Real-time pricing algorithms with uncertainty consideration for smart grid

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Dedication

This thesis is the culmination of input, work and encouragement of many people who have helped and accompanied me for the four years that I have spent at University of Essex. First of all, my deepest gratitude goes to my family, my parents and my brother for their endless love and unconditional support. I could not have achieved this without the continuous support and love of my family. Thanks to my Mother for all her kindness and support and my father for all his effort and protect. I wish the endless happiness for every second of their life. I would like to express my sincerest thanks to my PhD supervisor, Prof. Kun Yang, for steering me through and pushing me further than I can imagine. His eloquence, sharpness always impressed me deeply and made my every meeting and discussion with him always full of things I learned from him. He is a very knowledgeable person and I am really proud of having such supervisor. I would like to express my special thanks to my examiners and chair members and also all my friends for all I learned from them.

Abstract

In today modern life smart electrical devices are used to make the human lives more comfortable. Actually, this is the combination of electronics and communications that provides the opportunity for real time communication while the measured electricity by smart meters is sent to the energy provider. In this way smart meters in residential areas play an important role for two way interaction between several users and energy provider. Solving an optimization problem with regard to consideration of satisfaction of both sides of users and energy providers tends to achieve the optimum price that is sent to the users to optimize their consumption in peak demand periods that is the main goal of demand response management programs. As nowadays the renewable energy plays an important role in providing the request of the users specially in residential areas consideration of the concept of uncertainty is an important issue that is considered in this thesis. Therefore, solving the optimization problem in presence of load uncertainty is important topic that is investigated. Another interesting issue is consideration of users' number variation in presence of load uncertainty in dynamic pricing demand response programs which gives the advan-

tage of having good estimation of optimum consumption level of users according to the optimum announced price. In this thesis these issues are considered for solving an Income Based and Utility Base optimization problems that are further explained in upcoming chapters. In chapter III ,which provides the first contribution of the thesis a novel algorithm called Income Based Optimization (IBO) is defined and compared with previously proposed Utility Based Optimization problem (UBO).The price, users' consumption versus provided energy capacity by energy provider in 24 hours period are simulated and analysed. The effect of variation in other parameters dependant to the cost imposed to the energy provider and the parameters that affect the users level of satisfaction is also evaluated.

In Chapter IV, existence of load uncertainty is considered in proposed UBO algorithm when it is assumed that number of users in each time slot is varying based on different distributions such as Uniform or Poison. The results for the average gap between energy provider's generating capacity and consumption of the users are compared with when number of users kept constant in presence of load uncertainty in 24 hours period. Moreover, the effect of different distributions on the gap between generating capacity and the users consumption is evaluated assuming the number of users are increasing and following the distributions. The results for the announced price in 24 hours period is also evaluated and further is extended to the average announced price with respect to increase in number of users when it is assumed that user entry and departure type is varying based on different distributions and the load uncertainty also is existed.

In chapter V, the proposed IBO algorithm in chapter three is further extended to the Uncertain IBO and is called UIBO. Therefore, it is assumed that bounded uncertainty is added to the users consumption. This algorithm is further extended in a way that variation in number of users is considered based on different distributions. The results are evaluated for the average gap between generating capacity and users consumption in 24 hours period and is further extended with respect to consideration of the increasing pattern for the number of users in presence of load uncertainty and different types of distributions for the users number variation. With respect to consideration of UIBO algorithm the price in 24 hours period is evaluated and the results are further extended to evaluate the average price with respect to increasing pattern for number of users that are varying based on different distributions when the bounded uncertainty is added to the users consumption. Moreover, the achieved gain of the proposed algorithm based on the ratio of the variation of the announced price to the varying number of users is evaluated. Finally chapter VI provides the conclusion and suggestion for future work.

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Thanks to all who kindly helped me to achieve this level of science and knowledge. Special thanks to my parents and family.

Acronyms

Acronyms and abbreviations

x	Users consumption
L	Generated Capacity
α	Predefined constant in utility function
w	Users class indicator
k	k_{th} timeslot
i	i_{th} User
m_i^k	Minimum power consumption for user i in k_{th} timeslot
M_i^k	Maximum power consumption for user i in k_{th} timeslot
δ_i^k	Variation of load demand for ith user and k_{th} timeslot
σ^2	Variance of noise
a_k, b_k, c_k	Cost function coefficients in kth timeslot
$U(.)$	Utility function
$W(.)$	Welfare function

$C(L_k)$	Cost function
ξ	Maximum magnitude of load uncertainty
$E(.)$	Expectation
N	Number of users
P	Poisson distribution
U	Uniform distribution
C	constant
$N_{k\in k}^{\{p,u,c\}}$	users variation based on different distributions in kth timeslot

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Chapter 1

Introduction

In this thesis the interaction between several users and an energy provider is considered in a smart environment that includes smart meters that are connected to the energy provider. The main goal is to provide benefit for each sides (i.e. users and energy company).

Nowadays, electricity is the most important part of human lives. The electricity is produced in power grid, and is widely used in commercial and residential areas. In this research we focus on residential areas and interaction between several users with distributed company that is called Energy Provider. In residential areas, at homes, there are many appliances that consume electricity, from small water heater to large electrical vehicles that consume high amounts of electricity for charging. The Electrical grid involves different parts including generation, transmission, distribution company and finally end users, while generating company is responsible for producing the electricity and send it to transmitters through the electrical grid. An electric grid is a network of energy providers and users that are connected by distribution lines. The generating company produces the electricity. The electricity might be produced from various sources, such as wind, coal, solar, etc. Then, it is transferred to the distributed company that is responsible to buy electricity from wholesale market and sale it to the users based on their requirements. In previous traditional grids the interaction between distributed companies and users was off-line, which means this is not two way interaction between users and energy provider. However, the need for two way interaction between users and energy provider shifted the traditional power grids to the most advanced Smart Grids. A Smart Grid is a system which includes a variety of smart operational and energy measures including smart meters, smart appliances, renewable energy resources, and energy efficiency resources such as batteries that store energy in a case to be used in certain peak periods. In this area of research control of production and distribution of electricity specially in peak demand periods are important aspects that are studied in many literatures.

The concept of Smart Grid, at first, started with the notion of advanced metering infrastructure to improve performance of grid as well as supply reliability and then extended to the increased and bidirectional interaction between wholesale markets/transmission operation and retail markets/distribution operations [2]. Historically, the prospect of increasing the efficiency of system operation in power grids and the existing investment in the generation and transportation of electricity has been the key driver for introducing Demand Response Management (DRM) which nowadays involves various kinds of programs with the goal of control the load balance specially in peak periods. Implementation of Advance Metering Infrastructure (AMI) and other Smart Grid technologies will further increase the use of DRM resources in everyday operations [3]. The AMI has benefits for customers in a way that enhances billing accuracy, informed decision on energy usage, earlier identification of outages, prompts accelerated response and reduces costs, etc. This is also important to consider the role of DRM under markets in Smart Grid as experience with energy markets has shown that we need DRM to avoid occurrence of energy market crisis,as it can control the peak periods by definition of suitable programs, otherwise the power off might happen in some peak periods that is absolutely not desirable. DRM controls the energy demand and loads during critical peak situations to achieve a balance between electrical energy supply and demand. In this way, it can achieve better utilization of available energy and results in better and more reliable system [2]. The effort of operators to guide the consumption of end users through suitable pricing policies is referred to as DRM [4]. The US department of energy classifies DRM into two categories as having two options: price based and incentive based options. Which price based options is primarily offered technology to residential areas [5]. DRM is considered as one of the ingredients of Smart Grid as it deals with various aspects of it, as well as providing optimization solutions to overcome restrictions that occur in critical peak demand periods. Controlling the users' demand specially in peak time periods increases the grid security. Matching power production to power consumption is a complex problem in conventional energy grids. It becomes more complex by the introduction of renewable sources, that might exhibit significant output fluctuations due to their uncertain behaviour in certain time period. This problem can be mitigated by installing a network in the grid which is connected to the smart meters that control the power consumption of users by managing the energy cycles of various devices while also enabling information exchange between users and energy providers [6, 7, 8]. The flow of information between meters and the energy provider can be combined with pricing strategies so as to encourage a better match between power production and consumption. This provide two way interaction between both sides of residential and energy providers. [9, 10, 11, 12, 13]. As the main difference between traditional grids and Smart Grids is that the later provides two way flow of information and electricity between suppliers and consumers, therefore study in that area to improve the Smart Grids is an important aim that is followed by several research in that area. DRM plays crucial role in such a smart environment as it can enhance the efficiency of the grid by suggestion to the users the controlling and scheduling programs. in that case the consumptions of the users and generation of energy provider would be corresponded. There is many literature about demand response connectivity and information flow in Smart Grid. With respect to importance of DRM programs, in this thesis it is tried to define a novel objective function optimization problem to provide benefit for both users and energy providers. In this way we define and analysis an income based optimization. The average price, average load in 24 hours period as well as comparison over the gap between generating capacity and users consumption with/without presence of load uncertainty and user number variation are investigated. Therefore, it is assumed that number of users are varying based on different distributions in each hour .

Through sending and receiving the information in the grid there are uncertainties in accuracy that might be happen as a result of using renewable energy to provide electricity, i.e. wind/solar nowadays are very common in residential areas. Therefore, investigation in this area has been conducted to solve the optimization problem in presence of load uncertainty in the Smart Grid. The effect of increasing the number of users in a certain period of time which is divided into time slots that the number of users is kept constant in each slot is studied and is compared with respect to consideration of uncertainty in variation of number of users in each slot. In this way, users entry and departure type, when it is assumed to be varied in each time slot, follows Poisson or Uniform Distribution. The result is compared with the case the number of users is constant. In this case, with respect to consideration of existence of load uncertainty, three different systems based on users entry and departure types are defined and compared. The definition of these systems is based on variation in number of users in each time slot, that is assumed to be based on Poisson and uniform distribution. These systems are called Poisson Distribution System Analyse (PDSA), Uniform Distribution System Analyse (UDSA) and are compared with a system in which the number of users is kept constant that is called Constant System Analyse (CSA).

As the main goal in DRM programs is maximizing the benefit of energy provider, when satisfaction of users is also achieved, two different objective functions are investigated with and without consideration of load uncertainties. These Optimizations are called Utility Based Optimization(UBO) and Income Based Optimization(IBO), in presence of load uncertainty we call the IBO, Uncertain IBO (UIBO) and the UBO, Uncertain UBO (UUBO) respectively. Investigation over the price, average load and average gap between users consumption and energy provider generation is considered for both IBO and UBO algorithms with and without presence of load uncertainty, as well as user number variation in each time slot. The new proposed IBO algorithm which is presented in [2] is different with previously proposed UBO in [14] in case that in IBO optimum satisfaction of users is considered by solving their welfare optimization problem and is multiplied to the price that users pay to achieve the income which is aimed to be maximized considering minimizing the cost of providing electricity from the energy provider while in UBO it is the utility of users which is considered and subscribed by the cost imposed to energy provider. As the outline of the first contribution of this thesis related to the new proposed IBO algorithm in [2] we evaluate the price and investigate over the average load with respect to considering variation in number of users regardless of presence and availability of load uncertainty. Moreover, another contribution of this thesis in [4] is that the previously proposed UBO is enhanced in a way to consider load uncertainty subject to variation of users entry and departure type based on different distributions. The outline is related to evaluation of the average gap between consumed power and generating capacity as well as investigation over the price in 24 hours according to certain types of distributions. Another interesting outline of this thesis is also to improve the new proposed IBO algorithm in [3] with respect to adding load uncertainty in the users consumption and considering user number variation based on different distributions. As the outline , evaluating the average price and gap between generated capacity and user consumption is investigated.

For future research in this area consideration of the effect of load uncertainty and user number variation in the other types of utility functions rather than proposed UBO in [14] is suggested for further investigation. For example the Logarithmic utility function added with certain type of uncertainty with respect to different distributions for users entry and departure type for description of interaction between users and energy provider is suggested for further future investigation. The evaluation of the average gap between generating capacity and user consumption as well as study over the effect of different distribution types on the average load with regard to proposed logarithmic objective function is suggested for further future study in DRM area. With respect to the other types of previously proposed utility functions rather than one which is studied in this thesis another interesting suggestion for future research is to solve the problem of maximizing the net benefit of energy provider in a way that is mentioned in the proposed IBO algorithm with and without consideration of load uncertainty. There are more suggestions for future research that will be further explained in chapter 6 of this thesis.

In this thesis, the literature review section in Chapter 2 discusses about different aspects of DRM and gives the broad understanding of the demand response programs and related issues. Chapter 3 introduces the new algorithm that is called IBO, which is based on net benefit maximization of energy provider when the satisfaction of users is also achieved. In Chapter 4 load uncertainty and user number variation for each slot of the period of 24 hours of a day is investigated with respect to consideration of UBO algorithm. Chapter 5 discusses the load uncertainty and users number variation of the proposed IBO algorithm. Finally, Chapter 6 provides the conclusion and future work.

Chapter 2

Literature Review

2.1 Introduction

With respect to improvement in AMI technology the concept of Smart Grid started with goal of having more reliable, secure and advanced grid. The aim is negotiation of energy provider and users in order to get advantage from real time interaction, by producing optimum amount of electricity and sailing it to the consumers. There are different parameters that affects the consumption level of users, for instance time of day, kind of appliance that is using, type of users that affects their level of satisfaction, all these aspects affect the demand for electricity. Therefore, in some hours of the day the consumption reaches to its maximum value. In this situation energy provider obliged to provide the extra amount of electricity by buying from the wholesale market that is not beneficial as the same day price is usually high. In this way different types of DRM is designed to control the users' demand specially in peak periods. There are different types of DRM, however, real time pricing is one of the most important DRM programs as control the demand by announcing the appropriate price on real time to the users. It is assumed that users are equiped with smart meters and smart meters are connected to the Local Area Network (LAN). Therefore, solving an optimization problem in which satisfaction and benefit of both sides of users and energy provider is considered is an important target for investigation. There are many literature study social welfare optimization from different point of view. There are also different techniques for solving the problem. Therefore, the first step for solving the optimization problem is to translate it into mathematical language. The mathematical modelling is needed to describe the system. Then the mathematical model is used for formulation of the problem. In order to solve the problem different techniques existed that can be used depending on the kind of problem. In this section DRM in Smart Grid is considered and is explained from the various aspects.

2.2 Smart Grid

Smart Grid generally is related to using remote control and automation systems that provides a two way communication technology between different parts of the grid including generation, transmission, distribution companies and consumers. The Smart Grid offers many benefits for both sides of energy provider company and consumers, mostly seen in big improvements in energy efficiency on the electricity grid and in the energy users' homes, as it provides the opportunity for two way negotiation between subscribers and providers. There were issues related to the traditional grids, for instance for a century, the required data for producing the electricity was gathered while utility companies used to send their workers out to gather this information. They were responsible for reading the meters, measuring voltage and even also looking for broken equipments. With respect to improvement in electrical devices and appliances nowadays many options and products are being made available to electricity industry to modernize it. The grid refers to the network that carry electricity from the electric plants where it is generated to consumers. The Smart Grid means using a LAN connecting different parts of the electric utility grid. It includes adding a two way digital communication technology to devices associated with the grid. Each device on the network is equipped with sensors to gather data (e.g power meters, voltage sensors, fault detectors, and etc.). Also, the Smart Grid provides a two way digital communication between the device in the field and the utility operation section. A key feature of the Smart Grid is automation technology that lets the utility adjust and control each individual device or millions of devices via a remote control. One of the most important issues in Smart Grid is how to deal with users over consumption in peak demand periods. In this way DRM is used to tackle this problem in critical peak demand periods. Table 2.1, in [1] illustrates the difference between existing grid and the power grid.

Table 2.1: A brief comparison between the existing grid and the smart grid [1]

Existing Grid	Smart Grid
Electromechanical	Digital
One-Way communication	Two-way communication
Centralized generation	Distributed generation
Few sensors	Sensors throughout
Manual monitoring	Self-monitoring
Manual restoration	Self-healing
Few customer choices	Many customer choices
Limited control	Pervasive control

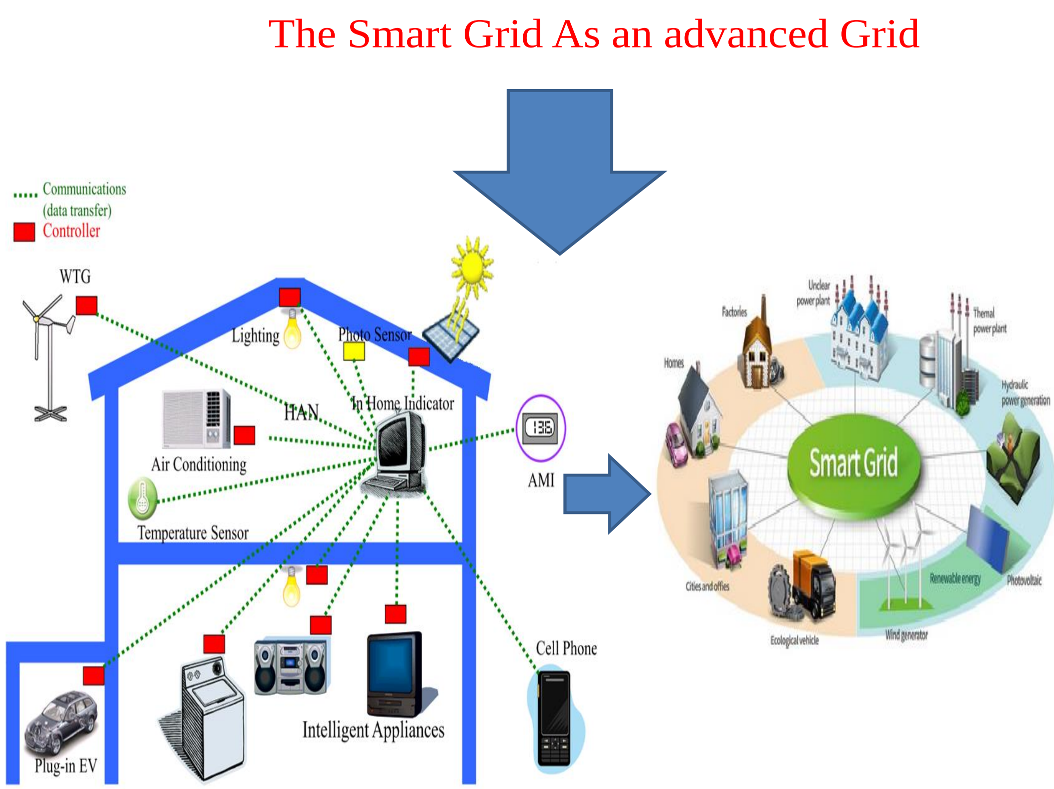

Figure 2.1: Illustration of a Smart home that is equipped with AMI technology

2.2.1 Features of the smart grid

Shifting from the previous traditional grids to the Smart Grid provides many advantages that are explained as bellow :
Reliability: The Smart Grid makes use of technologies such as state estimation, that improve fault detection and allow self-healing of the network without doing manual works. This will ensure more reliable supply of electricity [15].
Efficiency: There are many contributions to overall improvement of the efficiency of energy infrastructure which are anticipated from the deployment of smart grid technology, in particular including DRM, for example turning off air conditioners during short-term spikes in electricity price and reducing the voltage when possible on distribution lines are some basic examples of advantages of the Smart Grid. Therefore, in general DRM programs increases the efficiency of the grid in the Smart Grids.
Market-Enabling: The Smart Grid allows for systematic communication between suppliers as they announce the energy price and consumers as their behaviour affect on their consumption and permits both the suppliers and the consumers to be more flexible and sophisticated in their operational strategies. It means that when consumers consumption is controlled the peak hours is reduced and therefore the announced price will be controlled. This controlled price affect the electricity market. It can improve the electricity marketing economically.
As, it is mentioned in previous section the Smart Grid consists of different parts. The Advanced Metering technology plays an important role in Smart Grid, more specifically in DRM. Figure 2.2, shows the AMI in the Smart Grid as it plays an important role in DRM.

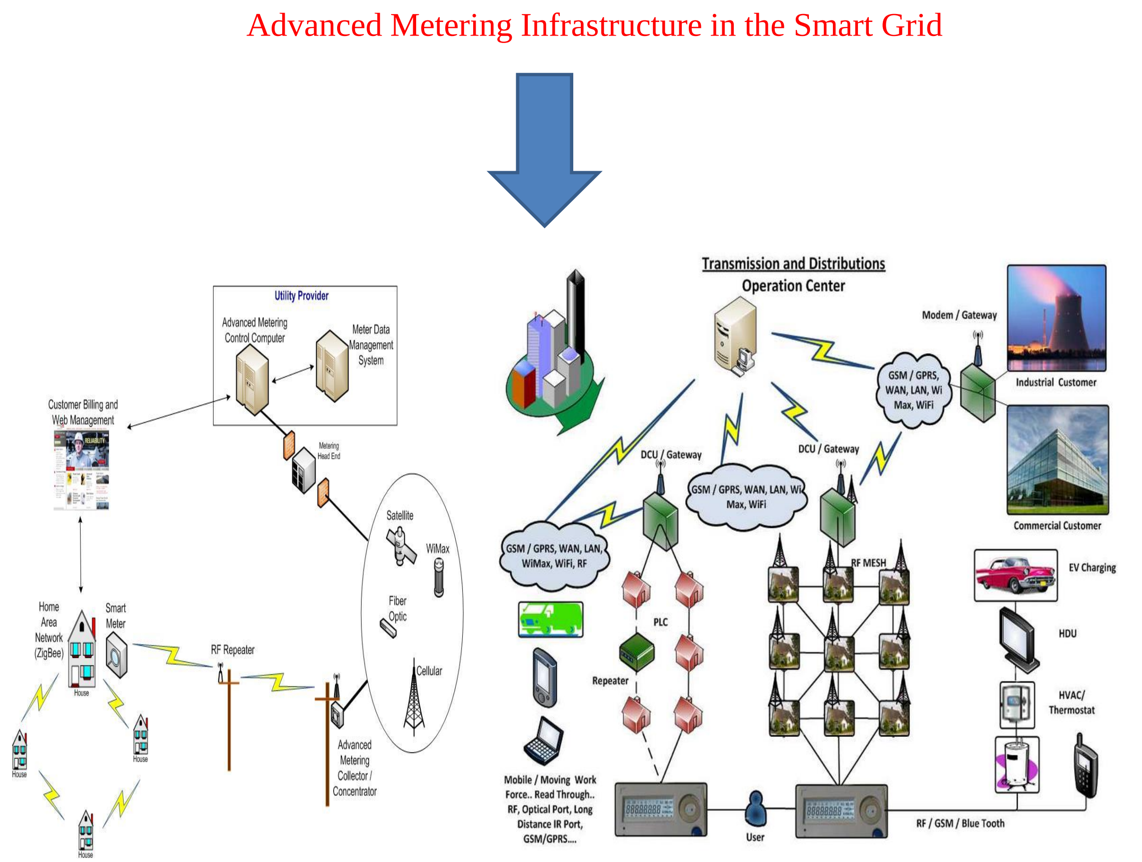

Figure 2.2: AMI as part of Smart Grid

2.3 Fundamentals of DRM

The most importance of DRM is that it controls the energy demand and loads during critical peak situations to achieve a balance between electrical energy supply and demand. In this way, it can achieve better utilization of the available energy and cause better and more reliable system [2] in which the grid is protected from sudden electrical changes. The US department of energy classifies Demand Response as having two options: Price Based and Incentive Based options. Which Price Based options and Direct Load Control which is one of the Incentive Based options are primarily offered technologies to residential areas [5]. The DRM is considered as one of the ingredients of Smart Grid as it deals with various aspects such as providing optimization solutions to overcome restrictions that occur in critical peak demand periods.

There are broad literatures about demand response connectivity and information flow in Smart Grid. DRM programs applied between Independent System Operators (ISOs) and whole sail markets, transmission system, distribution systems and customers. In this thesis, the interaction between distribution system and consumers is considered. In general, DRM in Smart Grid is divided into price based and incentive based programs which are explained briefly in the following sections.

2.3.1 Price Based DRM

This category involves programs that are listed as :

- Real Time Pricing (RTP) in which price of the unit electricity consumption is periodically changed.

- Time Of Use (TOU) tariffs which include various tariff for different time intervals of a day or seasons of a year and give customers time varying rates that reflect the cost of electricity in different time periods. If the price changes between hours or time periods are significant, customers adjust the timing of their flexible loads in order to take advantage of lower price periods [3, 16, 17].

- Critical Peak Pricing (CPP) that changes normal peak price with a higher price to provide reliability to the system. In this method of DRM, TOU prices are used except for certain peak days.

In general, it can be concluded that while the RTP describes a system that charges different retail electricity prices for several hours of the day as well as for different days, under TOU the retail price varies in a preset way within certain blocks of time [5]. In [18], a multi-layer DRM in which a utility can announce a limit for the demand and allocate the reduction to each user consumption and each of the users will have the freedom to choose what kind of loads to be controlled is considered. From the provider side the problem is solved as kind of resource allocation problem and from the users side the problem is solved as a kind of energy management tool within the network. This proposed approach can be customized to perform DRM in different sizes of the network. For instance, at the feeder, at the distribution circuit, and at the substation level. There is the work in about economic factors related to the type of DRM [19, 20, 11, 21]. The work in [5] provides broad investigation about DRM options and compares various schemes with each other. The most important factor associated with these two types of programs is the fluctuation of price rate.

2.3.2 Incentive Base DRM

According to Department of Energy (DOE) Incentive Based DRM can be listed as : Direct Load Control, Interruptible/Curtailable service (I/C), Demand Bidding/Buy Back, Capacity Market Program (CAP), Ancillary Service Markets (A/S) [2]. In general Incentive Based demand response can be considered as a program that requests consumers to hand in the load control rights to utilities with some contracted limits and incentives. This category requires more efforts from the utility side to take into consideration the system reliability, economic dispatch, consumer comfort and so on. As a type of mature Incentive Based demand response, Direct Load Control has been thoroughly studied. These programs provide customers with load reduction incentives. The incentives might be separated from, or additional to, their retail electricity rate, which may be fixed (based on average costs) or time-varying. Load reductions are needed and requested either when the system reliability conditions are treated or when prices are too high [2].

Fig 2.1, depicts the differences for operational time scale between incentive based and price based DRM. As it is appear various programs require different time scales. It should be considered in various timing periods in incentive based DRM the price is kept constant and consumers are incentivized to consume less energy based on the announced rate from the retailer that procures the electricity from the whole sail market. With respect to the importance of real time interaction between producers and consumers in the next subsection Real Time Pricing in demand response programs will be studied further.

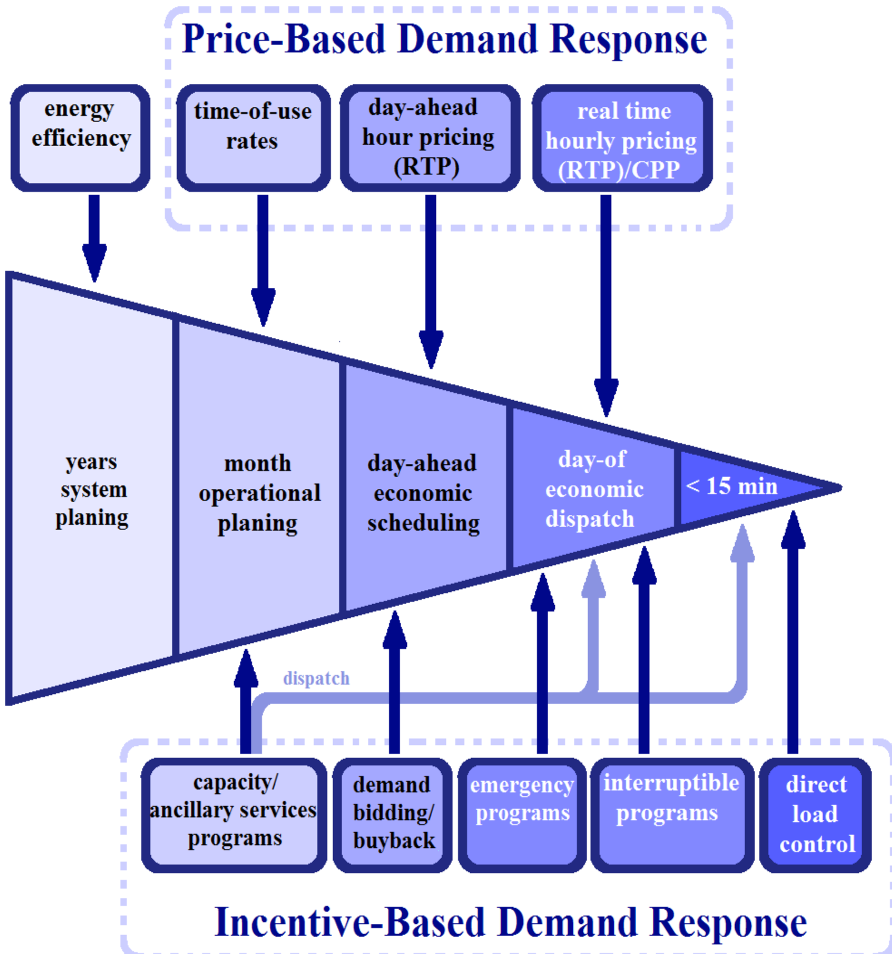

Figure 2.3: Illustration of how DRM works from the aspect of allocated timing programs

It should be considered in various timing periods in incentive based DRM the price is kept constant and consumers are incentivized to consume less energy based on the announced rate from the retailer. The study on kind/name of DRM effect on consumer behaviour reveals that end users are more interested to participate in real time price base DRM because in residential areas it makes possible two way negotiation between users and retailer that in this thesis is called energy provider.

2.4 DRM based on Real Time Pricing in the Smart Grid

Two way interaction between users and energy provider in today's Smart Grid leads to Real Time Pricing that provides the opportunity for both sides i.e. users and energy providers to maximize their own benefit through sending and receiving the information which is the price and consumed energy during different time slots. In this way, an optimization problem must be defined and solved by each side of users and energy provider separately. There are broad literature about this concept [14, 22, 17, 2, 3, 5, 18, 23, 24, 25, 26], that aim at maximizing social welfare which depends to some parameters such as type of appliance, time of day, number of users and etc. For solving the optimization problem several techniques might be used. For example, in [14], the original objective function is decomposed into several sub problems and each of them is solved by users and energy provider. As utility maximization has been used in many literature, it is tried to have a grasp to this concept by defining a new algorithm based on energy providers' Income Maximization with respect to satisfaction of all users. As it is expected the users consume energy more wisely when they are informed the updated price . The results have been proposed in [27]. Also,investigation over the effect of uncertainty as a result of using renewable energy or any unexpected events that may affect the consumption on users utility function has been considered. [28] discusses about the consideration of the effect of various types of the load uncertainty. According to the work in [29] Real Time Pricing (RTP) links hourly prices to the change that may occur in real time or day ahead cost of power, which means that hourly price rate is evaluated on real time or based on the historical data on day ahead.

The power grid consists of several parts, the generators, transmitters, distributors and end users. According to [30] Independent Power Producers (IPPs) sale energy to wholesale purchasing agency company, and Distribution Companies (Discos) procure energy from them and sale to the users. We call the Disco as energy provider which procures electricity from wholesale market, and announces the price based on its interaction with users. There are some parameters such as the time of a day, the number of users, the type of appliance and etc. that affect the announced price and consumption level of users. In order to achieve the goal of DRM, which is providing the maximum benefit for energy provider in a way that satisfaction of consumers is also achieved, several techniques have already been proposed to solve the optimization problem (i.e. Dynamic programming, Stochastic programming, etc.)

As is mentioned, with respect to the importance of research over DRM, there are broad related literature about it and the problem of providing benefit and satisfaction for both sides of users and energy provider has been formulated and solved in several ways. In this thesis basically it is focused on real time pricing as based on [14]. This is one of the most effective tools that encourage users to consume more efficiently. The Chapter 3 focuses on Real Time Pricing (RTP) in Smart Grid, with regard to the description of the interaction between several users and an energy provider through a model that has a goal of providing net benefit maximization to the energy provider when satisfaction of consumers is considered as well. In the proposed model in Chapter 3, the interaction between users and energy provider is considered in a way that 24 hours of a day is divided into 24 time slots and at the beginning of each time slot energy provider sends the updated price to the users based on aggregation of their optimum consumption as well as optimal generated capacity that is evaluated in the time frame between two time slots . Then, users optimize their consumption level based on the announced price. Then, the generated capacity is evaluated based on the optimum price in the period between two time slots. This algorithm is described in [27]. The interaction between energy provider and users for updating the consumption level of the users based on the optimal announced price is done in a way that users receive the optimal price and update their consumption based on the announced optimal price at the beginning of each time slot. Also the updated generated capacity based on the optimal price is achieved in the period between two time slots. At the beginning of each time slot the updated price is evaluated based on the optimal consumption and generating capacity. This proposed algorithm that is called IBO is compared with UBO that is explained in [14]. Moreover, in this thesis the effect of having load uncertainty is modelled as a kind of random variable which is added to the users' consumption. Also, variation in number of users in each time slot according to different distribution models is considered and analysed.

There are broad ranges of efforts such as practicing different types of DRM that have already been done to improve performance of the grid. Different aspects have already been considered to provide the satisfaction for both sides of users and energy provider. For instance, decreasing the gap between generated capacity and consumption, that is studied in [27], [14] is one target that has already been considered. Other aspects such as type of appliance, proper scheduling day time, effect of energy storage for proper scheduling to increase the social welfare, etc, also are interesting issues that have been studied in [31], [32].

Based on the importance of RTP that increases the efficiency of the grid broad literature exist. For instance, in [32] the social welfare problem is solved with respect to consumers utility maximization. The welfare is defined as the level of users satisfaction subscribed by the cost imposed to the Energy provider. In that research a general optimization is solved in the presence and without the presence of uncertainty as a result of renewable energy resources. Also a model including some consumers that each one uses different appliance is considered. Each type of appliance that a consumer may use is modelled as well. However, the responsiveness of the different levels of society which refers to the kind of user, i.e. industry, residential, etc. to specific price is not explained. This is further shown in [14] over description of parameter w as a factor that describes the kind of users. Moreover, the proposed algorithm is an off line algorithm as all decisions are made at once before day starts. Therefore, the users and energy provider do not benefit from two way real time interaction. In [21], also the study in [14] is improved in a way that for each specific appliance of each user a utility function is proposed. Then, the problem of social welfare optimization assuming there are some devices that store energy is solved. To solve the optimization in the presence of uncertainty non-linear programming is used. However, the author does not describe a proper algorithm in case that uncertainty due to renewable exists. Scheduling and shifting the demand from on peak to off peak periods is an important way to control the demand in peak hours. In [33] an algorithm with goal of shifting over consumption of users from peak to off- peak or mid-peak periods is proposed. However, it does not discuss how this shifting may affect the welfare as well as the users consumption and generated capacity. In [14], [17] a general utility function that depends to not only the consumption level of users, and the parameter which implies how different users respond to specific price is defined.

For example, if a user is from a residential group of the proposed society his response to specific announced price is different with a user who is from the industry section. This affects the utility function of users. Although it seems that the model is able to describe the interaction procedure between energy provider and users clearly, it does not discuss the net benefit maximization of the energy provider with respect to consideration of users' optimal demand. Moreover, it doesn't discuss the effect of uncertainty related to the uncertain behaviour of users. For example, this paper dose not discuss about the effect of using renewable energy in utility of the users. Moreover, although, the proposed algorithm in that paper tries to solve the social welfare optimization problem, but it does not discuss over the effect of increasing the number of users on average consumed load.

In [28], the optimization problem is solved with load uncertainty. In this case the actual power consumption of users is considered when a random variable representing load uncertainty is added to it. This variable reflects several variations in practical environment, such as effect of uncertainty in production of wind turbines or solar energy. The effect of this load uncertainty is shown on the price. However, it hasn't been investigated over the net benefit of energy provider. Moreover, although the author shows the effect of increasing the number of users on optimal price, but it dose not discuss about the randomly variation in the number of users in each time slot. The effect of load uncertainty on average welfare has not been investigated as well. In [34], the logarithmic utility function has been proposed and the price function is defined. However, the effect of load uncertainty on the proposed utility function has not been investigated. Also, the effect of users entry and departure type on the average gap between generation and consumption is not studied as well.

With respect to consideration of load uncertainty [35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45] adding users number variation to the constraint of proposed optimization problem is a novel idea that in this thesis will be explained further. Also, for solving the optimization problem many research have already been studied. [46, 47, 48, 49, 50, 51, 52, 53] that explain the techniques for solving an optimization problem. The technique that is used in this literature is Lagrange Relaxation, which is a strong technique for solving optimization problems that are defined based on appropriate constraints. According to [54], demand response issues can be investigated from several aspects. In this research, because of the importance of using Real Time Pricing in residential areas, this topic will be investigated.

2.5 RTP Issues

According to [54], Real Time Pricing DRM is generally performed in the residential areas instead of commercial and industrial sectors, since residential users are more sensitive to the electricity price, which means that their response to price variation is more sensible. Based on two way communications, smart metering could gather detailed information of users electricity usage patterns and provide automatic control to household appliances. In that case, the problem of providing benefit of energy provider when satisfaction of users also achieves is mathematically modelled and solved.

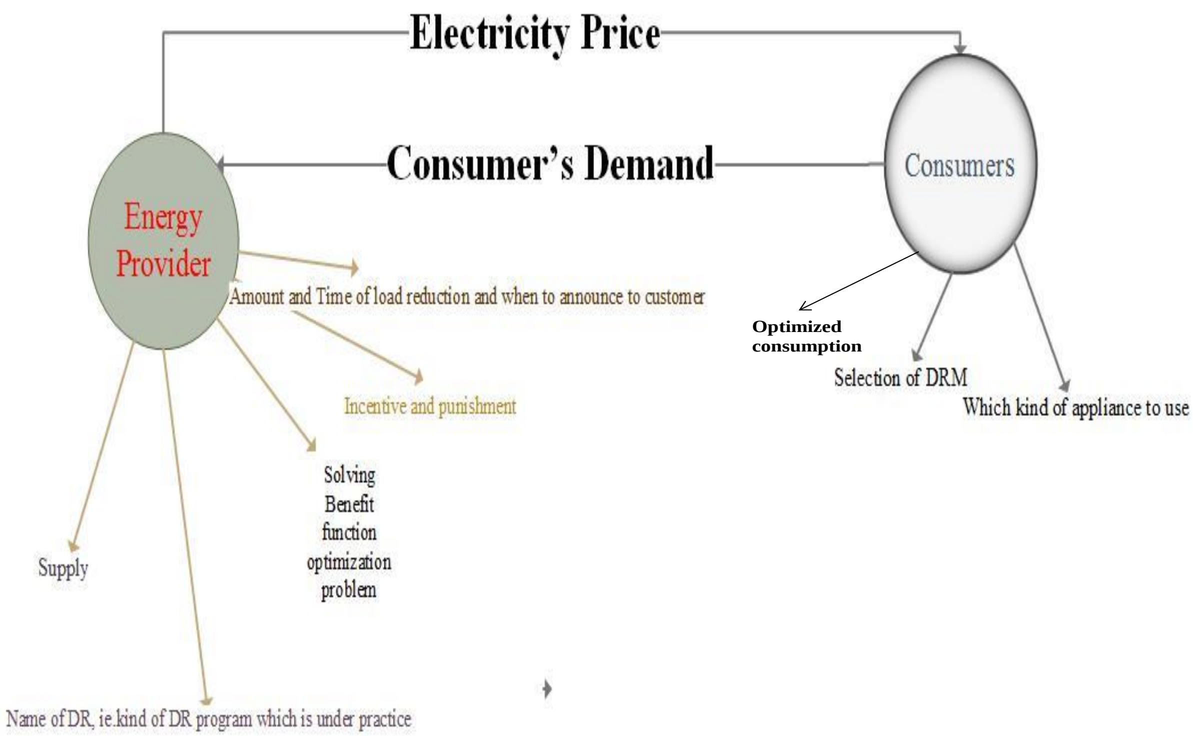

Figure 2.4: Illustration of the interaction between users and Energy provider in the Smart Grid with respect to important factors from their sides

Figure 2.4 illustrates the interaction between users and energy provider with respect to the points that are important for each side. The models in DRM defines based on different scenarios. For instance the scenario that is considered in this thesis is based on the interaction between one energy provider and several users, however, there are other scenarios based on the interaction between multi energy providers and several types of users.

2.5.1 DRM problem Formulation

Demand response is usually formulated as the following mathematical problems. Utility maximization : from the social perspective, the grid aims to increase the sum of comfort obtained by each user and to decrease the expense imposed to the energy provider. For example, the objective in [14] is to maximize the grids social welfare, i.e., the sum of utility functions of all users minus the cost function of the power utility, while the energy demand is constrained by the limited supply capacity. The price and demand interact with each other in a distributed manner, and finally converge to a winwin agreement beneficial to both the power utility and all users. Specially, if there is excess demand, additional energy would be bought from the spot electricity market to balance supply with demand [11], [55]. Thus, the social welfare maximization is to maximize the users utility minus the procurement capacity cost, the day ahead reserving energy cost and the real time balancing energy cost. The authors in [23] additionally involve the cost of operating rechargeable batteries in the utility maximization problem since the introduction of energy storage could further improve the performance of demand response. Therefore, the social welfare is the total user comfort minus the power utility cost and the energy storage operational cost. From the users point of view, it is desired to increase the level of satisfaction and to decrease the value at their electricity bill. For example, the goal in [56] is to maximize the users individual welfare, i.e. the value at their comfort minus payment. Similarly, the work in [57] is to maximize the profit of operating PHEVs, i.e. the revenue obtained by selling electricity minus the cost of charging vehicles.

Cost minimization: From the power utility viewpoint, it is desired to decrease the expense of generating and delivering electricity. The objective in [58] is to minimize the cost function imposed to the power utility. From the users viewpoint, it is desired to decrease the value at their individual electricity bill. For example, the goal in [59] is to minimize the energy bill of an air conditioner under the constraint that the indoor temperature is kept inside a user defined range. Similarly, the work in [60] is to minimize the electricity payment of a water heater on the condition that the water temperature reaches the predetermined comfort constraint.

Price prediction: Real time pricing has been widely considered to be one of the most efficient and economic price based programs, but if the power utility releases electricity rate only one hour ahead of time, the price prediction capability will be required by demand response. The authors in [58] found that the electricity price has high statistical correlations with the prices on yesterday, the day before yesterday, and the same day last week.
Other related issues such as renewable energy in [61, 62, 63], and energy storage are also investigated in [21], [64].

Renewable energy: integrating the uncertain and intermittent renewable generation (such as wind turbines and solar photovoltaic panels) into the bulk generation will be challenging, due to the reliability requirement that the generation and load should always remain balanced [61, 62, 63].

Energy storage: taking advantage of energy storage, users can charge their batteries or PHEVs within off-peak periods, and discharge them to drive other appliances within peak periods, instead of using the expensive electricity from the grid [21].

However, if all users try to charge their energy storage at the same time, it will cause an additional peak load and would make the grid vulnerable and unreliable. To alleviate such issues, the work in [64] strategically guides users when to charge and discharge their batteries or PHEVs. As an Example for a mathematical modelling and formulation in DRM, UBO [14] algorithm is explained in the next section.

2.5.2 UBO Problem Formulation

In this section , the problem of optimizing benefit for both users and energy provider using UBO algorithm is formulated. In [14], each user intends to choose its consumption level to maximize its own welfare function. However, individually optimal consumption levels may not be socially optimal for a general price announced by the energy provider. Therefore, the sum of all utility functions minus the cost imposed to the energy provider is adopted as the UBO and is maximized with goal of maximizing the utility function of all subscribers and minimizing the cost imposed to the energy provider.

The problem is formulated as the following equation:

$$\begin{aligned} &\max_{x_i^k \in I_i^k,\, L_k^{min} \leq L_k \leq L_k^{max}\ k \in K, i \in \{N\}} \sum_{k \in K} \sum_{i \in \{N\}} U(x_i^k, w_i^k) - C_k(L_k) \\ &\text{subject to } \sum_{i \in \{N\}} x_i^k \leq L_k, \forall k \in K \end{aligned} \tag{2.1}$$

According to [14], the problem is solved for one time slot and further is extended to k time slots. Therefore instead of the problem (2.1), the problem (2.2) is solved.

$$\begin{aligned} &\max_{x_i^k \in I_i^k,\ L_k^{min} \leq L_k \leq L_k^{max}\ k \in K, i \in \{N\}} \sum_{i \in \{N\}} U(x_i^k, w_i^k) - C_k(L_k) \\ &\text{s.t.} \sum_{i \in \{N\}} x_i^k \leq L_k, \forall k \in K \end{aligned} \tag{2.2}$$

In above formula, I_i^k indicates the range for minimum and maximum consumption of the users. It is assumed that 24 hours of the day is divided into 24 time slots. The K is the set of all time slots. The $C_k(L_k)$ achieves from [14] and the i is the users indices. Also L_k is the energy that is provided by energy provider. It is assumed that L_k units of energy which is provided in each slot is bounded between maximum and minimum value. It is also assumed that the minimum value of provided energy is more than minimum consumption level of users and the maximum value is not more than maximum consumption of the users. The parameter U describes the proposed utility function which has the characteristics that are explained in chapter three and indicates the level of satisfaction for the users.

2.6 How to solve DRM problems?

Demand response is usually formulated as optimization problems, which are solved by various approaches.

One of the most applied approaches for solving DRM problems is Convex optimization. It is the problem whose objective and constraint functions are convex. Demand response is usually formulated as utility maximization or cost minimization. It is noted that the utility function is concave, whereas the cost function is convex. The constraint functions of demand response are usually convex, or especially, linear. For example, the energy demand of one user is constrained by lower and upper bounds in [65], [14]. The minimum energy consumption level represents the baseline demand from must run household appliances such as refrigerator that should be on the whole day, whereas the maximum energy consumption level indicates the total energy demand if all appliances are on. In addition, users are concerned about whether their tasks will be completed within a time period, which means that the aggregate energy consumption should not be less than a threshold before a deadline [66], [23]. There are other approaches for solving the optimization problem in demand response programs. One of the most useful approaches is the game theory that studies selfish and rational individuals, and/or a model of interactive decision making processes. This approach is considered from various aspects. In [67, 64, 68, 69] this approach is also investigated. Another approach is Dynamic programming that decomposes the complex problem into a sequence of sub problems. Such a method consumes less time than heuristical approaches, especially for the sub problems with overlapping characteristics. This approach is studied in [70, 71, 72]. Another useful approach in solving demand response programs is Markov Decision Process that refers to sequential decision making based on periodic or continuous observation on Markov random dynamic systems. Due to the future price uncertainty, the problem of energy consumption scheduling to minimize the electricity bill of a whole day is naturally cast as a Markov decision process [73]. The basis is to assume that future prices depend on certain probability density functions, but independent of past prices and user activities. Similarly, with the uncertainty of wind generation, the reliability of smart grids will be affected, which is treated as a multi time scale Markov decision process,which is studied in [74]. In this thesis the problem of maximizing the income of energy provider subscribed by the cost imposed to it is defined and solved based on the Lagrangian relaxation technique. The next section describes the Summary of contribution of this thesis.

2.7 Summary of Contributions

In this section the benefit function optimization problem of energy provider with respect to its net benefit maximization is defined. This is calculated according to its Income which has been considered based on aggregation of users' optimal demand. Also, the effect of increasing the number of users on average load including generated capacity from the energy provider's side and total consumption of users from users' side has been considered and is compared with previously proposed utility based Optimization in [14]. Therefore, the following contributions are investigated:

- The general Income Based Optimization problem has been proposed in Chapter 3. This optimization problem is solved by energy provider and is based on the maximization of energy provider's net benefit with respect to its Income which achieves from the aggregation of the users' optimal demand multiplied to the price that is announced to the users. The existence and uniqueness of the optimal solution for the proposed IBO is proved and the feasible set is achieved. The comparison between UBO and IBO with respect to the average load and price has been investigated. The effect of increasing the number of users on average load has been investigated.

With respect to consideration of what already has been discussed the following questions will be investigated :

- How to solve the DRM problem in a way that maximum benefit of energy provider as well as the satisfaction of consumers achieves?
- How the change in some parameters such as number of users affect the generated capacity of energy provider and the consumption level of users?

Based on the algorithm in [27], the energy provider sends updated price to the users at the beginning of each time slot. Users optimize their consumption level based on the announced price and update their optimum consumption. In the period between two time slots, the optimal price and generated capacity is evaluated by solving the objective function. Then the optimal price is announced to the users and the sum of users' optimal consumption is sent to the energy provider. The generating capacity is updated by the energy provider in the period between two time slots. For the next time slot, the updated price achieves from the aggregation of users' optimal demand as well as the generated capacity provided by energy provider in each time slot. The effect of uncertainty in users' consumption is also investigated. With respect to consideration of load uncertainty the actual power consumption can be considered as adding δ_i^k as a random variable representing the load uncertainty that could reflect several variations in the grid. It could be used to model the variations of the load demand within a time slot or the distortion in the communication channel. In this case several models such as Gaussian model, Bounded uncertainty model and etc. are investigated in [28]. Therefore, the research over the following questions has been investigated. :

- How the proposed IBO is affected with respect to consideration of renewable energy that causes uncertainty in users' consumption?

- How the problem of utility/income maximization can be solved with respect to different types of uncertainty models such as Poisson or Uniform distribution for users' entry and departure type?

These problems are analysed in chapter four and five of this thesis. In this case, the previous IBO algorithm is considered when some noise is added on the consumption level of the users. The new algorithm is called UIBO, which captures the effect of variation in number of users also appears in the constraint.

In the proposed optimization problem, the optimal value of the consumption level of the users is considered. The price is updated at the beginning of each timeslot, using the gradient projection technique. Also, solving the problem with respect to different user number variations entry and departure types is considered. An interesting contribution that is further suggested as future work is solving the problem with regard to competition of two energy providers. In [17], this approach is considered for UBO. It can be further expanded over IBO as well. Investigation on different types of utility functions also is an interesting point that can be investigated further in future research.

There is a substantial amount of study on various forms of load side management, from classical direct load control to the more recent real time pricing [75, 76, 32]. The focus of some of this investigations is on optimization methods that minimize generation cost [77, 78, 79, 80]. Some investigations may follow the approach of maximizing utility profit or minimizing deviation from users' desired consumption as stated in [81, 82, 83]. Renewable resources can fluctuate rapidly and by large amounts. As, their level of penetration increases, the need for regulation services and operation reserves also increases [84], [85]. It can be provided by additional units at a higher cost or may be supplemented by real time pricing demand response as has already been implemented in [86, 87, 88, 89]. Demand response will not only be invoked to shave peaks and shift load for economic benefits, but will increasingly be called upon to improve security and reduces reserves [90]. In today's Smart Grids, direct interaction among energy providers and users has great importance in the users real life [14]. The glancing overview on demand response highlights its importance to be studied from different perspectives. Demand response must allow participation of large groups of users, and must also be dynamic and distributed. A glancing overview on demand response management programs from different aspects has been explained in [27], [91] respectively. The proposed algorithm in [27] is based on maximization of energy provider's income when satisfaction of consumers is considered as well. In this case, it is assumed that the energy provider solves an income based objective function that involves the optimized consumption level of users. In [91], real time pricing is considered when users are served by multiple energy providers. To match the consumption with provided supply, Real-Time Pricing (RTP)-based energy consumption scheduling scheme is considered, which consists of energy consumption allocation, energy provider selection and real-time pricing. In [34], a logarithmic objective function has been proposed to describe a distributed framework for demand response and users' adoption is also considered. In case of existence of renewable energy resources, the concept of load uncertainty has been studied in [28]. However, investigation over variation in the number of users based on proposed distributions which is studied in this thesis is a new concept under consideration. Smart Grid provides more efficient control over producing the electricity not only in residential areas, but also in commercial and industry section. Moreover, it plays an important role in decreasing the electricity consuming during the periods that maximum consumption is achieved. The most important ingredient of smart grid involves smart meters that are connected to the LAN. This provides two way interactions among users and energy providers, with the aim of reducing the peak power consumption in peak periods, which is the goal DRM [75], [76]. Recent interests in DRM has been towards real time interaction between users and energy providers via Energy Management System (EMS) which may be used as a component of the smart meter [28]. It makes the best use of electricity according to the announced energy price from the provider. In [58], real time pricing is considered with the goal of minimization of the price and the time. The key point is the achievable optimality when user type is considered to be confidential [14], [28]. In many investigations load uncertainty is considered in the context of forecasting the load or modelling upon stochastic [75], [92] in a way that the problem of DRM is solved with respect to consideration of different type of uncertainty. In [28], load uncertainty captures measurement errors through the communication links and the distributed algorithm in [58] is taken into account for various load uncertainty models. Although, [28] shows how diverse models of load uncertainty affect the consumption as well as the generating capacity, it does not discuss the effect of user distributions in certain periods. Therefore, in this work the effect of different distributions over variation in number of users that may enter to the grid is considered when it is assumed that number of users may vary randomly or based on Poisson process or may even be kept constant. The results are compared with [28] where load uncertainty is considered as bounded uncertainty that is added to the users' consumption. The contributions to this section can be summarized as below:

• The utility function is updated based on bounded uncertainty that is added to the consumption level of users, then three types of users' variation are modelled. Users whose variation is considered to be random, users whose variation is according to the Poisson process, and users that do not vary, and their number is kept constant. Also, the effect of increasing the number of users over the average gap and also price is investigated.

2.8 Related works

There is a lot of investigations related to the stochastic approach of load side management in which the constraint of objective function is defined based on different aspects, such as type of appliance. However, consideration of the concept of variation in the number of users with regard to stochastic approaches in the objective function's constraint is a novel study point which is investigated in this thesis.

There are many research on the effect of renewable energy, that is investigated from different aspects [93]. Some aspects focus on game theory approaches [94]. RTP is also investigated from the communication aspects [95]. The study over unstable energy providers and malicious users is also done by [96]. The concept of security in the smart grid is studied in [97]. In [98], a stochastic model for residential electric vehicles (EV) based on charging demand in smart grid is studied. Given that characteristics of extra load consumption follow people driving behaviours, random parameters such as arrival time and charging time of vehicles therefore determine the expected demand. In this case, a model for uncoordinated charging power demand of an EV based on stochastic process is developed and illustrated for different charging time distributions.

In [99], the impact of prices on users' load profiles when users are equipped with energy consumption scheduling devices is studied. The iterative stochastic approximation is used to design two RTP algorithms. The proposed algorithms eliminate the need to know the structure of the objective function. To simulate the operation of devices and users price responsiveness, a System Simulator Unit (SSU) is proposed that employs approximate dynamic programming. Simulation results reveal that using these algorithms reduces peak to average ratio and helps users reduce their energy expenses as well. In [100], an optimization based real time residential load management algorithm considering load uncertainty with respect to statistical estimation with the goal of minimizing energy payment for each user is proposed. In problem formulation, different types of constraints on the operation of various appliances such as must run or controllable-interruptible/non interruptible appliance have been proposed. The proposed algorithm benefits both users and energy providers by reducing energy expenses and improving peak to average ratio of the aggregate load demand.

Formulation of an optimization problem to minimize the electricity payment of users when only an estimate of users' future demand is available is considered. In [3], an optimization model to adjust the hourly load level of a given consumer in response to hourly electricity prices has been proposed. The objective of the model is to maximize the utility of the consumer subject to a minimum daily energy-consumption level, maximum and minimum hourly load levels, and ramping limits on such load levels. In [101], it has been shown that output symbols according to Poisson process coincides with the utilization factor of the channel on the real time basis. It means minimizing loss probability achieves the maximum spare time to transmit another information. A class of sources including Poisson process and continious Markov chain has been specified that traverses a finite state space and arbitrary random stay time. It is shown that the necessary and sufficient condition for the coincidence of values between the loss probability and utilization factor is that for each state, the stay time obeys an exponential distribution. This achieves the minimum loss probability.

In [102], decision making under uncertainty in energy systems has been studied. The decision making chain is fed by input parameters that are usually subject to uncertainties. The art of dealing with uncertainties has been developed in various directions. The new standard classification of modelling technique of uncertainties is proposed and compared. Based on the proposed comprehensive classification, it is concluded that each method is suitable for a specific type of uncertainty.

In [28], the proposed utility framework and distributed algorithm of real time pricing that is proposed in [14] has been extended to include the effect of uncertainty. The effect of diversity in types of load uncertainty on power consumption and generating capacity is evaluated. It is shown that load uncertainty increases the price.

Chapter 3

Optimal Real-time Pricing(ORTP) based on Income Maximization for Smart Grid

3.1 Introduction

Electricity is provided through an infrastructure consisting of electric utilities, power plants and transmission lines. Considering increased expectations of consumers, the lengthy process of exploiting new energy resources as well as the reliability issues indicates the importance of developing new methods to increase grid efficiency. According to [27] currently, the electricity is not efficient in most buildings. For instance, plug in hybrid electric vehicles potentially double the average household billing for consumed load. All these reasons indicate the importance of DRM. There is a wide range of DRM such as voluntary load management and direct load control. As it is mentioned in Chapter 2 in general DRM has been divided into incentive based and price based options. This thesis focuses on RTP which is offered by an energy provider and is announced to multiple users. In this case, a novel algorithm for the future smart grid is proposed. The algorithm is based on the net benefit maximization for the energy provider in a way that the satisfaction of consumers is considered as well. In this way, the algorithm achieves the goal of demand management programs which is benefit and satisfaction maximization for both sides of energy provider and users correspondingly.

3.1.1 M

otivation In this chapter an Income based optimization problem is defined and solved. This algorithm is based on optimization of the net benefit of energy provider. According to [103] the Income is the sum of all the wages, salaries, profits, interests payments, rents, and other forms of earnings received,etc. in a given period of time. Income per capita has been increasing steadily in almost every country. Many factors contribute to people having a higher income such as education, globalisation political circumstances such as economic freedom and peace. Increase in income also tends to lead people choosing to work less hours. Developed countries (defined as countries with a developed economy) have higher incomes as opposed to developing countries tending to have lower [104]. The concept of income in electricity marketing is an important factor that is studied from the point of users behaviour affect on their consumption as well as the provided amount of electricity. The concept of Electricity Marketing is important and affects the economy of countries. This topic is mostly related to consumers behaviour. Definition of an utility function depending on users consumption is important to solving the problem of maximizing the benefit of both sides of users as well as energy providers and minimizing the cost imposed to provider of electricity. There are many literature study in that area. For instance, in [105], [11] the social welfare problem is solved with respect to consumers' utility maximization. In these works a general objective function in the presence and without the presence of uncertainty is solved. Also, a model including some consumers that each one uses different appliance is considered. Each type of appliance that a consumer may use is modelled as well. However,as it is mentioned in chapter two the responsiveness of different levels of society to specific price is not explained. This is further shown in [21] over description of parameter which describes the kind of users in the utility function. Moreover, the proposed algorithm is an off-line distributed algorithm, as all decisions are made at once before the day starts. Therefore, the users and energy provider do not benefit from two way real time interaction. However, solving the problem with respect to consideration of two time scale is a point that is considered in that study. The works in [58, 14, 17] improves [21] in a way that for each specific appliance of each user a utility function is proposed. And, then the problem of social welfare optimization in a way that it is assumed there are some devices that store energy is solved.

In [14], a general utility function, dependent on not only the consumption level of the users, but also dependant to a parameter which implies how different users respond to specific price is defined. The technique used is Lagrange decomposition approach, which decomposes the problem into solvable sub problems that are solved by the users and energy provider separately. Although, it seems that the model is able to describe the interaction procedure between energy provider and users clearly, but it does not discuss over net benefit maximization of the energy provider with respect to consideration of optimum users' demand. Moreover, it does not discuss the effect of uncertainty related to the uncertain behaviour of users. The proposed algorithm in [14] tries to solve the social welfare optimization problem, but it does not discuss the effect of increasing the number of users on average consumed load. Also, solving an optimization problem regarding the income of energy provider with consideration of consumers' satisfaction has not been considered in [106, 55, 107]. In this thesis the net benefit function optimization problem is solved. Also, the effect of increasing the number of users on average load including generated capacity from the energy providers' side and total consumption of users from users' side has been considered and is compared with previously proposed utility based optimization in previous related works. The contributions of this chapter can be summarized as below:

- A new income based algorithm is proposed which describes the interaction between users and energy provider.

- The general income based optimization problem is proposed. This optimization problem is solved by energy provider and is based on the maximization of energy providers' net benefit with respect to its income which achieves from the aggregation of the users' optimal demand.

- The comparison between UBO and IBO regarding the average load is considered.

- The effect of increasing the number of users on average load is investigated.

The rest of this chapter is organized as follows: Section 3.2 describes the system model, Sections 3.3 and 3.4 discuss over problem formulation and problem solving, Section 3.5 is about the proposed distributed algorithm, Section 3.6 provides the simulation results, and finally section seven is the conclusion. The flowchart in Figure 3.1 shows the required steps that each side of users and energy provider considers with respect to the proposed algorithm.

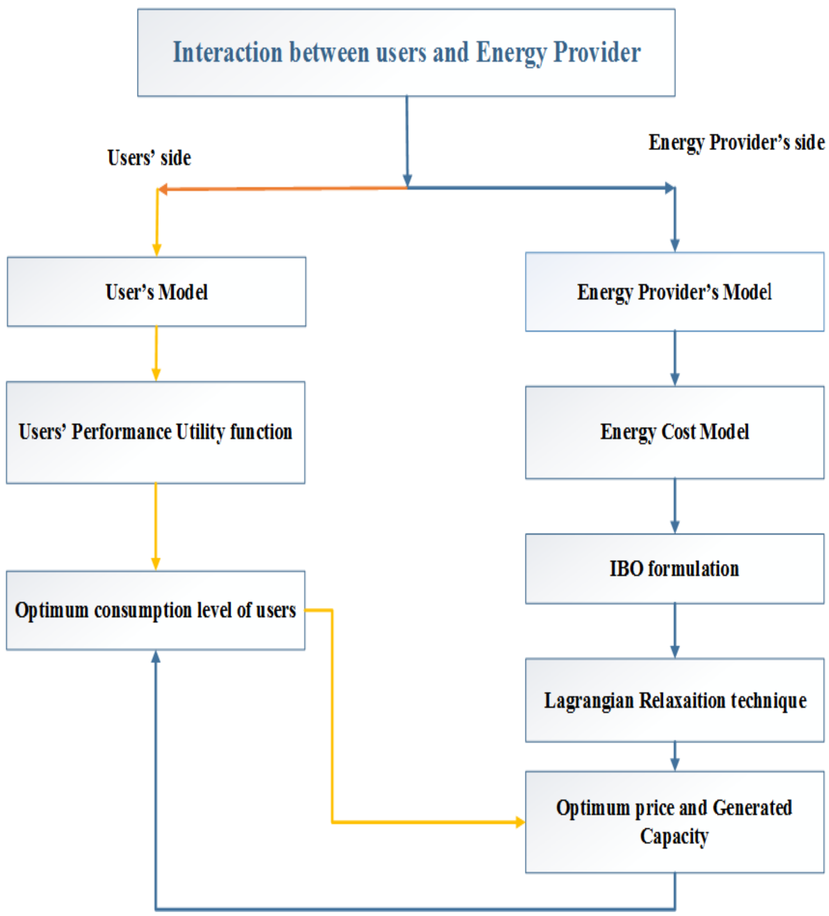

Figure 3.1: The required steps for negotiation between users and energy provider in the proposed algorithm

3.2 System Model

It is assumed that the users have smart meters which are connected to the energy provider by means of a LAN. The LAN provides the opportunity for two way communication between smart meters and the energy provider. It is also assumed that N users connect with one energy provider. There are some factors that each side of users and energy provider considers for negotiation with each other. From the energy providers' side, it is the aggregation of users' optimal demand that is considered to offer the appropriate price to the users. And from the users side it is the time of the day as well as the price that affects their consumption.

According to our proposed model, the 24 hours of a day is considered as the operation cycle of the users and is divided into some periods that are called time slots. The beginning of each time slot is called updating time. It is assumed that through the interaction between the energy provider and the users, they evaluate their optimum energy level at the beginning of each time slot by solving their welfare optimization problem. Therefore, the algorithm starts with an initial price which is updated based on aggregation of the users' optimal demand as well as the generating capacity at beginning of each updating time and also optimum generated capacity is provided by energy provider during the period between two updating times. In our proposed model, the updating time happens at the beginning of each time slot. Therefore, in the next updating time the same procedure is repeated and users optimize their consumption level based on the announced price.

3.2.1 User Objective Function

It is assumed that each user is an independent decision maker. The energy demand of the users may vary based on different parameters. For example, the time of the day, the season, the electricity price and etc. All these parameters affect the consumption patterns of users. Different response of different users to various prices can be modeled analytically regarding the concepts of micro economics. The utility function is defined as *U(x,w)* in which x represents the consumption level of users and w indicates the type of use. It is assumed that the utility functions have two important properties: first, the utility functions are non-decreasing which implies:

$$\frac{\partial\, U(x,w)}{\partial x} \geq 0 \tag{3.1}$$

And also if the second order derivative of U be considered as marginal benefit, it is non increasing, which means it should be less than zero:

$$\frac{\partial^2\, U(x,w)}{\partial x^2} \leq 0 \tag{3.2}$$

It is also assumed that for a fixed level of x the larger w achieves a larger utility. This property can be written as :

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

According to [14] various choices of utility functions are widely used in the communications and networking literature [105]. However, recent reports indicate that the behaviour of power users can also be accurately modelled by certain utility functions [108]. In this thesis, we consider quadratic utility functions corresponding to linear decreasing marginal benefit [109]:

The equation below describes the proposed utility function

$$U(x,w) = \begin{cases} wx - \dfrac{\alpha}{2}x^2 & 0 \leq x \leq \dfrac{w}{\alpha} \\ \dfrac{w^2}{2\alpha} & x \geq \dfrac{w}{\alpha} \end{cases} \tag{3.4}$$

In above formula, U is the proposed utility function. According to [14], [27], α is a positive predefined constant parameter which bounds the consumption of users in the proposed utility function. This parameter characterizes the saturation point of the utility. The higher the α the lower the power consumption to reach the saturation point [28]. Moreover, x is a power consumption level for each user. The welfare function of the users is defined as:

$$W(x,w) = U(x,w) - fx \tag{3.5}$$

Where f is the price. This price is the rate which is announced by energy provider at the beginning of each time slot. At the beginning of each slot users optimize their welfare as it is shown below:

$$Max(W(x,w)) \tag{3.6}$$

In this case the equation (5.5) is solved as Equation (3.7):

$$x_k^*(\sum_{i\in N} w_i, f_k) = \frac{\sum_{i\in N} w_i - f_k}{\alpha} \tag{3.7}$$

In this literature, the optimal consumption level for the users, regarding the constraints that bounds x between its maximum and minimum values, is achieved by solving (3.6) putting its first order derivative equal zero. The maximum of x is when the users turn on all their appliances including their lumps and its minimum level achieves when only the refrigerated is on.

3.2.2 Energy Providers Cost function

In this section a cost function which indicates the cost of providing L_k units of energy which is offered by the energy provider in each time slot k is suggested. According to [14], [27]

the cost function of providing electricity is assumed to be increasing and strictly convex.

$$C_K(L_k) = a_k L_k^2 + b_k L_k + c_k, \quad a_k > 0, b_k, c_k \geq 0 \tag{3.8}$$

In the above cost function the coefficients are pre-determined parameters where it is assumed that $a_k > 0$, $b_k, c_k \geq 0$ [14]. It is also assumed that these coefficients are evaluated based on hourly negotiation between energy provider and wholesale electricity market. The proof of convexity is explained in [58], with regard to consideration of two assumptions:

1. The cost functions are increasing, in the offered energy capacity, that is represented in Equations (3.9) and (3.10):

$$C_k(\hat{L}_k) \leq C_K(\tilde{L_K}) \ \ \forall(\hat{L}_k) \leq \tilde{L_K} \tag{3.9}$$

2. The cost functions are strictly convex. That means for each k, any $0 \leq \theta \leq 1$ and $\hat{L_K}$, $\tilde{L_K} \geq 0$ then :

$$C_k(\theta\hat{L}_k + (1-\theta)\tilde{L}_k\ ) \leq C_k(\hat{L}_k) + (1-\theta)C_k(\tilde{L}_k) \tag{3.10}$$

Therefore, Linear Piecewise Cost functions (LPC) and Quadratic Cost Functions (QCF) are two example cost functions that satisfy those assumptions.

Piece-wise linear functions and quadratic functions are two example cost function that satisfy those assumptions. In our research we use the piece-wise linear cost function for more simplification in the solution of the objective function that further will be explained. Equation (3.11) describes the proposed cost function:

$$C_k(L_k) = \begin{cases} a_k L_k + b_k & L_{min} \leq L_k \leq L_k \\ a_k L_{max} + b_k & L_k \geq L_{max} \end{cases} \tag{3.11}$$

Where $a_k > 0$, $b_k \geq 0$. The index k indicates the k_{th} timeslot and L_{min} and L_{max} achieve from aggregation of minimum and maximum required load correspondingly. It is assumed that the minimum required average load is guaranteed by energy provider. Also, the energy provider never provides more than maximum required average load. This means that generated capacity is also between the maximum and the minimum required average load.

3.3 Problem Formulation

3.3.1 IBO Problem Formulation

In this section,the interaction between the users and energy provider as an optimization problem is formulated and the existence and uniqueness of the solution is analysed the feasible set is found. In this model, the energy provider announces the price of electricity in real-time based on the aggregation of optimum consumption level of users which achieves from (3.6). The formulation of the optimization problem is done as below:

$$\begin{aligned}&\max_{x_i^k \in I_i^k,\, L_k^{min} \leq L_k \leq L_k^{max}\ k \in K, i \in \{N\}} \sum_{k \in K} \sum_{i \in N} (x_i^k)^*(f_k) f_k - C_k(L_k) \\ &\text{s.t.} \sum_{i \in \{N\}} x_i^k \leq L_k, \forall k \in K\end{aligned} \tag{3.12}$$

We call this objective function IBO as instead of the utility, in proposed Algorithm in [14] this is the income which is subscribed from the cost with goal of providing net benefit of energy provider with respect to consideration of users' satisfaction. In this objective function, f_k is a variable which indicates the fee that is paid by the users according to the announced price from the energy provider and x^* is a function of f_k which is achieved from solving (3.6). Also, K is the set of all time slots. As it is mentioned in chapter two we solve the problem in one time slot and then expand it to the K time slot,in a way that the users optimize their consumption based on the evaluated price in the previous slot and the same procedure is repeated. In the next chapter the algorithm is explained. The Figure 3.2 indicates the procedure. It should be noted that the cost is assumed to be fixed per time slot. However, its variation is based on the aggregation of users consumption achieved at the beginning of each time slot.

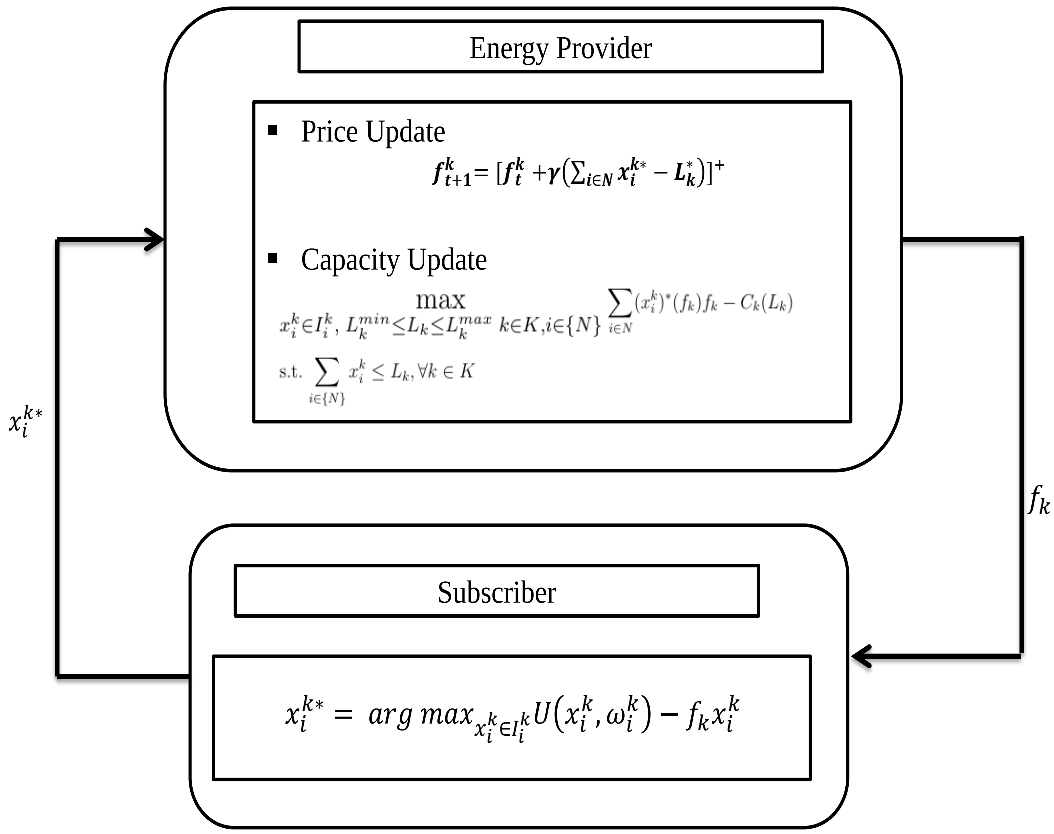

Figure 3.2: Illustration of the operation of the proposed algorithm and the interactions between the energy provider and subscribers in the system

Therefore, we solve equation (3.13) instead, and further expand it over the set of K time slots.

$$\begin{aligned} &\max_{x_i^k \in I_i^k,\, L_k^{min} \le L_k \le L_k^{max}\ k\in K, i\in\{N\}} \sum_{i\in N} (x_i^k)^*(f_k) f_k - C_k(L_k) \\ &\text{s.t.} \sum_{i\in\{N\}} x_i^k \le L_k, \forall k \in K \end{aligned} \tag{3.13}$$

One advantage of this idea is that the IBO provides the net benefit for energy provider in a way that satisfaction of all consumers has been considered , however, unlike UBO it is not needed to decompose the problem to sub problems that should be solved by users and energy provider separately. Moreover, without consideration of load uncertainty the generated capacity and users' consumption correspond and converge to maximum required load. In another word, the energy provider dose not feel too much changes in its electricity procurement because of the extra users demand. In thesis, it is assumed that the users utility function is defined based on small values for predefined parameter α, that means that the users can consume electricity in larger range of demand. Figure 3.3 describes how users with different parameter w achieve to their maximum level of satisfaction . It is appear that users with lower w has lower utility or in another word their level of satisfaction is lower in comparison with users with higher parameter w. As, it is shown in Chapter 2 and according to [78], the defined utility function depends on a predefined parameter called α. Based on the utility formulation in 3.4 the parameter α and w reacts in a same way, that means the more α refers to higher level of satisfaction or utility for the users. The proposed IBO algorithm is defined in a way to provide satisfaction for lower economical level of the society which gets to their maximum level of satisfaction with lower level of consumption. However, this algorithm is further analysed for larger values of parameter w.

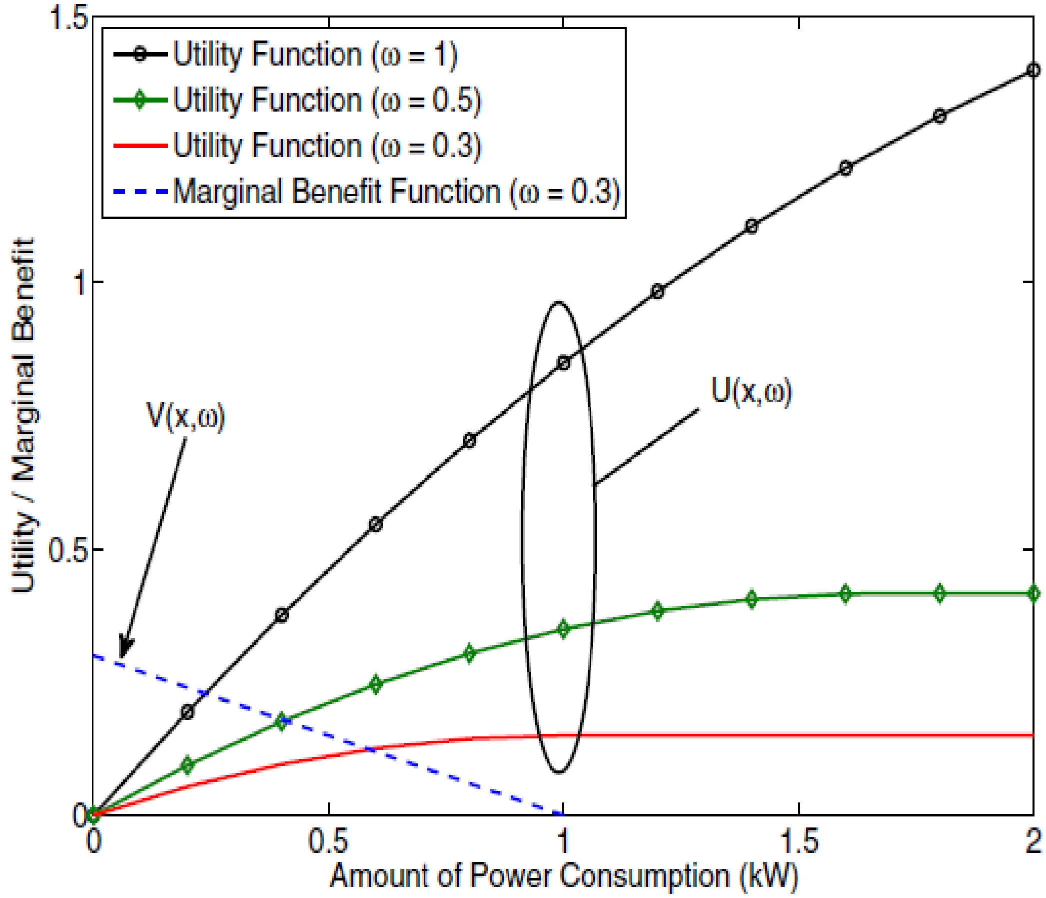

Figure 3.3: Sample utility functions for power subscribers (α= 0.3) [14]

3.4 Problem Solving

The main goal of this part is the investigation over the feasible set with respect to all its constraints for the problem (3.12). In order to prove availability of feasible set, the Lagrangian relaxation technique is used for finding out the feasible set over optimum value of f and L which represent the price and generating capacity. The Lagrangian is evaluated as [14], when λ_k is the Lagrangian multiplier :

$$\Lambda(f_k, L_k, \lambda_k) = \sum_{i \in N} (x_i^k)^*(f_k) f_k - C_k(L_k) - \lambda_k((x_i^k)^*(f_k) - L_K) \tag{3.14}$$

The technique for solving the optimization problem is also explained in [14]. According to [27], [110], the feasible set is achieved as (3.15):

$$\begin{cases} \lambda_k = a_k \\ f_k^*(\sum_{i \in N} w_i, a_k) = \dfrac{\sum_{i \in N} w_i + a_k}{2} \\ L_k^*(\sum_{i \in N} w_i, f_k^*) = \dfrac{\sum_{i \in N} w_i - f_k^*}{\alpha} \end{cases} \tag{3.15}$$

This feasible set is guaranteed as long as (3.16) is satisfied,

$$0 \leq (x_i^k)^*(f_k) \leq (\frac{w_i}{\alpha}) \text{ and } L_{min} \leq L_k \leq L_{max}. \tag{3.16}$$

Also $f_k^*(\sum_{i \in N} w_i, a_k)$ can be written as (3.17):

$$f_k^*(\sum_{i \in N} w_i, a_k) = \alpha \sum_{i \in N} x^*(f_k) + a_k \tag{3.17}$$

According to [27], for updating the price the equation below using gradient projection method is used.

$$f_{k+1} = f_k + \gamma[\sum_{i \in N} x_i^{k*}(f_k) - L_k^*(f_k)]] + \tag{3.18}$$

The above formulation for price and capacity indicates that the price is updated in each time slot as soon as the aggregation of optimized demand is revealed and then the optimum value for capacity provided by energy provider is achieved. In this formulation γ is the step-size, $x_i^{k*}(f_k)$ and $L_k^*(f_k)$ are the optimal consumption and generated capacity correspondingly. The flowchart below describes how the overall system works with respect to consideration of IBO algorithm.

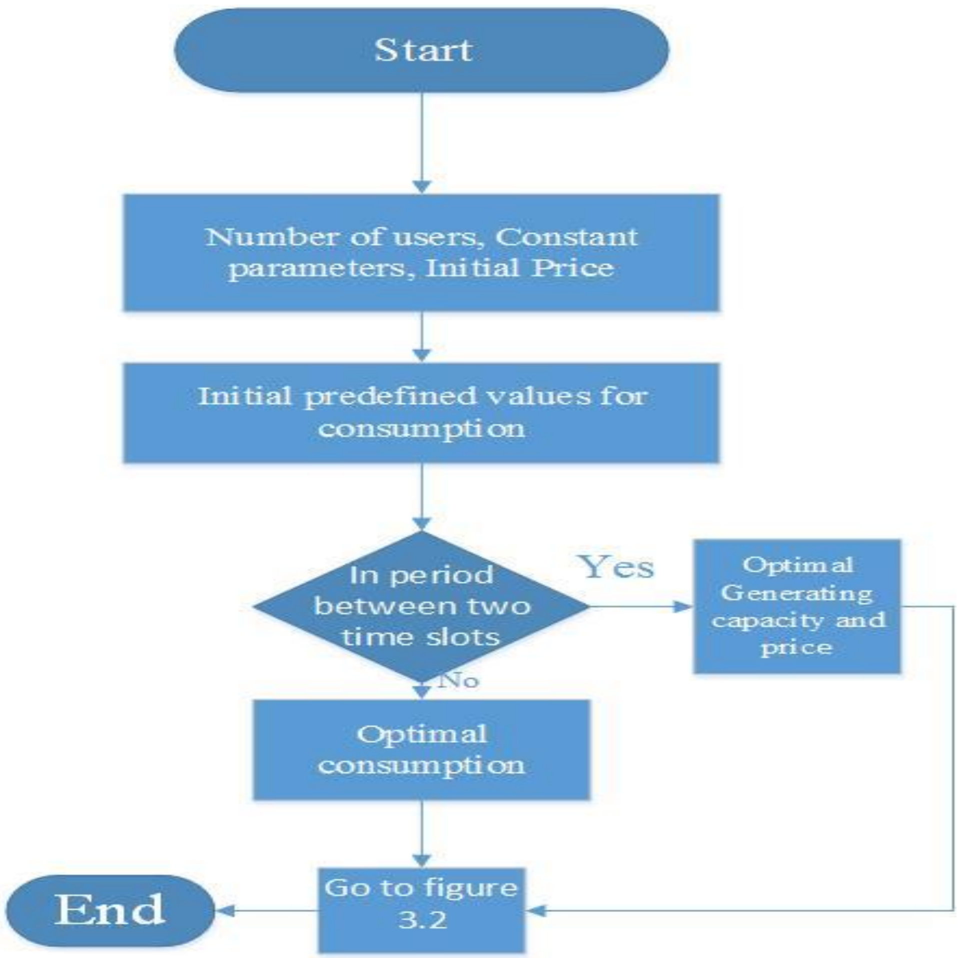

Figure 3.4: Illustration of how IBO works in DRM

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3.5 Distributed DRM Algorithm

In this section the proposed algorithm is explained. This algorithm which is proposed in [27] describes the interaction procedure between users and energy provider.

Algorithm 3.1 Executed by each user $i \in N$ (IBO)

```
Initialization
for all t ∈ T do
    Receive the new value of f_t^k from the energy provider
    Update the consumption value by solving (3.6)
    Communicate the updated value of x_i^{*k}(f_t^k) to the energy provider.
end for
```

Algorithm 3.2 Executed by energy provider (IBO)

```
Initialization
repeat
If this is the beginning of each time slot k ∈ K
Compute the new value of f_k^* using (3.17).
Broadcast the new value of f_K to all users.
else
Update the capacity value L_k by solving (3.15)
Receive x_i^k(f_k) from all users
Update total load
end
Until end of the intended period.
```

From the users' side, the algorithm 3.1 is executed by each user i. Also, Algorithm 3.2 is described from the point of view of energy provider. In above algorithms the interaction between users and the energy provider is shown. The algorithm starts with the initial price which is evaluated by energy provider at beginning of each time slot. In the period between two time slot the sum of optimal consumption of users and also optimum generated capacity of energy provider is evaluated. The updated price is announced to the users and the same procedure is repeated in a way that again at the beginning of each timeslot updated optimal price is announced to the users and users optimize their consumption again. Figure 3.2 illustrates how energy provider and users interact in IBO.

3.6 Performance Evaluation

In this section , the simulation results are presented and also the proposed algorithm is discussed as well. It is assumed that the number of users, N, is equal to 10. The entire time cycle is divided into 24 time slots, representing 24 hours of the day. The minimum and maximum power requirements vary in each time slot. While it is assumed that the maximum power requirement is when all the appliances are in use and the minimum power requirement is when only appliances such as fridges are on. We also assume that the parameter w is selected from the interval [1,4] and remains fixed through the interval. The parameter α is assumed to be small enough to let users to consume more energy in order to consider users with higher saturation rate, according to 3.2.1. Table 3.1 shows the considered parameters and their notations. To have a base line, we consider the proposed algorithm in [14], and we call it UBO ,

Table 3.1: Description of effective parameters (IBO)

PARAMETER	VALUE
No. of Users	10,20,30
Time of Day (hr)	[1,24]
Class of User's	[1,4]
Coefficients of Construction	a_k = 0.01,0.1,0.6,1 b_k=0
α	0.005

and compare it with our proposed IBO. The results of running UBO algorithm shows that generated capacity and total power consumption correspond and are bounded between the maximum and minimum required load. For small values of parameter α simulation results show that using IBO algorithm, users may have use up to their maximum demand. Simulation results have been shown in Figure 3.5. It is assumed that the gap appears in the time slot between 10-12 AM and the simulation results is considered for 24 hours timing period.

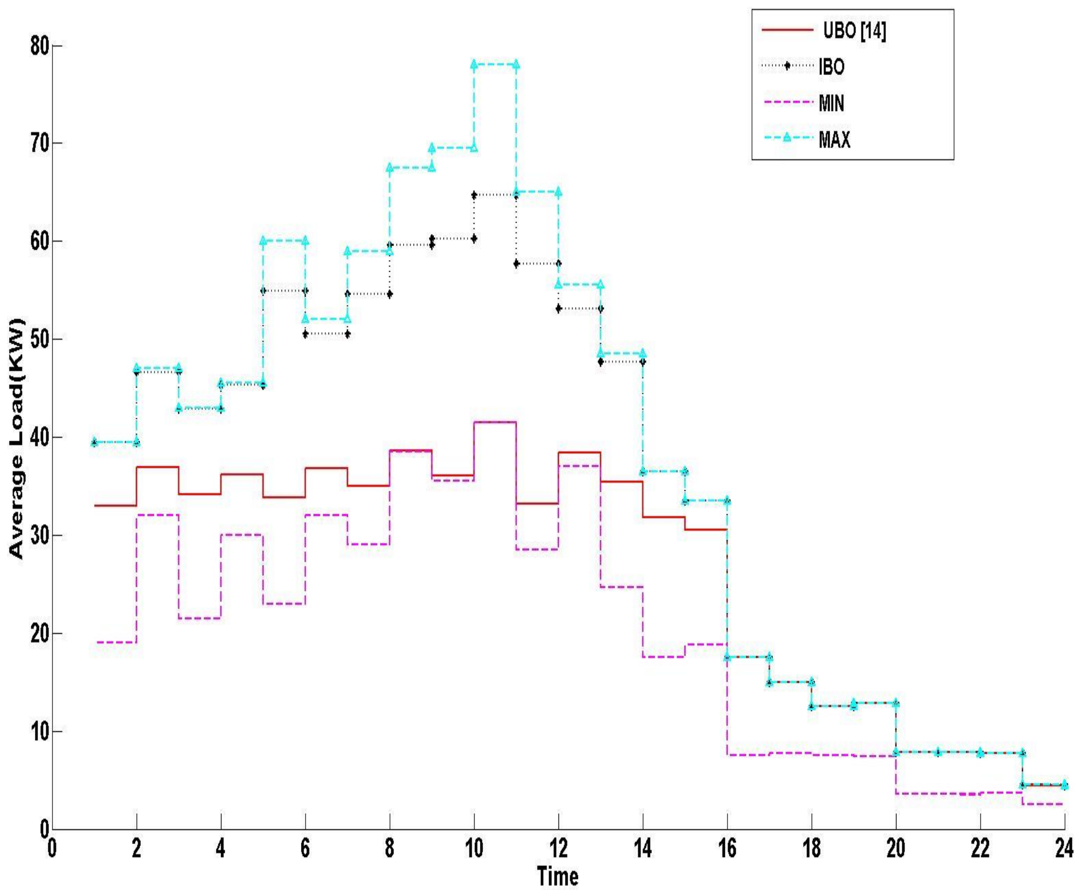

Figure 3.5: Comparison between average load for IBO and UBO algorithm for N=10 user

As, it is appear from Figure 3.5 the average load for IBO and UBO algorithms is limited between maximum and minimum power requirements. This result achieves according to 2.1 for UBO as well as 3.12 constraint of the proposed optimization problem. Moreover,it is assumed that according to the proposed scenario the users achieves to their maximum level of satisfaction with lower consumption. Figures 3.3 and 3.5 illustrate the in this proposed scenario users in IBO consume more average load.

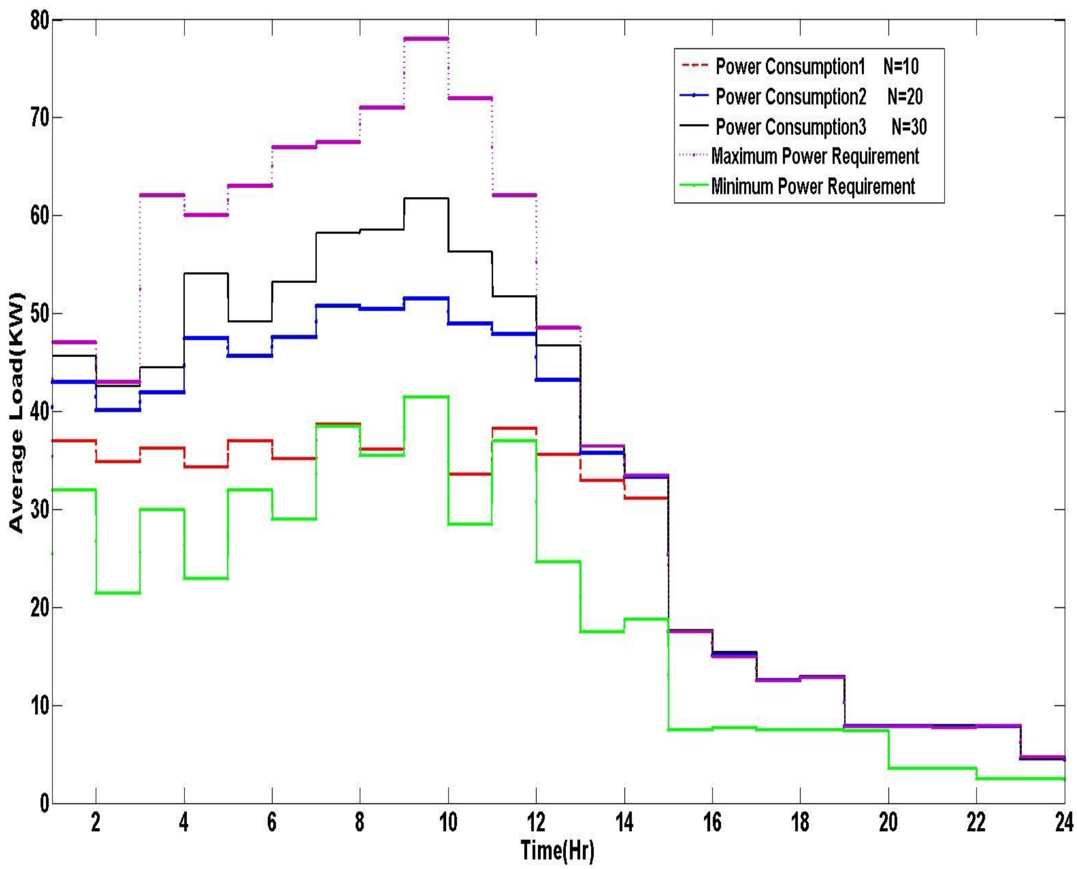

Figure 3.6: Effect of increasing the number of users on average load for UBO [14]

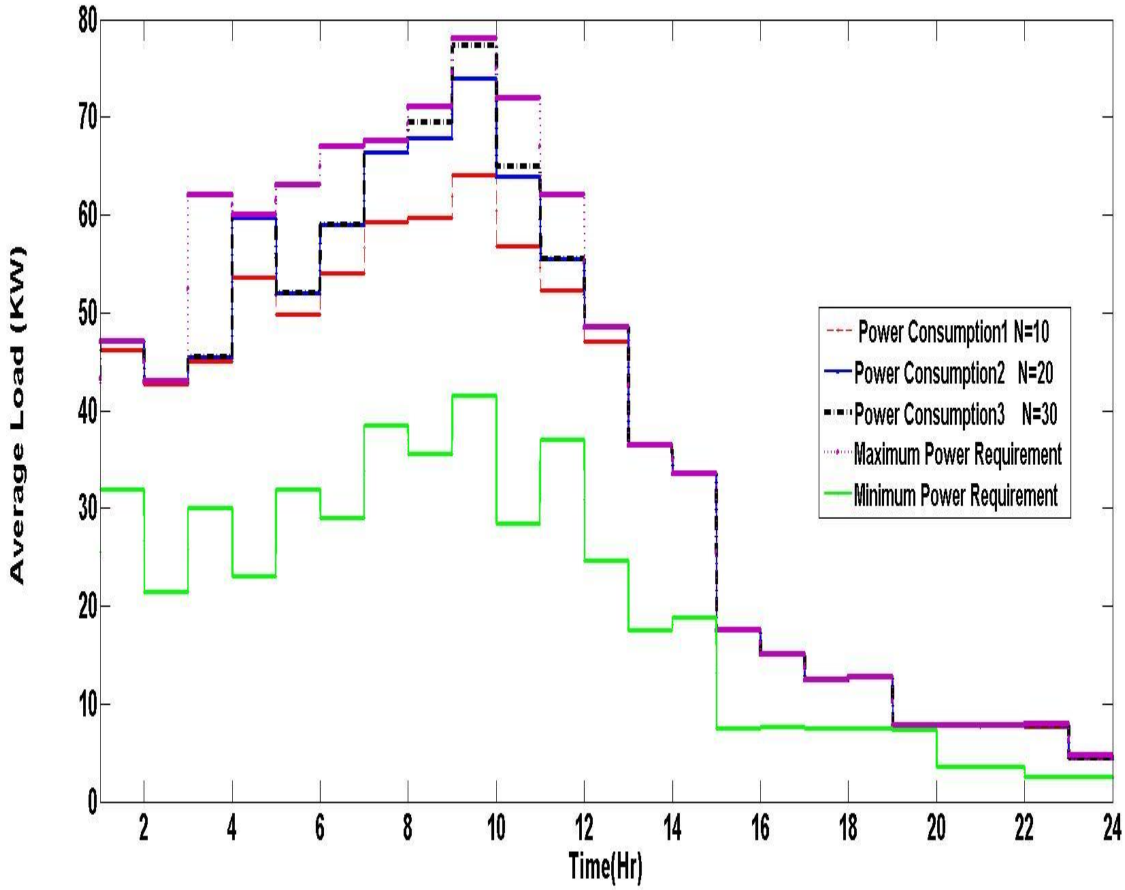

Figure 3.7: Effect of increasing the number of users on average load for IBO

Figures 3.6 and 3.7 describes the effect of increase in number of users for both UBO and IBO algorithms. It is expected that when number of users increase the consumption also increases. The simulation results confirm both algorithms.

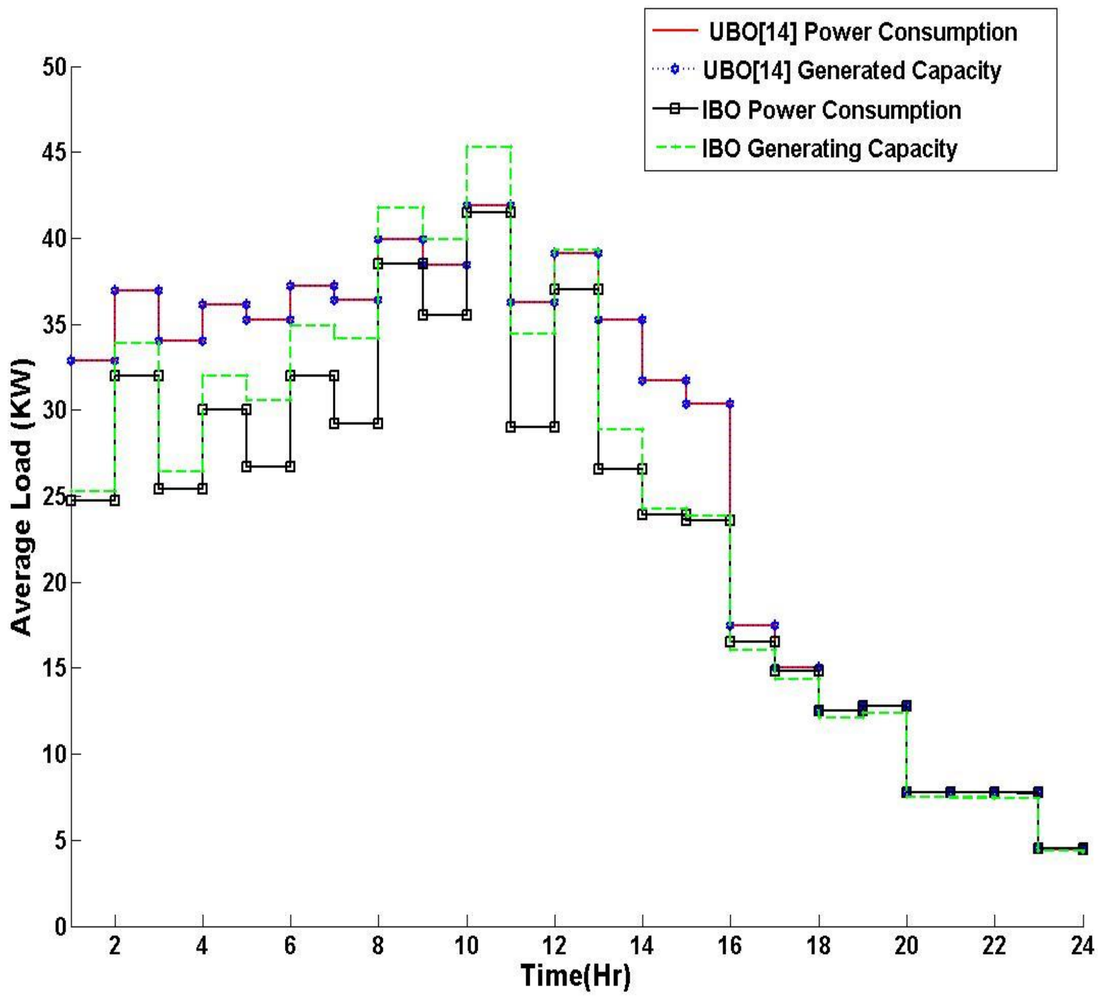

Figure 3.8: Effect of Parameter α on average load, $\alpha = 0.05$

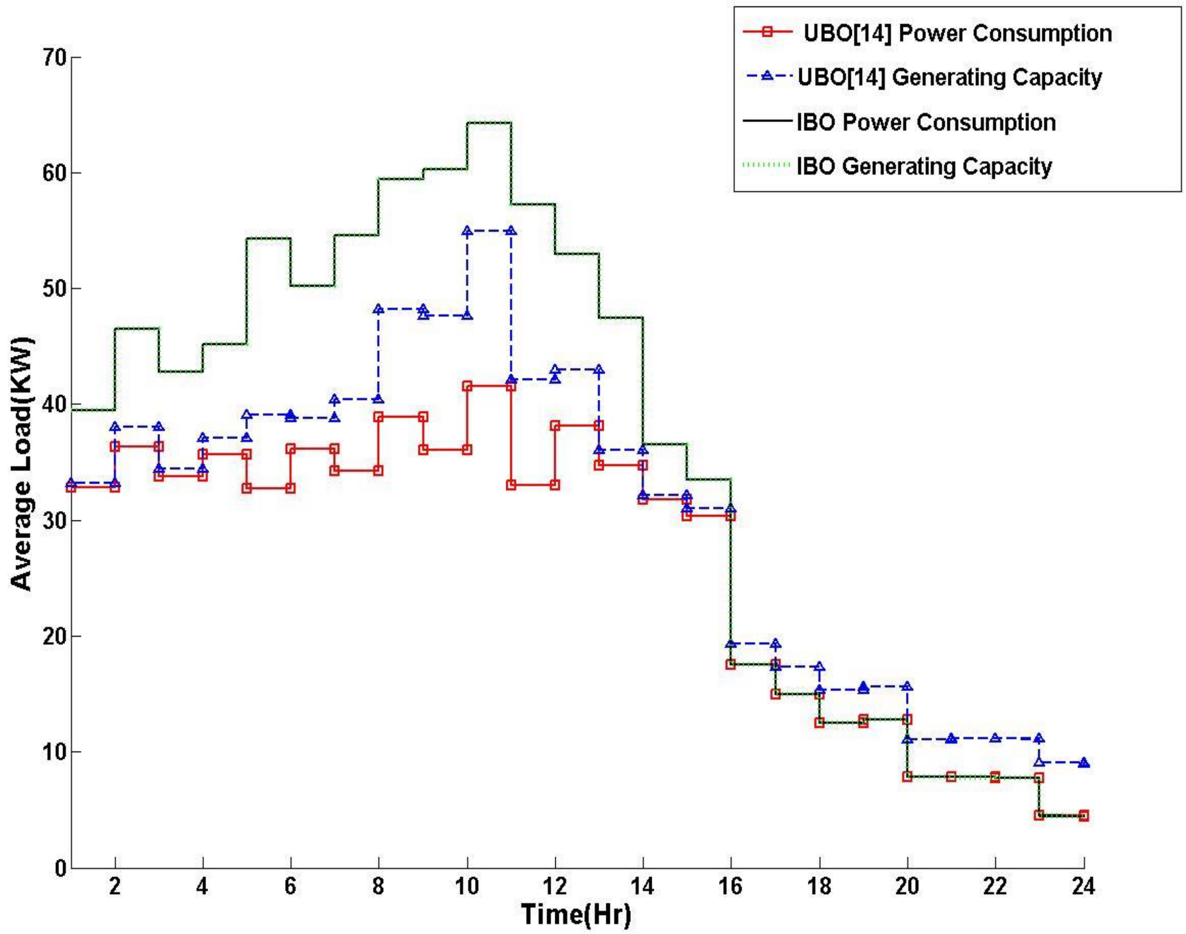

Figure 3.9: Effect of Parameter α on average load, $\alpha = 0.005$

Figures 3.8 and 3.9 describes the effect of the parameter α on the average consumed load. As, it is appear from these two figures when the parameter α is smaller the GAP between generating capacity and consumption for UBO is lower in comparison with IBO Algorithm. The reason is related to the effect of this parameter on the price as in IBO this parameter affects the price in a way that the more α the more the price which announced to the users. Therefore, the larger values of this parameter causes more gap between generating capacity and consumption. According to Figure 3.3, the physical meaning of this parameter is closely related to the parameter w which indicates level of satisfaction for users per amount of consumption.

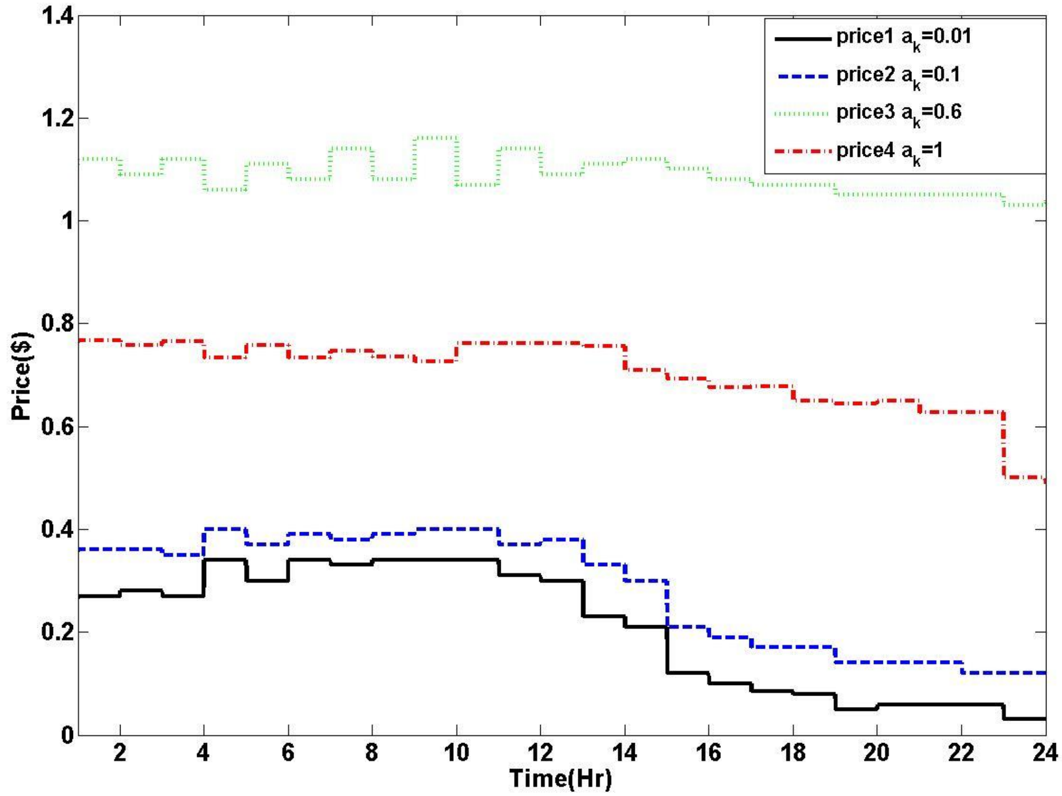

Figure 3.10: Effect of Parameter 'a' on Price

Figure 3.10 describes the effect of the coefficients of cost function on the price. As, it is expected increase in coefficients of the cost function directly affect the price. According to the solution of the optimization problem in IBO algorithm the price is dependant to the coefficient of cost function, therefore increase in this parameters affect the price. Figure 3.10 illustrates the effect of increase in this parameter for different hours of the day.

3.7 Summary

In today's smart grid, DRM plays an important role to increase the efficiency of the grid. There are various ranges of DRM programs, such as direct load control, voluntary load management, etc. However, Real Time Pricing is one of the most important programs in residential areas. With respect to the importance of dynamic pricing in smart grid a novel income based algorithm is proposed and is compared with previously suggested utility based algorithm.

Simulation results confirm that the performance of the proposed IBO algorithm regarding the small values of parameter α in utility function is better in case of consumption up to the maximum demand. The effect of increasing the number of users regarding the optimum price is considered as well. Simulation results show that when number of users increases the consumption for both IBO and UBO algorithms also increases. However, the gap between low and high number of users for IBO is lower in comparison with UBO.

In the next section solving the optimization problem with regard to load uncertainty in consumption is suggested. In this way, it is assumed that the problem is solved when bounded uncertainty is added to the consumption of the users. It can be modelled in a way to assume that load uncertainty is existed due to using renewable energy such as wind, solar and etc. In this case several uncertainty models can be considered as the added noise to consumption, which in this thesis it is focused on bounded uncertainty model which is described in [28].

Chapter 4

An Optimal Real Time Pricing Algorithm under Load Uncertainty and User Number Variation in Smart Grid

4.1 Introduction

In this section we discuss about the effect of renewable energy in consumption of the users and generation of the energy provider with goal of solving the DRM problem with the aim of maximizing benefit of both sides with respect to consideration of the effect of uncertainty in user number variation based on different distribution models. In this case it is important to have a glance on renewable energy which affects the utility as well as the cost in DRM.

According to [111], increasing renewable electricity generation is an essential component in achieving a doubling of the renewable energy share in the global energy consumption. It should be noted that this transition is technically feasible, but will require upgrades of old grid systems. The reason we study uncertainty in this chapter is basically related to some forms of renewable electricity, notably wind and solar, which are dependent on an ever fluctuating resource such as wind or sun. As electricity supply must meet electricity demand at all times, efforts are required to ensure that electricity sources or electricity demand is available for the grid in presence of uncertainty. In other words the grid should be able to absorb this variability as a result of renewable energy. Distributed renewable generation specially when the smaller-scale systems are matter, usually privately owned or might be operated by energy companies, represent a new and different business model for electricity. Traditional utilities are often uneasy about allowing such systems to connect to the grid due to concerns over safety, effects on grid stability and operation, and the difficulties in valuing and pricing their generation. This point make highlight the importance of smart grid in comparison with traditional grids.

The cost of fossil fuelled generating technologies is mostly higher than renewable electricity generating technologies. This also highlight the importance of study in that area. It should be noted that although renewable energy is cost effective in some points, but developing countries do not have access to sufficient basis to invest in renewable. However, due to advantages of running renewable energy in this chapter we discuss DRM with respect to uncertainty assuming appear as a result of uncertainty in renewable. One of the principal challenges in operating an electricity system is ensuring that the demand for electricity is always exactly equal to the supply. This is discussed in chapter two. In essence, a smart grid plays an important role to integrate renewable with a wide range of diverse electricity resources. For instance, in case a PV system and a set of commercial and industrial electricity consumers on an interruptible rate, all tied together with smart grid If the output of the PV system drops due to a cloud, then the smart grid interrupts service to those customers on the interruptible rate, and then when the cloud moves on, their service resumes. Therefore, it is important to define and solve DRM problems in presence of uncertainty.

In this section [28], is extended and three types of variation based on different distributions for users entry and departure have been considered . It is assumed that with respect to the consideration of load uncertainty, the number of users might be considered to be constant, vary based on uniform distribution or vary according to Poisson distribution. Consideration of uncertainty in number of users affects the consumption level of users as well as generating capacity. The idea of adding uncertainty to users utility subject to the consideration of different types of distributions for variation in users entry and departure and investigation over the gap between generating capacity and users consumption is the base line for this chapter. Figure 4.1 describes a flowchart for the required steps we consider for solving the DRM problem in presence of load uncertainty and user number variation, that for UBO algorithm is studied in this chapter. As, it is shown in figure 4.1 the output of the overall system depends on the kind of DRM problem which is selected. It should be noted depending on the proposed scenario different algorithms might be chosen to solve the DRM problem. This figure in general represents the system framework.

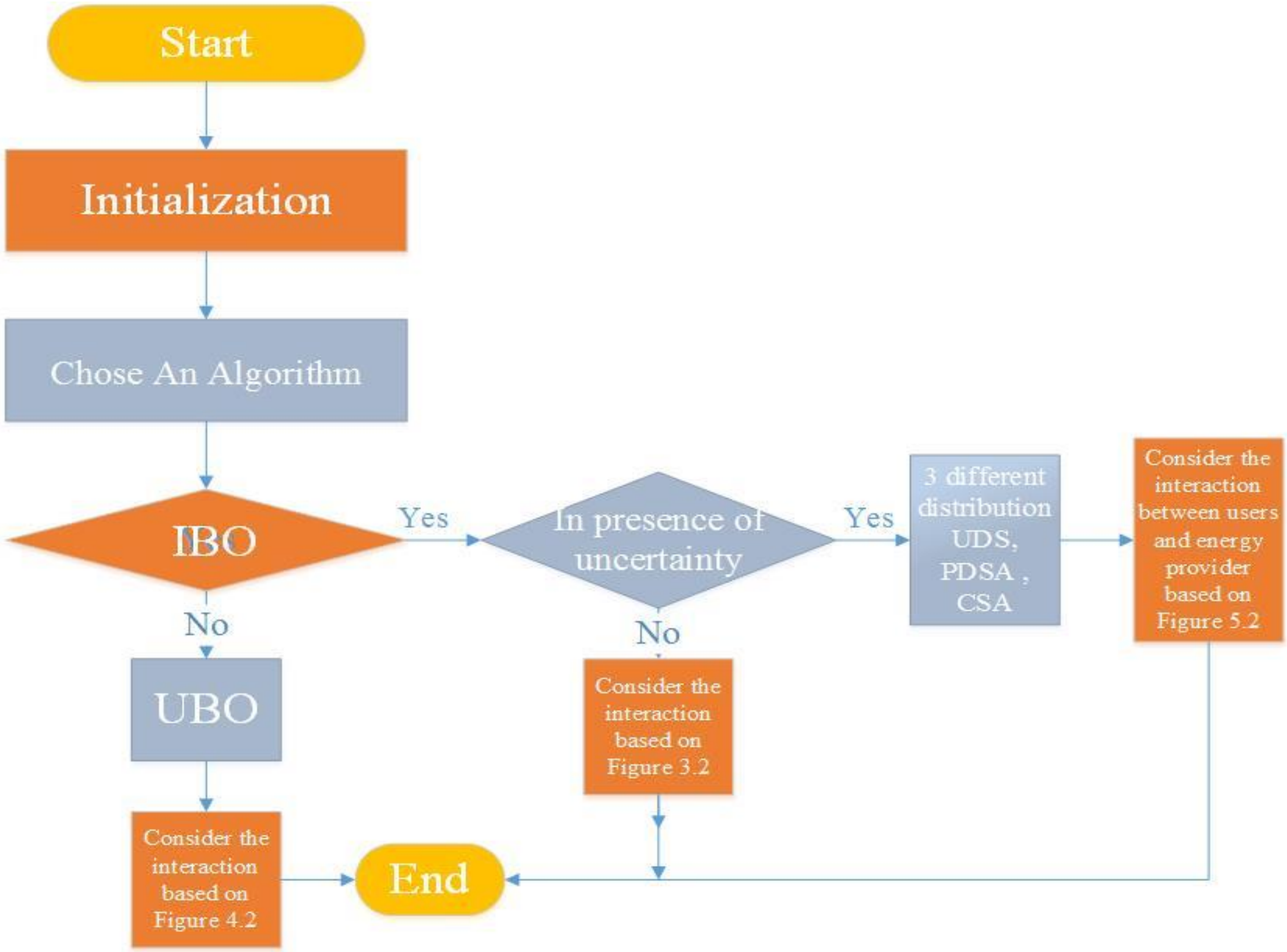

Figure 4.1: Flowchart for representation of the overall system framework

4.2 System model

Information exchange among energy provider and consumers happens at the beginning of each time slot. The proposed model in this chapter is similar to the proposed model in Chapter 3, however, different from [28] which explains that the power consumption may deviate from what was negotiated at the information exchange section due to load uncertainty with the constant consumers , in this chapter it is assumed that number of users may vary different distributions. It is also assumed that the energy provider is obliged to provide enough electricity to cover the minimum power consumption requirement. In this chapter, we consider three types of systems that perform based on different users entries or departure types. In this case it is assumed that the rate of users' departure or entries may be constant as in [28]. The investigation over such a system is called Constant System Analysis (CSA), and is compared with systems where the number of users may vary randomly or based on Poisson process, that are called Uniform Distribution System Analysis (UDSA) and Poisson Distribution System Analysis (PDSA) respectively.

4.3 Utility Function and Energy Cost Model

4.3.1 Consumer Utility function

The utility function shows the level of satisfaction of consumers. The proposed utility function in [58] is considered to be quadratic with saturation. Equation (3.1) represents the proposed utility function regardless of load uncertainty. In [28], the effect of load uncertainty appears in the utility function. The proposed utility function with regard to load uncertainty is defined as below:

$$\tilde{U}(x,w) = \begin{cases} wx - (\frac{\alpha}{2})x^2 - \frac{\alpha}{2}\sigma_\delta^2 & 0 \leq x \leq \frac{w}{\alpha} \\ \frac{w^2}{2\alpha} - \frac{\alpha}{2}\sigma_\delta^2 & x \geq \frac{w}{\alpha} \end{cases} \tag{4.1}$$

It is assumed that a random variable which represents the load uncertainty is added to the consumption level of users. Therefore, actual power consumption is represented as $\tilde{x_i}^k = x_i^k + \delta_i^k$. Where δ_i^k represents several variations of the load demand within a time slot that might be as a result of renewable fluctuations. It is assumed that the variance of δ_i^k is equal to σ_δ^2. Thus according to (4.1) load uncertainty reduces the utility proposed in (3.1) on the average. In [28], different uncertainty models have been analysed. However, in this thesis it is focused on bounded uncertainty model which limits the variation of the load demand between a maximum and minimum value.

4.3.2 Supplier Cost function

The cost function of providing electricity is assumed to be increasing and strictly convex. Therefore, linear piece-wise cost functions (LPC) and quadratic cost functions (QCF) are two example cost functions that satisfy those assumptions. The proposed cost function is the same as (3.8) that have the characteristics of (3.9) and (3.10).

4.3.3 Optimization problem

In [14], RTP is formulated as maximization of social benefits among the consumers and the energy provider, based on the subscription of aggregation of users' utility of energy provider cost function, while the constraint is the summation of the power consumption not exceeding the generating capacity at each timeslot. As maximization of aggregation of all users' utility functions and minimization of the cost imposed to energy provider is the goal that is followed by each sides of users and the energy provider, therefore, mathematically the optimization problem can be written as (2.1), (2.2). However, each user may choose his own optimal consumption level to maximize his welfare, which is described as the subscription of users' utility function of the cost imposed by the energy provider to the user. It should be noted that the individual optimized consumption level of users may not be socially optimized. In this case, the sum of all users' utility function minus the cost that is imposed by the energy provider is considered as the proposed objective function, while the consumption level of all users is adopted with limited source of energy which is provided by the energy provider.

The technique for solving optimization problem is explained in [112]. Also, the problem can be solved separately at each time slot by users and also the energy provider. In this case, each user determines the optimal consumption x_i^{k*} from

$$x_i^{k*} = \underset{x_i^k \in I_i^k}{\arg\max} \quad U(x_i^k, w_i^k) - \lambda^k x_i^k \tag{4.4}$$

Where λ^k is the Lagrange multiplier representing the energy price. Then x_i^{k*} is sent to the energy provider who determines the optimal L_k from

$$L_k^* = \underset{L_k^{min} \leq L_k \leq L_k^{max}}{\arg\max} \quad \lambda_k L_k - C_k L_k \tag{4.5}$$

The energy provider updates the price λ_k according to the gradient projection method.

$$\begin{aligned} \lambda_{t+1}^k = [\lambda_t^k - \gamma(\partial(\lambda_t^k))/(\partial\lambda^k)]^+ = \\ [\lambda_t^k + \gamma(\sum_{i \in N}(x_i^{*k}(\lambda_t^k) - L_k(\lambda_t^k))] \end{aligned} \tag{4.6}$$

Hence, the price is updated based on the above formulation. Where t is the iteration index and γ is the step size chosen to be small enough for convergence. The algorithm can be used to solve the optimization problem without knowing the ω_i^k. With regard to the consideration of the effect of load uncertainty, the maximization problem in (2.2) can be written as [92], [28]:

$$\begin{aligned} &\max_{x_i^k \in I_i^k,\, L_k^{min} \leq L_k \leq L_k^{max}\ k \in K, i \in \{N\}} \sum_{k \in K} \sum_{i \in N} E(U(\tilde{x}_i^k, \omega_i^k) - C_k(L_k)) \\ &\text{subject to} \sum_{i \in \{N\}} x_i^k + \delta_i^k \leq L_k, \forall k \in K \end{aligned} \tag{4.7}$$

According to [28], it is assumed that bounded uncertainty is added to the users' consumption, therefore the left hand side of the constraint in the above objective function might be written as (4.8):

$$\begin{aligned} \sum_{i\in N}(x_i^k+\delta_i^k) = \sum_{i\in N}(x_i^k) + \sum_{i\in N}(\delta_i^k) \leq \\ \sum_{i\in N}(x_i^k) + |\sum_{i\in N}(\delta_i^k)| \leq \sum_{i\in N}(x_i^k) + \sum_{i\in N}|(\delta_i^k)| \leq \\ \sum_{i\in N}(x_i^k) + N\epsilon \end{aligned} \tag{4.8}$$

It is assumed that $|\ \delta_i^k \ |\leq \epsilon$, $\forall i \in N$,$\forall k \in K$ and ϵ is maximum magnitude of load uncertainty. The constraint in (4.8) can be written as:

$$\sum_{i\in N}(x_i^k) \leq L_k^{eff}, \forall k \in K, \tag{4.9}$$

Where $L_k^{eff*} = L_k^* - N\epsilon$. It must be noted that the change in price affects the consumption and generating capacity . The equation (4.6) also is updated based on bounded uncertainty and can be written as [107]:

$$\begin{aligned} \lambda_{t+1}^k = [\lambda_t^k - \gamma(\partial(\lambda_t^k))/(\partial\lambda^k)]^+ = \\ [\lambda_t^k + \gamma(\sum_{i\in N}(x_i^{*k}(\lambda_t^k) - L_k^{*eff}(\lambda_t^k))]^+ \end{aligned} \tag{4.10}$$

Therefore,problem (2.1) might be written as [28]:

$$\begin{aligned} &\max_{x_i^k \in I_i^k,\ L_k^{min} \leq L_k \leq L_k^{max}\ k \in K, i \in \{N\}} \sum_{k \in K} \sum_{i \in \{N\}} \tilde{U}(x_i^k, w_i^k) - C_k(L_k) \\ &\text{subject to} \sum_{i \in \{N\}} x_i^k \leq L_k^{eff*}, \forall k \in K \end{aligned} \tag{4.11}$$

In this section, the models for variation of number of users are considered and compared. Therefore equation(4.9) is rewritten as(4.12) which is represented in [107]:

$$\sum_{i \in N} x_i^k \leq L_k - E(N_{k \in k}^{(p,u,c)})\epsilon \ , \forall k \in K \tag{4.12}$$

Where $N_{(k \in k)}^{(p,u,c)}$ represents the number of users in k_{th} timeslot, with regard to it's variation that may be considered based on Poisson process or uniform distribution, or may be kept constant which is represented by p, u, c. Therefore, the proposed objective function with regard to consideration of the bounded uncertainty model can be written as :

$$\begin{aligned} &\max_{x_i^k \in I_i^k,\ L_k^{min} \leq L_k \leq L_k^{max}\ k \in K, i \in \{N_{(k \in k)}^{(p,u,c)}\}} \sum_{k \in K} \sum_{i \in \{N\}} U(\tilde{x}_i^k, w_i^k) - C_k(L_k) \\ &\text{subject to} \sum_{i \in \{N\}} x_i^k \leq L_k - E(N_{k \in k}^{(p,u,c)})\epsilon \ , \forall k \in K \end{aligned} \tag{4.13}$$

For solving this optimization problem, when the number of users vary, the average number of users in the interval is considered as the expectation of $E[N_{(k \in k)}^{(p,u)}]$ which represents PDSA and UDSA respectively. It is assumed that $E(\delta_i^k)$ is equal to zero, which means that zero mean load uncertainty is considered. Therefore, considering variation in number of users, equation (4.13) can be written as:

$$\begin{aligned} &\max_{x_i^k \in I_i^k,\, L_k^{min} \leq L_k \leq L_k^{max}\ k \in K, i \in \{N_{(k\in k)}^{(p,u,c)}\}} \sum_{k \in K} \sum_{i \in \{N\}} \tilde{U}(x_i^k, w_i^k) - C_k(L_k) \\ &\text{subject to} \sum_{i \in \{N\}} x_i^k \leq L_k - E(N_{(k\in k)}^{(p,u,c)})\epsilon \text{ , } \forall k \in K \end{aligned} \tag{4.14}$$

Where $\tilde{U}$ is defined as (4.1). In the rest of the paper, the results for these three systems, with regard to bounded uncertainty are compared . Therefore,(4.4), (4.5) is written as (4.15), (4.16):

$$\tilde{x}_i^{*k} = \arg\max_{x_i^k \in I_i^k} \quad U(x_i^k, w_i^k) - \lambda^k \tilde{x}_i^k \tag{4.15}$$

$$L_k^{eff*} = \arg\max_{L_k^{min} \leq L_k \leq L_k^{max}} \quad \lambda_k(L_k^{eff*}) - C_k(L_k) \tag{4.16}$$

Figure 4.2, describes the interaction procedure between subscribers and energy provider with regard to consideration of load uncertainty.

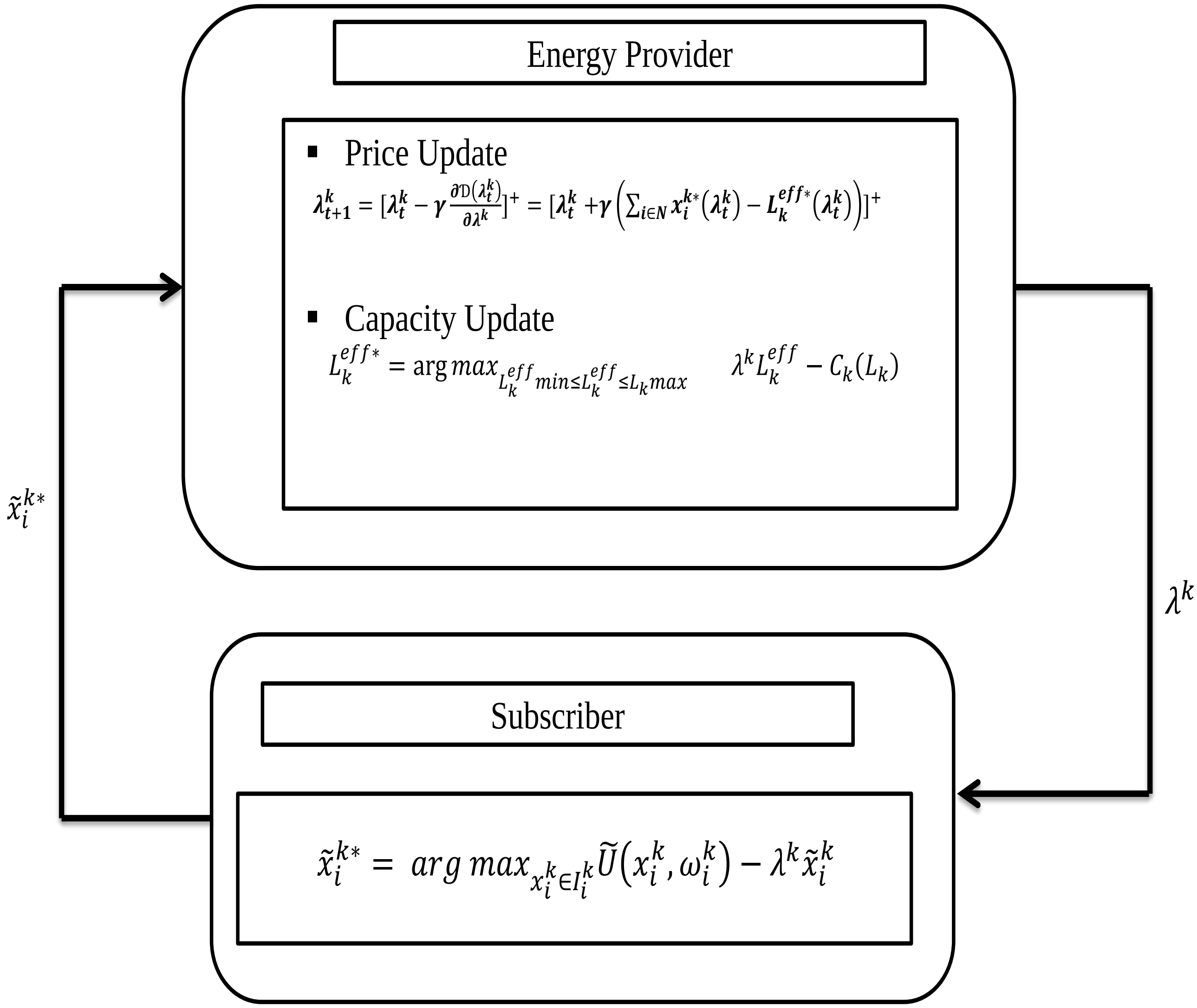

Figure 4.2: Illustration of the operation of the proposed algorithm and the interactions between the energy provider and subscribers in the system [107]

It is obvious from figure (4.2), that parameter λ_k which is assumed to be the announced price is sent to the subscribers and then the optimum consumption level of users is sent back to the energy provider .

The optimum consumption level of users is assumed to be affected by a randomly generated noise. The optimum generated capacity is evaluated and the price is updated as well.

With regards to consideration of the load uncertainty, the effective value of the generating capacity which is dependent on the number of users and parameter ϵ that is assumed to be a constant value, is updated in each time slot. It is assumed that the number of users vary based on the three types of users entry and departure including Uniform Distribution, Poisson Distribution and when the number of users kept constant.

In the next section, the distributed algorithm which explains the interaction procedure between users and the energy provider with regard to consideration of three types of users variation in presence of load uncertainty will be explained.

4.4 Distributed Algorithm

In the proposed distributed algorithm in [14], it is assumed that the number of users in each interval is kept constant, and the interaction between users and the energy provider is done in each timeslot using a LAN that is connected to the energy consumption controller unit .

In this section, it is assumed that users' arrival and departure may vary based on

Poisson Distribution or Uniform Distribution. According to [28], when bounded uncertainty applies to the grid, the constraint in objective function would be dependent on the number of users, therefore variation in the number of users based on different distributions affects the outcome of the proposed algorithm. Also, because of the uncertainty, the expectation of output from [28] running the Algorithms several times is considered.

Also, the variation in the number of users is considered between two timeslots. Therefore, the proposed algorithm in [14] is changed and explained in algorithms 4.1 and 4.2 from the users and the energy provider's side respectively.

According to the Algorithms with regard to three different proposed users' entry and departure type the users receive the announced price from the energy provider at the beginning of each timeslot. Each user optimizes his consumption level based on (4.15) and sends it to the energy provider.

Algorithm 4.1 Executed by each user $i \in N$(UUBO)

1: Initialization
2: Generate users interval/departure based on Poisson/Uniform distribution or set it as a constant value.
3: **for all** $t \in T$ **do**
4: Receive the new value of λ_t^k from the energy provider
5: Update the consumption value by solving(4.15)
6: Communicate the updated value of $x_i^{*k}(\lambda_t^k)$ to the energy provider.
7: **end for**

Algorithm 4.2 Executed by Energy provider (UUBO)

Initialization
repeat
Generate users interval/departure based on Poisson/Uniform distribution or set it as a constant value.
if $t \in T$ **then**
    Compute the new value ofλ_t^kusing(4.10).
    Broadcast the new value of λ_t^k to all users
    else
    Update the capacity value L_k^{eff*} by solving(4.16).
    Receive the Updated optimum consumption level of all users by solving(4.15).
    Update the total load.
    Accumulate the results for each time running the program
    Average the results
    Receive the new value of λ_t^k from energy provider
    Update the consumption value by solving (4.15)
    Communicate the updated value of $x_i^{*k}(\lambda_t^k)$ to energy provider.
end if
Until end of intended period.

With regard to users' entry and departure type, the energy provider computes the new value of price at the beginning of each timeslot and broadcast it to the users. At the moment the energy provider updates the optimum generating capacity based on updated optimum consumption level that is received from users. The average of results after several times running the algorithm is shown in the next section.

4.5 Simulation results and discussion

In this section, simulation results with regard to bounded uncertainty model for UUBO considering PDSA, UDSA and CSA are compared. The aim of this part is to investigate the effect of the distribution of users' interval and departure with and without consideration of load uncertainty on the average gap which might be appear between users' consumption and generating capacity in some time slots. Also, the effect of increasing the number of users is analysed as well. Simulation assumptions and parameters are described as explained in Table (3.1). However it is assumed that number of users are kept constant or varies based on Poisson or Uniform distribution. It is assumed that the variation in number of users obtains the values in a 24 hour time period. The consumer type represents the class of user that might be from a higher or lower level of society as it is explained in Chapter 3. It is also assumed that the minimum and maximum power requirement varies throughout the day, but remains fixed during a one hour period. The simulation results in this thesis are implemented by MATLAB. According to the algorithm the code starts with some initial values for the price and maximum and minimum consumption level of users. It is assumed that users consume more than equal the pre-defined consumption level and also the generating capacity dose not exceeded the maximum users' consumption. In order to analyse the result sets of users according to different distributions are produced. Then run the program for several times and take the average of the results. Figures 4.3, 4.4 and 4.5 illustrate the gap between generated capacity and power consumption. When it is assumed that the number of users is equal 10 users and 24 hours period of a day is considered for the simulation for PDSA, UDSA and CSA. As, it is appear the gap between generated capacity and consumption for UDSA is more than two other distributions. One reason would be the larger variance of uniform distribution in comparison with Poisson distribution as it is explained in [113]. Simulation results show that when number of users increases the gap between generated capacity and consumption decreases as expected because of the increase in users average consumption. We analyses the results for UDSA to investigate the effect of increase in number of users when it is increased to 50 and 100 users to see how it affects the gap between generrated capacity and consumption. As, it is appear from Figures 4.6 and 4.7, when number of users with respect to UDSA increases the gap between generated capacity and consumption decreases. For CSA and PDSA which the gap is less than UDSA the same result is achieved with respect to increase in number of users. Figure 4.8 illustrates the effect of increase in number of users on the gap between generated capacity and consumption when it is assumed that the average number of users increases up to 100. As, it is obvious when number of users increase the gap decreases,which is expected due to increase in users consumption.

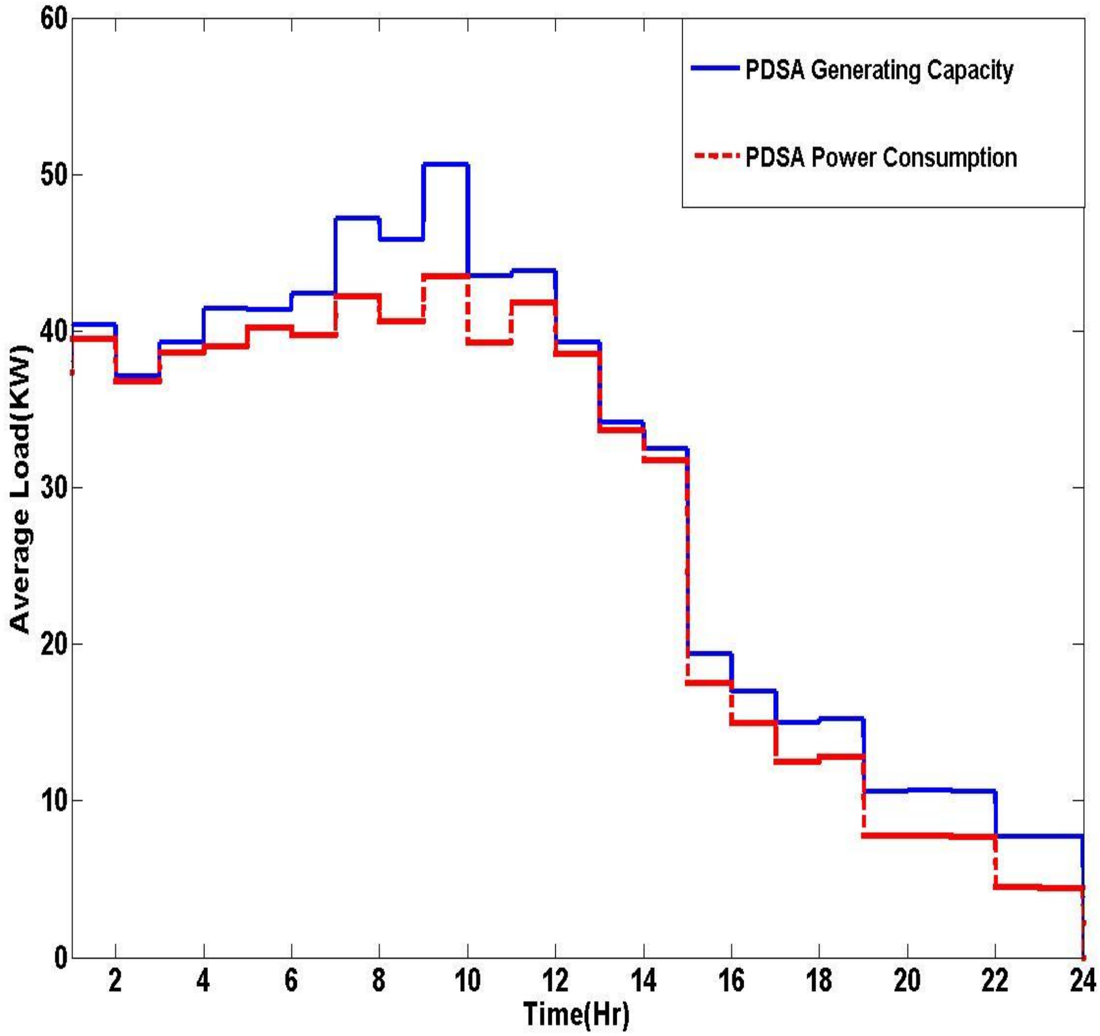

Figure 4.3: Comparison over the Gap between generated capacity and Consumption

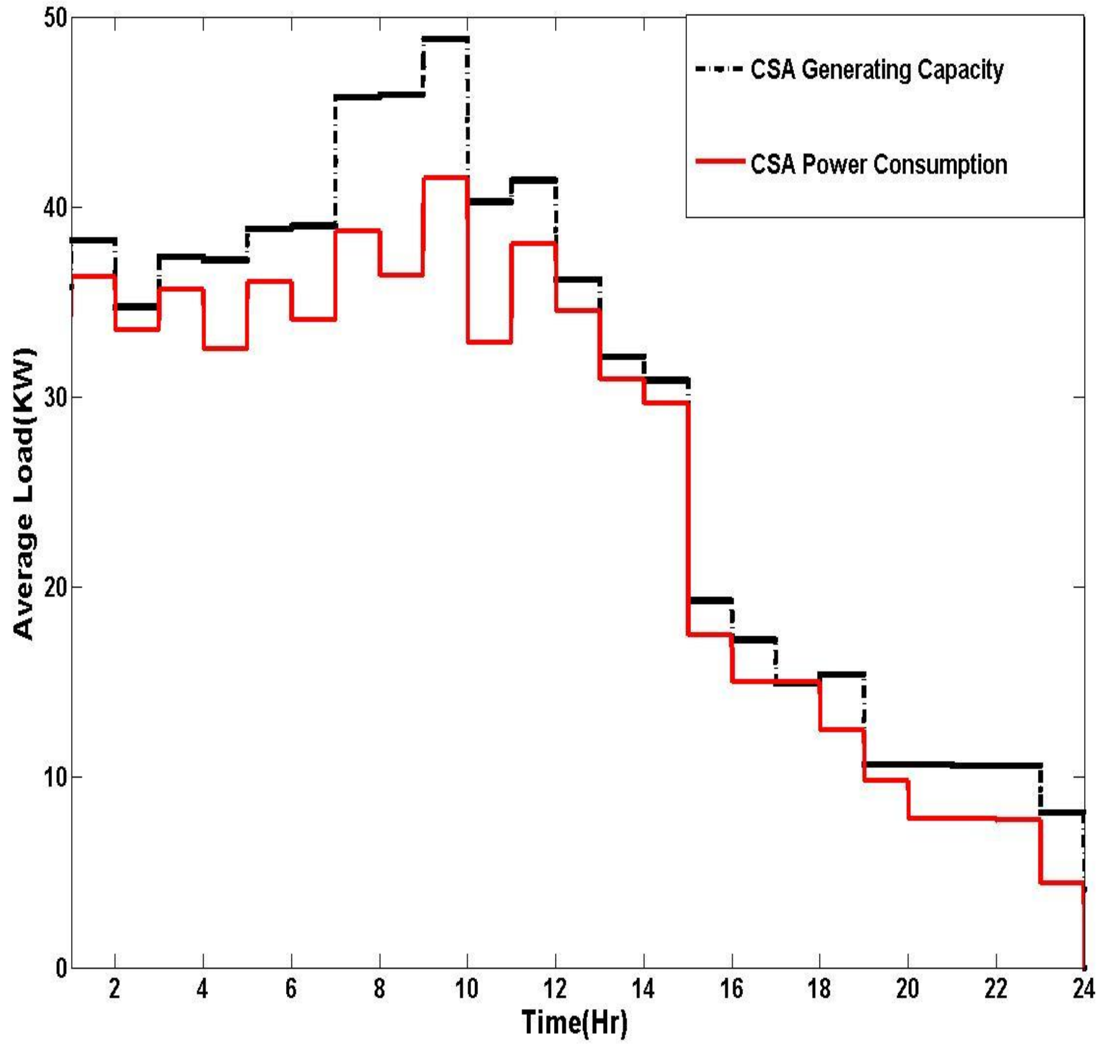

Figure 4.4: Comparison over the Gap between generated capacity and Consumption

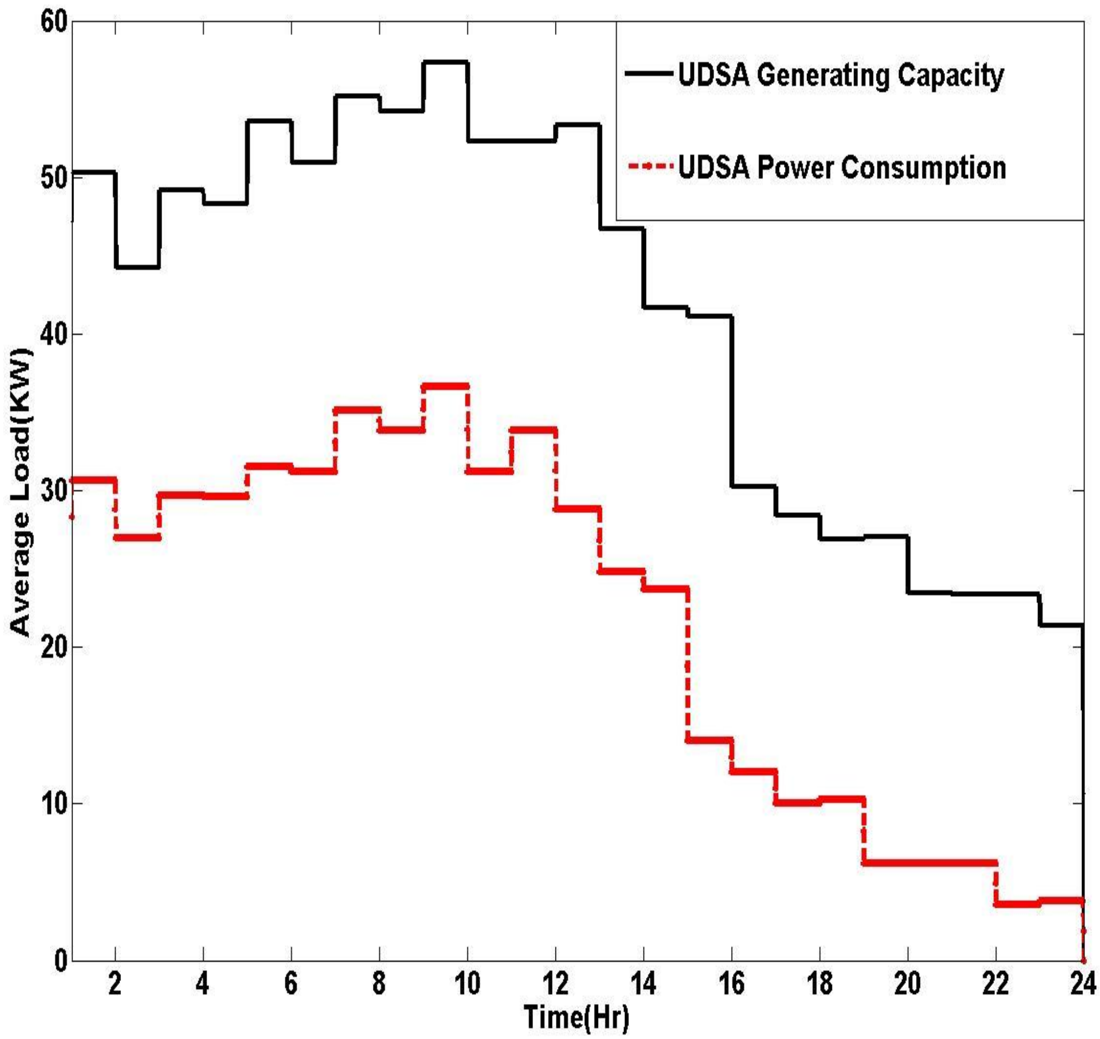

Figure 4.5: Comparison over the Gap between generated capacity and Consumption

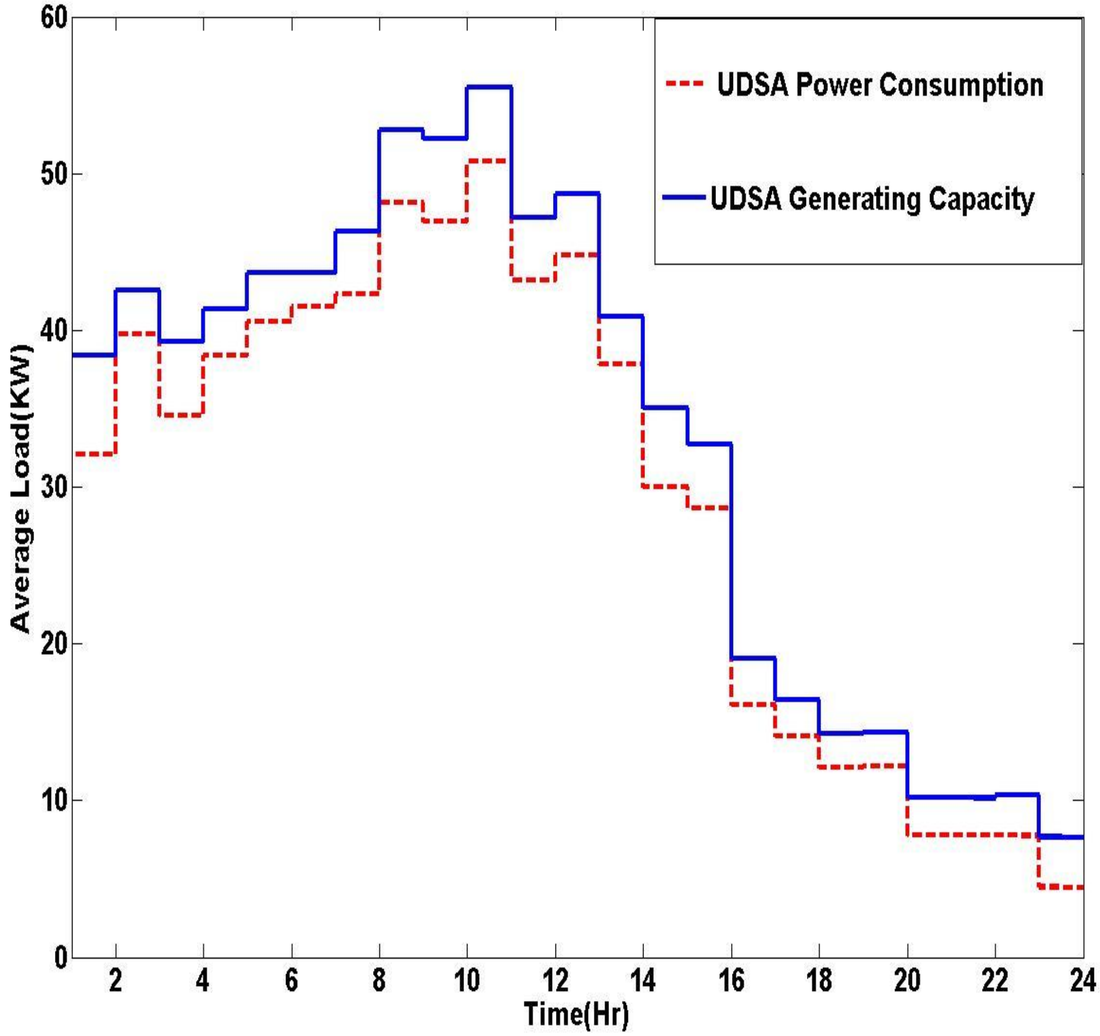

Figure 4.6: Comparison over the Gap between generated capacity and Consumption N=50

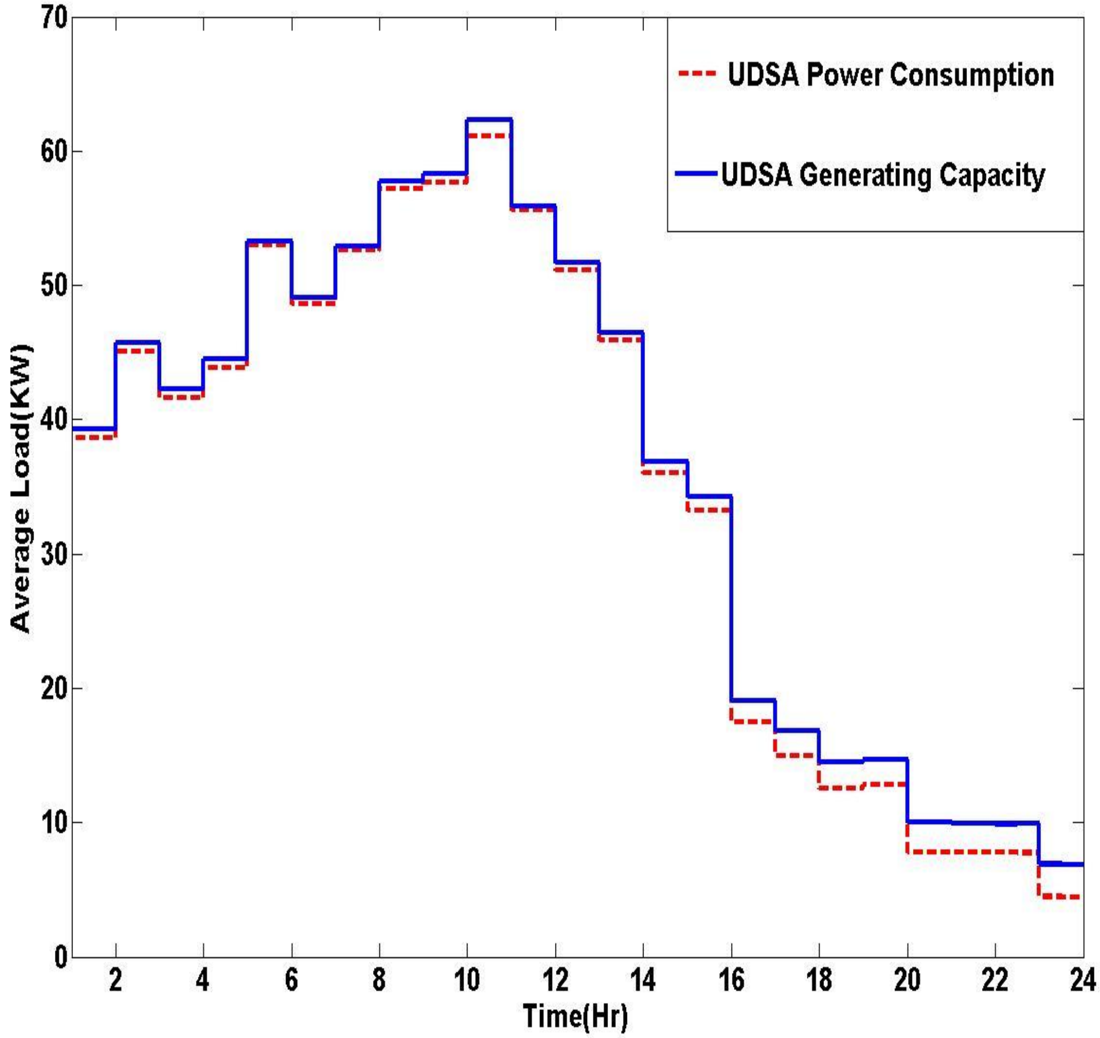

Figure 4.7: Comparison over the Gap between generated capacity and Consumption N=100

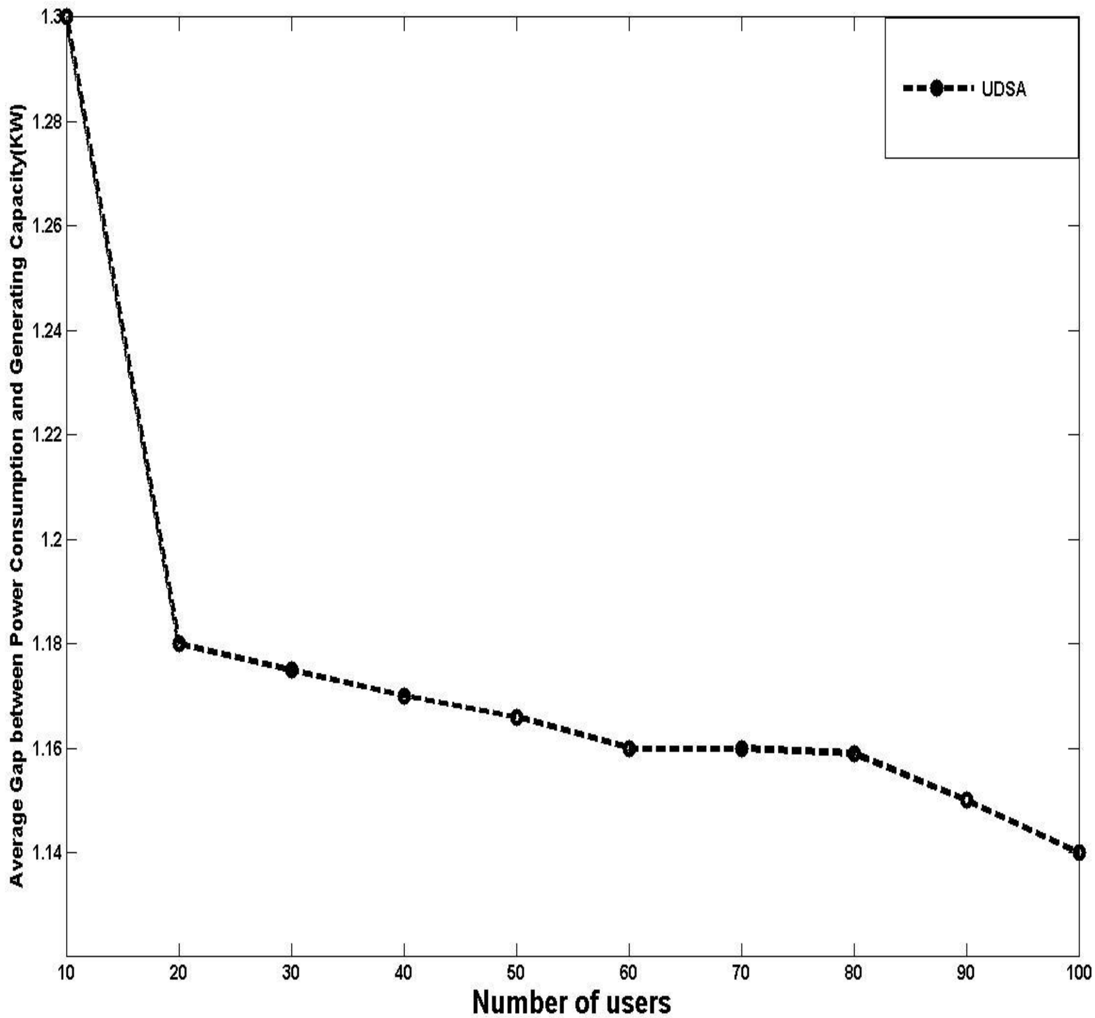

Figure 4.8: Comparison over the Gap between generated capacity and Consumption N=100

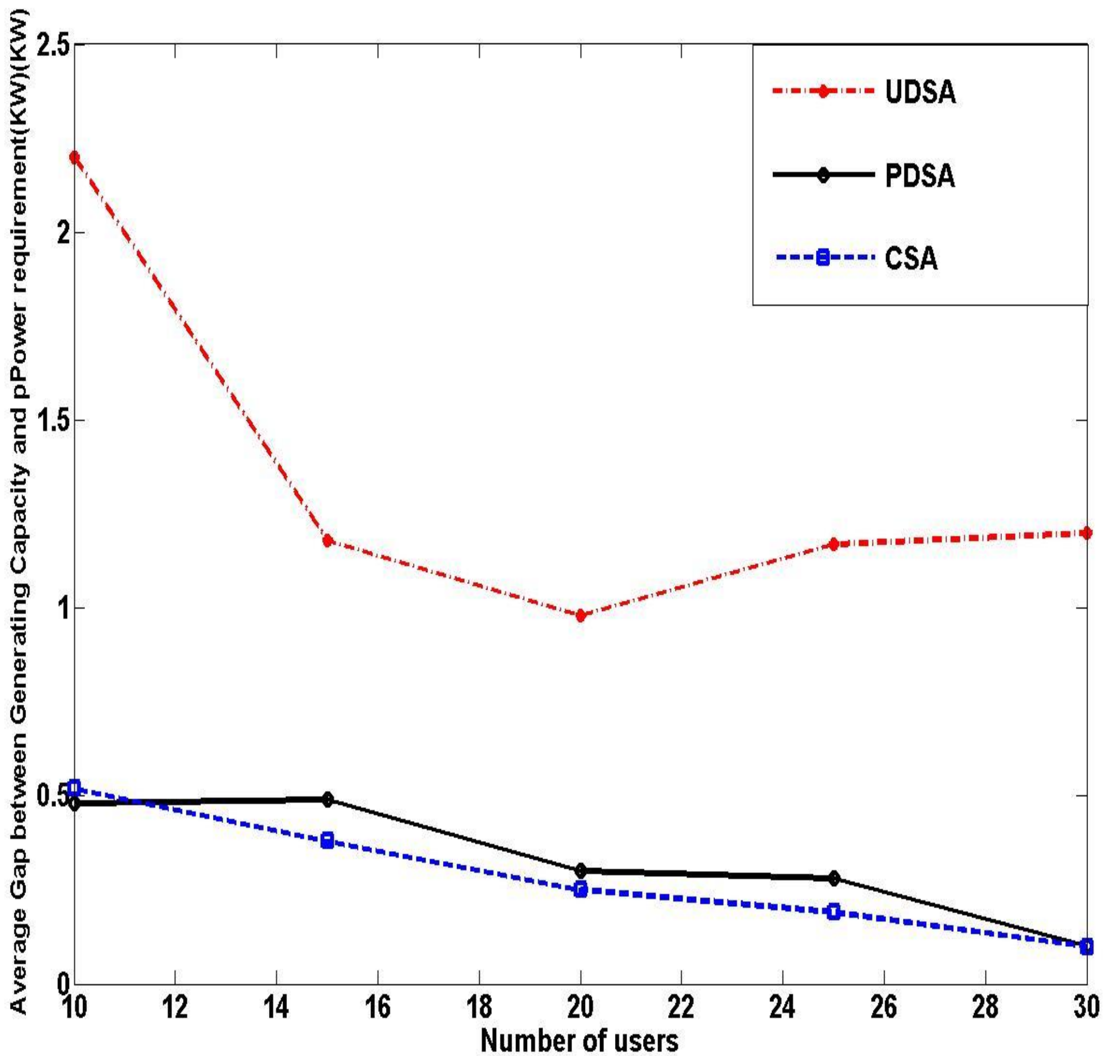

Figure 4.9: Comparison over the Gap between generated capacity and Consumption N=30

Figure 4.9 indicates that the gap between generating capacity and consumption for PDSA is close to CSA, which is because of equal variance and mean in Poisson distribution which is its characteristics. It is appear that when number of users in a period between two time slot is kept constant in comparison with availability of distributions there are more user entry and departure happening that affect the gap. In that case the average gap for CSA is lower in comparison with PDSA. Moreover, as it is mentioned beforehand, due to larger variance of uniform distribution in comparison with Poison distribution the distance between curves in Poisson and uniform distributions is more than the distance between curves between Poisson and when number of users is kept constant in certain timing period. Simulation results are considered for comparison over UUBO with regard to PDSA, UDSA and CSA in terms of average gap between generating capacity and consumption in different time slots. This gap appears because of consideration of the effect of load uncertainty which affects the generating capacity provided by energy provider [28]. According to [28] the generating capacity is also affected by the variation in number of users which is studied in [114]. Also, it is assumed that the energy provider procure the electricity from a wholesale market and provides exceeded than the requirements of the users. In another word users may consume up to the maximum provided electricity, however their consumption do not exceed the provided energy. Therefore, the gap appears as a result of consumer's behaviour. Depending on the kind of user some subscribers may achieve their maximum satisfaction with higher/lower amount of consumed electricity that this also can affect the gap between power requirement and the generating capacity. The announced price affects the users consumption. As, the announced price depends on the generating capacity and the consumption therefore load uncertainty and user number variation affects on it. Previously the study for UBO algorithm was done in [14]. According to [114] for systems PDSA and UDSA with respect to UUBO algorithm, the average gap for PDSA is lower in comparison with UDSA. It means that when users' arrival and departure in each time slot is according to the Poisson process, the average gap is lower in comparison with when users' arrival and departure is based on uniform distribution that is because of the announced price in PDSA which affects the users consumption. Also, when the number of users in each slot is kept constant, the average gap in CSA is lower in comparison with UDSA and PDSA. Investigation over the average gap between energy consumption and generated capacity in 24 hours of the day, given that the average number of users is increasing, reveals that when the number of users increases, the average gap decreases. Also, the average gap for UDSA is higher in comparison with two other systems. Comparison over PDSA and CSA also shows that the average gap between generated capacity and the consumption for PDSA is higher than CSA, that is because of the proposed price which is dependant to the generating capacity which is affected by the user number variation in each time slot.

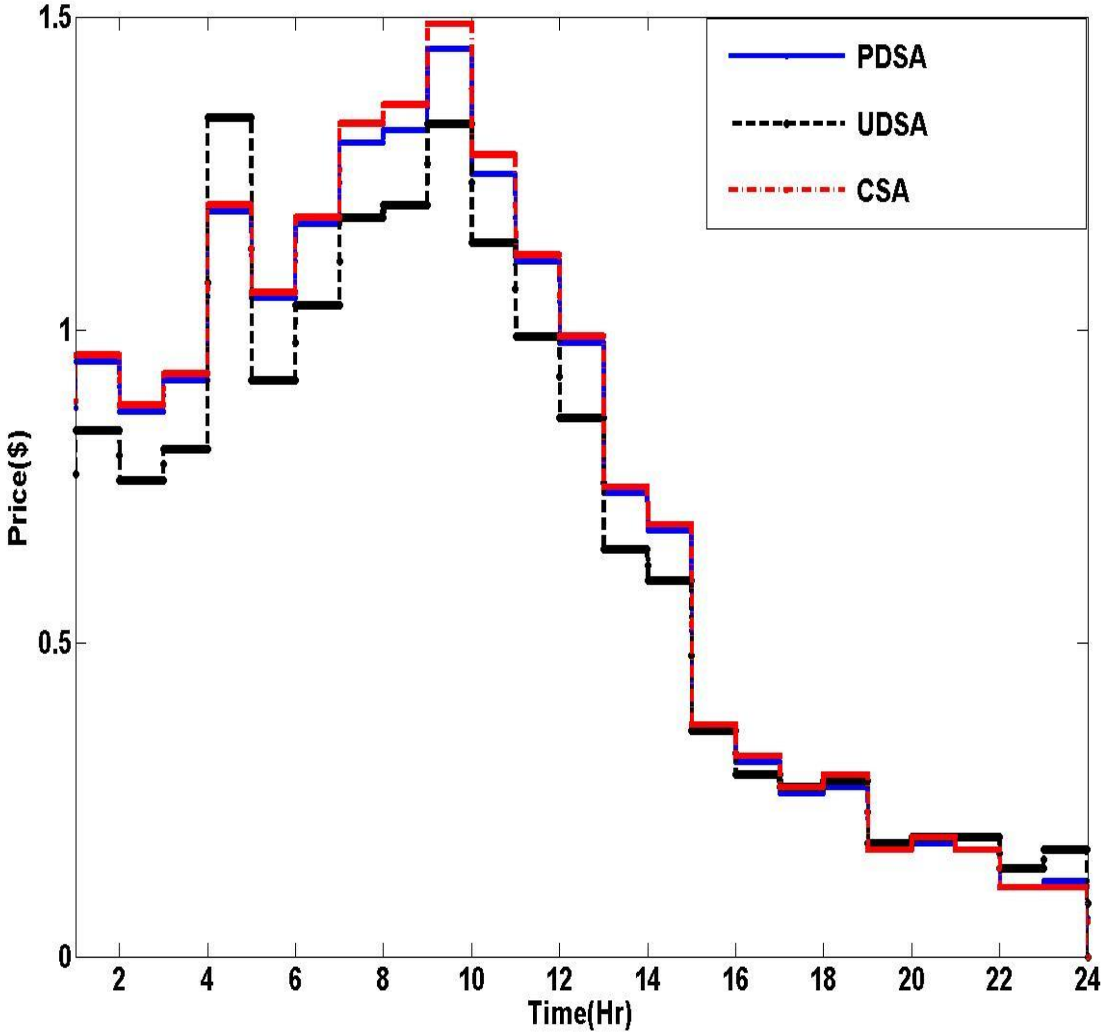

Figure 4.10: Comparison over the price for CSA, UDSA and PDSA, N=10

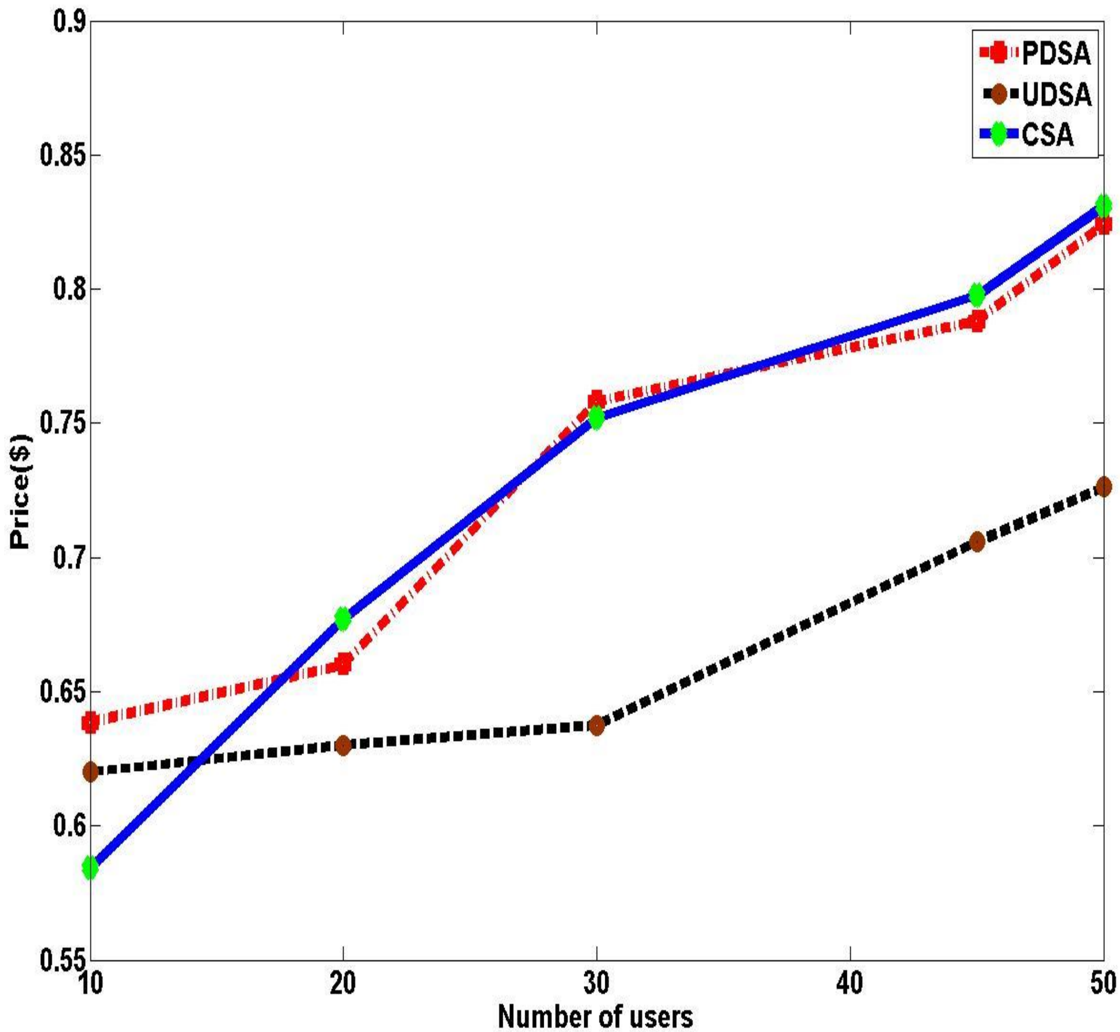

Figure 4.11: Comparison over the price for CSA, UDSA and PDSA, N=10

4.6 Summary

With respect to the importance of demand response management (DRM) in today's smart grid investigation over DRM programs is important topic that is followed by utility companies. The main goal for these programs is providing satisfaction for both sides of users and the energy provider. Utility based objective (UBO) function which was discussed in [58] does not discuss over the effect of load uncertainty . Uncertain utility based objective (UUBO)function which was presented in [28] does not consider the effect of variation in the number of users on the gap between generated capacity and consumption. In this thesis, three different distributions for users' interval and departure in a specific period to describe the effect of users' variation based on different distributions on evaluated gap between generated capacity and consumption, as well as the price is proposed. In that case the problem with respect to consideration of the effect of load uncertainty in the constraint of the proposed objective function in presence of load uncertainty is formulated. These distributions describe the users' departure and interval based on Poisson process, uniform distribution and constant number of users that are called PDSA, UDSA and CSA respectively. As in DRM programs the users consumption and generating capacity affects the announced price and vice versa, therefore in this section the difference between users' power consumption and energy provider generating capacity is considered as the gap which represent the waste of energy. The lower the gap the more satisfaction for both sides achieves in a way that users optimum consumption corresponds the provided power capacity by the energy provider. In this section the effect of consideration of different distributions for users entry and departure type in presence of load uncertainty is analysed. Simulation results reveals that the power consumption and generating capacity as well as the price are affected by the users entry and departure type. In order to analyse the system, three proposed distributions in presence of load uncertainty is investigated. It is shown that when number of users increases the gap between generated capacity and the consumption decreases. This is because of the increased aggregation of users' consumption that means the increased demand in a predefined period, which in this thesis is considered to be 24 hours period. The increased demand affects the announced price and the announced price at the beginning of each time slot in a way that the more the number of users the more the price and the less the gap for three proposed distributions in presence of load uncertainty.

Chapter 5

An Income-Based Real-Time Pricing Algorithm Under Uncertainties in Smart Grid

5.1 Introduction

With respect to importance of uncertainty in DRM programs in this section the study in Chapter 3 is improved in a way that load uncertainty is considered for the proposed IBO and then the results is further extended subject to variation in number of users based on different distributions. In this way UDSA, PDSA and CSA distributions are considered for the proposed IBO with respect to load uncertainty which in this section is called Uncertain IBO (UIBO). The algorithm achieves the goal of demand management programs based on real time pricing in which benefit of energy provider as well the satisfaction of consumers are both achieved, with respect to variation in number of users based on different distributions in 24 timing periods. According to the broad investigations about real-time pricing in smart grid, the problem of providing benefit and satisfaction for both sides has been solved in several ways. However, the concept of consideration of variation in number of users in each slot is a new idea that is discussed in this section. For demand response programs regardless of consideration of load uncertainty many investigations have already been done. As an example, in [105, 11, 58, 14, 27] the social welfare problem is solved regarding consumers' utility maximization. As, it is mentioned in the second chapter of this thesis with regard to the fact that the electricity is provided through an infrastructure consisting of electric utilities as well as other parts of the grid increased expectations of consumers, the lengthy process of exploiting new energy resources as well as the reliability issues indicates the importance of developing new methods to increase grid efficiency. In this section the study is focused on the effect of load uncertainty as well as variation in number of users based on different distributions effect on the average gap between power consumption and generating capacity. As, the announced price affects the users behaviour in this section price variation in 24 hours of a day is considered and the effect of users entry and departure distribution types on it is analysed further. The flow chart below indicates how the overall system works.

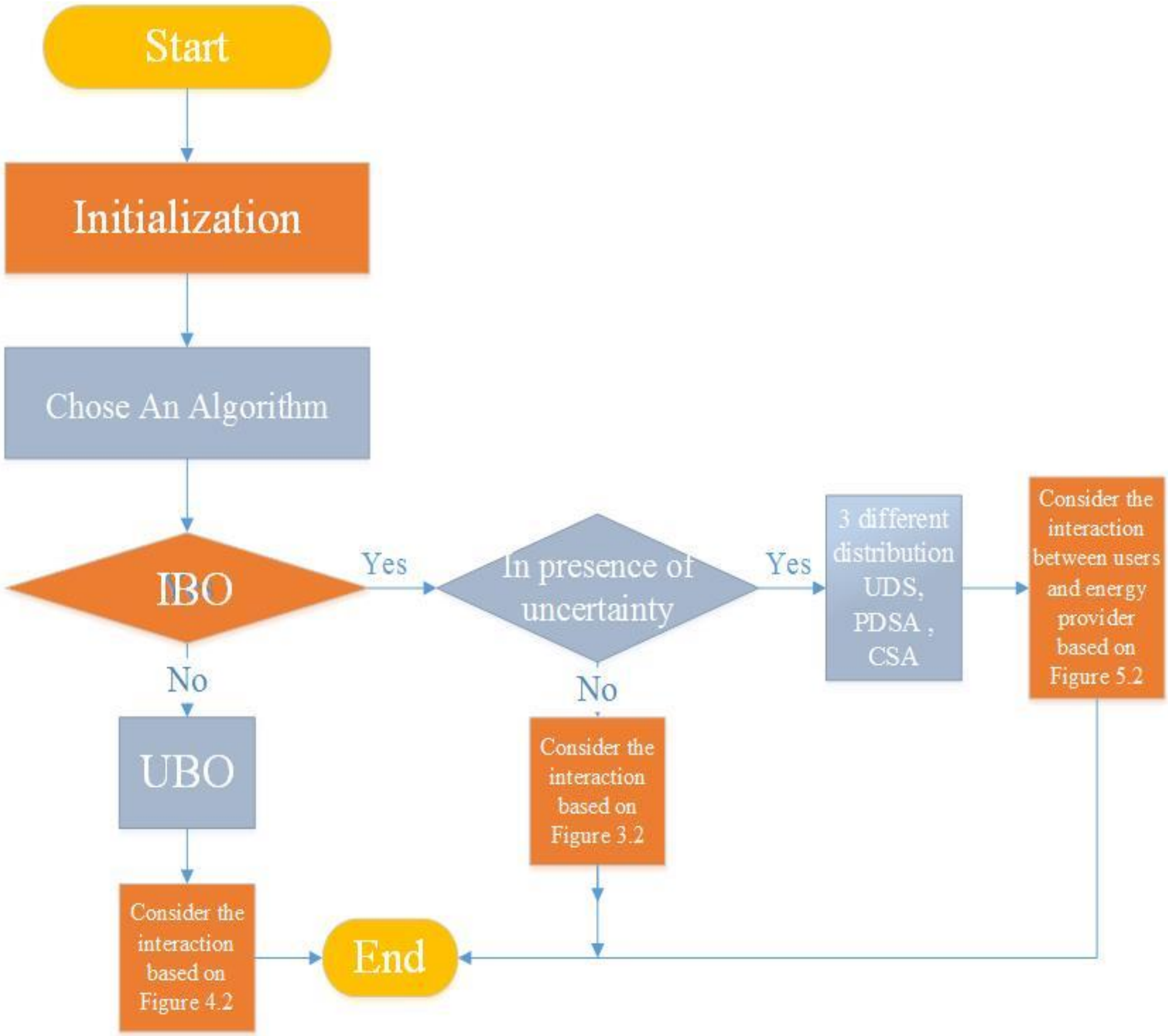

Figure 5.1: Description of how the overall system is working with respect to UIBO

5.2 System Model

The model which is considered in this section is similar to the described model in Chapter 4, however, it is different from what is explained in [28] which explains that the power consumption may deviate from what was negotiated at the information exchange section. In that case due to load uncertainty with the constant consumers using the electricity, it is assumed that number of users may vary randomly or based on Poisson distribution. It is assumed that the energy provider is obliged to provide enough electricity to cover the minimum power consumption requirement. Also, different, from Chapter 4 which solves the UBO, the income based problem is solved . According to the definition of a system, a system is defined as a group of independent items that interact regularly to perform a task. In this section, three types of systems that perform based on different users' entry or departure type has been investigated. In this case it is assumed that the rate of users' departure or entry may be constant as in [28] that is called Constant System Analysis (CSA), which is compared with systems where the number of users may vary randomly or based on Poisson process, that are called Uniform Distribution System Analysis (UDSA) and Poisson Distribution System Analysis (PDSA) respectively. In this section, these three systems with regard to the consideration of the income based objective function in presence of load uncertainty are investigated.

5.2.1 Users' Objective Function

It is assumed that each user is an independent decision maker. The energy demand of the users may vary based on different parameters. For example, the time of the day, the season, the electricity price, etc. All these parameters affect the consumption patterns of users. Different response of different users to various prices can be modeled analytically with regard to consideration of the concepts of microeconomics. Also, it is dependant to the kind of appliances each user may use. As, it is explained in Chapter 3, the utility function is defined as *U(x,w)* which indicates the level of satisfaction of each user. When the x represents the consumption level of users that in this section is considered with respect to added bounded uncertainty to it and the w is the parameter that shows how different types of users response to specific price, which is explained with further details in chapter three, in a way that the it's graph describes this parameter. The assumptions for the proposed utility functions are described as follow: first, the utility functions are non-decreasing which implies: It is assumed that the minimum required average load is guaranteed by energy provider. Also, energy provider never provides more than maximum required average load. This means that generated capacity is also bounded between maximum and minimum required average load. The proposed objective function has the same properties as explained in Chapter 3. However, different form it, the generating capacity is affected by user number variation that is considered to be varied based on the Poisson and uniform distributions the same as we considered previously for UBO and now we extend it for UIBO which is further explained in Section 5.3.

5.3 Problem Formulation

According to equations (4.8), (4.12), the problem (3.8) can be written as below. Where $L_k^{eff*} = L_k^* - N\epsilon$. It must be noted that the change in price affects the consumption and generating capacity . Therefore, problem in this chapter is written as:

$$\begin{aligned} &\underset{x_i^k \in I_i^k,\, L_k^{effmin} \leq L_k^{eff} \leq L_k^{effmax}\ k\in K, i\in\{N\}}{\text{Max}} \sum_{k\in K}\sum_{i\in\{N\}} \tilde{x}^{k^*} f_k - C_k(L_k) \\ &\text{subject to} \sum_{i\in\{N\}} x_i^k \leq L_k^{eff*}, \forall k \in K \end{aligned} \tag{5.1}$$

With respect to three different users entry and departure type, Equation (4.9) can be written as :

$$\sum_{i\in N} x_i^k \leq L_k - E(N_{k\in k}^{(p,u,c)})\epsilon\ , \forall k \in K \tag{5.2}$$

Where $N_{(k\in k)}^{(p,u,c)}$ represents the number of users in k_{th} timeslot, with regard to consideration of it's variation that may be considered based on Poisson process or Uniform Distribution, or may be kept constant which is represented by p, u, c.

For solving this optimization problem, when the number of users vary, the average number of users in the interval is considered as the expectation of $E[N_{(k\in k)}^{(p,u)}]$ which represents PDSA and UDSA respectively. It is assumed that $E(\delta_i^k)$ is equal to zero, which means that zero mean load uncertainty is considered. Therefore, considering variation in number of users, equation (5.1) can be written as:

$$\begin{aligned} &\underset{x_i^k \in I_i^k,\, L_k^{min} \leq L_k \leq L_k^{max}\ k\in K, i\in\{N_{(k\in k)}^{(p,u,c)}\}}{\text{maximize}} \sum_{k\in K}\sum_{i\in\{N\}} \tilde{x}_k^*.f_k - C_k(L_k) \\ &\text{subject to} \sum_{i\in\{N\}} x_i^k \leq L_k - E(N_{(k\in k)}^{(p,u,c)})\epsilon, \forall k \in K \end{aligned} \tag{5.3}$$

Figure 5.2, describes the interaction procedure between subscribers and energy provider regarding consideration of load uncertainty.

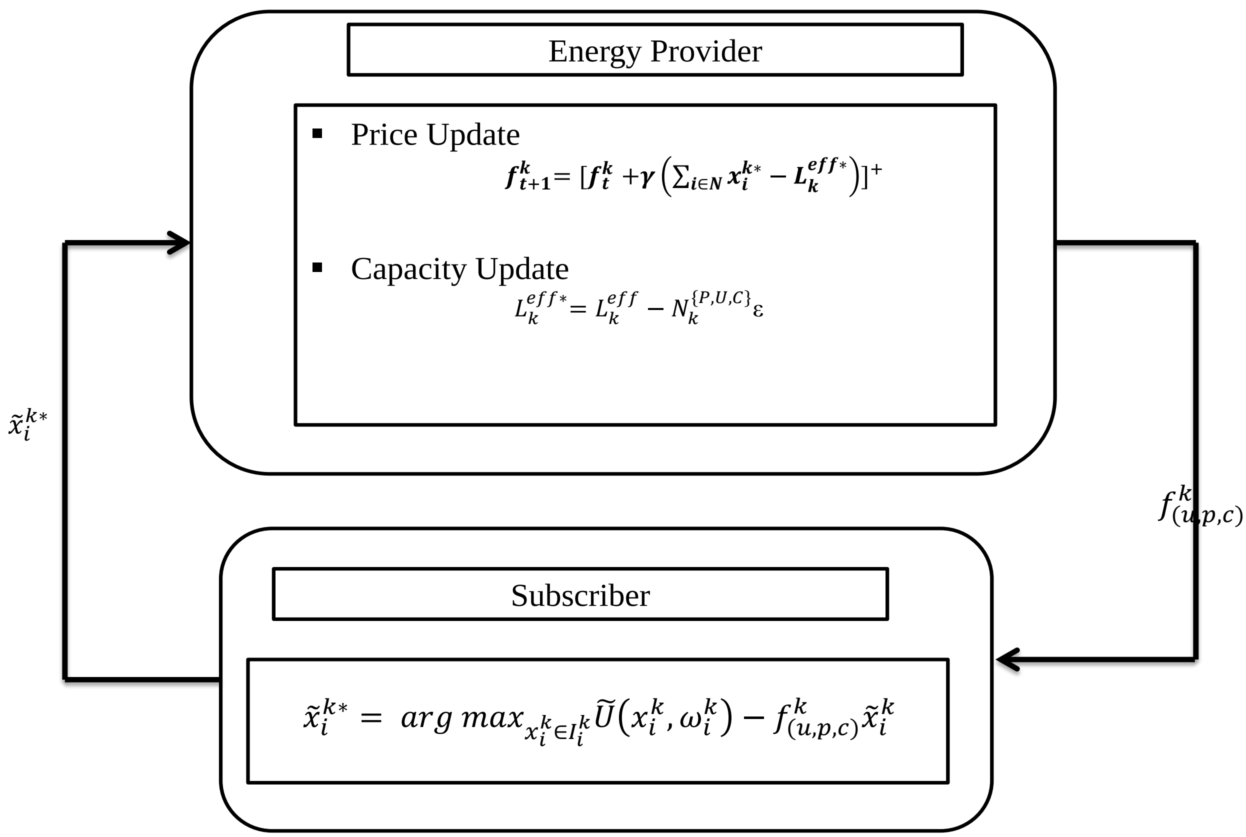

Figure 5.2: Description of the interaction between users and energy provider with respect to UIBO algorithm

5.4 Problem Solving

In this section, the Lagrangian relaxation technique is used in order to find out the feasible set over optimum value of f and L. The Equation (3.14) describes this technique. It should be noted that in this chapter also this technique is considered with respect to load uncertainty, which is assumed to be bounded and therefore is restricted between a maximum and minimum value. In this Section, Equation (3.9) is considered with respect to load uncertainty. Therefore the feasible set is achieved as below:

$$\begin{cases} \lambda = a_k \\ \tilde{f}_k^*(\sum_{i\in\tilde{N}} w_i, a_k) = \dfrac{\sum_{i\in\tilde{N}_k} w_i + a_k}{2} \\ \tilde{L}_k^*(\sum_{i\in\tilde{N}} w_i, f_k^*) = \dfrac{\sum_{i\in\tilde{N}_k} w_i - f_k^*}{\alpha} \end{cases} \tag{5.4}$$

$$x_k^*(\sum_{i\in\tilde{N}} w_i, \tilde{f}_k) = \frac{\sum_{i\in\tilde{N}} w_i - \tilde{f}_k}{\alpha} \tag{5.5}$$

$$\tilde{N}_k = N_{k\in K}^{(p,u,c)} \tag{5.6}$$

$$\tilde{f}_k = f_{k\in K}^{(p,u,c)} \tag{5.7}$$

With respect to consideration of optimal consumption for the users the equation below is achieved [115]:

$$\begin{cases} \tilde{f}_k^*(\sum_{i\in\tilde{N}} w_i, a_k) = \alpha\sum_{i\in\tilde{N}} x_k^*(\tilde{f}_k) + a_k \\ \tilde{L}_k^*(\sum_{i\in\tilde{N}} w_i, \tilde{f}_k^*) = \dfrac{\sum_{i\in\tilde{N}} w_i - \tilde{f}_k^*}{2\alpha} \\ \sum_{i\in N} w_i = \alpha\sum_{i\in\tilde{N}} x_k^*(\tilde{f}_k) + \tilde{f}_k \end{cases} \tag{5.8}$$

For updating the price the Equation (3.18) using gradient projection method is used and then is updated based on the achieved optimal generated capacity from solving the UIBO.

$$f_{t+1}^k = [f_t^k + \gamma(\sum_{i \in N}(x_i^{*k} - L_k^{eff*})]+ \tag{5.9}$$

Where $L_k^{eff*} = \tilde{L}_k^* - N\epsilon$. It must be noted that the change in price affects the consumption and generating capacity.

5.5 Distributed DRM Algorithm

In this section the proposed algorithm has been explained. This algorithm describes the interaction procedure between users and energy provider. From the users' side algorithm 5.1 is executed by each user i. Also, Algorithm 5.2 is described from the point of view of energy provider. The proposed algorithms are explained below:

Algorithm 5.1 Executed by each user $i \in N$ (UIBO)

```
Initialization
Generate users' interval/departure based on Poisson/Uniform distribution or set it as a constant value
for all t ∈ T do
    receive the new value of f_t^k from the energy provider
    Update the consumption value by solving (3.7)
    Average the results
    Communicate the updated value of x_i^{k*}(f_t^k) to the energy provider.
end for
```

Algorithm 5.2 Executed by Energy provider (UIBO)

Initialization
repeat
Generate users interval/departure based on Poisson/Uniform distribution or set it as a constant value.
if $t \in T$ **then**
    Compute the new value off_t^kusing (5.9).
    Broadcast the new value of f_t^k to all users
    else
    Update the capacity value L_k^{eff*} by using (5.8)
    Receive the Updated optimum consumption level of all users by solving (3.7)
    Update the total load.
    Accumulate the results for each time running the program
    Average the results
    Receive the new value of f_t^k from energy provider
    Update the consumption value by solving (5.5)
    Communicate the updated value of $x_i^{*k}(f_t^k)$ to energy provider.
end if
Until end of intended period.

The proposed algorithm involves two parts which are solved by the users and energy provider. At the beginning of each time slot users receive the updated price from energy provider. It is assumed that number of users varying in the period between two time slots. There are two distributions considered. The distributions are compared with the state in which the number of users is kept constant. The users update their consumption level and then send the updated consumption to the energy provider. It is assumed that the algorithm starts with some initial price which is updated by the energy provider at the beginning of each slot. It is executed by energy provider. Then in the period between two timeslot, according to the aggregation of users optimal demand energy provider procures the electricity from the wholesale market. Also, it is assumed that provided electricity is not more than the maximum requirements of the users. Because, in this section the effect of load uncertainty and users number variation is considered therefore the results are taken averaged. Algorithms (5.1) and (5.2) describes the Uncertain IBO, which is called (UIBO), and the results for this algorithm is further evaluated in the next section. The output of the algorithm would be the updated price and the optimal generated capacity, that affects the users consumption. In another way, the input of the algorithm would be the average number of users, constant predefined values, such as α, initial value of price and coefficients of the cost function which represents the cost imposed to the energy provider. It is assumed that the cost imposed to the energy provider varies under economic situation and affects the users level of satisfaction that obviously affect on their demand, which can be reflected on the parameter α as is explained in Chapter 2. The performance evaluation of the algorithm is examined in the next section. The focus on the next chapter is on the gap between generated capacity and the consumption as well as the announced price.

5.6 Performance Evaluation

The simulation parameters are as explained in Table (2.1) that shows the considered parameters and their notations. Figures (5.3-5.8) represents the simulation results. The simulator which is used in this section is MATLAB. Simulation results are achieved the same way as explained in Chapter 4. However, in this part the results are considered for UIBO algorithm. Figures (5.3) and (5.4) illustrate the appeared average gap between generating capacity and power consumption for different distributions. However, Figure (5.3) represents the results for $N = 10$ users while Figure (5.4) improves the results for various average number of users based on different distributions. In that case each point of Figure (5.4) is the average rate of 24 hours period gap between generating capacity and power consumption for increasing pattern of user number variation that is considered to be based on different distributions. As it is expected in general, increase in number of users increases the average aggregated consumption which reduces the average gap between generating capacity and power consumption. This trend is shown in Figure (5.4) with respect to different distributions. As it is appear from this figure, increase in number of users decreases the gap between generating capacity and users power consumption for all three considered distributions. However, according to [54] the variance of Uniform distribution is more than Poisson which indicates the rate of variation in Uniform in comparison with no distribution is more than Poisson.

Figures (5.5) and (5.6) investigate the price in a same way that was explained for the average gap between generating capacity and consumption. Simulation results from Figure (5.5) reveals the effect of different distributions in users entrance and departure type on the price in 24 hours period. Figure (5.6) reveals that when number of users increases the price correspondingly also is increased that is expected. This is based on the formula in Equation (5.9) which reveals that increasing the aggregation of the consumption level of the users directly affects the price. In another word, the price is directly dependant to the users power consumption. Again the reason for difference between price in case uniform distribution is considered comparing with constant number of users and the Poisson distribution is based on the difference in variance of these two distributions, that is explained for the gap as well.

The importance of study in this area is for prediction of human behaviours. This is an important issue in modelling and solving DRM problems.

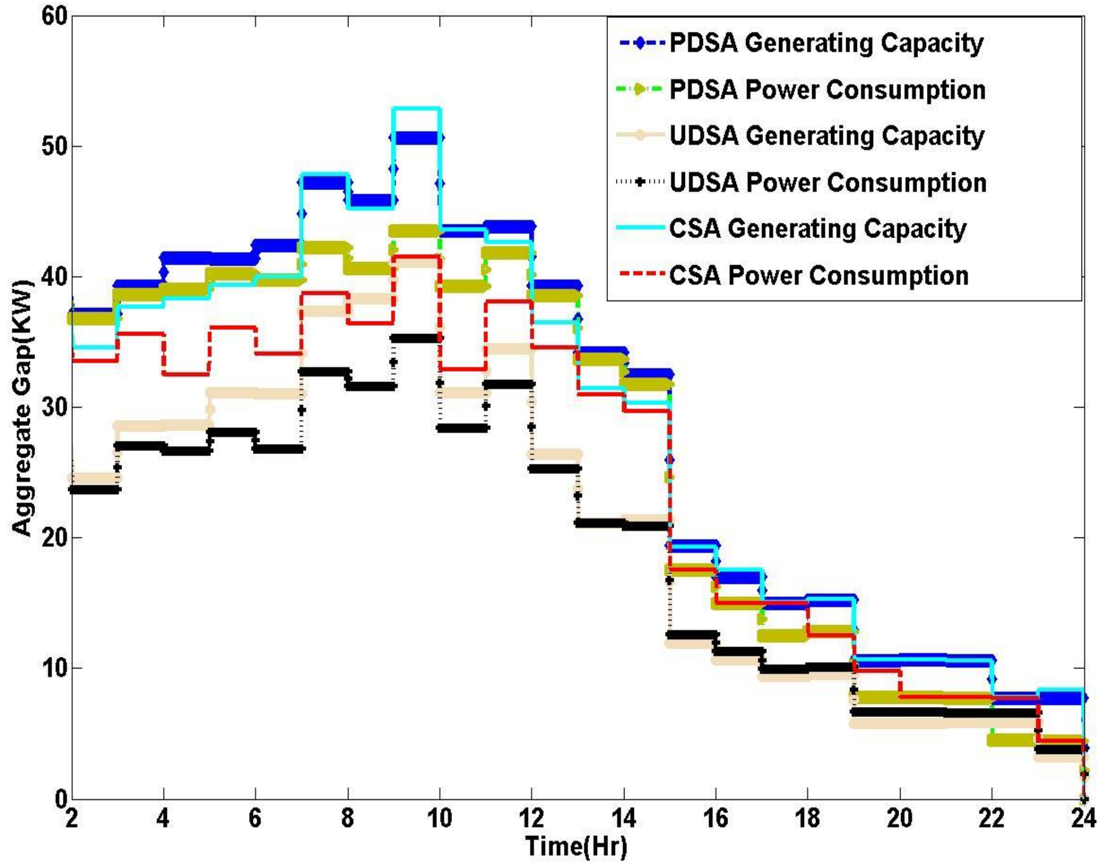

Figure 5.3: Comparison over the gap between generated capacity and consumption for PDSA, UDSA and CSA ,N=10

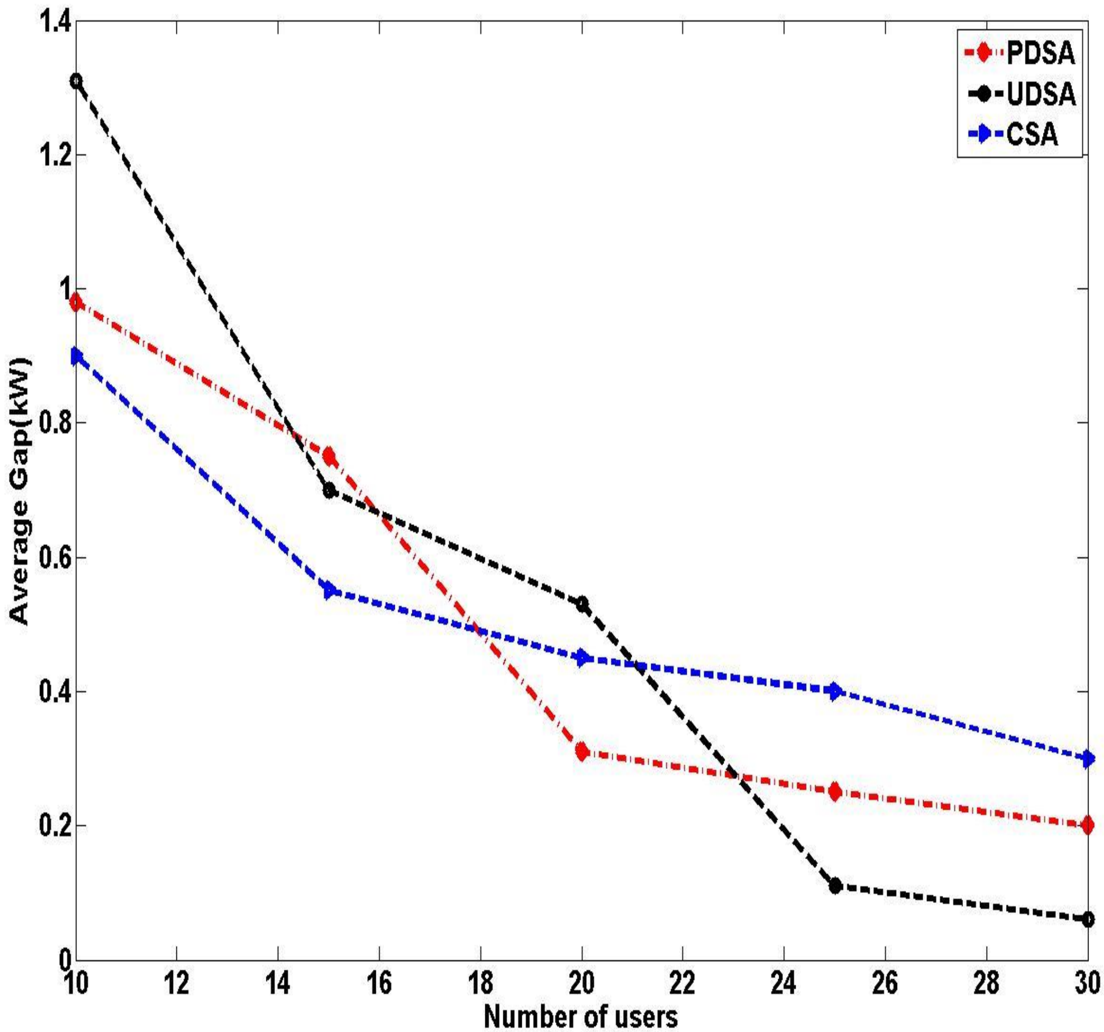

Figure 5.4: Investigation over the effect of increasing the average number of users on average gap between generated capacity and consumption for different distributions

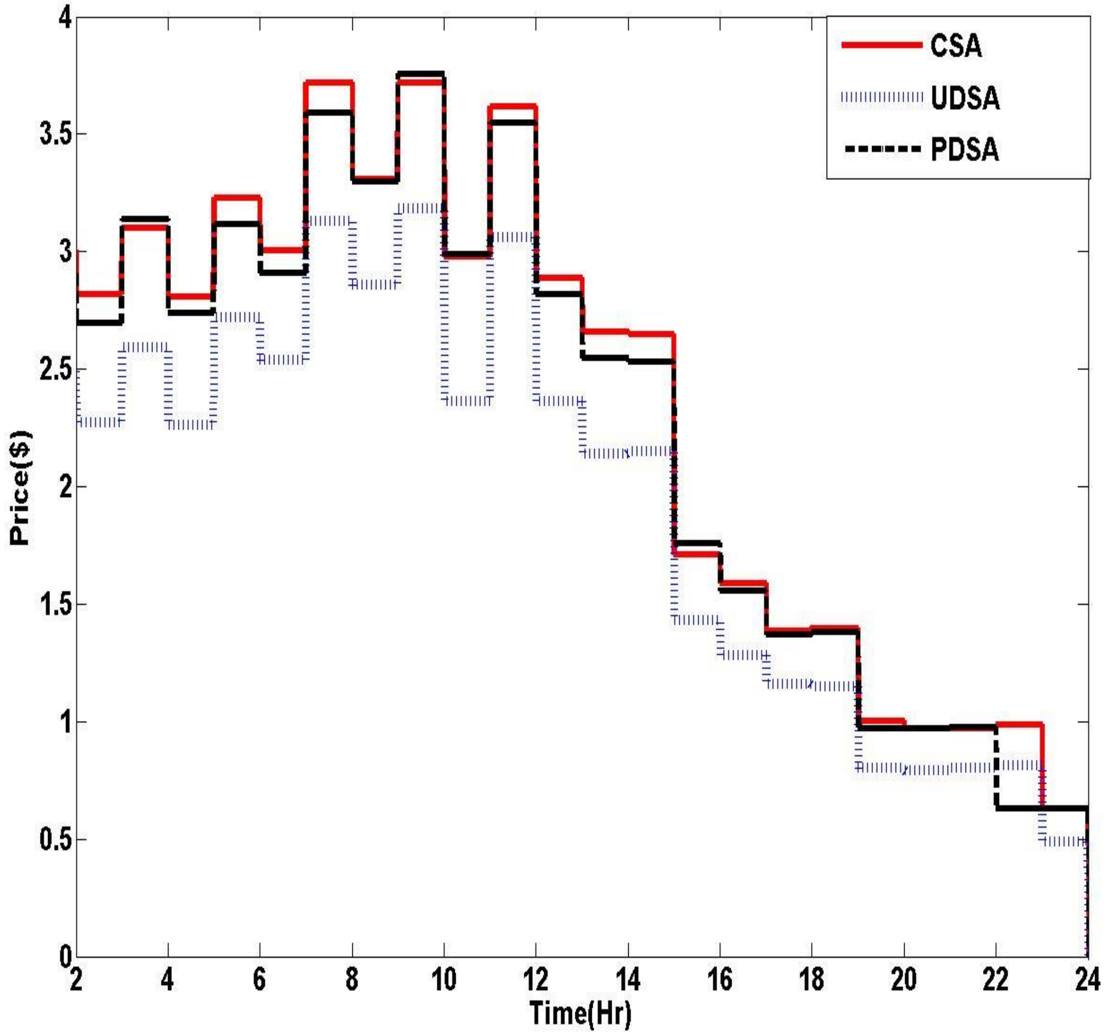

Figure 5.5: Comparison over the price for CSA,UDSAand PDSA

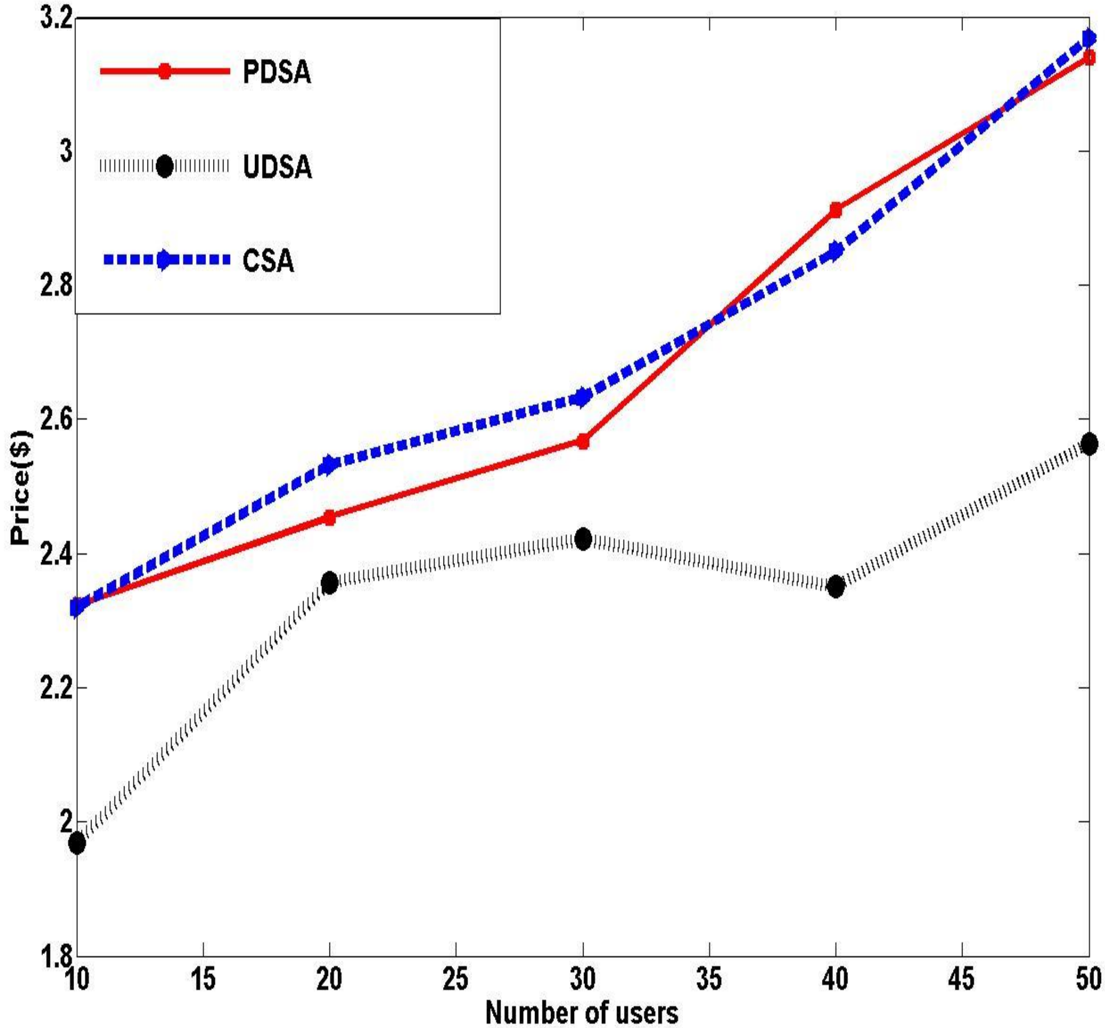

Figure 5.6: Investigation over the effect of increasing the number of users on price

In this section the gains coming from the proposed method with respect to different distributions is quantified . In this way the variation of the price over the variation in number of users is considered.The reason we considered the gain in this way is because of effect of price on users consumption and energy provider satisfaction. Therefore, the formulation is considered as :

$$\frac{\Delta P_{u,p,c}}{\Delta N_{u,p,c}} \tag{5.10}$$

In above formulation $\Delta P_{u,p,c}$ represents variation in price based on different users entry and departure type which is shown by u and p for Uniform and Possion distributions correspondingly and also when number of users kept constant as well which is shown by c. In the same way $\Delta N_{u,p,c}$ represents variation in number of users based on different distributions. In this way with respect to Figure (5.6) and Equation (5.10) the acheived gain for UDSA is about 1.5% when for PDSA it achieves 2.05% and for CSA is obviously more than PDSA with same reason as explained in chapter four. However, with respect to the achieved gain and the gap in Figure (5.4) it can be concluded that the demand in UDSA is more than the actual consumption, that means users consume up to the maximum provided generating capacity while their maximum demand is more than the provided capacity. The importance of investigation over different types of distributions is related to prediction of consumers behaviours in DRM programs. Understanding the consumer behaviour helps regulating agencies to set up the appropriate pricing rule , more beneficial scheduling programs and finally more consumer satisfactions with respect to satisfaction of distribution companies.

5.7 Summary

In this section the proposed IBO algorithm in Chapter 3 is improved to uncertain IBO or UIBO and is considered with respect to the load uncertainty and user number variation. The results for average gap between generated capacity and consumed load are compared for three different PDSA ,UDSA and CSA distributions for users entry and departure type. The effect of increasing the number of users on the gap is also investigated.

Moreover, The announced price is also evaluated in 24 hours period of time and then the results are extended in a way that it is assumed that number of users are increasing with respect to different distributions. All the results are achieved in a way that it is assumed that there is one energy provider that is interacting with several users. It is suggested for future research to investigate over the effect of load uncertainty with respect to UIBO when multi energy providers are competing together. Moreover, as additional improvement to that idea, investigation over different user number distribution on the gap as well as the price when multi energy providers are competing together in presence of load uncertainty is also suggested. In this section also the gain of the proposed algorithm is defined as the ratio of the variation of announced price to the user number variation. The results indicates the gain in PDSA is more than UDSA. Which describes the users behaviour when their entrance and departure distribution type is based on Poisson in comparison with Uniform and no distribution. Investigation over the users behaviour is an important topic that is studied in many DRM programs.

Chapter 6

Conclusion and Future work

In today's modern society electricity and electrical appliances play an important role in real-life. There are many appliances that use electricity from a small water heater to electrical vehicles that needs large amounts of electricity value to be charged. The rapid increase in using electric devices that provides daily requirements of consumers tend to rapid increase in electricity consumption specially in some specific timing periods. In this case the need for DRM programs in residential areas is undeniable. DRM programs control the consumption in peak demand periods. These are divided to incentive base and price based options. In incentive based DRM the consumption is controlled by getting incentive or punishment to consumers based on their amount of consumption in specific peak time periods. However, in price based DRM the consumption is controlled based on the announced price to the consumers. In this research, the focus is on price based options that nowadays are very common in residential areas. In traditional grids the electricity consumption information was measured manually and announced to the energy provider that basically is a distribution company which procures electricity from the whole sail market that usually is a generating company. Then, the energy provider used to compute the price and announce it to the consumers . The tariffs varied monthly or based on the season depending on the consumption level of the users. However, in those traditional grids users did not get advantage from two way interaction with energy provider to control their consumption in peak demand periods. Therefore, in the modern grids the smart meters that are connected to the Local Area Network (LAN) provide the opportunity for both sides of users and energy providers to benefit from two way interaction with exchange of real time price information. These modern grids that are called Smart Grids are designed to provide the benefit of both sides of users and energy providers. The Smart Grid provides the smart environment in each part of the generation, transmission, distribution and consumption section, for generating, transmitting, distributing and consuming of electricity more wisely and beneficially. The smart sensors in most applications provides fault detections and therefore increase the performance of the grid. Smart meters in residential areas can measure the appliance consumption and report it to the energy provider. According to the kind of DRM the energy provider controls the electricity consumption. In this research the interaction between several users and an energy provider is considered and modelled mathematically. It is assumed that an energy provider solves a problem that achieves the optimal price which provides satisfaction of both users and energy provider. According to the previous investigations the optimization problem is dependent to the utility of the users. The utility also is dependent to the users' consumption. However, in current research the proposed income based algorithm provides the net benefit of energy provider with regard to consideration of users' satisfaction. In Chapter 3, the Income Based optimization that is called IBO is compared with Utility Based optimization which is defined based on solving an optimization of the users' utility subscribed by the energy providers' cost. This Utility Based optimization problem that is called UBO is proved to be solvable and the feasible set is achieved. The technique for solving UBO is Lagrange Decomposition approach that decomposes the problem into solvable sub problems. However, for IBO algorithm it is assumed that the objective function is defined based on users' optimal consumption,when the optimal consumption is achieved according to the optimal announced price. For future research solving the objective function in presence of load uncertainty and user number variation is suggested especially when multi energy providers are competing together and also with the users. In Chapter 3, investigation over the average gap between generating capacity and power consumption , and the announced price is taken into consideration.

As it is mentioned, it is assumed that smart meters in residential areas measure the consumption and send it to the energy provider by means of a LAN. As in case users use renewable energy, the effect of uncertainty affect the users' consumption, hence in Chapter 4 the effect of load uncertainty in proposed UBO with respect to consideration of user number variation is studied. In previous research, the number of user was kept constant, however in that Chapter, three different systems are defined in which number of users is varying based on different distributions. It is assumed that the users entry and departure is based on Poisson process, Uniform distribution or it may kept constant. Therefore, in section four the effect of users' entry and departure type on average gap between generating capacity and users consumption as well as announced price in presence of load uncertainty is studied. Also, the effect of increase in number of users with respect to consideration of three proposed distributions is investigated. It is shown that with respect to consideration of the load uncertainty, the gap exists that varies based on users' entry and departure type. The effect of increasing the number of users with respect to consideration of the load uncertainty in UBO algorithm when user number variation is also considered shows that when number of users increases the gap between generating capacity and consumption decreases, that is because increase in average users consumption. Moreover, increasing the number of users increases the announced price. With respect to consideration of IBO algorithm in Chapter 5, in presence of load uncertainty and user number variation investigation over each user's average consumption versus generating capacity in 24 hours period is considered for three different proposed distributions. Moreover, it is shown that when number of users increases the average gap between generating capacity and consumption decreases. Investigation over the announced price for three different proposed distribution types for users entry and departure in 24 hours period is shown. Moreover, it is illustrated that when number of users increases the average announced price with respect to different distributions is also increased. The importance of study the concept of user number variation based on different distributions and consideration of the load uncertainty is more highlighted when users behaviour is modelled for DRM in Smart Grids. For future research in this area there would be wide range of investigations that interestingly can be taken into consideration. For instance, as it is mentioned in Chapter 2 there are many investigations over different types of utility functions to solve the DRM problems from different aspects. For example, the quadratic utility functions have already been proposed . However, based on mathematical characteristics of the suitable utility function that satisfy the proposed conditions in Chapter 3, other types of utility functions might be proposed and enhanced. Another suggestion is improvement of the proposed IBO algorithm in Chapter 3 with respect to consideration of multi energy providers that are competing with each other. In Chapter 3 it is assumed that there is one energy provider and there are several users that are connecting together, however solving the IBO optimization problem with respect to competition of the energy providers is a new idea that can be further developed with consideration of load uncertainty. Therefore, it is also interesting to consider the effect of load uncertainty for IBO algorithm when multi energy providers are competing together. This also again can be improved further in a way that the effect of different distributions in the constraint of the proposed problem be considered and the results get evaluated with respect to UIBO algorithm. Investigation on three proposed distributions UDSA, PDSA, CSA with/without consideration of load uncertainty is suggested with respect to UBO/IBO algorithm when multi energy providers are competing with each other and they are connected to the grid which consists of users that uses certain amount of electricity in certain period of time. This also can be improved further when users also compete with each other. The same idea also can be proposed for different utility functions. For example, if users use certain types of appliances that add more constraints to the proposed objective function the problem might be solved in another way. The other interesting suggestion for future research is solving the DRM problem with respect to different utility functions and different constraints when competition of multi energy providers and users are considered. For example, the proposed Logarithmic utility function in [34] can be considered with respect to load uncertainty and different types of uncertainty models can be evaluated with respect to consideration of multi energy providers and also it can be further improved when different types of distributions is considered in the constraint of the proposed objective function. It should be noted that DRM is a wide area of research that is connected to different branches of science such as economics as it uses mathematical economic electricity models, electronics and communication as the concept of advanced metering is related to the electrical appliances that are connected to the LAN, Management as it is related to putting some proper scheduling programs to control the over consumption in peak demand periods, and more specifically is related to mathematics as the problem of providing the satisfaction of both sides of users and energy providers should be defined and solved in an appropriate way.

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