OPTIMAL AGGREGATOR BIDDING STRATEGIES FOR VEHICLE-TO-GRID USING FUZZY OPTIMIZATION

BY

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Dedication

To my dear parents, sister and brother, for their endless love and support

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All praise is to ALLAH Almighty who made it possible for me to accomplish this research work successfully.

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LIST OF ABBREVIATIONS

The following acronyms/abbreviations are used in this thesis.

μ	:	Membership function
SOC_I	:	Initial state of charge of EV batteries
α	:	Percentage of regulation revenues taken by aggregator
β	:	Fixed price of energy charged by the aggregator to the customer
λ	:	Fuzzy objective
μ_{RR}	:	Membership function of responsive reserve price
μ_{ExD}	:	Membership function of expected percentage of regulation down deployments
μ_{ExR}	:	Membership function of expected percentage of responsive reserve deployments
μ_{ExU}	:	Membership function of expected percentage of regulation up deployments
μ_{In}	:	Membership function of income
μ_{regDw}	:	Membership function of regulation down price
μ_{regUp}	:	Membership function of regulation up price
$\overline{P_{RR}}$	:	Upper limit of responsive reserve price
$\overline{E_{xD}}$	:	Upper limit for expected percentage of regulation down deployments

$\overline{E_{xR}}$	:	Upper limit for expected percentage of responsive reserve deployments
$\overline{E_{xU}}$	:	Upper limit for expected percentage of regulation up deployments
$\overline{In}$	:	Upper limit for aggregator income
$\overline{P_{regDw}}$	:	Upper limit of regulation down price
$\overline{P_{regUp}}$	:	Upper limit of regulation up price
$\underline{P_{RR}}$	:	Lower limit of responsive reserve price
$\underline{E_{xD}}$	:	Lower limit for expected percentage of regulation down deployments
$\underline{E_{xR}}$	:	Lower limit for expected percentage of responsive reserve deployments
$\underline{E_{xU}}$	:	Lower limit for expected percentage of regulation up deployments
$\underline{In}$	:	Lower limit for aggregator income
$\underline{P_{regDw}}$	:	Lower limit of regulation down price
$\underline{P_{regUp}}$	:	Lower limit of regulation up price
$\widetilde{E_{xD}}$	:	Expected percentage of regulation down deployments fuzzy set
$\widetilde{E_{xR}}$	:	Expected percentage of responsive reserves deployments fuzzy set

$\widetilde{E_{xU}}$	:	Expected percentage of regulation up deployments fuzzy set
$\widetilde{In}$	:	Aggregator income fuzzy set
$\widetilde{P_{regDw}}$	:	Regulation down price fuzzy set
$\widetilde{P_{regUp}}$	:	Regulation up price fuzzy set
$\widetilde{P_{RR}}$	:	Responsive reserves price fuzzy set
A_v	:	Availability of the EV for V2G, 1 if the EV is available and otherwise 0
AGC	:	Automatic generation control
$ARIMA$	:	Autoregressive integrated moving average
COA	:	Centre of area
$Comp(t)$	:	Compensation factor to account for unplanned departures of EV
CR	:	Charge remaining in the EV
$Dep(t)$	:	Probability that EV will depart unexpectedly in hour t
$E[.]$	:	Expected value
E_{xD}	:	Expected percentage of regulation down deployments
E_{xR}	:	Expected percentage of responsive reserves deployments
E_{xU}	:	Expected percentage of regulation up deployments
EF	:	Efficiency of the battery charger
$ERCOT$	:	Electric reliability council of Texas
EV	:	Electric vehicle

$EV_{per}(t)$	:	Expected percentage of EVs remaining to perform V2G at hour t
FLC	:	Fuzzy logic controller
FLP	:	Fuzzy linear programming
FP	:	Final power draw of EV
$G2V$	:	Grid-to-vehicle
H	:	Number of charging hours
i	:	Index for EV
In	:	Aggregator income
ISO	:	Independent system operator
$L(t)$	:	Actual system load
$L_1 - L_4$	:	Intermediate system load values for membership functions classification
LDA	:	Day ahead system load
M_{ln}	:	Minimum day–ahead system load
M_{lx}	:	Maximum day–ahead system load
M_{pn}	:	Minimum day–ahead energy price
M_{px}	:	Maximum day–ahead energy price
$MAPE$	:	Mean absolute percentage error
M_c	:	Maximum charge of the battery
M_k	:	Mark up on energy price

M_nAP	:	Minimum additional power draw of an EV
MOM	:	Mean of maximum
MP	:	Power rating of the battery charger
$MPOP$	:	Maximum preferred operating point
MV	:	Maximum regulation signal from the ISO
M_xAP	:	Maximum additional power draw of EV
n	:	Resolution of energy price / system load data
$P(t)$	:	Actual system energy price
$P_1 - P_4$	:	Intermediate energy price values for membership functions classification
P_{DA}	:	Day-ahead energy price
P_{regDw}	:	Price of regulation down
P_{regUp}	:	Price of regulation up
P_{RR}	:	Price of responsive reserves
PD	:	Power draw of an EV
$PHEV$	:	Plug in hybrid electric vehicle
POP	:	Preferred operating point
R_{Dw}	:	Regulation down capacity
R_R	:	Responsive reserve capacity
R_{Up}	:	Regulation up capacity
RRS	:	Responsive reserve signal from the ISO

$RsRP$	:	Reduction in power available for spinning reserves
SOC	:	Battery state of charge
T_{Trip}	:	Time at which the trip is made
$Trip$	:	Reduction in SOC that results from commute trip
UC	:	Unit commitment
V	:	Regulation signal from the ISO
$V1G$	:	Unidirectional vehicle-to-grid
$V1G$	:	Vehicle-to-grid
$\Phi(B)$	:	Autoregressive polynomial
$\theta(B)$	:	Moving average polynomial
f_t	:	Forecasted quantity
B	:	Backshift operator
l	:	Degree of non-seasonal differencing

ABSTRACT

Full Name : Muhammad Abdul Hafeez Ansari

Thesis Title : Optimal Aggregator Bidding Strategies for Vehicle-to-Grid Using Fuzzy Optimization

Major Field : Electrical Power

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Electric Vehicles (EV), including battery electric vehicles (BEV) and plug in hybrid electric vehicles (PEHV), provide many advantages over the conventional internal combustion (IC) engines, such as reduced operating cost and the potential to run on locally connected distributed generation (DG). EVs can provide long term benefits to the environment, EV owners, and utilities. In addition to the financial benefits, EVs can potentially reduce air pollutants and greenhouse gas emissions. However, mass unregulated charging of EVs can burden the conventional power grid, raise the peak demand of the system, and seriously burden the distribution system network. Therefore, the charging of the EVs should be somehow managed.

In the smart grid environment, the vehicle-to-grid (V2G) concept has been introduced to increase the adoption rate of EVs while managing their impact on the power grid. Many researchers, utilities, and governmental bodies are working to properly utilize this large distributed energy resource. This distributed energy resource can support the grid in many ways, such as providing regulation service, spinning reserves, emergency reserves, reactive power support, load leveling, peak shaving, reducing emissions of thermal units, balancing wind and solar etc.

In this thesis, optimal bidding strategies for unidirectional V2G charging by the aggregator are developed under different fuzzy uncertainties. A fuzzy optimization is developed for finding the optimal bid for an aggregator. Different uncertainties are modeled using fuzzy sets, such as ancillary service prices and ancillary service deployments. Simulations show the benefits of these optimal fuzzy algorithms for the aggregator, EV owners, and the utility over existing deterministic algorithms, without any uncertainties.

ملخص الرسالة

الاسم الكامل: محمد عبدالحفيظ انصاري

عنوان الرسالة: الاستراتيجيات المثلى الذكية للمزايدة في عن طريق متنظيم شحن المركبات الكهربائية باستخدام طريقة من المركبة إلى الشبكة.

التخصص: هندسة كهربائية

تاريخ الدرجة العلمية: نوفمبر 2013م

المركبات الكهربائية (EV) متضمنا بطاريات المركبة الكهربائية (BEV) و المركبات الكهربائية الهجينة ذات القابس (PEHV) لديها فؤائد كثيرة مقارنة مع المحركات داخلية الإحتراق التقليدية (IC) و من هذه الفؤائد تقليل كلفة التشغيل و المجهود التشغيلي المولدات التوزيعية المربوطة محليا (DG). المركبات الكهربائية بإمكانها منح منافع على المدى البعيد للبيئة و مالكيها و المستخدمين. علاوة على المنافع المالية, كما تساهم بشكل كبير في التقليل من ملوثات الجو و من إنبعاثات الغازات الدفيئة. بالرغم من ان ثقل الشحن الغير منتظم لهذه المركبات قد يشكل عبئا على شبكة الطاقة التقليدية وهي حقيقةً ترفع من ذروة الطلب على الطاقة الكهربائية في شبكة النظام التوزيعية, نستطيع القول بأنها تشكل عبئ على النظام الكهربائي التقليدي, لذلك توجب ان تدار عملية شحن هذه المركبات بطريقة ما.

في بيئة الشبكة الذكية قدم مصلح من المركبة - الى – الشبكة (V2G) لرفع معدل الإعتماد المركبات الكهربائية اثناء إدارة تأثيرها على شبكة الطاقة. كثير من الباحثين و المستخدمين و الهيئات الحكومية يعملوا على الإستفادة بشكل صحيح من المصدر الكبير للطاقة التوزيعية. مصدر الطاقة التوزيعية من الممكن أن يدعم الشبكة بعدة طرق منها, توفير الخدمات التنظيمية و إحتيطات من وحدات التوليد وهي في حالة التشغيل و إحتيطات الطوارئ و دعم الطاقة غير الفعالة (الرَّدية) و تسوية الأحمال و تنعيم الذروة و خفض الإنبعاثات من الوحدات الحرارية و موازنة انتاج الطاقة المولدة من الرياح و الطاقة الشمسية ...إلخ.

في هذه الرسالة, تم تطوير إستراتيجيات المزايدة المثلى للشحن بتقنية الـ (V2G) أحادي الإتجاه بواسطة منظم الشحن تحت درجات متفاوتة من الضبابية (درجات من عدم الموثوقية) الذكية. تم تطوير درجات الضبابية الذكية المُثلى من أجل الحصول على المزايدة للمنظم (للمجمع). تم تمثيل درجات عده من الضبابيات الذكية مختلفة عدة عوامل في النظام بحاجة لأن نتوقعها جيداً , مثل أسعار الكهرباء للخدمات المساندة و الإشاراة اللازم ارسالها للمركبات المربوطة بالشبكة لتحديد نسبة تزويد المركبة من الخدمات المساندة التي تمت المزايدة بها. المحاكاة أظهرت الفؤائد من هذه الخوارزميات الضبابية المثلى لمنظم شحن المركبات (للمجمع) و لمالكي المركبات الكهربائية و الفائدة من وجود الخوارزميات بدرجة من الضبابية على نفس الخوارزميات مع فرضنا عدم وجود أي درجة من الضبابية.

CHAPTER 1

INTRODUCTION

1.1 Background

The electrical grids have been in existence for more than 100 years. Most existing electrical infrastructures were designed to supply electrical power in a regulated environment. The utility in a particular region owns large central generating units to supply power to the end customers with predictable loads. The central dispatch system is facing new challenges recently due to many factors, such as demand increase, capacity limitations, distributed and stochastic generation, environmental concerns, and new smart grid technologies [1].

One of the newer, potentially smart, demands will come from the deployments of electric vehicles (EV) or plug in hybrid electric vehicles (PHEV). Electric vehicles are expected to receive mass acceptance from the public in the near future due to their promising benefits to the environment and the vehicle owners. Figure 1-1 shows the sale of new PHEVs in the US from 1999 to 2011. Note that the sales increased to a peak of more than 350,000 units during 2007 due to the incentives by the government [2].

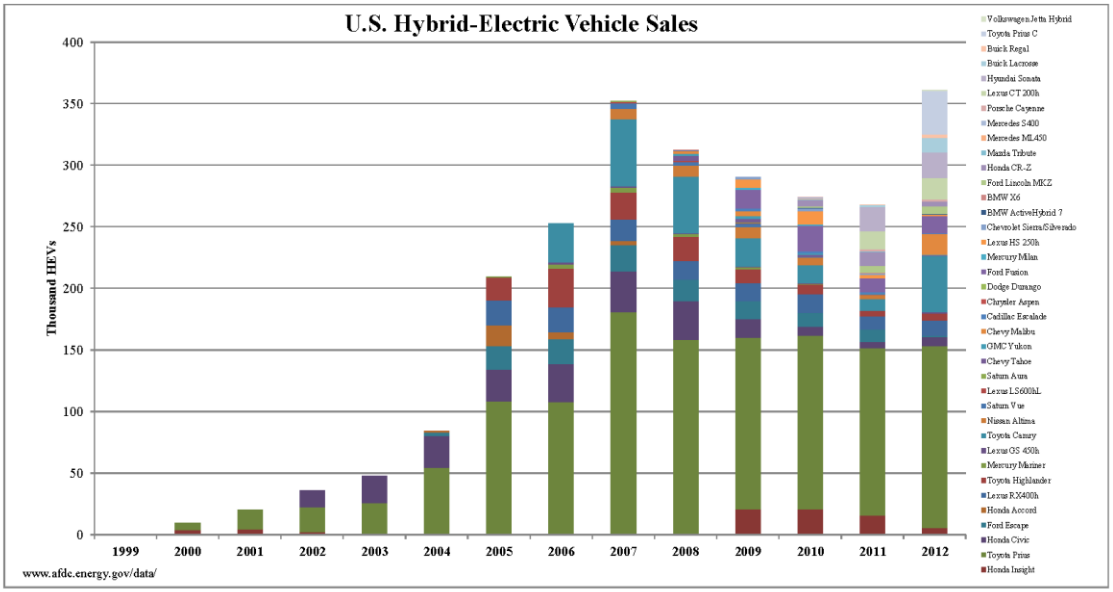

Figure 1-1: U.S HEV sale from 1999 to 2011. (From U.S. DOE alternative Fuels Data Centre, http://www.afdc.energy.gov/data/tab/vehicles/data_set/10301)

There are numerous benefits that come out of the electrification of the transport system over the traditional internal combustion engines such as lower operating costs and potential to charge from the local renewable distributed generation. However, there are challenges ahead of its full implementation, such as high initial cost of EVs, charging issues, limited power capacity. In addition, if not properly controlled, EVs can create power shortages. Some of the benefits of EVs, if properly integrated and controlled are [3], [4]:

- Reduced environmental impact due to hydrocarbon emissions
- Reduced petroleum consumption and fuel costs
- Lower operating costs
- Generated revenues
- Electrical power grid support

The capital cost of the EVs is higher than the traditional vehicles. Due to the higher initial cost, research has been conducted by utilities, governmental agencies and researchers to determine if EVs can be utilized for additional services. Therefore, the concept of vehicle to grid (V2G) was developed. V2G concerns EV integration with the electrical power grid. Studies have shown that vehicles, on average, are available idle for 90% of the day. Using this fact, the EVs can be utilized for electricity grid support and can generate revenue for the vehicle owner [5]. If this revenue helps offset the initial cost of EV, it will increase the incentive to purchase an EV. The basic concepts of V2G and the provision for energy and ancillary service from an EV are now well defined.

The proper implementation of V2G concept is beneficial for all the participants. Utilities will be benefiting from this controllable distributed source of energy and their operations and controls will be improved. In addition, EV owner will generate revenues from its EV and charge their cars at low energy price [6]. Power flow in an EV can be both unidirectional and bidirectional, depending on the service provided by EV. With V2G, an EV can participate in many energy markets such as regulation, spinning and non-spinning reserves, peak energy and energy market [7], [8].

In this chapter, the basic concepts of V2G are introduced. The direct and the aggregated bidding of the EVs capacity for the V2G implementation are explained. The different uncertainties of the electricity market and the use of fuzzy set theory for handling them are also explained. Finally, the objectives of this thesis are listed in the last section.

1.2 The Concept of Aggregator Bidding

The relationship between the EVs and the utility/ISO for V2G implementation can be classified as one of two types: a direct architecture and an aggregated architecture [9]. The direct architecture for V2G implementation is shown conceptually in Figure 1-2. It assumes that there is a direct line of communication between the EV and the system operator. In the direct architecture, the EV can bid and perform services during its charging.

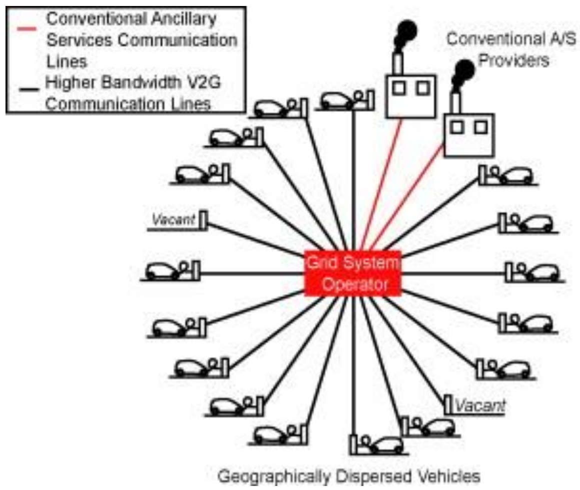

Figure 1-2: Direct architecture for V2G implementation [9]

The direct architecture is conceptually simple but the infrastructure and communication requirement is immense. There are also various drawbacks in direct architecture such as prediction of individual EV availability, peak power capability, and market requirements. The bidding capacity of a resource providing ancillary services in most electricity markets should not be less than 1 MW, making the direct architecture very difficult to implement with this market requirement [7], [10].

Aggregated architecture is more suited for V2G implementation. An aggregator is an intermediate agent that combines a considerable amount of EVs and bid their aggregated capacity in the market. Figure 1-3, shows the concept of aggregated architecture.

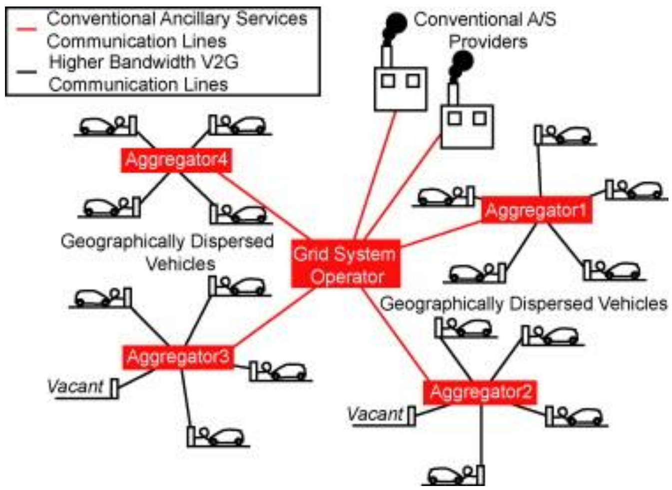

Figure 1-3: Aggregated architecture for V2G implementation [9]

In the aggregated architecture, the aggregator can bid into the market at any time as the collective behavior of the driving profile and the electric vehicle availability can be predicted while the individual electric vehicle can leave the charging station as per its requirements. The aggregated architecture overcomes the main problems of direct architecture; the aggregation of electric vehicles can be treated like a conventional ancillary service source and will remove the communication burden on grid system operator. The aggregated architecture is feasible and extensible for V2G implementation from the power system operator perspective [11]. As the individual EV can disconnect whenever the customer desire to, he/she will also be concerned about the amount of power available in the battery for travelling. Therefore, it is the job of the aggregator to develop bidding strategies that will balance the EV energy needs and maximize profits by participating in different markets during the EV availability.

1.3 Handling Uncertainties using Fuzzy Sets

In an ideal situation, electricity market bidding is done under the assumption that all the parameters are deterministic. This is equivalent to the assumption that the forecasting of these parameters is perfect. However, in practice, there are always errors in the forecasted parameters [12]. There are several ways to handle the forecast uncertainty, such as fuzzy set theory, stochastic models, and probability theory.

In this thesis, the uncertainties of the different electricity market parameters are handled using fuzzy theory. The concept of handling uncertainties using the fuzzy set was first introduced by Zedah, a mathematician, in 1965 [13]. The basic idea behind the fuzzy set is quite simple. In a conventional/crisp set, an element either belongs to or does not belong to a set. Hence the value of membership for an element is either yes or no. In the fuzzy set theory, a degree of membership is allowed to a range over the interval [0, 1]. Thus the membership function of fuzzy set maps each element of the universe of discourse to its range space, which in mostly assumed to be unit interval. One major difference between the crisp and the fuzzy values is that crisp sets have unique membership functions whereas fuzzy sets have infinite number of membership functions that can represent it. Fuzzy sets/logic treats the complex and ambiguous problem in a subjective way; it solves the problem like a human thinks of it. In considering a complex problem, humans reason approximately about its behavior, a capability that computers don’t have, and thus maintains only a generic understanding of the problem. The fuzzy reasoning offers a good solution when few numerical data exist and the information available is imprecise. It provides a way to understand the system behavior by allowing one to interpolate approximately between inputs and outputs in a logical way. Fuzzy systems can be classified as structured numerical estimators. They define the real world problem in a linguistic way and then define some rules based on human expertise. As they are numerically model-free estimators and dynamic systems, they can improve the system performance for an uncertain, imprecise, and noisy environment [14].

There is virtually no problem for which one can say the information is absolute, with no error, uncertainty and impreciseness. Uncertain information can take many different forms. There are uncertainties due to the complexity of the power system such as, in this work, uncertainty due to the behavior of individual electric vehicle movements, uncertainty in the price of the electrical energy and ancillary services, uncertainty in the electrical power load, uncertainty in the spinning reserve requirement in the power system, and uncertainty in deployment signals. These uncertainties arise due to the lack of sufficient data, impreciseness and the inability to perform adequate measurement and forecasting inaccuracies.

The problems characterized by ambiguous, uncertain and imprecise information can be modeled by fuzzy set theory. The following are the conditions where it is suitable to formulate problems within fuzzy framework [14]:

1. When human interaction is involved in the process.
2. When an intelligent system has to be designed based on the human expertise and interactions (e.g. human descriptive).

3. When a system is very complex or its exact mathematical modeling is not possible or too difficult.
4. The mathematical model is difficult to evaluate in a real time operations.
5. When the noise level is high in the data set or the data available is uncertain.

Fuzzy system can achieve robustness, tractability and lower cost solutions. Virtually all the engineering fields can be fuzzified and defined in a fuzzy environment such as fuzzy arithmetic, fuzzy graph theory and fuzzy probability theory etc. Moreover, applied fields can also be fuzzified such as fuzzy neural networks, fuzzy mathematical programming and fuzzy pattern recognition.

Momoh *at el*. [15], suggested a guideline on the use of fuzzy set theory for power system problems:

1. ***Description of original problem***: State the problem in a mathematical and linguistic form.
2. ***Defining thresholds for variables***: For each fuzzy variable, define the thresholds (acceptable ranges) based on the human expertise of the system.
3. ***Fuzzy quantization***: Memberships functions are constructed based on the threshold values defined in step 2. The functions should be defined in a way that reflects the change of satisfaction degree with the change in variables evaluated by experts.
4. ***Selection of the fuzzy operations***: The fuzzy operations and reasoning should be properly defined so that the results obtained should reflect like those of an expert.

Fuzzy set theory has been mainly applied in electrical power systems in two categories:

1. ***Planning***: includes power system expansion planning, and long and midterm scheduling of the system.
2. ***Operations:*** includes security assessment (dynamic and static), forecasting (price, load, and reserves), controller designs (PSS, exciter and FACTs devices controllers), and diagnosis (transformer and rotating equipment).

1.4 Thesis Objectives

The main aim of this research is to develop bidding algorithms for an aggregator under different electrical power system uncertainties. With the deregulated environment of the power system, the bidder must take into account several uncertainties in order to avoid financial losses. These electricity market uncertainties will be dealt with in this work using the fuzzy set theory.

The following are the major contributions of this thesis:

1. The development of a smart fuzzy-based preferred operating point (POP) selection method. This formulation will take into account several uncertain parameters, such as energy price, system load, and the number of hours for EV availability.
2. The development of an optimal bidding strategy for the provision of regulation in ancillary service market considering the different power system uncertainties. The uncertainties will be handled using the fuzzy set theory.
3. The development of an optimal coordinated bidding strategy for regulation and spinning reserves for participation in both markets with consideration of uncertainties.

4. The strategies are developed by using the fuzzy linear programming technique. All developed strategies/algorithms are tested against other charging schemes published previously and the results are compared.

1.5 Thesis Layout

This thesis consists of seven chapters. In the first chapter, the role of an aggregator as a market participant and the basic concepts of vehicle-to-grid are explained in details. The importance of managing EV charging is highlighted. The handling of different uncertainties using the fuzzy set theory is also introduced.

In the second chapter, a brief literature review of the vehicle-to-grid implementation is introduced. The literature related to the V2G concepts as part of the smart grid technologies is presented. The work related to the bidding strategies of electric vehicles is presented and finally the work done on handling the different uncertainties using the fuzzy set theory is presented.

In the third chapter, the main techniques that are used in this thesis for developing the optimal bidding strategies under different fuzzy uncertainties are explained in detail. The fuzzy logic and the fuzzy linear programming technique are well defined in this chapter. The fuzzy logic is used for the smart charging of electric vehicles and the fuzzy linear programming is used for the developing the optimization strategies in the day-ahead ancillary service market.

In the fourth chapter, the electric market overview and forecasting of electricity market parameters is presented. The change from vertically integrated utility to the decentralized electricity market is explained. The roles and functions of different market participants in this market structure are highlighted. The ancillary service market is explained in a greater detail as the work in this thesis is directly related to the aggregator participating in the day-ahead ancillary service market. The different market parameters are forecasted as the aggregator is bidding in the day-ahead market, so before bidding its capacity in the electricity market, the aggregator will try to anticipate the future values of the market to maximize the profits. Forecasting of different electricity market parameters such as regulation up/down prices, spinning reserves prices, and ancillary services deployments signals are done using the autoregressive integrated moving average (ARIMA) technique.

In the fifth chapter, a smart charging algorithm for the electric vehicle charging using the fuzzy logic technique is developed. This fuzzy logic controller combines the previously published charging algorithms such as price-based, load-based and maximum regulation based in a fuzzy logic frame work to take the advantage of each algorithm and the proposed fuzzy logic algorithm is working better than the individual previous algorithms. The fuzzy logic algorithm can also be implemented easily in the real time systems participating in the real time electricity market.

In the sixth chapter, an optimized algorithm for the optimal aggregator bidding strategy for regulation service using the fuzzy linear programming technique is proposed. The fuzzy set theory is used to model the uncertainties of the forecasted data in the day-ahead ancillary service market such as regulation prices and the regulation deployment signals.

In the seventh chapter, the algorithm proposed in chapter six is extended to include the spinning reserves and its deployments in the formulation to make it a coordinated aggregator bidding strategy for the ancillary service bidding. In addition to the spinning reserves, the different parameters related to the electric vehicles are also incorporated in the formulation such as EVs availability, compensation factor, travel time, and trips etc. The different EVs parameters make the formulation more realistic and are included in a deterministic and probabilistic way. Only the electricity market parameters are handled in a fuzzy framework.

CHAPTER 2

LITERATURE REVIEW

Electric vehicles (EV) and plug-in hybrid electric vehicles (PHEV) have become a popular topic of research due to their promising benefits. Utilities and researchers are continuing to develop the needed technologies for widespread use of EVs. In this chapter, a detailed overview of research activities related to the V2G implementation is presented. The chapter is divided into three sections. Section 2.1 presents the literature about the V2G concept. Section 2.2 gives a summary of the optimal bidding of V2G services in different electricity markets. In Section 2.3, uncertainty modeling using the fuzzy set theory will be surveyed.

2.1 Vehicle-to-Grid Concept

Initially, the electric vehicles were considered as a load that only burdens the power system network [16], but the idea that EVs can be used to support the electrical grid system in a way that is beneficial for both the EV owner and the electricity power grid was first introduced in [17]. This leads to further development of the vehicle-to-grid (V2G) concept later in [5], [7]. The concept of V2G is continuously developing and with the technological advancements, researchers have implemented pilot projects for V2G [18]. In [18], different charging approaches were suggested to be used for V2G. The V2G concept is divided into two types; unidirectional V2G and bidirectional V2G. Unidirectional V2G is also called load only V2G that performs EV load control and regular V2G, in which power is injected from grid to vehicle. Unidirectional V2G or load only regulation is also called as V1G, in some literature [19]. Some authors consider V2G as a means to deliver power from parked vehicle to the electrical grid while G2V as a way to provide the energy to the vehicle from the grid [9]. In bidirectional V2G, power can be transferred from vehicle-to-grid or the other way and most authors have considered V2G as a common terminology for bidirectional power flow. Since the introduction of the benefits of the electric vehicles, V2G basics have been fully defined and the potential benefits in different electricity market have been explored [5], [7], [8]. The most beneficial market for V2G service is the regulation service market and is carefully addressed in [5]. In [7], different electricity markets such as: base load, peak, spinning reserve and regulation, are further explored. It was initially suggested that EVs can provide spinning reserve and regulation, however several other works have also consider EVs to provide peak load shaving and base energy [17], [20], [21]. Among all, regulation service is the most promising and beneficial market for V2G. These results are confirmed in [5], [7], [22]–[25].

2.2 Vehicle-to-Grid Bidding

EVs were first introduced in the mid-19th century. The high cost, low speed and their short range, as compared with internal combustion engines, led to their decline [26]. However, in the last two decades, an interest in the electric vehicles has developed due to the problems associated with internal combustion engine vehicles and its negative impact on the environment. The concept of V2G has sparked this interest due to the potential support of EVs to the aging power grids. Early work in this area focuses largely on the basic concepts and simulations to show the potential benefits of EVs. One of the early studies discusses the leveling of system loads by controlling the charging and discharging of EVs

[27]. Researchers are still working on the ways to use the EVs for load leveling. One such study [28] also publishes the load imposed by the EV or PHEV on the electrical grid. This study used a historical database of the driving profiles of vehicles for predicting the parking times. Kempton and Tomic [5], [7], [8], presents in detail the benefits of V2G integration and provides a detail overview of the potential revenues for different markets. They looked extensively into several issues, such as stabilizing the electrical grid and supporting renewable energy. They also discussed different services an EV can provide, such as regulation service, reduction in peak load, spinning reserves and base load. In their work, it was concluded that the regulation service has the most potential in terms of earning. In [29], Kempton *at el*. performed a practical demonstration of V2G integration, providing real time frequency regulation service in PJM electricity market. Other studies also confirms that EVs are well suited for regulation services [23], [24]. Brooks demonstrated a bidirectional V2G ancillary service for EV through an aggregator. It was demonstrated that an EV can respond to four-second regulation signal from the ISO [30]. These studies however, did not properly address the aggregator role, revenue structure and the different uncertainties in the deregulated electricity market structure.

Many other studies have looked at the potential benefits of electric vehicles and V2G with unit commitment problem. These include the charging and discharging of EVs for peak loading shaving and load leveling. Some of these studies have also focused on reducing the thermal unit emissions and balancing wind and solar through V2G integration [31]–[34]. Sabir and Venayagamoorthy also considered the limitation of the parking lot for EV charging [34]. However, these studies did not consider the aggregator and bidding strategies. Also, the uncertainties associated with the EVs such as their availability, SOC, battery capacity are not considered. They considered EVs as simply a battery storage medium. Venayagamoorthy *at el*. [35] and Peterson *at el*. [36] have developed the concept of optimal buying and selling of bulk V2G energy. In [37], the author has investigated different grid related support by EVs such as reactive power support, peak shaving, emergency reserves and off grid applications. Most of the optimization work done by Sabir *at el*. is based on intelligent techniques, such as particle swarm optimization. In a real power system, it is difficult to solve the optimization with intelligent techniques as the number of electric vehicles will be large, so does the optimization parameters. In [38], author have considered the electric vehicles with the economic dispatch. They have considered the charge/discharge behavior of electric vehicles and wind power, the optimization problem is solved using particles swarm optimization. However, these studies did not investigate the aggregator standpoint nor did they consider the uncertainties of the power system market. Khodayar *at el*. [39] presents a mixed integer programming methodology to solve the security constraint unit commitment (SCUC) problem with the aggregated PEVs as a distributed source of bidirectional energy and volatile wind power. The main focus of the paper is the secure operation of the power system with EVs and wind, while considering some of the uncertainties of EVs such as their availability. Since the formulation presented was not market-based, the uncertainties associated with the electricity market such as price and load is not considered.

Guille and Gross [40] explored thoroughly the participation of aggregator and provides a framework for V2G implementation. They propose the aggregator as a link between the market participants and the utility for all types of energy markets, as well as providing the battery charging services. They introduce the concept that aggregator can provide “package deals" such as battery guarantee and maintenance, as a way to attract large number of EV owners to create an aggregation of sizable impact. The communication requirements are also highlighted. Quinn *at el*. [9] mainly focuses on the effect of communication architecture on different parameters of V2G services. They showed the importance of aggregator for V2G services by introducing the availability factor. Without aggregator, if an EV has a contract with the utility directly, it cannot leave for any unplanned departure until the end of the contract period while an aggregator, with many EVs, can schedule the capacity based on historical data, and can maintain the contracted availability for V2G service and with this, an individual EV can leave as per the EV owner requirement, but its revenues will be reduced. These studies however deal with the aggregator, but they do not address any algorithms for ancillary services, bidding strategies nor with any uncertainty of the power system.

Several other recent studies have focused on the bidirectional V2G services. One such study was done by Han and Sezaki [41] in which optimal charging control was pursued for each EV by using dynamic programming. This study divided the whole EV availability time into two periods, one for charging EV and another period for regulation services. An optimization strategy should consider both options. This study performs the optimization for regulation service however; it does not address the regulation algorithm followed by the individual EV. In [42], Rotering and Ilic proposed optimal scheduling strategy for single EV performing regulation service, this also segregates the charging period from the regulation period. However, one major drawback of this study is that it assumes the battery state of charge (SOC) is unaffected by the regulation service. The bidirectional V2G has a great potential, but with its benefits there are serious challenges in its implementation. With the bidirectional power flow, additional hardware is required. Many issues, such as interconnections related problems and anti-islanding protection problems, must be addressed [43]. Also its impact on distribution system should be investigated carefully. Battery cell degradation due to the cyclic wear is also a significant problem with bidirectional V2G [36], [44], [45] . Apart from the technical difficulties in using bidirectional V2G, customers may also not allow the utility to draw power from their batteries and they can be left stranded for their unexpected departures [46].

Vehicle to grid integration is still at the initial phase of implementation and the bidirectional V2G integration will not be a straightforward task. The first step should be to introduce the unidirectional V2G; it will avoid many technical and nontechnical hitches. There will be no need for an extra hardware and battery cycling problem will not be of concern [47]. Additionally, unidirectional V2G can be charged by standard SAE J1772 charging stations [48]. Unidirectional V2G makes customers feel more comfortable as the utility cannot draw energy from their batteries. The basic concepts of unidirectional V2G regulation service are explained in [45]. It is a load-only regulation that varies the charging of EVs around a set point called preferred operating point (POP). Reference [45] does not explain the charging algorithms used by the EV for controlling the POP. A unidirectional V2G aggregator charging algorithm is discussed in [49] . The algorithm controls the charging of EVs as either on or off based on the regulation signal from the ISO/utility. When the EV is connected, it charges the EV battery based on the rating and capacity of the charger. While charging the EV, it also keeps track of the battery state of charge (SOC). It does not perform any optimization and when the desired SOC is achieved, the charging of EV is disconnected.

A considerable amount of work in unidirectional V2G has been done by Sortomme and El-Sharkawi. In [47], unidirectional regulation algorithm is developed; several smart charging algorithms and their optimized algorithms are developed and compared. In this work [47], it is assumed that electric vehicles are available during the office hours for nine-hours and the aggregator can charge and perform bidding for ancillary service during this period. Later this work is extended in [50] to consider the spinning reserves in the bidding strategy in addition to the regulation service bidding. They developed the combined bidding algorithm for both the regulation services and spinning reserves. The optimization is also performed for the whole day and considering the unplanned departures by the electric vehicles. The algorithms for price and system load constraint optimization are also developed so that the customers can charge the EVs at low energy prices with price constraints; and the power system network will not be burdened by the EVs load, if load constraint is applied. Unlike previously suggested algorithms, the formulation presented in their work is a linear program that can be solved by any linear program solver. The authors have suggested a well-defined bidding structure for the aggregator, but they ignored the different uncertainties associated with the deregulated electricity market, such as price, load and regulation signal deployments in their bidding strategies. There are always errors related with the forecasted quantities and these forecasting errors are not dealt with in their work.

In [51], two optimization approaches ”divided” and ”global” are proposed for participating in the day-ahead energy market. In divided approach, an EV participates individually while the global approach takes the benefit of EV aggregation to bid in the electricity market. While [51] presents the basic theory of the concept, [52] presents the numerical analysis supporting the ideas. The two approached are compared and the result shows the benefit of the global approach in comparison with the divided approach. Later, a more comprehensive work is done in [53] from an EV aggregator, participating in two types of electricity market; day-ahead reserve market and the hour-ahead reserve market. The main objective of Bessa *et al.* work is to reduce the cost of aggregator, so that it can attract more EV owner for charging their cars, which indirectly will increase the aggregator income. The main drawback of their work is that, they did not compare how effective their algorithm is on the actual day of operation. They have not compared the expected and actual aggregator costs.

2.3 Handling Uncertainties using Fuzzy Sets

Fuzzy set theory has been applied in many diverse applications of power system network, mainly in the fields of power system operations and planning. The main focus of the fuzzy set theory is in the area of modeling different uncertainties and fuzzy-based intelligent controllers. In the electrical power system, one of the subfield that is very well addressed is the unit commitment (UC) problem with different fuzzy-based uncertainties such as load, production cost and spinning reserves. Most of fuzzy-based UC optimization has been done using the integer programming and intelligent techniques such as particle swarm, genetic algorithm, simulated annealing and ant colony. Only a few deal with fuzzy linear programming. A brief literature review related to the modeling of uncertainties using the fuzzy set theory for the UC problem is presented here as the UC problem resembles the optimal bidding strategy in terms of problem formulation.

A. H. Mantawy *at el*. [54], [55] proposed the unit commitment solution method with fuzzy genetic algorithm and fuzzy simulated annealing. In this work, fuzzy logic is used for modeling the uncertainties in load demand and the spinning reserves. In [56], Saber *at el*. presented fuzzy based unit commitment using simulated annealing considering the uncertainties in the load and spinning reserve while in [57] presented adaptive fuzzy based unit commitment problem solution with the particle swarm. The fuzzy membership functions are applied to the weights assigned to the particle. Fuzzy theory is also applied for modeling the uncertainties of wind and solar energies in addition to the thermal generators scheduling problem. In [58], Liang and Jian presented their work on the generator scheduling with the fuzzy wind and solar energy systems. They solve a comprehensive power system network with fuzzy genetic algorithm considering the uncertainties in fuel cost, load demand, spinning reserves requirement, available water for pumped storage, wind speed and solar radiations. The main application of these references is the unit commitment problem.

The application of fuzzy logic to price based unit commitment is addressed by Daneshi *at el*. [59], In this paper, the UC problem is expressed as a mixed integer linear programming with the uncertainties in the electrical market energy price that is modeled by fuzzy set theory. The objective is to maximize the profits of the generating company under the deregulated and uncertain environment.

Zimmermann [60], presented the way to convert a linear program into a fuzzy linear program. The fuzzy linear programming provides a framework for solving the optimization problems by modifying the standard linear program to include the uncertainties in the high and low limits of the scheduled data. It converts the objective and the constraints of the linear program into satisfaction functions of fuzzy sets. The optimum solution is achieved by maximization of the intersection of the satisfaction functions. In [61], Venkatesh *at el*. presented fuzzy mixed integer linear programming for the unit commitment problem. In this work, they transform the objective function and the constraints related to load demand and spinning reserves into fuzzy objective function and fuzzy constraints while an extension of this work is done in [62] that includes the renewable energy sources along with the thermal generators. The uncertainties are incorporated in the objective function and the renewable generation. The membership functions are defined for the total fuel cost and the wind energy generator system.

In [63], electric vehicles infrastructure using the fuzzy logic controller has been proposed. They have proposed the charging and discharging of the EVs depending on the individual battery status and the electrical power grid status. Two controllers have been proposed in this paper, the charging station controller and the V2G controller. This paper presents novel work in this area, but this work deals with the controller design and does not address the uncertainties of the power system. In addition, it is not an aggregator profit maximization approach.

To the best of our knowledge, the uncertainties in the optimal bidding strategies of the ancillary services using V2G have not been addressed by the fuzzy set theory. In the deregulated market structure, it is necessary to model the different uncertainties so that the aggregator can maximize its profits while taking into account different uncertain factors during its optimization.

CHAPTER 3

FUZZY LOGIC AND FUZZY LINEAR PROGRAMMING (FLP)

The concept of fuzzy sets and fuzzy logic has been well developed in the last several decades. The term fuzzy was first introduced by Professor Lofti Zadeh in multivalued sets in a seminal paper 'Fuzzy Sets' in 1965 [64]. Multivalued logic concept was first introduced in 1920 to deal with uncertainties in quantum mechanics. Zadeh applied the multivalued logic to set theory and introduced the concept of fuzzy sets – sets in which elements can belong to a particular set but with different degree. According to the fuzzy principle, 'everything is a matter of degree' while in the conventional logic, everything is bivalence (TRUE or FALSE, 1 or 0); fuzzy logic is multivalence (the fuzzy variables can take any value from 0 to 1). Fuzzy set theory is a shift from the conventional mathematics problem solving to more human based solving technique [65]. Over the last few decades, the fuzzy theory has gained widespread popularity; many Japanese scientists have used the theory of fuzzy sets in many practical applications. The fuzzy set theory has been mainly used for two purposes: designing fuzzy logic controllers and modeling uncertainties. Traditionally, engineers rely on mathematical models for their design. But, the more complex the system is the less effective and the more time-consuming the mathematical model becomes. This was the fundamental concept that provides the motivation for fuzzy set theory formulated by Zadeh. He proposed the *Principle of Incompatibility*.

Zadeh stated that [66] :

As the complexity of a system increases, our ability to make precise and yet significant statements about its behavior diminished until a threshold is reached beyond which precision and significance (or relevance) becomes almost mutually exclusive characteristics.

The main reason to use the fuzzy set theory in designing the controllers or formulating the problem is its ability to incorporate human experience, intelligence and heuristics into the system.

This chapter introduces the concept of fuzzy logic and fuzzy linear programming that will be applied for the aggregator bidding strategies. Fuzzy set theory is used to model the uncertainties in concerning the electricity market. This is extremely important for the aggregator to consider in order mitigating bidding risks.

3.1 Fuzzy Sets and Fuzzy Logic

The classical set theory was introduced by a German mathematician Georg Cantor (1845-1918) [65]. In this theory, *a universe of discourse, U*, is defined for a set of objects that have the same characteristics. A classical set is a collection of all objects/numbers that either belong to the set or do not belong to the set. There is a definite boundary in the case of the classical set. A classical set theory is defined by $A = \{x \in U \mid P(x)\}$ where the element of A have the property P, and U is the universe of discourse. The *characteristic function* $\mu_A(x)$: $U \rightarrow \{0,1\}$ is defined as '0' if x is not an element of A and '1' if x is an element of A. In fuzzy set theory, the concept of characteristics function is extended to more generalized form, known as *membership function*: $\mu_A(x)$: $U \rightarrow [0, 1]$. The membership function can take any value between 0 and 1. The set which is defined by this membership function is called a *fuzzy set*. In fuzzy set theory, membership is no longer 'TRUE' or 'FALSE', but a matter of degree. The degree of membership function is important.

3.2 Fuzzy Logic Controller

The fuzzy logic controller (FLC) was initially introduced as a model-free controller, based on human knowledge only, but now the current research has advanced the fuzzy controller models and they guarantee stability and robustness of the system. Fuzzy logic controllers are a type of non-linear controllers. Figure 3-1 shows the block diagram of a fuzzy logic controller. There are five main components in a fuzzy logic system.

- Fuzzification module (fuzzifier).
- Knowledge base.
- Rule base.
- Interface engine.
- Defuzzification module (defuzzification).

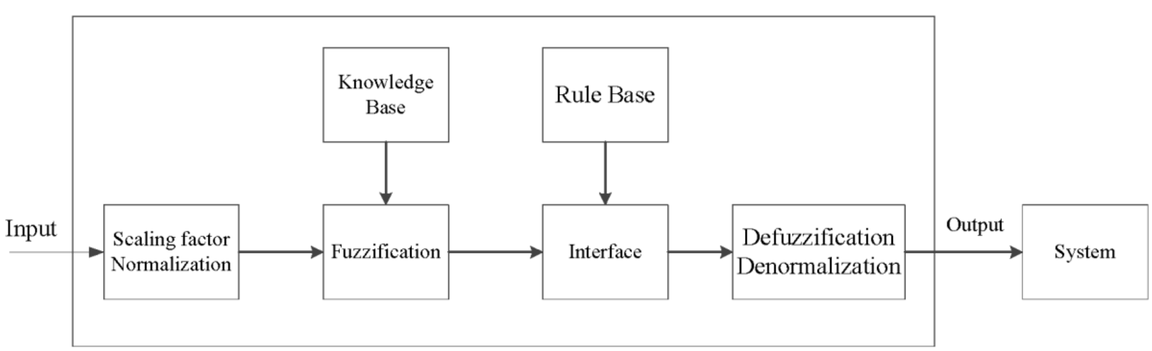

Figure 3-1: Typical fuzzy logic controller

Automatic changes in the design parameters of any of the five elements create an adaptive fuzzy controller. Fuzzy logic controller with fixed elements is called as non-adaptive fuzzy controller. The detail of the different elements can be found in standard textbooks.

3.3 Linear Programming

Linear programming (LP or Linear optimization) can be defined as a mathematical technique of maximizing or minimizing a linear function subject to some linear constraints. The constraints can be equality or inequality constraints. Linear programming is always convex and its feasible set is a convex polyhedron. Solving a linear program involves finding a point on the edges of the feasible set where the function has the smallest or the largest value depending on the objective of the problem. Linear programming problems can be expressed in the canonical form as [67]:

$$\begin{aligned} &Maximize\ c^T x \\ &Subject\ to{:}\ Ax \ \leq b, Cx = d, \\ &and\ x \ \geq 0 \end{aligned} \tag{3.1}$$

Where *x* represents the vector of unknown variables to be optimized, *A*, *b* and *c* are vectors of known coefficients and *T* is the transpose operator. The expression to be maximized or minimized is called the objective function. The equality and inequality conditions are the constraints which specify the convex region. Linear programming has been applied to solve many engineering problems, such as energy, transportation, planning, scheduling, manufacturing etc.

3.3.1 Methods of Solving Linear Problem

There are various methods for solving a linear program depending on the problem dimension. Some of the methods are the graphical method, simplex method, active-set method, and interior point method. The graphical method is only valid for two dimensional problems and the other methods are more general and can solve problems with many variables [67]. There are also various computer software packages available for solving the linear optimization problems, such as Matlab, ILOG, GAMS, and AIMMS.

3.4 Fuzzy Linear Programming

The fuzzy set theory is a mathematical technique that allows the modeling of imprecise or conflicting engineering problems. The uncertainties and imprecision's come from various factors in the real life problems. Fuzzy linear programming is an extension of linear programming (LP) that allows the modeling of the uncertainties in the model parameters [14]. The linear program formulation of (3.1) can be modified to include the possible uncertainties in the high and low limits of the schedule data. In pursuit of a fuzzy formulation, some of the elements in the LP are reformulated as fuzzy objectives and fuzzy constraints.

Fuzzy linear programming provides a framework for handling optimization problems. It transforms the objectives and constraints into satisfaction functions of fuzzy sets. The optimality is achieved by maximizing the intersection of these satisfaction functions of the problem [60] in addition to various crisp constraint in the problem. Fuzzy optimization can be solved by any software package that can solve regular linear optimization.

Consider a problem comprising of number of objectives, I, and a number of constraints, J. Let each objective be associated with a fuzzy set $Z_i = \{u_i, \mu_{Zi}(u_i) \in U_i\}$. The subscript i refer to the i^{th} objective function, u_i is the value the i^{th} objective function and U_i is i^{th} objective space. $\mu_{Zi}(u_i)$ is the membership function that defines the satisfaction parameter of the degree of closeness of the i^{th} objective to the optimal value. Similarly, let each constraint be associated with a fuzzy set $C_j = \{u_j, \mu_{Cj}(u_j) \in U_j\}$. The subscript j refers to the j^{th} constraint. u_j is the value the j^{th} constraint assumes and U_j is j^{th} constraint space. $\mu_{Cj}(u_j)$ is the membership function that defines the satisfaction parameter of the degree of closeness of the j^{th} constraint to the optimum.

Mathematically, fuzzy optimization is stated as [60]:

$$Maximize\ \lambda$$

where,

$$\lambda = min\{\mu_{Z1}, \mu_{Z2}, \mu_{Z3}, \dots, \mu_{Zi}, \mu_{C1}, \mu_{C2}, \mu_{C3}, \dots, \mu_{Cj}\}$$

The *min* function determines the minimum of the satisfaction values. All the membership functions are defined in the range of [0, 1]. During the optimization, λ assumes a value that equals the least of all the satisfaction parameters. As λ is maximized, individual fuzzy satisfaction parameters relating to objectives and constraints are consequently optimized.

CHAPTER 4

ELECTRICITY MARKET OVERVIEW AND FORECASTING OF MARKET PARAMETERS

In this chapter, an overview of the electricity market, and the forecasting of different electricity market parameters that are later used in the vehicle-to-grid (V2G) bidding, is presented. The electricity power industry has undergone restructuring process in many parts of the worlds in the last few decades. The level of restructuring is different in different countries depending on the system and requirements.

With the restructuring of the power system, only the economics of the power system has changed, the fundamental concepts and operation of the power system remains the same. The load and the generation have to be balanced at all times in the system. To achieve this goal in real time, several functions have been established to manage the system effectively. In this chapter, the ancillary service market, regulation and spinning reserve, is explained. In the last section of this chapter, forecasting of the different parameters of ancillary service market, such as regulation service and spinning reserves prices and deployments, is presented.

4.1 Electricity Markets

Electricity (both power and energy) is now considered as a commodity. An electricity market is a system of trading, purchasing and selling, through bids and offers. But there are important differences between the electrical energy and other commodities such as wheat and oil. These differences have reflective impacts on the rules and organization of the electricity market. The main differences are [68]:

- The electricity energy is linked with a physical system that functions much faster than any other market.
- The electrical energy cannot be stored on a large scale like any other commodity. The load and the generations must be balanced at all time, in order to avoid mismatch in the system that can lead to the collapse of the whole electrical system.
- The electrical energy generated from one generator cannot be directed to any particular customer. Once the power is injected into the system, it cannot be distinguished.

There are mainly two types of electricity markets, which are further classified into different services:

- Day Ahead Market

Day-ahead market is a kind of forward market in which hourly Locational marginal prices (LMP) are calculated for the next day based on the demand bids, generation offers and the scheduled bilateral transactions.

- Real Time Market (Spot Market)

Real-time market is a spot market in which current LMPs are calculated usually five-minute intervals based on the operating conditions of the grid. The real time prices are updated on the independent system operator (ISO)/utility websites. Transactions are settled hourly between the different market participants.

Within each type of market, there is a framework by each ISO for different services such as energy, ancillary services, and congestion managements. Based on the services, ISO is providing, these services are also referred as the energy market and ancillary service market. In this thesis, the formulation for V2G bidding is simulated for day-ahead ancillary service market. The ancillary service data is taken from the ERCOT ISO [69] for all the simulations. The three months data, from 21st July 2010 – 20th Oct 2010, of regulation up/down prices, regulation deployments signals, spinning reserve prices and the spinning reserves deployments are used. A brief overview of the ancillary service market is explained in the next section.

4.2 Ancillary Service Market

The federal energy regulation commission (FERC) defines the ancillary services as [70]:

> “Those services necessary to support the transmission of electric power from seller to purchaser given the obligations of control areas and transmitting utilities within those control areas to maintain reliable operations of the interconnected transmission system”

The ancillary services are needed to support the power system network in many ways from maintaining the voltage level in the transmission network to the reliable operation of power system. They also keep the required level of power quality and safety. By means of these services, we keep the load and generation in balance. In the deregulated power system network today, it is the duty of the independent system operator (ISO) to perform different duties such as, balance between supply and demand, stabilizing power system, and maintaining power quality on economic basis in a competitive environment. The different types of ancillary services an ISO can provide in a competitive market are [70], [71]:

- Frequency control (Regulation Service)
- Spinning and non-spinning reserves
- Voltage Control
- Load following
- Black start capability
- Automatic generation control
- Grid loss compensation
- Emergency control actions
- Reactive power control
- System protection

In this thesis, the main work is focused on two types of ancillary service markets, regulation and spinning reserve (responsive reserves) market.

4.2.1 Regulation Market

The regulation service market handles the rapid fluctuations in the power system due to small unintended changes in the generations and loads. The regulation service tries to keep the system frequency as close as possible to the nominal value and tries to avoid any inadvertent interchanges with other power systems. Generating units that have high up/down ramp rates can provide this service. The units that provide the regulation service should be connected to the power system; must be equipped with a governor and usually operate under automatic generation control (AGC). The regulation service is a preventive security measure to avoid any disturbance in the system.

4.2.2 Spinning Reserves Market

Reserves are designed to handle a large and unpredictable power shortage in the power system that could result in destabilizing the system. Reserve service is a kind of corrective action. Reserves services are usually divided into two categories: spinning reserves and non-spinning reserves. The units that provide the spinning reserves must respond to any disturbance immediately. Usually, these units are always connected to the power system and supposed to contribute very quickly in case of disturbance. The non-spinning reserves are not connected to the power system, but they can be brought online after short notice and are generally slow. In some cases, the customers who agree to have their load disconnected can also indirectly support the system reserve capacity.

4.3 Forecasting Electricity Market Parameters using ARIMA Models

In this thesis, optimal aggregator V2G bidding strategies are developed for the day-ahead markets. In the day-ahead market, the aggregator will try to forecast the different future (next day) market parameters. As the aggregator is bidding in the ancillary service market, so aggregator should try to bid in the market by forecasting the ancillary service prices, such as regulation up/down prices and spinning reserves (also called as responsive reserves in ERCOT market) price. Also the deployment signal from the ISO should also be forecasted for both the regulation and spinning reserves. In this thesis, the electricity market considered is the Electricity reliability council of Texas (ERCOT). The simulations are performed on a three months period, and so is the forecasting. All the prices and deployments data are taken from the ERCOT archives. for a period of three months from 21st July, 2010 to 20th Oct, 2010 [69].

The forecasting of all the markets parameters is done using the autoregressive integrated moving average (ARIMA) method. The ARIMA model based forecasting is done using the Matlab Econometrics toolbox [72]. The errors in the forecasted data are calculated using the mean absolute percentage error (MAPE). The MAPE error is given by the following formula. It is usually expressed in percentage.

$$M = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \tag{4.1}$$

4.3.1 Autoregressive Integrated Moving Average (ARIMA) Model

Electricity market parameters estimation is becoming increasingly important in the day-ahead competitive market. It is necessary to estimate future quantities for developing bidding strategies. ARIMA is a class of stochastic processes that are used to analyze time series [73]. The general steps for forecasting using the ARIMA model are as follows [74]:

A. Model Identification

In the first step, a general ARIMA model is selected to model the data to be forecasted. The data is modeled by inspecting the main characteristics of the data. In most markets, the price, load, and other data to be forecasted are usually periodic. They are repetitive daily, weekly, monthly or yearly. If f_t denotes the forecasted quantity at time t, the ARIMA formulation can be proposed as:

$$\Phi(B)f_t = \theta(B)\epsilon_t \tag{4.2}$$

where,

f_t is the forecasted quantity at time t and $\Phi(B)$ and $\theta(B)$ are functions of backshift operators B. $\Phi(B)$ is the autoregressive polynomial and $\theta(B)$ is moving average polynomial. ϵ_t is the error term and B is the backshift operator. The functions $\Phi(B)$ and $\theta(B)$ can be of the form $\Phi(B) = 1 - \sum_{l=1}^{\Phi} \Phi_l B^l$and/or $(1 - B^l)$ and $\theta(B) = 1 - \sum_{l=1}^{\theta} \theta_l B^l$. To include the seasonality in the ARIMA model different factors depending upon the daily$(1 - \Phi_{24}B^{24})$, weekly$(1 - \Phi_{168}B^{168})$, monthly $(1 - \Phi_{720}B^{720})$ or yearly can be included.

In this forecasting of different electricity market parameters, such as regulation up/down prices, spinning reserves prices, and deployment signals; we are considering them for the day-ahead market, so daily and weekly seasonality are considered. For example, it is expected that the behavior of tomorrow's noon prices to be strongly correlated with those of today.

B. Stationary Transformation

In order to make the series stationary, a transformation of the data is necessary. In the second step, a logarithmic transformation is usually applied to attain a more stable variance and mean of the series.

C. Parameter Estimation

In the third step, the parameters of the functions specified in the previous steps have to be estimated. Good estimation can be done when the data is stationary (previous step) and by using maximum likelihood method [73]. In statistics, maximum likelihood is a method of estimating the parameters of a statistical model. When applied to a data set and given a statistical model, maximum-likelihood estimation provides estimates for the model's parameters.

In this work, matlab command ‘estimate’ is used to find estimate the parameters of the model.

D. Model Validation

In this step, the model assumed in step A is validated on the residuals (actual quantity minus fitted quantity, as estimated in step B. Residuals must satisfy the requirements of white noise; constant variance, zero mean and normal distribution. These requirements can be checked by different plots such as the autocorrelation and partial autocorrelation plots. If the hypothesis on the residuals is validated by these plots then the model can be used for forecasting.

In Matlab, the ‘infer’ command is used to find the residuals.

E. Forecasting Parameters

In the last step, the model that is assumed and validated is used for forecasting the different quantities. In Matlab ‘forecast’ command is used to forecast the day-ahead quantities using the model.

4.3.2 Forecasting of Regulation Up Prices

All the ARIMA forecasting is done using the Matlab Econometric Toolbox following the steps highlighted in the previous section. As a sample result, the graphs of the actual and the forecasted regulation up prices for one week, from 4th Oct, 2010 to 10th Oct, 2010, are shown in Figure 4-1.

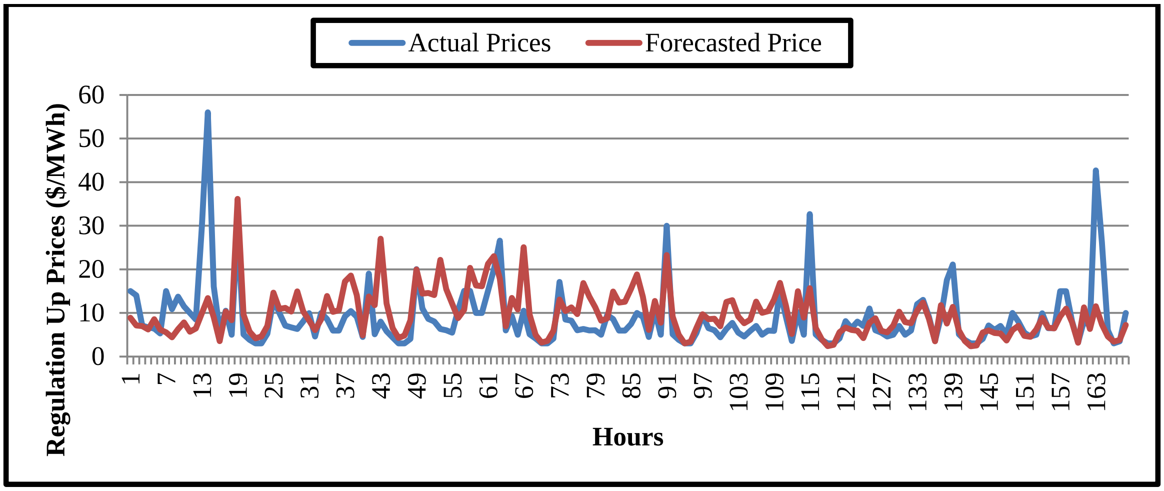

Figure 4-1: Forecasting of regulation up prices from 4th Oct, 2010 to 10th Oct, 2010

The mean absolute percentage error of the selected week is shown in Table 4-1 and the mean absolute percentage error (MAPE) of the whole forecasting of three months data is shown in Table 4-2.

Table 4-1 Daily mean absolute percentage error of the selected week

Days	**4th Oct, 2010**	**5th Oct, 2010**	**6th Oct, 2010**	**7th Oct, 2010**	**8th Oct, 2010**	**9th Oct, 2010**	**10th Oct, 2010**
MAPE	10.5464	5.9326	6.4810	5.0905	4.9407	3.3448	7.69127

Table 4-2 Mean absolute percentage error of the whole forecasted period

Forecasted Period	**21st July 2010 to 20th Oct 2010**
MAPE	8.326728 %

4.3.3 Forecasting of Regulation Down Prices

The graph between the actual price and forecasted price of regulation down for week from 4th Oct, 2010 to 10th Oct, 2010 is shown in Figure 4-2. Table 4-3 shows daily mean absolute percentage error of the selected week while Table 4-4 shows the mean absolute percentage error of the whole forecasted period.

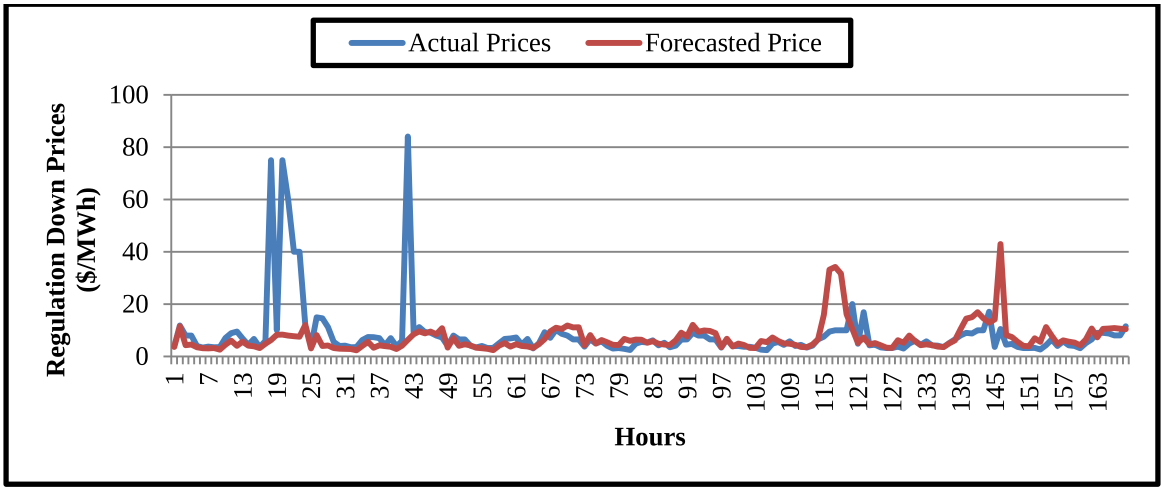

Figure 4-2: Forecasting of regulation down prices from 4th Oct, 2010 to 10th Oct, 2010

Table 4-3 Daily mean absolute percentage error of the selected week

Days	**4th Oct, 2010**	**5th Oct, 2010**	**6th Oct, 2010**	**7th Oct, 2010**	**8th Oct, 2010**	**9th Oct, 2010**	**10th Oct, 2010**
MAPE	24.1974	16.2327	2.19316	1.8557	8.7602	3.3905	7.3936

Table 4-4 Mean absolute percentage error of the whole forecasted period

Forecasted Period	**21st July 2010 to 20th Oct 2010**
MAPE	9.583074%

4.3.4 Forecasting of Responsive Reserve Prices

The graph between the actual price and forecasted price of responsive reserves for week from 4th Oct, 2010 to 10th Oct, 2010 is shown in Figure 4-3. Table 4-5 shows daily mean absolute percentage error of the selected week while Table 4-6 shows the mean absolute percentage error of the whole forecasted period.

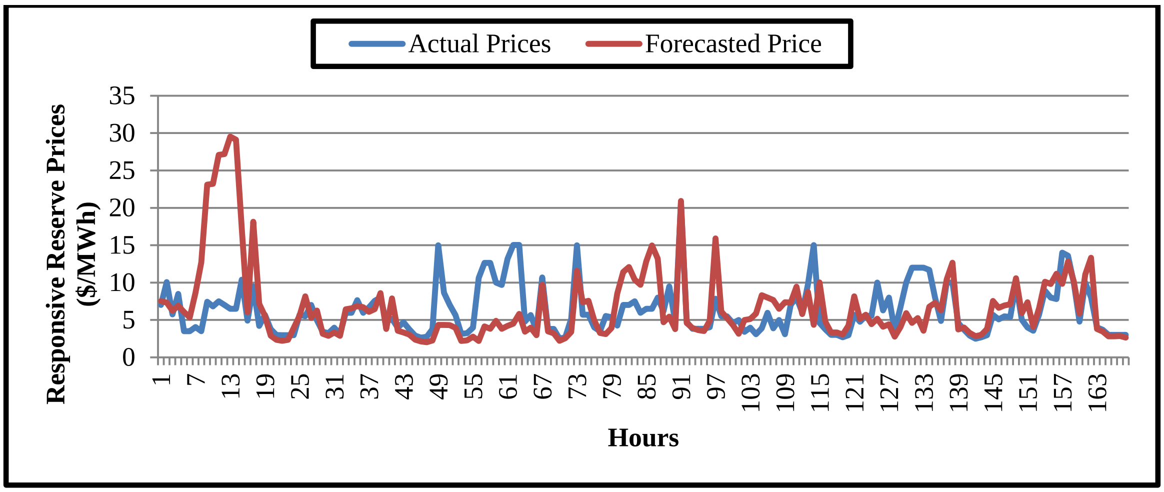

Figure 4-3: Forecasting of responsive reserve prices from 4th Oct, 2010 to 10th Oct, 2010

Table 4-5 Daily mean absolute percentage error of the selected week

Days	4th Oct, 2010	5th Oct, 2010	6th Oct, 2010	7th Oct, 2010	8th Oct, 2010	9th Oct, 2010	10th Oct, 2010
MAPE	10.4322	1.12529	5.4532	3.3702	3.4657	3.4189	1.932

Table 4-6 Mean absolute percentage error of the whole forecasted period

Forecasted Period	21st July 2010 to 20th Oct 2010
MAPE	6.777%

4.3.5 Forecasting of Regulation Up Deployments Signals

The graph between the actual and the forecasted regulation up deployments signals for week from 20th Aug, 2010 to 26th Aug, 2010 is shown in Figure 4-4. Table 4-7 shows daily mean absolute percentage error of the selected week while Table 4-8 shows the mean absolute percentage error of the whole forecasted period.

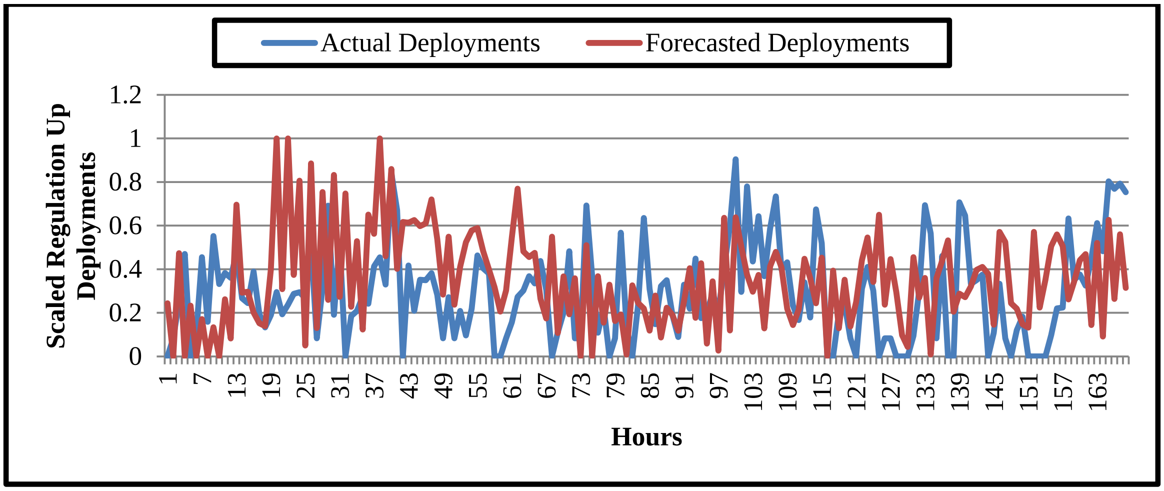

Figure 4-4: Forecasting of regulation up deployments from 20th Aug, 2010 to 26th Aug, 2010

Table 4-7 Daily mean absolute percentage error of the selected week

Days	20th Aug, 2010	21st Aug, 2010	22nd Aug, 2010	23rd Aug, 2010	24th Aug, 2010	25th Aug, 2010	26th Aug, 2010
MAPE	31.4974	36.5435	26.6176	21.6537	23.2820	30.2136	29.9532

Table 4-8 Mean absolute percentage error of the whole forecasted period

Forecasted Period	**21st July 2010 to 20th Oct 2010**
MAPE	28.4844%

4.3.6 Forecasting of Regulation Down Deployments Signals

The graph between the actual and forecasted signals of regulation down deployments for week from 20th Aug, 2010 to 26th Aug, 2010 is shown in Figure 4-5. Table 4-9 shows daily mean absolute percentage error of the selected week while Table 4-10 shows the mean absolute percentage error of the whole forecasted period.

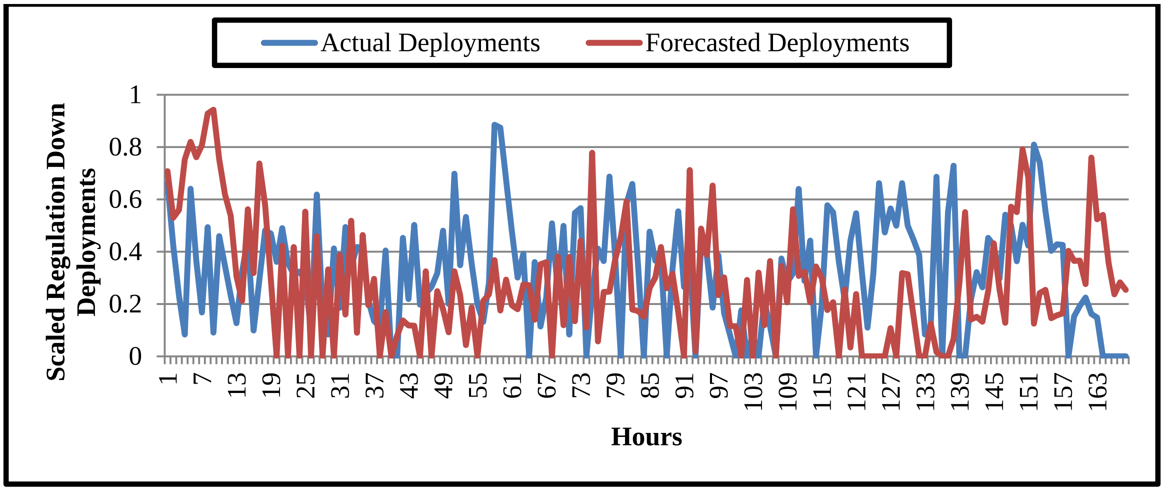

Figure 4-5: Forecasting of regulation down deployments from 20th Aug, 2010 to 26th Aug, 2010

Table 4-9 Daily mean absolute percentage error of the selected week

Days	**20th Aug, 2010**	**21st Aug, 2010**	**22nd Aug, 2010**	**23rd Aug, 2010**	**24th Aug, 2010**	**25th Aug, 2010**	**26th Aug, 2010**
MAPE	35.7060	21.7926	32.0084	27.5211	23.200	38.1259	33.7908

Table 4-10 Mean absolute percentage error of the whole forecasted period

Forecasted Period	**21st July 2010 to 20th Oct 2010**
MAPE	31.327847%

4.3.7 Forecasting of Responsive Reserve Deployments Signals

The graph between the actual and forecasted signals of responsive reserves signals for week from 20th Aug, 2010 to 26th Aug, 2010 is shown in Figure 4-6. Table 4-11 shows daily mean absolute percentage error of the selected week while Table 4-12 shows the mean absolute percentage error of the whole forecasted period.

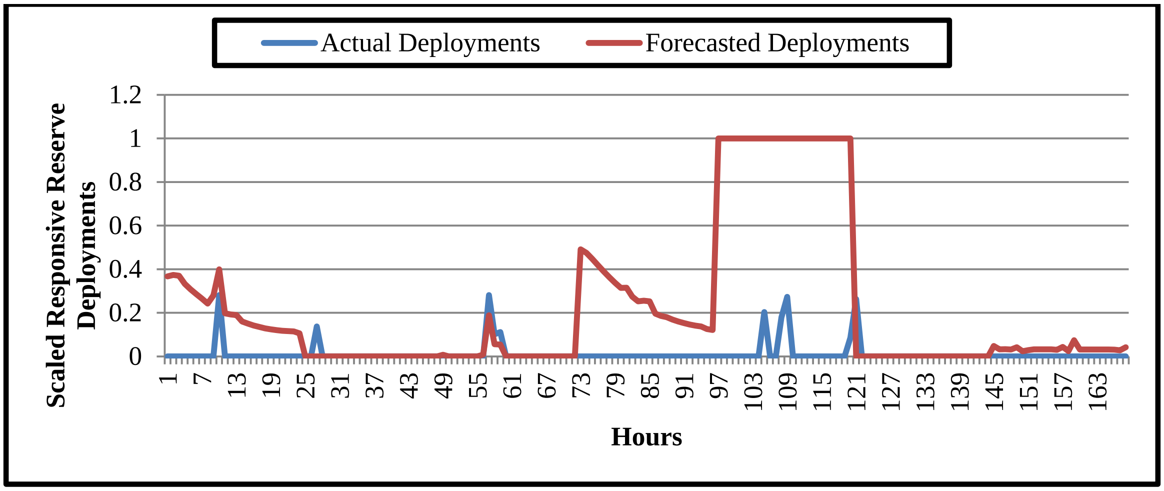

Figure 4-6: Forecasting of responsive reserve deployments from 20th Aug, 2010 to 26th Aug, 2010

Table 4-11 Daily mean absolute percentage error of the selected week

Days	20th Aug, 2010	21st Aug, 2010	22nd Aug, 2010	23rd Aug, 2010	24th Aug, 2010	25th Aug, 2010	26th Aug, 2010
MAPE	22.5258	2.8077	2.4204	28.7277	97.189	5.3738	3.6176

Table 4-12 Mean absolute percentage error of the whole forecasted period

Forecasted Period	21st July 2010 to 20th Oct 2010
MAPE	24.77 %

CHAPTER 5

SMART CHARGING OF ELECTRIC VEHICLES USING ADAPTIVE FUZZY LOGIC

In this chapter, a novel smart charging algorithm based on the fuzzy logic is proposed. This fuzzy logic algorithm takes the energy price, system load, and the number of charging hours in a fuzzy logic framework. The proposed fuzzy logic algorithm is compared with previous published algorithms and is proved to result in higher profits for the aggregator.

A considerable amount of work in unidirectional V2G has been done previously. In [47], a unidirectional regulation algorithm to be followed by an EV is proposed. Several "smart" charging algorithms were proposed in [47], [75]. These algorithms are load-only regulation, i.e. only unidirectional V2G that controls the charging level of an electric vehicle is considered. The charging schemes are based on the real time communication of system load, energy price, regulation signal deployments and the charging hours of the electric vehicles. The proposed algorithm combines the individual smart charging algorithms in a fuzzy logic framework. The aggregator generates profits by participating in the ancillary service market and by charging the EVs. These algorithms are simulated over a hypothetical group of 10,000 EVs in a real electricity market, the Electric Reliability Council of Texas (ERCOT) area. Commuter cars are used in the simulations and it is assumed that all the EVs are available during the charging hours from 8 A.M. to 5 P.M. The results show the benefit of the proposed fuzzy logic based charging from the aggregator point of view, while each algorithm has its own specific advantages that are explained later in this Chapter. In the next section, the market algorithm assumed to be implemented for deploying the regulation service is explained.

5.1 Regulation Service Deployment Algorithm

An EV can perform the regulation service by varying its actual charging rate above or below its scheduled charging rate, which is called the preferred operating point (POP). The value of the POP in the system is scheduled by the aggregator. The term POP is derived from the ancillary service market and is the average level of the energy providing regulation service [49], [45]. For a generator providing ancillary service, the term POP is the output power generated by the generator while for unidirectional V2G, the POP is the power draw level of an EV. By varying the charging rate of an EV below/above its POP, regulation up/down capacity is provided. As a single EV has insufficient capacity for providing this regulation service, the aggregator aggregates many EVs and bid their combined capacity in the electricity market. The aggregator controls the charging of EVs according to the regulation signal provided by the system operator. Regulation service deployment algorithm was proposed by Sortomme *et al.* and is shown in Figure 5-1 [47]. The graphical descriptions of different variables are shown in Figure 5-2 and Figure 5-3. The graph shown in Figure 5-2 is very important. This is the regulation algorithm followed by all the EVs. If the regulation signal from ISO (V) is positive, the EVs have to perform the regulation down by increasing their charge rate according the regulation signal and their capacity. If the regulation signal from ISO (V) is negative, the EVs have to perform the regulation up by decreasing their charge rate according the regulation signal and their capacity. This regulation algorithm is providing the regulation service by changing the EVs. The EVs draw power according to this algorithm, this algorithm is later used for calculating the actual power draw of EVs. Note that in order to perform the regulation service by the aggregator, communication between the aggregator and the system operator is required.

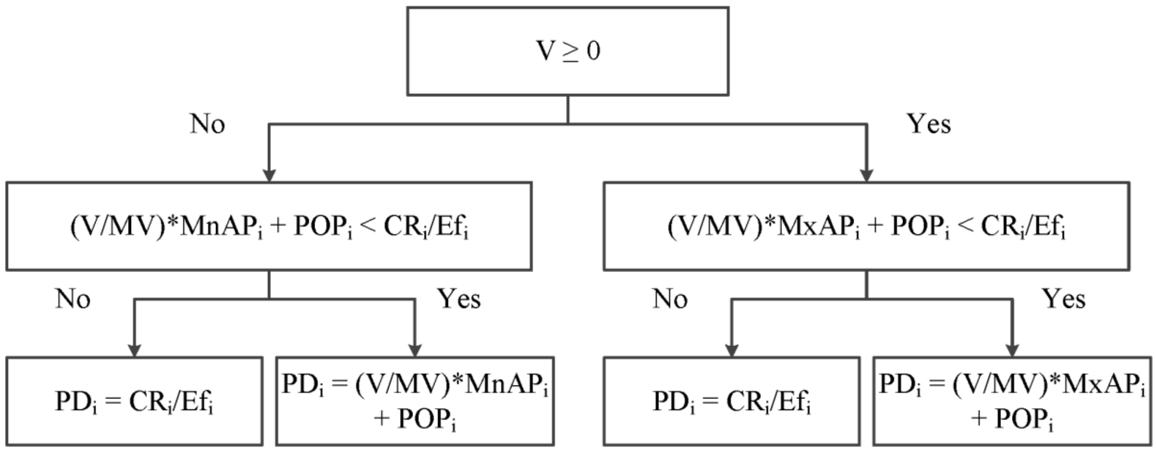

Figure 5-1: Regulation algorithm flowchart [47]

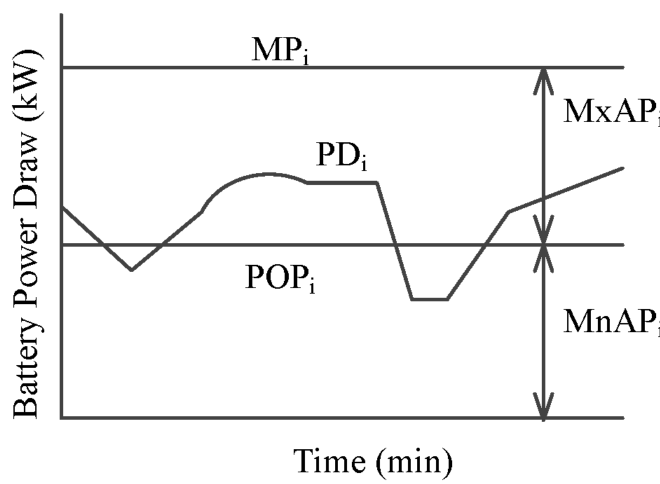

Figure 5-2: Regulation signal around the preferred operating point [47]

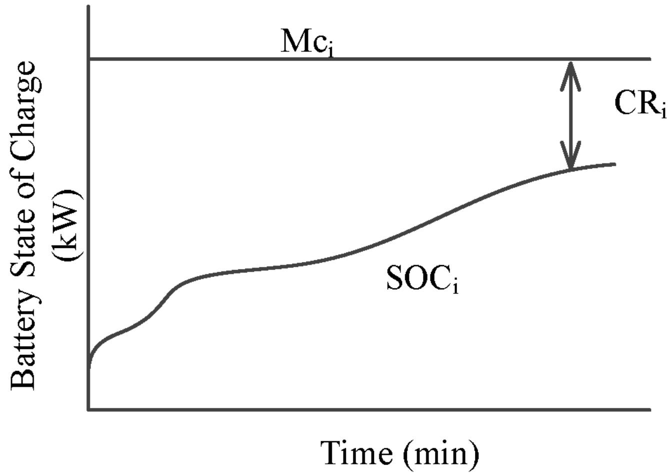

Figure 5-3: Battery state of charge while performing regulation [47]

5.2 Smart Charging Algorithms

The regulation capacity is based on the charging rate of the EV. The charging rate is selected by varying the POP; therefore the aggregator must schedule the value of POP smartly to maximize the profits. Previously, price based and load based smart charging algorithms were proposed for the EV charging [75]. However, these were not considered for regulation capacity bidding. Later, a modified charging algorithm that tends to maximize the regulation capacity was proposed [47]. In this chapter, a new fuzzy based algorithm is proposed in a fuzzy logic framework to overcome the shortcoming of the previous algorithms. The shortcoming is that if one is using the price algorithm, it will only charge the EVs based on the system energy price regardless of the impact on the power system. Similarly, if load algorithm is used the algorithm will not take care of on how much energy price, the EVs are charging. Also, the previous algorithms are not as much beneficial as the proposed fuzzy algorithm. Figure 5-4 shows the three smart charging algorithms suggested in [47], [75] and the one to be proposed in this chapter.

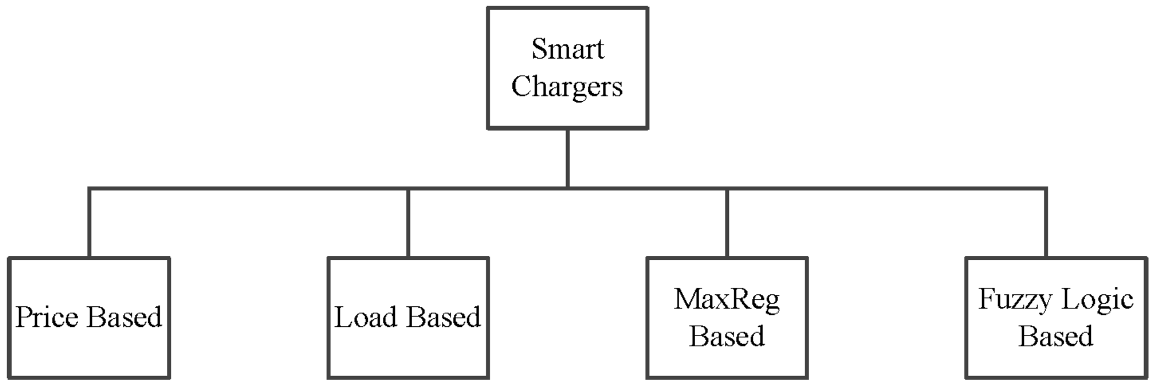

Figure 5-4: Smart charging algorithms

5.2.1 Price Based Charging

The price based algorithm sets the value of the POP based on the energy price in the system. The EVs charge more and provide more regulation down capacity when the energy price is low. The POP is selected based on:

$$POP_i(t) = \frac{M_x - P(t)}{M_x - M_n} MP_i \tag{5.1}$$

where,

$$M_{px} = max\big(P_{DA}(t_0 : t_0 + 24 \cdot 60/n)\big) \tag{5.2}$$

$$M_{pn} = min\big(P_{DA}(t_0 : t_0 + 24 \cdot 60/n)\big) \tag{5.3}$$

5.2.2 Load Based Charging

This algorithm sets the value of the POP based on the load in the system. The EVs charge more and provide more regulation down capacity when the load on the system is low. The POP is selected based on:

$$POP_i(t) = \frac{M_x - L(t)}{M_x - M_n} MP_i \tag{5.4}$$

where,

$$M_{lx} = max\left(L_{DA}(t_0: t_0 + 24 \cdot 60/n)\right) \tag{5.5}$$

$$M_{ln} = min\left(L_{DA}(t_0: t_0 + 24 \cdot 60/n)\right) \tag{5.6}$$

5.2.3 Maximum Regulation (MaxReg) Based Charging

The MaxReg based algorithm sets the value of the POP based on the battery level and the number of hours available for battery charging. The MaxReg based bids the regulation up/down capacity during the whole charging period. The POP is selected based on:

$$POP_i(t) = \frac{M_{c_i} - SOC_i}{H} \tag{5.7}$$

5.2.4 Proposed Fuzzy Logic Based Charging

A novel adaptive fuzzy logic based charging algorithm is proposed that combines the features of the previous chargers in a fuzzy logic framework. Section 3.2 explains the fuzzy logic controller and is briefly discussed here. A FLC reflects the mechanism implemented by the humans without any complete knowledge of the control object in a mathematical form. Here the control system works on the set of rules defined by human's past experience about the system. There are five main components of a fuzzy logic controller [76]:

- Fuzzification module (fuzzifier)
- Knowledge base
- Rule base
- Interface engine
- Defuzzification module (defuzzifier)

In the fuzzifier, the values of input variables are measured and it converts the crisp data into fuzzy linguistic values. The knowledge base consists of a database and linguistic control rule base. It provides necessary definitions for the fuzzification process such as membership functions, fuzzy set representation, etc. The rule base is the control strategy of the fuzzy logic system. It is usually obtained from the expert human knowledge and expressed as a set of IF-THEN rules. The defuzzification process converts the output variable into corresponding universe of discourse. Various techniques are used for the defuzzification such as maximum method, height method and the centroid method [76].

Automatic changes in the design parameters of any of the above elements create an adaptive fuzzy system. In this study, the membership function of the input and the output variables are made adaptive in nature i.e. the universe of discourse and the membership functions varies based on the energy price and system load inputs.

5.2.4.1 Membership Functions

The input of the fuzzy logic controllers are the energy price, system load and the charging hour. The output of the fuzzy logic controller is the POP for the EVs. The triangular membership functions are assumed for every input and output variable. The membership functions for energy price, system load and the POP will be adaptive as the universe of discourse will change for these functions each day. Three membership functions; low (L), medium (M) and high (H), are defined for each input/output variable.

a. Energy Price

Figure 5-5 shows the membership function of the energy price. The membership function is made adaptive by varying the universe of discourse of energy price based on a particular day.

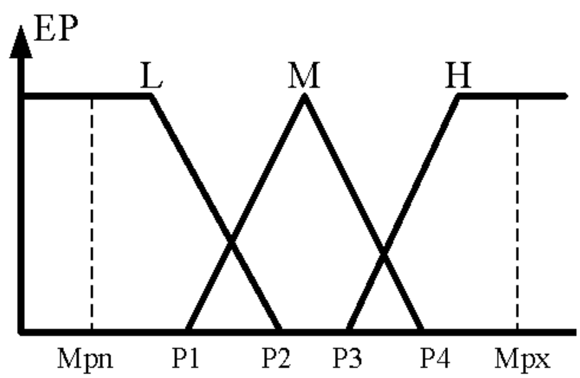

Figure 5-5: Membership function of energy price

b. System Load

Figure 5-6 shows the membership function of the system load. The membership function is made adaptive by varying the universe of discourse of system load based on the system load for a particular day.

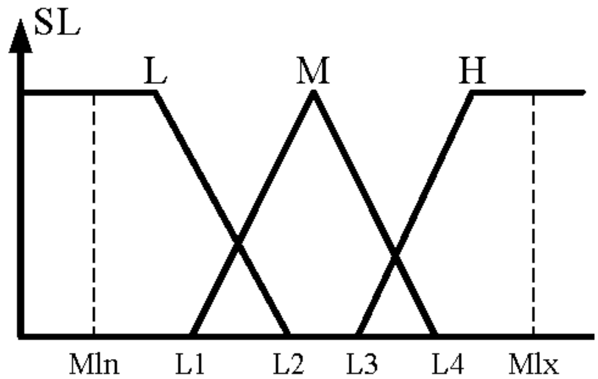

Figure 5-6: Membership function of system load

c. Charging Hours

Figure 5-7 shows the membership function for the charging hours. The charging hour is also divided into three membership functions based on the day time. The charging hour is divided as follows:

- HIGH: 8 A.M. – 11:30 A.M.
- MEDIUM: 10 A.M. – 3:15 P.M.
- LOW: 1:30 P.M. – 5:00 P.M.

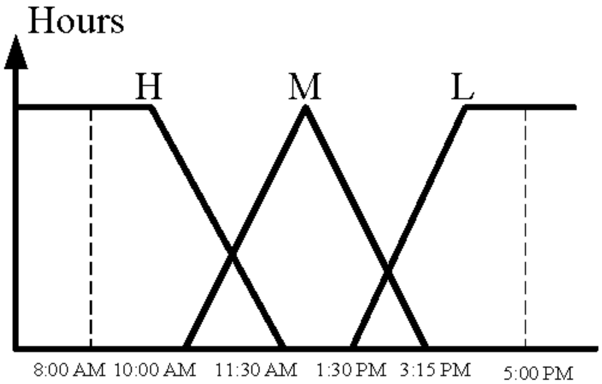

Figure 5-7: Membership function of charging hours

d. Preferred Operating Point

Figure 5-8 shows the membership function for the output i.e. POP. The output membership function is also made adaptive based on the maximum POP (up to which the EV can be charged) available in the battery.

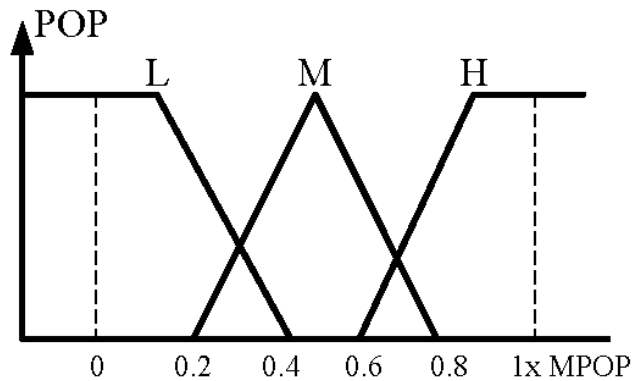

Figure 5-8: Membership function of preferred operating point

5.2.4.2 Rule Base (Decision Matrix)

A set of rules which relate the inputs to the output variables is defined in the fuzzy rule database. These rules are defined based on the human intelligence. The three inputs, energy price, system load and the charging hours, result in a total of 27 rules. These rules are shown in Table 5-1-Table 5-3.

Table 5-1 POP fuzzy value when the charging hours is LOW

Price \ Load	**L**	**M**	**H**
L	H	H	M
M	H	M	M
H	M	M	L

Table 5-2 POP fuzzy value when the charging hours is MEDIUM

Price \ Load	**L**	**M**	**H**
L	M	M	L
M	M	M	L
H	L	L	L

Table 5-3 POP fuzzy value when the charging hours is HIGH

Price \ Load	**L**	**M**	**H**
L	M	L	L
M	L	L	L
H	L	L	L

5.2.4.3 Defuzzification

The most popular defuzzification method is the centroid calculation, which returns the center of area under the curve and, therefore, is considered here for defuzzification. The general formula for the defuzzification is taken from [76].

5.3 Simulations

The four different algorithms, price-based, load-based, MaxReg-based and the proposed fuzzy–based, are simulated over a hypothetical group of 10,000 EVs in the ERCOT area. The simulations are performed for the commuter cars that are available during the day time from 8 A.M. to 5 P.M. at the workplace. It is assumed that all the EVs are available during this nine hours period and the aggregator can potentially sell regulation services during this period. For this study, different system data such as system load, energy price, regulation up/down prices and regulation deployments are taken from ERCOT archives for a period of three months from 21st July, 2010 to 20th Oct, 2010 [69]. In this study, five minutes resolution is considered. The day ahead load and price forecasts are generated to match the load forecast errors in [77] for the system load, and to match the error distribution found in [78] for the energy price.

The EVs are a hypothetical group of three different types of EVs that are available in the market; Nissan Leaf, Mitsubishi i-MiEV and the Tesla Model-S. Battery specification, EV performance, and other specifications are given in [79]–[83]. Among this hypothetical group, it is assumed that 50% of EVs are Nissan Leaf, 20% are Mitsubishi i-MiEV and 30% are Tesla Model-S. It is also assumed that each EV has a charging efficiency of 90%. Each EV arriving at the workplace with an SOC of greater than 95% will not participate in the regulation service.

The aggregator profit comes from two different sources, regulation revenues and the markup on the energy sale supplied to the customer [47]. The aggregator gets 20% of the regulation up and down revenues and $ 0.05/kWh over the energy purchased from the market for the EV battery charging. In this way, the aggregator is not exposed to the variations in market energy prices and passes the energy cost to the EV owners.

5.4 Results and Discussions

The simulations are performed for each hour from 8 A.M. to 5 P.M. for the period of three months. Comparison of charging profile for each smart charging algorithm is shown in Figure 5-9-Figure 5-12 for Aug 2nd, 2010. The price and the load algorithm follow almost the same pattern. They schedule the POP to be highest at the start of the charging period as the system load and energy prices are low in the morning. In the afternoon, the POP decreases to a lower value due to the high energy price and loads. The MaxReg algorithm keeps the POP to almost constant value during the whole charging period and sells both regulations up and down capacity during each hour. However, the proposed fuzzy algorithm efficiently varies the value of the POP based on the energy price, system load and the charging hours. During initial hours it keeps the POP to nearly constant value similar to MaxReg while during the last hours it follows the pattern of price and load algorithms. It combines the advantages of other methods and overcome their shortcomings.

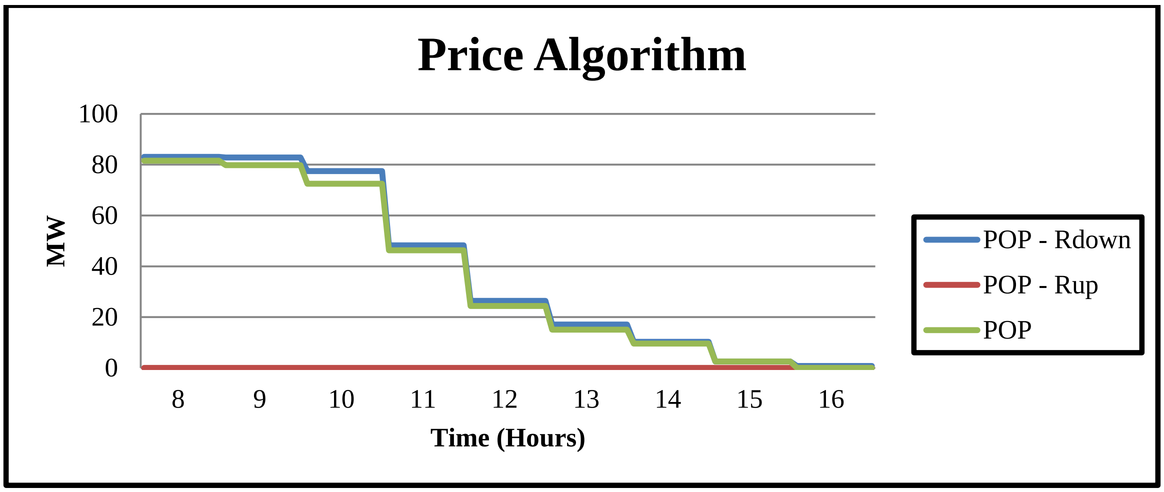

Figure 5-9: Price based POP selection algorithm

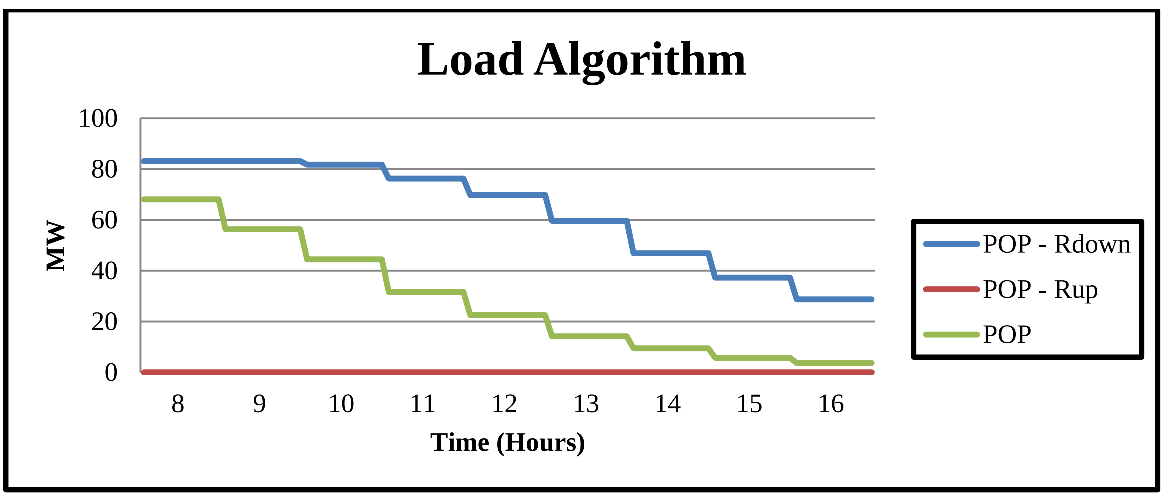

Figure 5-10: Load based POP selection algorithm

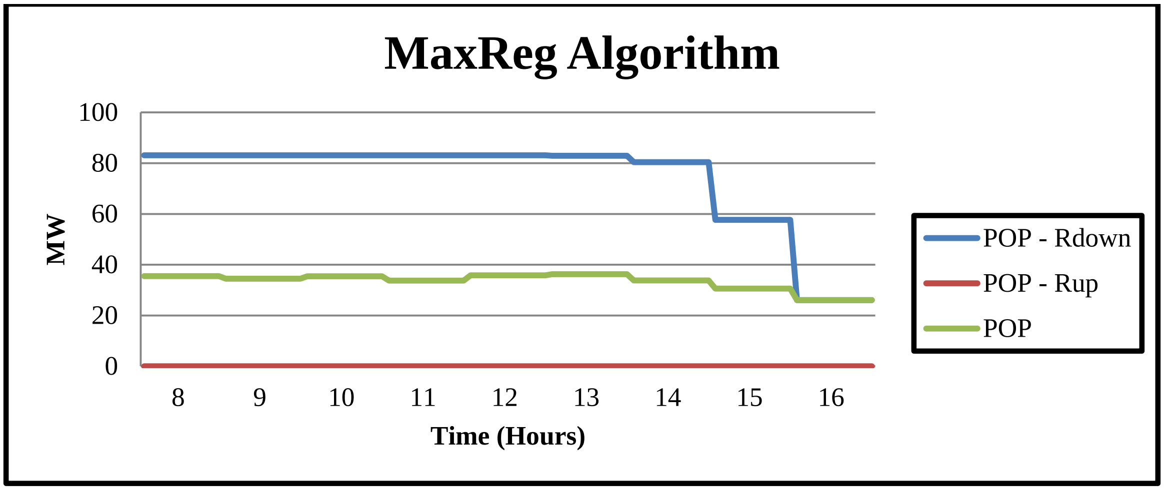

Figure 5-11: MaxReg based POP selection algorithm

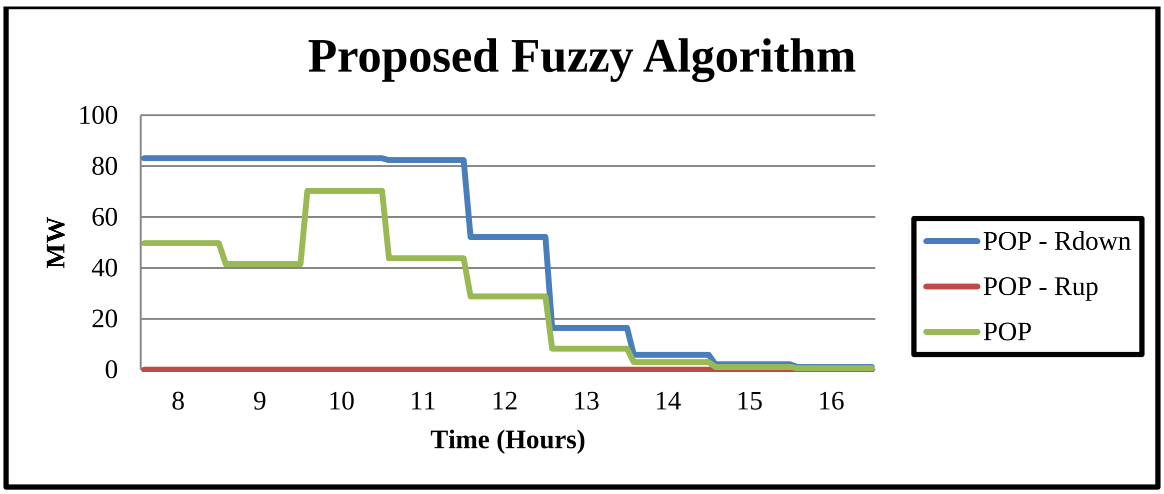

Figure 5-12: Proposed fuzzy logic based POP selection algorithm

By examining the different algorithms from the aggregator point of view, the proposed fuzzy algorithm results in the highest profits. The profit is 0.21% higher as compared to MaxReg which increase the profit by $ 3300. The price and load algorithms performance is not as good as MaxReg and fuzzy algorithms, in terms of aggregator profit. Table 5-4 shows the profits of aggregator for three months duration, by each algorithm.

Table 5-4 Aggregator Profits for Three Months Period

Algorithms	Price	Load	MaxReg	Proposed Fuzzy
Profits ($ 1000)	1438.1	1345.72	1519.2	1522.5

From the power system point of view it is desirable that the EVs not burden the power system network. It is evident from Figure 5-13 that the load based algorithm results in the lowest peak and the proposed fuzzy based algorithm results in almost similar load as that of load based algorithm. It can also be seen that the price based algorithm results in the highest value of the peak load.

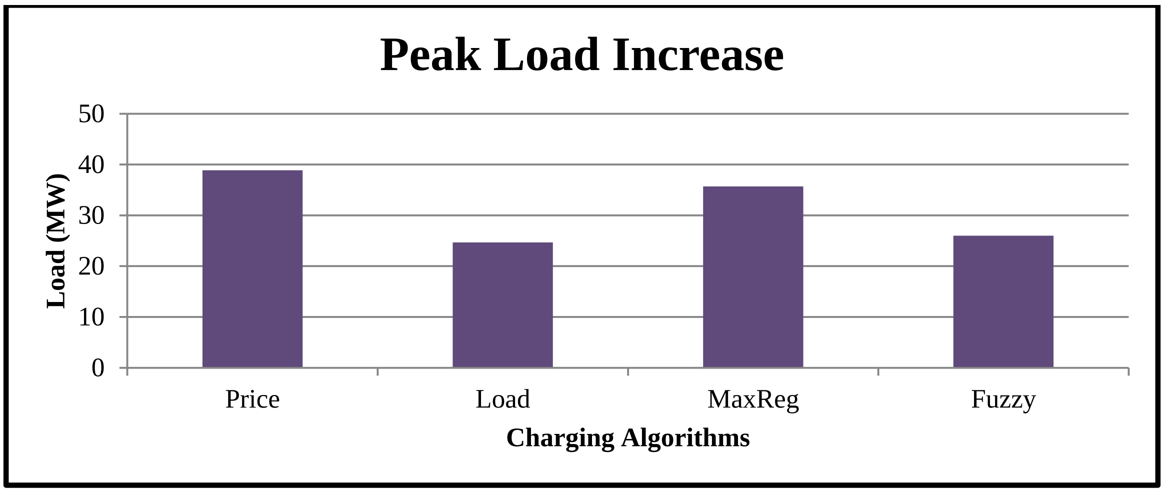

Figure 5-13: Peak load increase by each algorithm

The amount of average regulation up and down capacities during each hour is shown in Figure 5-14 and Figure 5-15, respectively. It is evident from Figure 5-14 that the price, load and fuzzy algorithms have high regulation up during the first five hours and after hour twelve, most of the electric vehicles are charged so the price and load algorithms bid very low after hour twelve, while the fuzzy algorithm still bids some amount of regulation up capacity. The MaxReg algorithm bids almost constant regulation up capacity during the whole charging period. The Fuzzy algorithm bids the high regulation down capacity during the initial and middle of the charging period while the MaxReg algorithm bids almost in every hour except for the last hour, as shown in Figure 5-15. The price and the load algorithms follow the MaxReg algorithm pattern but bids considerable less amount. This is evident from Figure 5-15.

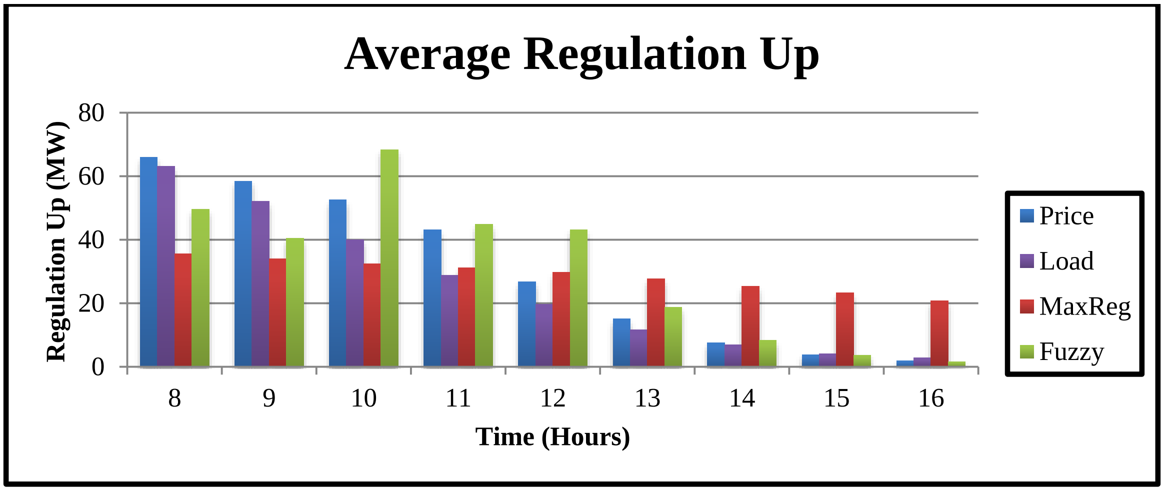

Figure 5-14: Average regulation up capacity by each algorithm

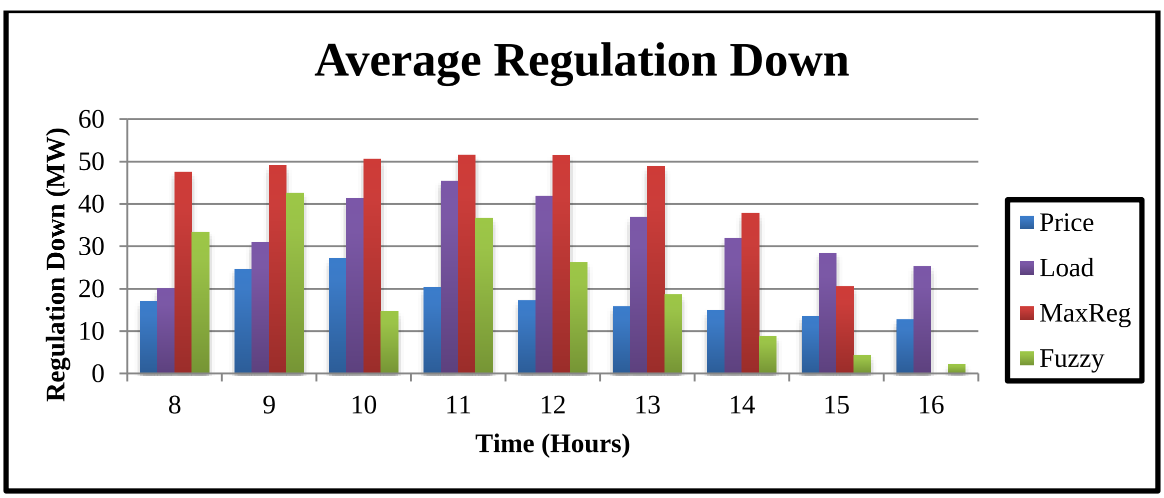

Figure 5-15: Average regulation down capacity by each algorithm

Although the main focus of this study is to generate maximum profits for the aggregator, but it is also desirable to verify that the charging of the EVs are not done at very high energy prices. From the EV owner perspective, the vehicle should be charged at the lowest possible cost. Figure 5-16 shows the average price of energy per kWh for different algorithms. The price based algorithm results in the lowest energy cost and the fuzzy based algorithm also results in a very close cost, while the MaxReg algorithm results in the highest energy price.

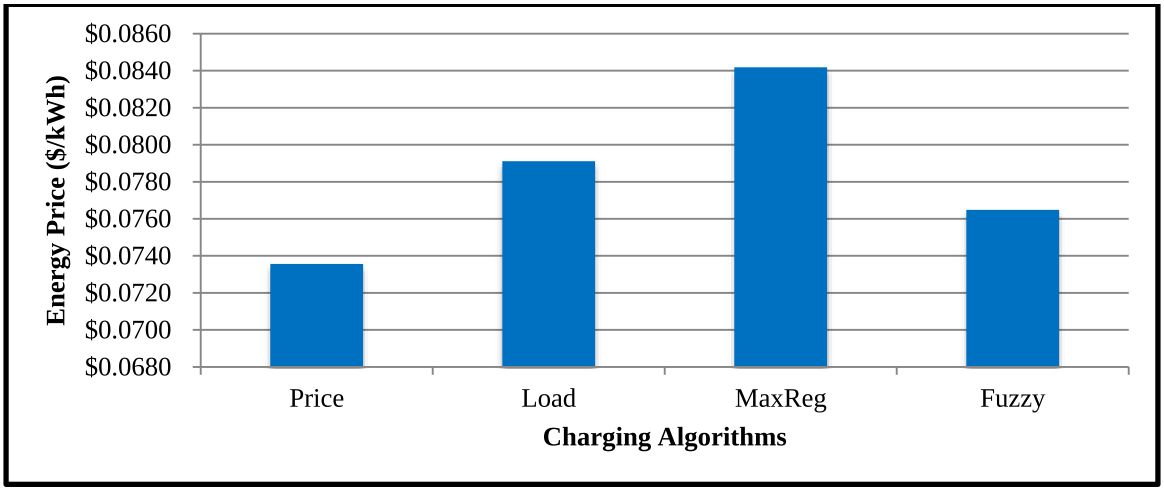

Figure 5-16: Average energy price per kWh charged to EV owner

5.5 Conclusion

This chapter presents a novel adaptive fuzzy smart charging algorithm for the unidirectional electric vehicles. Simulations are performed on a hypothetical group of commuter EVs. Previously different algorithms were proposed for the smart charging and each has its own specific benefits while the proposed fuzzy based algorithm combines their benefits and generates higher revenues for the aggregator. It also results in a lower energy price for charging the electric vehicles and the impact on the system load is reduced as compared with the previous algorithms. One of the main advantages of the smart chargers is that they can be easily implemented for real time systems and the proposed fuzzy algorithm can be easily incorporate in any previous real time system as the fuzzy logic controllers are easy to implement and requires little or no additional hardware.

CHAPTER 6

OPTIMAL BIDDING OF REGULATION SERVICES FOR UNIDIRECTIONAL VEHICLE-TO-GRID USING FUZZY LINEAR PROGRAMMING (FLP)

In the previous chapter, a fuzzy logic based smart charging algorithm was proposed that combines previously proposed algorithms in a fuzzy logic framework and generates higher profits for the aggregator. The proposed algorithm was equally beneficial for the electric vehicles (EV) owner and power system; as it charges the EV at a lower cost and the load on the power system was not much increased. However, the proposed algorithm does not guarantee that the optimal profits for the aggregator are realized out of its available resources. In order to achieve the maximum profits, the aggregator will have to optimize the bidding parameters i.e. the preferred operating point (POP) and the regulation up/down bidding capacities.

In this chapter, a novel optimal fuzzy based charging scheme is proposed that optimizes the charging of EVs and the bidding of regulation services in the electricity market through unidirectional V2G, considering the different electricity market uncertainties. The work presented in this chapter is built upon that of [47]. The fuzzy set theory is used to model the uncertainties in the forecasted data of the electricity market, namely those of regulation up/down prices, and regulation deployment signals. The electricity market parameters are forecasted using the autoregressive integrated moving average (ARIMA) model presented in chapter 4. The algorithm is simulated over the same hypothetical group of 10,000 EVs in the real electricity market, Electric Reliability Council of Texas (ERCOT) area as used in the last chapter. Commuter cars are used in the simulation and it is assumed that all the EVs are available during the charging hours from 8 A.M. to 5 P.M., i.e. during office hours only. Results show the benefit of the proposed algorithm against the deterministic algorithm of [47] with no market uncertainty.

6.1 Regulation Algorithm

An EV can perform regulation up and down by varying its charging rate below or above its scheduled value, or its preferred operating point (POP). This value of the POP is scheduled by the aggregator in the system. The electric vehicles in this chapter follow the same regulation algorithm described in the last chapter. The details can be referred to in Section 5.1.

6.2 Optimal Charging Algorithm using Fuzzy Linear Programming (FLP)

The regulation capacity is based on the extent of moving the actual charging rate of the EVs above or below their assigned POPs. Therefore the aggregator must schedule the POP smartly to maximize the profits. Previously, different smart charging algorithms were proposed for the electric vehicles charging [47], [75], but the smart chargers were not optimized. Along with the smart algorithms, their analogous optimal chargers were proposed in [47]. However, these algorithms lack the modeling of the uncertainties of the electricity market parameters, such as price, and regulation deployments. In this chapter, a new optimized FLP algorithm is proposed for EV scheduling. It optimizes the charging and bidding of the EVs considering different market uncertainties.

6.2.1 Fuzzy Model - Objective

The main objective of the optimization is to generate the maximum revenues from the regulation service by scheduling EV charging. The fuzzy objective function is defined as:

$$In = \alpha \sum_{t} \left(P_{regUp} \cdot R_{Up} + P_{regDw} \cdot R_{Dw} \right) + Mk \sum_{t} \sum_{i} \left(E(PD_i) \right) \tag{6.1}$$

The fuzzy set for the aggregator income is defined as:

$$\widetilde{In} = \left\{ [In, \mu_{In}], \underline{In} \leq In \leq \overline{In} \right\} \tag{6.2}$$

The fuzzy set is built using the income In that defines the objective function in (6.1). The possible values of In can be defined through the constraint within the definition of fuzzy set in (6.2). There is a minimum value of In below which the aggregator will not be willing to participate and the membership function is zero at that income. Also, there is an upper value of In above which all the income is acceptable. The limits of the income will be decided by the aggregator. In this thesis, it is assumed that the income less that 10% of the average deterministic income [47] is not acceptable and 10% above the average deterministic income [47] are all acceptable. Within this 10% range, above and below, all the incomes will be acceptable with some degree depending upon the membership function.

The membership function In in (6.2) is defined as:

$$\mu_{In} = \begin{cases} 0, & In \leq \underline{In} \\ \dfrac{In - \underline{In}}{\overline{In} - \underline{In}}, & \underline{In} \leq In \leq \overline{In} \\ 1, & In \geq \overline{In} \end{cases} \tag{6.3}$$

This function is graphically presented in Figure 6-1:

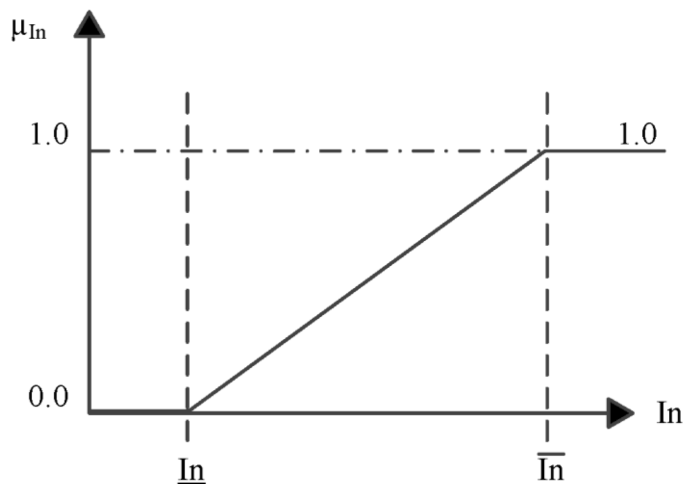

Figure 6-1: Fuzzy model of total aggregator income

6.2.2 Fuzzy Model – Regulation Up/Down Prices

The fuzzy uncertainty model of the regulation up/down prices is developed and can be represented as:

$$\widetilde{P_{regUp}} = \left\{\left[P_{regUp}, \mu_{regUp}\right], \underline{P_{regUp}} \leq P_{regUp} \leq \overline{P_{regUp}}\right\} \tag{6.4}$$

This model is developed assuming that there is a certain regulation price below which the aggregator will not be willing to participate. The minimum regulation prices should be such that the aggregator is making profits after covering all its expenses. In this work, the minimum and the maximum regulation prices are estimated using the mean absolute error between the forecasted and actual market data for the simulation period using an ARIMA model. The membership function for the price of regulation up is given in (6.5) and the graphical representation is similar to that in Figure 6-1.

$$\mu_{regUp} = \begin{cases} 0, & P_{regUp} \le \underline{P_{regUp}} \\ \dfrac{P_{regUp} - \underline{P_{regUp}}}{\overline{P_{regUp}} - \underline{P_{regUp}}}, & \underline{P_{regUp}} \le P_{regUp} \le \overline{P_{regUp}} \\ 1, & P_{regUp} \ge \overline{P_{regUp}} \end{cases} \tag{6.5}$$

A similar fuzzy modeling is made for the regulation down prices and its membership function as shown in (6.6) and (6.7).

$$\widetilde{P_{regDw}} = \left\{\left[P_{regDw}, \mu_{regDw}\right], \underline{P_{regDw}} \le P_{regDw} \le \overline{P_{regDw}}\right\} \tag{6.6}$$

$$\mu_{regDw} = \begin{cases} 0, & P_{regDw} \le \underline{P_{regDw}} \\ \dfrac{P_{regDw} - \underline{P_{regDw}}}{\overline{P_{regDw}} - \underline{P_{regDw}}}, & \underline{P_{regDw}} \le P_{regDw} \le \overline{P_{regDw}} \\ 1, & P_{regDw} \ge \overline{P_{regDw}} \end{cases} \tag{6.7}$$

6.2.3 Fuzzy Model – Regulation Up/Down Deployments

The expected values of regulation deployments are calculated using the historical deployment signals from ERCOT ISO [69]. The hourly actual averages are calculated and the deviations from the forecasted values (obtained using ARIMA) are calculated so that the membership functions of E_{xU} and E_{xD} can be defined. The fuzzy model for E_{xU} is shown in (6.8) and its membership function is in(6.9).

$$\widetilde{E_{xU}} = \left\{[E_{xU}, \mu_{ExU}], \underline{E_{xU}} \leq E_{xU} \leq \overline{E_{xU}}\right\} \tag{6.8}$$

$$\mu_{ExU} = \begin{cases} 1, & E_{xU} \leq \underline{E_{xU}} \\ \dfrac{\overline{E_{xU}} - E_{xU}}{\overline{E_{xU}} - \underline{E_{xU}}}, & \underline{E_{xU}} \leq E_{xU} \leq \overline{E_{xU}} \\ 0, & E_{xU} \geq \overline{E_{xU}} \end{cases} \tag{6.9}$$

The graphical representation of the E_{xU} membership function is shown in Figure 6-2. The expected regulation deployments are defined in an opposite manner to that of regulation prices. If the expected deployments are kept low, the EVs will be available in the market for providing the regulation service for the whole charging period. If they are charged during the early hours, their capacities to provide regulation in the later hours will be diminished.

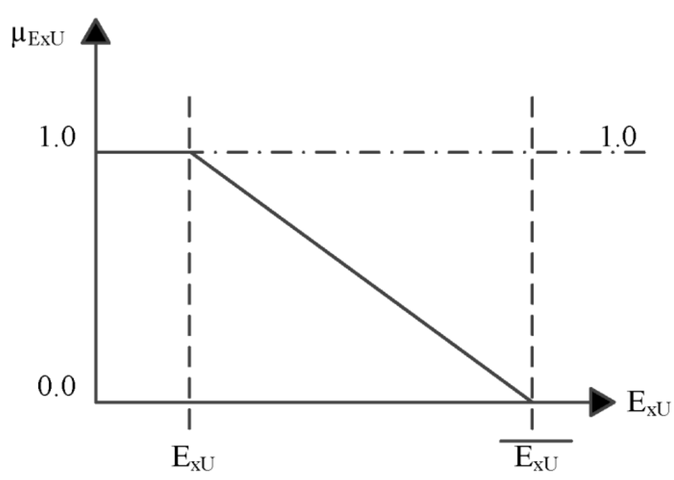

Figure 6-2: Fuzzy model of expected regulation up deployments

The fuzzy model for the expected regulation down deployment is similar to expected regulation up deployment and its membership function is:

$$\widetilde{E_{xD}} = \left\{[E_{xD}, \mu_{ExD}], \underline{E_{xD}} \le E_{xD} \le \overline{E_{xD}}\right\} \tag{6.10}$$

$$\mu_{ExD} = \begin{cases} 1, & E_{xD} \le \underline{E_{xD}} \\ \dfrac{\overline{E_{xD}} - E_{xD}}{\overline{E_{xD}} - \underline{E_{xD}}}, & \underline{E_{xD}} \le E_{xD} \le \overline{E_{xD}} \\ 0, & E_{xD} \ge \overline{E_{xD}} \end{cases} \tag{6.11}$$

6.2.4 Complete Fuzzy Linear Programming for EV Charging

As a market participant, the aggregator will strive for the maximum benefits from its V2G assets. The aggregator profits come from the two sources: regulation service bidding and the charging of EVs. The aggregator will get a portion of the regulation service bidding and a fixed markup over the energy used for EV charging [47]. The uncertainties are considered in a fuzzy set by calculating the forecasting errors in the actual and the historical data of ERCOT ISO for the regulation up/down prices and the regulation deployments. The membership functions of the income, regulation prices and the expected deployments have to be translated into the fuzzy constraints. These transformations are done in (6.12) - (6.16)

$$\begin{gathered} \lambda \le \mu_{In} = \frac{In - \underline{In}}{\overline{In} - \underline{In}} \\ \Rightarrow \left(\overline{In} - \underline{In}\right) \cdot \lambda + \underline{In} \le In \end{gathered} \tag{6.12}$$

$$\begin{gathered} \lambda \le \mu_{regUp} = \frac{P_{regUp} - \underline{P_{regUp}}}{\overline{P_{regUp}} - \underline{P_{regUp}}} \\ \Rightarrow \left(\overline{P_{regUp}} - \underline{P_{regUp}}\right) \cdot \lambda + \underline{P_{regUp}} \le P_{regUp} \end{gathered} \tag{6.13}$$

$$\lambda \leq \mu_{regDw} = \frac{P_{regDw} - \underline{P_{regDw}}}{\overline{P_{regDw}} - \underline{P_{regDw}}}$$
$$\Rightarrow \left(\overline{P_{regDw}} - \underline{P_{regDw}}\right) \cdot \lambda + \underline{P_{regDw}} \leq P_{regDw} \tag{6.14}$$

$$\lambda \leq \mu_{ExU} = \frac{\overline{E_{xU}} - E_{xU}}{\overline{E_{xU}} - \underline{E_{xU}}}$$
$$\Rightarrow \left(\overline{E_{xU}} - \underline{E_{xU}}\right) \cdot \lambda + E_{xU} \leq \overline{E_{xU}} \tag{6.15}$$

$$\lambda \leq \mu_{ExD} = \frac{\overline{E_{xD}} - E_{xD}}{\overline{E_{xD}} - \underline{E_{xD}}}$$
$$\Rightarrow \left(\overline{E_{xD}} - \underline{E_{xD}}\right) \cdot \lambda + E_{xD} \leq \overline{E_{xD}} \tag{6.16}$$

$$\lambda = min\{\mu_{In}, \mu_{regUp}, \mu_{regDw}, \mu_{ExU}, \mu_{ExD}\} \tag{6.17}$$

The complete optimal fuzzy formulation (OptFuzzy) is stated below:

$$Maximize\ \lambda \tag{6.18}$$

Subject to:

$Aggregator\ Income\ of$ (6.1)

$Aggregator\ Income\ fuzzy\ constraint\ of$ (6.12)

$Regulation\ up\ price\ fuzzy\ constraint\ of$ (6.13)

$Regulation\ down\ price\ fuzzy\ constraint\ of$ (6.14)

$Expected\ regulation\ up\ fuzzy\ constraint\ of$ (6.15)

$Expected\ regulation\ down\ fuzzy\ constraint\ of$ (6.16)

$$R_{Up}(t) = \sum_{i=1}^{cars} MnAP_i(t) \tag{6.19}$$

$$R_{Dw}(t) = \sum_{i=1}^{cars} MxAP_i(t) \tag{6.20}$$

$$MxAP_i(t) \ \leq POP_i(t) \tag{6.21}$$

$$\sum_{t} E\big(PD_i(t)\big) + SOC_{I,i} \leq M_{ci} \tag{6.22}$$

$$\big(MxAP_i(1) + POP_i(1)\big)Ef_i + SOC_{I,i} \leq M_{ci} \tag{6.23}$$

$$POP_i(t) \leq MP_i \tag{6.24}$$

$$MxAP_i(t) + POP_i(t) \leq MP_i \tag{6.25}$$

$$MxAP_i(t) \geq 0 \tag{6.26}$$

$$MnAP_i(t) \geq 0 \tag{6.27}$$

$$POP_i(t) \geq 0 \tag{6.28}$$

$$E\big(PD_i(t)\big) = MxAP_i(t) \cdot E_{xD} + POP_i(t) - MnAP_i(t) \cdot E_{xU} \tag{6.29}$$

In this fuzzy optimization, the objective is to maximize the minimum membership of the fuzzy variables and, thus, maximize the aggregator profits. The cost of aggregator such as charging station infrastructure cost and other running costs such as communication and personnel are assumed to be fixed.

In order to avoid burdening the power system network with the charging of electric vehicles, the load-constrained can be added to the optimization problem as follows:

$$\sum_{i=1}^{cars} POP_i(t) = \frac{M_x - L(t)}{M_x - M_n} \sum_{i=1}^{cars} MP_i \tag{6.30}$$

Similarly, in order to limit charging at periods of high energy costs, the following constraint can be added:

$$\sum_{i=1}^{cars} POP_i(t) = \frac{M_x - P(t)}{M_x - M_n} \sum_{i=1}^{cars} MP_i \tag{6.31}$$

6.3 Case Study

The simulations are performed in the ERCOT area on a hypothetical group of 10,000 EVs used by commuters. These simulations are performed for a period of three months from 21st July, 2010 to 20th Oct, 2010 [69]. Electricity Market parameters such as energy price, load and the regulation signal are taken from the ERCOT database for the simulation period. All the simulations are performed in Matlab using the CVX toolbox to solve the optimization problem [84]. The simulations are performed on the EVs at workplace from 8 A.M to 5 P.M. In this nine-hour period, the aggregator can potentially sell the regulation service and charge the electric vehicles. In this study, five-minute-resolution signal is used because of the available data. However, an EV can follow regulation signals of much higher resolution [29], [30]. The day-ahead load is generated in a similar manner as mentioned in [77].

The autoregressive integrated moving average (ARIMA) model is used to forecast the different electricity market parameters including regulation up/down prices and the expected regulation deployments. The hourly expected percentages of the regulation capacity is calculated for the historic data using the formulation presented in [47] and then the forecast is done using ARIMA as presented in chapter 4. After forecasting the parameters, the mean absolute error between forecasted and actual values are calculated to incorporate these forecasting inaccuracies into the fuzzy formulation. The mean absolute errors of the forecasted data are shown in Table 6-1.

Table 6-1 Mean absolute percentage error of forecasted quantities over simulated period

Electricity Market Parameters	**MAP Errors**
Regulation Up Prices	8.327 %
Regulation Down Prices	9.5831 %
Regulation Up Deployments	28.48 %
Regulation Down Deployments	31.327 %

In this simulation study, three different kinds of EVs available in the market are considered: Nissan Leaf, Mitsubishi i-MiEV and Tesla Model-S. Battery specifications, EV performance and other specifications are given in [79]–[83]. Among this hypothetical group, it is assumed that 50% of EVs are Nissan Leaf, 20% are Mitsubishi i-MiEV and 30% are Tesla Model-S. It is also assumed that each EV has a charging efficiency of 90%. Each EV arriving at the workplace with an SOC of greater than 95% will not participate in the regulation service. All the EVs that are used in these simulations can be charged from a standard 240V supply, and it is assumed that the charger has an efficiency of 90%.

Two types of simulation studies are performed and compared: deterministic [47] and the proposed fuzzy based. Using each algorithm, expected day-ahead aggregator profits are obtained by evaluating the corresponding objective function. The expected profits are calculated using the forecasted market parameters. To further assess the effectiveness of the proposed FLP formulation, the actual aggregator profits on the bidding day are calculated for both the deterministic and proposed fuzzy algorithms. The actual aggregator profits are calculated from the algorithm presented in Figure 5-1. The actual aggregator profits are calculated using the actual (realized) market parameters, such as energy price, regulation prices and the regulation deployments.

The aggregator profit comes from two different sources; regulation revenues and the markup on the energy sale supplied to the customer. The aggregator gets 20% of the regulation revenues and $0.05/kWh over the energy purchased from the market for the EV battery charging. In this way, the aggregator is not exposed to the energy price variations. Rather, it passes the energy cost to the EV owner.

6.4 Results and Discussion

The deterministic and the proposed fuzzy optimization are performed for three different cases:

- With no load and price constraint in the optimization.
- With load constraint included in the optimization.
- With price constraint included in the optimization.

In the first case, there is no additional constraint for the aggregator to take care of the system load and system energy price and is expected to result in highest profit. The load constraint is not a problem for the aggregator as the main goal of the aggregator is to maximize profits, not maintaining the balancing in the power system, but the system operator can impose this limit on the aggregator to avoid the system collapse. The price constraint can be advantageous to the EV owner as the electric vehicles will be charging at the lowest cost.

6.4.1 Case # 1: With no Load and Price Constraint

The deterministic and the proposed fuzzy based algorithms are run each day from 8 A.M. to 5 P.M. daily for the period of three months. All the vehicles are assumed available during the charging period.

6.4.1.1 Charging Profiles

The charging profiles and regulation service provided by each algorithm are compared for 15th September, 2010. This day is randomly selected. Figure 6-3 shows the regulation up and down prices on 15th September, 2010 for the charging period. Both the prices are low at the start of the charging period and increases in the late afternoon of the day. The POP, regulation up capacity, and regulation down capacity by each algorithm are shown in Figure 6-4-Figure 6-6.

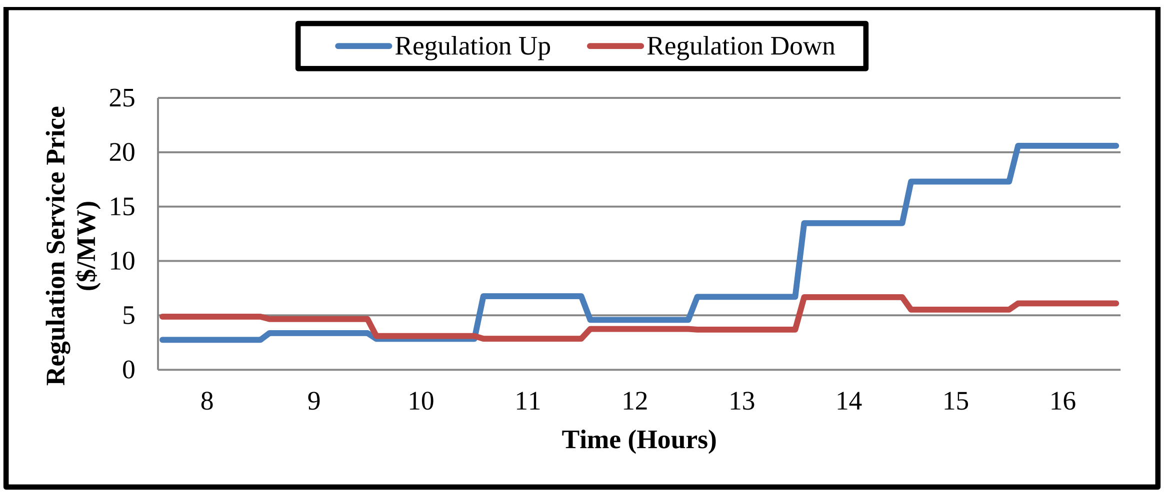

Figure 6-3: Hourly regulation service prices on 15th Sep, 2010

The POP of the electric vehicles for 15th September, 2010 is shown in Figure 6-4. As the prices of the regulation up/down are higher at the end of the charging period, the deterministic algorithm sets the POP to be higher at the last three hours. Although the fuzzy based algorithm follows the pattern of deterministic algorithm, it sets the values of POP to a more moderate level to take advantage of the uncertainties in the forecasted values and also bids high in the first few hours.

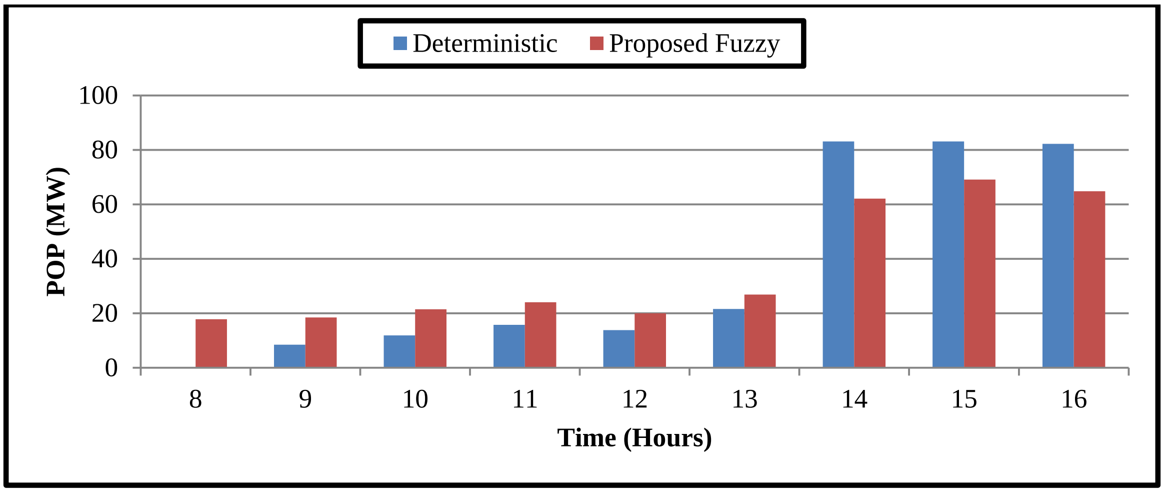

Figure 6-4: POP by each algorithm on 15th Sep, 2010

The regulation up bidding capacity is shown in Figure 6-5. Both the algorithms, deterministic and fuzzy, sets the regulation up capacity high at the end of the charging period as the regulation up prices is high. The deterministic algorithm sets the regulation up capacity higher than the fuzzy algorithm, but sets lowers at the starting of the charging period.

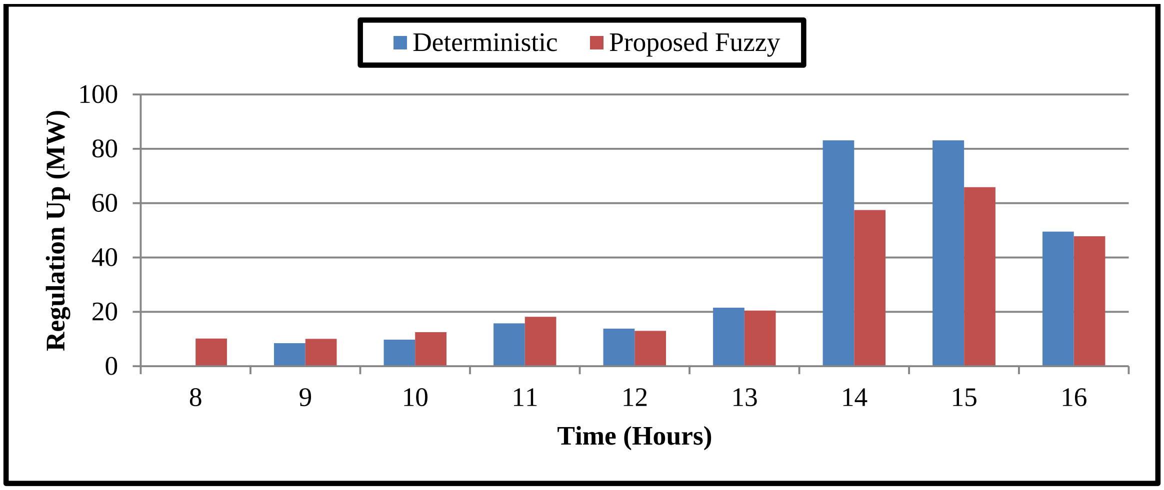

Figure 6-5: Regulation up by each algorithm on 15th Sep, 2010

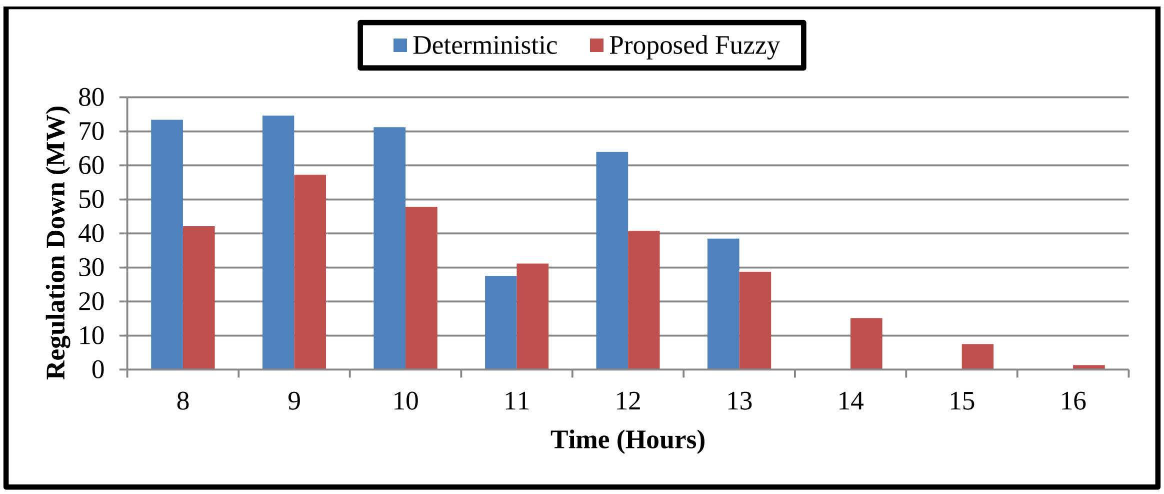

Figure 6-6: Regulation down by each algorithm on 15th Sep, 2010

The average regulation capacities and the average POP during the simulation period are shown in Figure 6-7 - Figure 6-9. The average POP is usually set to higher values at the end of the charging period as the prices are usually higher in the mid-day. The fuzzy algorithm sets the average POP to be little higher at the start of the charging period while the deterministic is a bit higher than fuzzy during the end of the charging period. The average regulation up also follows the same pattern as that of the average POP. The average regulation down capacity is shown in Figure 6-9. The deterministic algorithm is a little higher than fuzzy in the initial charging hours, then in the remaining hours, fuzzy algorithm bids higher.

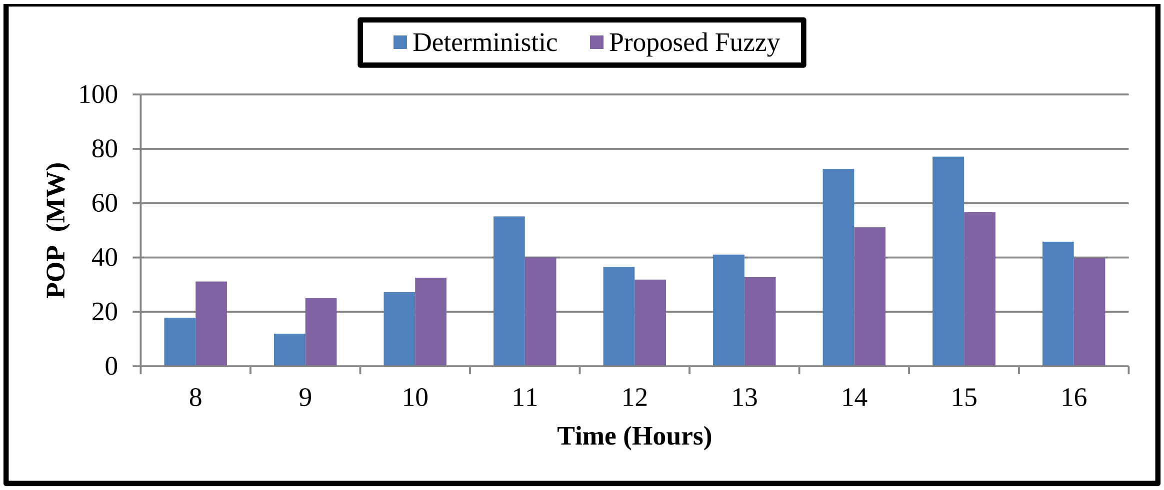

Figure 6-7: Average POP by each algorithm

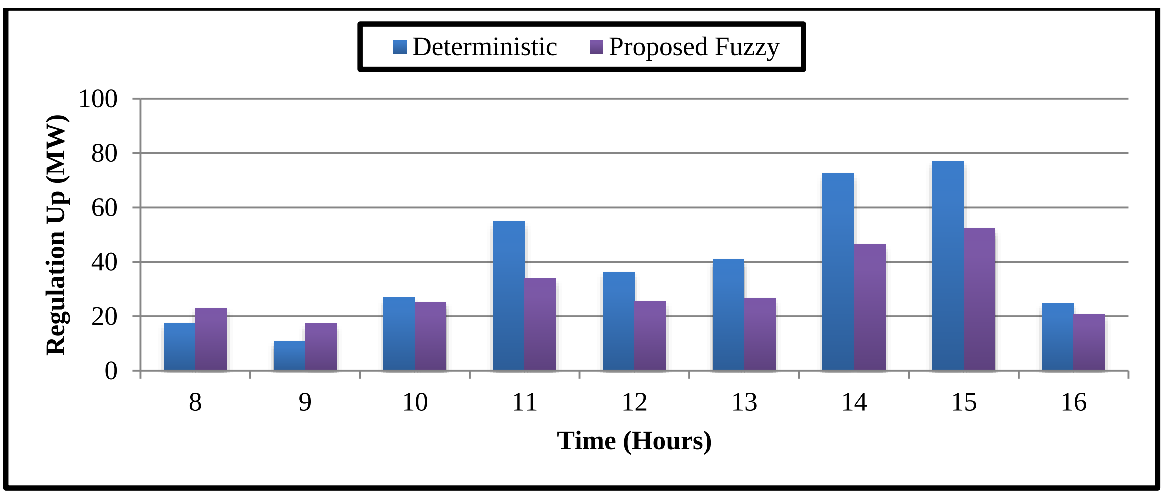

Figure 6-8: Average regulation up by each algorithm

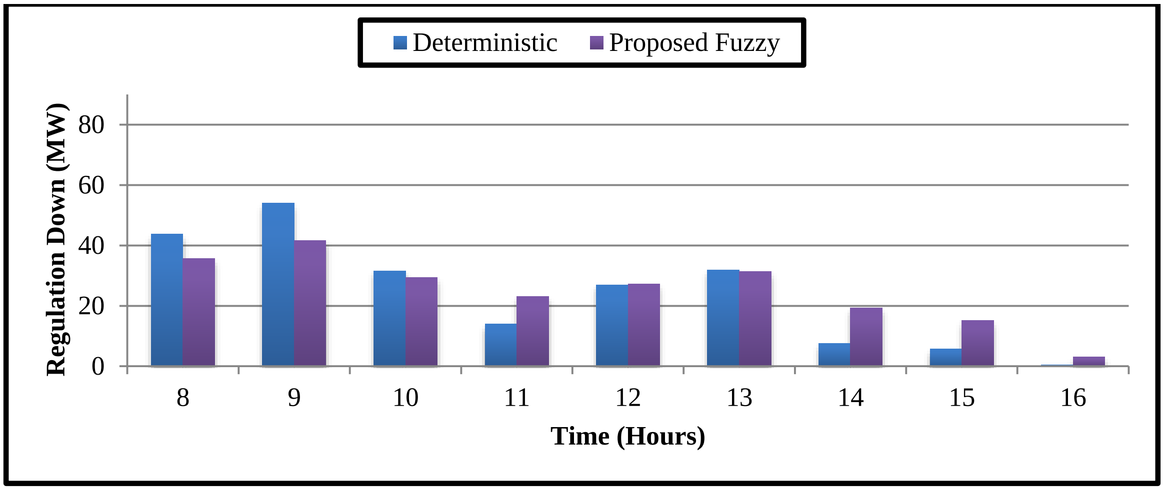

Figure 6-9: Average regulation down by each algorithm

6.4.1.2 Quarterly Results

The section analyzes the expected and actual profits of an aggregator for the deterministic and proposed fuzzy based algorithms. Figure 6-10 shows the comparisons of the expected and actual profit of an aggregator for an average day. Although the deterministic algorithms expected profits are higher than the fuzzy algorithms, the actual profits of the fuzzy algorithm end up higher by about 2.9% than the deterministic actual profits. This shows the superiority of the proposed method.

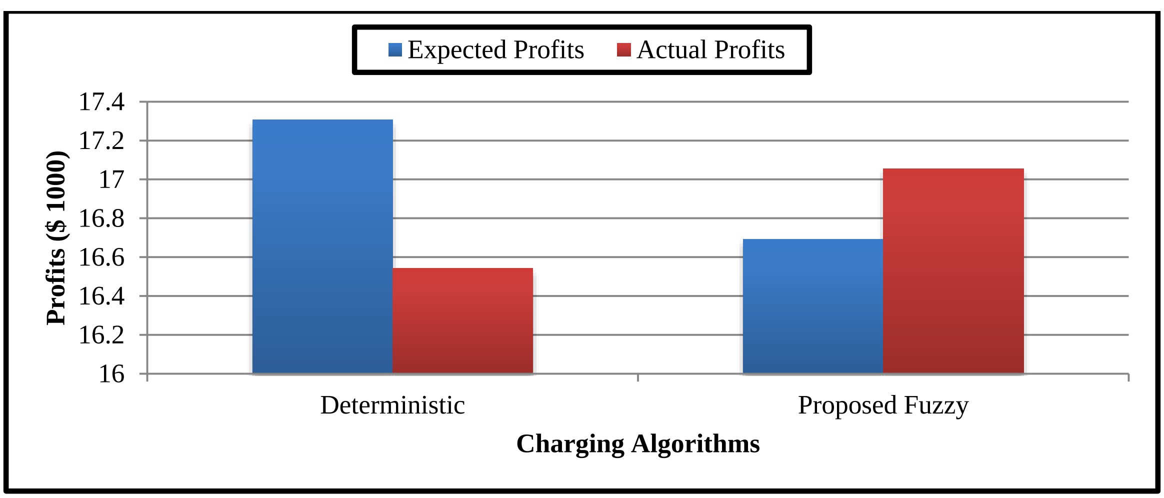

Figure 6-10: Expected and actual profits of an aggregator for an average day

When comparing the aggregator profits on the whole simulation period of three months, the expected aggregator profits comes out to be $ 1592k which is 3.58% more than the expected fuzzy profits while on the actual bidding day, the fuzzy generates more profits i.e. $ 1569k which is 3% more than the deterministic actual profits and 2.2% more than the fuzzy expected profits. On the actual day, the fuzzy algorithm performs better than deterministic algorithm. This is evident from Figure 6-11.

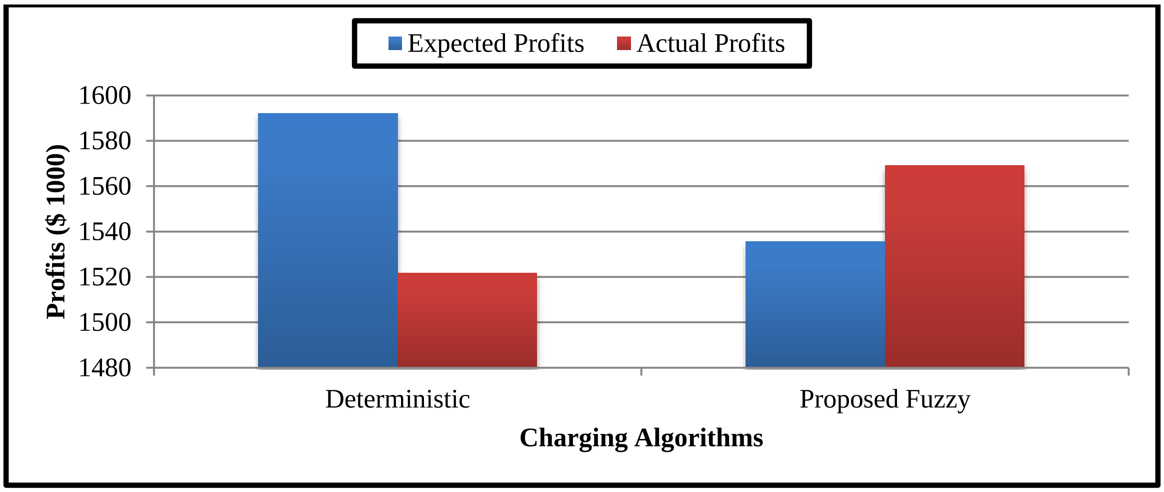

Figure 6-11: Total expected and actual profits of an aggregator

From the EV owner perspective, it is desired to charge the EVs at low energy cost. The average energy price per kWh of energy is shown in Figure 6-12. The fuzzy based algorithm results in a slight reduction in price of 0.2% of that of the deterministic algorithm. This is because in both algorithms, the energy price is taken as deterministic. This proves that the added profits of the fuzzy algorithm come from regulation provision rather than from EV owner increased cost; which is very desirable.

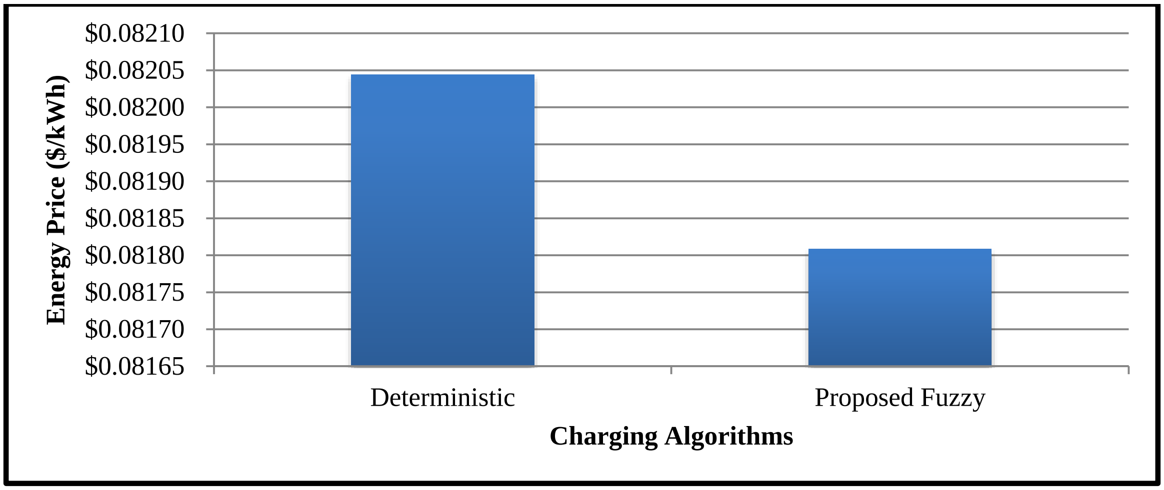

Figure 6-12: Average price per kWh of energy charged to customers

From the power system perspective, the charging of EVs should not stress the power system. The average peak and the peak load increase by deterministic and proposed fuzzy algorithm is shown in Figure 6-13. The proposed fuzzy algorithm results in a slightly lower peak and average peak load than the deterministic algorithm. This shows that the proposed fuzzy algorithm is also supporting the power system network.

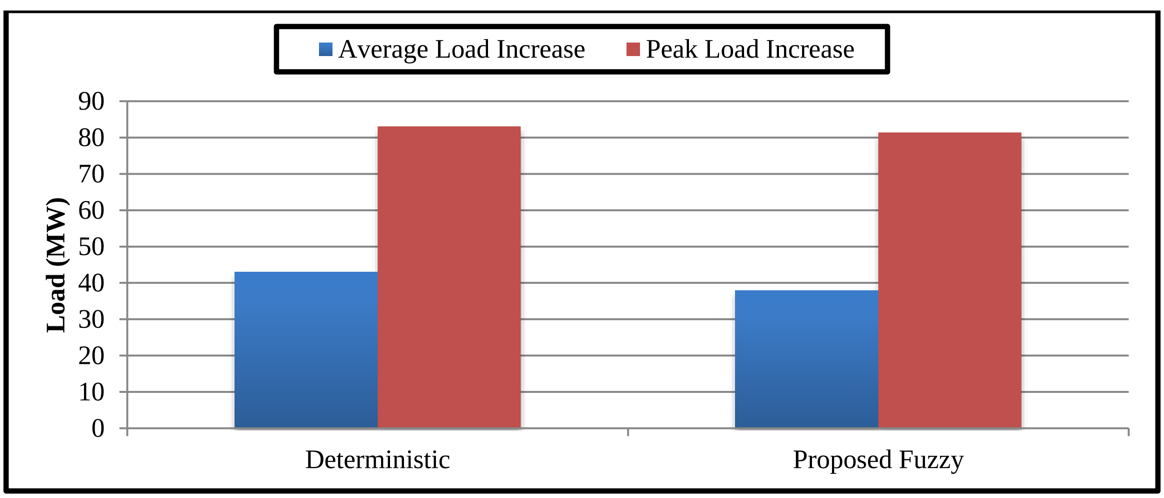

Figure 6-13: Daily average peak and peak load increase by different algorithm due to EV charging

6.4.2 Case # 2: With Load Constraint

In this case, the same optimization problem is solved with an extra load constraint mentioned in (6.30) is added to order to avoid the burdening of the power system network. Both deterministic and proposed fuzzy optimization algorithms are simulated for the same charging period from 8 A.M. to 5 P.M. daily for the three-month period.

6.4.2.1 Charging Profiles

The electric vehicles average POP, regulation up and regulation down capacities are shown in Figure 6-14-Figure 6-16. The deterministic and the proposed algorithms follow the same pattern and bid almost the same capacities for the POP and regulation up except for the first 2-3 charging hours, in which the proposed fuzzy bids a little higher than the deterministic as shown in Figure 6-14 and Figure 6-15.

Both the deterministic and proposed fuzzy algorithm bids the regulation down capacities in a similar fashion and bids highest in the middle of the charging period. The proposed fuzzy algorithms bids a little lower than the deterministic algorithm in every hour as shown in Figure 6-16.

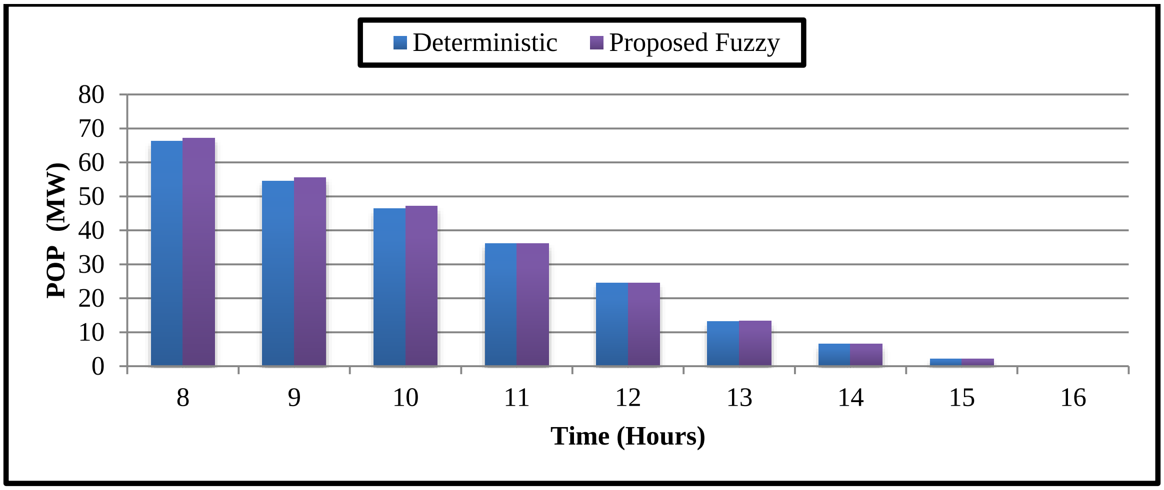

Figure 6-14: Average POP by each algorithm with load constraint

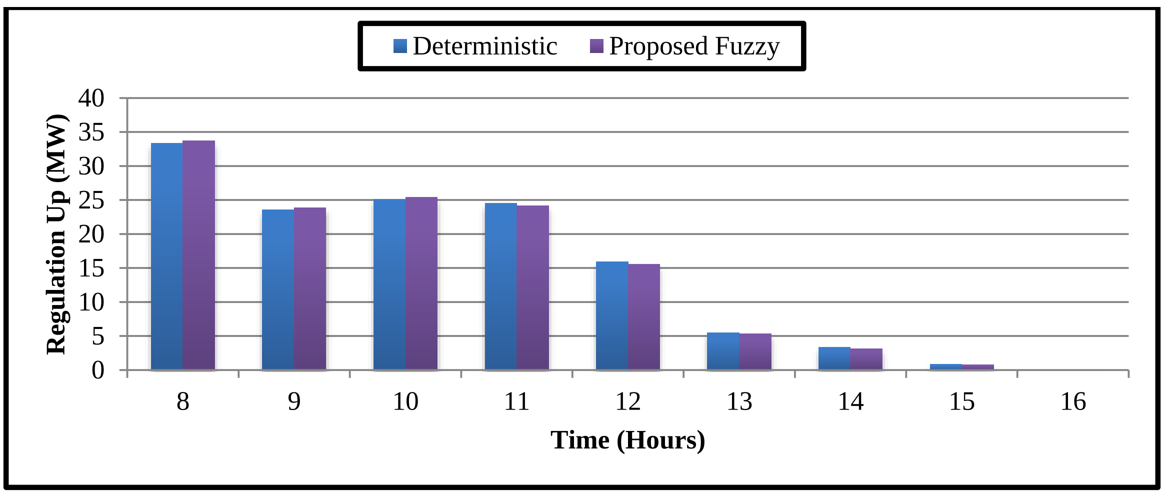

Figure 6-15: Average regulation up by each algorithm with load constraint

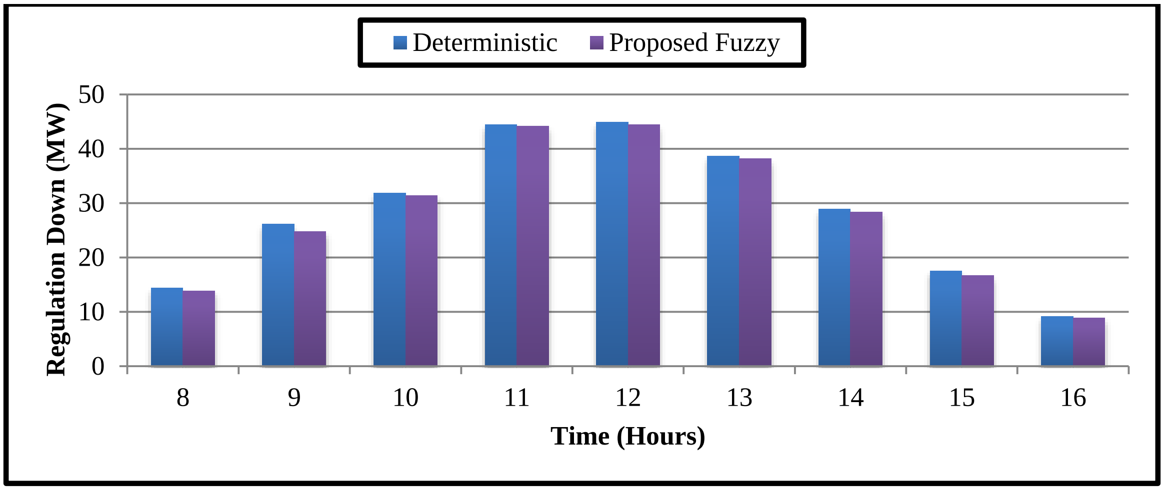

Figure 6-16: Average regulation down by each algorithm with load constraint

6.4.2.2 Quarterly Results

This section presents the aggregator profits for the different algorithms: deterministic and proposed fuzzy. The expected and the actual profits for an average day is shown in Figure 6-17 while Figure 6-18 presents the total expected and actual profits of an aggregator for the three months period.

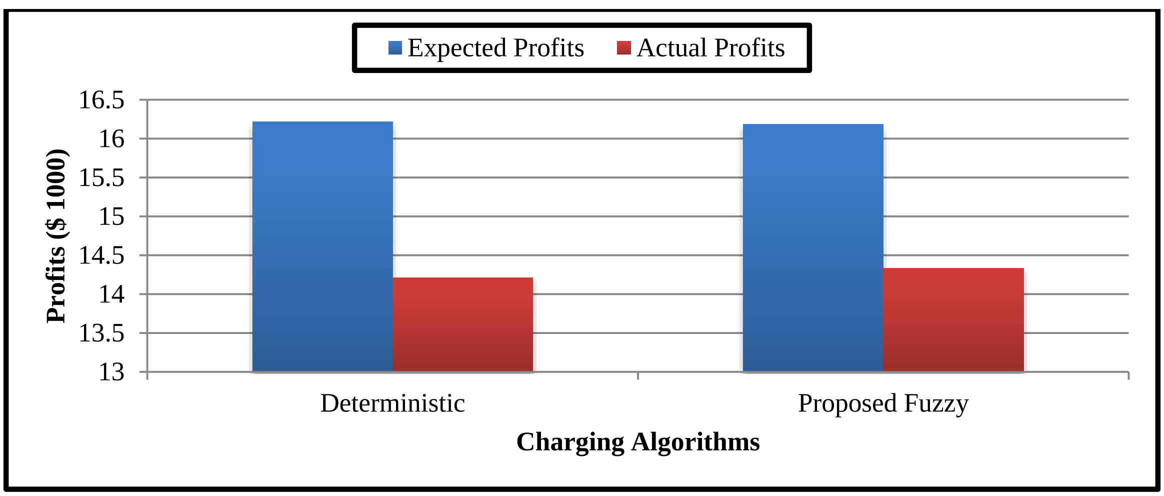

Figure 6-17: Expected and actual profits of an aggregator for an average day with load constraint

With the load constraint added in the optimization, the aggregator expects a little lower profit than the deterministic algorithm in the day-ahead bidding while on the actual day of bidding; the aggregator gets a little higher profit with the use of proposed fuzzy algorithm as compares with the deterministic algorithm.

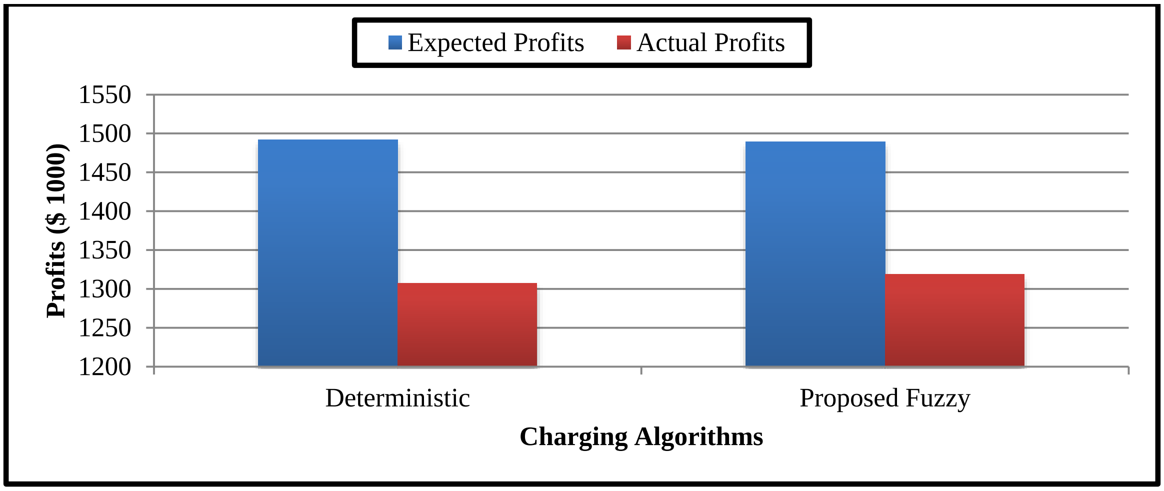

Figure 6-18: Total expected and actual profits of an aggregator with load constraint

It is also desirable to charge the EVs at the lowest price; Figure 6-19 shows the average price charged to EV owners their electric vehicles. The proposed fuzzy algorithm results in 1% higher price as compared with the deterministic algorithm. The price increase by the fuzzy algorithm is not much higher and can result due to the fact that the energy price is considered in the formulation as a deterministic price.

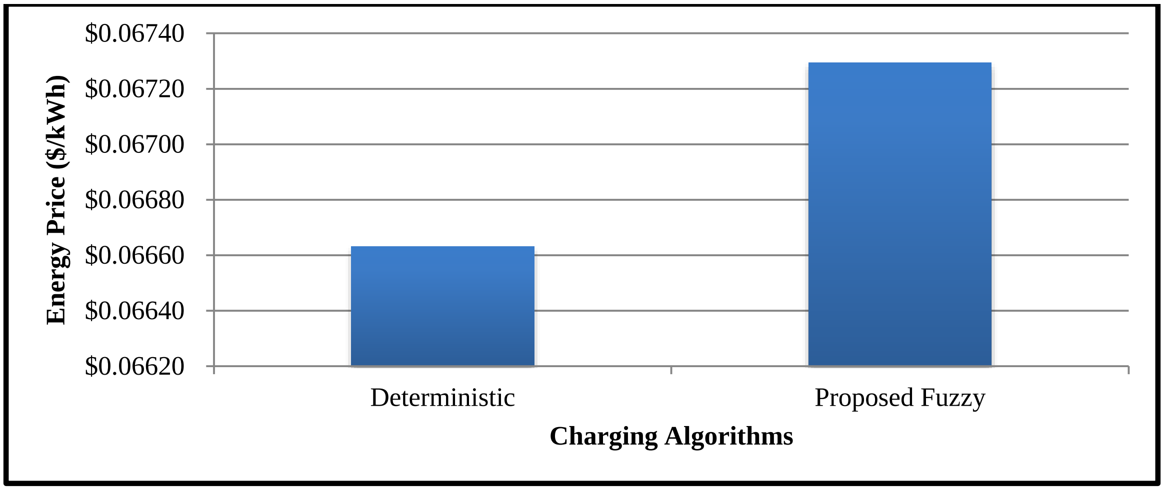

Figure 6-19: Average price per kWh of energy charged to customers with load constraint

The charging of EVs should not stress the power system. The average peak and the peak load increase by deterministic and proposed fuzzy algorithm is shown in Figure 6-20. The proposed fuzzy algorithm results in a slightly lower peak and average peak load than the deterministic algorithm. This shows that the proposed fuzzy algorithm is also supporting the power system network with load constraint also.

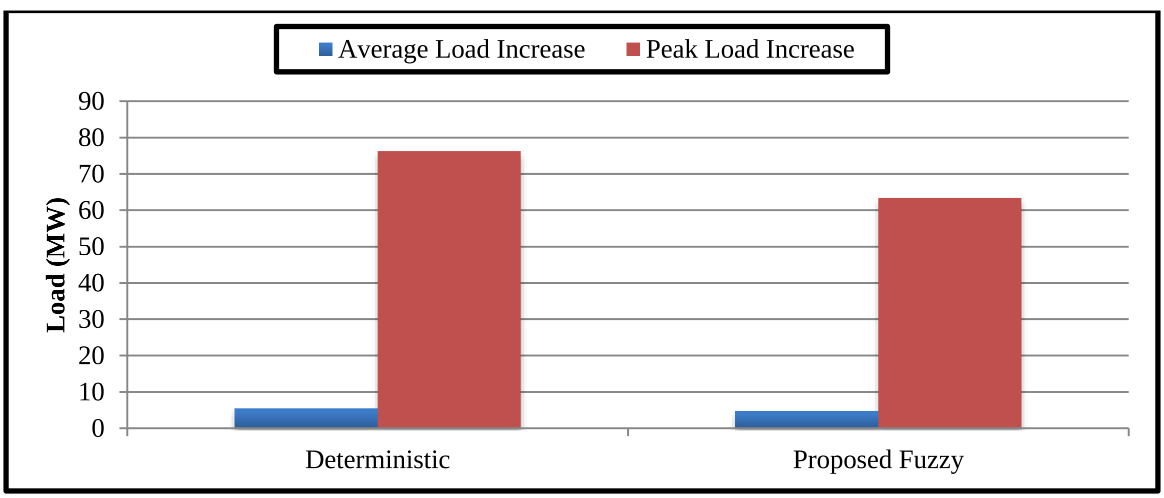

Figure 6-20: Daily average peak and peak load increase by different algorithm due to EV charging with load constraint

6.4.3 Case # 3: With Price Constraint

In this case, the same optimization problem is solved with an extra price constraint mentioned in (6.31) is added to order to avoid the charging of electric vehicles at higher electricity prices. Both the optimization, deterministic and proposed fuzzy algorithm are simulated for the same charging period from 8 A.M. to 5 P.M. daily for a period of three months.

6.4.3.1 Charging Profiles

The charging profiles for the POP, regulation up and down capacities with the price constraint are shown in Figure 6-21-Figure 6-23. The averages POP of the EVs are higher for the proposed fuzzy algorithm in the first 5 hours of the charging periods. In the last 4 charging hours, the deterministic algorithm has higher value of the POP.

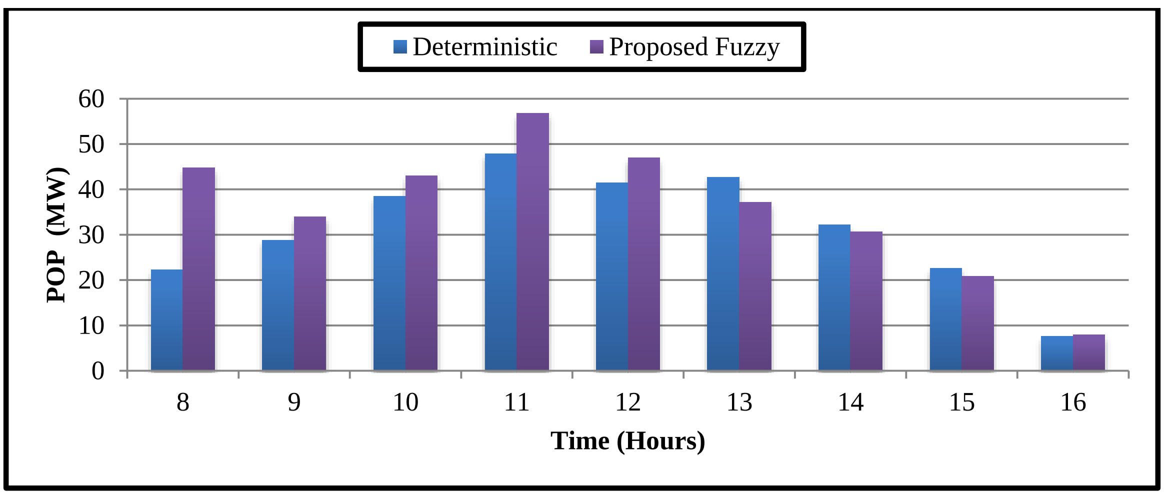

Figure 6-21: Average POP by each algorithm with price constraint

The regulation up bidding capacity of the for the whole charging period is higher for the proposed fuzzy algorithm than the deterministic algorithm as shown in Figure 6-22 while the regulation down capacity is higher for fuzzy algorithm in the first two charging hours and then remains lower as shown in Figure 6-23. The POP, regulation up/down capacities in both the deterministic and proposed fuzzy algorithm almost follows the same pattern.

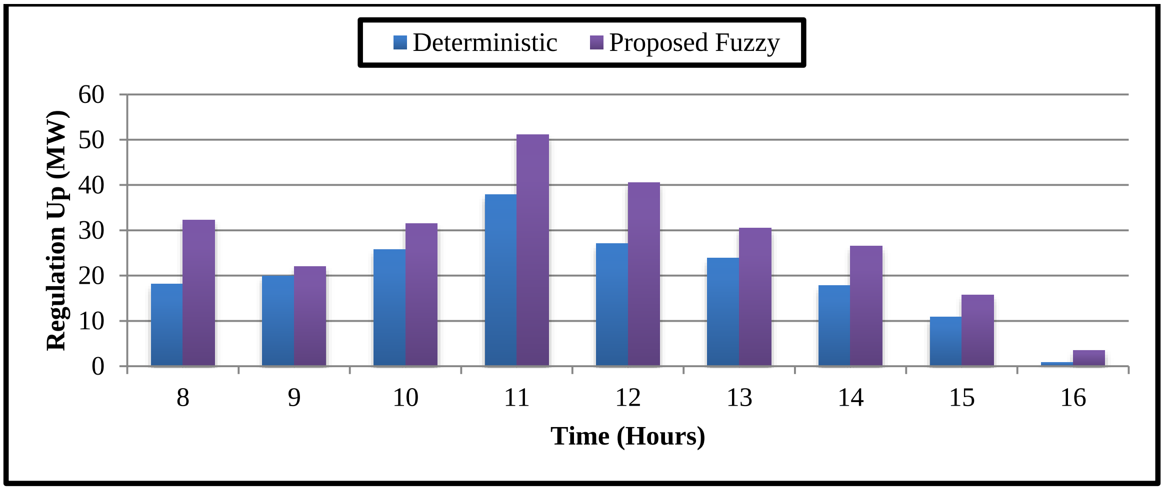

Figure 6-22: Average regulation up by each algorithm with price constraint

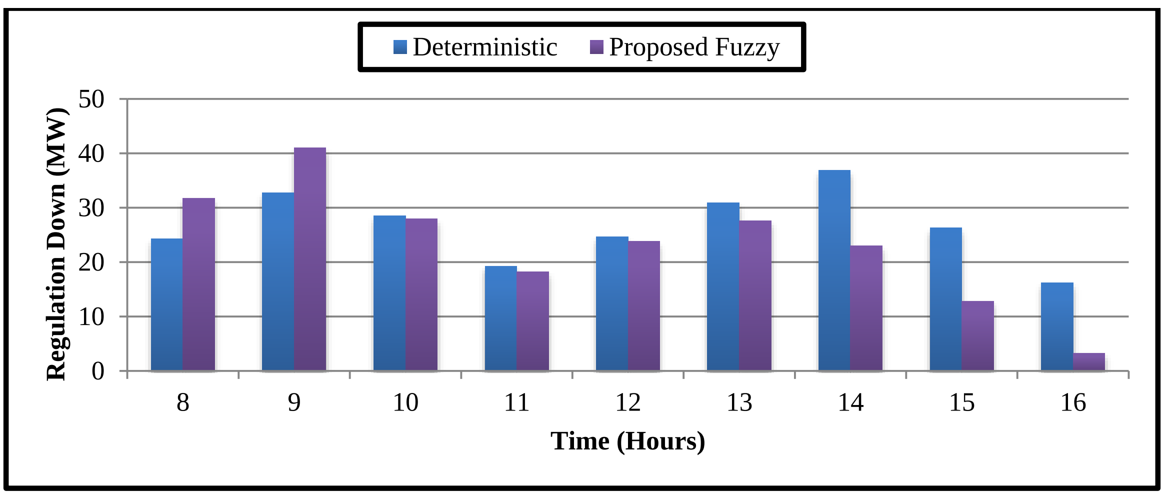

Figure 6-23: Average regulation down by each algorithm with price constraint

6.4.3.2 Quarterly Results

This section presents the aggregator profits for the different algorithms: deterministic and proposed fuzzy. The expected and the actual profits for an average day is shown in Figure 6-24 while Figure 6-25 presents the total expected and actual profits of an aggregator for the three months period.

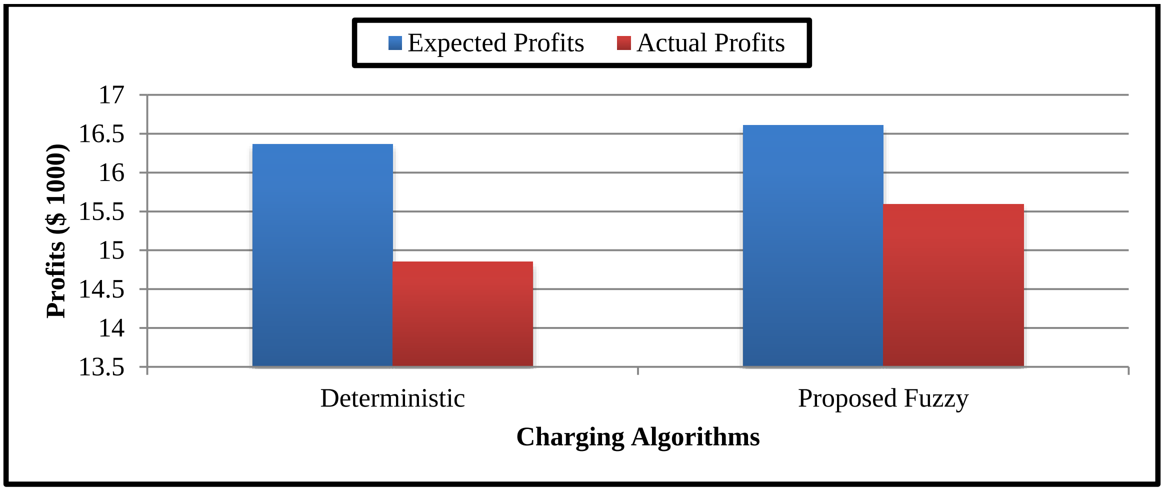

Figure 6-24: Expected and actual profits of an aggregator for an average day with price constraint

With the price constraint added in the optimization, the aggregator expects a higher profit than the deterministic algorithm in the day-ahead bidding and also on the actual day of bidding, the aggregator get a considerable higher profits with the use of proposed fuzzy algorithm as compares with the deterministic algorithm. On the actual day, the aggregator gets 4.75% higher profits with the use of proposed fuzzy algorithm.

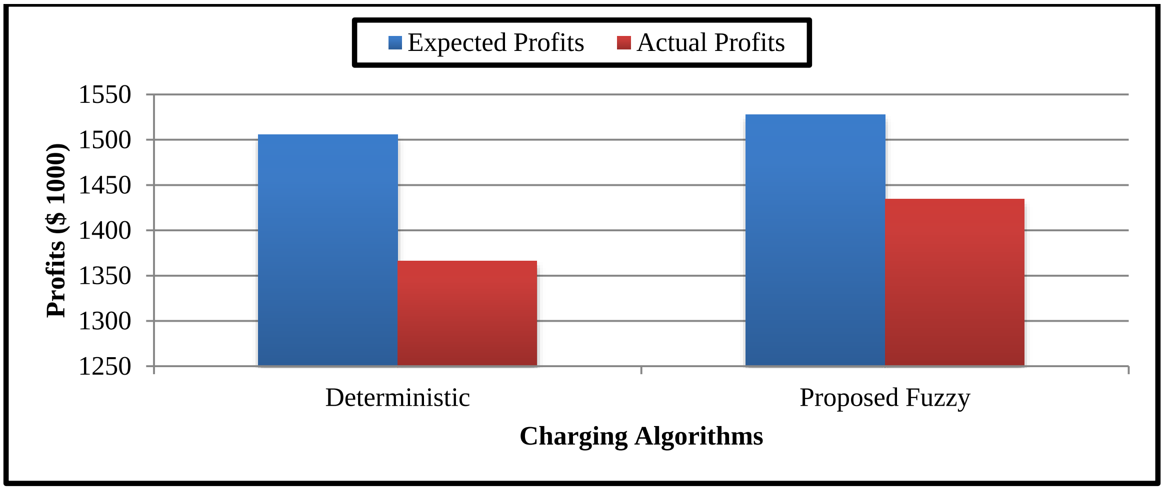

Figure 6-25: Total expected and actual profits of an aggregator with price constraint

Figure 6-26 shows the average price charged to EV owners their electric vehicles. The proposed fuzzy algorithm with the price constraints results in a lower cost. The cost is reduced to around 4% as compared with the deterministic algorithm.

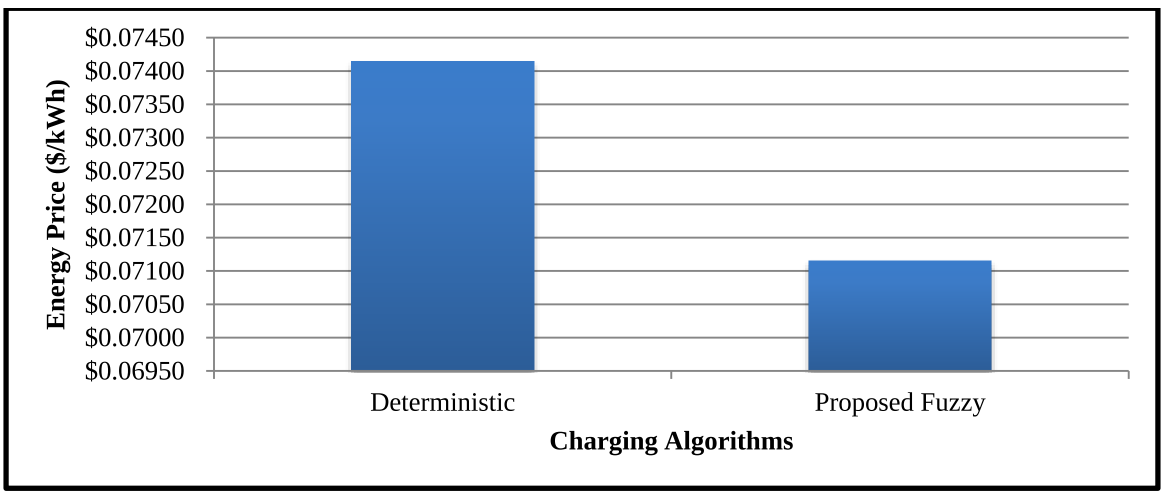

Figure 6-26: Average price per kWh of energy charged to customers with price constraint

The charging of EVs should not stress the power system. The peak and average peak load increase by deterministic and proposed fuzzy algorithm is shown in Figure 6-27. The proposed fuzzy algorithm results in a slightly lower peak and average peak load than the deterministic algorithm. This shows that the proposed fuzzy algorithm is also supporting the power system network with the price constraint also.

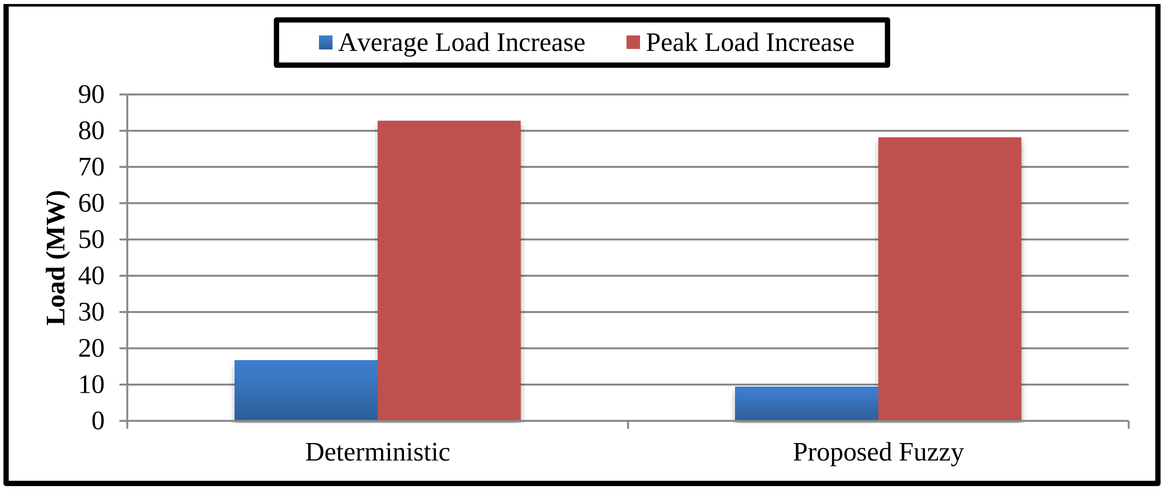

Figure 6-27: Daily average peak and peak load increase by different algorithm due to EV charging with price constraint

6.5 Conclusions

In this chapter, optimal aggregator bidding strategy of regulation services for unidirectional V2G charging is developed with different fuzzy uncertainties. A fuzzy optimization algorithm is proposed for the optimal bidding of regulation capacities by the electric vehicles. Different uncertainties are modeled using fuzzy sets, such as day-ahead regulation up/down prices and deployments. Simulations are performed for the deterministic and proposed fuzzy algorithms that show the benefits of the proposed fuzzy algorithm for the aggregator and the EV owners by taking into account the different market uncertainties. Different case studies were simulated with the price and load constraint to avoid the burdening of the power system network and to charge the electric vehicles at the lower possible cost. It is observed that the highest aggregator profits are obtained without any price/load constraint in the system. Addition of the load constraint in the formulation minimized the impact of EV load on the system and is sometimes necessary for the system security and stability while the additional of price constraint is very beneficial to the EV owner, as EV owner cost has to pay minimum cost for each kWh consumed.

CHAPTER 7

COORDINATED BIDDING OF ANCILLIARY SERVICES FOR UNIDIRECTIONAL VEHICLE-TO-GRID USING FUZZY LINEAR PROGRAMMING (FLP)

In the previous chapter, an optimal charging strategy for electric vehicles using the fuzzy optimization technique was proposed. The aggregator profits for different cases, with deterministic and fuzzy optimization, were calculated considering the different uncertainties. The proposed algorithm, fuzzy based, performed much better than the deterministic algorithm based on the actual day of bidding. Apart from different advantages, the algorithm proposed in the previous chapter was only for nine hour charging period, the spinning reserves (responsive reserves) capacity was ignored, and different uncertainties of the electric vehicles were ignored such as the EV availability, their trip time and durations.

In this chapter, an extension of the previous chapter’s work is done. A novel optimal fuzzy based coordinated charging scheme for unidirectional vehicle-to-grid is proposed. The proposed algorithm optimizes the charging of EVs and the bidding of ancillary services in the electricity market through unidirectional V2G, considering the different electricity market uncertainties. The work presented in this chapter is built upon the work presented in [47], [50], with the incorporation of different market uncertainties and with the modification of the objective function. The fuzzy set theory is used to model the uncertainties in the forecasted data of the electricity market such as those of ancillary services prices including regulation up/down prices and responsive reserve prices, and ancillary services deployment signals. The electricity market parameters are forecasted using the autoregressive integrated moving average (ARIMA) model, also mentioned in the previous chapter, presented in chapter 4. The algorithm is simulated over the same hypothetical group of 10,000 EVs in the real electricity market, Electric Reliability Council of Texas (ERCOT) area as used in the previous chapters. Commuter cars are used in the simulation and the simulation is performed for the whole twenty four hours. It is assumed that the battery SOC at the end of the day will be the initial SOC for batteries next day. Additionally EVs uncertainties are also considered but not in a fuzzy logic framework. Results show the benefit of the proposed fuzzy algorithm against the deterministic algorithm of [50] with no market uncertainty.

7.1 Ancillary Services Algorithm

An EV can supply the ancillary service to the electrical grid by varying its charging rate below or above its scheduled value, or its preferred operating point (POP). This value of the POP is scheduled by the aggregator in the system. The electric vehicles in this chapter have to follow the two algorithms, one for the regulation service and one for the responsive reserves (spinning reserves). The regulation algorithm is the same as mentioned in the previous chapters and shown in Figure 5-1. The details for the regulation algorithm are explained in section 5.1. The algorithm for responsive reserve is shown in Figure 7-1. To perform in the ancillary service market, an EV will first follow the regulation signal and then follow the responsive reserve signal from ISO. The calculated power draw by following the regulation signal will be used as a reference to calculate the EV dispatch for the responsive reserve signal. This will be the total power draw by an EV until the next signal comes from the ISO. Graphical descriptions of different variables are shown in Figure 7-2.

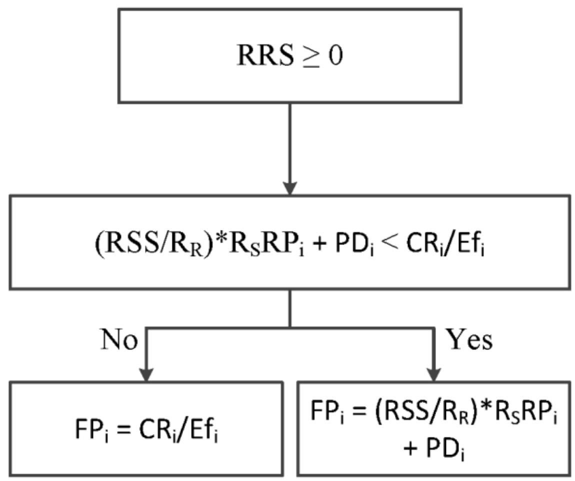

Figure 7-1: Responsive reserve algorithm flowchart [50]

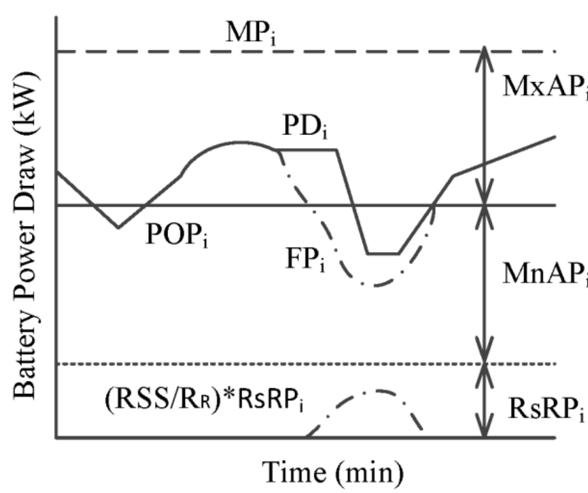

Figure 7-2: Ancillary service signals around the preferred operating point [50]

7.2 Coordinated Charging Algorithm using Fuzzy Linear Programming (FLP)

The ancillary service capacity is based on the extent of moving the actual charging rate of the EVs above or below their assigned POPs. Therefore the aggregator must optimize the value of the POP to maximize the profits. Previously, different optimized charging and bidding algorithms were proposed for the electric vehicles [47], [50], but they mainly lack the modeling of different uncertainties of the electricity market parameters, such as price and ancillary service deployments. In the last chapter, an algorithm is proposed but that algorithm bid the capacity into the market only for nine hour and different EV parameters were not considered. In this chapter, a novel optimized FLP based coordinated bidding of vehicle-to-grid ancillary services is proposed. It charges the electric vehicle as well as bid the ancillary services in the electricity market for the whole day considering the different market uncertainties.

7.2.1 Fuzzy Model - Objective

The main objective of the optimization is to generate maximum revenues from the regulation service by scheduling EV charging. The objective function in this formulation is different and more practical than the objective that was used in Chapter 6. Previously, it was assumed that the aggregator revenues comes from two different sources, first from a fixed percentage of the ancillary services revenue α, and secondly from a fixed percentage of the energy supplied to the customer Mk. While in this chapter, a more realistic objective function is considered i.e. the aggregator income here also comes from two sources; first the aggregator will take all the ancillary services revenue and second supply the energy to the customer at a fixed rate and the variations on the fixed rate and the market energy price will be the aggregator profit. This fixed rate is considered very low i.e. 50% of the kWh domestic energy price (from the ISO or Utility) to attract the EV owners to charge their cars from the aggregator charging station.

The fuzzy objective function is defined as:

$$In = \sum_t \left(\left(P_{regUp} \cdot R_{Up} + P_{regDw} \cdot R_{Dw} + P_{RR} \cdot R_R \right) \cdot EV_{Per} \right) \\ + \beta \sum_t \sum_i \left(\left(E(PD_i) \right) \cdot EV_{Per} \right) \tag{7.1}$$

In this objective function, the aggregator charges fixed price to the customer and purchases the power at market price for the energy and thus assumes the risk associated with real time pricing. The cost function for this condition that is subtracted from the In is given by:

$$C = \sum_i \sum_t \left(E(FD_i) \right) \cdot P(t) \cdot EV_{per} \tag{7.2}$$

The fuzzy set for the aggregator income is defined as:

$$\widetilde{In} = \left\{ [In, \mu_{In}], \underline{In} \leq In \leq \overline{In} \right\} \tag{7.3}$$

The fuzzy set is built using the income In that defines the objective function in (7.1). The possible values of In can be defined through the constraint within the definition of fuzzy set in (7.3). There is a minimum value of In below which the aggregator will not be willing to participate and the membership function is zero at that income and an upper value of In

above which all the income is acceptable. The same limits of In is used as that mentioned in Section 6.2.1.

The membership function In in (7.3) is defined as:

$$\mu_{In} = \begin{cases} 0, & In \leq \underline{In} \\ \dfrac{In - \underline{In}}{\overline{In} - \underline{In}}, & \underline{In} \leq In \leq \overline{In} \\ 1, & In \geq \overline{In} \end{cases} \tag{7.4}$$

This function is graphically presented in Figure 7-3:

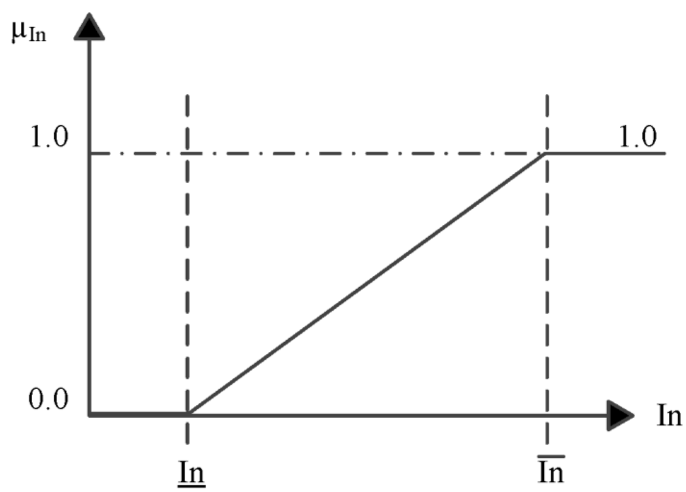

Figure 7-3: Fuzzy model of total aggregator income

7.2.2 Fuzzy Model - Regulation Up/Down Prices

The fuzzy uncertainty model for the regulation up and down prices is considered the same as that mentioned in Section 6.2.4. The same fuzzy model is also used here in this chapter.

7.2.3 Fuzzy Model – Responsive Reserve Prices

The fuzzy uncertainty model of the responsive reserve prices is developed in the same way as regulation up/down model and can be represented as:

$$\widetilde{P_{RR}} = \left\{[P_{RR}, \mu_{RR}], \underline{P_{RR}} \le P_{RR} \le \overline{P_{RR}}\right\} \tag{7.5}$$

This model is developed assuming the same criteria that there is a certain responsive reserve price below which the aggregator will not be willing to participate. The minimum responsive reserve prices should be such that the aggregator is making profits after covering all its expenses. In this work, the uncertainties of the minimum and the maximum responsive reserve prices are estimated using the mean absolute error between the forecasted and actual data using an ARIMA model. The membership function for the price of responsive reserve price is given in (7.6) and the graphical representation is similar to that shown in Figure 7-3.

$$\mu_{RR} = \begin{cases} 0, & P_{RR} \le \underline{P_{RR}} \\ \dfrac{P_{RR} - \underline{P_{RR}}}{\overline{P_{RR}} - \underline{P_{RR}}}, & \underline{P_{RR}} \le P_{RR} \le \overline{P_{RR}} \\ 1, & P_{RR} \ge \overline{P_{RR}} \end{cases} \tag{7.6}$$

7.2.4 Fuzzy Model – Regulation Up/Down Deployments

The expected values of the regulation up/down deployments are calculated in a similar fashion as mentioned in Section 6.2.3. The same models are used and the details can be referred to the previous chapter.

7.2.5 Fuzzy Model – Responsive Reserve Deployments

The expected values of responsive reserve deployments are calculated using the historical deployment signals from ERCOT ISO [69]. The hourly actual averages are calculated and the deviations from the forecasted values (obtained using ARIMA) are calculated so that the membership functions of ExR can be defined. The fuzzy model for the ExR is shown in (7.7) and its membership function is in (7.8).

$$\widetilde{E_{xR}} = \left\{[E_{xR}, \mu_{ExR}], \underline{E_{xR}} \le E_{xR} \le \overline{E_{xR}}\right\} \tag{7.7}$$

$$\mu_{ExR} = \begin{cases} 1, & E_{xR} \le \underline{E_{xR}} \\ \dfrac{\overline{E_{xR}} - E_{xR}}{\overline{E_{xR}} - \underline{E_{xR}}}, & \underline{E_{xR}} \le E_{xR} \le \overline{E_{xR}} \\ 0, & E_{xR} \ge \overline{E_{xR}} \end{cases} \tag{7.8}$$

The graphical representation of the ExR membership function is shown in Figure 7-4. It is similar to the membership function of the regulation up/down deployments.

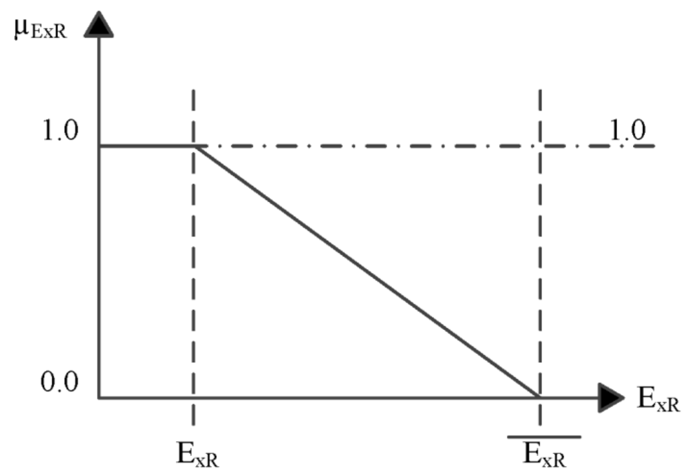

Figure 7-4: Fuzzy model of expected responsive reserves deployments

7.2.6 Complete Coordinated Fuzzy Linear Programming for EV Charging

As the aggregator is a market participant, it will strive for the maximum benefits from its V2G assets. The aggregator profits come from the two sources: ancillary service revenues and from the charging the EVs. The aggregator will get the whole of the ancillary revenues and charge the electric vehicles at a fixed rate, so that there are no variations of the price for the EV owner. The aggregator will, at some time get the profit from this energy variation when energy price is low in the electricity market (lower than the aggregator is charging to EV owner) and sometimes will be at a loss when the energy price is high in the electricity market (higher than the aggregator is charging to EV owner). In the previous formulations presented the aggregator was getting a portion of the ancillary services revenue and a fixed markup over the energy used for EV charging [47], [50].

Previously only deterministic algorithms were proposed [47], [50], but in this chapter uncertainties are considered in a fuzzy set by calculating the forecasting errors in the actual and the historical data of ERCOT ISO for the ancillary services prices and the ancillary service deployments. The membership functions of the income, ancillary services prices and the expected deployments have to be translated into the fuzzy constraints. These transformations are done in (7.9) - (7.16).

$$\begin{aligned} &\lambda \leq \mu_{In} = \frac{In - \underline{In}}{\overline{In} - \underline{In}} \\ &\Rightarrow \left(\overline{In} - \underline{In}\right) \cdot \lambda + \underline{In} \leq In \end{aligned} \tag{7.9}$$

$$\begin{aligned} &\lambda \leq \mu_{regUp} = \frac{P_{regUp} - \underline{P_{regUp}}}{\overline{P_{regUp}} - \underline{P_{regUp}}} \\ &\Rightarrow \left(\overline{P_{regUp}} - \underline{P_{regUp}}\right) \cdot \lambda + \underline{P_{regUp}} \leq P_{regUp} \end{aligned} \tag{7.10}$$

$$\lambda \le \mu_{regDw} = \frac{P_{regDw} - \underline{P_{regDw}}}{\overline{P_{regDw}} - \underline{P_{regDw}}}$$
$$\Rightarrow \left(\overline{P_{regDw}} - \underline{P_{regDw}}\right) \cdot \lambda + \underline{P_{regDw}} \le P_{regDw} \tag{7.11}$$

$$\lambda \le \mu_{RR} = \frac{P_{RR} - \underline{P_{RR}}}{\overline{P_{RR}} - \underline{P_{RR}}}$$
$$\Rightarrow \left(\overline{P_{RR}} - \underline{P_{RR}}\right) \cdot \lambda + \underline{P_{RR}} \le P_{RR} \tag{7.12}$$

$$\lambda \le \mu_{ExU} = \frac{\overline{E_{xU}} - E_{xU}}{\overline{E_{xU}} - \underline{E_{xU}}}$$
$$\Rightarrow \left(\overline{E_{xU}} - \underline{E_{xU}}\right) \cdot \lambda + E_{xU} \le \overline{E_{xU}} \tag{7.13}$$

$$\lambda \le \mu_{ExD} = \frac{\overline{E_{xD}} - E_{xD}}{\overline{E_{xD}} - \underline{E_{xD}}}$$
$$\Rightarrow \left(\overline{E_{xD}} - \underline{E_{xD}}\right) \cdot \lambda + E_{xD} \le \overline{E_{xD}} \tag{7.14}$$

$$\lambda \le \mu_{ExR} = \frac{\overline{E_{xR}} - E_{xR}}{\overline{E_{xR}} - \underline{E_{xR}}}$$
$$\Rightarrow \left(\overline{E_{xR}} - \underline{E_{xR}}\right) \cdot \lambda + E_{xR} \le \overline{E_{xR}} \tag{7.15}$$

$$\lambda = min\{\mu_{In}, \mu_{regUp}, \mu_{regDw}, \mu_{RR}, \mu_{ExU}, \mu_{ExD}, \mu_{ExR}\} \tag{7.16}$$

The complete coordinated fuzzy formulation (OptcoFuzzy) is stated below:

$$Maximize\ \lambda \tag{7.17}$$

Subject to:

$Aggregator\ Income\ of$ (7.1)

$Aggregator\ Income\ fuzzy\ constraint\ of$ (7.9)

$Regulation\ up\ price\ fuzzy\ constraint\ of$ (7.10)

$Regulation\ down\ price\ fuzzy\ constraint\ of$ (7.11)

$Responsive\ reserve\ price\ fuzzy\ constraint\ of$ (7.12)

$Expected\ regulation\ up\ fuzzy\ constraint\ of$ (7.13)

$Expected\ regulation\ down\ fuzzy\ constraint\ of$ (7.14)

$Expected\ regulation\ down\ fuzzy\ constraint\ of$ (7.15)

$$R_{Up}(t) = \sum_{i=1}^{cars} MnAP_i(t) \tag{7.18}$$

$$R_{Dw}(t) = \sum_{i=1}^{cars} MxAP_i(t) \tag{7.19}$$

$$R_R(t) = \sum_{i=1}^{cars} RsRP_i(t) \tag{7.20}$$

$$\sum_{t=1}^{T_{trip,i}} E\big(FD_i(t)\big) \cdot Comp_i(t) + SOC_{I,i} \leq M_{ci} \tag{7.21}$$

$$\sum_{t} E\big(FD_i(t)\big) \cdot Comp_i(t) + SOC_{I,i} - Trip_i \leq M_{ci} \tag{7.22}$$

$$\big(MxAP_i(1) + POP_i(1)\big) \cdot Comp_i(1) \cdot Ef_i + SOC_{I,i} \leq M_{ci} \tag{7.23}$$

$$RsRP_i(t) \ \leq POP_i(t) - MnAP_i(t) \tag{7.24}$$

$$\big(MxAP_i(t) + POP_i(t)\big) \cdot Comp_i(t) \ \leq MP_i \cdot Av_i(t) \tag{7.25}$$

$$Comp_i(t) = 1 + \frac{Dep_i(t)}{1 - Dep_i(t)} \tag{7.26}$$

$$EV_{PER}(t) = \begin{cases} 1 - \sum_{t=1}^{t} \sum_{i} Dep_i(t)\,, & if\ t\ < T_{trip,i} \\ 1 - \sum_{t=T_{trip}}^{t} \sum_{i} Dep_i(t)\,, & if\ t \geq T_{trip,i} \end{cases} \tag{7.27}$$

$$MxAP_i(t) \geq 0 \tag{7.28}$$

$$MnAP_i(t) \geq 0 \tag{7.29}$$

$$RsRP_i(t) \geq 0 \tag{7.30}$$

$$POP_i(t) \geq 0 \tag{7.31}$$

$$\begin{aligned} E\big(FP_i(t)\big) = MxAP_i(t) \cdot E_{xD} + POP_i(t) - MnAP_i(t) \cdot E_{xU} \\ - RsRP_i(t) \cdot E_{xR} \end{aligned} \tag{7.32}$$

In this fuzzy optimization, the objective is to maximize the minimum membership of the fuzzy variables and, thus, maximize the aggregator profits. The cost of aggregator such as charging station infrastructure cost and other running costs such as communication and personnel are assumed to be fixed and are considered as negligible.

The optimization formulation is constrained by the battery capacities as incorporated in (7.21) - (7.23). Equation (7.21) constraints that the total battery charged must be less than or equal to the battery capacity until the first commute trip. Equation (7.22) included the energy lost while commuting the EV, the effect of driving the EV in incorporated here. Equation (7.23) limits that the battery should not be charged before the end of the scheduling period. The equations (7.24) - (7.25) are due to the rate limitations. Unlike the previous chapter and other formulations [47], there is an availability factor $Av_i(t)$ that is used. As this formulation is considered for the whole day, the EV availability and trip times have to be considered. If the EV in not available, EV is on a trip, then $Av_i(t) = 0$ and that particular EV will not participate in the bidding. If the EV is available, EV is available on charging station, then $Av_i(t) = 1$ and that particular EV will be available for bidding in the market.

The driving profiles of the electric vehicles can be predicted with significant certainty if there is a considerable number of EVs available. This must be accounted to by the aggregator in order to ensure that the EVs always have the capacity to follow the deployment signal from the ISO even if a certain number of EVs have unexpectedly departed. For a large number of EVs, this is statistically predictable [50]. Equation (7.26) and (7.27) takes care of the unexpected EV departure and the compensation factor used for that unexpected departure. Equation (7.28) - (7.31) are related to the EV battery capacity. The constraint in equation (7.32) shows that expected energy received is a function of the bidding parameters i.e. POP, regulation up capacity, regulation down capacity and the responsive reserve capacity.

In order to avoid the excess burdening the power system network with the charging of electric vehicles, the load-constrained can be added to the optimization problem as follows:

$$\sum_{i=1}^{cars} POP_i(t) = \frac{M_{lx} - L(t)}{M_{lx} - M_{ln}} \sum_{i=1}^{cars} MP_i \tag{7.33}$$

Similarly, in order to charge the EVs at a lower energy price, the following constraint can be added. This constraint will be an added advantage to the aggregator as it will be charging the EVs at time of lower energy cost.

$$\sum_{i=1}^{cars} POP_i(t) = \frac{M_{px} - P(t)}{M_{px} - M_{pn}} \sum_{i=1}^{cars} MP_i \quad (7.34)$$

7.3 Case Study

The simulations are performed for a period of three months from 21st July, 2010 to 20th Oct, 2010. All the simulations are done on the ERCOT area with a hypothetical group of 10,000 EVs used by commuters [69]. The system is simulated on Matlab using CVX toolbox to solve the optimization problem [84]. Each day simulation starts at 6 A.M. in the morning and ends at 6 A.M next day morning. The final SOC of the EVs on the simulation day will be the initial SOC for the next day. Electricity Market parameters such as energy price, load and the ancillary service signals are taken from the ERCOT database for the simulation period. Ancillary service deployments are taken for five minute resolutions because of the available data, but an EV can follow the deployment signals of much higher resolution [29], [30]. The day-ahead load of the ERCOT system is generated in a similar manner as mentioned in [77].

The electricity market parameters, such as ancillary service prices and deployments are forecasted using autoregressive integrated moving average (ARIMA) model. This includes the parameters, such as regulation up/down prices, responsive reserve prices, expected regulation up/down deployments and expected responsive reserve deployments. The hourly expected percentages of the ancillary service capacity is calculated for the historic data using the formulation presented in [47], [50] and then the forecast is done using ARIMA as presented in chapter 4. After forecasting the parameters, the mean absolute error between forecasted and actual values are calculated to incorporate these forecasting inaccuracies into the fuzzy formulation. The mean absolute errors of the forecasted data are shown in Table 7-1.

Table 7-1 Mean absolute percentage error of forecasted quantities over simulated period

Electricity Market Parameters	**MAP Errors**
Regulation Up Prices	8.327 %
Regulation Down Prices	9.5831 %
Responsive Reserve Prices	6.777%
Regulation Up Deployments	28.48 %
Regulation Down Deployments	31.327 %
Responsive Reserve Deployments	24.77 %

In this simulation study, the same EV data is used as mentioned in the previous chapter. Three different kinds of EVs that are available in the market are considered: Nissan Leaf, Mitsubishi i-MiEV and Tesla Model-S. Battery specifications, EV performance and other specifications are given in [79]–[83]. Among this hypothetical group, it is assumed that 50% of EVs are Nissan Leaf, 20% are Mitsubishi i-MiEV and 30% are Tesla Model-S. It is also assumed that each EV has a charging efficiency of 90%. Previously EV with SOC greater than 95% were considered in the simulations, but in this study all the EV are considered in the optimization problem. All the EVs that are used in these simulations can be charged from a standard 240V supply, and it is assumed that the charger has an efficiency of 90%.

Each EV is assigned a random driving profile from the 2009 National Household Travel Survey data [85]. The EV commute times, morning and evening, commute durations, EV unexpected departures probabilities and additional trips are considered in a similar manner as mentioned in [50]. In the previous chapter's study, 500 driving profile were considered, but in this study 100 EV driving profiles are considered to save the computation time.

Two types of simulation studies are performed and compared: deterministic and the proposed fuzzy based as was done in the previous chapter. Using each algorithm, expected day-ahead aggregator profits are obtained by evaluating the corresponding objective function. To further assess the effectiveness of the proposed FLP formulation, the actual aggregator profits on the bidding day are calculated for both the deterministic and proposed fuzzy algorithms. The actual aggregator profits are calculated from the algorithm presented in Figure 5-1 and Figure 7-1. The actual aggregator profits are calculated using the actual bidding day market parameters such as energy price, ancillary service prices and the ancillary service deployments while the expected profits are calculated using the proposed FLP with forecasted market parameters.

The aggregator profit, as mentioned previously, comes from two different sources; ancillary service revenues and from the variation between the market and fixed (to the EV owner) energy price. The energy cost for the EV owner is fixed at $0.05/kWh. This low cost of energy for EV charging is considered to attract the EV owner to charge their EV form the aggregator charging infrastructure and also the EV owner will not be exposed to the energy price variations.

7.4 Results and Discussions

The deterministic and the proposed fuzzy optimization are performed for three different cases:

- With no load and price constraint in the optimization.
- With load constraint included in the optimization.
- With price constraint included in the optimization.

The first case results in the highest aggregator profits as there is no additional constraint in the optimization problem that can minimize the profits. The load constraint is not a problem for the aggregator as the main goal of the aggregator is to maximize profits, not maintaining the balancing in the power system, but the system operator can impose this limit on the aggregator to avoid the system collapse. In these simulations, as the objective function is changed, the price constraint can be advantageous to the aggregator as the EVs will be charged when energy price is low and the EV is charged a fixed rate for the charging.

7.4.1 Case # 1: With no Load and Price Constraint

The deterministic and the proposed fuzzy based algorithms are run each day from 6 A.M. to 6 A.M. next day for the period of three months. During this period, it is considered that there is no difference between the weekdays and weekends. All the vehicles are assumed to be available, as per the availability factor, during the simulation period.

7.4.1.1 Charging Profiles

The charging profiles and the ancillary services provided by each algorithm are compared for 2nd August, 2010. This day is selected because it better reflects the price variations; prices are not much random on this day. The hourly ancillary service prices are shown in Figure 7-5. All the prices are higher in the late afternoon. The POP and ancillary service capacities are shown in Figure 7-6 - Figure 7-9.

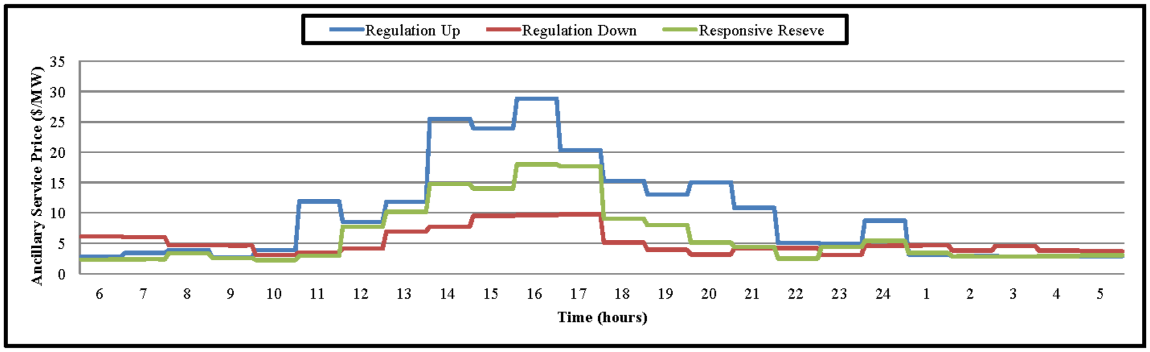

Figure 7-5: Hourly ancillary service prices for 2nd Aug, 2010

The POP of the EVs are usually set to a higher value at the end of the simulation day, to keep the EVs participate in the market for the whole day. If they are fully charged, then they will not be able to participate later. The POP is also set at the mid of the day before its commute time, so that the EV are charged for that particular commute.

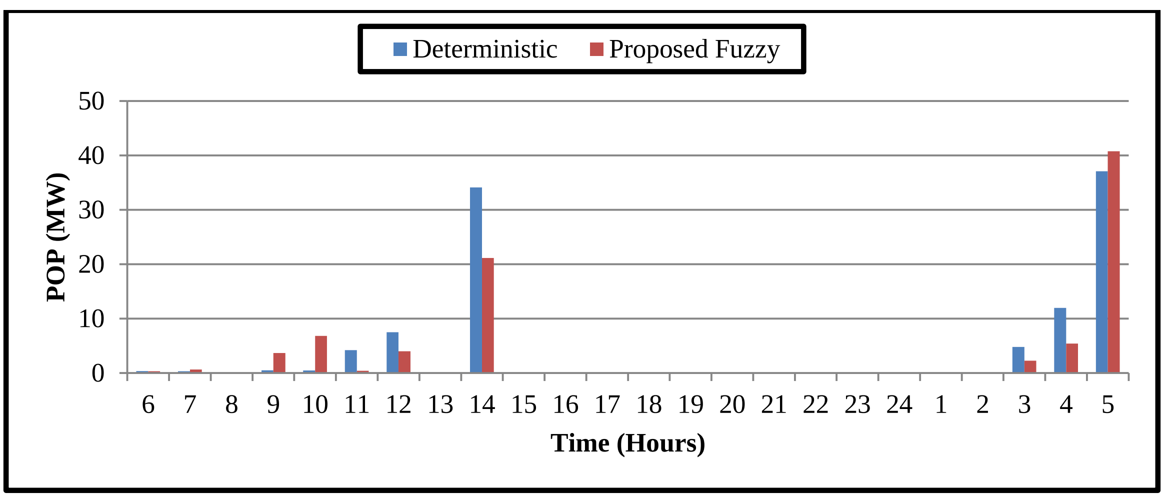

Figure 7-6: POP by each algorithm on 2nd Aug, 2010

The regulation up capacity is highest in the afternoon, so both the algorithms bid regulation up at the afternoon period. The deterministic algorithm bids very little regulation up while the fuzzy algorithm has bid almost 21 MW at 2 P.M. The regulation down capacity is shown in Figure 7-8. Both the algorithms have the same trend. The regulation down capacity is mostly sold at the night time while there is a local maxima at 12 P.M. in the day. The fuzzy algorithm bids higher regulation capacity as compared with the deterministic one. The responsive reserve capacity is sold at the end of the simulation period to completely charge the EVs.

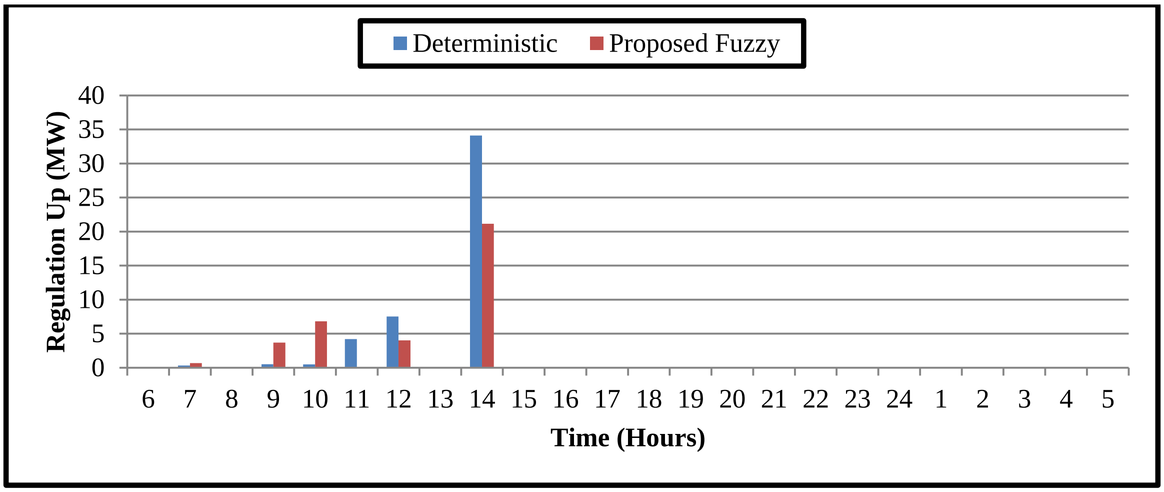

Figure 7-7: Regulation up by each algorithm on 2nd Aug, 2010

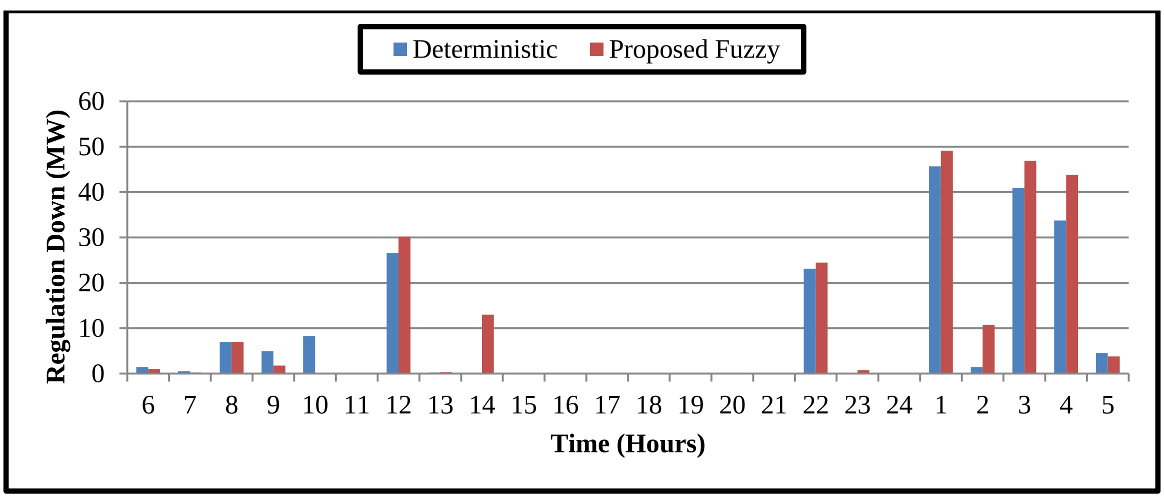

Figure 7-8: Regulation down by each algorithm on 2nd Aug, 2010

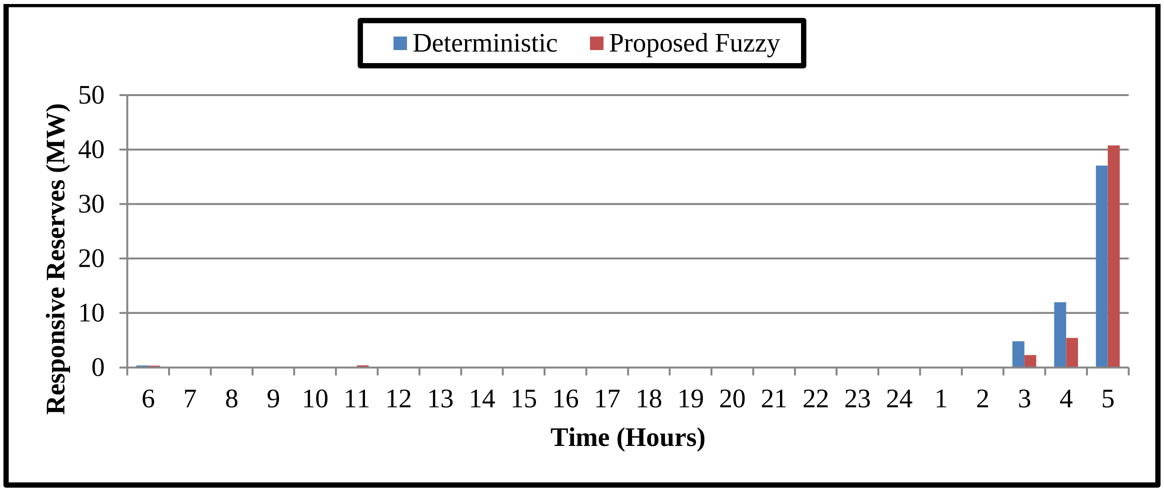

Figure 7-9: Responsive reserve by each algorithm on 2nd Aug, 2010

The POP for an average day is shown in Figure 7-10. Both the algorithms almost follow the same pattern and keep the POP to a lower value in the early six hours and in the middle of the day set a little higher value. But both the algorithms set the POP to be highest at the end of the simulation day i.e. 6 A.M. next day. This is because if the EV are charged at the start of the simulation day, they will be not be able to participate in the bidding later.

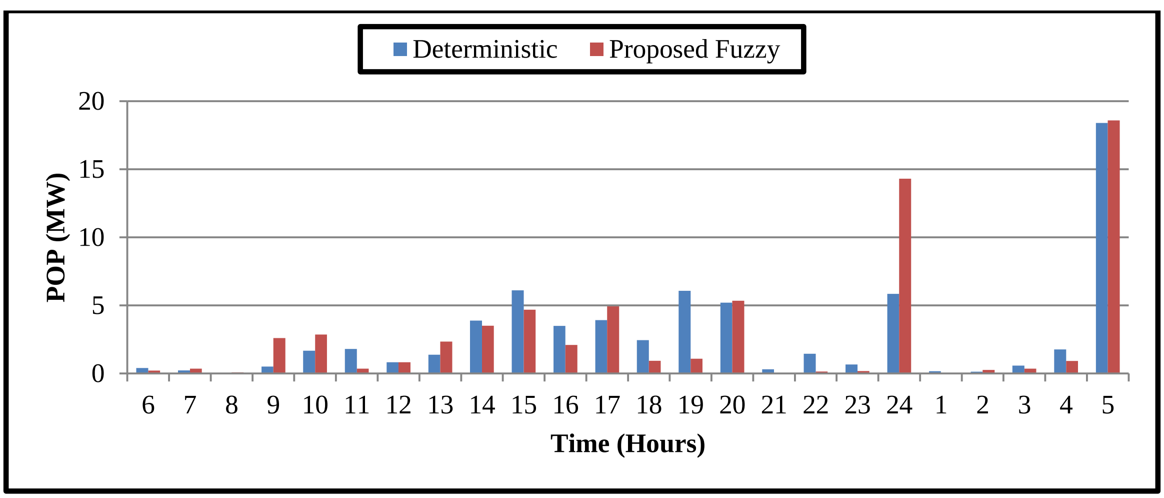

Figure 7-10: Average POP by each algorithm

The ancillary services by the algorithms are shown in Figure 7-11 - Figure 7-13. In the average regulation up, sometime the deterministic algorithm bids higher than the proposed fuzzy algorithm and sometime vice versa. The average regulation down capacity is shown in Figure 7-12. The deterministic algorithm and the fuzzy algorithm both follows the same pattern and bids in almost every hour. In almost every hour, the proposed fuzzy algorithm is a little higher than deterministic algorithm. As the electric vehicles make their first trip after 8 A.M. so the regulation capacities before the 8 A.M. is usually zero.

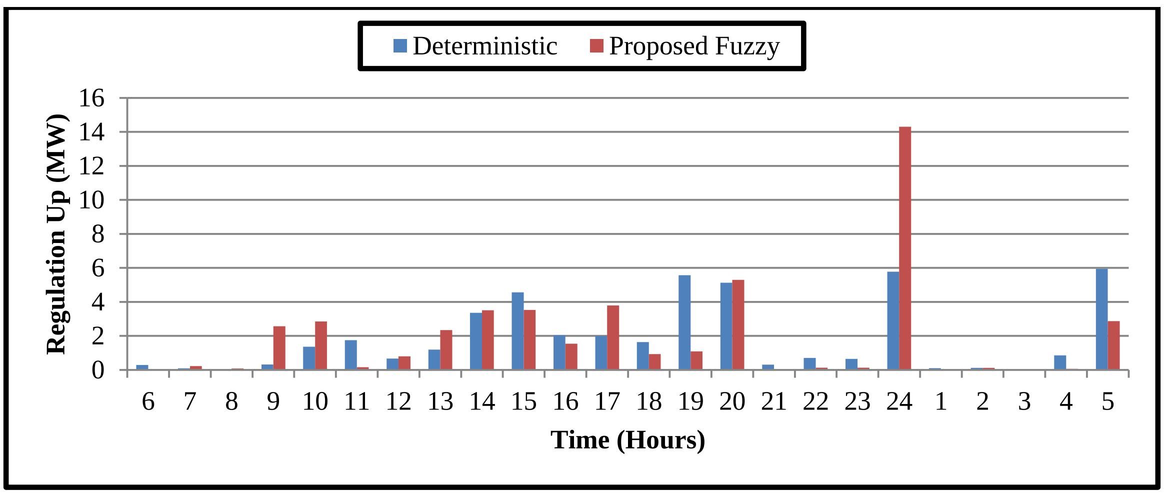

Figure 7-11: Average regulation up by each algorithm

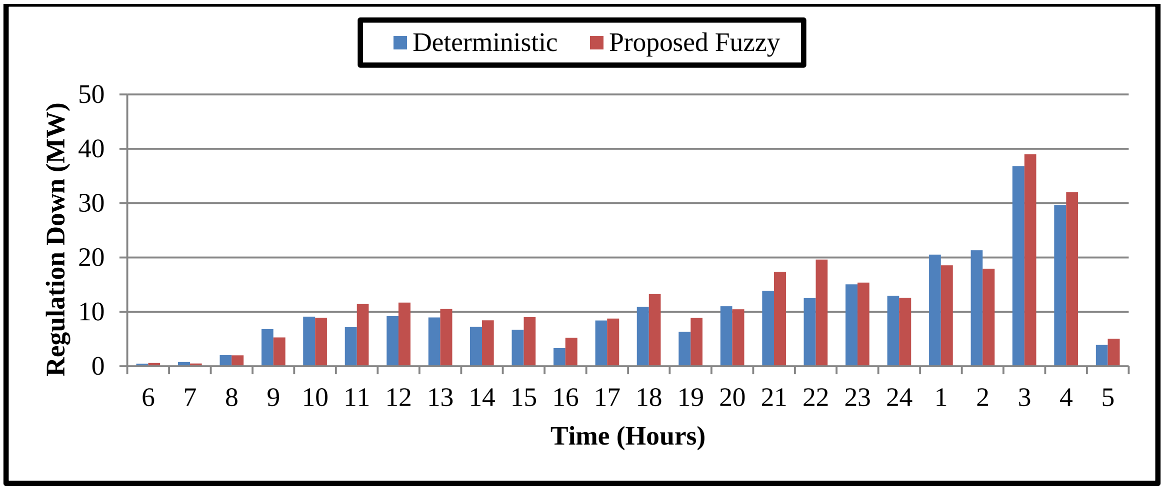

Figure 7-12: Average regulation down by each algorithm

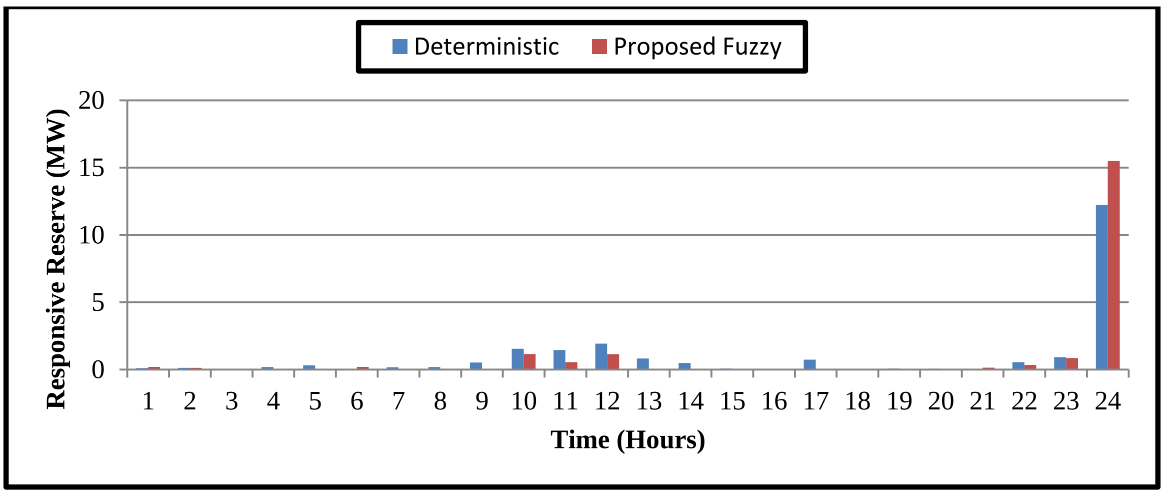

Figure 7-13: Average responsive reserve down by each algorithm

The responsive reserve capacity is shown in Figure 7-13. Both the deterministic and the proposed fuzzy algorithms mainly bid the responsive reserve at the end of the charging period to make the electric vehicles charge close to 100%.

7.4.1.2 Quarterly Results

The section analyzes the expected and actual profits of an aggregator for the deterministic and proposed fuzzy based algorithms. Figure 7-14 shows the comparisons of the expected and actual profit of an aggregator for an average day. Although the deterministic algorithm expected profits are higher than the fuzzy algorithm, the actual profits of the fuzzy algorithm end up higher by about 6.22% than the deterministic actual profits. This shows the superiority of the proposed algorithm.

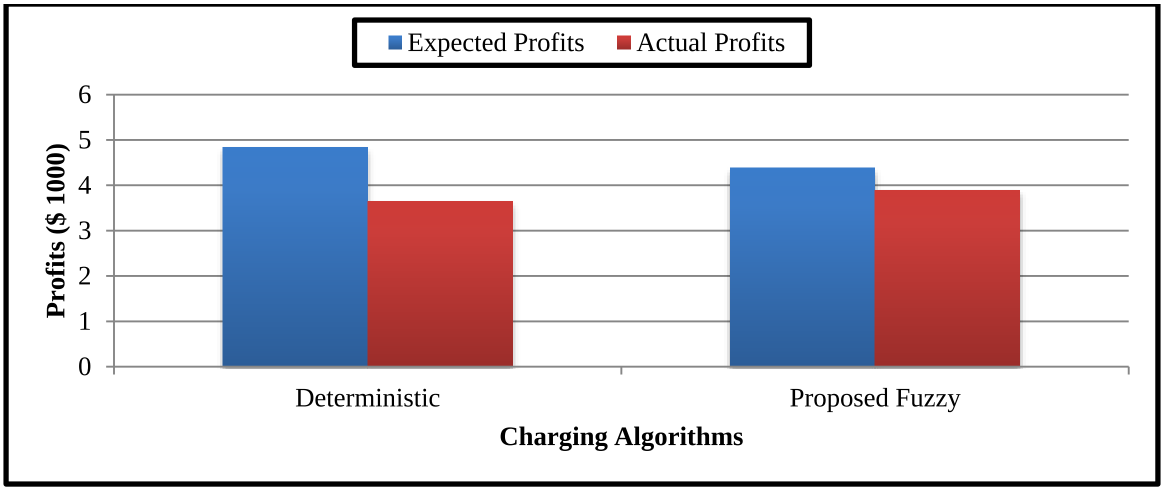

Figure 7-14: Expected and actual profits of an aggregator for an average day

When comparing the aggregator profits on the whole simulation period of three months, the expected aggregator profits comes out to be $ 444.932k which is 9.39% higher than the expected proposed fuzzy profits while on the actual bidding day, the proposed fuzzy generates more profits i.e. $ 357.99k which is 6.21% higher than the deterministic actual profits and 11.2% less than the expected fuzzy profits. On the actual day, the fuzzy algorithm performs better than deterministic algorithm. This is evident from Figure 7-15.

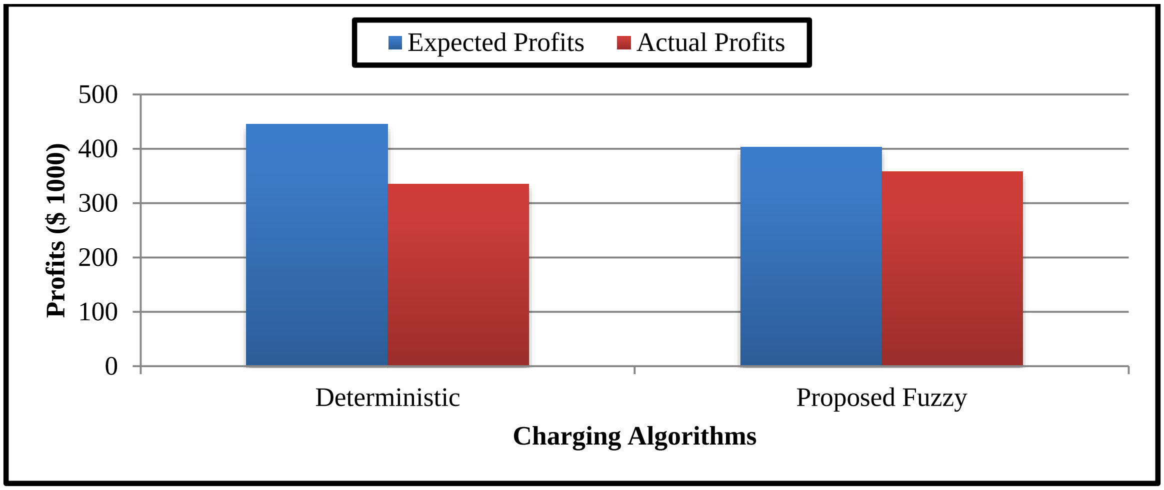

Figure 7-15: Total expected and actual profits of an aggregator

From the power system perspective, the charging of EVs should not stress the power system. The peak and the average peak load increase by deterministic and proposed fuzzy algorithm is shown in Figure 7-16. The proposed fuzzy algorithm results in a slightly higher peak load (about 4MW increase), while the average peak load increase is the same as that of deterministic algorithm. This shows that the added advantage, of aggregator using this fuzzy algorithm is slightly burdening the power system.

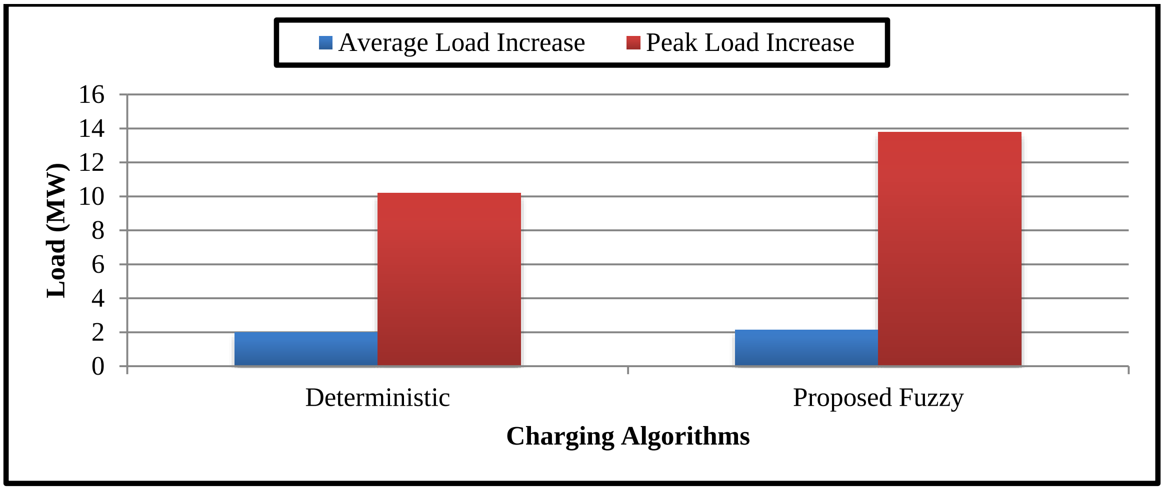

Figure 7-16: Daily average peak and peak load increase by different algorithm due to EV charging

7.4.2 Case # 2: With Load Constraint

In this case, the same optimization problem is solved with an extra load constraint mentioned in (7.33) is added to order to avoid the burdening of the power system network. Both the optimization, deterministic and proposed fuzzy algorithm are simulated for the same charging period from 6 A.M. to 6 A.M. next day for a period of three months.

7.4.2.1 Charging Profiles

The electric vehicles average POP, ancillary service capacities are shown in Figure 7-17. The POP almost follows the same pattern as that of the previous case and bids the most at the end of the simulation day and bids very small capacity during the day.

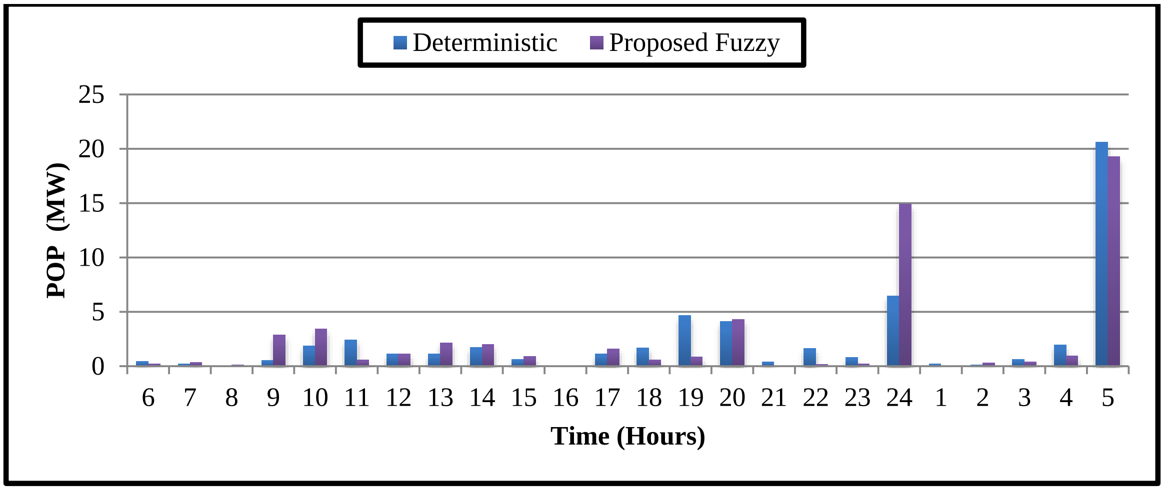

Figure 7-17: Average POP by each algorithm with load constraint

The ancillary services by the algorithms are shown in Figure 7-18 - Figure 7-20. In the average regulation up, sometime the deterministic algorithm bids higher than the proposed fuzzy algorithm and sometime vice versa. The average regulation down capacity is shown in Figure 7-19. The deterministic algorithm and the proposed fuzzy algorithm both follows the same pattern and bids in almost every hour. The proposed fuzzy algorithm is a little higher than deterministic algorithm except a few hours. As the electric vehicles make their first trip after 8 A.M. so the regulation capacities before the 8 A.M. is usually zero or very low.

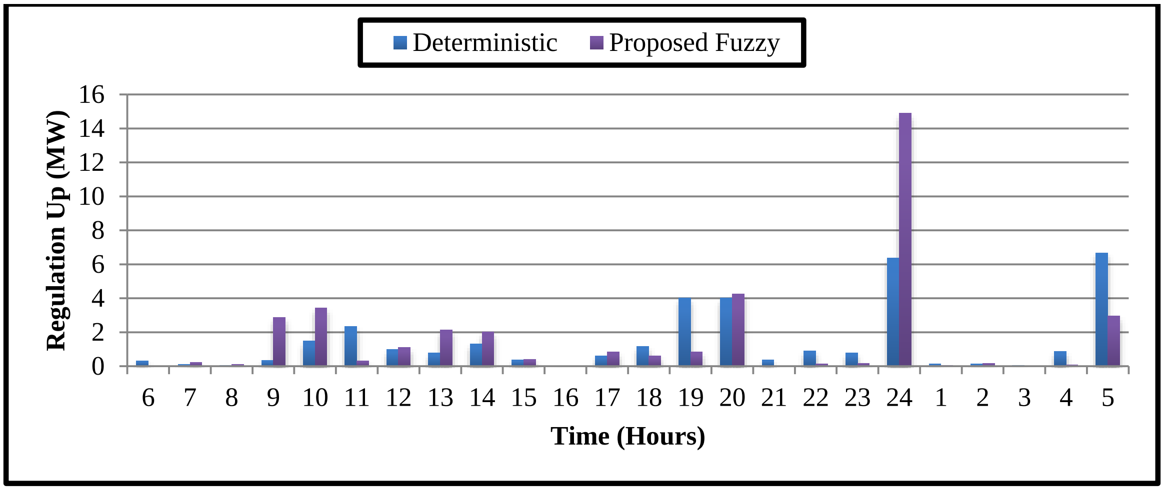

Figure 7-18: Average regulation up by each algorithm with load constraint

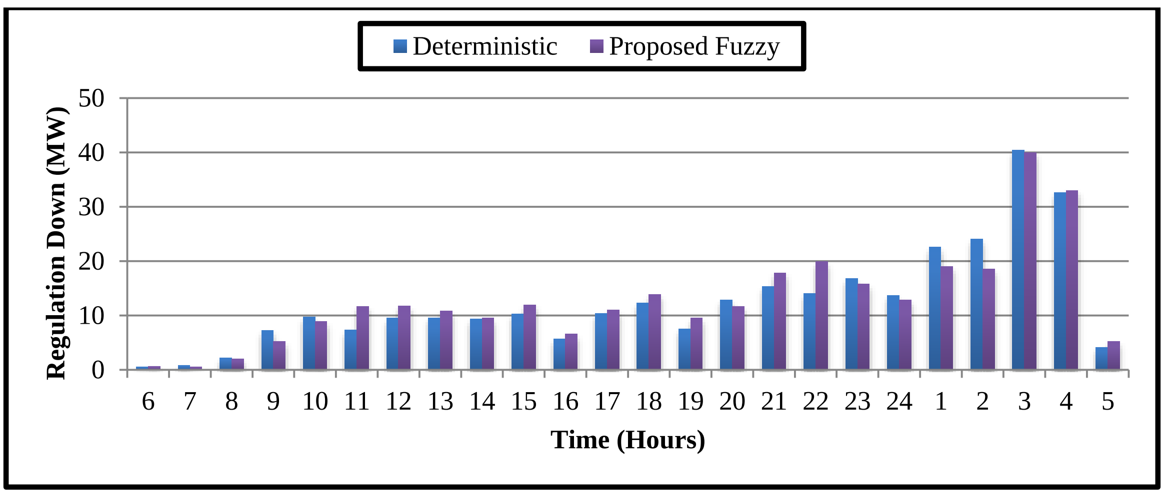

Figure 7-19: Average regulation down by each algorithm with load constraint

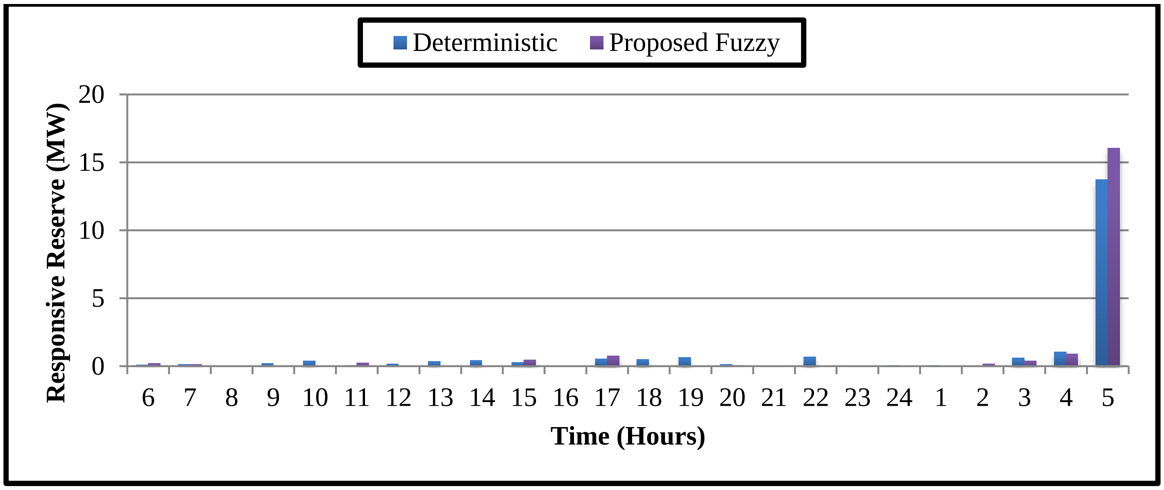

Figure 7-20: Average responsive reserves by each algorithm with load constraint

The responsive reserve capacity is shown in Figure 7-20. Both the deterministic and the proposed fuzzy algorithms mainly bid the responsive reserve at the end of the charging period to make the electric vehicles charge close to 100% of their capacities.

7.4.2.2 Quarterly Results

This section presents the aggregator profits for the different algorithms: deterministic and proposed fuzzy. The expected and the actual profits for an average day is shown in Figure 7-21 while Figure 7-22 presents the total expected and actual profits of an aggregator for the three months period.

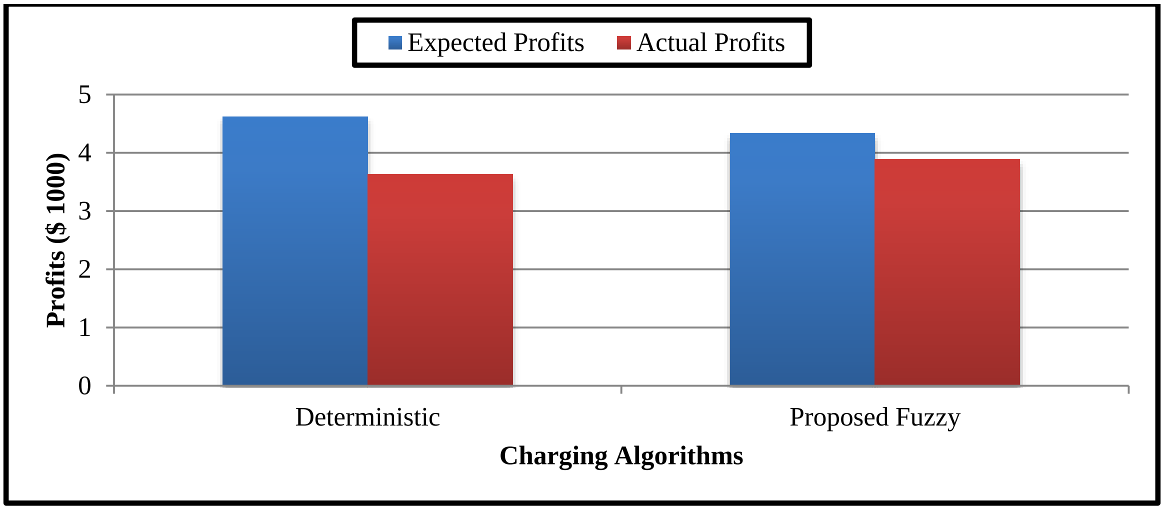

Figure 7-21: Expected and actual profits of an aggregator for an average day with load constraint

With the load constraint added in the optimization, the aggregator expects a little lower profit than the algorithm without load constraint and it is evident from the figures. The aggregator expected profits, in the day-ahead bidding, using the fuzzy algorithm is 6.21% lower than the deterministic algorithm, while on the actual day of bidding, the aggregator get a little higher profits using proposed fuzzy algorithm as compared with the deterministic algorithm. The actual profits, using the proposed fuzzy algorithm, are 6.92% higher than the deterministic algorithm. The same trend for the day-ahead expected and actual profits comparison is evident from the total profits graph as shown in Figure 7-22.

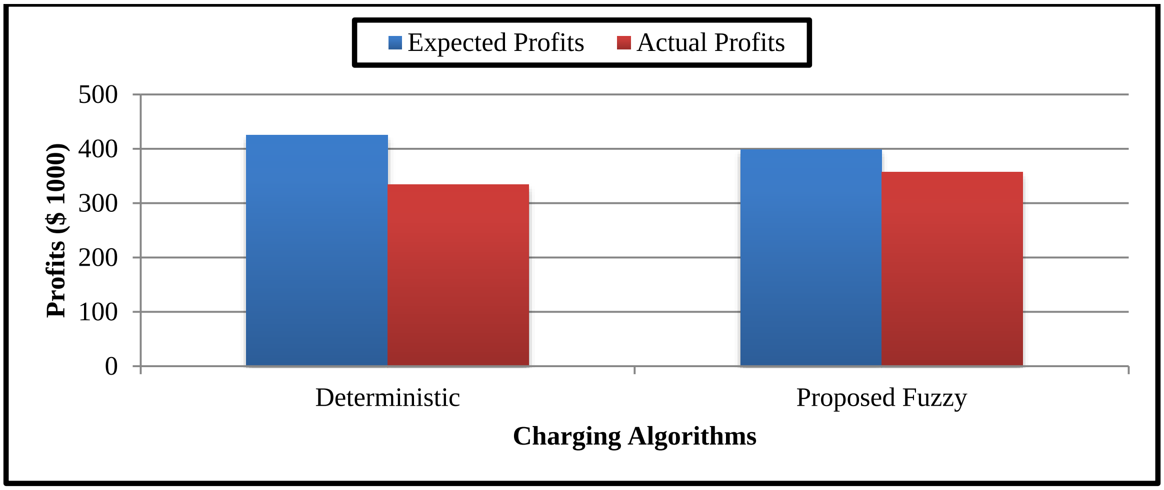

Figure 7-22: Total expected and actual profits of an aggregator with load constraint

The charging of EVs should not stress the power system network. The peak and the average peak load increase by deterministic and proposed fuzzy algorithm is shown in Figure 7-23. The proposed fuzzy algorithm results in a slightly higher peak and average peak load than the deterministic algorithm. This shows that the proposed fuzzy algorithm is affecting the same as that of the deterministic algorithm. There is no additional burden by the proposed fuzzy algorithm on the power system network.

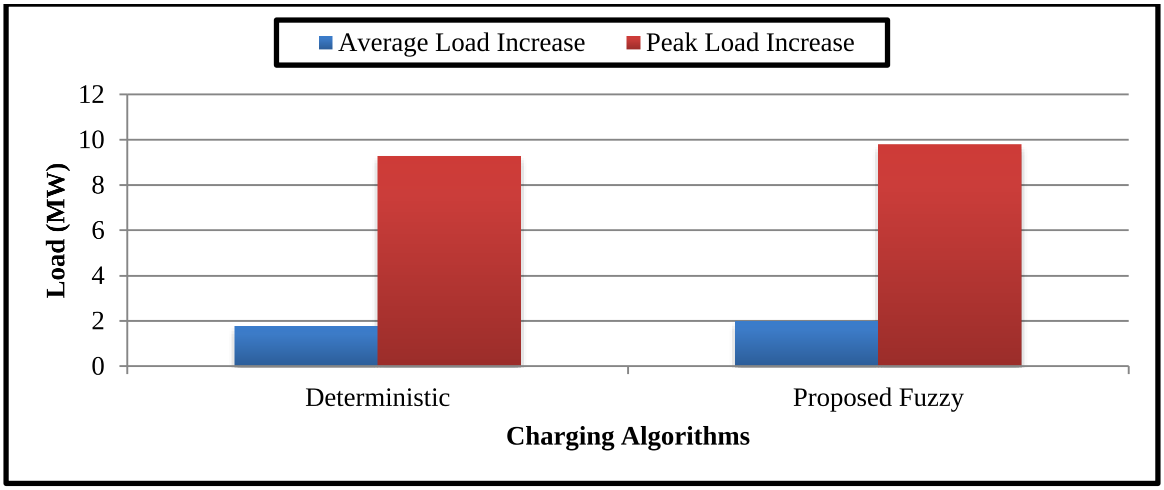

Figure 7-23: Daily average peak and peak load increase by different algorithm due to EV charging with load constraint

7.4.3 Case # 3: With Price Constraint

In this case, the same optimization problem is solved with an extra price constraint mentioned in (7.34) is added to order to avoid the burdening of the power system network. Both the optimization, deterministic and proposed fuzzy algorithm are simulated for the same charging period from 6 A.M. to 6 A.M. next day for a period of three months.

7.4.3.1 Charging Profiles

The charging profiles for the POP, ancillary service capacities with the price constraint are shown in Figure 7-24 - Figure 7-27. The POP behaves the same pattern as that of the previous cases and bids most of its capacity in the last simulation hour i.e. 6 A.M.

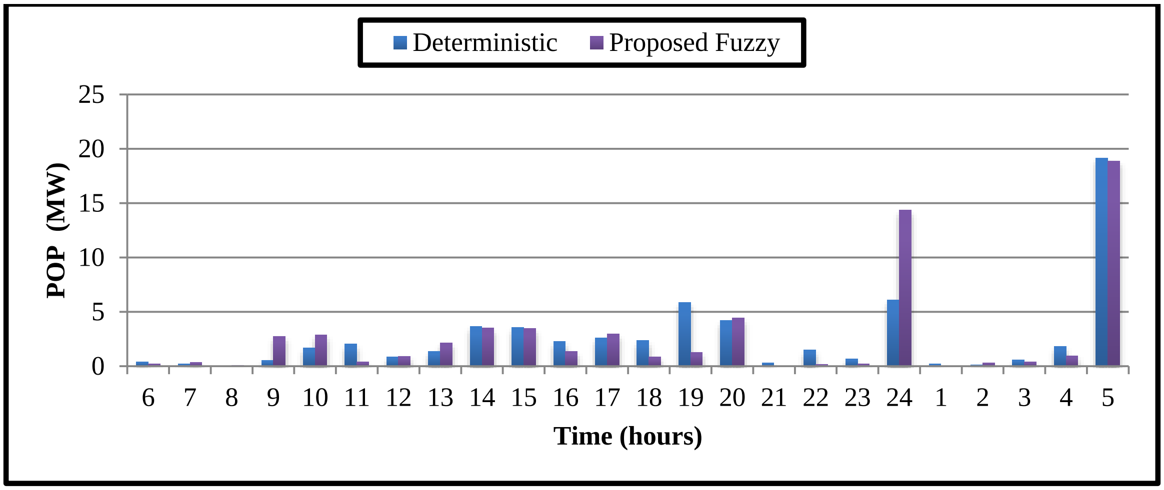

Figure 7-24: Average POP by each algorithm with price constraint

The ancillary services by the algorithms are shown in Figure 7-25 - Figure 7-27. In the average regulation up, sometime the deterministic algorithm bids higher than the proposed fuzzy algorithm and sometime vice versa similar to the previous cases. The average regulation down capacity is shown in Figure 7-26. The deterministic algorithm and the proposed fuzzy algorithm both follows the same pattern and bids in almost every hour. The proposed fuzzy algorithm is a little higher than deterministic algorithm except a few hours. As the electric vehicles make their first trip after 8 A.M. so the regulation capacities before the 8 A.M. is usually zero or very low.

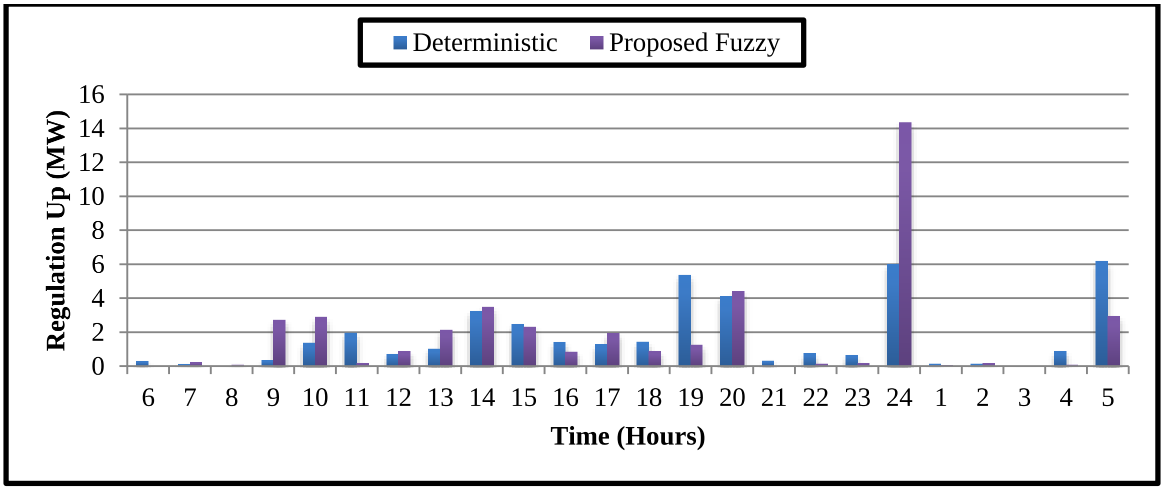

Figure 7-25: Average regulation up by each algorithm with price constraint

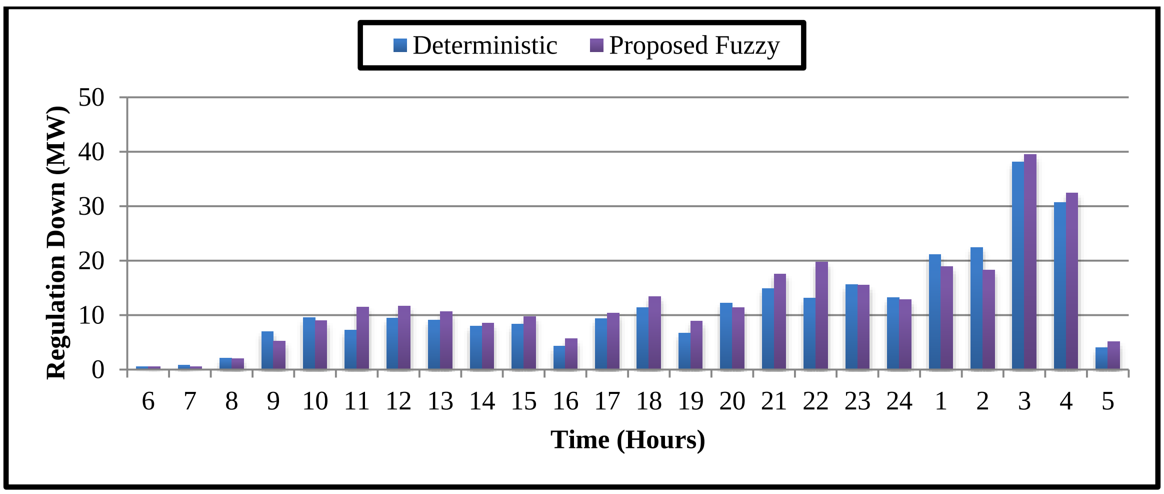

Figure 7-26: Average regulation down by each algorithm with price constraint

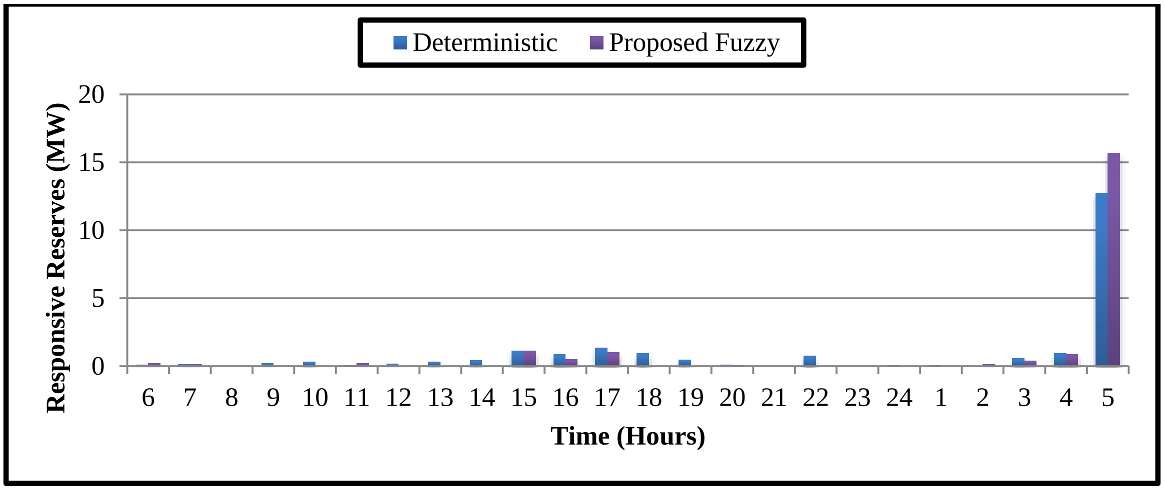

Figure 7-27: Average responsive reserves by each algorithm with price constraint

The responsive reserve capacity is shown in Figure 7-27. Both the deterministic and the proposed fuzzy algorithms mainly bid the responsive reserve at the end of the charging period to make the electric vehicles charge close to 100% of their capacities.

7.4.3.2 Quarterly Results

This section presents the aggregator profits for the different algorithms: deterministic and proposed fuzzy. The expected and the actual profits for an average day is shown in Figure 7-28 while Figure 7-29 presents the total expected and actual profits of an aggregator for the three months period.

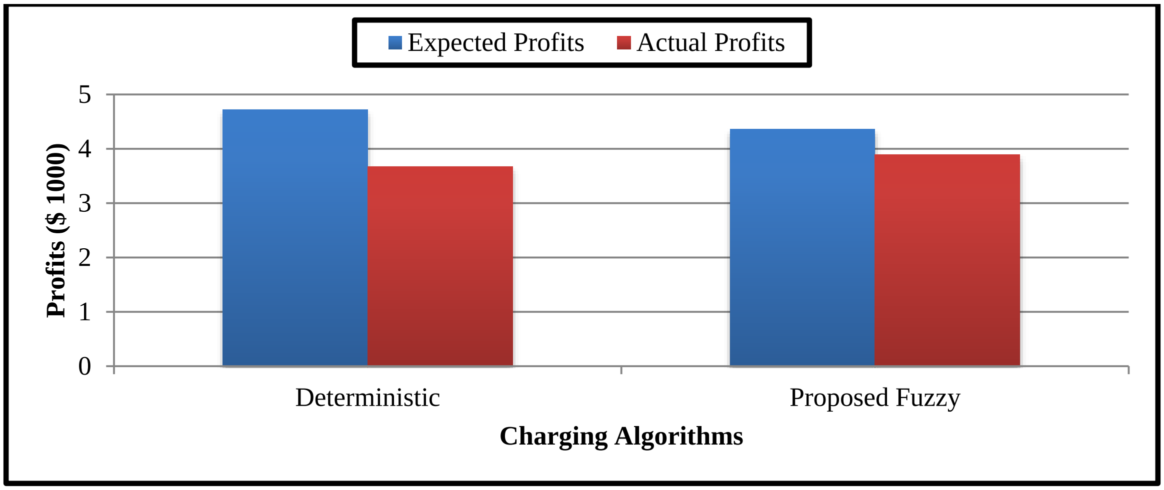

Figure 7-28: Expected and actual profits of an aggregator for an average day with price constraint

With the price constraint added in the optimization, the aggregator expects a higher profit than the deterministic algorithm in the day-ahead bidding and also on the actual day of bidding, the aggregator get a considerable higher profits with the use of proposed fuzzy algorithm as compares with the deterministic algorithm. On the actual day, the aggregator gets 5.74% higher profits with the use of proposed fuzzy algorithm.

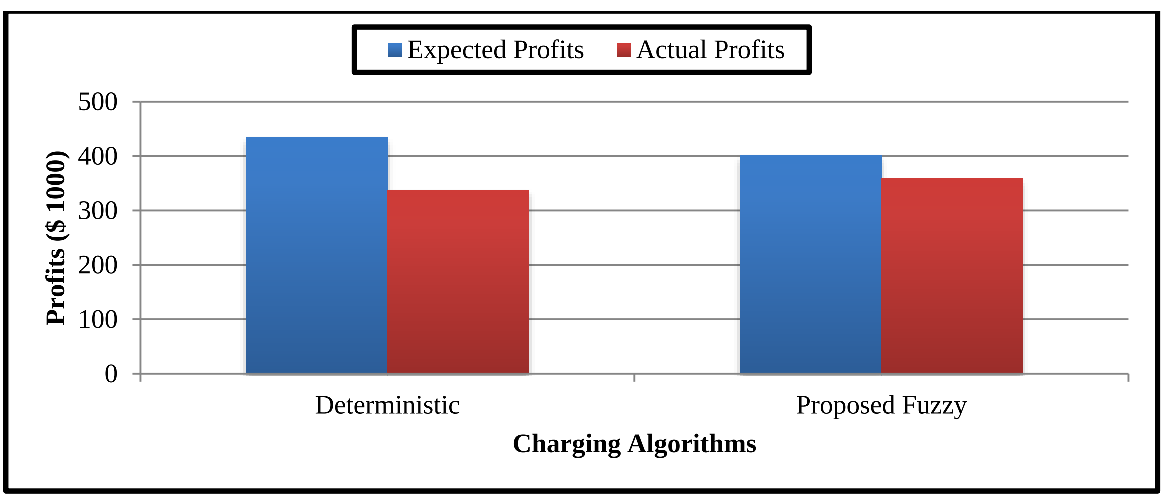

Figure 7-29: Total expected and actual profits of an aggregator with price constraint

The charging of EVs should not stress the power system network. The peak and the average peak load increase by deterministic and proposed fuzzy algorithm is shown in Figure 7-30. The proposed fuzzy algorithm results in almost the same peak and average peak load as resulted by the deterministic algorithm. This shows that there is no additional burden by the proposed fuzzy algorithm on the power system network.

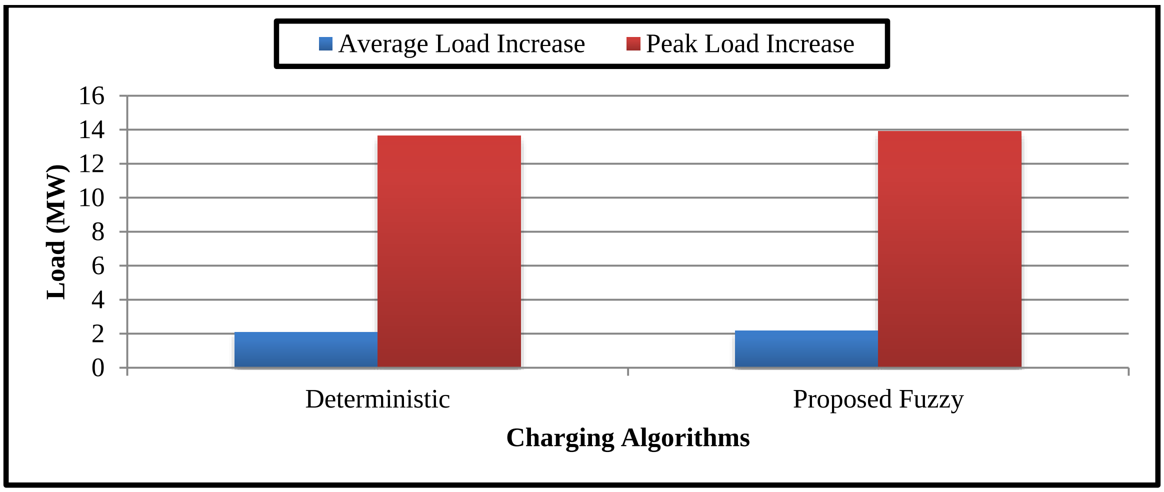

Figure 7-30: Daily average peak and peak load increase by different algorithm due to EV charging with price constraint

7.5 Conclusions

In this chapter, the benefits of coordinated bidding of ancillary services for unidirectional V2G with fuzzy market uncertainties are investigated. The proposed fuzzy algorithm for V2G is found to be more beneficial for the aggregator in terms of profits on the actual bidding day as compared with the previous proposed deterministic algorithm. The new objective function proposed is also beneficial for EV owner and aggregator, as the owner is not exposed to the energy price variations and has to pay a fixed cost for charging EV, while the aggregator can take advantage of the varying market prices by predicting the future values of the market. Different market uncertainties are modeled using the fuzzy set theory such as ancillary service prices and deployments signals. Furthermore, different cases were simulated with the load and price constraint that avoids the burdening of the power system network and charge the electric vehicles at low price cost.

CONCLUSIONS AND FUTURE WORK

In this thesis, optimal aggregator bidding strategies for unidirectional vehicle-to-grid using fuzzy uncertainties is presented for the day-ahead ancillary services market. A fuzzy based smart charger and fuzzy optimization based bidding strategies is developed for an aggregator. Different electricity market uncertainties are incorporated using the fuzzy set theory such as regulation prices, responsive reserve prices, regulation, and responsive reserve deployments. The algorithms are compared with the previously published deterministic algorithms, without the uncertainties in the bidding. The algorithms, deterministic and proposed fuzzy, are simulated on the hypothetical group of 10,000 EVs, operating in the real electricity market ERCOT. The electricity market data are taken from the ERCOT ISO website for the simulation period.

First, a novel smart charging algorithm based on the fuzzy logic control is presented. Previously different smart charging algorithms were presented in the literature, such as price based, load based and MaxReg based smart charging algorithms. In fuzzy smart charging, taking the advantage of fuzzy logic, previous published charging algorithms were combined in a fuzzy logic controller. The proposed fuzzy based smart charger results in the highest profits for the aggregator. The proposed algorithm, not only benefits the aggregator, but also charges the EVs at lower energy cost and the impact on the power system is also reduced. While each previous algorithm has its own specific merits, such as the load algorithm impacts the power system lowest, but they were only targeting one specific task.

Second, optimal aggregator bidding of regulation service for unidirectional V2G is developed using the fuzzy linear programming. A fuzzy optimization is proposed for the finding the optimal bidding for the aggregator. Different electricity market uncertainties are modeled using the fuzzy sets, such as regulation up/down prices and regulation deployments signals. Previous published deterministic algorithm is compared with the proposed fuzzy algorithm. The deterministic algorithm perform better than the fuzzy algorithm for the expected profits while on the actual day of bidding, proposed fuzzy results in higher profits than the deterministic. The actual profits are the real profits of the aggregator and the difference between the expected and the actual profits are minimized for the proposed fuzzy algorithm. Load and Price constraint are also simulated so that the impact of EV charging on the grid is minimized and the EVs are charged at lower energy price respectively.

As the EV can participate in different electricity markets, so in the last section of the thesis, coordinated bidding of the aggregator for the ancillary services, regulation services and responsive reserves, are investigated. The formulation presented in this chapter is an extension of the previous work with detail modeling of ancillary service market parameters and EVs parameters. Moreover, the objective function is also changed and the EVs are charged at a fixed cost. The new objective function is beneficial to both EV owners and aggregator as the owners will not be exposed to energy price variations. Different electricity market uncertainties are modeled with the fuzzy sets. The expected and the actual aggregator profits are compared for both the deterministic and fuzzy algorithms. On the actual day of bidding, the fuzzy algorithms results in a higher profit as compared with the deterministic profits. Similar to the previous work, the simulations are also performed with the load and price constraints.

In this thesis work, the main objective achieved is the incorporation of electricity market uncertainties for day-ahead aggregator bidding using the fuzzy set theory. The proposed fuzzy algorithms results in a higher profits on the actual day of bidding and generates more profit for the aggregator as compared with the previous deterministic algorithms.

The work in this thesis can be further extended in many directions and some of them are:

- The work in this thesis has focused on unidirectional V2G bidding. In addition to the unidirectional V2G, bidirectional V2G for participating in the energy market can be done.
- The different parameters related to EVs such as their availability, departure times, trip duration and SOC reduction are dealt here in a deterministic and probabilistic manner. They can also be fuzzified.
- The forecasting should be improved further, so that greater benefits out the available resources can be obtained.

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