because of using less error-prone prediction based on ANN-model. Hence, it gives a higher profit ratio than others. Again, there is no demand prediction model used in DOA for which DOA purchases all the available resources from EPs. As a result, its profit ratio gives comparatively a lower graph.

4.1.3.2 Impacts of increasing number of users

With the increasing number of users, the demand also gets increased and so does the user utility, SGO's power utilization efficiency, power ratio and profit of ODPT, ODPT (W/O ANN), ODPT (FRP) and DOA.

In Fig. 4.6, we plot the average user utility over the number of users. From the graph, we can see that the average utility of ODPT, ODPT (W/O ANN), ODPT (FRP) and DOA rise steadily over the number of users within the range 0.95 to 1. The average utility graphs of ODPT (W/O ANN) and ODPT (FRP) rise more gradually comparative to ODPT average utility. This is because both have got a fixed range of profit that causes linear increase in demand with the increasing number of users. Thus, the SGO purchases more power from EPs to satisfy user demands and thus the utility is increased. The DOA average utility graph is almost stabilized in the highest value, i.e., 1 over the number of users. This is because, the DOA communicates with user in real time in a distributed manner to get the user demand. Therefore, it causes the methodology to provide the highest user utility.

Fig. 4.7 demonstrates the SGO's average utilization efficiency over the number of users. In the figure, the ODPT and ODPT (W/O ANN) graphs show a higher utilization efficiency than the other two. In fact, they provide the highest efficiency. This is caused by the fact that the estimation models of ODPT and ODPT (W/O ANN) give almost accurate prediction of user demand over the increasing number of users. It follows that the SGO of the two systems purchase exactly the amount of power that they are going to sell, which is not more than the demanded power. Thus, the efficiency of ODPT and ODPT (W/O ANN) get maximized. The graphs of ODPT (FRP) and DOA remain at low level for the same reason, that is, their SGOs purchase more power than the user demand.

Fig. 4.8 demonstrates the SGO's average profit over the number of users. Since the average utilization efficiency of every system rises with the number of users, shown in Fig. 4.7, the corresponding profit also get increased shown in Fig. 4.8. Since the power utilization efficiency of ODPT is the highest amongst all, its profit also remains higher. Again, the power utilization efficiency of ODPT (W/O ANN) is comparatively higher than that of ODPT (FRP). But, due to its fixed selling price (4 times of purchasing price), its profit remains lower than the ODPT (FRP). The DOA gives the lowest profit among all as it provides the lowest power utilization efficiency, depicted in Fig. 4.7.

Fig. 4.9 represents the SGO's profit ratio over the number of users. The graphs in the figure demonstrates a higher profit ratio of ODPT and ODPT (W/O ANN) because of the accuracy of the prediction models they have used. With the increasing number of users, the prediction model can more accurately predict the upcoming user demand, hence can predict the accurate profit to make. On the other hand, ODPT (FRP) could not reach to the optimal result due to its profit limit and DOA doesn't use any prediction model to estimate the profit. Thus, they both provide a lower profit ratio graphs.

The average execution time of the proposed algorithm over the number of users is shown in Fig. 4.10. From this figure, it is evident that the proposed ODPT system can be solved in polynomial time.

4.2 Summary

The performance of the proposed ODPT system has come out with an efficient trade-off between the user utility and the profit of SGO. Though the utility of the ODPT is slightly lower than DOA, it gives a higher performance on other metrics.

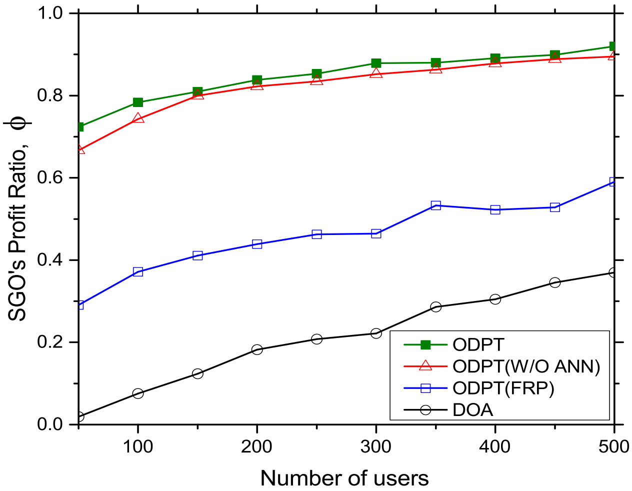

Figure 4.9: Profit ratio of SGO of the studied smart grid power management system over the number of users

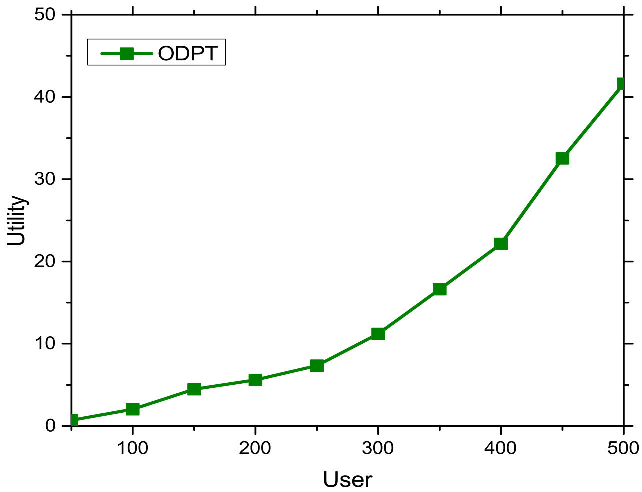

Figure 4.10: Average execution time in each time slot (sec)

Chapter 5

Conclusion

5.1 Summary of Project

In this report, we have explored dynamic energy demand based on dynamic pricing scheme of power. We have revised the prediction model ANN with respect to price and time. To achieve the optimal utility with optimal profit, we have formulated an optimization function which gives the ideal solution. We have considered a multiple provider system for which the possibility of power failure tends to zero.Our proposed ODPT offers an efficient way of utilizing the overall resources in SGO over a time slot. It prioritizes user demand through calculating their demand preferences and helps to maximize their utility. Through the performance evaluation, we have been able to show that, our proposed model performs better and works more efficiently than a number of state-of-the-art protocols in the literature.

5.2 Discussion

While developing the ODPT model for smart grid, we have faced lots of difficulties. We have to go through the existing literatures to get an insight into the current research state of smart grids and to find out the points where further improvements are needed. Coming up with a unique idea that overcomes the limitations of previous works was the main challenge. Designing a new model for smart grid was the main attention of our work. Making a trade-off between the user utility and operator benefit was the main interest of our work. We have to find out the methodology to make the solutions workable and develop a model. Then we evaluated our model's performance and feasibility in the real world using a modeling tool (AMPL) and an optimization tool (Knitro) . Comparing our model with ODPT(O/W ANN), ODPT(FRP) and DOA [17], we can observe a substantial improvement of the performance. Therefore, our proposed ODPT model provides better solutions of the existing problems and shows promising development in the field of smart grid.

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Appendix A

List of Acronyms

EP	Energy Producer
SGO	Smart Grid Operator
DOA	Distributed Online Algorithm
ODPT	Optimal Dynamic Pricing for Trade-off
FRP	Fixed Range Profit
W/O ANN	Without ANN model
FFBP-ANN	Feed-Forward Multilayer Perceptron Model coupled with Error-Back-Propagation ANN model
DECC	Department of Energy and Climate Change
NIST	National Institute of Standard and Technology
DESCO	Dhaka Electricity Supply Company

Appendix B

List of Notations

Notation	Definition
$\omega_{i,t}$	User i's preference at time slot t
$d_{i,t}$	user i's demand at time slot t
D_t	Total power demand of all users at time slot t
$x_{i,t}$	Allocated power to user i at time slot t
$U(x_{i,t}, \omega_{i,t})$	User i's utility at time slot t
S_t	Per unit selling price of SGO to users at time slot t
$C_{j,t}$	Per unit power purchase price by SGO from EP j at t
$y_{j,t}$	Purchased power from producer j at time slot t
A_j^t	The available power of producer j at time slot t
P_{SGO}^t	Overall profit of SGO at time slot t
P_{exp}^t	Expected profit of SGO at time slot t
η	SGO's power utilization efficiency
h_1, h_2	Nodes in the hidden layer in ANN model
w_{ab}	The weight between node a in the input and node b in the hidden layer in ANN model
$\delta_{d_{i,t}}$	Error signals from the output layer to the hidden layer
d	Observed data in ANN
α	Learning rate