# OPTIMAL STRATEGIES FOR BIDDING V2G SERVICES USING STOCHASTIC PROGRAMMING

BY

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بسم الله الرحمن الرحيم

*DEDICATED TO*

*My Beloved Parents*

*My Beloved Bhai and Bhabi*

*And*

*My best friend and Twin brother Sheraz Khalid*

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*In the Name of Allah, the Most Beneficent, the Most Merciful.*

Praise belongs to Allah, the Lord of all the worlds (2) The All Merciful, the Very-Merciful. (3) The Master of the Day of Requital. (4) You alone do we worship, and from You alone do we seek help. (5) Take us on the straight path (6) The path of those on whom You have bestowed Your Grace, Not of those who have incurred Your wrath, nor of those who have gone astray. (7)

Al-Fatiha

In the name of Allah, the most Merciful, the most Gracious. All praise is due to Allah; we praise Him, seek His help, and ask for forgiveness. Peace be upon the Prophet Mohammad, his family, his companions, and all those who followed him until the Day of Judgment.

I then would like to show my deepest gratitude and respect to my family, especially my parents, the ones to whom I owe all the success in my life. No words can express my gratitude to them, but I pray God to bless them and reward them. Any success in my life so far is mostly charged to them and consequently any success in the future will have their signature as well.

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# THESIS ABSTRACT (ENGLISH)

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Electric Vehicles (EVs) have been gaining popularity among general public due to their additional benefits over conventional vehicles and reduced environmental effects. However, adoption of EVs is not easy since mass unregulated EV charging can cause adverse effect on the power grid. The Vehicle-to-grid (V2G) technique turns out to be effective for the integration of EVs with the grid. Its purpose is to provide energy and ancillary services with this flexible/responsive load demand. Since a single EV has very low capacity, the EV aggregator is an essential entity for the provision of V2G services to the electricity market. However, trading in the day-ahead electricity market is risky due to uncertain prices, load demands, and deployment signals. In this thesis, optimal bidding strategies for unidirectional V2G are developed to be used by an EV aggregator to participate in regulation and responsive reserve markets while considering the uncertainties associated with market variables such as prices and deployment signals.

Stochastic programming (SP) is used to formulate this optimization problem with the objective of maximizing the total profits of an EV aggregator participating in the

ancillary services market. In SP, several scenarios of stochastic variables are generated to incorporate uncertain behaviour. ARIMA models are used for this purpose. Besides stochastic optimization, analogous deterministic strategies with forecasted data of market variables are also discussed to show the effectiveness of proposed work. Simulation results demonstrate that the proposed stochastic algorithm outperforms the deterministic counterpart in terms of the aggregator profit with a negligible impact on the benefits of the other participants.

# THESIS ABSTRACT (ARABIC)

| | |
|---|---|
| **الاسم** | محمد وقّاص خالد |
| **العناوان** | الاستراتيجيات المُثلى لطرح العطاء باستخدام تقنية من المركبة إلى الشبكة باستخدام البرمجة العشوائية |
| **الدرجة** | ماجستير في العلوم |
| **التخصص الرئيسي** | الهندسة الكهربائية |
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المركبات الكهربائية (**EVs**) اكتسبت شعبية في اوساط عامة الناس وذلك يعود لفوائدها التي تفوق المركبات التقليدية وهي أيضا أقل تأثرا على البيئة. غير أنه تبني فكرة وجود المركبات الكهربائية ليس بالسهل بسبب كثافة وفوضوية إعادة شحن هذه المركبات وهذا يؤثر سلباً على الشبكة الكهربائية. تَبَيَّنَ أن تقنية من المركبة إلى الشبكة (**V2G**) ستكون فعّالة في عملية دمج أو ربط المركبات الكهربائية مع شبكة الكهرباء. والغرض منهذه التقنية هو تزويد الطاقة والخدمات المساعدة بطريقة مرنة ومتجاوبةفي الحمل الكهربائي. بما أن قدرة المركبة الكهربائية الواحدة قليلة جداً, فإن وجود مشغِّل للمكبات الكهربائي يعتبر كيان أساسي لتمكين عمل تقنية من المركبة إلى الشبكة من التفاعل مع السوق الكهربائي. مع العلم بأن المتاجرة (المضاربة) في سوق الكهرباء ليوم مقبل يحمل درجة من الخطورة بسبب عدم تأكدية في الأسعار والطلب على الحملوالإشارات التي تعبر مدىحاجة السوق للكهرباء.في هذه الأطروحة تم تطوير استراتيجيات لطرح العطاء الأمثل لوحادي الإتجاه من تقنية من المركبة إلى الشبكة ليتم استخدامها بواسطة مُشَغِل المركبات الكهربائية للمشاركة في سوق الكهرباء للخدمات المساندة بتقديم خدمة تنظيم الطاقة وتوفير الإحتياطي من الطاقة مع الأخذ بعين الإعتبار مبدأ الريبة المترابط مع المتغيرات المتعلقة بالسوق مثل السعر والإشارات التي تعبر مدى حاجة السوق للكهرباء.

تم استدام البرمجة العشوائية (Stochastic Programming) لصياغة معادلات الحل الأمثل مع الأخذ بعين الإعبار أن الهدف الرئيسي هو تعظيم الربح الكلي لمُشَغِل المركبات الكهربائية من خلال المساهمة (المضاربة) في سوق الكهرباء للخدمات المساندة. تم استخدام طريقة الأريما (ARIMA) في البرمجة العشوائية لإنتاج أو توليد عدة سيناريوهات للتعبير عن السلوك غير المؤكد.جنبا إلى جنب استخدام الحل الأمثل العشوائي متخذا استراتيجية كما لو أن المتغيرات المرتبطة بالسوق تم توقعها بشكل قطعي لإظهار فعالية العمل المقترح نتائج المحاكاة تثبت أن نتائج الخوارزمية العشوائية المقترحة تفوق نتائج النظرية القطعية من حيث الربح الناتج عن المُشَغِل المركبات الكهربائية مع عدم وجود تأثير ملحوظ استفادة المشاركين الاخرين.

# CHAPTER 1 INTRODUCTION

## 1.1 BACKGROUND

Electric Vehicles (EVs) have been gaining momentum among the general public due to their additional benefits over conventional internal combustion engine (ICE) vehicles and due to their reduced adverse environmental effects. In some countries, subsidies on EVs are provided by legislation to increase their market acceptance [1]. EVs are environmental-friendly, have low operating cost, can run on locally produced renewable energy sources, and more efficient than ICE vehicle. They can convert about 60% of electrical energy into power while traditional vehicles can convert only 20% [1]. However, some challenges are impeding EV participation in the market, such as their cost, short driving range (around 100-200miles), and long charging time (4 -8 hours to fully charge). In addition, integration of EVs with the electric power grid is a major challenge. Charging EVs would require additional power that causes extra load on the grid. So, power system operators have to modify their operations to include a large

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The American Recovery and Reinvestment Act (ARRA), HR 1 of the 111th Congress, provides a minimum tax credit of $2500 per vehicle is increased by $417 kW/h in excess of 4 kWh, to a maximum of $7500. Full credits for plug-in hybrids will be given to the first 250 000 sold PHEVs. Aftermarket conversions of HEVs to PHEVs are eligible for a credit of 10% of conversions costs up to $40 000.

number of EVs without having negative impacts on grids. Researchers have developed several smart charging strategies for EVs to interact intelligently with the electric power grid but such infrastructure is still in its infancy.

The Vehicle–to-grid (V2G) technique turns out to be effective for the integration of EVs with the grid. Its purpose is to provide energy and ancillary services with flexible/responsive load demand [2–4]. With V2G, an EV can participate in various types of electricity markets, peak energy, frequency regulation, spinning reserve, non-spinning reserve and bulk energy [2], [4–6]. V2G technique can be used as unidirectional or bidirectional. Unidirectional V2G consists of the electric grid providing power to electric vehicles. It's a conventional way to charge batteries. Bidirectional V2G enables vehicles to discharge energy back to the power grid along with charging. Since most of the EVs are idly parked in residential or industrial parking lots for most of the time, power in their batteries can be used to support the electric grid by letting electricity flow from the car to the power lines and back to the car, whenever needed [3].

Note that integration of EVs to the grid via V2G services is beneficial for all participants [4], [7]. Utilities serving large penetrations of EVs will have additional responsive/flexible load that can serve to improve the power system operation and control, by providing regulation services through EVs instead of using costly generators. Moreover, EV owners can generate revenues or charge their cars at lesser cost. EVs can also be used to counteract the variability of renewable energy sources and to increase its viability [3], [8], [9].

Aggregating a large number of EVs into single fleet to combine their capacities for participation in electricity markets is very important for the successful implementation of V2G technology. Since the minimum amount of bid size in regulation market is often 1 MW [10], [11], the services of the aggregator are required. The aggregator may be the utility itself or any third party acting as a middle entity.

Aggregated bidding of V2G services in electricity markets has several challenges, though. Note that the primary use of EVs is in the transportation system instead of supporting electric grid. EVs can be disconnected from grid whenever their owners desire. In general, EV owners might not be concerned about grid support and would probably be hesitant to do so when it comes at their inconvenience [12]. Also, the bidding strategies are affected by uncertain market variables such as market prices, load demands and regulation signal. So, EV aggregators have to take care of these uncertainties while developing charging strategies. Stochastic programming (SP) approach has efficiently been used in several works to deal with such uncertainties [9], [13–16]. In SP, the uncertainties are modeled by generating a large number of possible scenarios for each stochastic variable. Then, a reduced set of scenarios with their probability of occurrence are used to obtain the optimal solution. The salient feature of this technique is that the optimization has to be done using information with significant uncertainty.

For an aggregator, a successful bidding strategy will satisfy the EV transportation needs within the expected time constraints while meeting the aggregator's objective of

maximizing its profits from respected market where capacity is bid considering uncertain behavior of EVs and market variables.

## 1.2 MOTIVATION AND PROBLEM DESCRIPTION

Exploitation of EVs in electricity market has recently attracted the attention of many researchers. A major issue with integrating EVs with the power system is the additional load on the grid due to the charging of a large number of EVs. Therefore, smart charging algorithms are required to minimize possible adverse impacts. Several approaches have been developed to address this issue [17]. Vehicle-to-Grid (V2G) is proposed as an efficient technique for providing services to the power grid while offering benefits to EV owners. V2G can be either unidirectional or bidirectional. Most of the work in this area is done on bi-directional V2G, as under this structure EVs can participate in various electricity markets; regulation, spinning reserves, peak and bulk energy markets. But the implementation of bi-directional V2G is more challenging than that of unidirectional V2G due to the requirement of additional hardware and the increasing cycling wear on EV batteries [4]. Several works have shown that provision of regulation is the most profitable among the services that V2G can offer [3], [5], and that EVs can follow regulation dispatch signals accurately [18], [19]. However, these regulation signals are uncertain and cannot be known in advance. This uncertainty may put EV aggregators at risk of not charging their cars as contracted.

Since a single EV has very low capacity, the EV aggregator is an essential entity to participate in energy market. Therefore, algorithms for optimal bidding strategies to be use by aggregator are required. There are various works that discuss bidding of aggregated EV capacity in energy markets and a very few works on optimal bidding of regulation and ancillary services. But neither of these works modeled the uncertainties associated with market participation of EV aggregator such as energy or regulation prices, regulation signals or EV availability. Considering uncertainties of these variables is essential for the aggregator in order to maximize its profits at a reasonable risk.

## 1.3 THESIS OBJECTIVES

In this research, a V2G bidding strategy is developed to be used by an EV aggregator to bid in ancillary services market with the objective of maximizing its profits while considering uncertainties, such as those due to market prices and deployment signals. Stochastic programming approach is used as an optimization tool. The main contributions of this work can be summarized as follows:

1) Modeling the uncertainties associated with market participation of EV aggregators, such as prices and deployment signals.

2) Developing an optimal V2G algorithm to be used by EV aggregators to participate in regulation and ancillary services markets.

3) Studying the effectiveness of the new algorithm by way of a case study based on realistic power system data.

## 1.4 THESIS APPROACH

The approach that is used to fulfill the objectives is comprised of following steps:

1) Forecast of uncertain future market prices and regulation signals using historical data.
2) Implementation of Scenarios Generation technique for each stochastic variable.
3) Implementation of Scenario Reduction technique to make optimization tractable.
4) Development of a profit-maximizing Stochastic V2G program to be used by an EV aggregator for bidding in the Regulation Services market during limited parking hours.
5) Extension of the proposed algorithm for entire-day charging while considering EV availability and reduction in battery due to uncertain EV trips (home – office).
6) Development of Maximum Load based algorithm to limit negative impact due to charging.
7) Development of Maximum Price based algorithm to charge EVs at lower cost.
8) Development of an unidirectional V2G algorithm for combined participation in regulation and Spinning Reserve markets.
9) Studying the impacts of the proposed algorithm on market participants such as aggregator, EV owners and power system utilities.

## 1.5 THESIS ORGANIZATION

This thesis is organized as follows:

Chapter 2 contains extensive literature survey on vehicle-to-grid technology, aggregator concept, bidding strategies to be use by EV aggregator under this technique and the use of stochastic programming in electricity market.

Chapter 3 briefly describes the stochastic programming and related concepts and explains scenario generation technique using ARIMA methods to model uncertainties associated with market parameters. Scenario reduction technique is also explained.

In chapter 4 an optimal day-ahead regulation bidding strategy for unidirectional V2G algorithm has been proposed for use by an EV aggregator during limited hours. Two algorithms have been simulated, Stochastic and Deterministic, and there comparison is carried out.

In Chapter 5, the algorithm proposed in previous chapter has been extended to combine bidding in regulation and responsive reserve market while considering uncertainties associated with each market parameters. Two new algorithms, Maximum Load and Maximum Price based, have also been investigated and compared them with their Deterministic counter-parts.

Chapter 6 presents the conclusions drawn from this research work and directions for the possible future work.

# CHAPTER 2 LITERATURE SURVEY

Electric vehicles offer many benefits over traditional vehicles, such as lower operating costs and potential to run on locally produced renewable energy sources. Integration of EVs with electric grid is most effectively described under the vehicle-to-grid concept. This chapter presents a detailed literature review on the V2G and other important concepts related to this technique.

## 2.1 VEHICLE-TO-GRID

The idea of Vehicle-to-grid (V2G) was first introduced in [20], suggesting that the parked EVs can be used to support electric grid system in a way that is beneficial for both grid and EV owners. This idea advances the previous theory in which EVs were considered as additional loads only [21]. The concept of V2G is still undergoing changes and suffering different interpretations. A charging approach to be used in V2G services is suggested in [6], where V2G concept is divided into load only V2G that performs EV load control and regular V2G where power injection from vehicle to grid is allowed. This load-only V2G is called V1G in [22]. In [23], the authors defined V2G as a means to deliver power from parked vehicles to electric grid and G2V as a means to provide electrical energy from the grid to the vehicles. With most of the development occurring in

the last decade, V2G basics were more fully explored and potential revenues from different markets were shown [2], [3], [5]. Participation of EVs in regulation services is carefully addressed in [5]. In [3] four power markets are analyzed; base load, peak, spinning reserve and regulation. It was suggested that EVs should initially provide spinning reserve and regulation. Several works also consider EVs to provide peak load shaving and base energy [20], [24], [25]. Among all, however, regulation service is the most promising and highest-earning service. These results are confirmed in [3], [5], [26–29]. Several other techniques are also suggested to integrate EVs to the electricity network [18], [19], [30]. Demand management approach based on Agent-based energy hubs is proposed in [30], where three different types of agents, energy hub, EV managers and EV agents are modeled. It is assumed that EV manager is an entity that serves an intelligent interface between EV agents (EV owners) and energy hubs and exchanges necessary information. Pilot projects are discussed in [18], [19] where the conventional vehicles are converted to EVs with bidirectional power converters and verified that EVs can accurately respond for regulation signals. These studies, however, did not include aggregator and bidding strategies.

## 2.2 THE AGGREGATOR CONCEPT

The concept of an aggregator was firstly introduced in [25] and the same idea is proposed in [31]. The key motivation for aggregating a large number of vehicles in a group is to allow EVs to participate in energy market in more effective way. Since a single EV has very low power capacity, it cannot bid in the market individually. Hence,

the best solution is to aggregate EVs under single entity that will serve as a middle entity between the EV owners and the electricity market. The other main advantage of the aggregator is that the forecasting uncertainty of total available power in each hour is considerably less to that of a single vehicle [31]. The aggregator has the responsibility of respecting the EV owner's mobility needs while providing services to the electricity market [25]. Recently, a conceptual framework for an aggregator is proposed in [32] where a "package deal" model is defined in which the aggregator offers electric energy, battery maintenance or parking services with competitive prices to attract EVs to participate in V2G. It also provides the structure for incorporating the communication control infrastructure. EV availability factor is introduced in [23] to encourage the existence of aggregator. It explains that if a single EV has a direct contract with utility then it is not possible for EV to leave until the contract period ends. In contrast, in the aggregated system, the required availability factor can be scheduled by forecasting the historical driving behavior. However, these studies did not address algorithms for aggregator bidding strategies in electricity market.

## 2.3 AGGREGATED BIDDING

Aggregator bidding strategies in energy and reserve market have been developed by several authors in the recent years. The first algorithm is developed in [33], where optimal aggregator bidding strategies for bidirectional regulation is shown using dynamic programming with the objective of maximizing the aggregator profit. This study is only valid for regulation services, while bidirectional power flow capability can be used in

bulk energy sales. Another dynamic programming approach is described in [34], where two optimization algorithms for each EV are shown: (a) optimization of charging time and charging rates while minimizing total cost and (b) optimization with generating revenues by participating in reserve market through V2G services. This approach did not fully address the aggregator profit/loss optimization. These works used dynamic programming, however, this technique is only efficient for a small scale system. A linear programming approach for EV aggregator to participate in day a-head electricity market using bidirectional V2G technique is shown in [35], with the objective of minimizing cost while defining the optimal charging and discharging plan for EVs. However, actual market price is considered instead of forecasted values to study the effects of price variations on charging schedules. Also, ancillary services are not considered. Heuristic algorithm is used to optimize the EV charging schedules to minimize the charging cost and flatting the load curve while meeting the demand response requirements in regulated market is shown in [36]. However, this work did not consider the aggregator concept and optimal bidding strategies in the electricity markets.

The most comprehensive work for unidirectional V2G regulation is presented in [4], where three smart charging heuristic techniques are explored for combined capacity of many EVs. Among three heuristic techniques named, maximum regulation-based, load-based and price-based, basics of later two were also discussed in [37]. An optimization algorithm for aggregator biding in regulation market is also developed in [4] with the objective of maximize the aggregator profit; it shows that this algorithm provides benefits for all market participants as well. But this work considers only nine hours of charging

period; i.e. EVs can participate in V2G only in day time during office hours. Also, the uncertainties in EV availability, market prices and load are not considered. This work is extended in [7], where, a combined bidding strategy for V2G services in regulation and spinning reserve markets using unidirectional V2G is devised. This algorithm is run for the complete day while considering unexpected departures of EVs during contract periods. This paper discussed the benefits of combined bidding in two markets. However, these works consider only the expected values of regulation signals received by aggregator from system operator. For the energy and regulation prices, simple persistence forecast is used. Since the regulation signals and prices are very uncertain, better models of their uncertainties should be included.

Authors in [38] used a naive forecasting technique to optimize bids for EV aggregator participating in day ahead energy and reserve market. It also categorizes some variables that need to be forecasted to participate in market bidding. The individual EV charging is controlled with the objective of maximize aggregator's profit while decreasing the EV owners' cost. In [39], better statistical forecasting tools are used and two optimization approaches "divided" and "global" are proposed to participate in day a-head energy market. The divided approach does not use the idea of aggregator but dispatch each EV individually. In contrast, the global approach takes advantage of EV aggregation to participate in bidding process. Merits and demerits of both approaches are discussed. Work in [40] presents numerical analysis supporting these approaches. Where, a non-responsive EV load approach is compared with divided and global approach. Results show that optimized bids allow a considerable cost reduction when compared to non-

responsive load approach. More comprehensive study is done in [41] to support the concept of EV aggregator; two optimization algorithms are proposed (1) day-ahead reserve bidding and (2) hour-ahead reserve bidding and shows that presenting hour a-head bids improves reliability.

The use of the expected or forecasted values of these input variables is the technical limitations in the previous bidding strategic works. Some recent works discuss uncertainties of these variables, [42] considers the stochastic nature of uncertain variables such as EV driving patterns and energy market prices to optimize charging/discharging of EVs with the objective to minimize their transportation cost by participating in electricity energy and ancillary services market while ensuring reliability of energy supply. Authors in [43] mentioned the significance of forecasting trip modules using perfect forecasts in their optimization algorithm. Probabilistic approach is used for the first time in [44] to model the uncertainties in achievable power capacity (APC), where the capacity that aggregator will bid in the market is based on the probability distribution of APC with the objective to maximize aggregator profit while considering the penalties on contracted power shortage. This work is limited to estimate the amount of power capacity to be delivered from vehicle to grid i.e. discharging EVs but the power required to charge EVs is not considered. However, in these works an optimized bidding strategy for an aggregator is not provided and the benefits to other system participants are not explained.

Several other works have looked at other potential benefits from V2G. Coordination of V2G services with thermal unit commitment (UC) has been proposed by many

researchers. In [45], [46] PSO is used for thermal UC while incorporating EV charging/discharging, feeder loading and EVs parking time constraints are considered in [45], and reduction in total cost and emission though balancing of wind and solar is discussed in [46]. Stochastic thermal unit commitments in coordination with V2G and wind energy are discussed in [13], [15], [16].

## 2.4 UNIDIRECTIONAL VS. BIDIRECTIONAL V2G

Most of the discussed works have used bidirectional power flow for V2G regulation; it is because aggregator can participate in more markets with high percentage of revenues using bidirectional charging. But, its implementation has many challenges. For example, power flow from the vehicle to the grid needs additional hardware to be incorporated in EVs [4]. Also, anti-islanding protection and its interconnection are other issues that warrants careful consideration [47]. Increased battery cycling wear is also worrisome in bidirectional power flow [47], [48]. Additionally, customers would be hesitant to allow power discharging from their vehicles. Therefore, it is expected that unidirectional V2G be adopted first. Using this concept, EVs can participate in V2G regulation easily and without any additional requirements, as discussed previously. However, benefits are less in unidirectional V2G ;it has been shown that aggregator's profits can be reduced to up to four times those of bi-directional V2G [4], [5]. But, in certain markets, profits of unidirectional V2G may be higher than bidirectional due to their reduced capital cost. Hence, the logical first step for EV integration is to use them in unidirectional V2G.

The concept of unidirectional V2G regulation was first presented in [6], where the idea of preferable operating point (POP) to provide upward/downward regulation was established. POP defines a level of power consumption by EVs that can be increased and decreased to provide downward and upward regulation, respectively. It is constrained between zero and the maximum power draw of the battery. Though the basic principles were explained in [6], the algorithm for selecting optimal POP was not developed. The algorithm for regulation provision for an aggregator using unidirectional was developed in [49], where a bang-bang charging (all on or all off) strategy is used to dispatch each EV battery following regulation signal while taking care of desired SOC upon departure. The most comprehensive work for aggregator bidding strategies in regulation market using unidirectional V2G is described in [4], [7] and bidirectional V2G bidding strategies are explored in [38], [41]. However, none of these algorithms consider the uncertainties of the stochastic variables.

## 2.5 STOCHASTIC PROGRAMMING

Most of these works did not consider uncertainties in market variables such as energy and regulation prices, regulation/deployment signals, loads, and EV plug in times. In fact, none of the aggregator profit-maximizing bidding strategies considered the stochastic nature of the problem. In order to properly address the stochastic nature of the problem, stochastic programming can be used. This technique is extensively used in literature to model uncertainties in optimization [13], [15], [16], [9], [50]. In [13], coordinated trading of wind and thermal energy including V2G services is described and shows that

coordination with EVs results in expected profit maximization while minimizing the expected emissions. However, this work considers EVs as responsive load only hence no aggregator bidding strategies are developed. In [15], modeling of EV fleets constraints are incorporated in SCUC and four cases are developed using mixed integer programming with the objective to minimize total operating cost while incorporating uncertainties due to EV availabilities and renewable energy sources. In [16], stochastic unit commitment of thermal generators in coordination with wind power and PHEV charging loads is described with the objective to minimize the operating cost. It also, addressed the ancillary service provision via PHEVs. In [9], a practical model for V2G system is developed to support energy management within realistic configuration of micro-grid while considering uncertainties related to wind energy output and EVs. Stochastic programming is used to deal with uncertainties associated with wind energy and EV uncertainties are modeled by robust optimization. However, these works did not consider the uncertainties associated with ancillary services market variables such as prices and deployment signal, also V2G bidding strategies are not described.

# CHAPTER 3 STOCHASTIC PROGRAMMING AND SCENARIO GENERATION

Stochastic programming (SP) has gained popularity among the engineering community in the recent years. It allows users to incorporate uncertain parameters to their models while it had been a difficult task to solve such problems as deterministic models. In this regards, a SP model can be viewed as a mathematical programming model with uncertainty about the values of some of the parameters. Generally in SP, the uncertain parameters are then represented by a distribution function in a single-period case or by stochastic processes in a multi-period case [51].

Note that most of the decision making problems faced by electricity market participants are accompanied by uncertainties. For example, market energy prices are unknown at the time when producers and consumers submit their bids and offers to the market. Similarly, demand and the amount of regulation services required to balance supply and demand are also uncertain. However, such uncertain parameters compel market participant to make decisions without perfect information. This motivates the use of stochastic programming to tackle such problems. As stated by The Stochastic Programming Community [52], " SP is a framework for modeling optimization problems that involve uncertainty". In this chapter, some basic stochastic programming concepts are defined that are used throughout in this thesis.

## 3.1 RANDOM VARIABLE

In Stochastic Programming (SP), uncertain parameters are represented by random variables and the variables whose values change over time are known as stochastic process. For example, the market energy price over one week is a stochastic process. Uncertain parameters are usually represented by scenarios, or a finite set of realization, in SP [53]. For instance, random variable $\lambda$ can be represented by $\lambda(\omega)$, $\omega = 1..N_\Omega$, where $\omega$ is the scenario index and $N_\Omega$ is the number of scenarios considered. We denote $\lambda_\Omega$ by the set of possible scenarios of random variable, i.e. $\lambda_\Omega = \{\lambda(1),...,\lambda(N_\Omega)\}$. Note that $\lambda$ may represent a vector of random variables. For instance, if random variable $\lambda$ characterizes the 24 hours electricity prices of tomorrow, $\lambda(\omega)$ is a 1 x 24 vector representing one possible realization of these prices.

Each realization $\lambda(\omega)$ is associated with a probability $\pi(\omega)$ defined as:

$$\pi(\omega) = P(\omega \mid \lambda = \lambda(\omega)), \quad where \quad \sum_{\omega \in \Omega} \pi(\omega) = 1 \tag{3.1}$$

## 3.2 SCENARIOS

As stated above, a convenient way of representing random variable or stochastic processes is to generate a set of sufficient number of scenarios so that the most plausible realizations of the considered stochastic processes are covered. For this purpose, generally a large number of scenarios are generated to represent a single stochastic

variable. Note that, this may make the problem very large and computationally intractable. Thus, it is required to develop procedures that reduce the initially generated number of scenarios without significantly altering its statistical characteristics. Scenario generation and reduction procedures are described next in this chapter.

## 3.3 TWO-STAGE STOCHASTIC PROGRAMMING

In most of the decision making problems, decision makers has to make decisions without certain information. To solve such problems using SP, multi-stage stochastic programming is used to characterize these uncertainties via scenarios. At each stage the amount of information available to the decision maker is different and represents a point where decisions are made. Thus, in two-stage stochastic programming, decisions are made at two points. For instance, say $x$ and $y$ are two different types of decision variables and a random variable $\lambda$ represented by a set of scenarios $\lambda(\omega)$ . Firstly, decisions represented by $x$ are made before knowing the values of random variable $\lambda$ , whereas $y$ decisions are made after realization of $\lambda$ and depend on the values of previously made $x$ decisions. Thus, the decisions represented by $y$ are the functions of $x$ decisions and the realization of $\lambda(\omega)$ . The decision making process is as follows [51]:

1- Decisions represented by $x$ are made.

2- $\lambda(\omega)$ ,the actual realization of the random variable $\lambda$ , is realized, then

3- Decisions represented by $y(x,\omega)$ are made.

As described, there are two different types of decision variables in two-stage stochastic programming. First stage decisions are called here-and-now decisions. These decision variables are independent of the random variables and are made before their realization. Hence, the variables representing here-and-now decisions are independent of scenarios. Decisions that are made on the second stage are known as wait-and-see decisions. These decisions are made after knowing the actual values of the random variables. Consequently, these decisions depend on each plausible realization of the random variables. If random variables are represented by a set of scenarios, a second-stage decision variable is defined for each single scenario considered.

Following is the general expression of two-stage stochastic linear programming [51],

$$\underset{x}{Maximize}\ z = c^T x + \varepsilon\{Q(\omega)\} \tag{3.2}$$

Subject to:

$$Ax = b, x \in X \tag{3.3}$$

And,

$$Q(\omega) = \underset{y(\omega)}{Maximize}\ q(\omega)^T\ y(\omega),\ \ \forall \omega \in \Omega \tag{3.4}$$

Subject to:

$$T(\omega)x + W(\omega)\,y(\omega) = h(\omega),\ \ \forall \omega \in \Omega \tag{3.5}$$

$$y(\omega) \in Y, \ \forall \omega \in \Omega \tag{3.6}$$

Where, $c, q(\omega)$, $A, b, T(\omega)$, $W(\omega)$ *and* $h(\omega)$ are known input data vectors and matrices of appropriate size. Any of these variables can depend on scenarios. $x$ represents the first stage, here-and-now, decisions that are independent of scenarios and $y(x,\omega)$ are the second stage, wait-and-see, decision that are defined for each scenario.

With some assumptions [53], the deterministic equivalent of the above two stage linear stochastic problem can be expressed as below:

$$\underset{x, y(\omega)}{Maximize} \ \ z = c^T x + \sum_{\omega \in \Omega} \pi(\omega) q(\omega)^T y(\omega) \tag{3.7}$$

Subject to:

$$Ax = b \tag{3.8}$$

$$T(\omega)x + W(\omega)y(\omega) = h(\omega), \ \forall \omega \in \Omega \tag{3.9}$$

$$x \in X; \ y(\omega) \in Y, \ \forall \omega \in \Omega \tag{3.10}$$

## 3.4 SCENARIO GENERATION USING ARIMA MODELS

The set of scenarios which models the uncertain parameters are disposed as a scenario tree. Figure 3.1 shows an example of a two-stage stochastic programming scenario tree.

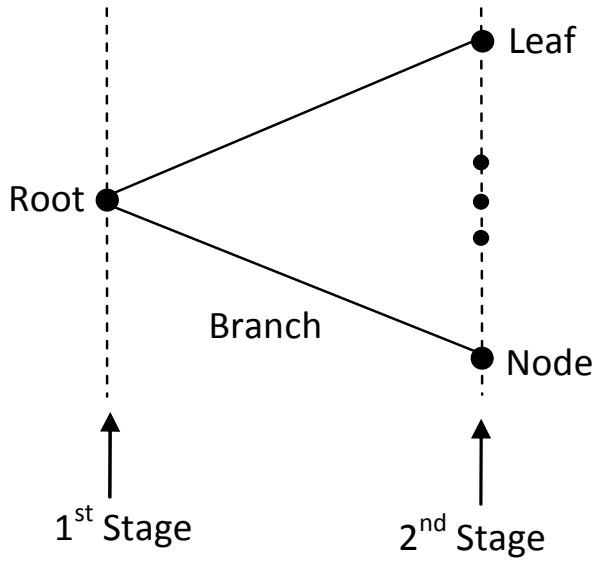


Figure 3.1: Scenario tree for two-stage SP [51]

It can be seen that, basically, a scenario tree is a set of nodes and branches [53]. Nodes are the decision making points. First node represents the beginning of planning horizon and called a root node. Second stage nodes are connected to root node via branches. These are known as leaves in two-stage stochastic programming since these are last nodes. Each path between root node and a leave is known as a scenario. Thus, number of nodes in the last stage i.e. number of leaves is equal to the number of scenarios. Each branch has associated a probability of occurrence. In this way, the probability of a scenario is the product of all branches probabilities associated with that scenario.

In engineering literature, several methodologies are proposed to build scenario tree [54], [55], [56]. In this thesis, scenario tree is constitute in two steps. Firstly a large set of scenarios is generated by a path-based method using ARIMA models. Secondly, scenario-reduction technique based on Kantorovich distance [51] between probability

distributions is used to obtain sufficient number of scenarios. Details are given in scenario reduction sub heading.

Path-based models generate scenarios via time series models. Hence, the scenario sets acquired by time series models indicate a scenario fan instead of scenario tree. An example of a scenario fan is given in Figure 3.2. To transform a scenario fan to a scenario tree, scenarios have to be bundled together [55].

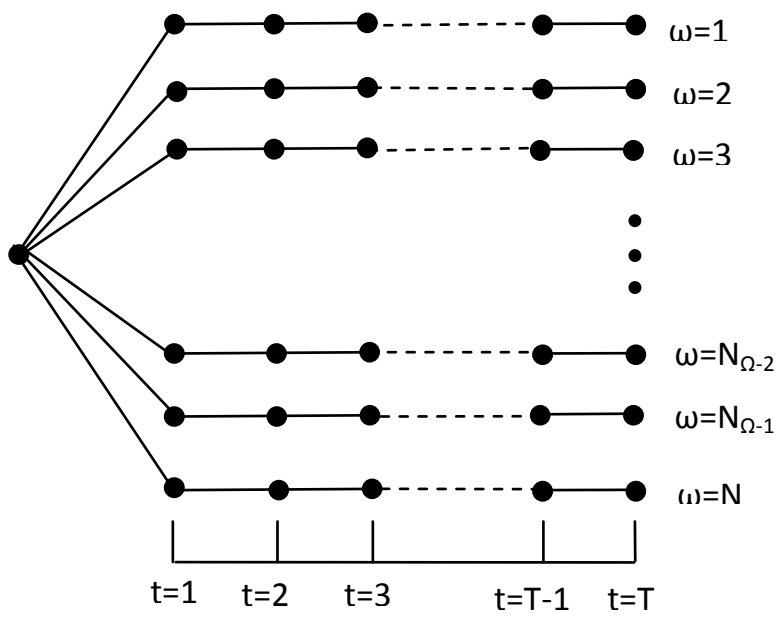


Figure 3.2: Scenario fan example [52]

### 3.4.1 ARIMA Models

The acronym ARIMA stands for "Auto-Regressive Integrated Moving Average". ARIMA is a linear model that is able to forecast and represent time series [57]. ARIMA models are completely defined by three parameters *p,d, and q*, where

- $p$ represents the number of AR terms

- $d$ represents the number of non-seasonal differences

- $q$ represents the number of MA terms (lagged errors)

Generally, an ARIMA model is given in the following form

$$\varphi(B)(1-B)^d \lambda_t = c + \theta(B)\varepsilon_t \tag{3.11}$$

where $\lambda_t$ is the variable to be forecasted at period $t$, c is a constant term, and $\varepsilon_t$ represents the error term that follows normal distribution with zero mean and $\sigma$ standard deviation. B is delay operator such that

$$B^d(\lambda_t) = \lambda_{t-d} \tag{3.12}$$

Note that the ARIMA model can only be applied on stationary series i.e. series with constant mean and variance. Thus, non-stationary series have to be transformed into stationary series first. Generally two types of transformations are used, series differentiation and logarithmic transformation. The former is used to get a constant mean while the later is used to obtain constant variance. Series differentiation is represented by $(1-B)^d$ term in (3.11).

$\varphi(B)$ and $\theta(B)$ are polynomials of order $p$ and $q$, respectively. $\varphi(B)$ is defined as,

$$\varphi(B) = 1 - \sum_{i=1}^{p} \phi_i B^i \tag{3.13}$$

where parameters $\varphi_i, i = 1...p$, are the coefficients of the polynomial $\varphi(B)$ ,and $p$ is the order of the auto-regressive term of the ARIMA model.

$\theta(B)$ is defined as,

$$\theta(B) = 1 - \sum_{j=1}^{q} \theta_j B^j \tag{3.14}$$

Where parameters $\theta_j$, $j = 1 \ldots q$, are the coefficients of the polynomial $\theta(B)$ and $q$ is the order of the moving average term of the ARIMA model.

It can be noted that ARIMA model in (3.11) also relates actual values of forecasted parameters to past values through $\varphi(B)$ , and actual errors to past errors through $\theta(B)$ .

ARIMA models should be improved to represent a time series which shows seasonal characteristic appropriately. To include seasonality in ARIMA models three additional parameters are required. These parameters are seasonal counter parts of $p$, $d$ and $q$. Thus S-ARIMA model is completely defined by $(p,d,q)$x$(P,D,Q)_s$.

The general form of the S-ARIMA models is given by,

$$\varphi(B)\phi(B)(1-B)^d(1-B^S)^D P_t = c + \theta(B)\Theta(B)\varepsilon_t \tag{3.15}$$

Where,

$$\phi(B) = 1 - \sum_{i=1}^{P} \phi_i B^{iS} \tag{3.16}$$

$$\Theta(B) = 1 - \sum_{j=1}^{Q} \theta_j B^{jS} \tag{3.17}$$

$\phi_i$ are the coefficients of seasonal autoregressive (SAR) polynomial and $P$ is the order of this polynomial, $\Theta_j$ are the coefficients of seasonal moving average (SMA) polynomial and Q is the order of this polynomial. $(1-B^S)^D$ is the seasonal differencing term where $D$ and $S$ represents the order of seasonal differencing and the order of seasonality respectively.

The methodology presented in [58], [59] to build ARIMA models is comprises of the following steps and explained in Figure 3.3.

Step 1) Specifying an ARIMA model

Step 2) Estimation of the parameters of the model,

Step 3) Model validation, and

Step 4) Forecasting

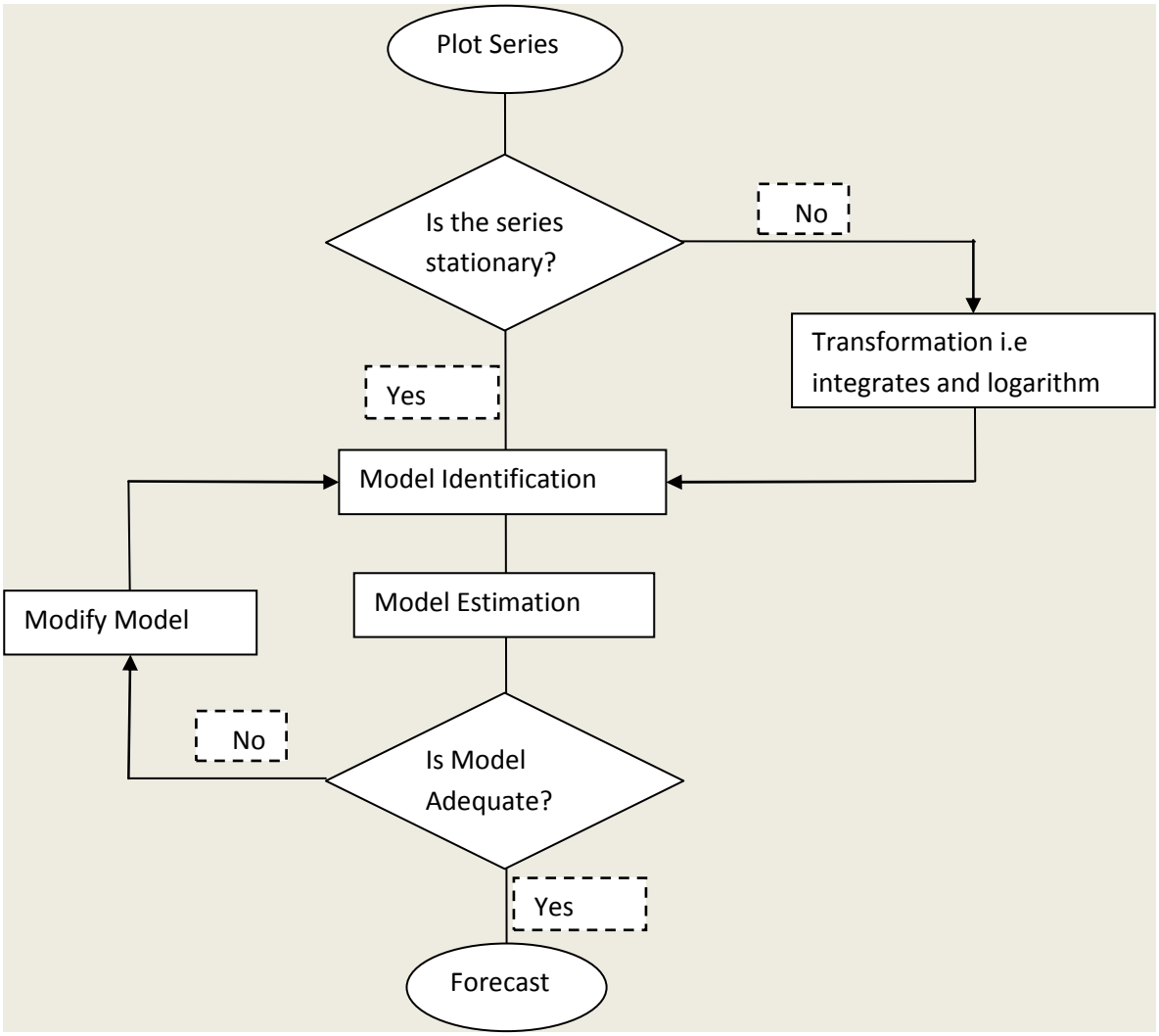


Figure 3.3: Flow chart for building ARIMA models

Step1):

In this step, the considered time series is made stationary. Some transformation of the original series may be required. Logarithmic transformation is applied to get constant variance and the series needs to be differenced to get zero mean. To identify the necessary level of differencing, plots of the data and autocorrelation are examined. Also at this stage, the number of autoregressive ($p$) and moving average ($q$) parameters that are

necessary to yield an effective model need to be decided. This initial selection of $p$ and $q$ is based on the autocorrelation and partial autocorrelation plots. Further modification of the selection is based on engineering judgment and physical knowledge.

Step2):

At the next step, the parameters are estimated. These estimated parameters are used in the last stage (Forecasting) to calculate new values of the series. The estimation process is performed on the transformed data from step 1. Thus, after generating the forecasts, the new series needs to be integrated (integration is the inverse of differencing) so that the forecasts are expressed in values compatible with the input data.

Step3):

In this step, the ARIMA model identified in step 1 is validated. For this purpose, generally two tests are performed on the residuals (actual values minus predicted values).

- Residuals should follow the normal distribution, zero mean and constant variance.
- Residuals should be uncorrelated.

A Histogram of the residuals is used to verify the first test. Plots of autocorrelation and partial autocorrelation are observed to check time dependency (correlation) of residuals. If the given two conditions are satisfied, then the assumed ARIMA model can be used to predict future values. Otherwise, the procedure needs to be repeated from step

1 by modifying the assumed model. For model modification, a careful inspection of the residuals autocorrelation plot is required.

Step 4):

In this step, future values are predicted using parameters estimated in step 2. It should be noted that the errors in the predicted values increase with the increase in forecasting period, i.e. the forecasting error in last period is typically greater than the error of first period.

Further details on the ARIMA model can be studied in [57]. The forecasting and scenario generation procedures are explained next.

### 3.4.2 Forecasting

Once the ARIMA model is verified and parameters are estimated it can be use for forecasting using (3.15). Its linear time series model is given as

$$\begin{aligned}\lambda_t^f = c + \varphi(\lambda_{t-1}, \lambda_{t-2}, ..., \lambda_{t-p}) + \phi(\lambda_{t-S}, \lambda_{t-S-1}, ..., \lambda_{t-S-P}) \\ + \theta(\varepsilon_t, \varepsilon_{t-1}, ..., \varepsilon_{t-q}) + \Theta(\varepsilon_{t-S}, \varepsilon_{t-S-1}, ..., \varepsilon_{t-S-Q})\end{aligned} \tag{3.18}$$

Where, $\lambda_t^f$ represents the forecasted value of $\lambda_t$. It is obtained by using values of $\lambda$ variable prior to $t$ $(\lambda_{t-1}, \lambda_{t-2}, ..., \lambda_{t-p})$ and values of error terms at time $t$ and prior to $t$ $(\varepsilon_t, \varepsilon_{t-1}, ..., \varepsilon_{t-q})$.

The methodology used to forecast $\lambda$ in periods from $t...N_t$ is as follows:

Step 1) Initialize $\varepsilon_t = 0$: setting it to its expected value considering that $\varepsilon_t$ is a white noise process, i.e., $\varepsilon_t \in \mathrm{N}(0,\sigma)$ .

Step 2) Forecast $\lambda_t^f$ : Evaluate (3.18) to obtain the forecast of $\lambda$ in period *t* i.e. $\lambda_t^f$ .

Step 3) Initialize $\varepsilon_{t+1} = 0$.

Step 4) Forecast $\lambda_{t+1}^f$ : Again evaluate (3.18) to get forecast of variable $\lambda$ in period *t+1*, $\lambda_{t+1}^f$ , considering that $\lambda_t$ is known and equal to $\lambda_t^f$

....

Step $N_t$+2) Forecast $\lambda_{N_t}^f$ : Considering that $\lambda_t, \lambda_{t+1}, ...\lambda_{N_t-1}$ are known and equal to their forecasted values from previous steps. Again,(3.18) is evaluated to calculate $\lambda_{Nt}^f$ .

### 3.4.3 Scenario Generation

Scenario generation procedure for a stochastic process $\lambda$ is based on the forecasting methodology explained above and sampling of the error terms from their distribution $\varepsilon_t \in \mathrm{N}(0,\sigma)$ . Unlike the forecasting procedure, the error term is not considered equal to its expected value but randomly generated according to a normal distribution.

Following are the steps required to generate scenarios of the random process $\lambda_t(\omega),\ t = 1...N_t,\ \omega = 1...N_\Omega$ , where $N_t$ is the forecasting horizon and $N_\Omega$ is the number of required scenarios.

1) Initialize the scenario counter $\omega = 0$.

2) Initialize the period counter $t = 0$ and update scenario counter $\omega = \omega + 1$.

3) Update period counter $t = t + 1$.

4) Randomly generate error $\varepsilon_t(\omega)$ from normal distribution such that $N(0, \sigma)$.

5) Evaluate (3.18) to obtain forecasted value at period $t$ by observing historical data and generated error.

6) Incorporate forecasted value as the most recent entry in the time series.

7) Check period counter $t \leq N_t$.

8) Reset the time series to its default values.

9) Check scenario counter $\omega \leq N_\omega$.

Figure 3.4 shows the flow chart for scenario generation procedure.

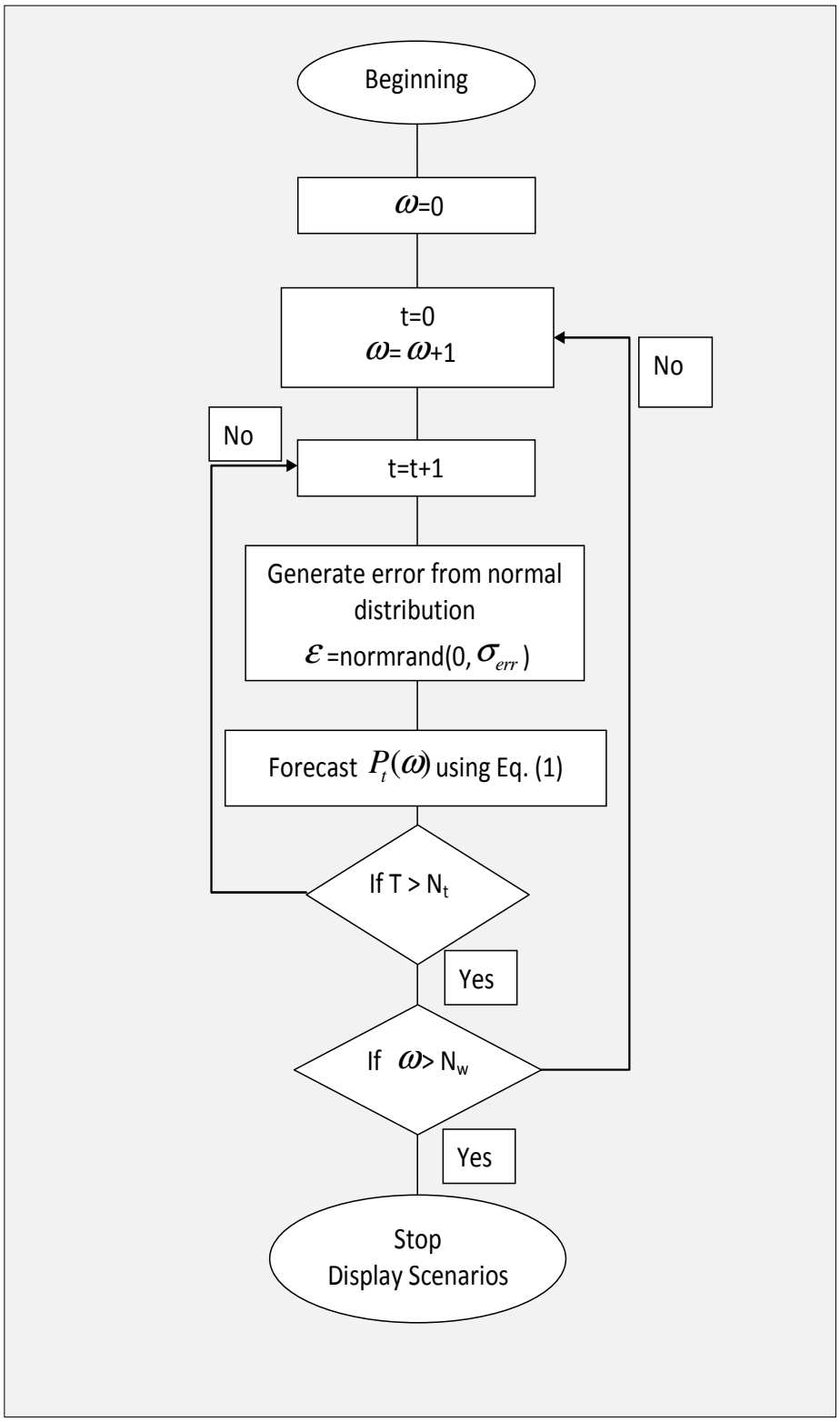


Figure 3.4: Scenario generation flow chart

### 3.4.4 Scenario Reduction

To represent the uncertainty in a decision making process, large number of scenarios is needed. This makes computation of the problem intractable. Therefore a mathematical technique for reducing the number of scenarios is required. A reduced scenario tree which is close to original one can be obtained if the closeness is measured by probability distance. In Stochastic optimization problems, one of the most commonly used probability distance is the Kantorovich distance which is defined as [60][51],

$$D_K(Q,Q') = \sum_{\omega \in \Omega \setminus \Omega_S} \pi_\omega \min_{\omega' \in \Omega_S} v(\omega,\omega') \tag{3.19}$$

Where, $\omega$ and $\omega'$ are the scenarios, $Q$ and $Q'$ are the probability distribution function in the initial and selected scenario set $\Omega$ and $\Omega_S$ , respectively and $\pi_\omega$ represents probability of each scenario.

$v(\omega,\omega')$ is the continuous, non-negative, symmetric function known as cost function and is given by a norm,

$$v(\omega,\omega') = \left\| \lambda(\omega) - \lambda(\omega') \right\| \tag{3.20}$$

Further details on Kantorovich distance can be found in [61]. Several heuristic scenario reduction techniques can be developed using (3.19). Generally two different techniques backward reduction and forward selection are used. In this study, fast forward reduction algorithm based on forward selection method is used since it is more suitable

for electricity market problems [51] where preliminary drastic reduction is required for problem tractability.

It is an iterative process starting with an empty set ( $\Omega_S = 0$ ) and selecting a scenario in each iteration from the set of un-selected scenarios ( $\Omega / \Omega_S$ ) that minimizes the Kantorovich distance between reduced and original set. These selected scenarios are placed in $\Omega_S$ while deleting them from the original set after iteration. The algorithm stops after selecting a specified number of scenarios. In the end, the probabilities of each non-selected scenarios is transferred to its closest selected scenario.

The step by step algorithm is given below.

Step 0): First step is to calculate the cost function $v(\omega, \omega')$ for each pair of scenario $\omega$ and $\omega'$ from the original set $\Omega$ using (3.20).

Step 1): In this step first scenario is selected. It is an important step because reduced scenario set is build from this scenario. Generally, it the most equidistant one from the rest and can be interpreted as the average scenario. It is selected by computing distances such that,

$$d_\omega = \sum_{\substack{\omega'=1 \\ \omega' \neq \omega}}^{N_\Omega} \pi_{\omega'} v(\omega, \omega'), \quad \forall \omega \in \Omega$$

$$Select : \omega_1 \in \min_{\omega \in \Omega} d_\omega$$

$$Set : \Omega_j^{[1]} = \{1 \ldots N_\Omega\} \setminus \omega_1$$

Step i): A new scenario is added to the reduced scenario set in each iteration until the required numbers of scenarios are selected. Scenarios are selected as given below,

$$v^{[i]}(\omega,\omega') = \min\{v^{[i-1]}(\omega,\omega'), \omega^{[i-1]}(\omega,\omega_{i-1})\}, \quad \forall \omega,\omega' \in \Omega_j^{[i-1]}$$

$$d_\omega^{[i]} = \sum_{\omega' \in \Omega_j^{[i-1]} \setminus \{\omega\}} \pi_{\omega'} v^{[i]}(\omega,\omega'), \ \forall \omega \in \Omega_j^{[i-1]}$$

$$Select: \omega_i \in \min_{\omega \in \Omega_j^{[i-1]}} d_\omega^{[i]}$$

$$Set: \Omega_j^{[i]} = \Omega_j^{[i-1]} \setminus \omega_i$$

Step $N_{\Omega_S} + 1$ ): This is the last step where probabilities of non-selected/discarded i.e. $\omega \in \Omega_D$ where, $\Omega_S + \Omega_D = \Omega$ , scenarios are redistributed among the selected scenario set $\omega \in \Omega_S$ . This is carried out as give below.

$$\pi^*_\omega \leftarrow \pi_\omega + \sum_{\omega' \in J(\omega)} \pi_{\omega'}, \ \forall \omega \in \Omega_S$$

$$where, \ J(\omega) = \{\omega' \in \Omega_D \mid \omega = j(\omega')\}$$

$$j(\omega') \in \min_{\omega'' \in \Omega_S} v(\omega'',\omega')$$

Finally, the set of reduced scenarios $\omega \in \Omega_S$ with associated probabilities $\pi^*_\omega$ are obtained.

# CHAPTER 4 STOCHASTIC PROGRAMMING BASED BIDDING STRATEGY FOR V2G REGULATION SERVICES

## 4.1 INTRODUCTION

In this chapter, an optimal bidding strategy is proposed to be used by EV aggregators to participate in day ahead regulation services while considering the uncertainties associated with regulation prices and regulation deployment signals. The case under investigation is that of an EV aggregator having control over a large number of commuter cars, which are typically available between 8 AM and 5 PM. Stochastic programming is used to incorporate the uncertainties into this optimization problem. The optimization aims to determine the optimal preferred operating points and the amount of regulation up/down bids that maximize the expected profit of the EV aggregator while satisfying the constraints likely to be imposed by market and EV owners.

## 4.2 PROBLEM DESCRIPTION

This section gives a description of the Regulation algorithm, briefly explains the execution of the two stage stochastic programming approach for this work, and the data preprocessing required for the optimization.

### 4.2.1 Regulation Algorithm

Aggregated EVs can be used to provide regulation services to the grid through unidirectional V2G by charging their batteries around the preferable operating point (POP). This set point is an average level of operation for a market participant providing regulation services. With respect to generators, POP is the level of generated power while it is a level of power draw for EVs. In this way regulation up and down can be performed with only unidirectional power flow, i.e. charging batteries only. The aggregator controls the charging of each EV according to its capacity and requirement to fulfil the deployment signal received from the system operator. Figure 4.1 shows the regulation algorithm [4]. For regulation down signal, aggregator increases the charging rate of each EV, consequently draws more power from the grid and vice versa for regulation up signal. In order to calculate the new charging rate i.e. $PD_i$, the percentage of received deployment down/up signal is multiplied by maximum/minimum available power *(MxAP/MnAP)* of that EV and then adding it to its current *POP* as shown in Figure 4.1. This algorithm also ensures that the EV would not charge beyond its maximum limit. Figure 4.2 and Figure 4.3 show graphical descriptions of variables. Figure 4.2 shows that the maximum available power (*MxAP*) of each EV for regulation down is a difference between maximum power draw (*MP*) and the preferred POP. While minimum available power for regulation up is equal to the POP. Figure 4.3 shows that the charge remaining (*ChR*) in each EV is the difference between maximum charge limit (*MC*) and state of charge (SOC). It also shows that SOC is non-decreasing variable due to unidirectional strategy.

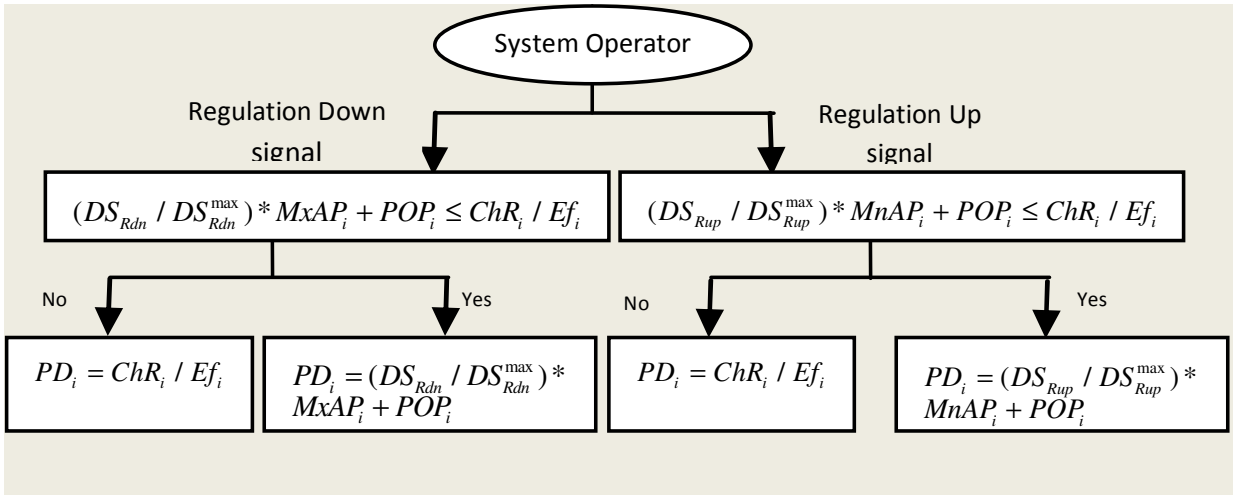


Figure 4.1: Regulation Algorithm flow chart [4].

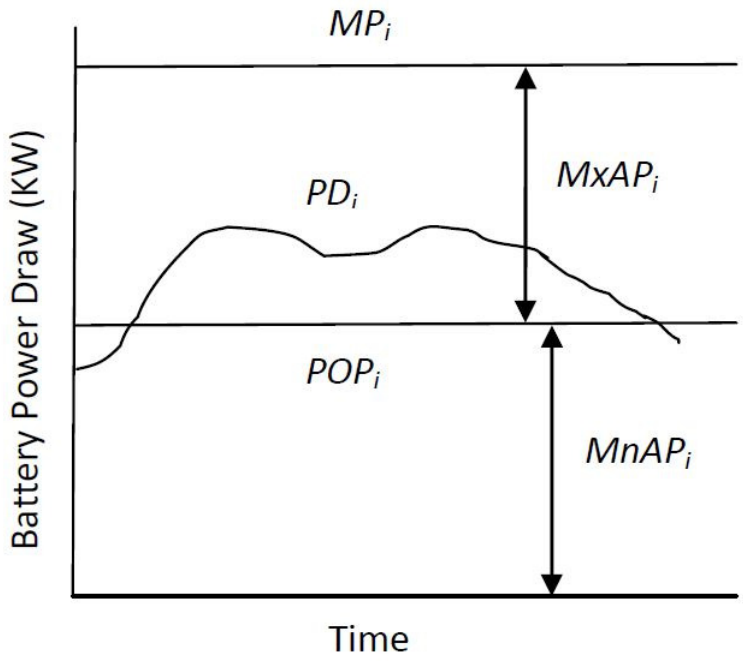


Figure 4.2: Graphical description of regulation around the POP [4].

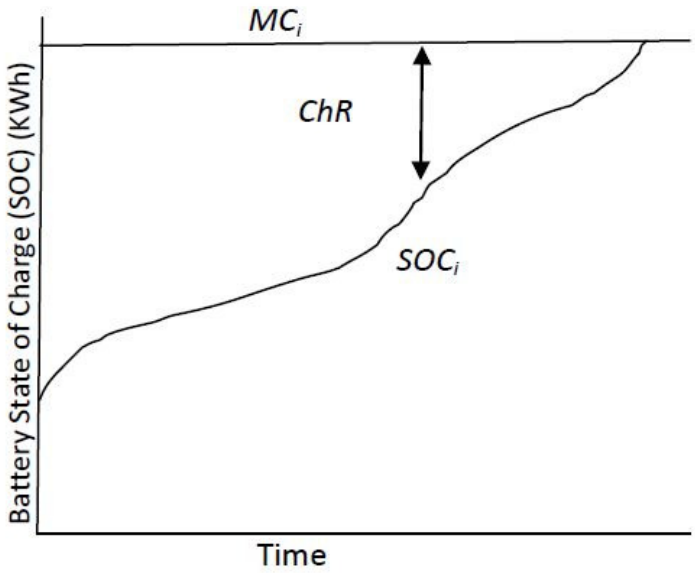


Figure 4.3: Graphical description of SOC while performing regulation [4]

### 4.2.2 Stochastic Programming

A two-stage stochastic program is devised in order to take uncertainties into account. In SP, several scenarios of each stochastic variable are generated, and a scenario tree is built, as explained in Chapter 3. These scenarios are mutually exclusive and need to reflect the statistical properties of each variable. A probability of occurrence is assigned to each scenario in the tree. The decision variables are categorized into two stages. The first stage decisions are "here-and-now" and the second stage decisions are "wait-and-see". In this work, the first stage decisions are the hourly preferred operating point of each EV and hourly bids of regulation up and down services that are submitted to the market. The only second stage decision is the expected power draw of each EV in each

hour as it depends on the realized scenario. The four stochastic variables considered are the regulation up and down prices and deployment signals.

### 4.2.3 Scenario Generation and Reduction

To generate scenarios of each stochastic variable, Auto Regressive Integrated Moving Average (ARIMA) modelling is used. The required historical data for energy price, load and regulation up and down prices and signals are taken from available ERCOT archives [10]. Thousands of scenarios are required to represent each stochastic variable. However, to use all the generated scenarios is not computationally efficient. Therefore, scenario reduction is needed to make the optimization problem tractable. Scenario reduction is used to reduce the large number of scenarios without significantly changing the statistical attributes of the original scenario sets.

## 4.3 MATHEMATICAL FORMULATION

Regulation services can be provided to the grid using aggregated EVs by charging their batteries around the preferable operating point (POP). The regulation capacities depends on the POP. Therefore, the aggregator needs to adjust POP in a way that maximizes its regulation capacities while satisfying the constraints likely to be imposed by EV owners. An aggregator participating in electricity markets is vulnerable to uncertainties in market parameters, such as prices and regulation deployment signals. From the aggregator perspective, it is important to consider the stochastic nature of these market variables while developing strategies. Several smart charging and optimization

algorithms have been developed for aggregators [4], [7], [37–39] but none of them modelled the uncertainties. In this chapter, stochastic bidding strategy based on [4] is proposed that incorporates uncertainties of the market variables. This algorithm is to be used by an aggregator for scheduling EVs with the objective of maximizing its profit while satisfying constraints likely to be set by the customers and utilities. The mathematical formulation of the objective function is as follows:

$$\underset{(POP_{ti}, MxAP_{ti}, MnAP_{ti}, PD_{tsi})}{Maximize} \quad E[PROFIT] \tag{4.1}$$

$$E[PROFIT] = \sum_{s=1}^{Ns} \pi_s * [PF\_Percent_s + PF\_MrkUp_s] \tag{4.2}$$

$$PF\_Percent_s = \alpha * \sum_{t=1}^{Nt} \{\rho_{ts}^{Rdn} * CR_t^{Rdn} + \rho_{ts}^{Rup} * CR_t^{Rup}\} \tag{4.3}$$

$$PF\_MrkUp_s = Mk * \sum_{t=1}^{Nt} \sum_{i=1}^{Ni} PD_{tsi} \tag{4.4}$$

$$CR_t^{Rdn} = \sum_{i=1}^{Ni} MxAP_{ti} \tag{4.5}$$

$$CR_t^{Rup} = \sum_{i=1}^{Ni} MnAP_{ti} \tag{4.6}$$

$$PD_{tsi} = DS_{ts}^{Rdn} * MxAP_{ti} + POP_{ti} - DS_{ts}^{Rup} * MnAP_{ti} \tag{4.7}$$

Equation (4.2) represents the expected aggregator's profits that come from two sources. The first is the fixed percentage, $\alpha$, of the revenue obtained from providing regulation services, as shown in (4.3). The second source is a fixed mark-up over the market price of energy which is passed on the customers, as shown in (4.4). The aggregator cost is assumed to be constant because the price of energy is passed on to the EV owner with a mark up over it. Overhead costs like, charger maintenance, communication between EV owner and aggregator and battery degradation are neglected. Equation (4.5) and (4.6) represent the aggregated capacity of all EVs at each hour for regulation down and regulation up, respectively. The expected power draw of each EV at each hour and scenario is modelled in (4.7). It shows that the power draw of each EV is a function of POP and uncertain regulation up/down dispatch signals that are received from system operator. Unlike previous optimization algorithms, the uncertainties of these dispatch signals are taken into account using SP. Stochastic variables are regulation up/down prices and deployment signals and represented by $\rho_{ts}^{Rup} / \rho_{ts}^{Rdn}$ and $DS_{ts}^{Rup} / DS_{ts}^{Rdn}$ respectively. And, the decision variables are $POP_{ti}$ , $CR_t^{Rdn}$ and $CR_t^{Rup}$ , and $PD_{tsi}$ . The aggregator will bid the capacities represented by the first three variables into the market.. This optimization is subjected to the following constraints:

$$\sum_{t=1}^{N_t} PD_{tsi} + SOC\_I_i \leq MC_i, \forall s,i,t \tag{4.8}$$

$$\left(MxAP_{1i} + POP_{1i}\right) Ef_i + SOC\_I_i \leq MC_i \tag{4.9}$$

$$MxAP_{ti} + POP_{ti} \leq MP_{ti}, \forall t, i \tag{4.10}$$

$$MnAP_{ti} \leq POP_{ti}, \forall t, i \tag{4.11}$$

$$MxAP_{ti} \geq 0 \tag{4.12}$$

$$MnAP_{ti} \geq 0 \tag{4.13}$$

$$POP_{ti} \geq 0 \tag{4.14}$$

Constraint (4.8) limits the total energy stored in the battery from charging by the battery capacity. Constraint (4.9) ensures that the battery will not charge too soon during the scheduling period. The maximum charge rate constraint is imposed by (4.10). Equations (4.11) - (4.14) represents the ancillary service constraints.

## 4.4 CASE STUDY

A case study with an aggregator that serves a hypothetical group of 10,000 EVs used by commuters in the Houston area is simulated for an 85-day period (28$^{th}$ July – 20 October, 2010). Each simulation day starts from 8 A.M to 5 P.M since commuter cars are typically available during this period. This provides sufficient time for the aggregator to sell regulation services and charge the EVs without noticeable inconvenience to the consumers. For this study, electricity market parameters, such as energy prices, regulation up/down price and deployment signals, are taken from the available ERCOT historical data [10]. Available deployment signal are of five-minute-resolution. Equation

(4.15) and (4.16) are used to calculate the hourly expected percentage of these five-minute regulation up/down signals for the entire simulation period so each variable would have the same resolution.

$$DS_{ts}^{Rdn} = \frac{\int_{RS_{\min}}^{0} RS.\Pr[RS].dRS}{\int_{RS_{\min}}^{0} RS.dRS} \tag{4.15}$$

$$DS_{ts}^{Rup} = \frac{\int_{0}^{RS\max} RS.\Pr[RS].dRS}{\int_{0}^{RS\max} RS.dRS} \tag{4.16}$$

In this study, the aggregator receives revenues from two sources, one from fixed percentage over ancillary services, $\alpha$ , and second is the fixed mark up over energy price that is supplied to the EV owners. Consequently, variation in market energy price will not affect aggregator income and therefore, aggregator has no incentive to charge EVs at higher energy prices. The aggregator has to pay market energy price for net energy used each hour. For this study, it is assumed that the aggregator

- Receives 20% of the regulation service revenues.
- Charges $0.05/kWh over the market energy price.
- Bids its capacities at $0/MWh to ensure acceptance.

It is also assumed that no market participant has market power, which means that the market operates at near pure competition.

Three different types of EVs that are currently available in the market, are considered; Nissan Leaf, Mitsubishi i-MiEV, and the Tesla Model S. The battery capacities, driving efficiency and other EV specification are taken from [62–64]. The percentage of each type of EV among the hypothetical group and their specifications are given in Table 4.1. The charging station are assumed to be rated at 230 V, 30 A [65].

Table 4.1: Electric Vehicles specifications

| Model | Percentage (%) | Battery Capacity (kWh) | Charger Rating (kW) | Charger Efficiency |
|---|---|---|---|---|
| Nissan Leaf | 50 | 24 | 3.3 | 0.9 |
| i-MiEV | 20 | 24 | 3.3 | 0.9 |
| Tesla Model- S | 30 | 85 | 20 | 0.9 |

Three months data from ERCOT market (July 21 – 20 Oct, 2010) are used to adjust ARIMA models for all stochastic variables. The MATLAB environment (MATLAB (2012) has been used to implement the ARIMA model.

### 4.4.1 ARIMA Model for Regulation down prices

The ARIMA model is used to generate scenarios for regulation down prices is shown in (4.17). This model is selected after several trials and it is validated by performing tests on residuals as described in Chapter 3.

$$(1-\phi_1 B^1-\phi_2 B^2)(1-\phi_{24}B^{24})(1-B^1)(1-B^{24})\log(\rho_t^{Rdn}) \\ =(1-\theta_1 B^1-\theta_2 B^2)(1-\theta_{24}B^{24})\varepsilon_t^{Rdn} \tag{4.17}$$

Hourly generated values from this model depend on previous values of prices as a product of four terms: 1 hour ago and 2 hour ago, 1 day ago, hourly differentiation, and daily differentiation. First two terms means that the generated value in the next hour is correlated to regulation down price this hour, previous hour the same day and same hour yesterday. It can also be seen from autocorrelation and partial autocorrelation functions as shown in Figure 4.4 and Figure 4.5. Hourly generated values from this model also depends on previous values of errors as a product of 2 terms: 1 h ago and 2 hour ago and 1 day ago.

The error term $\varepsilon_t^{Rdn}$ in the specified model is a random number obtained from a normal distribution with zero mean and constant variance, i.e. a white noise process. The standard deviation of $\varepsilon_t^{Rdn}$ is considered constant and is calculated from ARIMA model. Its value is equal to 0.1077. The error variance and estimated parameters of (4.17) are given in Table 4.2.

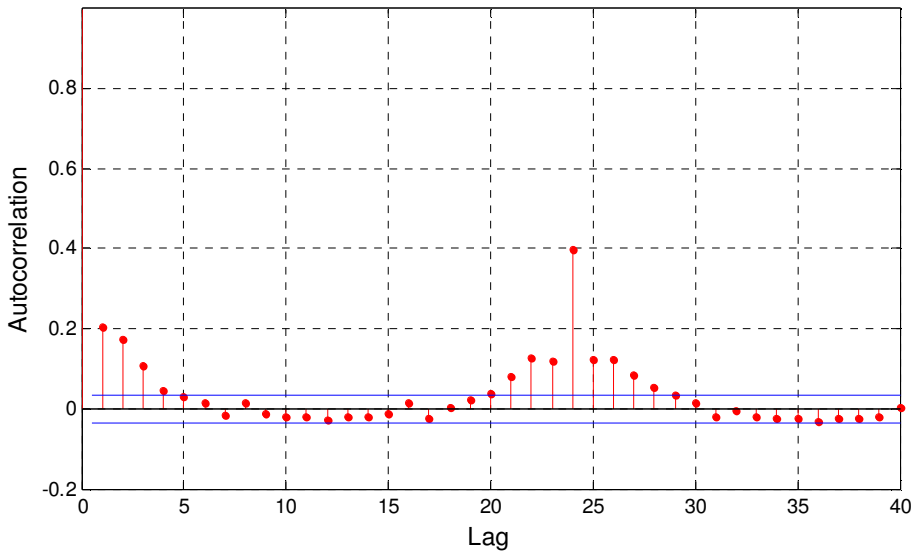


Figure 4.4: Autocorrelation function for Regulation Down prices

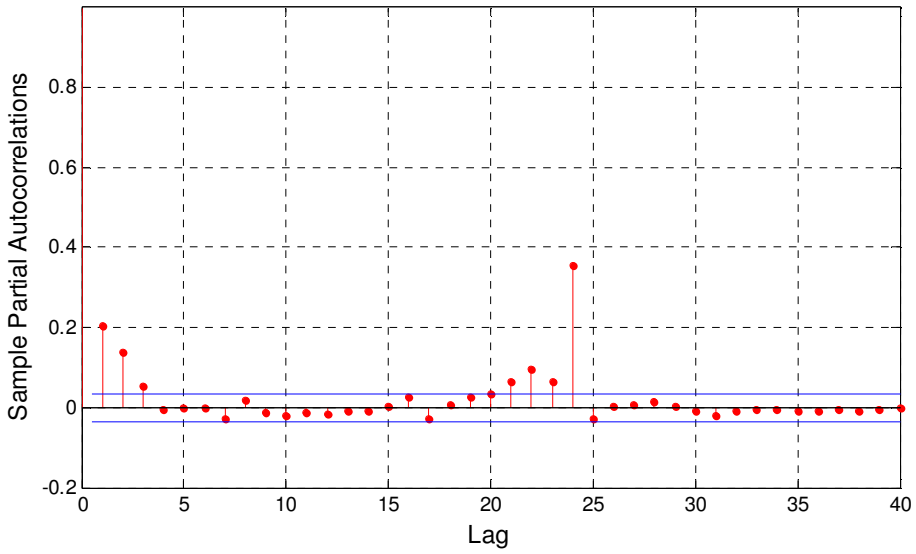


Figure 4.5: Partial Autocorrelation function for Regulation Down prices

Table 4.2: ARIMA model parameters for Regulation down prices

| $\rho_t^{Rdn}$ (ARIMA(2,1,1)(2,1,1)$_{24}$) | | | | | | |
|---|---|---|---|---|---|---|
| $\phi_1$ | $\phi_2$ | $\phi_{24}$ | $\theta_1$ | $\theta_2$ | $\theta_{24}$ | Error Variance |
| 0.1195 | 0.086 | -0.75787 | -0.7443 | -0.1708 | 0.634844 | 0.0116 |

### 4.4.2 ARIMA Model for Regulation up prices

Similarly, ARIMA model for regulation up prices is shown in (4.18) and its estimated parameters are given in Table 4.3. Again, the term $\varepsilon_t^{Rup}$ is generated from $N(0,\sigma_{err}^{Rup})$, where $\sigma_{err}^{Rup}$ is a standard deviation of $\varepsilon_t^{Rup}$ with a constant value 0.1063.

$$(1-\phi_1 B^1)(1-\phi_{23}B^{23}-\phi_{24}B^{24})(1-B^1)(1-B^{24})\log(\rho_t^{Rup}) = (1-\theta_1 B^1-\theta_2 B^2-\theta_3 B^3-\theta_4 B^4)(1-\theta_{23}B^{23}-\theta_{24}B^{24})\varepsilon_t^{Rup} \tag{4.18}$$

Table 4.3: ARIMA model parameters for Regulation up prices

| $\rho_t^{Rup}$ (ARIMA(1,1,2)(4,1,2)$_{24}$) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| $\phi_1$ | $\phi_{23}$ | $\phi_{24}$ | $\theta_1$ | $\theta_2$ | $\theta_3$ | $\theta_4$ | $\theta_{23}$ | $\theta_{24}$ | Error Variance |
| -0.7648 | -0.0156 | -0.2373 | 0.2722 | -0.6102 | -0.3083 | -0.0764 | 0.1202 | -0.5810 | 0.01130 |

### 4.4.3 ARIMA Model for Regulation up/down deployments

Then the ARIMA model is adjusted for hourly expected deployment signals for regulation up/down as obtained from (4.15) - (4.16). This ARIMA model is given in (4.19) and its estimated parameters are shown in Table 4.4. The term $\varepsilon_t^{DS}$ is generated from $N(0,\sigma_{err}^{DS})$, where $\sigma_{err}^{DS}$ is a standard deviation of $\varepsilon_t^{DS}$ with a constant value 0.1965

and obtained from ARIMA model. Note that this value is higher than the value of standard deviation corresponding to the error terms of regulation prices. This is due to the fact that the regulation deployment signal is more volatile than the regulation prices.

$$(1-\phi_1 B^1-\phi_2 B^2)(1-\phi_{23}B^{23}-\phi_{24}B^{24})(1-B^1)(1-B^{24})(DS_t^{Rup/Rdn}) = (1-\theta_1 B^1-\theta_2 B^2)(1-\theta_{23}B^{23}-\theta_{24}B^{24})\varepsilon_t^{DS} \quad (4.19)$$

Table 4.4: ARIMA model parameters for Regulation up/down Deployment signal

| $DS_t^{Rdn/Rup}$ (ARIMA(2,1,2)(2,1,2)$_{24}$) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| $\phi_1$ | $\phi_2$ | $\phi_{23}$ | $\phi_{24}$ | $\theta_1$ | $\theta_2$ | $\theta_{23}$ | $\theta_{24}$ | Error Variance |
| 0.7132 | -0.2128 | -0.1685 | -0.1534 | -1.5332 | 0.5332 | 0.1404 | -0.6710 | 0.0386 |

### 4.4.4 Generated Scenarios

One thousand scenarios for each stochastic variable are generated for each day (between 28th July to 20 October, 2010) using the respective fitted ARIMA model and previous week data. For instance, Figure 4.6 shows the generated scenarios of regulation up prices with the blue bold line representing the actual day regulation up prices for July 31, 2010. Actual day values are highlighted to show the effectiveness of the generated scenarios. Similarly, Figure 4.7 - Figure 4.9 show the scenarios generated for regulation down prices and regulation up and down deployment signals respectively.

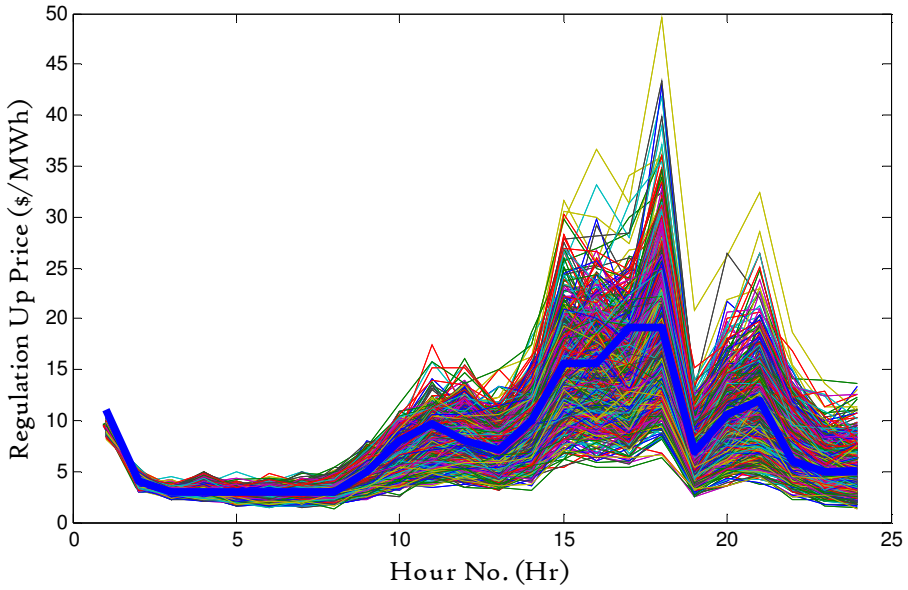


Figure 4.6: Scenarios and actual day profile of Regulation Up prices for July 31, 2010

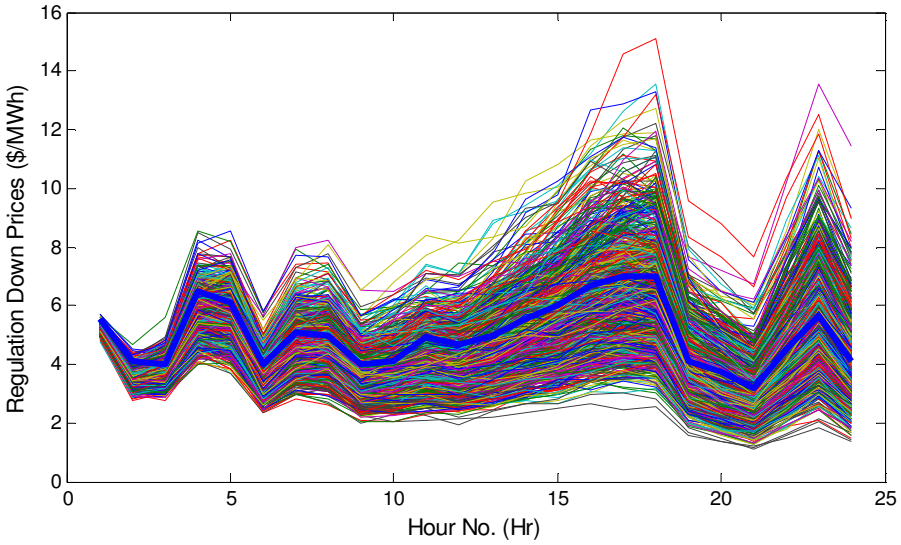


Figure 4.7: Scenarios and actual day profile of Regulation Down prices for July 31, 2010

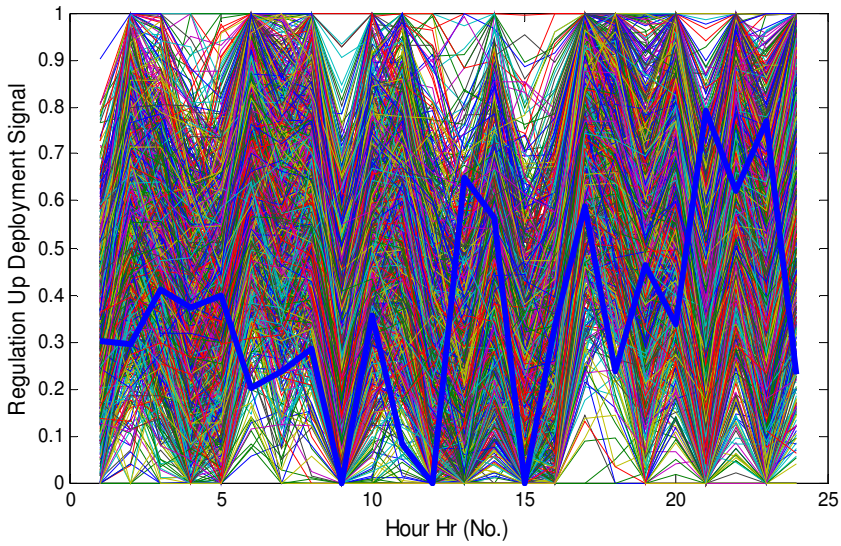


Figure 4.8: Scenarios and actual day profile of Regulation Up deployment signal for July 31, 2010

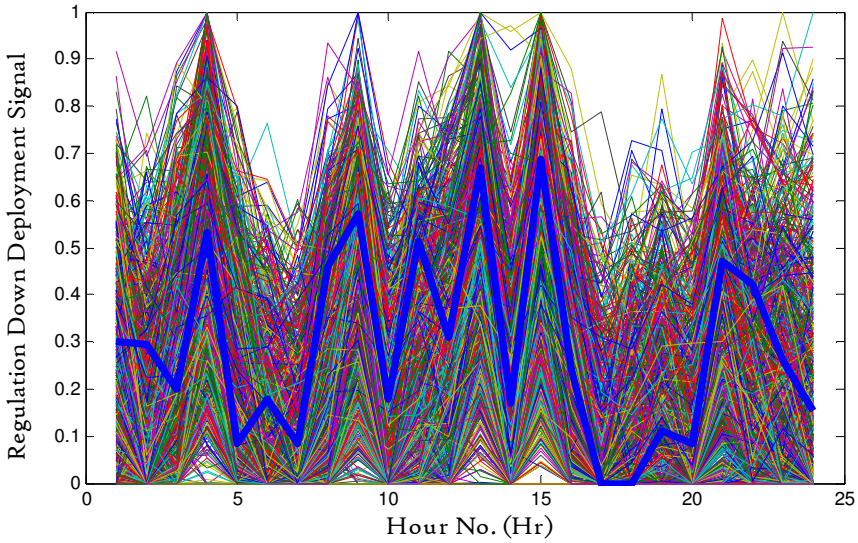


Figure 4.9: Scenarios and actual day profile of Regulation Down deployment signal for July 31, 2010

### 4.4.5 Reduced Scenarios

By considering one thousand scenarios for each stochastic variable, a single day complete scenario tree consists of $1000^4$ scenarios which yield an optimization problem that is intractable. Therefore, the scenario reduction technique presented in Chapter 3 is applied to each stochastic variable, resulting in three scenarios for each type of regulation services prices and five scenarios for each type of deployment signals. The three bold lines red, blue and green in Figure 4.10 and Figure 4.11 represents the set of reduced scenarios associated with Regulation up prices and Regulation down prices for July 31, 2010 respectively. Reduced scenarios of Regulation up and down deployment signals are shown in Figure 4.12 and Figure 4.13. The number of reduced scenarios associated with deployment signals is higher than that of prices' scenarios because of their high volatility.

As a result, a single day's reduced scenario tree is composed of 225 (3x3x5x5) scenarios. The composition of scenario tree and probability calculation of each scenario is described in [51]. This process is repeated for all days for the entire simulation period.

### 4.4.6 Deterministic Solution

The deterministic algorithm is also simulated by considering a single scenario and replacing stochastic variables by their forecasted values. In this simulation the aggregator used the point forecast for each market variable to optimize the day ahead bid instead of considering several scenarios. These forecasted values are obtained by using the fitted ARIMA model. The mean absolute errors of the forecasted data are shown in Table 4.5.

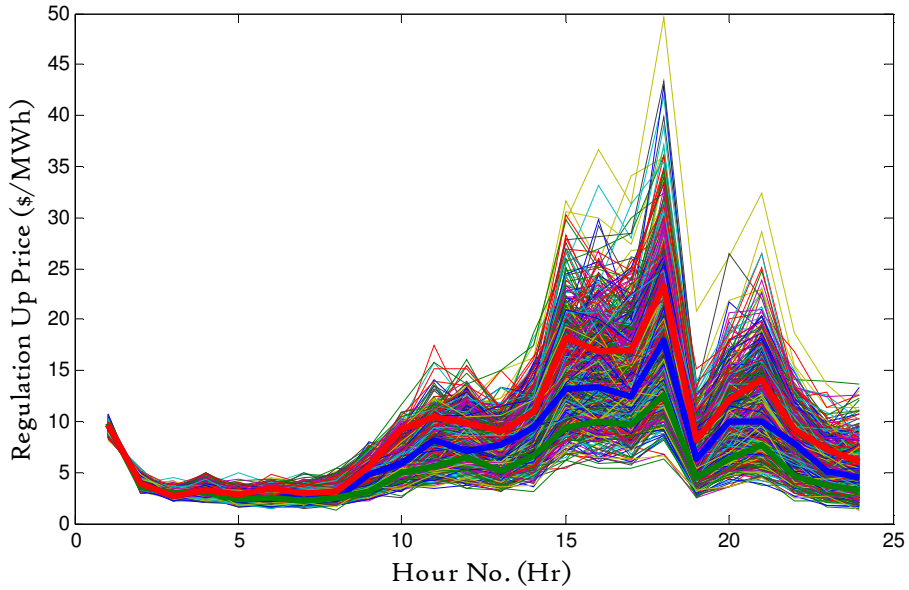


Figure 4.10: Set of Reduced scenarios for Regulation Up Prices for July 31, 2010

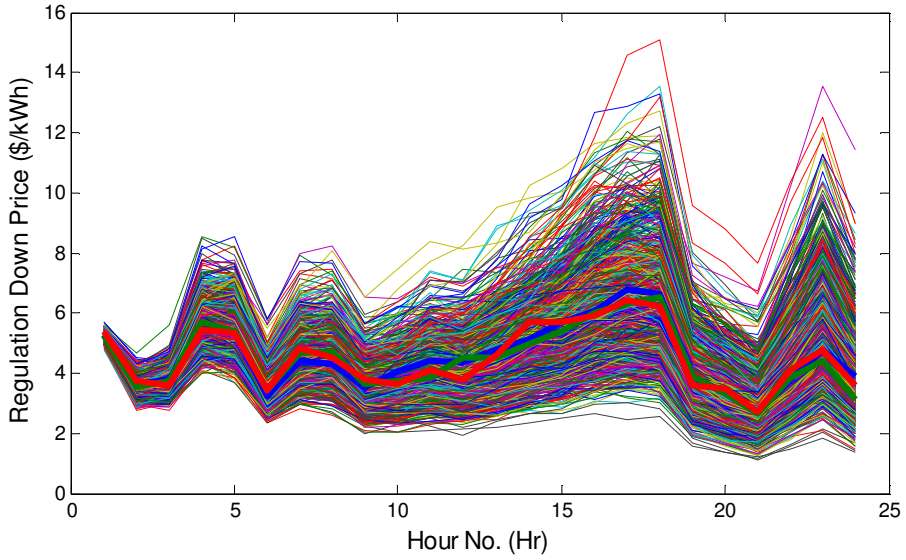


Figure 4.11: Set of Reduced scenarios for Regulation Down Prices for July 31, 2010

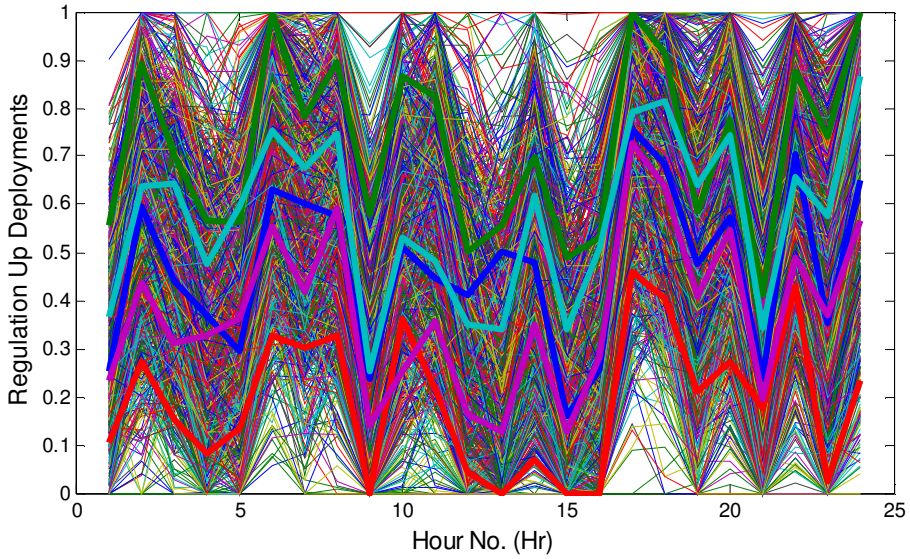


Figure 4.12: Set of Reduced scenarios for Regulation Up Deployment signal for July 31, 2010

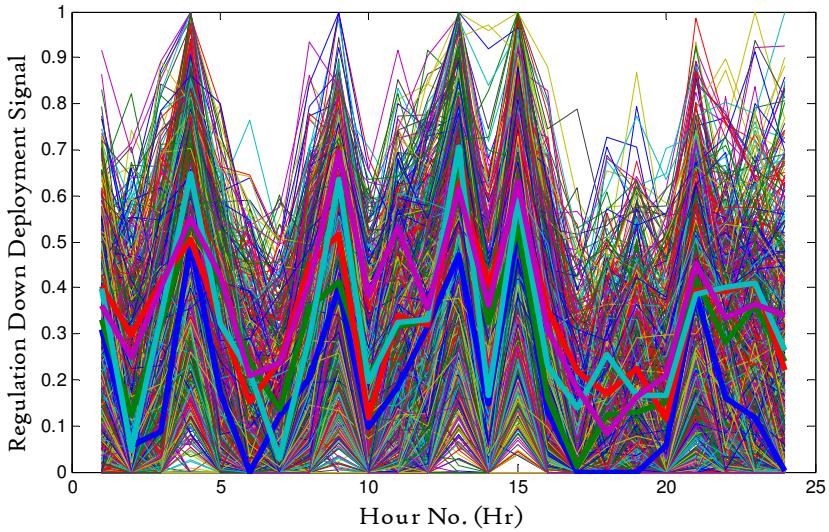


Figure 4.13: Set of Reduced scenarios for Regulation Down Deployment signal for July 31, 2010

Table 4.5: Mean Absolute Errors 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 % |

The algorithms are implemented using CPLEX 12.4 that calls OPL modeling language [66]. Using a PC with a Core(TM) i3 2.13 GHz CPU and 8GB of RAM. The processing times of stochastic and deterministic single day simulations are 270 and 45 seconds, respectively.

## 4.5 RESULTS AND ANALYSIS

Two algorithms, Deterministic and Stochastic, are run for nine-hour charging periods from 8 A.M. to 5 P.M. for each day between July 28, 2010 and Oct 20, 2010. It is assumed that EVs are always available for charging during this period. Comparison of

average charging profiles and regulation up/down bidding capacities during the charging period are shown in Figure 4.14 - Figure 4.16. It can be seen from Figure 4.14 that both algorithms initially schedule low POPs, thus saving capacity to bid throughout the charging period. Notice that the stochastic algorithm schedules comparatively low POPs to get benefit from uncertain market parameters, except for the last hour where POP is considerably high to top off the battery.

Average regulation up bidding capacity is shown in Figure 4.15. The deterministic algorithm bids more regulation up capacity in later hours to take advantage of high regulation up prices during mid day which is typical, while the stochastic algorithm bids a moderate level of regulation up capacity due to uncertain behavior of regulation prices.

Figure 4.16 shows the regulation down bidding capacity for both algorithms. Deterministic bids high regulation down capacity initially and its amount decreases noticeably throughout the charging period as EVs charge except for the local maxima at hours 13 and 14 where regulation down prices are comparatively higher. On the other hand, Stochastic is able to bid high level of regulation down capacity throughout the charging period except for the last hour. During this hour, since the mark-up on energy sold is greater than price of regulation capacity, the algorithm finds it most profitable to finish charging all of the cars at the maximum allowable levels. This behaviour is typical for both algorithms.

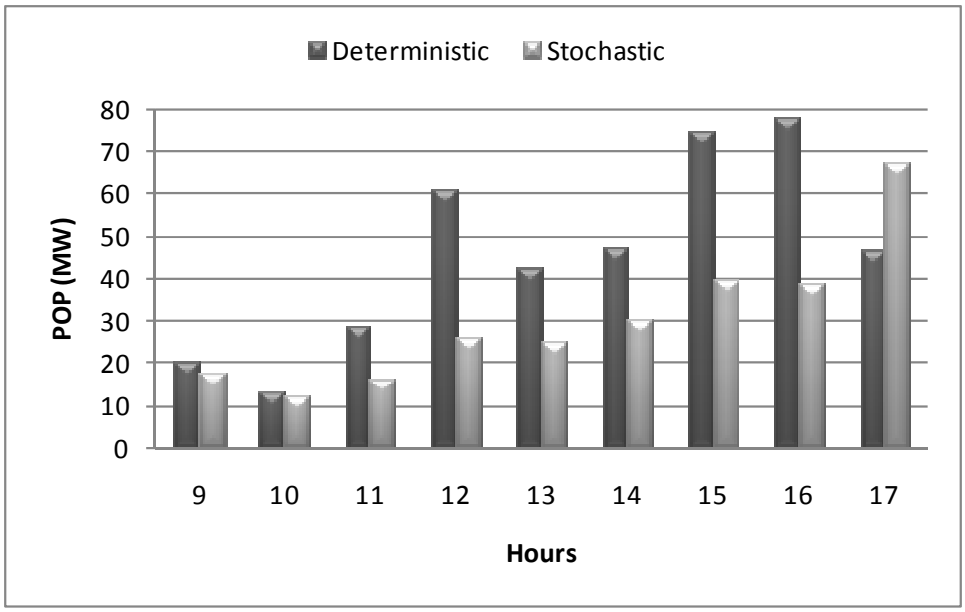


Figure 4.14: Average POP for Deterministic vs Stochastic

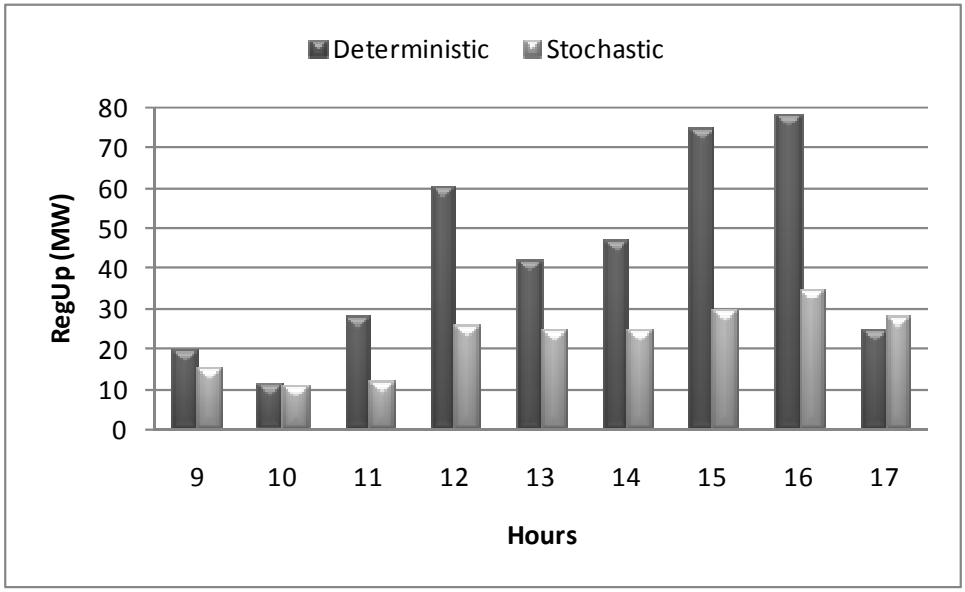


Figure 4.15: Average Regulation up capacity for Deterministic vs Stochastic

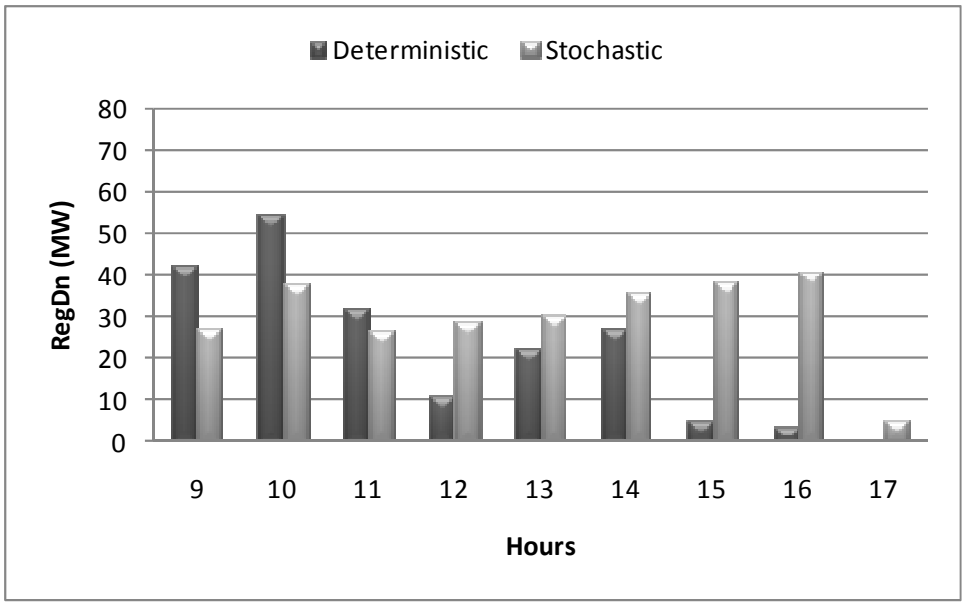


Figure 4.16: Average Regulation down capacity for Deterministic vs Stochastic

Figure 4.17, shows the comparison of expected and actual profits for the two optimization algorithms during the complete simulation period. The expected profits are simply the value of the objective function given by (4.1) at the optimal bidding schedule. The actual profits for both optimizations are obtained using actual day prices and respective regulation bids. It can be seen that the expected profits deviate less from actual profits in Stochastic, which depicts that more realistic results are obtained when uncertainties are considered. For Deterministic, the actual profits are 4.42% less than the expected profits, while it is only 0.54% higher in stochastic optimization. It can also be seen that actual profits obtained from proposed optimization is approximately 1.9% higher than the actual profits achieved from the simpler deterministic algorithm. This clearly shows the effectiveness of the proposed stochastic algorithm.

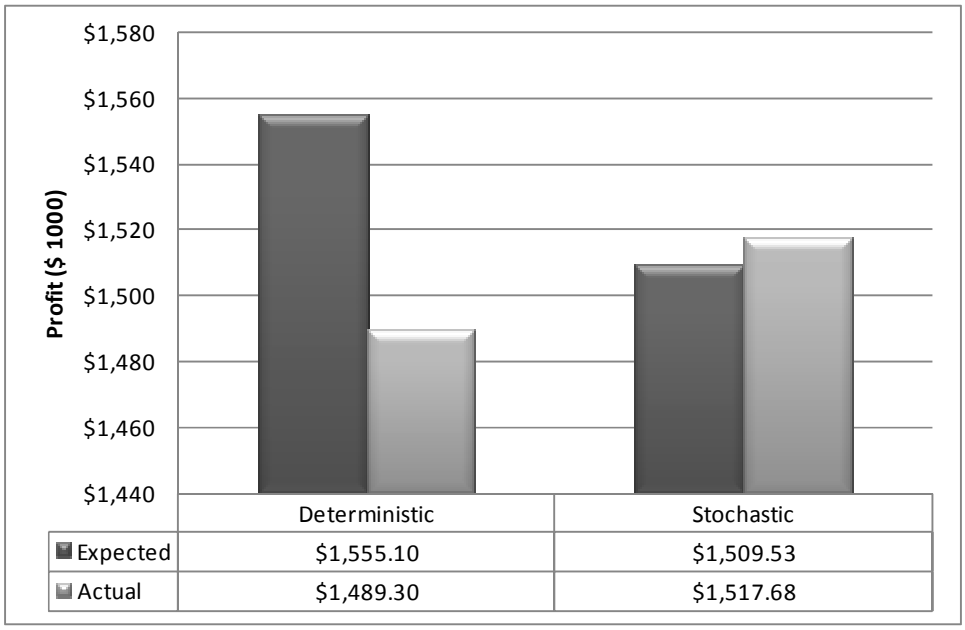


Figure 4.17: Expected and Actual profit comparison for both algorithms

The impacts of both bidding algorithms on the system peak and average load increases due to EV charging are shown Figure 4.18. It can be seen that both algorithms have almost equal peak load increases while Stochastic has a slightly higher increase in the average load. Note that this can be minimized by adding a system load constraint to the formulation, as given in [4], on the expense of expected profit. Inclusion of such constraint is not necessary unless system operators have issues with the average load increase.

From the EV owner perspective, it is desired to charge the EVs at lower cost. Figure 4.19 shows the average energy price per kWh paid by EV owner. It is obtained by subtracting 80% of ancillary services revenue from the total cost paid by EV owner.

Stochastic charges EVs at a slightly higher rate. However, this difference is very small of $0.005/kWh.

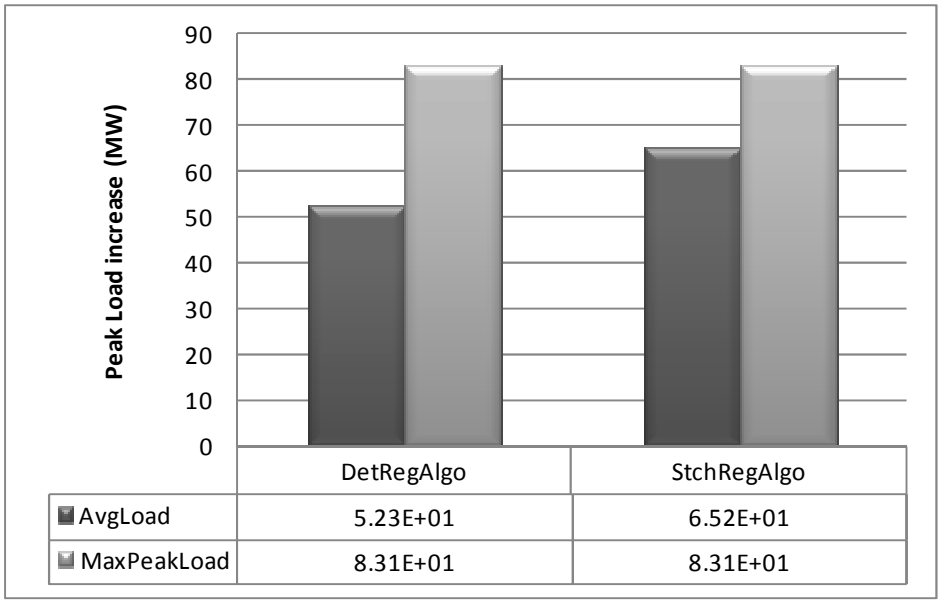


Figure 4.18: System peak and average load increase due to EV charging

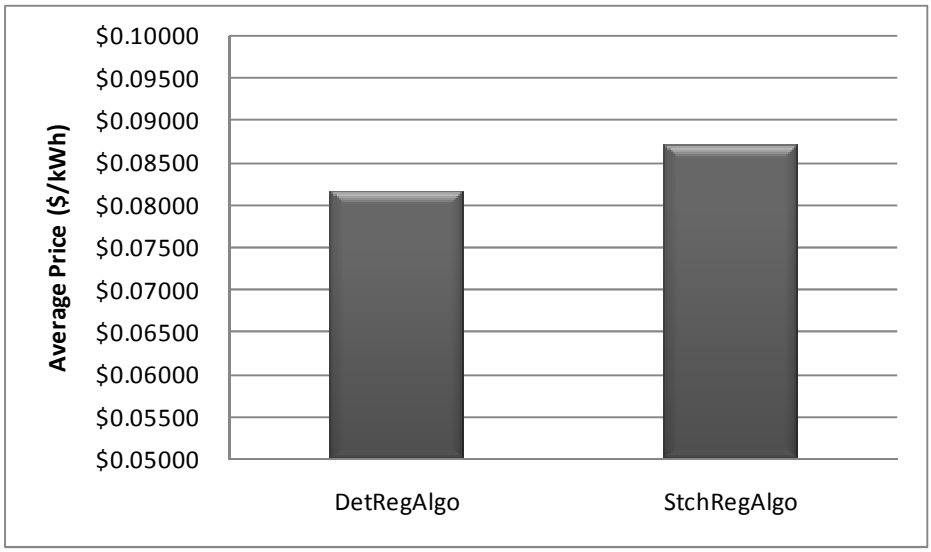


Figure 4.19: Average price per kWh of energy charge to the EV owner

## 4.6 CONCLUSION

In this chapter, an optimal day-ahead regulation bidding strategy for unidirectional V2G algorithm is proposed for use by an EV aggregator. It demonstrates the benefit of considering uncertainties associated with different market variables. Stochastic programming with scenario generation technique is used to incorporate uncertainties. The simulations in the Houston area with large number of hypothetical EVs show that Stochastic outperforms the Deterministic. It shows that actual day profits are close to expected profit when uncertainties are considered which depicts more realistic results. On the other hand, Deterministic gives high expected profits that seem lucrative but on the actual day, Deterministic fail to generate these profits. Uncertainty modelling also affects the system average peak load increase and EV owners have to pay 0.005 $/kWh more on average. However, these issues can be addressed by incorporating additional constraints as given in the next chapter.

# CHAPTER 5 OPTIMAL COMBINED BIDDING STRATEGIES FOR V2G SERVICES BASED ON STOCHASTIC PROGRAMMING

## 5.1 INTRODUCTION

In the previous chapter, an optimal bidding strategy to be used by EV aggregators to participate in day-ahead regulation services market is proposed by taking into account the uncertainties associated with the market parameters using stochastic programming. It shows that stochastic algorithm outperforms the deterministic one. Building on the success achieved so far, a more elaborated bidding strategy is presented in this chapter.

In this chapter, an optimal combined bidding strategy for regulation and responsive reserve markets is proposed. The proposed strategy is based on unidirectional V2G algorithm as shown in [4], [7] to be used by EV aggregators while considering uncertainties associated with both markets parameters such as regulation up/down and responsive reserve prices and deployment signals. Stochastic programming technique as discussed in Chapter 3 is used to encounter these uncertainties. The optimization aims to determine the optimal preferred operating points and the amount of regulation up/down

and responsive reserve bids that maximize the expected profit of the EV aggregator while satisfying the constraints likely to be imposed by market and EV owners. The case under investigation is of an EV aggregator having charging control over a large number of commuter electric vehicles whenever they are plugged-in. Unlike the previous algorithm, simulations are performed for the complete day with a new objective function which is more realistic and lucrative. Additionally, uncertainties associated with EV availability are also considered.

## 5.2 PROBLEM DESCRIPTION

This section gives a description of the combined bidding strategy for regulation and responsive reserve market, briefly explains the stochastic programming (SP) approach.

### 5.2.1 Combined Ancillary Services Algorithm

Aggregated EVs can be used to provide regulation up and down services by increasing or decreasing the vehicle power draws from its preferable operating point (POP). In the same way, responsive reserve services can be provided through unidirectional V2G algorithm by decreasing the power drawn from the schedule POP. The value of POP for each EV is scheduled by the aggregator according to its capacity and requirement to fulfil the deployment signal receives from the system operator. In this algorithm, an aggregator has to consider two different signals from the system operator, one for regulation services and the other for responsive reserve, while setting the value of POP for each EV. For this purpose the algorithm shown in Figure 5.1 is used, in

conjunction with the regulation algorithm discussed in Chapter 4 and shown in Figure 4.1, to incorporate responsive reserve signal.

To dispatch an EV using these algorithms, firstly an aggregator will follow the regulation algorithm and obtain the power draw for each EV as explained in Chapter 4. Then the responsive reserve algorithm is followed to calculate the EV's dispatch to the responsive reserve signal. This gives the final power draw for each EV until the next signal is received from the system operator. A graphical description of the different variables is shown in Figure 5.2. It shows that the maximum available power (*MxAP*) of each EV for regulation down is a difference between maximum power draw (*MP*) and the preferred POP. The reduction in power drawn for each EV available for responsive reserve is denoted by *RsRP*. And minimum available power (*MnAP*) for regulation up is equal to the difference between POP and *RsRP*.

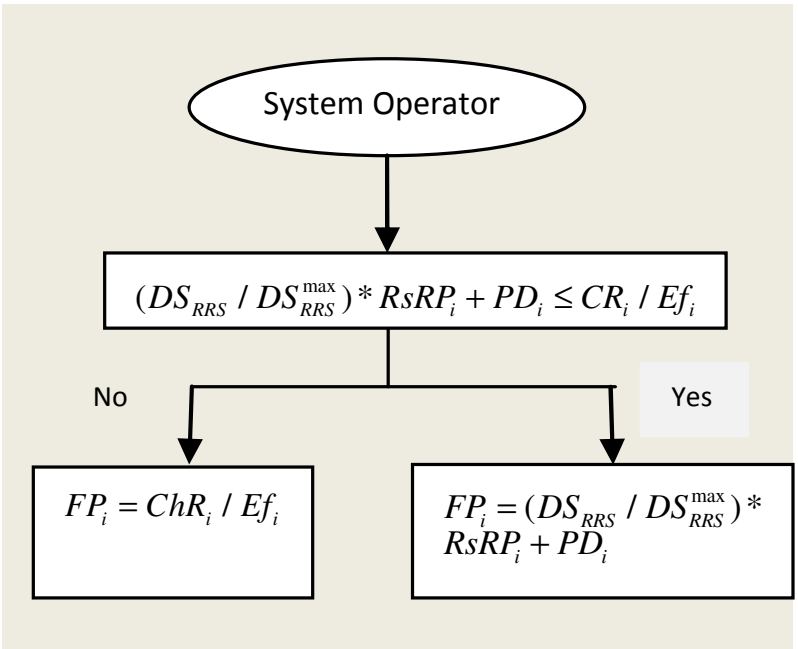


Figure 5.1: Responsive reserve algorithm flow chart

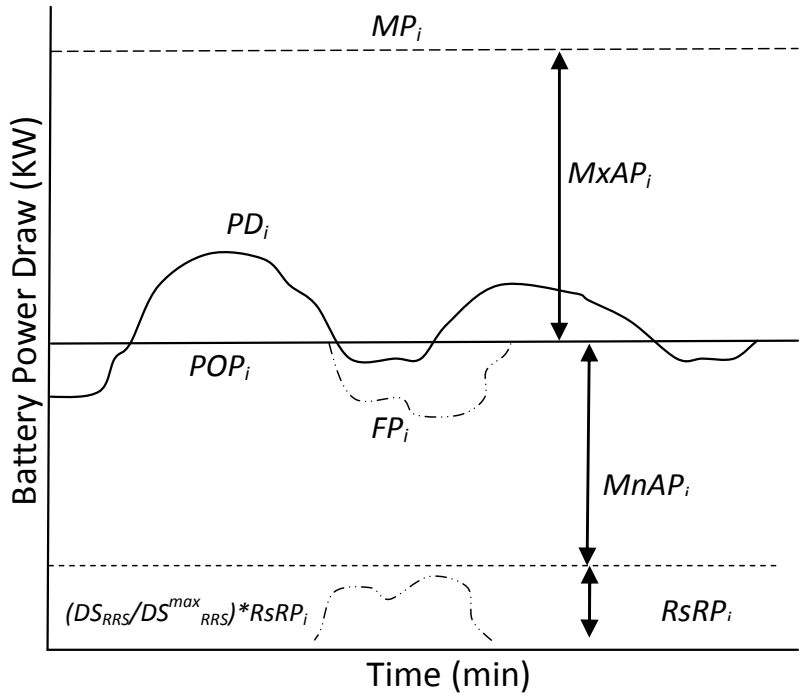


Figure 5.2 Graphical description of ancillary services around the POP [7]

### 5.2.1 Stochastic Programming and Scenario Generation and Reduction

Stochastic Programming technique applied in this chapter is similar to Chapter 4 with some additional considerations. In this chapter, the first stage decisions are the hourly preferred operating point of each EV, hourly bids of regulation up/down capacities and responsive reserve capacity that are to be submitted to the regulation and reserves market. The only second stage decision is the expected final power draw of each EV in each hour as it depends on the realized scenarios. Six stochastic variables are used in this work:

regulation up/down prices and deployment signals and responsive reserve prices and its deployments.

Again Auto Regressive Integrated Moving Average (ARIMA) modelling is used to generate scenarios for stochastic variables. Required historical data such as energy price, demand, regulation up/down prices and deployment signals, and responsive reserve prices and deployment signals are taken from available ERCOT archives [10]. Thousands of scenarios are required to represent each stochastic variable. However, to use all the generated scenarios is not computationally efficient. Therefore, scenario reduction technique is used to reduce the large number of scenarios without significantly changing the statistical attributes of the original scenario sets.

## 5.3 MATHEMATICAL FORMULATION

Regulation services can be provided to the grid using aggregated EVs by charging their batteries around the preferable operating point (POP). Thus, regulation capacities depends on the POP. Therefore, the aggregator needs to adjust POP in a way that allows to trade high regulation capacities to maximize its own profits while satisfying the constraints likely to be imposed by EV owners and/or the system operator. Since the aggregator is a market participant, it is safe to assume that it will struggle to maximize its own profit. Several smart charging and optimization algorithms have been developed for aggregators but none of them modelled the uncertainties in an elaborate manner. The algorithm presented in the previous chapter incorporates uncertainties of the market

variables. But this algorithm is simulated for only nine hours simulation period and limited to regulation services market only. In this chapter, an optimal combined bidding algorithm is proposed that considers the shortcomings from the previous algorithm and uses a new objective function.

The mathematical formulation of this algorithm is as follows:

$$\underset{(POP_{ti}, MxAP_{ti}, MnAP_{ti}, RsRP_{ti}, FP_{tsi})}{Maximize} \quad E[PROFIT] \tag{5.1}$$

$$E[PROFIT] = \sum_{s=1}^{Ns} \pi_s * [Income_s - Cost_s] \tag{5.2}$$

$$Income_s = \sum_{t=1}^{Nt} \{\rho_{ts}^{Rdn} * CR_t^{Rdn} + \rho_{ts}^{Rup} * CR_t^{Rup} + \rho_{ts}^{Rrs} * CR_t^{Rrs}\}.EVPer_t + \beta * \sum_{t}^{Nt} \sum_{i}^{Ni} FP_{tsi}.EVPer_t \tag{5.3}$$

$$Cost_s = \rho_t^{En} * \sum_{t}^{Nt} \sum_{i}^{Ni} FP_{tsi}.EVPer_t \tag{5.4}$$

where,

$$EVPer_t = \begin{cases} 1 - \sum_{t=1}^{t} \sum_{i} Dep_{ti}, \ if \ t < T_{T\_Trip_i} \\ 1 - \sum_{t=T\_Trip}^{t} \sum_{i} Dep_{ti}, \ if \ t \geq T_{T\_Trip_i} \end{cases} \tag{5.5}$$

$$CR_t^{Rdn} = \sum_{i=1}^{Ni} MxAP_{ti} \tag{5.6}$$

$$CR_t^{Rup} = \sum_{i=1}^{Ni} MnAP_{ti} \tag{5.7}$$

$$CR_t^{Rrs} = \sum_{i=1}^{Ni} RsRP_{ti} \tag{5.8}$$

$$FP_{tsi} = DS_{ts}^{Rdn} * MxAP_{ti} + POP_{ti} - DS_{ts}^{Rup} * MnAP_{ti} - DS_{ts}^{Rrs} * RsRP_{ti} \tag{5.9}$$

The objective is to maximize the aggregator profit, which is its income minus its costs, as shown in (5.2). The aggregator income comes from two sources, the revenue obtained from providing the ancillary services for grid support and those obtained by selling energy to EV owners at a fixed rate. Aggregator income is shown in (5.3). Equation (5.4) shows the aggregator cost that it has to pay to buy energy from market. The Overhead costs like, charger maintenance, communication between EV owner and aggregator and battery degradation are neglected. $EVPer_t$ is the percentage of the electric vehicles remaining to perform V2G at hour *t* and $Dep_{ti}$ represents the probability of $i^{th}$ EV to depart unexpectedly in hour *t*. These parameters are used to model unexpected departures of EVs [7].

In this algorithm, aggregator receives all revenues that come from the provision of ancillary services and selling energy to EV owners at fixed rate, instead of getting some percentage over ancillary revenues and mark up over energy price, which was the case in the previous algorithm. This arrangement provides the aggregator with the benefits of getting higher profits and offering energy to EV owners at constant rate with more

reliable service at the expense of facing higher energy price risks since with higher energy prices, the aggregator may end up with negative figures. Moreover, this arrangement is also beneficial for EV owners since they are charging their vehicles at lesser cost than the average electricity price and without any threat of price variations.

Equation (5.6) - (5.8) represent the aggregated capacity of all EVs at each hour for regulation up/down and responsive reserve. The expected power draw of each EV at each hour and scenario is modelled in (5.9). It shows that the power draw of each EV is a function of POP, uncertain regulation up and down dispatch signals, and responsive reserve deployment signal that are received from the system operator. Unlike previous optimization algorithms, the uncertainty of these dispatch signals is taken into account using SP. Stochastic variables are regulation up/down and responsive reserve prices and deployment signals and represented by $\rho_{ts}^{Rup} / \rho_{ts}^{Rdn}$, $DS_{ts}^{Rup} / DS_{ts}^{Rdn}$, $\rho_{ts}^{Rrs}$ and $DS_{ts}^{Rrs}$. The decision variables are $POP_{ti}$, $CR_t^{Rdn}$, $CR_t^{Rup}$, $CR_t^{Rrs}$ and $PD_{tsi}$. The aggregator bids the capacities represented by the first four variables into the market. This optimization is subjected to the following constraints:

$$\sum_{t=1}^{T\_Trip_{1,i}} (FD_{tsi}.Comp_{ti}) + SOC\_I_i \le MC_i, \forall s,i,t \tag{5.10}$$

$$\sum_{tr=1}^{N_{tr}-1} \sum_{T\_Trip_{tr,i}}^{T\_Trip_{tr+1,i}} (FD_{tsi}.Comp_{ti}) + SOC_i \le MC_i, \forall s,i,t \tag{5.11}$$

$$0.99.MC_i \leq \sum_{t=1}^{Nt}(FD_{tsi}.Comp_{ti}) + SOC\_I_i - \sum_{tr=1}^{N_{tr}} trip_{tr,i} \leq MC_i, \forall s,i,t \tag{5.12}$$

$$(MxAP_{1i} + POP_{1i}).Comp_{1i}.Ef_i + SOC\_I_i \leq MC_i \tag{5.13}$$

$$(MxAP_{ti} + POP_{ti}).Comp_{ti} \leq MP_{ti}.Av_{ti}, \forall t,i \tag{5.14}$$

$$RsRP_{ti} \leq POP_{ti} - MnAP_{ti}, \forall t,i \tag{5.15}$$

$$MxAP_{ti} \geq 0 \tag{5.16}$$

$$MnAP_{ti} \geq 0 \tag{5.17}$$

$$RsRP_{ti} \geq 0 \tag{5.18}$$

$$POP_{ti} \geq 0 \tag{5.19}$$

where

$$Comp_{ti} = 1 + \frac{Dep_{ti}}{1 - Dep_{ti}} \tag{5.20}$$

Constraints (5.10) and (5.12) limits the total energy stored in the battery from charging by the battery capacity. Equation (5.10) and (5.11) constraints that the total battery charged must be less than or equal to the battery capacity until the first commute trip and duration between first and second commute respectively. The reduction in SOC due to commute trip is modeled (5.12) by subtracting the amount of energy used during

commute which is represented by $trip_i$. Equation (5.12) also ensures that at the end of each day battery should be at least 99% charged to provide reliable service to the consumers. Constraint (5.13) ensures that the battery will not charge too soon during the scheduling period. The maximum charge rate constraint is imposed by (5.14). Equations (5.15) - (5.19) represents the ancillary service and charge rate constraints. $Comp_{ti}$ represents a compensation factor of the *ith* EV to account for unplanned departures at hour *t* and modelled in (5.20). Unplanned departures of EV's must be considered by the aggregator to guarantee that the remaining connected EVs have enough capacity to follow regulation signal. Unplanned departures are more statistically predictable for large number of electric vehicles.

EV availability factor is used in this optimization since EVs are not available for charging during the whole day. It is represented by $Av_{ti}$. This binary variable is multiplied by the maximum power an EV can pull from the charger in (5.14). Whenever the EV is on commute or unplugged this variable is 0 and it is 1 for the EVs that are available for charging. It means that unplugged EV with $Av_{ti} = 0$, is not available for charging and bidding capacities by making all decision variables related to that EV to zero. Only EVs with $Av_{ti} = 1$ can be charged and bid their capacity for that hour. Most probable commute times and durations can be predicted using historical data. Vehicle energy usage can also be forecasted using historical data. From these, daily vehicle usage profiles can be generated for use in scheduling the optimal allocation of EV capacities.

Though this formulation only considers two planned daily trips, it can be easily extended to any number of trips to fit the daily driving profile.

Electric vehicles charging causes extra load on the system. To restrain this extra load during peak hours, the aggregator can add the load constraint shown in (5.21) to this algorithm [7]. It will ensure that EVs will not charge during high load periods.

$$\sum_{i}^{N_i} POP_{ti} \leq \frac{L_{\max} - L_t}{L_{\max} - L_{\min}} . \sum_{i}^{N_i} MP_i \quad \forall t \tag{5.21}$$

Similarly, price constraint can be added to this optimization. This constraint provides the aggregator with additional advantage of charging EVs at lower energy prices.

$$\sum_{i}^{N_i} POP_{ti} \leq \frac{\rho_{\max}^{En} - \rho_t}{\rho_{\max}^{En} - \rho_{\min}^{En}} . \sum_{i}^{N_i} MP_i \quad \forall t \tag{5.22}$$

## 5.4 CASE STUDY

A case study with an aggregator that serves a hypothetical group of 10,000 EVs used by commuters in the Houston area is simulated for an 84-day period (28$^{th}$ July – 19 October, 2010). Each simulation day starts from 6 A.M and ends at 6 A.M. the next day. At the end of each simulation day, EVs are fully charged by the aggregator so that consumers can use them the next day. For this study, electricity market parameters such as energy prices, net loads, ancillary services prices, and deployment signals are taken from the available ERCOT historical data [10]. Available deployment signal are of five-

minute resolution. Equation (4.15), (4.16) and (5.23) are used to calculate the hourly expected percentage of these five-minute deployment signals for the entire simulation period [7] so each variable would have the same resolution.

$$DS_{ts}^{Rrs} = \frac{\int_{0}^{RRS\max} RRS.\Pr[RRS].dRRS}{\int_{0}^{RRS\max} RRS.dRRS} \tag{5.23}$$

In this algorithm, aggregator income comes from two sources, the first is the revenue obtained from providing the ancillary services to the grid support and the second by selling energy to the EV owners at a fixed rate. Cost of aggregator is the amount of money that he has to pay market energy price for net energy used each hour. Consequently, aggregator profit is vulnerable to the energy prices since he is further selling energy at constant rate. Whenever, energy prices are high aggregator may end up at loss and vice versa. Moreover, with this arrangement, the aggregator can give incentives to EV owners to charge their cars by setting lower fixed rates at certain time periods. For this study, it is assumed that the aggregator

- Receives 100% of the ancillary services revenues,
- Charges fixed rate of $0.05/kWh which is almost 50% of the average market price in ERCOT, and
- Bids its capacities at $0/MWh to ensure acceptance.

It is also assumed that no market participant has market power, which means that the market operates at near perfect competition.

In this simulation study, the EVs are the same as those used in the previous chapter, and their specification are shown in Table 4.1. Three different types of EVs that are available in the market, are considered; Nissan Leaf, Mitsubishi i-MiEV, and the Tesla ModelS. The battery capacities, driving efficiency and other EV specification are taken from [62–64]. The charging station are assumed to be rated at 230 V, 30 A [65].

Each EV is assigned a random driving profile from the 2009 National Household Travel Survey data [67]. Each profile has unique morning and evening trip times, commute duration and distances. Start time of morning commute ranged between 7 A.M. to 9 A.M and for evening trips ranged between 4 P.M to 7 P.M. Unexpected departures probability are also assigned to each driving profile at each hour to incorporate uncertain driving behavior as mentioned in [7]. It was estimated that for commute there was a 10% chance of leaving work early and 20% chance of an additional evening trip after the commute home. It is also assumed that at 3 A.M. all EVs returned home with 0% probability of additional trip until 6 A.M. 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.

Three months data from ERCOT market (July 21 – 20 Oct, 2010) are used to adjust ARIMA models for all stochastic variables. The MATLAB environment (MATLAB (2012) has been used to implement the ARIMA model.

### 5.4.1 Adjusted ARIMA Models for Regulation up/down prices

The ARIMA models adjusted for regulation up/down prices are given in sections 4.4.1 and 4.4.2. The same models are used in this chapters.

### 5.4.2 Adjusted ARIMA Model for Regulation up/down deployments

The ARIMA model adjusted for regulation up/down deployments are given in sections 4.4.3. The same models is used in this chapters.

### 5.4.3 Adjusted ARIMA Model for Responsive Reserve prices and deployments

Adjusted ARIMA model for responsive reserve prices are shown in (5.24) and its estimated parameters are shown in Table 5.1 . The term $\varepsilon_t^{RRS}$ is generated from $N(0,\sigma_{err}^{RRS})$ , where $\sigma_{err}^{RRS}$ is a standard deviation of $\varepsilon_t^{RRS}$ with a constant value 0.1449.

$$(1-\phi_1 B^1)(1-\phi_{23}B^{23}-\phi_{24}B^{24})(1-B^1)(1-B^{24})\log(\rho_t^{RRS}) = (1-\theta_1 B^1-\theta_2 B^2-\theta_1 B^3-\theta_2 B^4)(1-\theta_{23}B^{23}-\theta_{24}B^{24})\varepsilon_t^{RRS} \quad (5.24)$$

Table 5.1: ARIMA model parameters for Responsive reserve prices

| $DS_t^{Rdn/Rup}$ (ARIMA(2,1,2)(2,1,2)$_{24}$) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| $\phi_1$ | $\phi_{23}$ | $\phi_{24}$ | $\theta_1$ | $\theta_2$ | $\theta_3$ | $\theta_4$ | $\theta_{23}$ | $\theta_{24}$ | Error Variance |
| 0.108 | -0.057 | -0.843 | -0.726 | -0.149 | -0.046 | -0.041 | 0.081 | 0.683 | 0.021 |

The value of Responsive reserve deployment signal is zero most of the time since responsive reserve service is seldom used. It is not easy to predict the trend and to adjust

ARIMA model for such variable. Therefore, instead of generating scenarios for responsive reserve deployments, profiles from the original data are selected to be used as reduced scenarios with some assumed probabilities as discussed in the next section.

### 5.4.4 Scenario Generation and Reduction

Scenario generation technique is same as in chapter 4. One thousand scenarios of all stochastic variables are generated for each day (between 28$^{th}$ July to 20 October, 2010) using the respective fitted ARIMA models and previous week data apart from responsive reserve deployment signal. Figure 5.3 shows the generated scenarios of responsive reserve prices with the blue bold line representing the actual day responsive reserve prices for July 31, 2010.

Then the scenario reduction technique is applied in the same manner as in chapter 4, resulting in three scenarios for each type of stochastic variable. The three bold lines red, blue and green in Figure 5.4 represents the set of reduced scenarios associated with responsive reserve prices for July 31, 2010. Generated and reduced set of scenarios for remaining stochastic variables are shown in the previous Chapter.

For responsive reserve deployment signals, three profiles for each day are selected from original data to be used as reduced set of scenarios. First scenario is selected according to the given hour persistence forecast method. This method assumes that the value for a given hour tomorrow will be the same as it was for the given hour today. It is assumed that the chances of this profile to be occur is 50%. So the assigned probability of this scenario is 0.5. For the selection of second scenario, it is assumed that there are 30%

chances of having same value of the given hour tomorrow as it was for the given hour yesterday. Thus, the profile of yesterday is selected with 0.3 probability as a second scenario. The Third scenario will follow the profile of the same day of the previous week with the probability of 0.2. For example, the selected set of scenarios for 31$^{th}$ July are, the profile of 30th July with 0.5 probability, 29th July with 0.3 probability and 24th July with 0.2 probability.

In this chapter, all stochastic variables are reduced to the set of three scenarios. Consequently, a single day reduced scenario tree is composed of 729 (3x3x3x3x3x3) scenarios. Composition of scenario tree and probability calculation of each scenario is described in [51]. This technique is applied for all days of the entire simulation period.

### 5.4.5. Deterministic Solution

The deterministic algorithm is also simulated by considering a single scenario and replacing stochastic variables by their forecasted values. In this simulation the aggregator used the point forecast for each market variable to optimize the day ahead bid instead of considering several scenarios. These forecasted values are obtained by using the fitted ARIMA model. Persistence forecast is used for responsive reserve since ARIMA model cannot be fitted for such variable as given in Section 5.4.3. The mean absolute errors of the forecasted data are shown in Table 5.2. Net load and prices are taken from Houston congestion management zone and forecasted in the same way as given in [7].

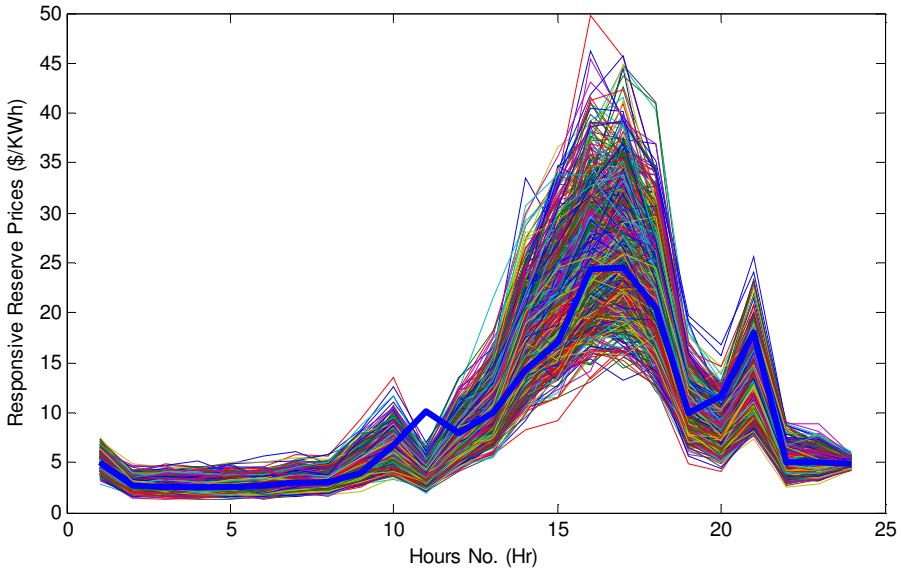


Figure 5.3: Scenarios and actual day profile of responsive reserve prices for July 31, 2010

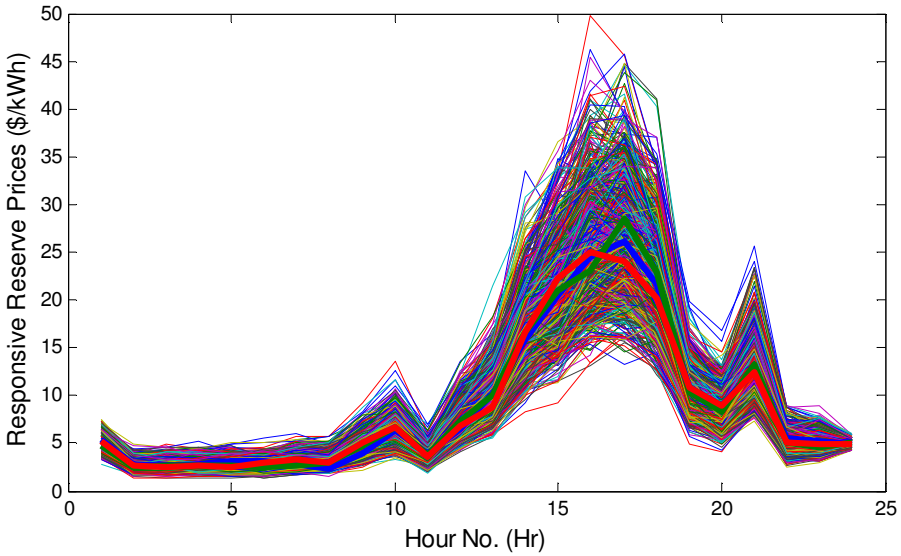


Figure 5.4: Set of Reduced scenarios for Responsive Reserve Prices for July 31, 2010

Table 5.2: Mean Absolute 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 % |

## 5.5 RESULTS AND ANALYSIS

Six algorithms are simulated for all 24 hours for each day between 28 July, 2010 to 19th Oct, 2010. These are categorized into three sections as follows,

- Stochastic and deterministic simulations without constraints.

- Stochastic and deterministic simulations with maximum load constraint (OptLoad)

- Stochastic and deterministic simulations with maximum price constraint (OptPrice)

### 5.5.1 Simulations without Constraints

In this section, two simulations, stochastic and deterministic, are done for the entire 84 days. The average POP level for both algorithms are shown in Figure 5.5. It can be seen that both algorithms initially schedule low POPs because charging the EVs during early hours will limit the ability to sell energy later, thus saving capacity to bid throughout the charging period, except for the few hours in the mid day where prices for regulation up are usually high. The POP is then set high and regulation up capacity is sold to get more profit. Then the POP is scheduled low until the last hours to top off the battery. Also, notice that the stochastic algorithm comparatively schedules high POP except for the last hour. This is due to the less battery capacity available as a result of higher POP scheduled in previous hours. This trend is similar for regulation up and responsive reserve capacities.

Comparison of average regulation and responsive reserve bidding capacities during the charging period are shown in Figure 5.6 - Figure 5.8. It can be seen that the bidding of regulation up capacities are more than the responsive reserve for both algorithms, since selling regulation up will result in a lower SOC at the end of the hour and allowing for more capacity to be sold the next hour. This is due to the generally higher values of regulation up deployment signals. This has been reported in [7] as well. Figure 5.7 shows that the responsive reserves are rarely sold during the whole day except for the last hour where all vehicles are charged at their maximum rates to get 99% charged and to be used

for the next day. It can be notice that the stochastic algorithm continuously bids higher values of regulation up capacities except for the few mid day hours between 3 P.M. and 5 P.M. where regulation up prices are at their peak when uncertainty is not considered. Due to the incorporation of uncertainty stochastic algorithm also took advantage of high prices in the later hours. The reason for lower capacity in the last hour is already discussed above.

Figure 5.8 shows that both algorithms bid regulation down capacities throughout the day. However, stochastic algorithm continuously have lower capacities than the deterministic algorithm. This behavior indicates that vehicles are charged at higher rates in stochastic algorithm which is confirmed from the Figure 5.5. For deterministic algorithm, regulation down capacities are very high during late hours, which indicates that it keeps the battery capacity until the last hour. At this hour, the level of POP and regulation up capacity is very high to top off the battery. However, stochastic algorithm keeps regulation capacities at moderate level to get benefit from the uncertain market parameters throughout the day. There is no charging schedule during the first two hours of the day, this is because the morning trip of vehicle starts from 7 A.M, whereas, EVs are 99 % charged until 6 A.M.

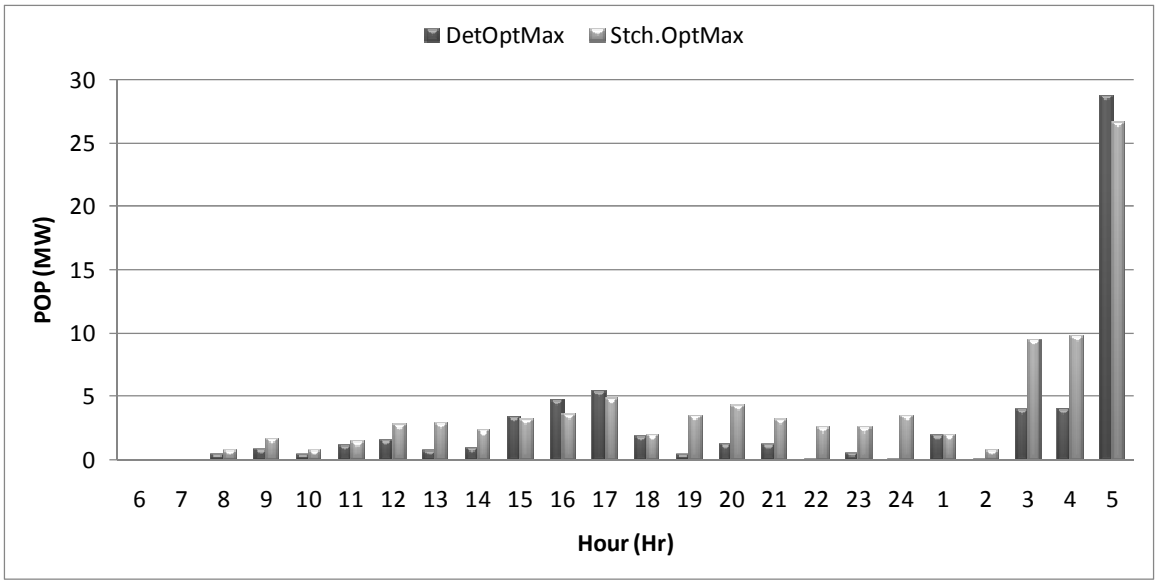


Figure 5.5: Average POP for unconstrained algorithms

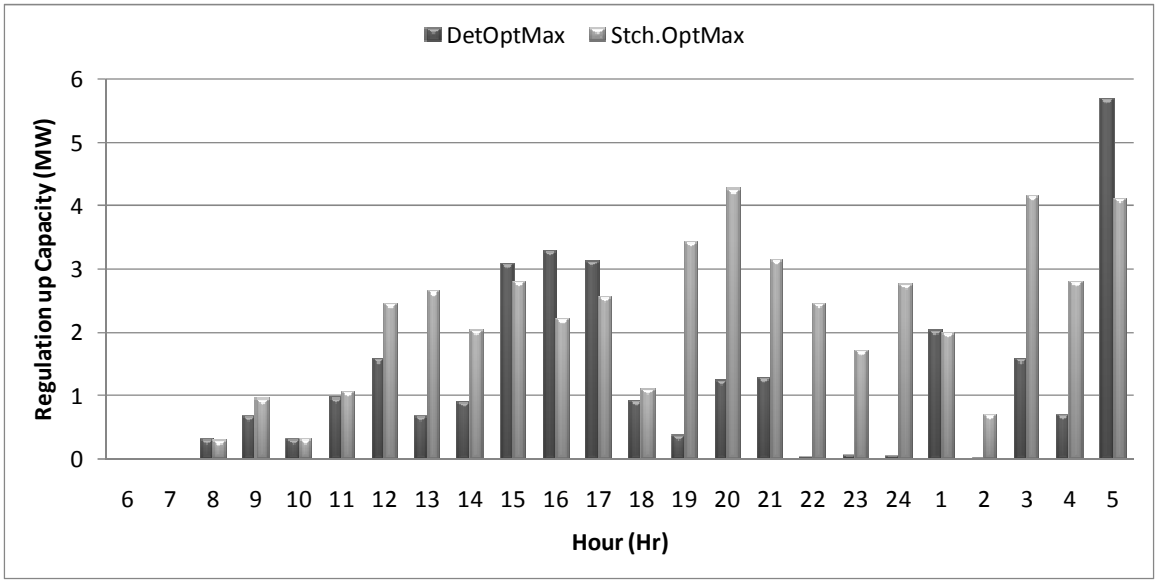


Figure 5.6: Average Regulation Up Capacity for unconstrained algorithm.

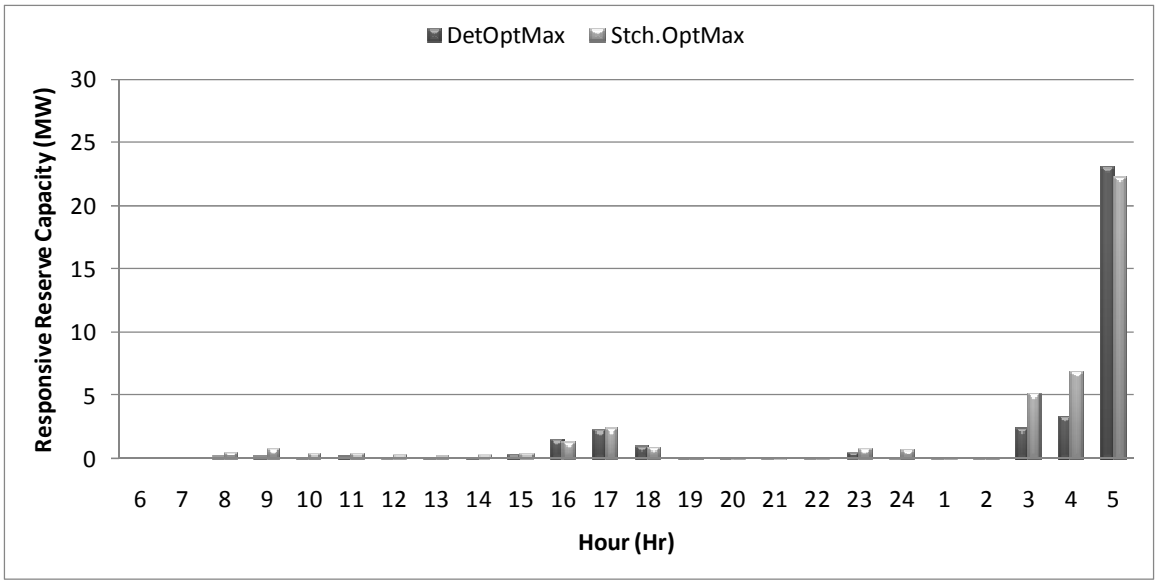


Figure 5.7: Average Responsive Reserve Capacity for unconstrained algorithms

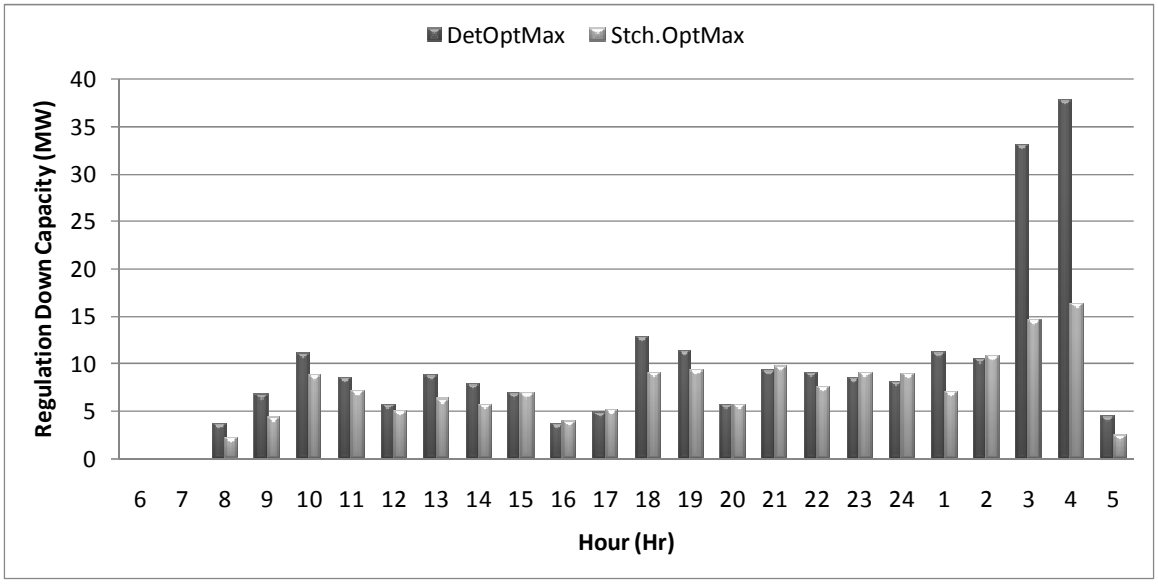


Figure 5.8: Average Regulation Down Capacity for unconstrained algorithms

Figure 5.9 shows the comparison of expected and actual profits for the two optimization algorithms during the complete simulation period. The expected profits are

simply the value of the objective function given by (5.1) at the optimal bidding schedule. The actual profits for both optimizations are obtained through combined ancillary services bidding algorithm described in section 5.2.1 using actual day prices and respective regulation bids. It can be seen that the expected and actual profits obtained from proposed stochastic algorithms are higher than its deterministic counterpart. Expected profits are 5.82% higher while a increase of 8.42% is achieved on the actual day. Moreover, the deviation of expected from actual profits is also a point of consideration. For stochastic optimization its value is 15.3% which is comparatively lower than the value that is recorded from deterministic algorithm i.e. 17.36%. Hence, from these figures it can be concluded that more realistic results are obtained when uncertainties are considered. Figure 5.10 shows expected and actual profits comparison for both algorithm on average day. This shows that the aggregator's daily profit increase is almost 250$ if he uses the proposed optimization. This increase in profit is basically achieved by avoiding the loss that results from inefficient forecast during deterministic algorithm. In fact, by considering uncertainties associated with market variables aggregator may avoid such losses. This clearly shows the effectiveness of the proposed stochastic algorithm.

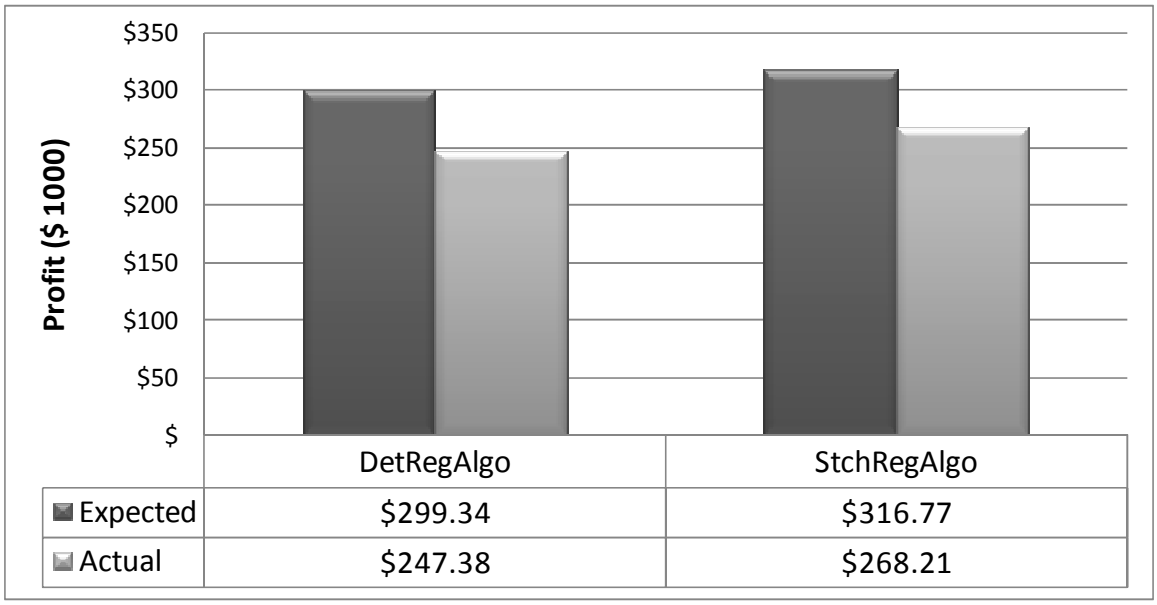


Figure 5.9: Expected and Actual profits comparison for both algorithms (unconstrained optimization).

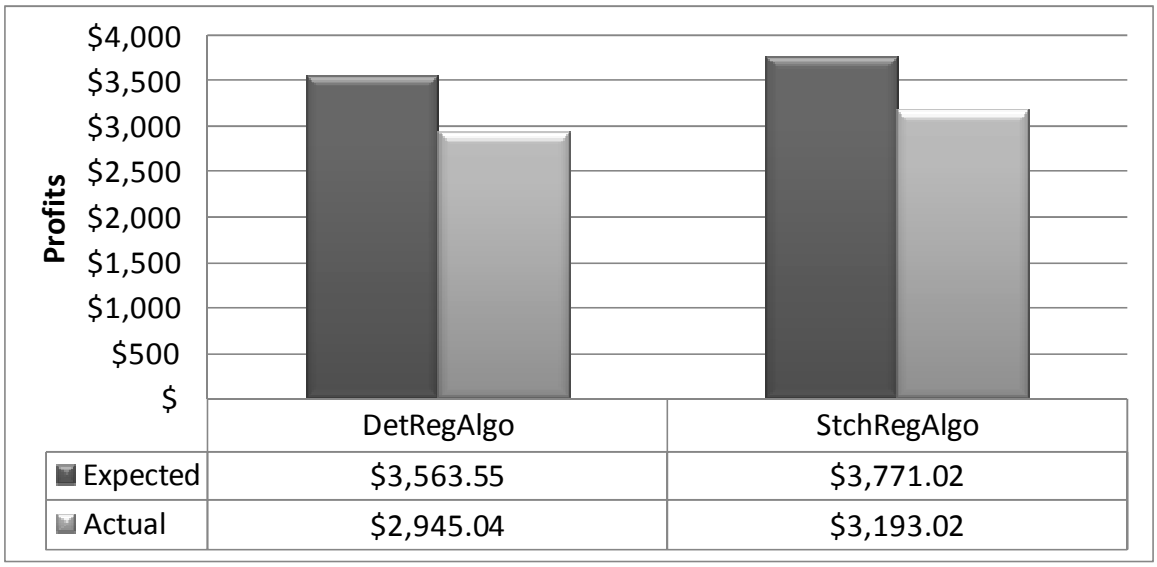


Figure 5.10: Daily average profits comparison for both algorithms (unconstrained optimization).

The deterministic algorithm previously proposed in [7] is also improved by considering hourly average expected values of regulation signals instead of constant values. The comparison is shown in Figure 5.11. It can be seen that the profits are 2.34% higher when the proposed algorithm is used.

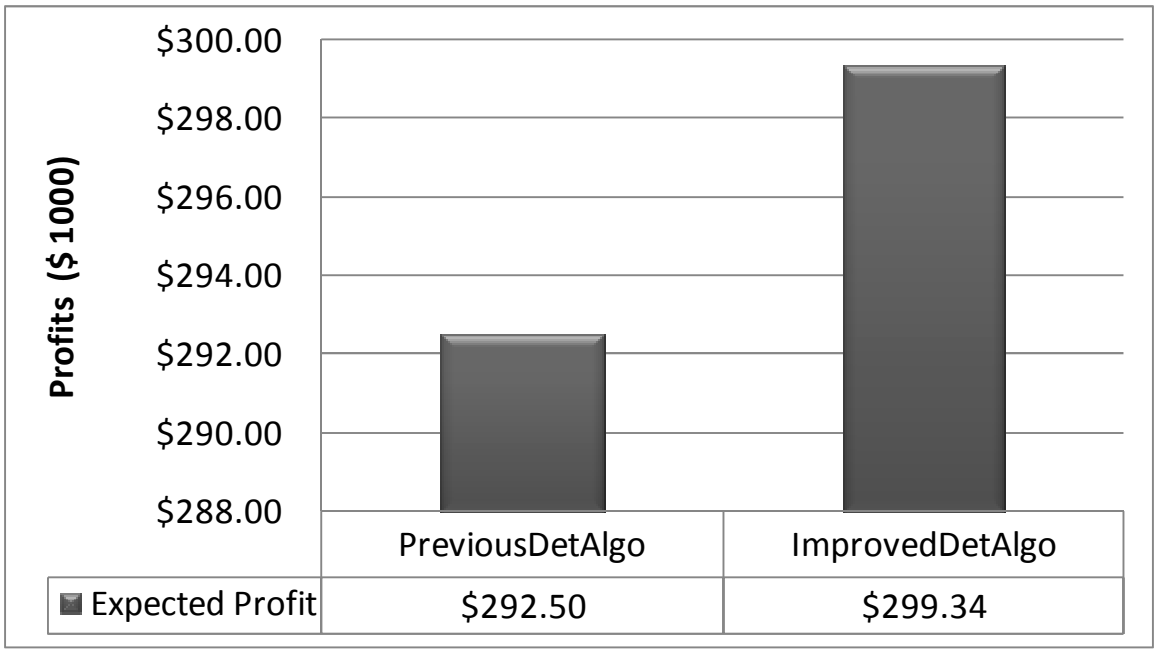


Figure 5.11: Expected profit comparison of deterministic algorithms

The impacts of both bidding algorithms on the system peak and average load increases due to EV charging are shown Figure 5.12. It can be seen that both algorithms have almost equal peak load increases while Stochastic has a slightly less increase in the average load. Note that this can be further minimized on the expense of expected profit by adding a system load constraint to the formulation. However, inclusion of such

constraint is not necessary unless system operators have issues with the average load increase.

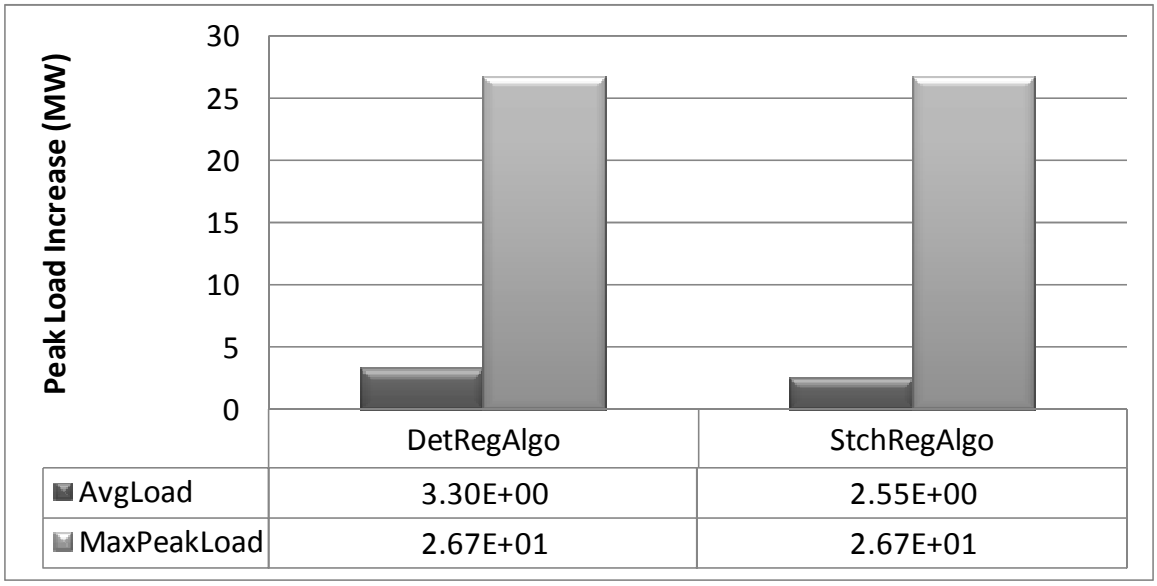


Figure 5.12: Maximum and Average peak loads for both algorithms (unconstrained optimization).

This arrangement is also beneficial for EV owners. Their participation in this aggregator program provide them with the benefit of charging their vehicles at about half prices. Note that the average energy cost in the Houston area is 10 cents/kWh and the aggregator is assumed to be charging the EVs at a fixed rate of 5 cents/kWh. Moreover, they are invulnerable to the risk of high energy prices while charging their EVs.

### 5.5.2 Simulations with Load Constraints (OptLoad)

In this section, two simulations stochastic and deterministic are done with an extra constraint as given (5.21). Average charging profile and regulation and responsive

reserve bidding capacities for both algorithms under load constraints are shown in Figure 5.13 - Figure 5.16 . It can be seen that both algorithms follow the same trend as in the previous case except for the hours between 2 P.M and 7 P.M., where low POP is scheduled. Consequently, less regulation up and responsive reserve capacities are bid. The reductions in POP are due to the higher values of mid-day loads. It can also be seen that in the later hours stochastic algorithm schedules higher values of POP and bidding capacities. This is due to the less battery capacity charged during the day as a result of maximum load constraint. In this case, stochastic algorithm bids slightly higher values of regulation down capacities during mid day hours due to the lower values of POP and regulation up. All other trends are similar to the previous base case.

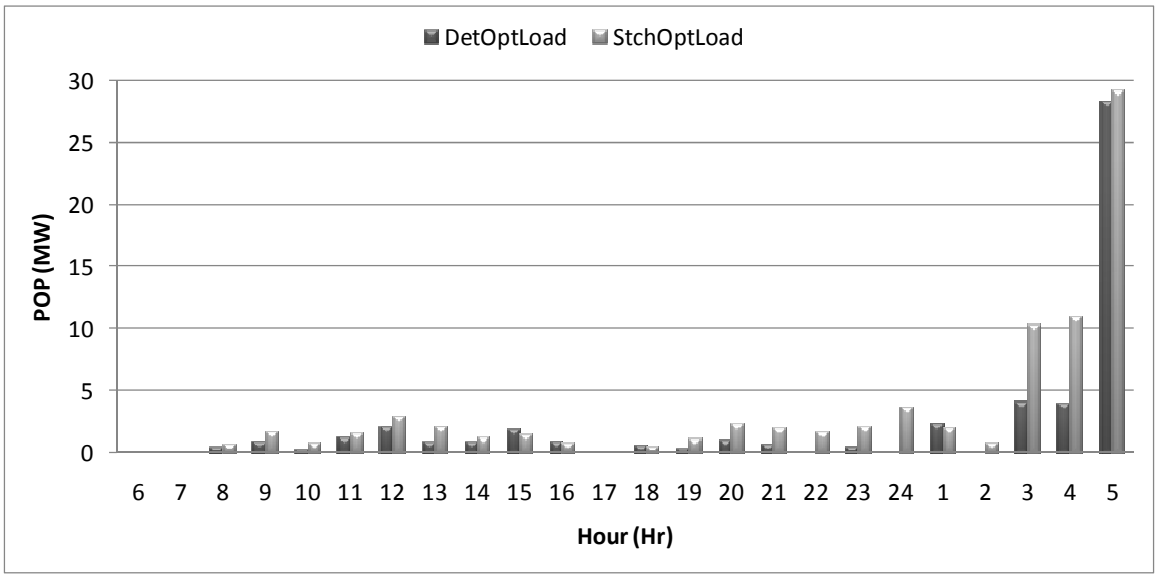


Figure 5.13: Average POP under Load constraints (OptLoad)

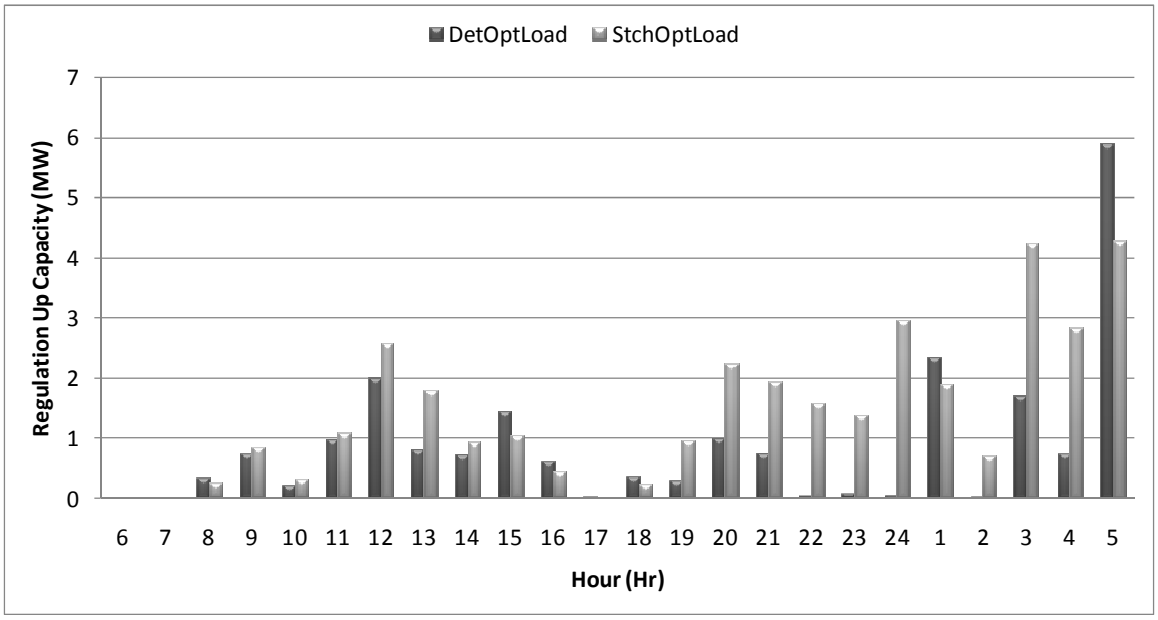


Figure 5.14: Average Regulation Up Capacity under Load constraints (OptLoad)

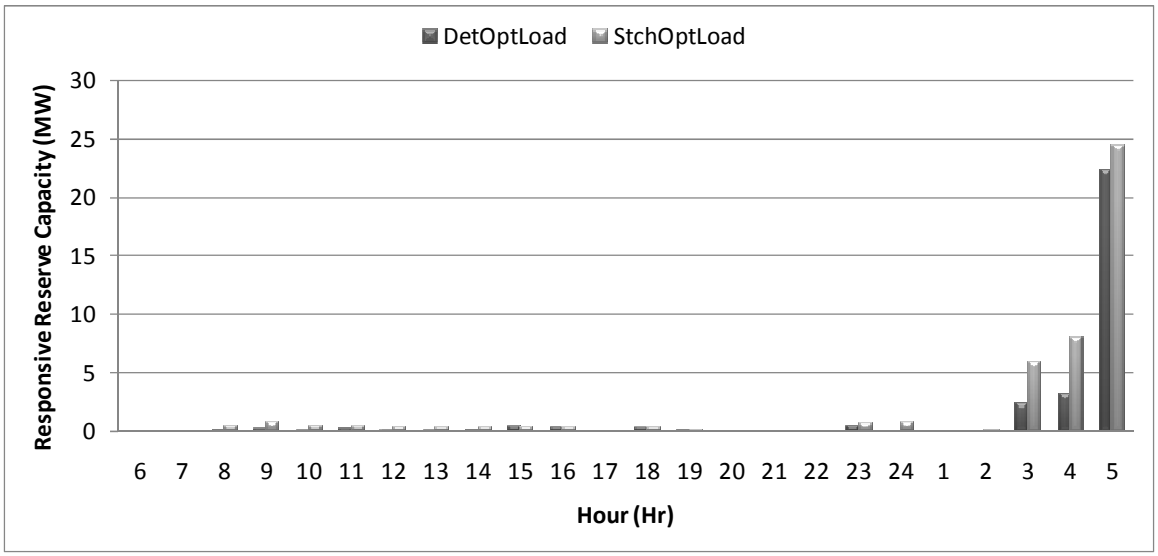


Figure 5.15: Average Responsive Reserve Capacity under Load constraints (OptLoad)

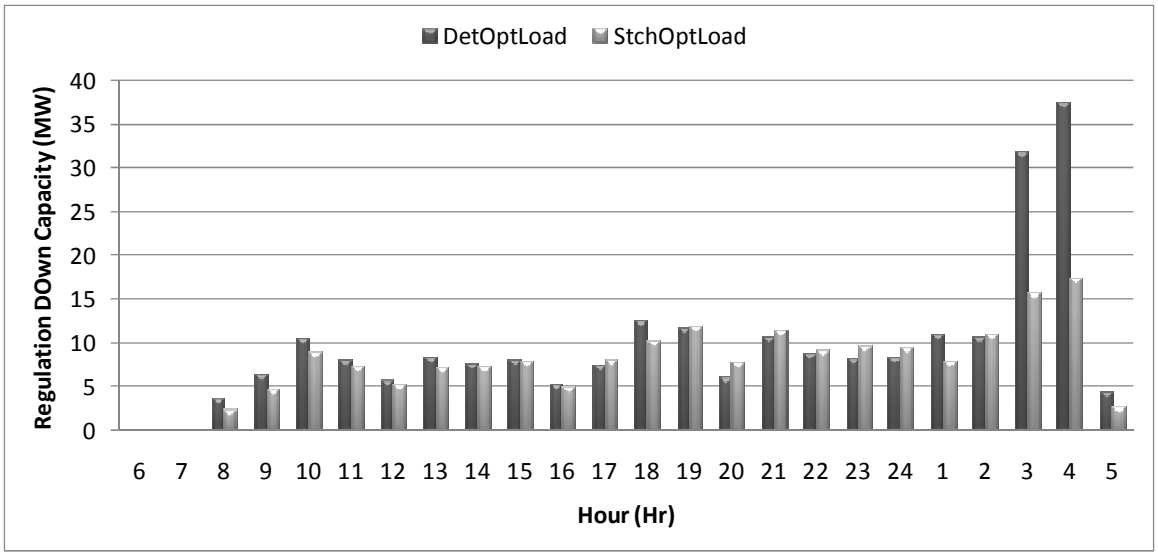


Figure 5.16: Average Regulation Down Capacity under Load constraints (OptLoad)

Figure 5.17 shows the comparison of expected and actual profits for the two optimization algorithms during the complete simulation period. The expected and actual profits obtained from stochastic algorithms are higher than the deterministic algorithm. Expected profits are 1.50% and actual profits are 4.18%. higher. The deviation of expected from actual profits in both algorithms are almost same. For stochastic optimization its value is 12.02% which is slightly lower than 14.29% that is recorded from deterministic algorithm. Figure 5.18 shows expected and actual profits comparison for both algorithms on average day. This shows that the aggregator's daily actual profit increase is almost 123$ if he uses the stochastic optimization with load constraint. However, note that these profits are considerably lower than the profits presented in the previous case due to the additional constraint on POP. A similar behaviour has been observed in [7].

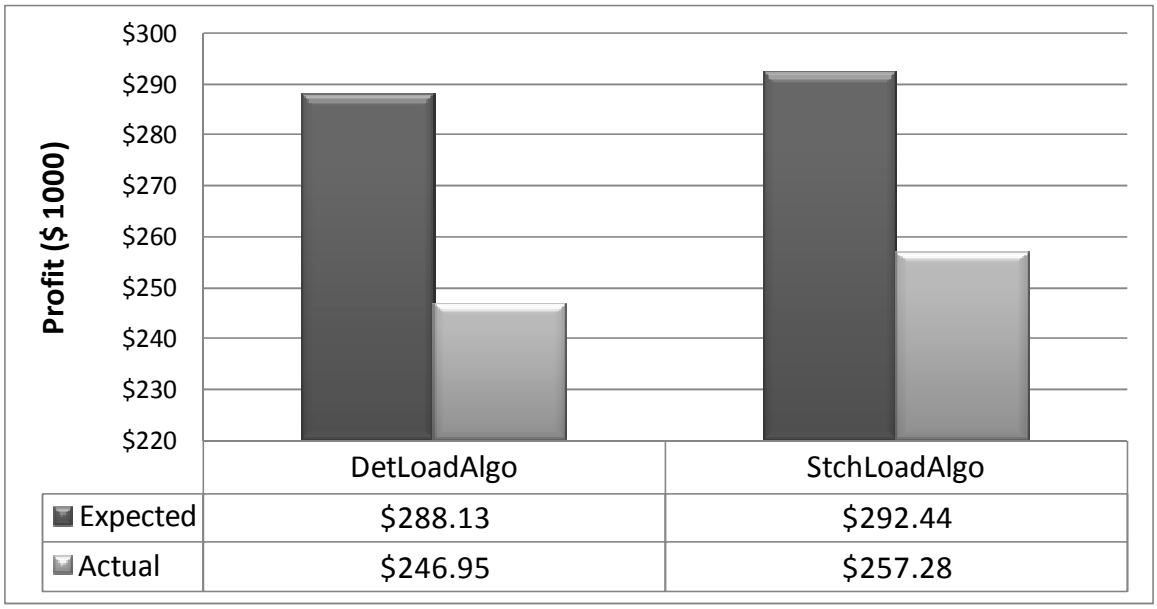


Figure 5.17: Expected and Actual profits comparison for both algorithms (OptLoad).

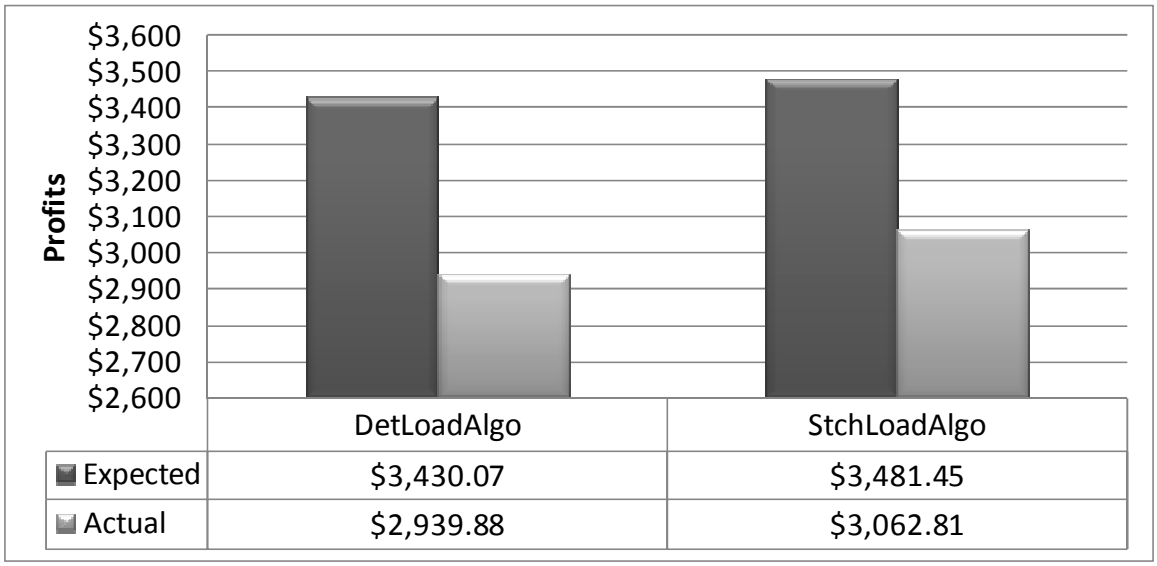


Figure 5.18: Daily average profits comparison for both algorithms (OptLoad)

The impacts of both bidding algorithms on the system peak and average load increase due to EV charging are shown Figure 5.19. Stochastic algorithm causes high increase in

the system peak load. On average, both algorithms work quite well. Note that these values are considerably lower than those presented in the previous case.

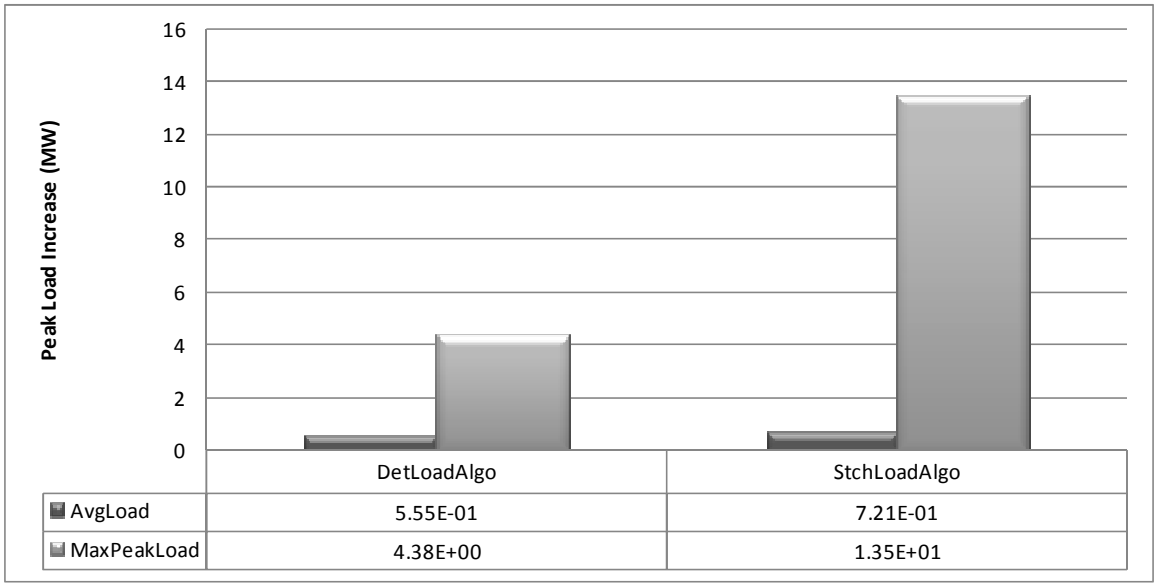


Figure 5.19: Maximum and Average peak load increase for both algorithms (OptLoad).

### 5.5.3 Simulations with Price Constraints (OptPrice)

In this section, two simulations, stochastic and deterministic are done with an extra constraint as given in (5.22). By adding this constraint aggregator will actually try to avoid high market price hours to charge EVs. Hence decreasing its cost on energy purchase. Average charging profile and regulation and responsive reserve capacities for both algorithms under price constraints are shown in Figure 5.20 - Figure 5.23 . It can be seen that the trend of bidding capacities are almost same as in the previous cases i.e high regulation up capacity then responsive reserve, responsive reserve bids seldom during the

whole day except for the last hour to top off batteries, regulation down capacities bids throughout the day. Similarly, other trends and reason are same except for the hours between 3 P.M and 7 P.M. where slightly low POP is scheduled. And, consequently less regulation up and responsive reserve capacities are bid. The reduction in POP are due to higher mid day energy prices.

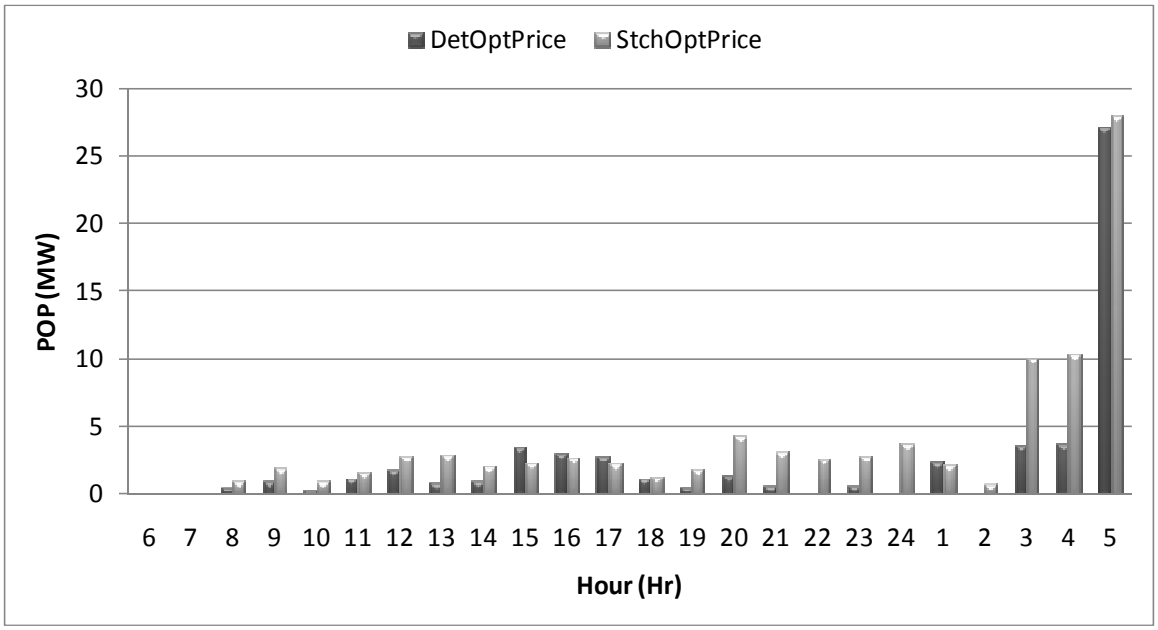


Figure 5.20: Average POP under Price constraints (OptPrice)

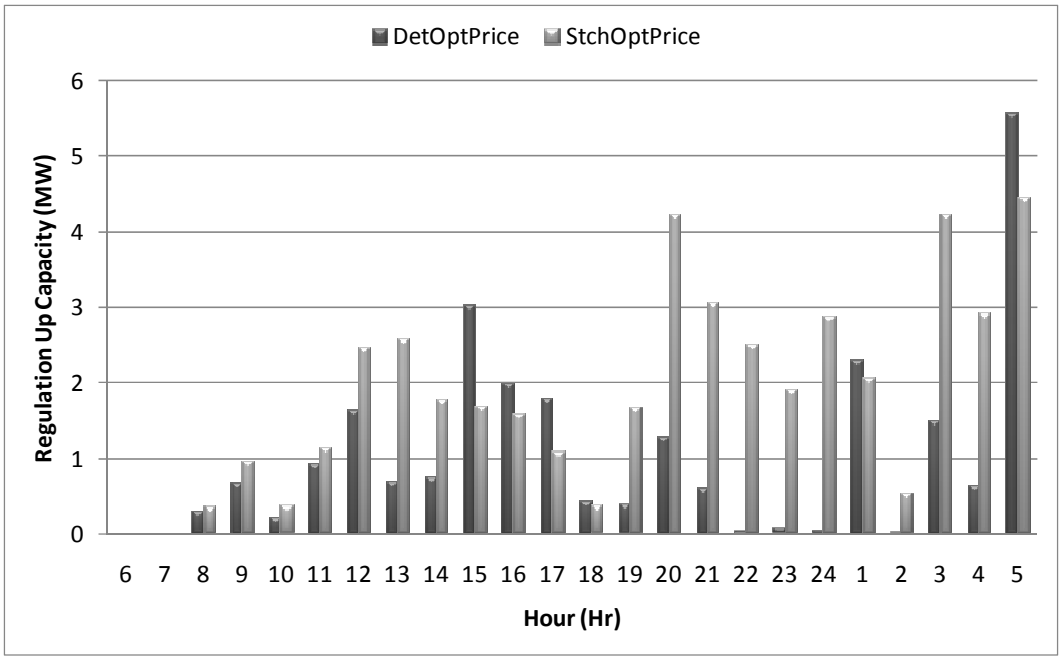


Figure 5.21: Average Regulation Up Capacity under Price constraints (OptPrice)

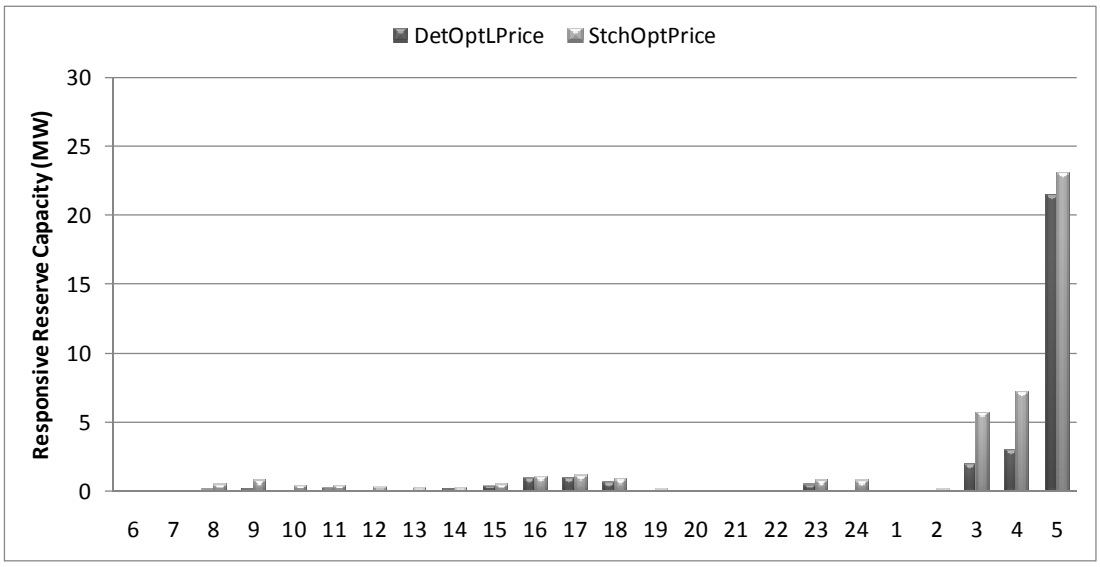


Figure 5.22: Average Responsive Reserve Capacity under Price constraints (OptPrice)

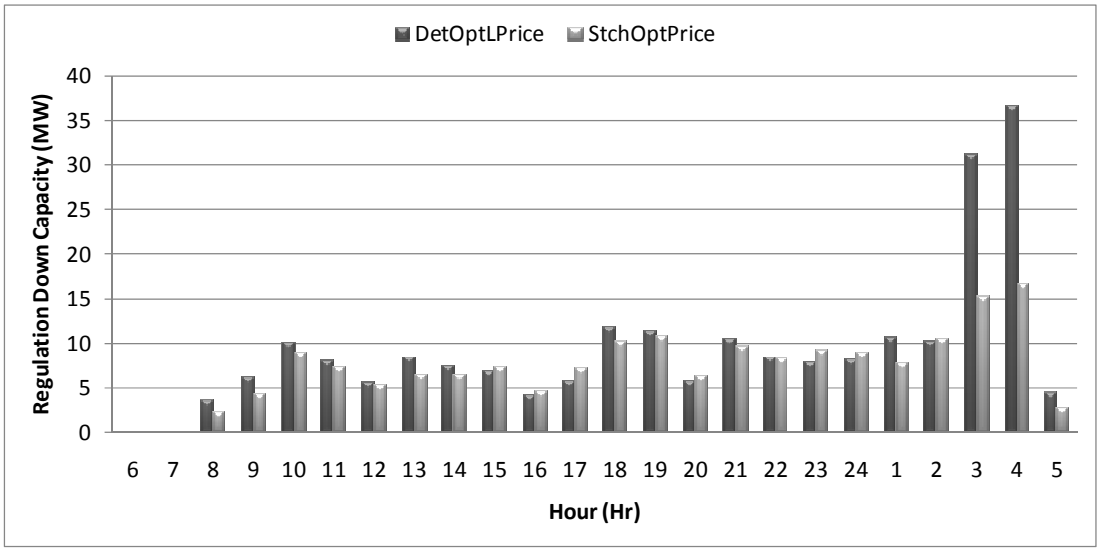


Figure 5.23: Average Regulation Down Capacity under Price constraints (OptPrice).

Figure 5.24 shows the comparison of expected and actual profits for the two optimization algorithms during the complete simulation period. It can be seen that the expected and actual profits obtained from proposed stochastic algorithms are higher in this case also. Expected profits are 3.08% and actual profits are 8.48%. higher. The deviation of expected from actual profits in stochastic algorithms is 11.14% which is considerably lower than 15.56% that is recorded from deterministic algorithm. Figure 5.25 shows the expected and actual profits comparison for both algorithms on average day. This shows that the aggregator's daily actual profit increase is almost 250$ if he uses the stochastic optimization instead of deterministic with price constraint. This increase in profit is basically achieved by avoiding the loss that results from inefficient forecast during deterministic algorithm. In fact, by considering uncertainties associated with

market variables aggregator may avoid such losses. This clearly shows the effectiveness of the proposed stochastic algorithm.

For stochastic optimization, note that the expected profits in this case are lower than the profits reported in base case while actual day profits are almost same. This concludes the competency of OptPrice case over base case in terms of expected and actual profits deviation.

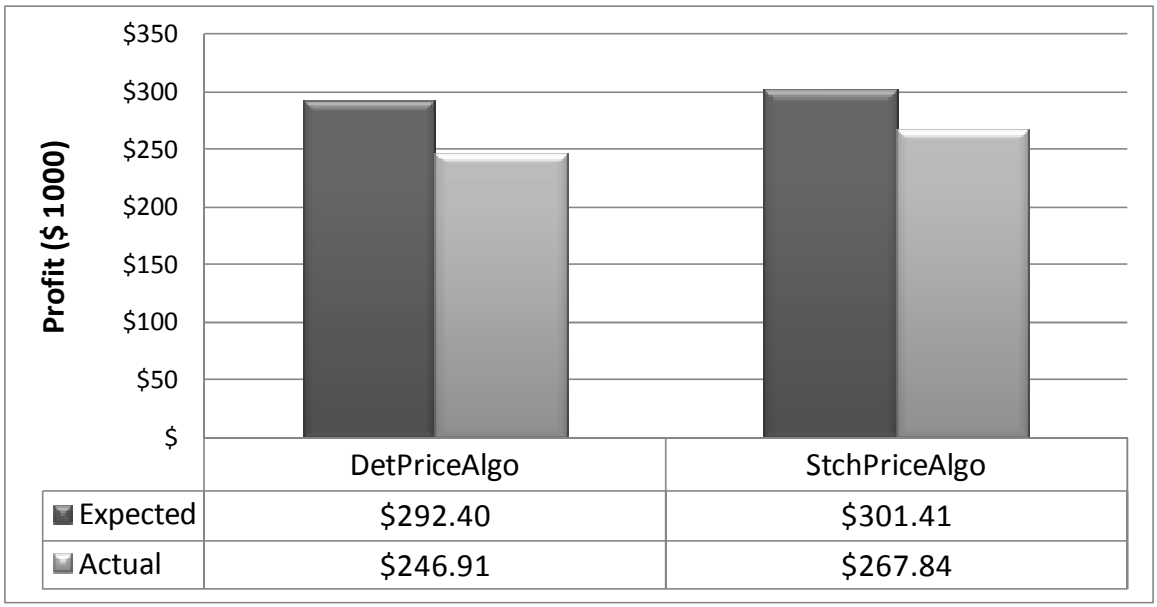


Figure 5.24: Expected and Actual profits comparison for both algorithms (OptPrice)

The impacts of both algorithms on the system peak and average load increase due to EV charging are shown Figure 5.26. Stochastic algorithm causes high increase in the system peak load. On average, both algorithms work quite well. Note that these values are still lower than those presented in the previous case.

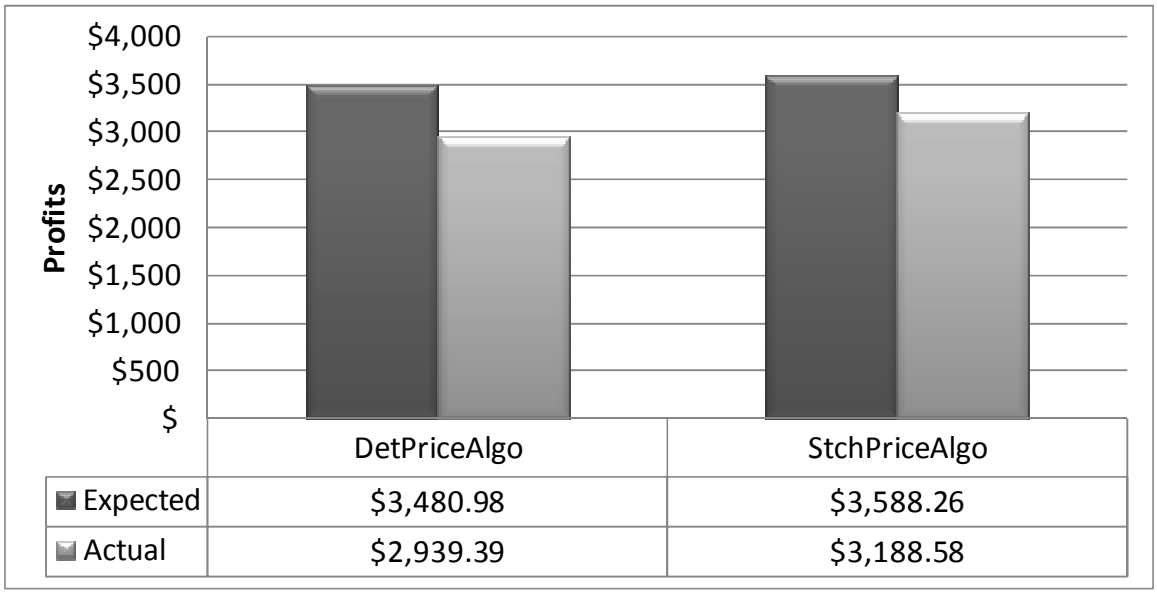


Figure 5.25: Daily average profits comparison for both algorithms (OptPrice).

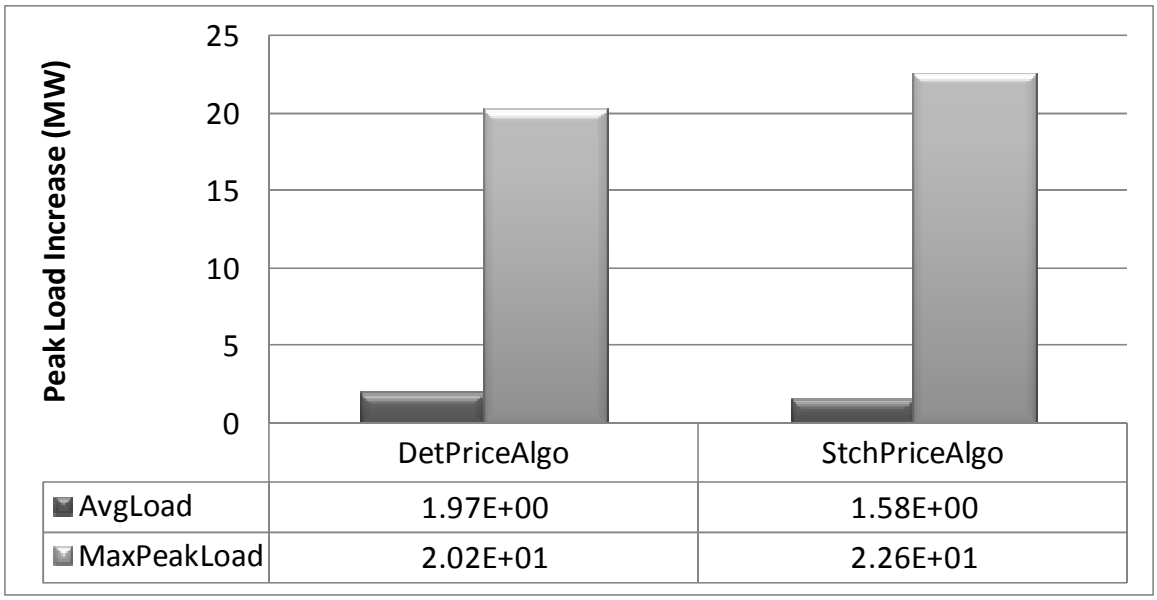


Figure 5.26: Maximum and Average peak load increase for both algorithms (OptPrice).

## 5.6 CONCLUSION

In this chapter, an optimal algorithm for combined bidding of regulation and responsive reserve services that is based on unidirectional V2G algorithm is proposed. It demonstrates the benefits of considering uncertainties associated with different market variables such as market prices and deployments signals. Stochastic programming with scenario generation technique is used to incorporate uncertainties. The simulations in the Houston area with large number of hypothetical EVs show that Stochastic outperforms the Deterministic. Three different cases are simulated to check its effectiveness. It shows that profits achieved from stochastic algorithm is considerably higher than the deterministic profits for all three cases and the deviation of expected profits from actual day profits is also less which depicts more realistic results. Moreover, stochastic algorithm keeps regulation capacities at moderate level to get benefit from the uncertain market parameters throughout the day.

In this chapter, new objective function is used which is more lucrative than the previous one for aggregator perspective. Also, it has benefits for EV owners. Firstly, the fixed rates set by aggregator are considerably less than the average energy market price to attract customers. Secondly, due to the fixed rates they are invulnerable to the market energy price that is uncertain. However, more incentives can be provided to EV owners by decreasing the fixed rates from 0.05$/kWh.

# CHAPTER 6 CONCLUSION AND FUTURE WORK

## 6.1 CONCLUSION

In this thesis, an optimal day-ahead regulation bidding strategy for unidirectional V2G algorithm is proposed for use by an EV aggregator. The deterministic optimal charging algorithms are used to set the preferred operating point about which the regulation capacity is bid. Stochastic optimal bidding algorithms, analogous to the deterministic charging algorithms are then formulated. It demonstrates the benefits of considering uncertainties associated with different market variables. Stochastic programming with scenario generation technique is used to incorporate uncertainties. ARIMA models are used to generate scenarios. The simulations in the Houston area USA with large number of hypothetical EVs show that Stochastic outperforms the Deterministic.

At first, optimal stochastic bidding algorithm is developed for regulation services during limited office parking hours. The objective is to maximize aggregator profit that comes from two sources. First, by taking some percentage of ancillary services provision revenues and second from the mark up over energy price. Under this arrangement Deterministic gives high expected profits that seem lucrative but on the actual day it fails.

However, stochastic optimal algorithm causes slightly increase in system average peak load and EV owner cost.

Since unidirectional V2G can also provide responsive reserve services to grid, an optimal stochastic combined bidding for regulation and responsive reserves is formulated. This formulation also takes into account the uncertainty in electric vehicle behaviour and compensate accordingly. New objective function is used, where aggregator charge EVs at a fixed rate while taking all ancillary service revenues. It shows that this arrangement provides higher profit to aggregator while protecting costumers from high energy market price risks. Three cases i.e. unconstrained, OptLoad and OptPrice are studied with stochastic and deterministic strategies. For all three cases profits obtained from stochastic algorithm are noticeably higher than the deterministic profits and the deviation of expected profits from actual day profits is also less which depicts more realistic results. Moreover, stochastic algorithm keeps regulation capacities at moderate level to get benefit from the uncertain market parameters throughout the day.

## 6.2 FUTURE WORK

The following subjects are recommended for future work.

a. The developed optimal stochastic bidding strategies can be modified to incorporate bidirectional V2G algorithm for EV charging.
b. The proposed stochastic algorithm can be extended to participate in energy market by considering large number of EVs available with aggregator.

c. The effects of the proposed algorithm on distribution system performance, such as losses, voltage profile and line overloads, can be studied.

d. The effectiveness of the proposed stochastic algorithm can be studied by combined bidding in energy and regulation services market through stochastic RES sources and EVs, respectively.

# NOMENCLATURE AND SYMBOLS

| | |
|---|---|
| $\alpha$ | Fixed percentage of regulation revenues taken by aggregator. |
| $Av$ | Availability of *ith* EV at hour *t*. |
| $\beta$ | Fixed rate that aggregator charge EV owners |
| $CR^{Rdn}$ | Regulation down capacity of aggregator |
| $CR^{Rup}$ | Regulation up capacity of aggregator |
| $CR^{RRS}$ | Responsive reserve capacity of aggregator |
| $ChR$ | Charge remaining of $i^{th}$ EV |
| $Comp$ | Compensation factor of *ith* EV to account for unplanned departures |
| $DS_{Rdn}$ | Regulation down deployment signal |
| $DS_{Rup}$ | Regulation up deployment signal |
| $DS_{RRS}$ | Responsive reserve deployment signal |
| $Dep$ | Probability that *ith* EV will depart unexpectedly |

| | |
|---|---|
| $Ef$ | Efficiency of EV battery |
| $EVPer$ | Expected percentage of EVs remaining to perform V2G |
| $\varepsilon$ | Error term |
| $\pi$ | Probability |
| $\sigma$ | Standard deviation |
| $FP$ | Final power draw of the *ith* EV combining the effects of regulation and responsive reserves |
| $L$ | Daily load at hour t. |
| $MC$ | Maximum Charge Capacity of $i^{th}$ EV |
| $Mk$ | Aggregator Mark Up over energy price |
| $MP$ | Maximum possible power draw of $i^{th}$ EV |
| $MnAP$ | Minimum Available Power |
| $MxAP$ | Maximum Available Power |
| $POP$ | Preferred Operating Point |
| $\rho^{Rdn}$ | Price of Regulation Down |

| | |
|---|---|
| $\rho^{Rup}$ | Price of Regulation Up |
| $\rho^{RRS}$ | Price of responsive reserve |
| $\rho^{En}$ | Energy market price |
| $PD$ | final power draws of $i^{th}$ EV |
| $PROFIT$ | Total expected profit |
| $PF\_Percent$ | Profit over fixed percentage of the revenue obtained from providing regulation services. |
| $PF\_MrkUp$ | Profit from fixed Mark up over energy price |
| $RsRP$ | Reduction in power draw available for spinning reserves of *ith* EV. |
| $RS$ | Regulation signal |
| $RRS$ | Responsive reserve signal |
| $SOC$ | State of Charge of battery |
| $SOC\_I$ | Initial State of Charge |
| $Trip_i$ | The reduction in SOC that results from the commute trip |
| $T\_Trip_i$ | Time of commute trip |

| | |
|---|---|
| $t$ | Bidding period |
| $s$ | Scenarios |
| $i$ | Electric Vehicles |
| $N_t$ | Number of Hours |
| $N_s$ | Number of scenarios |
| $N_i$ | Number of EVs |
| $N_{tr}$ | Number of Trips |

# ACRONYMS AND ABBREVIATIONS

| | |
|---|---|
| EV | Electric Vehicles |
| PHEV | Plug-in Electric Vehicle |
| V2G | Vehicle-to-Grid |
| SP | Stochastic Programming |
| ARIMA | Auto Regressive Integrated Moving Average |
| ICE | Internal Combustion Engine |
| G2V | Grid-to-Vehicle |
| APC | Achievable Power Capacity |
| UC | Unit commitment |
| SCUC | Security constrained unit commitment |
| SAR | Seasonal Auto Regressive |
| SMA | Seasonal Moving Average |
| ERCOT | Electric Reliability Council of Texas |

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# LIST OF PUBLICATIONS

The following papers are expected to be published from the work described in this thesis:

**Conference**

[1] Muhammad Waqas Khalid, Ali T. Al-Awami, Eric Sortomme, "Stochastic Programming based Bidding Strategy for V2G services", IEEE Innovative Smart Grid Technologies – Europe 2013, Copenhagen, Denmark, 6-9 October 2013.(Accepted)

**Journals**

[2] "Optimal Combined bidding Strategies for V2G Services based on Stochastic Programming". (To be submitted to IEEE Transactions on Vehicular technology)

# VITAE


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