

**MARKET-BASED PLANNING OF ELECTRIC VEHICLE AND
BATTERY STORAGE SYSTEM AGGREGATORS**

BY

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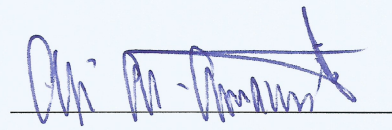
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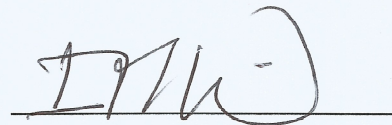
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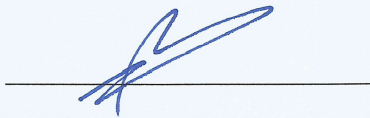
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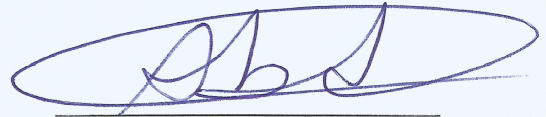
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This work is dedicated to my loving parents, wife and daughter without whom after god's
help this work wouldn't have been possible

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LIST OF ABBREVIATIONS

i, k, t, d, w, y	Indices for EV, bus number, hour, day, week and year numbers
p	Index for trip number
$\alpha^D, \alpha^U, \alpha^R$	Estimated regulation down, regulation up, and responsive reserve commands (as % of bid capacities)
δ	Compensation factor for unplanned departures.
η	Battery charging/discharging efficiency
φ and Φ	Minimum and maximum permissible SOC limits (as % of the energy capacity (MC))
π	Probability that a random EV departs
π^A	Accumulated probability of random departure
σ^E	Forecasted energy price (\$/kWh)
$\sigma^D, \sigma^U,$ σ^R	Forecasted price of regulation down, regulation up and responsive reserve (\$/kWh)
τ^p	Trip time for p-th scheduled trip
v	EV availability; 1 if EV is available, 0 otherwise

ω	Expected % of EVs remaining to perform V2G
r	Discount rate
E	Energy needed for scheduled trip at $t = \tau^p$ (kWh)
BatC	Battery replacement cost (\$/kWh)
BiC	Retrofit cost to support bidirectional V2G (\$/kW)
ChC	Battery charger cost (\$/kW)
ComC	Communications cost for each EV (\$)
SC	Smart meter cost for each EV (\$)
NP	Total number of scheduled trips per day
T	Time span in operation day (hours).
NY, NW	Number of years and number of weeks
NT	Total available EVs in the targeted region
NEV	Number of EV usage profiles
B	Energy tariff charged to the customer (\$/kWh)
γ	Percentage of EVs participating in aggregation
DC	Discharging cost (\$/kWh)

SOC	Estimated state of charge (kWh)
POP	Preferred operating point (kW)
AP^D, AP^U, AP^R	Power capacity available for regulation down, regulation up, and reserves (kW)
$E[\cdot]$	Expected value
MP, MC	Maximum power (kW) and energy ratings (kWh)
R^D, R^U, R^R	EVA's capacity bid of regulation down, regulation up, and responsive reserve (kW)
FP	Final power draw (kW)
FP^-	A conservative estimation of the final power draw
TP	Project's total payoff (\$)
OpP	Annual operation payoff (\$)
InvC	investment cost (\$)
OpI, OpC	Expected daily operational income and cost to EVA
g	EV depreciation cost paid by EVA to EV owners
P^α, Q^α	Real and reactive power injection vectors in phase α for all buses

P_k^α	Real power injected by bus k phase α
P_{kj}^α	Transferred real power in phase α between bus k and j
$J_{P\theta}^{\alpha\beta}$	A matrix that links real power from phase α with voltage angle from phase β
$J_{QV}^{\alpha\beta}$	A matrix that links reactive power from phase α with voltage magnitude from phase β
$G^{\alpha\beta}$	The admittance matrix real part that links between phase α and phase β
$B^{\alpha\beta}$	The admittance matrix imaginary part that links between phase α and phase β
$V_k^\alpha, \theta_k^\alpha$	Voltage magnitude and angle in phase α for bus k

ABSTRACT

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Due to accelerated advancements in battery manufacturing recently, the battery has become more economically viable than ever before for power grid applications. Given their fast response, batteries are known for their efficacy in providing ancillary services (AS), such as frequency regulation and reserve services, to the bulk power grid. Electric vehicle (EV) also could provide these services because it is considered as a moving battery. For an investor willing to provide AS to the electricity markets via battery energy storage system (BESS) or EVs, proper planning could be a challenge.

In this research, a linear planning model for EV aggregator and BESS is proposed for an investor who would like to provide ancillary services (AS) to the electricity market. On the side of BESS, a model is developed to maximize the investor long-term profits by identifying the optimal power capacity, energy capacity and location considering the different physical properties such as degradation due to cycling and the distribution network. For EV planning, which considered as a moveable battery, the fleet size which is a function of the energy tariff is decided. For both options, the proposed models are analyzed and compared assuming that they have the same investment cost. Linear models for unbalanced distribution network are used to provide a more realistic and complete system model that results in an optimal payoff for EV and BESS. Linear programs are used

to optimize the daily bidding strategy in the ancillary services (AS) market by reflecting all prices to the present worth.

To ensure computational tractability, the fuzzy linear program (FLP) is used to handle the uncertainties of inaccurate AS price forecasts in the BESS model. To verify its effectiveness, the proposed FLP-based optimization is compared with its deterministic counterpart. Simulation results using real data obtained from the Electric Reliability Council of Texas market (ERCOT) demonstrate the effectiveness of the proposed FLP-based model, as compared to its deterministic counterpart, in identifying the optimal BESS size in a computationally tractable manner while capturing the market-related uncertainties.

ملخص الرسالة

الاسم الكامل: عمار محمد علي مقبل

عنوان الرسالة: تخطيط المركبات الكهربائية ونظام تخزين الطاقة في شبكة توزيع للمشاركة في أسواق الخدمات الكهربائية المساعدة

التخصص: هندسة كهربائية

تاريخ الدرجة العلمية: أبريل 2019

نظرًا للتطورات المتسارعة في تصنيع البطاريات مؤخرًا، أصبحت أنظمة البطاريات لتخزين طاقة أكثر فاعلية من أي وقت مضى لتطبيقات شبكات الطاقة. ونظرًا لاستجابتها السريعة، فإن البطاريات معروفة بفعاليتها في توفير الخدمات المساعدة، مثل تنظيم التردد وخدمات الاحتياطي، إلى شبكة الطاقة الكهربائية. يمكن أن توفر السيارة الكهربائية هذه الخدمات أيضًا لأنها تعتبر بطارية متحركة. ومع ذلك، بالنسبة للمستثمر الذي يرغب في تقديم الخدمات المساعدة إلى أسواق الكهرباء عبر نظام البطاريات أو السيارات الكهربائية، قد يكون التخطيط السليم تحديًا.

في هذا البحث، سيتم اقتراح نموذج تخطيط خطي للسيارات الكهربائية ونظام البطاريات لتخزين الطاقة الكهربائية للمستثمر الذي يرغب في توفير الخدمات المساعدة لسوق الكهرباء. في جانب البطاريات، سيتم تطوير النموذج لتعظيم أرباح المستثمر على المدى الطويل من خلال تحديد قدرة الطاقة المثلى للمحول، وقدرة طاقة تخزين البطارية والموقع مع مراعاة الخصائص الفيزيائية المختلفة مثل التدهور بسبب استخدام البطارية وخصائص شبكة التوزيع. بالنسبة إلى تخطيط السيارات الكهربائية، الذي يعتبر بمثابة بطارية متحركة، سيتم تحديد حجم الأسطول الذي هو جزء من تعريف الطاقة. بالنسبة لكلا الخيارين، سيتم تحليل النماذج المقترحة ومقارنتها بافتراض وجود نفس تكلفة الاستثمار. سيتم استخدام نماذج خطية لشبكة التوزيع غير المتوازنة التي ستوفر نموذج نظام أكثر واقعية وكاملة ينتج عنه أفضل القرارات. سيتم استخدام البرامج الخطية مثل GAMS لتحسين استراتيجية العطاءات اليومية في سوق الخدمات المساعدة (AS) من خلال عكس جميع الأسعار إلى القيمة الحالية.

لضمان قابلية التتبع الحسابي، سيتم تصميم النموذج على أنه برنامج خطي ضبابي (FLP)، بشكل رئيسي، غير دقيق لتوقعات السعر للخدمات المساعدة. للتحقق من فعاليتها، يقارن التحسين المقترح القائم على FLP مع نظيره المحدد. تظهر نتائج المحاكاة باستخدام بيانات حقيقية تم الحصول عليها من سوق ERCOT فعالية النموذج المقترح القائم على FLP، مقارنة بالنظير المحدد، في تحديد حجم البطاريات الأمثل بطريقة قابلة للحوسبة، بينما يتم التقاط حالات عدم اليقين المرتبطة بالسوق.

CHAPTER 1

INTRODUCTION

1.1 Background

Energy security and environmental sustainability become major world concerns. As a result, the vision of energy sources and how this energy is generated and consumed has changed. On the generation side, the world starts to move in the direction of using sustainable energy and renewable resources like wind and solar to supply the demand. Due to the penetration of these resources, a large effort is needed to achieve the optimal utilization by allowing the load to be more responsive by participating in the electricity market. Due to the high pollution associated with using fossil fuel and how that affects the environment, in addition to the high penetration of renewable energy, the research is increasing in the direction of using batteries and clean energy to reduce the dependence on the fossil fuel [1],[2].

The transportation sector is one of the large consumers of energy that comes mainly from fossil fuel. For example, in the US the transportation sector consumes about 27 % of the total energy [3]. This percentage makes this sector experiences many transformations to ensure energy security and environmental stability. One of these transformations is shifting to the electric vehicles (EVs) to reduce the carbon emission. Although its good impact on the environment, the rapid increase of EV 's in the Electric system can stress the

system more. As a result, many services associated with Vehicle to grid (V2G) are proposed. Vehicle to grid charging (V2G) is a description of the system that used the bi-directional flow of energy between the power grid and the plugged in EV's in order to exchange services. Those services can eliminate stress and even improve the operation of the grid. The concept of V2G was firstly proposed in [4]. That concept converts the EV from being just like an ordinary load as in [5] to battery storage that can be used to support the grid.

A single EV can't participate in those services because it doesn't have enough capacity. As a result, an intermediate party called aggregator should organize this between the considerable number of EV owners and the energy market [6]. The most important thing for EV aggregators is to maximize their profits while maintaining the EV owner's satisfaction. This maximization could be done by operations or planning process of the aggregators. In the operation side, the bidding and charging strategies are optimized and on the planning side, the contract design between the aggregators and EVs owners could be optimized [7-9].

Battery energy storage systems (BESS) have attracted the world's attention in recent years especially in integrating BESS with renewable resources to achieve high reliability, reduction in emission and energy independence [10]. Recently, researches proposed different use for BESS, rather than store energy, as frequency regulation source due to their fast ramping response [11]. In addition, using BESS as frequency regulation provider proved its profitability according to a 2010 NREL report with annual profits approximated in the US electricity market as 236 to 439 \$/ KW [12].

1.2 Ancillary Services and Power Markets

There are big differences between ancillary services (AS) and system services (SS). System operator provides SS to all the connected costumers, while AS is bought from the network users by the system operator [13]. Ancillary services refer to the services that are provided by the grid to ensure the continuity of the power flow in the grid and guarantee the security of the electrical system. That includes black start capability (the ability to restart a grid following a blackout), frequency response, fast reserve and provision of reactive power and other various services [14], [15]. There are different methods for frequency regulation, including generator inertia, adding and subtracting generation assets, dedicated demand response and electricity storage. Each of the mentioned methods has advantages, disadvantages and response time [16].

Frequency regulation and reserves are the most suitable AS to be provided by the energy storage (BESS) and that because of the high-speed response of the BESS [1],[17],[18]. So, from that planning for BESS investment to provide the ancillary services is crucial and BESS sizing in addition to the full utilization of the EVs must be considered in research to get the maximum profits and ensure that the system will be secure.

In the United States, seven distinct power markets exist. Each is either operated by an independent system operator (ISO) or Regional Transmission Organization (RTO). ISOs/RTOs are responsible to ensure the reliability requirement and manage the operation of energy and ancillary services market in their territories. The ASs provided by those markets can mainly be categorized into three types, Spinning Reserves, Regulation, and Non-spinning Reserves. The names and details of those types can differ from market to another [19].

The market data used in this research is from The Electricity Reliability Council of Texas (ERCOT). ERCOT is power market operator that was established in 2001 and currently supplies 85 % of the demand in Texas. In the day-ahead market (DAM), ERCOT conducts AS plan and provides AS market information that identifies the prices and needed capacities each hour for the next day. Each participant should submit his bids to the ISO (ERCOT). Finally, the DAM is executed and the excepted bids are posted. In real-time, the accepted bids participant receives deployment signal defining the needed percentage from the total bided capacity. Table 1-1 summarizes the AS provided by ERCOT [20].

Table 1-1 AS provided by ERCOT

Product	Description
Regulation up	Immediately decrease in the power output to response to deployment signal to bring the frequency to nominal
Regulation down	Immediately increase in the power output to response to deployment signal to bring the frequency to nominal
Responsive reserves	Should respond to the signal within few minutes
Non spinning reserves	• Should respond to the signal within 30 minutes • Run for at least one hour

1.3 Research Objectives

The main objective of this thesis is to propose two investment options. The first one is to invest in EV aggregation by providing ancillary services namely regulation up/down and reserve to the electricity market by using the storage battery of the EVs, in addition, to

charge those EVs with constant charging tariff. The second option is to invest in BESS by buying battery power and energy capacities and also using them to provide ancillary services to the grid. Both options are integrated with the unbalanced distribution network and the planning and operation aspects are investigated. Moreover investing in BESS contains uncertainties associated with the market prices which needed to be handled in this research.

The milestones of this research are the following:

- To propose a planning model for BESS to participate in AS market taking into account distribution constraints.
- To propose a planning method for EV aggregator (EVA) to participate in AS market.
- To compare the investment in EVs with the investment in BESS
- To apply fuzzy optimization to the BESS model to handle uncertainties associated with market prices.

1.4 Approach

To achieve our objectives, the work will be divided into steps (Figure 1-1) as following:

1. BESS linear deterministic planning problem will be formulated without including the distribution network constraints. The results will be tested to make sure that the model is correct.
2. EVs linear deterministic planning model will also be formulated separately and results are obtained.

3. Comparison between investing in EVs aggregation with deploying distributed BESS is conducted to see which one is more profitable.
4. Incorporating the linear model of the unbalanced distribution network with the two systems (EVA and distributed BESS) effectively and in a computationally tractable manner.
5. Deciding in the uncertain parameters and writing BESS model as fuzzy linear optimization.
6. Concluding and comparing to make the best decision.

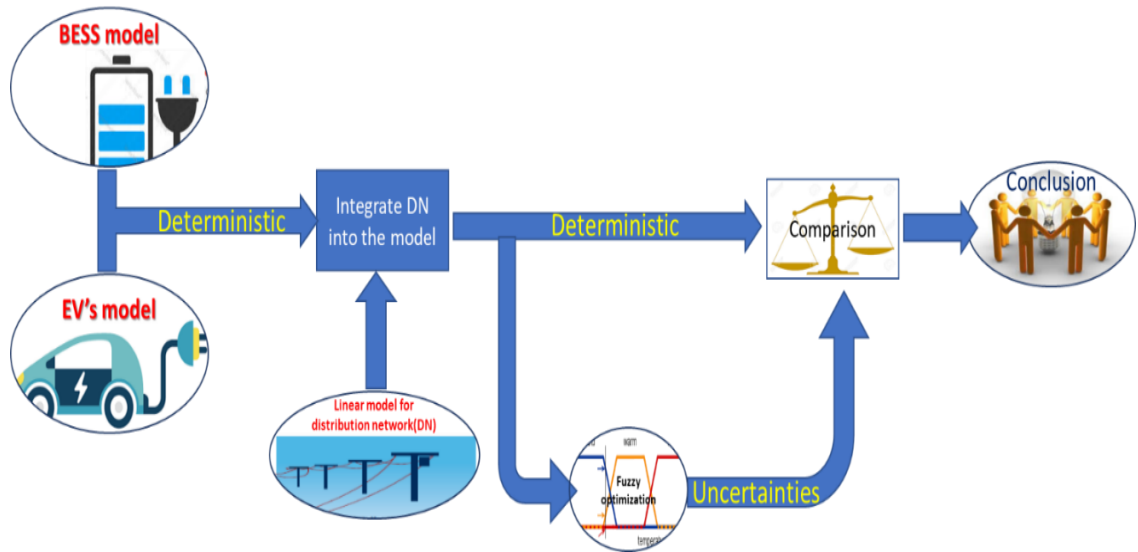


Figure 1-1 Work plan

CHAPTER 2

LITERATURE REVIEW

2.1 EV Aggregator

The number of EVs in the last years has increased dramatically due to its good impact on the environment in addition to reducing the dependence on fossil fuel [21]. China, for example, is planning to integrate around 200 million EVs by 2050 [22]. Reference [16] reported that the CO_2 emission could be reduced by 2.2 tons/year if a conventional car is replaced by EV. Also, using EV instead of conventional cars could reduce fuel consumption by 6.5 million barrels/ day globally [23].

Reference [23] mentioned that renewable resources could be used to produce the energy for EV and this system (renewable resources and EVs) can be scheduled optimally. That is important as mentioned before because the integration of renewable resources in the electrical system is increasing day after day. In [24], Game theoretical analysis is used to study the profitability of electric vehicle charging stations that are equipped with renewable resources and compared them with the conventional charging stations. The effect of Large-scale hybrid electric vehicle on the integration of wind turbines in the US electricity system is studied in [25] to prove that the wind power can be increased by 6% from the total generation in the US, if 50 % of conventional vehicles are converted to a hybrid ones.

EV batteries as any normal battery, have a rapid response to the change in the operating point. As a result, that gives EVs high potential to provide AS to the system operator [26]. In [27] and [28], it is shown that EVs can participate in primary frequency regulation in a large-scale system and also in microgrids. Full consideration of vehicle to grid (V2G) optimization is presented in [8], [9] and [29]. Two charging approaches were proposed in [30]. The first one was considering EV as a controllable load which called unidirectional V2G and the second one was bidirectional V2G which allowed the power to flow in two directions, from the EV, and to the EV. In reference [8], the charging of unidirectional V2G is optimized for use by an aggregator to participate in the ancillary services markets by considering 10000 commuter EVs. The unidirectional approach is compared with the bidirectional in providing the frequency regulation and reserves to the market. The unidirectional V2G EVs can supply the market by varying the charging rates slightly above or below the nominal value during the scheduling period [9], [29]. The role of the aggregator is to act as a mediator between the system operator (SO) and the EV owners. The aggregator will send bids to AS market and buy energy to charge EVs. In [31] dispatch algorithm is proposed to minimize the daily costs in a centralized system consists of EVs, BESS, and renewable resources. All the EVs references mentioned earlier handled the feasibility of EV aggregator from an operational point of view. However, they did not approach the EV from a planning standpoint.

Most of the papers that considered planning in EV focus in charging stations [32], [33], [34]. Reference [32] used a multi-objective evolutionary algorithm to locate the charging stations in the radial distribution system and that for a pre-determined number of EVs. Reference [33] included renewable resources (solar and wind) and BSS in the

optimization and form the problem as a second-order conic form to minimize the loss. The life cycle of BESS integrated with a charging station is proposed in [34]. References [32], [33] and [34] used the nonlinear model to include the distribution system constraints and they did not consider the number of EVs in the fleet as decision variable nor did they consider identifying the best incentives tariff that paid by the EV owners to the EVA in order to charge there EVs.

2.2 BESS Planning

The optimal sizing of BESS in a system that includes renewable resources is discussed in many papers and that due to the uncertainties of the renewable resources which could be overcome with the integration of the BESS. Reference [35] suggested a method to find the optimal size of BESS integrated with wind turbine and considered wind and load uncertainties. Two parts of the operational strategy are proposed in [36] for distribution companies. Those two parts are day-ahead and real-time wherein day-ahead the load, wind, solar and prices should be forecasted and in real time the gap between the forecasted and real value is considered. The objective here is to locate BESS in the network in order to minimize the cost and the loss by developing a highly nonlinear model for the network and BESS. Stochastic planning formulation for BESS in Microgrid using Monte Carlo Simulation (MCS) is proposed in [37]. Although uncertainties in wind generation are considered, the network constraints are neglected. Reference [38] used a similar Stochastic approach but with Radial IEEE distribution system nonlinear model to simulate the line and voltage limits. A deterministic approach to optimize the battery sizing and location in the distribution network is proposed in [39],[10]. The uncertainty effects of the

wind power resources using point estimate method (PEM) is presented in [40] where the naturally inspired particle swarm optimization (PSO) is combined with the Tabu search (TS) to solve the problem. Stochastic mixed-integer linear programming (MILP) is used to optimize the sizing and location of a storage system in the distribution system and that to minimize the costs of investment and operation [41],[11]. In [11] Two level of the profit-maximizing strategy was introduced to include planning and control. A framework has been developed to get the optimal BESS planning and control in the primary control market. The problem has been studied from the energy capacity point of view to achieve a balance between the capital cost and the operating cost. BESS degradation was considered here as a weighting factor which depends on the BESS lifetime. The uncertainty in transmission and energy using the stochastic multistage co-planning is introduced in [42], where different renewable and load scenarios were generated to see the effect of that in the investment decisions. In addition, the model includes the battery degradation due to the self-life and charge/discharge cycle. Table 2-1 summarized some of the references.

2.3 Fuzzy Optimization

Fuzzy optimization (FO) is also another approach to handle uncertainty. This concept is firstly introduced in 1965 by Zadeh [43]. One of the important benefits of this technique is that as the number of uncertain parameters increase, the size of the problem will not increase significantly. FO is applied to many power system to handle uncertainties associated to the system operations in [44],[45], [46], [47],[48], and [49]. In [44]-[46], FO is used for the unit commitment of the thermal units with the integration of renewable resource. In [47], FO is used to optimize the bidding of ancillary services by electric vehicle

aggregator to minimize the operating cost and increase profits. In [48], the concept of FO is applied to an electric vehicle parking slot to optimize the bid energy for EV's charging in the energy market. The participation of load in optimizing the bidding strategies in the virtual power plant (VPP) using FO is discussed in [49]. The demand response is divided into load curtailment and load shift with specific capacities and prices determined by the consumers. The factors that affect the decision making of the VPP are the price of energy and the offer information (capacity and price) by the demand response participants.

2.4 Distribution Network

Distribution Network (DN) modeling is gaining much more attention lately with the increased participation of the demand side management programs, penetration of renewable resources and small-scale generators within DN [50]. DN possesses special characteristics that make applying normal power flow tools used in transmission networks ineffective [51]. Examples of those characteristics are high R/X ratio, unbalanced feeders, and its radial operation. Few works have been reported in the literature to linearly model power flow in DN, such works are presented in [51-55]. In [51] and [52], the voltage is linearized in a balanced distribution network as real and imaginary parts. This method is accurate, however, the difficulty of restricting voltage magnitude to a certain limit, required the problem to be nonlinear. In [53] and [54], the unbalanced distribution network model is considered and developed as linear equations. Where in [53], the load flow is modeled based on the rectangular form.

Table 2-1 Summary of the literature

References	What handled
[8] E. Sortomme(2011) [9]E. Sortomme(2012) [29]E. Sortomme(2012) [47]M. Ansari (2015)	• Operation ☐ Unidirectional [8] ☐ Bidirectional [9] ,[28],[46] ☐ No network constraints [8],[9],[28] ,[46] ☐ frequency regulation and reserves to the AS market[8],[9],[28] ☐ Deterministic [8],[9],[28] ☐ Uncertainty [46]
[32] W. Yao (2014) [33] O. Erdinç (2017) [34] Y. Zheng (2014)	• Charging stations ☐ Minimize losses or costs [31],[32],[33] ☐ Renewable resources(solar and wind) [32] ☐ Nonlinear [31],[32],[33] ☐ Balanced [31],[32],[33] ☐ No best incentives for EVs [31],[32],[33] ☐ Pre-determined No of EVs[31],[32],[33]
[37] H. Alharbi(2018) [38]Y. Zhang (2017) [10]Y. M. Atwa (2010) [40]M. Sedghi(2016) [41] R. Fernández- Blanco(2017) [11]Y. J. A. Zhang(2018) [42]T. Qiu(2017)	• BESS planning ☐ Stochastic planning formulation for BESS [36],[40],[11],[41] ☐ Minimize the costs of investment and operation and Losses or profit-maximizing ☐ point estimate method (PEM)[39] ☐ network constraints are neglected[11],[41] ☐ Radial IEEE distribution system nonlinear model [37] ☐ Heuristic optimization[39][37][36] ☐ BESS degradation [41]

2.5 Gaps in the literature

As seen from the literature, battery energy storage system (BESS) and EV aggregator (EVA) planning are not studied fully as a participant to AS market. In EVA planning, most of the research focused on the operational optimization of the EVA by

optimally schedule the charging process to get the maximum profits but planning for the long term aspects is untouched and required to be investigated in this research. In addition, most of the research concentrated on locating the charging stations by considering the nonlinear network model which makes it difficult to plan for a big system so the need for proposing a linear model for the unbalance distribution network is essential in our objectives to target EV aggregator planning. the literature did not consider the number of EVs in the fleet that will participate in the AS market as a decision variable nor did they consider identifying the best incentives or charging tariff that will be paid by for EV owners to the EVA for charging their EVs. In BESS planning, most of the literature references considered integrating BESS with renewable resources to reduce losses or cost, however investing in BESS to participate in AS market is not approached. Moreover, handling uncertainties using stochastic approach increases the size of the problem significantly that put us in a situation where we need to find another method to include the uncertainties in the model without affecting the problem's size. Those gaps are handled in this thesis by achieving the objectives of this research as following:

- To propose a planning model for BESS to participate in AS market taking into account distribution constraints.
- To propose a planning method for EV aggregator to participate in AS market.
- To compare the investment in EVA with the investment in BESS.
- To apply fuzzy optimization to the BESS model to handle uncertainties associated with market prices.

CHAPTER 3

EV AGGREGATOR PLANNING MODEL FOR ANCILLARY SERVICES BIDDING

This chapter will discuss the deterministic optimization of EV aggregator(EVA) as a linear model to participate in AS market by bidding regulation up/down and reserve capacities to the AS market. EVA here is considered as an agent between the EV owners and the electricity market or grid. A linear model of EVA will be integrated with a linear model of the unbalanced distribution network to see the effects of introducing network constraints in the optimal results. The EVA model is explained and formulated as linear equations where the objective is to maximize the total profits in the studied period.

3.1 EV Aggregator (EVA) Planning Model

Since one car has small capacity and can't participate in AS market, The EV's aggregator in this planning problem is assumed to have a large number of EVs. The aggregator provides charging services to the EV's owners with a constant tariff, β , and purchases energy from the day-ahead energy market with a price of (σ_{tdw}^E) . Participating in the AS market occurs on the day-head by bidding regulation up (AP_{tdw}^U), regulation down (AP_{tdw}^D) and reserves (AP_{tdw}^R) capacities to system operator with a price of σ^U, σ^D and σ^R respectively.

Each participating EV has a trip profile consisting of multiple pre-scheduled trips. Unexpected random departure is expected to happen some hours during the day, which makes the EV unavailable during those hours. This departure is handled by calculating the EVs percentage remain to perform V2G (ω_t). v_{it} is a binary number that is defined to restrict EV availability to a certain hour in a day.

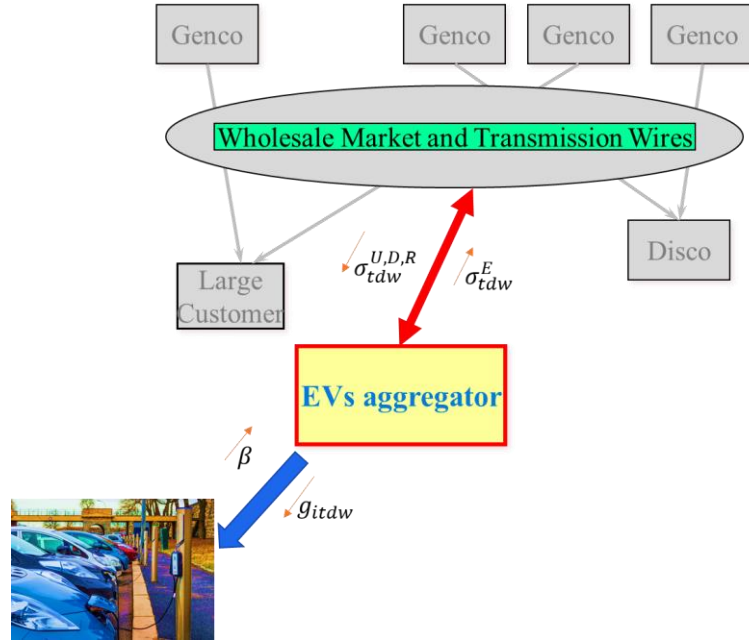


Figure 3-1 EV aggregator planning model in a pool-based electricity market for energy and AS.

Regulation services can be performed by EVs by varying the charging rate of the bidirectional inverter that responses to charge the EV around an operating point (POP_{tdw}). This term comes from the market of AS and it refers to the average operation level of the market participant to provide regulation. In the case of a generator, POP is the output power and in the case of the battery, POP is either the power drawn or injected into the system. Figure 3-2 describes the three regulation services (up, down and reserve) and how can the POP changes according to bidding capacity of each service. For example, if the aggregator

bid a capacity of AP_{tdw}^U for a particular hour t , POP should be reduced when received signal for the AS market with a maximum capacity equals to the bid capacity.

Drawing energy from the EV will reduce the battery life, so the aggregator will compensate the EV owner with constant price depending on the cost of batteries at the studied period.

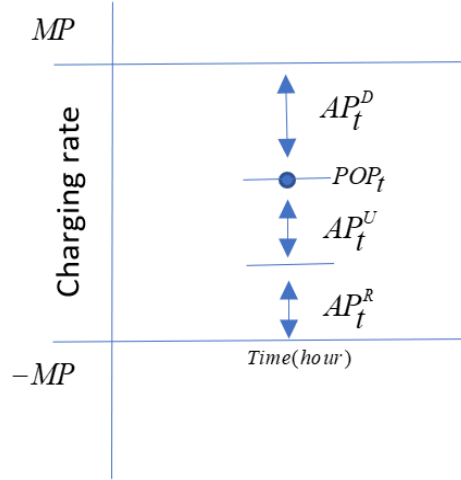


Figure 3-2 The ancillary services around an operating point (POP)

3.2 Problem Formulation

In this section, the deterministic planning optimization of the EV aggregator as an ancillary services participant is discussed to maximize the total profit TP . This model is formulated and developed from reference [56] as follows:

$$TP = \sum_{y=1}^{NY} (1+r)^{-y} \cdot OpP_y - InvC \quad (3-1)$$

$$InvC = \sum_{i=1}^{NEV} (SC + ComC + BiC \cdot MP_i) \quad (3-2)$$

$$OpP_y = \sum_{w=1}^{NW} \sum_{d=1}^7 (OpI_{dw} - OpC_{dw}) \quad (3-3)$$

$$OpI_{dw} = \sum_{t=1}^T \omega_t (\sigma_{tdw}^D R_{tdw}^D + \sigma_{tdw}^U R_{tdw}^U + \sigma_{tdw}^R R_{tdw}^R) + \beta \sum_{t=1}^T \omega_t \sum_{i=1}^{NEV} E[FP_{itdw}] \quad (3-4)$$

$$OpC_{dw} = \sum_{t=1}^T \omega_t \sum_{i=1}^{NEV} \sigma_{tdw}^E E[FP_{itdw}] + \sum_{t=1}^T \sum_{i=1}^{NEV} g_{itdw} \quad (3-5)$$

$$R_{tdw}^D = \sum_{i=1}^{NEV} AP_{itdw}^D \quad (3-6)$$

$$R_{tdw}^U = \sum_{i=1}^{NEV} AP_{itdw}^U \quad (3-7)$$

$$R_{tdw}^R = \sum_{i=1}^{NEV} AP_{itdw}^R \quad (3-8)$$

Equation (3-1) is to calculate the total profits for the studying time period with a number of years equals to NY. This objective function has two terms. The first one is the total profit during the year (OpP_y) referred to the present worth value using the interest rate. The second term is the investment cost which only introduced in the first year. Relations (3-2) and (3-3) are the investment cost and yearly profits respectively. The investment cost in (3-2) is the cost of infrastructure (SC), the communication cost ($ComC$) and the cost of the bi-directional charger (MP). MP in (3-2) is multiplied by BiC which is the cost in \$/kW, the value of MP depends on the studied EV, for example Nisan leaf has an inverter of 2 kW. The profit in (3-3) consists of the daily costs (OpC_{dw}) subtracted from daily incomes (OpI_{dw}). The daily incomes (OpI_{dw}) is from participating in AS market by bidding regulation capacities and reserve (R_{tdw}^D, R_{tdw}^U and R_{tdw}^R) with prices of $\sigma_{tdw}^D, \sigma_{tdw}^U$ and σ_{tdw}^R depending on the bidding time t , and selling energy to EV owners with a constant tariff equals to β multiplied by the expected power draw of all EVs ($E[FP_{itdw}]$) at time t as appeared in eqns. (3-4). The operating costs (OpC_{dw}) in equation (3-5) are from buying energy from the market with a price of σ_{tdw}^E and the degradation cost

(g_{itdw}) due to the reduction in the EV life battery in the discharging process. the total bidding capacity at each time period is the summation of all EVs capacities and that is applied for R_{tdw}^D , R_{tdw}^U , R_{tdw}^R as in equations (3-6), (3-7) and (3-8).

$$E[FP_{itdw}] = (POP_{itdw} + \alpha_{itdw}^D AP_{itdw}^D - \alpha_{itdw}^U AP_{itdw}^U - \alpha_{itdw}^R AP_{itdw}^R) v_{it} \quad (3-9)$$

$$\omega_t = 1 - \frac{1}{NEV} \sum_{i=1}^{NEV} \pi_{it}^A \quad (3-10)$$

$$\pi_{it}^A = \sum_{h=\tau_i^{p-1}}^{\tau_i^p} \pi_{ih}, \tau_i^{p-1} \leq t < \tau_i^p \text{ where } \tau_i^0 = 1, p = 1, 2, \dots, NP \quad (3-11)$$

$$SOC_{it} = SOC_{i,t-1} + E[FP_{itdw}] \delta_{it} \eta_i - E_{it} \quad (3-12)$$

$$g_{itdw} = \max\left(-\frac{DC_i E[FP_{itdw}^-] \delta_{it}}{\eta_i}, 0\right) \quad (3-13)$$

$$E[FP_{itdw}^-] = (POP_{itdw} - \alpha_{itdw}^U AP_{itdw}^U - \alpha_{itdw}^R AP_{itdw}^R) v_{it} \quad (3-14)$$

$$DC_i = 0.042 \left(\frac{BatC}{312} \right) + \frac{\beta(1-\eta_i^2)}{\eta_i} \quad (3-15)$$

$$\delta_{it} = (1 - \pi_{it})^{-1} \quad (3-16)$$

Relation (3-9) is the total power drawn ($E[FP_{itdw}]$) where the subscripts t, d, and w represent hour, day and week, respectively. $E[FP_{itdw}]$ for each EV is a function of the preferable operating point (POP_{itdw}). It also depends on the bidding capacities of the expected regulation down, regulation up and responsive reserve AP_{itdw}^D , AP_{itdw}^U , AP_{itdw}^R which are decision variables. α_{itdw}^D , α_{itdw}^U and α_{itdw}^R are the regulation signals that are received from the system operator to decide the percentage from the bidding capacities to

be provided by the EVA. v_{it} here will take either 0 or 1 based on the trip profile of each EV. For example if v_{it} is 0 that means the EV is not available connected to the charger so the EVA cannot use this EV to provide AS services to the system operator and based on that $E[FP_{itdw}]$ also will be 0 which means no power draw from the EV at that specific hour (t).

As we can see from equations (3-4) and (3-5) the daily incomes and costs depend on the possibility of the unexpected departure π_{it}^A for each EV by calculating the percentage of EVs reminding (ω_t) to perform the AS for each hour t . ω_t is a percentage that depends on the accumulated probability in (3-11) for each car to depart at time t as in equation (3-10). π_{it}^A is reset to zero after each trip hour τ_i^p due to the assumption of the certain knowing of the availability of the EV in this time. NP here is the number of total scheduled trips during the day, so if we have two trips, one at τ_i^{p-1} and the other at τ_i^p , π_{it}^A is calculated in the period when $\tau_i^{p-1} < t < \tau_i^p$, $t < \tau_i^{p-1}$ and $t > \tau_i^p$ as in relation (3-11).

The state of charge SOC_t can be defined as in (3-12) where E_{it} is the energy consumed during the trip and $SOC_{i,t-1}$ is the previous state of the battery. As seen from (3-12), $E[FP_{itdw}]$ is multiplied by two parameters. The first one is η_i , which is the efficiency of battery charging and discharging and that depends on the bi-directional inverter. The second one is δ_{it} , which is the compensation factor. The compensation factor equals to 1 when EV is for sure available and less than 1 when there is a possibility for unexpected departure based on equation (3-16).

Eqns. (3-13), (3-14) and (3-15) are included to count for the degradation cost (g_{itdw}) which is the reduction in the battery life due to the discharging process and that

converted to positive cost. degradation cost (g_{itdw}) is the maximum between two the two terms 0 and $-\frac{DC_i E[FP_{itdw}^-] \delta_{it}}{\eta_i}$. So when $E[FP_{itdw}^-]$ is positive the maximum will be zero and that for the case when the EV is charging and here there is zero g_{itdw} because there is no reduction in the battery life due to the charging action. When $E[FP_{itdw}^-]$ is negative which means discharging action, the maximum will be $-\frac{DC_i E[FP_{itdw}^-] \delta_{it}}{\eta_i}$ and the degradation cost is calculated because of the reduction in battery life due to discharging action.

DC is the cost of deregulation per kWh where the term $BatC/312$ is to normalized the deregulation cost in [57] for battery with a cost of 312 \$/kwh with the one used in this research and the second term is the cost of the lost energy due to cycling, developed in [29] which must be paid by the aggregator. As seen from (3-14) that the degradation cost is effected by the regulation up AP_{itdw}^U and the reserve AP_{itdw}^R [29]. In (3-16), the compensation factors for unexpected departures is calculated.

$$\varphi_i MC_i \leq SOC_{it} \leq MC_i, \forall t \leq T - 1 \quad (3-17)$$

$$\Phi_i MC_i \leq SOC_{iT} \leq MC_i \quad (3-18)$$

$$(POP_{itdw} + AP_{itdw}^D) \delta_{it} \eta_i \leq MC_i - SOC_{it} \quad (3-19)$$

$$(POP_{itdw} - AP_{itdw}^U - AP_{itdw}^R) \delta_{it} \eta_i + SOC_{it} \geq E_{it} \quad (3-20)$$

$$(POP_{itdw} + AP_{itdw}^D) \delta_{it} \leq MP_i v_{it} \quad (3-21)$$

$$POP_{itdw} - AP_{itdw}^R - AP_{itdw}^U \geq -v_{it} MP_i \quad (3-22)$$

$$AP_{itdw}^D, AP_{itdw}^U, AP_{itdw}^R \geq 0 \quad (3-23)$$

$$POP_{itdw} \geq -v_{it}MP_i \quad (3-24)$$

$$|SOC_{itdw} - SOC_{i,t-1,d,w}| \leq v_{it}MP_i/\eta_i \quad (3-25)$$

Constraints (3-17) to make sure the SOC_{it} is within the accepted available energy capacity MC_i and greater than a certain limit to make sure that the EV battery is not drawn completely to protect the battery from deep discharging. Relation (3-18) to ensure that the EV is at acceptable SOC_T at the beginning of each day (T) so that the EV owner can go to his trips during the day. Constraints (3-19) and (3-20) are to relate the energy limit of the battery for each EV with the decision variables of the AS bid capacities and POP . Both constraints are important to make sure that there is sufficient energy in the EV's battery so in real time if all the capacity is needed. Relation (3-19) is to restrict the regulation down and relation (3-20) is to restrict regulation up and reserve. Constrains (3-21), (3-22), (3-24) and (3-25) are to account for the capacity of the power inverter MP_i and relates this capacity to the decision variable. Relation (3-25) will make sure that performing the regulation up or down at any instant will not violate the power capacity of the inverter. This optimization problem has six decisions variables β , POP_{tdw} , AP_{tdw}^D , AP_{tdw}^U and AP_{tdw}^R .

3.3 Distribution network model

The model, proposed in [54], is used to linearly model the distribution network, and perform three-phase load flow. This model is used because it provides a linear compact model that can be applied to unbalance DN system and easily integrated with the linear model of the BESS and EV. Moreover, it provides the voltage magnitude and phase as separate quantities with high currency as validated in this work.

This model is based on the following two equations:

$$P_k^\alpha = V_k^\alpha \sum_j^N \sum_\beta^{a-c} V_j^\beta \left(G_{kj}^{\alpha\beta} \cos \theta_{kj}^{\alpha\beta} + B_{kj}^{\alpha\beta} \sin \theta_{kj}^{\alpha\beta} \right) \quad (3-26)$$

$$Q_k^\alpha = V_k^\alpha \sum_j^N \sum_\beta^{a-c} V_j^\beta \left(G_{kj}^{\alpha\beta} \sin \theta_{kj}^{\alpha\beta} - B_{kj}^{\alpha\beta} \cos \theta_{kj}^{\alpha\beta} \right) \quad (3-27)$$

These two equations in ((3-26), (3-27)) represent the real and reactive power injected at each bus, respectively. It is clear that ((3-26), (3-27)) are nonlinear, and in order to linearize them the following assumptions are made:

- 1- Because we have a distribution network so the voltage drop between two nodes will be small due to the short distance. As a result, the value of θ_{kj}^α should be close to zero , so we can approximate $\sin \theta_{kj}^\alpha$ and $\cos \theta_{kj}^\alpha$ as $\theta_k^\alpha - \theta_j^\alpha$ and 1 respectively.
- 2- In normal conditions, voltage magnitudes are close to 1 pu and any change of voltages will be around 1 so we can assume that $V_k = (1 + \Delta V_k)$ and $V_j = (1 + \Delta V_j)$ where ΔV_k and ΔV_j are the change in the voltage from the nominal value.

Hence the multiplication of two voltages are linearized as follows:

$$\begin{aligned} V_k(V_k - V_j) &= (1 + \Delta V_k)(1 + \Delta V_k - 1 - \Delta V_j) \\ &= (1 + \Delta V_k)(\Delta V_k - \Delta V_j) = \Delta V_k + \Delta V_k^2 - \Delta V_j - \Delta V_k \Delta V_j \end{aligned} \quad (3-28)$$

So from (3-28) and as a second step ΔV_k^2 and $\Delta V_k \Delta V_j$ can be neglected without causing high errors because they are a second order of a small magnitude that is smaller than V_k and V_j .

$$V_k(V_k - V_j) \approx (\Delta V_k - \Delta V_j) \approx (V_k - V_j) \quad (3-29)$$

Taking these assumptions into account, equations (3-26) and (3-27) are linearized and rearranged in a matrix format as follows:

$$\begin{bmatrix} P^A \\ P^B \\ P^C \\ Q^A \\ Q^B \\ Q^C \end{bmatrix} = \begin{bmatrix} J_{PV}^{AA} & J_{PV}^{AB} & J_{PV}^{AC} & J_{P\theta}^{AA} & J_{P\theta}^{AB} & J_{P\theta}^{AC} \\ J_{PV}^{BA} & J_{PV}^{BB} & J_{PV}^{BC} & J_{P\theta}^{BA} & J_{P\theta}^{BB} & J_{P\theta}^{BC} \\ J_{PV}^{CA} & J_{PV}^{CB} & J_{PV}^{CC} & J_{P\theta}^{CA} & J_{P\theta}^{CB} & J_{P\theta}^{CC} \\ J_{QV}^{AA} & J_{QV}^{AB} & J_{QV}^{AC} & J_{Q\theta}^{AA} & J_{Q\theta}^{AB} & J_{Q\theta}^{AC} \\ J_{QV}^{BA} & J_{QV}^{BB} & J_{QV}^{BC} & J_{Q\theta}^{BA} & J_{Q\theta}^{BB} & J_{Q\theta}^{BC} \\ J_{QV}^{CA} & J_{QV}^{CB} & J_{QV}^{CC} & J_{Q\theta}^{CA} & J_{Q\theta}^{CB} & J_{Q\theta}^{CC} \end{bmatrix} \begin{bmatrix} V^A \\ V^B \\ V^C \\ \theta^A \\ \theta^B \\ \theta^C \end{bmatrix} \quad (3-30)$$

Equation (3-30) represents again the real and reactive power injected by the buses. The Jacobian-like matrix is an $N \times N$ matrix, where N is the number of buses multiplied by 3, and it exclusively depends on impedances of the system, which means it will be calculated once assuming no system reconfiguration occurs. The following relations give examples of three entries from the matrix:

$$J_{QV}^{AA} = -B^{AA} \quad (3-31)$$

$$J_{PT}^{CA} = -\left(\frac{-\sqrt{3}}{2} * G^{CA} + \frac{-1}{2} * B^{CA} \right) \quad (3-32)$$

$$J_{QV}^{CB} = \left(\frac{-\sqrt{3}}{2} * G^{CB} + \frac{1}{2} * B^{CB} \right) \quad (3-33)$$

Solving equation (3-30) will determine all injected real and reactive powers for all buses and all phases. The next step is to find the transferred power between connected buses. In order to calculate those powers, the following formula, proposed by [58], is used after rewriting it in per phase format as in (3-35). This equation is derived from (3-34) after applying the previous two assumptions:

$$P_{kj}^{\alpha} = \frac{r_{kj}^{\alpha} V_k^{\alpha 2} - r_{kj}^{\alpha} V_k^{\alpha} V_j^{\alpha} \cos \theta_{kj}^{\alpha} + x_{kj}^{\alpha} V_k^{\alpha} V_j^{\alpha} \sin \theta_{kj}^{\alpha}}{r_{kj}^{\alpha 2} + x_{kj}^{\alpha 2}} \quad (3-34)$$

$$P_{ij}^{\alpha} \approx \frac{r_{kj}^{\alpha} x_{kj}^{\alpha}}{r_{kj}^{\alpha 2} + x_{kj}^{\alpha 2}} \frac{V_k^{\alpha} - V_j^{\alpha}}{x_{kj}^{\alpha}} + \frac{x_{kj}^{\alpha 2}}{r_{kj}^{\alpha 2} + x_{kj}^{\alpha 2}} \frac{\theta_k^{\alpha} - \theta_j^{\alpha}}{x_{kj}^{\alpha}} \quad (3-35)$$

3.4 Integrating Distribution network model with EV

To integrate the EVA model with the model of the unbalanced DN, the total number of EVs to be studied is distributed among the network so each bus in the system will contain a certain number of EVs. In the case of consuming power from the grid to charge EVs in bus k , this power is considered as a load. On the other hand, injecting power to the grid from the EVs batteries is considered a negative load.

$$power_{tdw}^k = \begin{cases} POP_{tdw}^k + APD_{tdw}^k & (a) \\ POP_{tdw}^k - APU_{tdw}^k, -APR_{tdw}^k & (b) \end{cases} \quad (3-36)$$

$$|LF_{kj}^{\alpha}| \leq LF_{kj}^{max}, \forall t \quad (3-37)$$

$$V_{min} \leq V_k^{\alpha} \leq V_{max}, \forall t \quad (3-38)$$

$$\theta_{min} \leq \theta_k^{\alpha} \leq \theta_{max}, \forall t \quad (3-39)$$

In this study, the EVs are assumed to consume /inject real power only, so from figure 3-2, there are two extreme scenarios regarding the power injected or consumed by the EVs. The first one when the EV is required to provide the full down regulation capacity (APD_{tdw}) and zero up regulation/reserve (APU_{tdw}, APR_{tdw}). In this case, the EV will consume high power from the DN depending on POP as in (3-36). The second scenario when the investor is required to provide the full up regulation and reserve (APU_{tdw}, APR_{tdw}) and zero down regulation (APD_{tdw}). In this case, the EV will inject high power to the network as in (3-36). In both scenarios ((3-36) a and b), DN limitations should not be violated. The variable $power_{tdw}$ from equation (3-36) is added to the left side of equation (3-30) depends on the location of the EV. When $power_{tdw}$ is positive, it is considered as a load. On the other hand, when $power_{tdw}$ is negative, it is considered a negative load. Relation (3-37) refers to the maximum transfer power between bus k and j . The inequality (3-38) and (3-39) are to limit the voltage magnitude and angle to the excepted allowed value by the system operator.

3.5 EVA planning results

In this section, the optimization model of EVA (3-1)-(3-25) integrated with the distribution model (3-30),(3-36)-(3-39) is solved to maximized the aggregator's profits. This planning problem has two sets of decision variables. The first set is the most important and that includes the number of EVs in the fleet to participate in AS (γ) and the energy tariff paid by the EV owners to the EVA (β). The second set is the operational and network decision variables POP , AP^D , AP^U , AP^R , LF and V .

3.5.1 Description of the case study

The objective of this case study is to examine the profitability of EVA investment in providing AS and to investigate the effects of including unbalanced distribution network (DN) in the final decisions.

The project is assumed to have 12 years lifetime with a discount rate of 5%. The 12 years period is the approximate lifetime in the USA for the average light-duty vehicle. While the current expectation of Li-ion battery life is slightly lower than that, it is expected to be achievable in the future with appropriate management system [59]. The cost of maintenance and installation is taken in the energy and power costs with 190 \$/kW and 200 \$/kWh for the power and energy capacities respectively [56]. The bi-directional inverter efficiency is assumed to be 90 % for both charging and discharging.

The case study is assumed to take place in Houston, Texas with about 70000 EVs (50% Nissan Leaf, 20% Mitsubishi i-MiEVs and 30% Tesla Model S). The EVs are assumed to follow one of the 100 trips profile available from EVs in Houston. The data regarding the prices of regulation up and down, the reserves and the energy, in addition to the ancillary services deployment signal is also taken from the Electric Reliability Council of Texas (ERCOT) market information [60]. The average prices for one day are shown in figure 3-3.

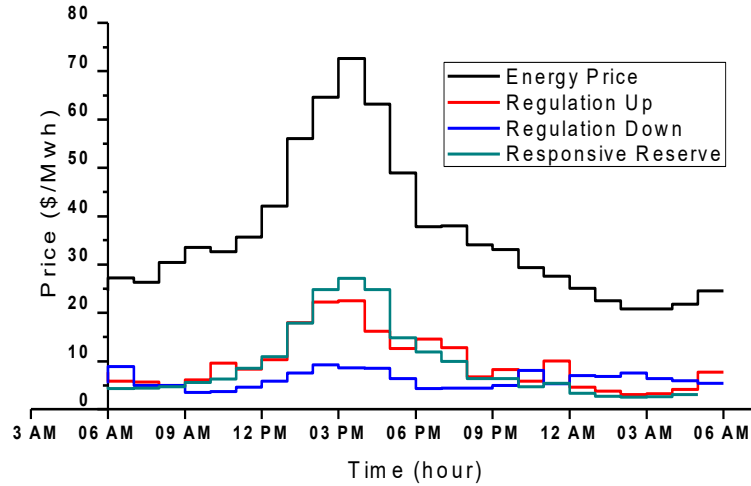


Figure 3-3 Average prices during the day

In order to test the proposed model, IEEE 13 bus unbalanced test system is used. For simplicity, all transformers and voltage regulators are ignored. In addition, EV is considered to inject/draw real power only, so reactive power can be ignored because of its small amount compares to the reactive power. Figure 3-4 shows the system used and the peak load for each phase (A, B, C) in each bus in kW. As seen from figure 3-4, not all the phases are available in some buses that because the system is unbalanced. References [61] and [62] provides full details about the system. Small modifications are made by generating random load profiles from two categories of loads (household and commercial) by introducing random error added to two profiles. Those random profiles are distributed among the different buses[49] in the system so that each phase in the bus will have a different load profile. Figure 3-5 shows one normalized load profiles for one day. All lines in the system have a line thermal capacity of 700 kVA except the main line that connects bus 632 with 671 which has a thermal limit of 1400 kVA. More details about the system are available in the appendix.

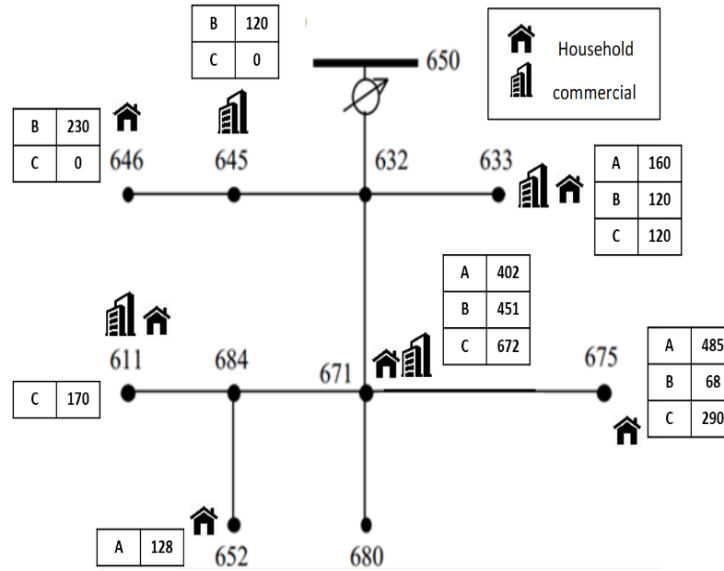


Figure 3-4 One-line diagram of the IEEE 13 unbalanced radial bus system with the peak load of each bus in kW.

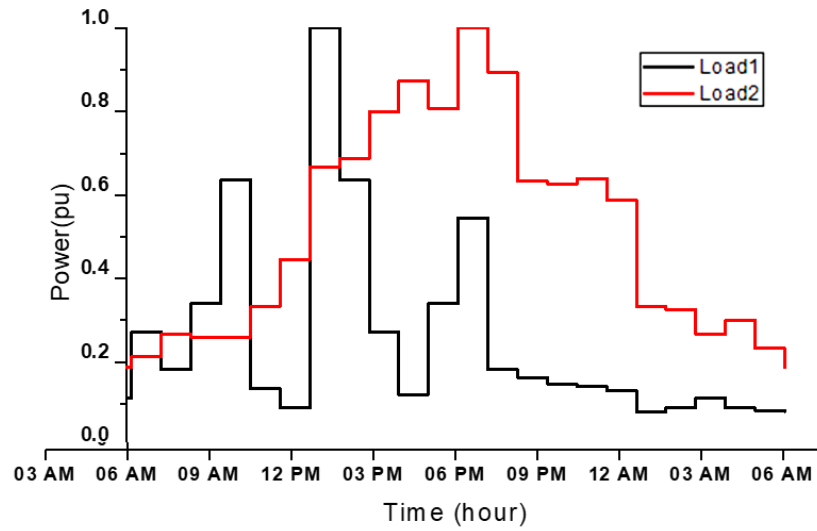


Figure 3-5 Normalized load profiles for one day.

Table 3-1 Parameters and constants.

Parameter	Value	Parameter	Value	Parameter	Value
r	5%	NT	70,000	Φ	0.99
NEV	100 EVs	T	24 h	$ComC$	88.4 \$/kW
NY	12 Years	BiC	186.7 \$/kW	ChC	186.7 \$/kW
NW	52 Weeks	η	0.9	SC	36.1 \$/kW
φ	0.1				

The main outputs of this planning optimization are Energy tariff charged by the customer (\$/kWh) (β) and the total profits during the studied period of 12 years. The percentage of EVs participation in AS depends on the β which will range from $\beta_{min} = 0$ to $\beta_{max} = 0.12$ \$/kWh. No EVs will participate if $\beta = 0.12$ and in between, linear relations will be assumed with different slopes as shown in figure 3-6.

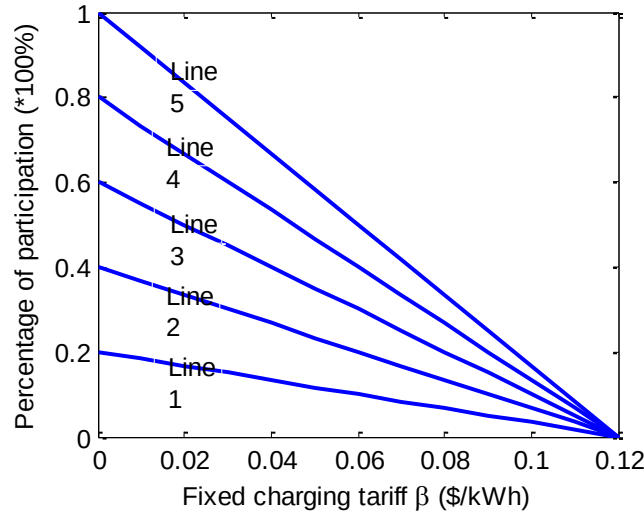


Figure 3-6 The Relation Between β And The EVs Participant $\gamma_o = 0.2, 0.4, 0.6, 0.8, \text{ and } 1.0$.

As seen from equation (3-4), β is multiplied by other decision variables (POP , AP^D , AP^U , AP^R) which makes the problem nonlinear. To solve this problem the iterative approach is used where β is increased by 0.01 in the range between 0 and 0.1 \$/kWh.

3.5.2 Results without DN

In this sub-section, the result of the EVA planning is obtained by solving equations (3-1)-(3-25) and ignoring the unbalanced distribution model. The optimization here is conducted for 366 days.

This section will provide results for two cases as follows:

- There are two trips (morning and evening). Each one lasts for one hour. The EVs are assumed to be available at the rest of the day connected to the charger except those two hours. This trip schedule is proposed by many of the literature review papers like [48],[47], and [9]. The investment cost here is computed assuming that each EV will have a charger at home. At each trip hour, the EV will go and return home.
- The EV here will not be available at the period between the two trips, where the investment cost here is the same as the previous case. This case is more realistic in which that the EV will go to work at morning and will return at evening and because the investment cost is only calculated to install the charger at home, so the EV will not be available in between.

For the first case, figure 3-7 shows the optimal profits for line 3 (participation of 60 % ($\gamma = 0.6$)) when β is increased by 0.01 in the range between 0 and 0.1 \$/kWh. It is clear that the higher payoffs occur when β is 0 which corresponding to 60 % participation of the total 70000 EVs. We can conclude that the profits coming from AS participation are higher than the profits coming from charging the EVs which forces the EVA to attract the maximum number of EVs by setting β equals to 0. This is expected because the EV trips consumption is small in this case, so no much profits will come from charging EVs as a result, utilizing the EV's battery that is available for 22 hours in AS will yield more profits. Table 3-2 shows the optimal profits for the five lines ($\gamma = 0.2, 0.4, 0.6, 0.8, 1$) all of them happened when β equal to 0. All the results for the other four lines follow the same pattern as figure 3-7.

Table 3-2 EVA optimal decision for the first case.

Line	Investment cost (Millions\$)	Fixed charging tariff β (\$/kWh)	Percentage of participation (γ)	EV Aggregator Payoff (Millions\$)
1($\gamma = 0.2$)	23.46	0	20 %	109.3
2($\gamma = 0.4$)	46.92	0	40 %	218.6
3($\gamma = 0.6$)	70.38	0	60 %	327.9
4($\gamma = 0.8$)	93.84	0	80 %	437.2
5($\gamma = 1$)	117.3	0	100 %	546.9

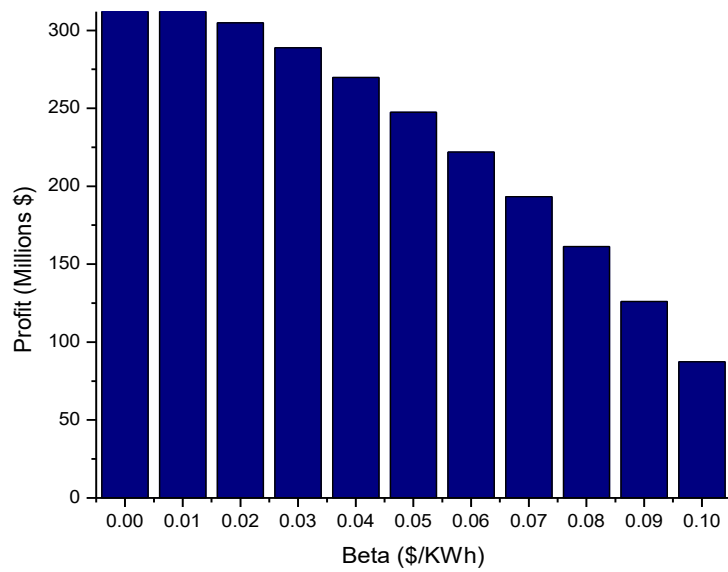


Figure 3-7 EVA Profits versus B for line 3 with a participation of 60 % ($\gamma = 0.6$) case one.

For the second case when EVs here are not available at the period between the two trips, figure 3-8 shows the optimal EVA payoffs. As seen, the optimal profits happen when β equals 0.02 \$/kWh. EVs are not available between trips, so that reduced the profits from AS participation which forces the EVA to increase β in order to get profits from charging

the EVs. Table 3-3 shows the optimal profits for the other lines which also happened at β equals 0.02 \$/kWh.

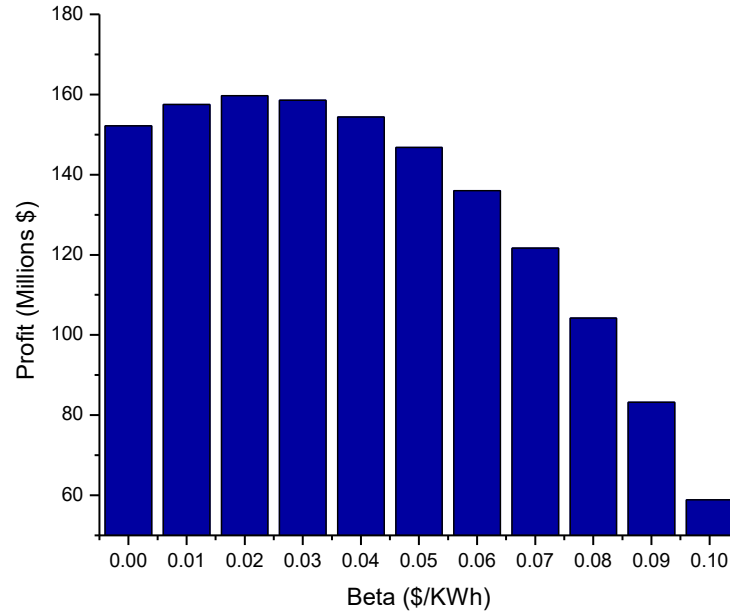


Figure 3-8 EVA profits versus β for participation of 60 % ($\gamma = 0.6$) case two.

Table 3-3 EVA optimal decision for the second case.

Line	Investment cost (Millions\$)	Fixed charging tariff β (\$/kWh)	Percentage of participation (γ)	EV Aggregator Payoff (Millions\$)
1($\gamma = 0.2$)	19.55	0.02	16.67 %	53.23
2($\gamma = 0.4$)	39.11	0.02	33.33 %	106.46
3($\gamma = 0.6$)	58.66	0.02	50.00 %	159.70
4($\gamma = 0.8$)	78.21	0.02	66.67 %	212.92
5($\gamma = 1$)	97.76	0.02	83.33 %	266.15

Figure 3-9 Compares the first and second case. In addition to the shift of the optimal β to 0.02 \$/kWh, it is clear that the total profits are reduced by about 50 % when the EVs are not available between the trips.

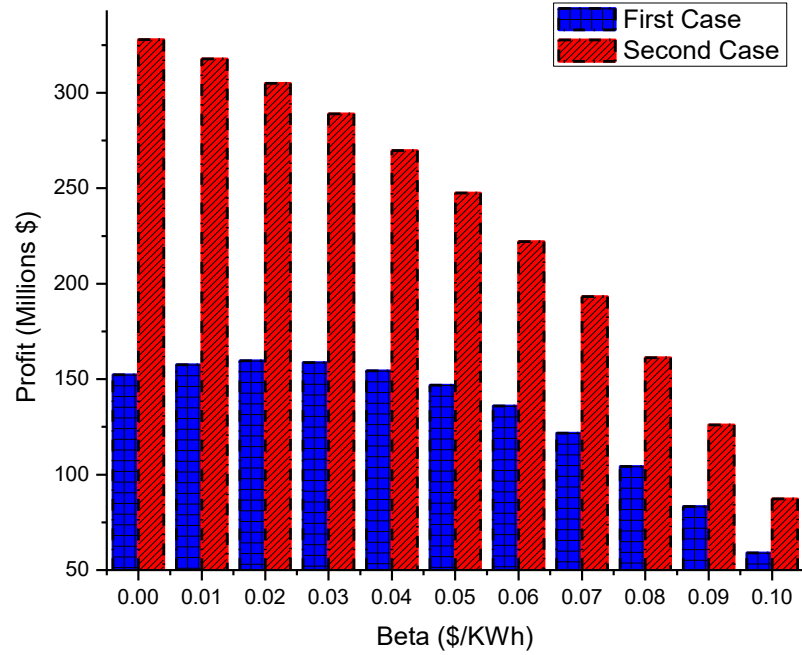


Figure 3-9 EVA profits versus β for line 3 with a participation of 60 % ($\gamma = 0.6$) (case one and two).

3.5.3 Results with DN

In this section, the results of the EV model integrated with unbalanced distribution network (IEEE 13 buses) are presented. As mentioned before in the case study description, the number of EVs available is 70000. Due to the small size of the network, we can't include this high number. In order to solve this problem and also make the comparison between the EVA and BESS fair, the optimal investment cost obtained from BESS planning in table 4-3 (5.47 million) is used as an investment cost for EVA. This investment cost could be used to estimate the total number of EVs in the network using equation (3-2) which calculated to be 3500 EVs.

This number is assumed to be distributed equally among the different buses in the system as seen from figure 3-10 and we considered only the second case where EVs are

not available in the period between the two trips because as described before this is more realistic.

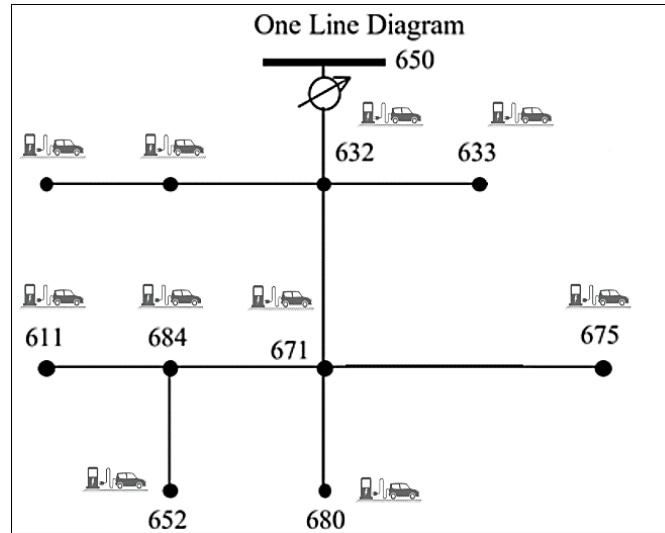


Figure 3-10 EVs distribution in the DN.

Figure 3-11 shows the optimal profits along with the investment cost for line 3 (participation of 60 % ($\gamma = 0.6$)). As seen, the optimal profits of 6.1 million occurred when β is 0.05 \$/kWh and required an investment cost of 2.1 million. That is corresponding to 1225 EVs participants. The aggregator here tried to attract a smaller number of EVs due to the network voltage and line constraints in order to bid higher capacities to AS market without exceeding those limits.

As seen in table 3-4, the optimal decision depends mainly on the relation between β and the number of EVs participated. When the slope of the relationship increases the optimal β also increases. Form that we can conclude that the availability of more EVs in the system restricts the EVA from bidding capacities to AS market due to the thermal and voltage limits which causes the increase in the energy tariff β so the AVA will try to get

more profits from charging EVs than participating in AS market by attracting less EVs by increasing β to attract less EVs.

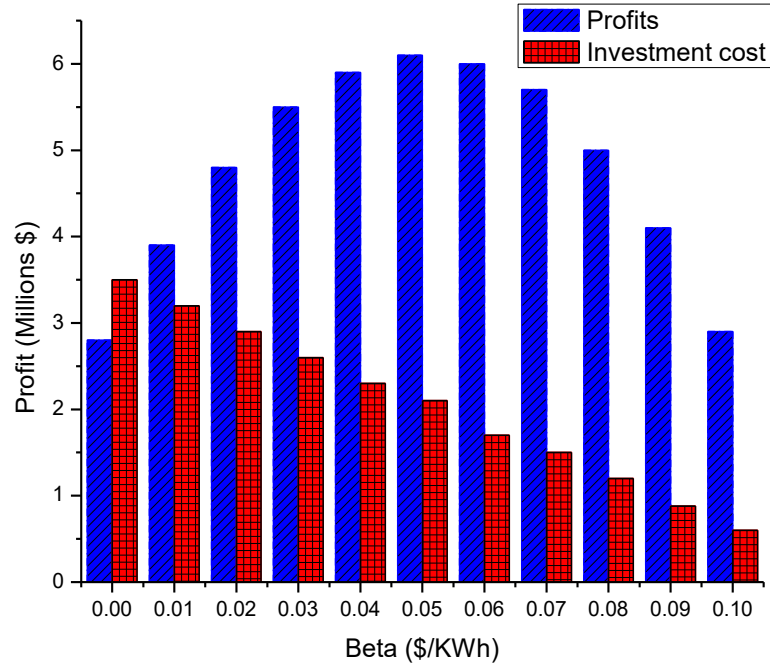


Figure 3-11 EVA profits along with investment cost versus β for line 3 with the participation of 60 % ($\gamma = 0.6$) in DN.

Table 3-4 EVA optimal decision for including DN.

Line	Investment cost (Millions\$)	Fixed charging tariff β (\$/kWh)	Number of EVs participated	EV Aggregator Payoff (Millions\$)
1($\gamma = 0.2$)	0.978	0.02	583	2.60
2($\gamma = 0.4$)	1.560	0.04	933	4.65
3($\gamma = 0.6$)	2.1	0.05	1225	6.10
4($\gamma = 0.8$)	2.35	0.06	1400	7.25
5($\gamma = 1$)	2.93	0.06	1750	8.17

Trying to increase the EVs in the system from 3500 to 4000 can cause higher profits for line 1, 2, 3, 4 and 5 ($\gamma_0 = 0.2, 0.4, 0.6, 0.8$, and 1.0) as seen from table 3-5, however in the case of line 5 (Figure 3-6), the problem is infeasible when $\beta=0$, as seen from figure 3-12, which corresponding to 100 % participation of 4000 EVs. This high number of EVs can't be handled by the distribution network and some of the constraints can't be met. The optimal profits of 8.78 million occurred when β equals to 0.07 rather than 0.06 in the case of 3500 EVs and that corresponding to 2.8 million investment cost.

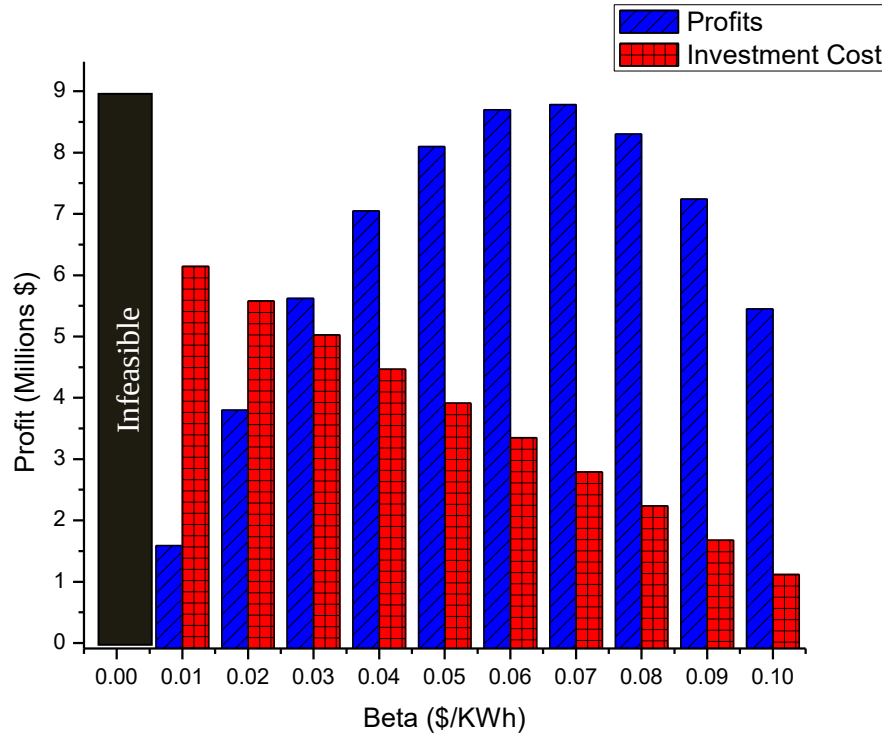


Figure 3-12 EVA profits along with investment cost versus β for line 5 with the participation of 100 % ($\gamma = 1$) in DN(4000 EVs).

Table 3-5 EVA optimal decision for including DN (4000 EVs).

Line	Investment cost (Millions\$)	Fixed charging tariff β (\$/kWh)	Number of EVs participated	EV Aggregator Payoff (Millions\$)
1($\gamma = 0.2$)	1.00	0.03	600	2.95
2($\gamma = 0.4$)	1.56	0.05	933	5.10
3($\gamma = 0.6$)	2.34	0.05	1400	6.59
4($\gamma = 0.8$)	2.68	0.06	1600	7.82
5($\gamma = 1$)	2.80	0.07	1666	8.78

In the previous cases, the EVs are assumed to be distributed equally in the network as shown in figure 3-10. The distribution of the 3500 EVs will be changed so that EVs are in 633, 646 and 671 as shown in figure 3-13. Those buses are chosen because in the BESS optimization most of the capacities are located there.

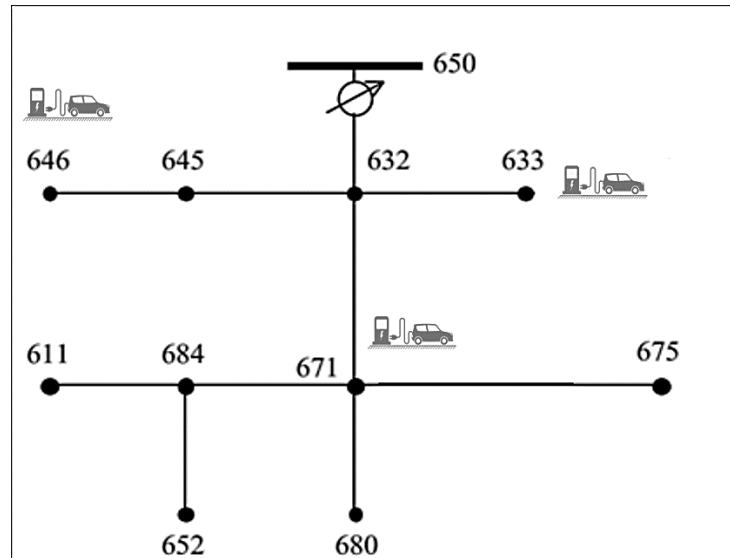


Figure 3-13 EVs distribution in the DN.

Table 3-6 summaries the results of all lines. The optimal aggregator payoff for all lines is slightly less than the previous case where EVs are distributed across the buses equally and that due to the additional loads of EVs placed on one bus could highly cause

overloading those bus and exceeding the thermal limits of the line. What is interesting here is that the optimal β is the same for all lines.

Table 3-6 EVA optimal decision for including DN when EVs in 633, 646 and 671.

Line	Investment cost (Millions\$)	Fixed charging tariff β (\$/kWh)	Number of EVs participated	EV Aggregator Payoff (Millions\$)
1($\gamma = 0.2$)	0.98	0.02	583	2.20
2($\gamma = 0.4$)	1.56	0.04	933	4.58
3($\gamma = 0.6$)	2.10	0.05	1225	5.90
4($\gamma = 0.8$)	2.35	0.06	1400	7.03
5($\gamma = 1$)	2.93	0.06	1750	8.07

CHAPTER 4

BESS PLANNING MODEL FOR ANCILLARY

SERVICES BIDDING

This chapter will discuss the deterministic optimization of BESS as a linear model to participate in AS market by bidding regulation up/down and reserve capacities. The BESS model has derived from EV aggregator also as a linear model where the objective is to maximize the total profits in the specific studied period. BESS here is considered to be owned by an investor who will deal with the electricity market or grid. A linear model of BESS will be integrated with a linear model of the unbalanced distribution network to see the effects of introducing network constraints in the optimal results.

4.1 BESS Planning Model

The investor, as a market participant, is assumed to be constrained by a pre-defined investment cost. This investment cost must be distributed between the energy capacity (MC) and the power capacity (MP) of the BESS system. All other costs are assumed to be negligible. The market participant will buy/sell energy from/to the day-ahead energy market to charge/discharge the BESS at a price of (σ_{tdw}^E). The BESS also participates in the day-ahead ancillary services (AS) markets by bidding a regulation up capacity (AP_{tdw}^U), regulation down capacity (AP_{tdw}^D) and reserve capacity (AP_{tdw}^R). Cost will come from a reduction in BESS life which translated into degradation cost.

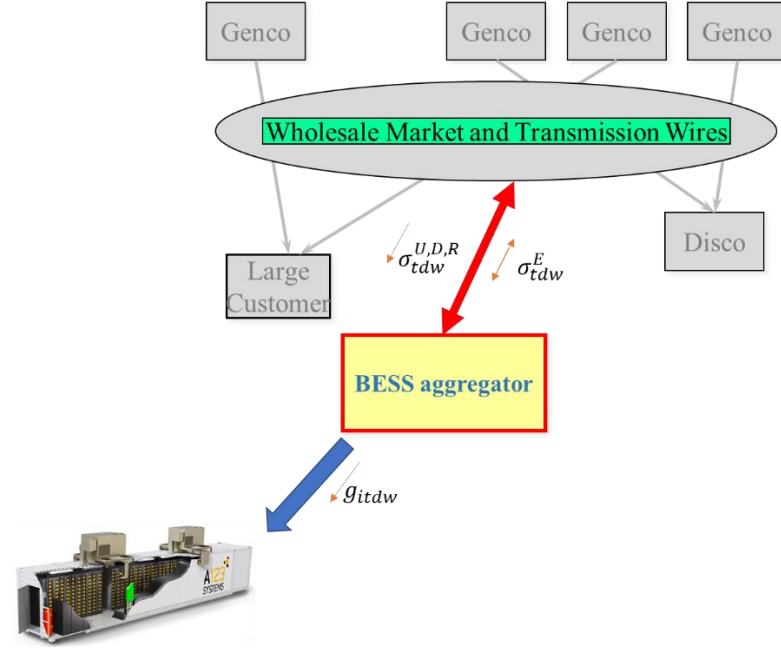


Figure 4-1 BESS aggregator planning model in a pool-based electricity market for energy and AS

Unlike EV aggregator, here BESS is totally owned by the aggregator and stationary all the time. In addition, BESS planning gives the advantage of placing the capacity in the system, unlike EV where the owners are already determined. As a result, the planning investment cost is a decision variable in BESS planning and predetermined in EV aggregator planning. In the mechanism of bidding to SA or energy market, the same rules of EV aggregator are applicable here in that the aggregator will submit capacities in day-ahead bases. In real-time, the BESS may receive a deployment signal from the ISO that specifies the percentage of the AS bid capacities needed at that time. Consequently, the BESS must move its charging/discharging rate above or below its POP to provide the called upon ancillary service.

4.2 Problem formulation

In this section, the deterministic optimization of the BESS as an ancillary serviced provider is formulated to maximize the total profit. This formulation is derived from the previous chapter with some modifications. For example:

- The BESS is stationary and available all the time. That means the availability parameter (v_{it}) equals to one at all hours. In addition, there is no trip consumption ($E_{it} = 0$) and the probability of departure will be equaled to zero ($\pi_{it}^A = 0$).
- No need to make the BESS almost fully charged at the end of the day which means that constraint (3-18) is relaxed more than EV aggregator.
- As mentioned before that the investment cost in BESS aggregator is not constant compared to the EV case. As a result, the maximum limit will be introduced as the maximum allowed investment cost and the actual investment will be the decision variable.

From that, we can formulate the problem as:

Maximize

$$TP = \sum_{y=1}^{NY} (1+r)^{-y} \cdot YP - InvC \quad (4-1)$$

Subject to:

$$InvC = ChC * MP + BatC * MC \quad (4-2)$$

$$InvC \leq InvC_{max} \quad (4-3)$$

$$YP = \sum_{w=1}^{NW} \sum_{d=1}^7 (In_{dw} - C_{dw}) \quad (4-4)$$

$$In_{dw} = \sum_t (\sigma_{tdw}^D AP_{tdw}^D + \sigma_{tdw}^U AP_{tdw}^U + \sigma_{tdw}^R AP_{tdw}^R) \quad (4-5)$$

$$C_{dw} = \sum_t \sigma_{tdw}^E E[FP_{tdw}] + \sum_t Deg_{tdw} \quad (4-6)$$

$$E[FP_{tdw}] = (POP_{tdw} + \alpha_{tdw}^D AP_{tdw}^D - \alpha_{tdw}^U AP_{tdw}^U - \alpha_{tdw}^R AP_{tdw}^R) \quad (4-7)$$

$$SOC_t = SOC_{t-1} + E[FP_{tdw}]\eta \quad (4-8)$$

$$DC = 0.042(BatC/312) \quad (4-9)$$

$$g_{tdw} = \max(-DC \cdot E[FP_{tdw}^-]/\eta, 0) \quad (4-10)$$

$$E[FP_{tdw}^-] = (POP_{tdw} - \alpha_{tdw}^U AP_{tdw}^U - \alpha_{tdw}^R AP_{tdw}^R) \quad (4-11)$$

$$\varphi_i MC \leq SOC_t \leq MC, \forall t \leq T - 1 \quad (4-12)$$

$$\Phi_i MC \leq SOC_T \leq MC \quad (4-13)$$

$$(POP_{tdw} + AP_{tdw}^D) \leq MP \quad (4-14)$$

$$POP_{tdw} - AP_{tdw}^R - AP_{tdw}^U \geq -MP \quad (4-15)$$

$$POP_{tdw} \geq -MP \quad (4-16)$$

$$AP_{tdw}^D, AP_{tdw}^U, AP_{tdw}^R \geq 0 \quad (4-17)$$

$$(POP_{tdw} + AP_{tdw}^D)\eta \leq MC - SOC_t \quad (4-18)$$

$$|SOC_{tdw} - SOC_{t-1,d,w}| \leq MP/\eta \quad (4-19)$$

This formulation is derived from EVA and has the same description so here the formulation is described briefly. As stated before the objective is to maximize the overall investor profits. As seen in (4-1), this objective function has two parts, the first one is the total profits during certain year reflected to present value and the second one is the investment cost which assumed to occurs at the beginning of the project. The two relations, (4-2) and (4-3), are added differently than EVA. In equation (4-2), the investment cost, which includes the cost of acquiring power capacity (MP) (i.e. mainly bidirectional inverter's cost) and the cost for acquiring energy capacity (MC) (battery bank cost). In constraint (4-3), the maximum limit is defined for the investment cost based on the available budget ($InvC_{max}$).

In (4-4), the annual profit is defined as subtraction of daily operation cost C_{dw} from the daily incomes In_{dw} in a full year. The daily incomes come from bidding regulation up/down and reserve capacities to the AS market, in addition to sell energy to the energy market (which is supposed to be negative cost if a discharging action is scheduled) ,in the other hand the costs are due to charging the BESS and the degradation cost (DC) due to the discharging action as stated by (4-5) and (4-6).

Equation (4-7) and (4-8) are to calculate the total expected power and the state of charge respectively. Where the state of charge SOC_t depends on the previous and current state of the BESS. The life of BESS is reduced when there is a discharge action. This reduction is considered here as a cost per kWh as in equation (4-10). Where g_{tdw} is a positive value when $E[FP_{tdw}^-]$ is negative (discharge action) and zero when $E[FP_{tdw}^-]$ is

positive. Relation (4-11) states that the degraded drawn energy is related to regulation up and reserve which is a more conservative formulation of the drawn power [29]. Equation (4-9) is used to normalized the cost in [57] for a battery cost of 312 \$/kWh with the cost used in this paper.

To avoid discharging the BESS deeply or out of the capacity inequality (4-12) is included. Constraint (4-13) is introduced to force SOC to be at least half of the BESS capacity at the end of the operation day. To link the power capacity MP to the decision variables and limit this capacity to the rated power of the inverter, constraint (4-14)-(4-16) are added. All AS bided capacities are positive values as shown in relation (4-17). Constraint (4-18) is to ensure that providing more regulation down will not overly commit the BESS than its maximum capacity MC . Relation (4-19) is used to make sure that the power transfer to the BESS between any two hours is within the power capacity of the inverter MP , where η is the efficiency of the bi-directional inverter.

4.3 Integrating Distribution network model with BESS

To integrated the BESS with the model of the unbalanced DN, the investment cost in equation (4-2) is modified to (4-20) which spends on the power capacity (bi-directional inverter MP^k) and the energy capacity (battery storage MC^k) that installed in bus i and the total investment cost is the summation of all the capacities at the different buses.

$$InvC = \sum_{k=1}^{Nbus} (ChC * MP^k + BatC * MC^k) \quad (4-20)$$

So now the BESS is not just installed on one bus as previous. That implies having all decision variable for each BESS that installed in bus k such as

APU_{tdw}^k , SOC_{tdw}^k and POP_{tdw}^k . The total profit is the summation of the profit of each BESS in bus k .

In the case of consuming power from the grid, this power is considered as a load. On the other hand, injecting power to the grid is considered a negative load. In this study, the BESS are assumed to consume /inject real power only, so from figure 3-2, there are two extreme scenarios regarding the power injected or consumed by the BESS. The first one when the BESS's investor is required to provide the full down regulation capacity (APD_{tdw}) and zero up regulation/reserve (APU_{tdw}, APR_{tdw}). In this case, the BESS will consume high power from the DN depending on POP as in (3-36). The second scenario when the investor is required to provide the full up regulation and reserve (APU_{tdw}^k, APR_{tdw}^k) and zero down regulation (APD_{tdw}^k) as in. In this case, the BESS will inject high power to the network as in (3-36). In both scenarios ((3-36) a and b), DN limitations should not be violated.

$$power_{tdw}^k = \begin{cases} POP_{tdw}^k + APD_{tdw}^k & (a) \\ POP_{tdw}^k - APU_{tdw}^k, -APR_{tdw}^k & (b) \end{cases} \quad (4-21)$$

$$|LF_{kj}^\alpha| \leq LF_{kj}^{max}, \forall t \quad (4-22)$$

$$V_{min} \leq V_k^\alpha \leq V_{max}, \forall t \quad (4-23)$$

$$\theta_{min} \leq \theta_k^\alpha \leq \theta_{max}, \forall t \quad (4-24)$$

Relation (3-37) refers to the maximum transmission power between bus k and j . The inequality (3-38) and (3-39) are to limit the voltage magnitude and angle to the excepted allowed value by the system operator.

$$\sum_{k=1}^{Nbus} X^k \leq NA, \forall t \quad (4-25)$$

$$MC^k \leq X^k * M \quad (4-26)$$

$$MP^k \leq X^k * M \quad (4-27)$$

$$MC^k \geq X^k * L \quad (4-28)$$

Equation (4-25) is to restrict the available locations to install BESS to a maximum of NA buses, where X^k is a binary number that takes either 0 or 1. Relations (4-26) and (4-27) are included to force the buses without BESS ($X^k = 0$), to set the power and energy capacities (MP^k, MC^k) to zero. In the case of $X^k = 1$, MP^k and MC^k are less than a large number (M) and the exact value will be based on the investment cost in constraints (4-2) and (4-3). Constraint (4-28) is to define the minimum BESS capacity limit (L) at the installed bus.

This optimization problem has two sets of decision variables. The first set is the long-term planning decision variables $InvC, MC, MP$, and X . Those variables are the most important result to the investor and will determine the best size, location, and investment cost. The second set is the intermediate variables, which include the operational and the network decision variables ($POP_{tdw}, AP_{tdw}^D, AP_{tdw}^U, AP_{tdw}^R, LF$ and V).

4.4 BESS planning results

In this section, the optimization model of BESS (4-1)-(4-19) integrated with the distribution model (3-30),(4-20) -(4-28) is solved to maximized profits.

4.4.1 Description of the case study

The main purpose of this case study is to investigate the profitability of BESS in providing AS and examine how can the unbalanced distribution network (DN) affects the final decision of the best BESS's sizes and locations in the system. A comparison between the case of planning where BESS is connected to a single bus with the case of including DN constraints is conducted to see the effectiveness of that in the total profits.

The project is assumed to have 12 years lifetime with a discount rate of 5%. The 12 years period is the approximate lifetime in the USA for the average light-duty vehicle. while the current expectation of Li-ion battery life is slightly lower than that, it is expected to be achievable in the future with appropriate management system [59]. The cost of maintenance and installation is taken in the energy and power costs with 190 \$/kW and 200 \$/kWh for the power and energy capacities respectively [56]. The bi-directional inverter efficiency is assumed to be 90 % for both charging and discharging.

All data, including regulation, energy prices and deployment signals with a one-hour resolution, is obtained from the Electric Reliability Council of Texas (ERCOT) market information for the year of 2016 [60]. Running the proposed optimization model for one-year data would require excessive computation time. To reduce the computational time of the code, weighed representative days are used and that for the case of DN optimization. However, in the case of not including DN, the optimization will be performed using 366-day data. Those days are chosen so that the summation of the distances between the chosen days and whole year days is the minimum [63] [56]. The results from those representatives' days are multiplied by constant to represent the whole year. Where this

constant is the total days in a year (366) divided by the number of the representative days. The average prices for one day are shown in figure 4-2.

In order to show how accurate could be the clustered data, we represented a full year with ten days. The optimization problem is conducted for the model without network constraints for the one year (366 days) and for the ten days scaled by 36.6 and results are presented in table 4-1.

Table 4-1 Optimal investment decision for one year and 10 days scaled

	Investment cost (Millions\$)	Power Capacity (MW)	Energy Capacity (MWh)	Expected Profits (Millions\$)
One year	15	35.42	33.67	20
10 days	15	35.47	33.62	19.8

As shown from table 4-1, both cases are close to each other and the ten days data 1 % less than using the full year days, which validates the clustering approach.

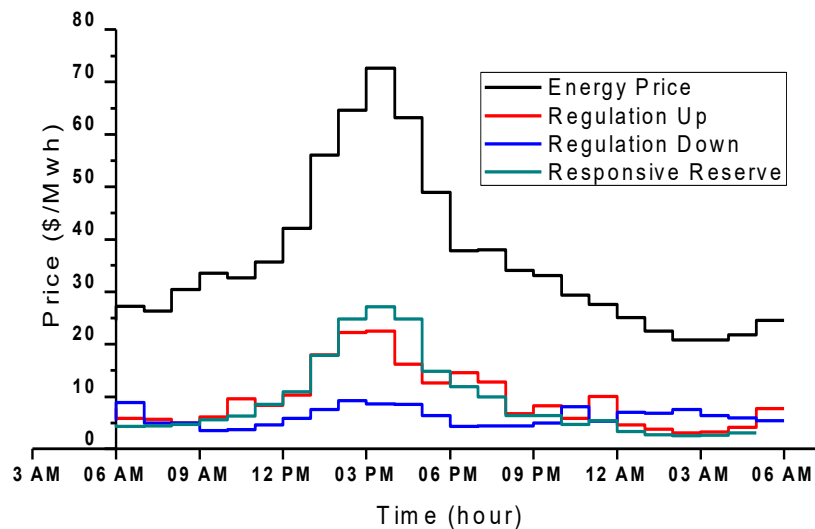


Figure 4-2 Average prices during the day

To test the proposed model, the IEEE 13-bus distribution test feeder is used [61]. This distribution feeder represents an unbalanced distribution system. For simplicity, all transformers and voltage regulators are ignored. In addition, BESS is considered to inject/draw real power only, so we can ignore the reactive power because of its small amount compare with the reactive power. In addition, distributed generation (DG) namely solar is integrated with the model in bus 633, 680 and 684 with capacities of 600,400 and 300 kW respectively. Figure 4-3 shows a one-line diagram of the system used and the peak load for each bus (in kW). References [61] and [62] provides full details about the system. the total location available in this network (NA) are 20 locations and that calculated based on the number of phases available at each bus in the system(see the appendix for more information). Small modifications are made by generating random load profiles for two categories of load (household and commercial). Those profiles are distributed among the different buses[49]. Figure 4-4 shows two normalized load profiles for one day. All the other parameters are summarized in table 4-2. All lines in the system have line thermal capacity of 700 kVA except the main line that connects bus 632 with 671 which has a thermal limit of 1400 kVA. More details about the system are available in the appendix.

Table 4-2 Optimization parameters

parameter	value	parameter	value
NY	12	r	5 %
η	0.9	V_{min}	0.95
$BatC$	200	V_{max}	1.05
ChC	190	NA	20
$InvC_{max}$	30 M\$	M	1000 MWh
L	100 kWh	Φ	0.5
		φ	0.1

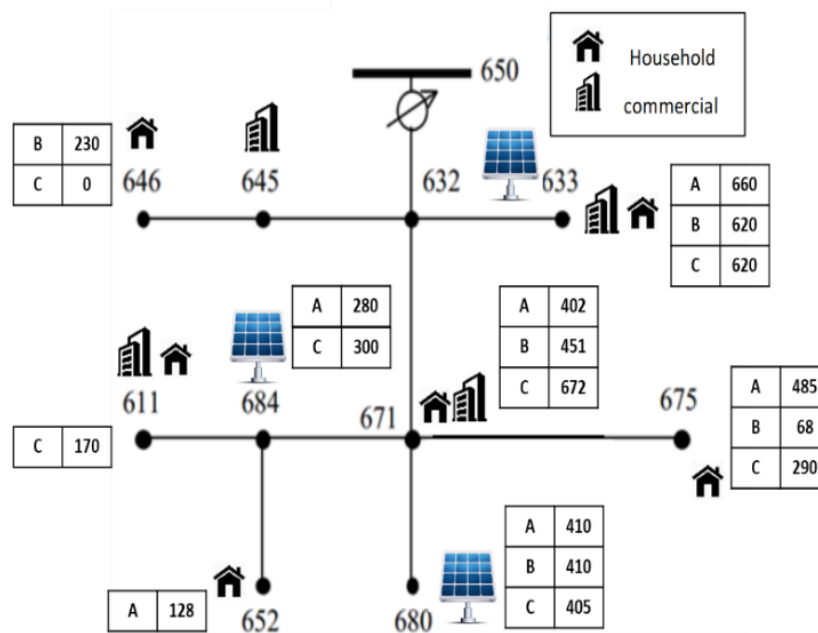


Figure 4-3 One-line diagram of the IEEE 13 unbalanced radial bus system with the peak load in each bus in kW.

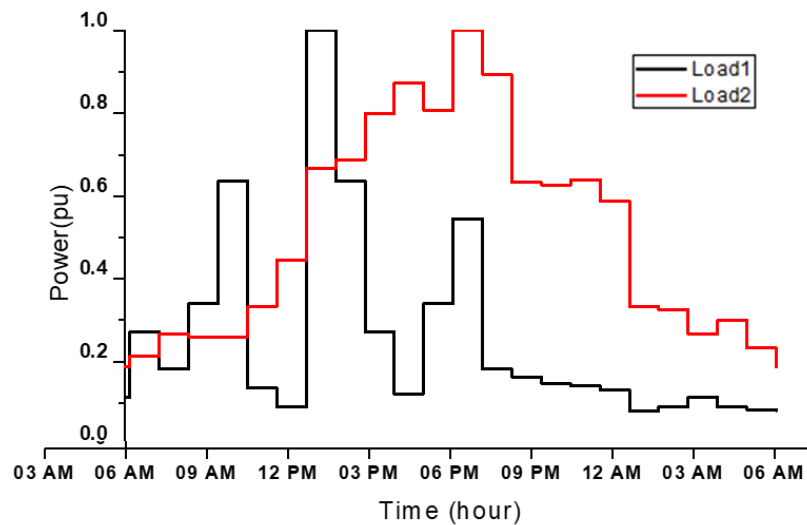


Figure 4-4 Normalized load profiles for one day

4.4.2 BESS siting and sizing including DN

The outputs of the optimization when no restrictions put on NA (all buses are available) are obtained in this sub-section. Figure 4-5 shows the optimal locations and sizes

of MP and MC where A, B, and C are the different phases in a certain bus. As seen, most of the BESS capacities are located in buses 633 and 671. That is expected because those buses are connected to the main feeder and that will allow BESS's owner to bid higher capacities to the AS market and charge/discharge BESS faster. In addition, the line connects 632 and 680 is the main line that has a higher thermal capacity than all other lines figure 4-5.

Even though NA was 20, 11 locations were chosen. Based on the inequality constraints (4-25), the summation of X_b (number of location) could be less than NA and 11 locations are enough in this network to obtain the optimal profits and maintaining the system constraints within the limits.

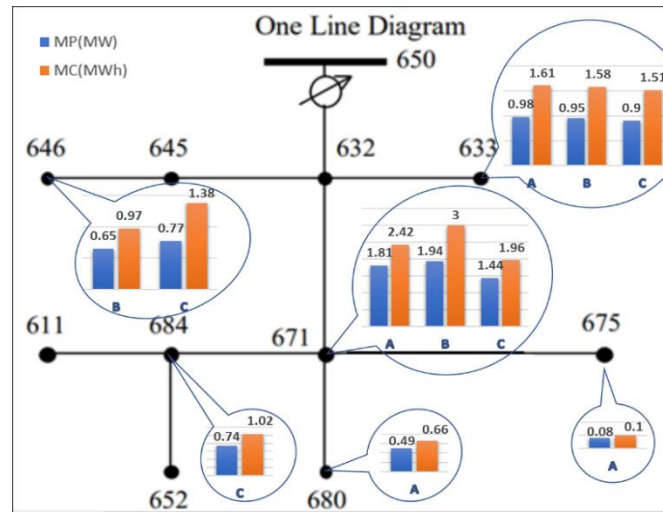


Figure 4-5. BESS siting and sizing when NA=20

To show the binding constraints and how frequently those constraints happened, figure 4-6 is plotted. As seen, the lines 632-671 and 632-633 are most frequently reached the limit. The voltage at bus 646 most of the time reached the limit which restricts the bus from placing more BESS.

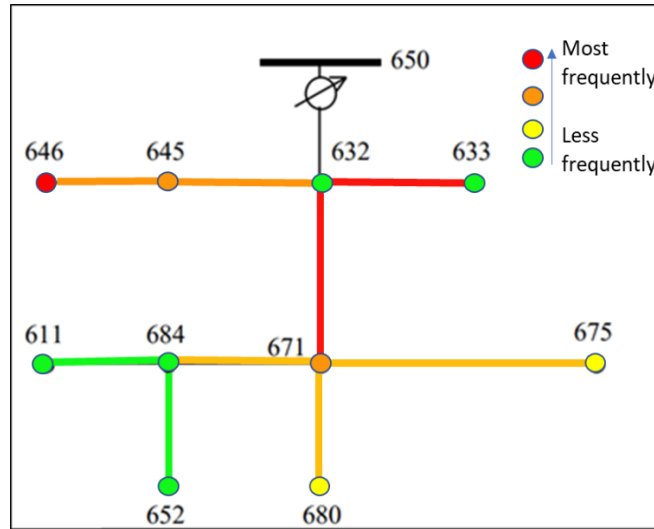


Figure 4-6 A graph shows how frequently the voltage limit (colored dots) and line limits (colored lines) are reached.

Using the optimal investment cost obtained from including DN to perform the optimization without DN is shown in table 4-3. Due to the limitation of voltage and line flow which forces the optimizer to bid less capacities in congested hours, including DN expected 21.56 % reduction in the profits. Including DN invested more in energy capacities (MC) than in power capacities (MP) due to the line and voltage constraints.

Table 4-3 Comparison between including DN And not

	Investment cost (Millions\$)	Power Capacity (MW)	Energy Capacity (MWh)	Expected Profits (Millions\$)
DN	5.47	11.12	16.77	6.51
No DN	5.47	14.4	13.7	8.3

4.4.3 Change the number of allowed buses (NA)

In this section, the effects of changing the allowed number of buses (NA) are studied. Table 4-4 shows the optimal investment cost, profits, power capacity, energy capacity, and the best locations when NA is 11, 8, 5, 3, and 1. It is obvious that restricting

the allowable locations by reducing the number of buses used to locate the BESS reduces the optimal investment cost and consequently the expected profits decreases as well.

There is an observable trend when NA is greater or equal to 3. This trend is locating BESS capacities always on the three phases of bus 671. As seen in figure 4-3, this bus is located in the center of the system and has four paths to charge/discharge energy through. In addition, the lines connected 632 and 671 have a higher thermal limit which allows BESS to charge/discharge and bid higher capacities. Sometimes as in bus 633, the power capacity is higher than the line limit and that due to the ability of the BESS to supply the load connected to the same bus.

Table 4-4 Optimal decisions when NA 11,8,5,3 and 1

NA		11			8			5			3			1		
Investment cost (Millions\$)		5.47			5.10			4.06			3.25			0.55		
Expected Profits (Millions\$)		6.51			6.12			4.87			3.88			0.69		
Phase	Bus	A	B	C	A	B	C	A	B	C	A	B	C	A	B	C
Power Capacity (MW)	633	0.98	0.95	0.89	0.98	0.95	0.90	0.85	-	0.69	-	-	-	-	-	-
	671	1.8	1.9	1.4	2.38	2.12	1.65	2.4	2.1	2.4	2.38	2.12	2.39	1.5	-	-
	646	-	0.65	0.77	-	-	0.66	-	-	-	-	-	-	-	-	-
	675	0.08	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	680	0.49	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	684	-	-	0.74	-	-	0.74	-	-	-	-	-	-	-	-	-
Energy Capacity (MWh)	633	1.61	1.58	1.51	1.61	1.59	1.51	1.39	-	1.17	-	-	-	-	-	-
	671	2.42	3	1.96	3.19	3.3	2.22	3.18	3.29	3.25	3.19	3.29	3.25	1.3	-	-
	646	-	0.97	1.38	-	-	1.17	-	-	-	-	-	-	-	-	-
	675	0.13	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	680	0.66	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	684	-	-	1.02	-	-	1.03	-	-	-	-	-	-	-	-	-

4.4.4 Validation of the linear DN model

The linear unbalanced power flow is a newly introduced model. To verify this model, a comparison with the nonlinear unbalanced power flow (AC power flow) is conducted in this section for the case of NA=11. As seen from relation (3-36) there are two scenarios. The first one when BESS draw high power from the network (23-a) and the second one with high power injected into the network (23-b).

As seen in figure 4-7, The maximum error is about 0.34 % which happened in the C phase of bus 611, 671, 675, 680, and 684, while other buses show lower errors. In addition, figure 4-8 shows the voltages error at the high-power injection. The errors are slightly higher than in the first case with about 0.42 %. In the two cases, the linear model shows a good approximation of the nonlinear model.

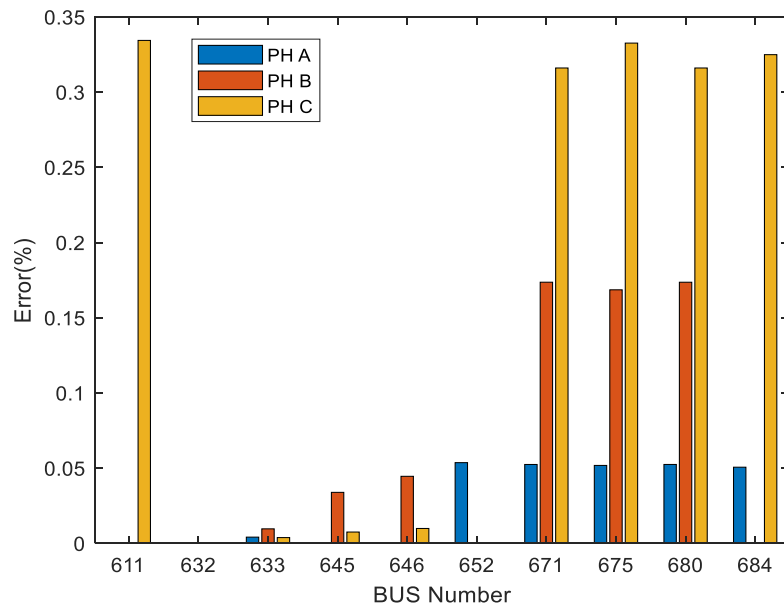


Figure 4-7 Voltages magnitude error between the linear and nonlinear model in percentage at the different buses (23-A).

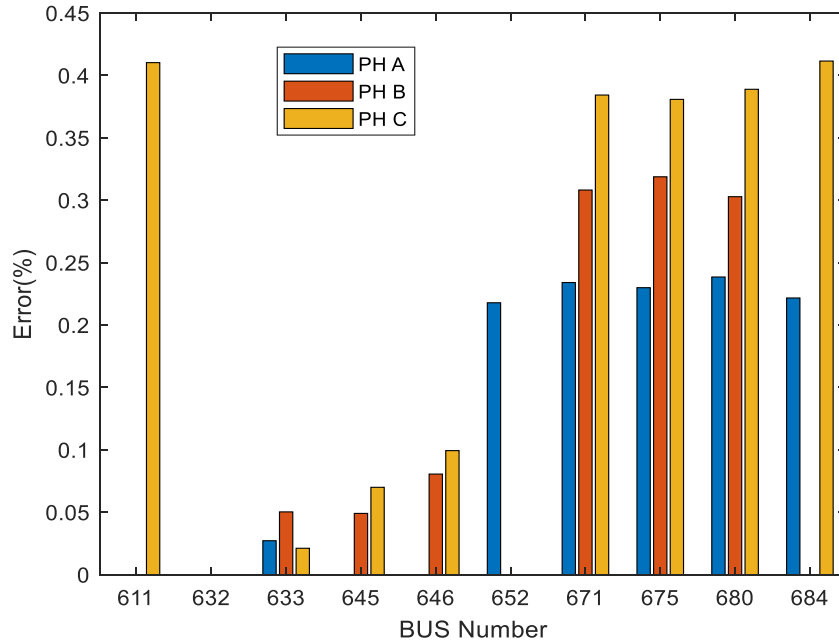


Figure 4-8 Voltages magnitude error between the linear and nonlinear model in percentage at the different buses (23-B).

As seen in figure 4-9 which shows histograms of the approximation error in the two cases, most of these errors, which defined as the percentage difference between the AC power flow and the proposed linear power flow during the studied period, are in the range from 0 to 0.1 %. That also proves the currency of the proposed linear power flow.

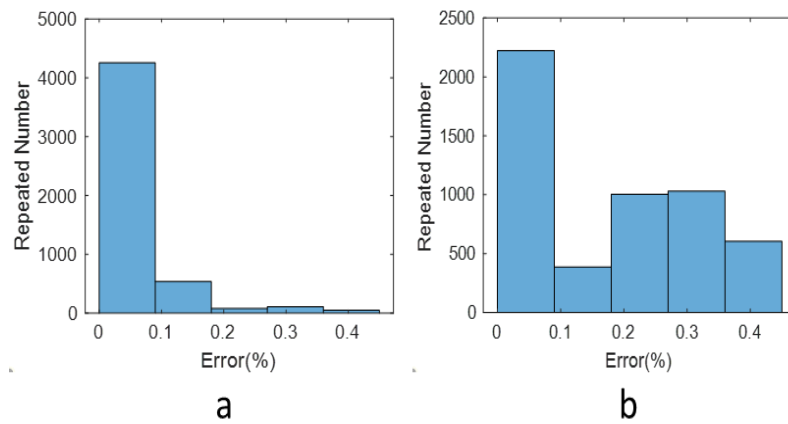


Figure 4-9 Histogram of the error for the two cases when (NA=12).

4.4.5 Sensitivity analyses

This section studies the effect of changing some of the key parameters on the results. All the cases in this section are for NA equals 20.

4.4.5.1 Effect of changing the energy capacity cost

In the previous cases, the energy capacity cost used is 200 \$/kWh and as we know that in the recent years, there has been considerable progress in technologies related to battery storage systems which could reduce the price of BESS capacity in the future. Based on Green Car Reports lithium-ion battery cost will fall to 100 \$/kWh by 2025 [64]. The prices in this sub-section are assumed to be 100 \$/kWh which is half the price used before.

Figure 4-10 shows the new sizing and siting results, which occur in the same buses when *BatC* was 200 \$/kWh. Due to the lower price, more energy capacities are placed on some buses. The power capacities for the inverter are almost the same because what restrict them are the network constraints. The investment cost is decreased by about 20% which cause an increase in profits by 42% as shown in table 4-5.

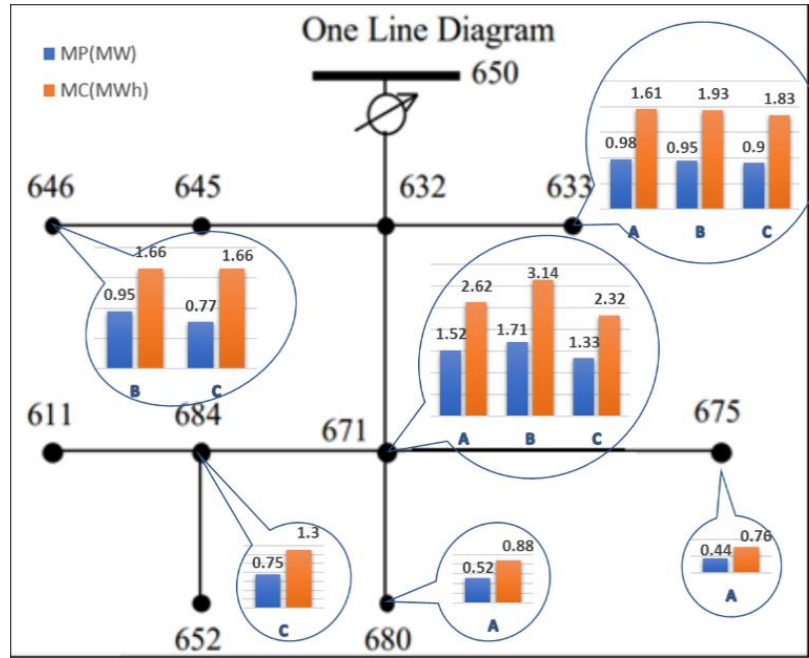


Figure 4-10 BESS siting and sizing when NA=20 for *BatC* equals to 100\$/kWh.

Table 4-5 Optimal decision for *BatC* equals to 200 and 100\$/kWh

	Investment cost (Millions\$)	Power Capacity (MW)	Energy Capacity (MWh)	Expected Profits (Millions\$)
200\$/kWh	5.47	11.12	16.77	6.51
100\$/kWh	4.41	10.82	19.73	9.24

4.4.5.2 Effect of changing the power capacity cost

In the base case, the cost of power capacity (inverter) was 190 \$/kW. In this subsection, the cost is reduced to 100 \$/kW. The results in figure 4-11 showed the same sitting and sizing as figure 4-5 for most of the buses which interestingly shows that this reduction will not affect the optimal decision. Hence, what limits the power capacity is the network constraints and how much can the BESS charges/discharges from/to the system, not the capacity cost.

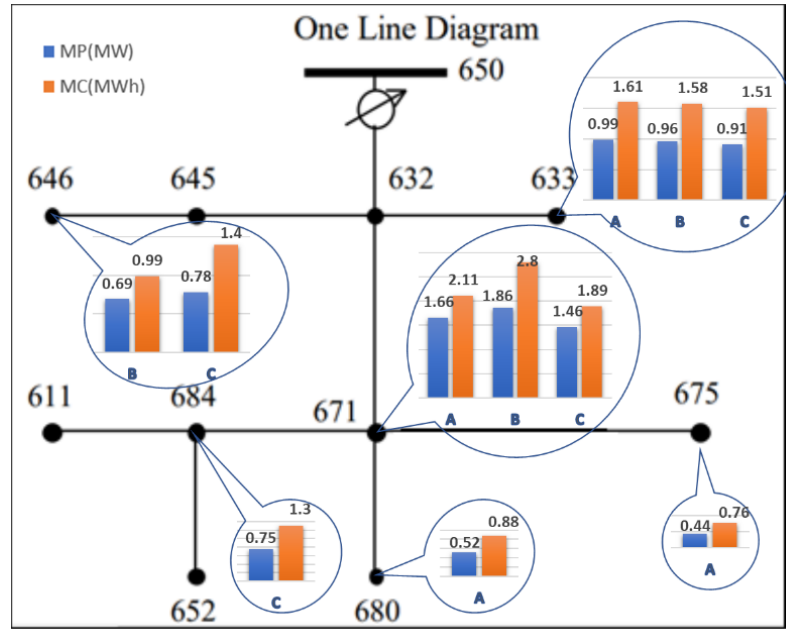


Figure 4-11 BESS siting and sizing when $NA=20$ for $InvC$ equals to 100\$/kW.

As showed in table 4-6, the 1 million \$ reduction in the cost is directly translated as an increase in the profits by the same amount, which illustrates the limited effect of the power price on the final siting and sizing results.

Table 4-6 Optimal decision for $InvC$ equals to 190 and 100\$/kW.

	Investment cost (Millions\$)	Power Capacity (MW)	Energy Capacity (MWh)	Expected Profits (Millions\$)
190\$/kW	5.47	11.12	16.77	6.51
100\$/kW	4.51	11.05	16.83	7.5

4.5 Comparing EVs and BESS investing

4.5.1 EV versus BESS without DN

To compare EV with BESS in the case of ignoring DN, the optimal investment cost obtained from EV planning in section 3.5.2 is used as investment cost limit for the BESS

planning. Comparing the first case when EVs are available all the time except for two hours with BESS, BESS investment provides lower profits than EVA. In line 3 ($\gamma = 0.6$) for example, BESS profit is 67 % less than EV for the same investment cost. These results indicate that EVA is more profitable in AS participation than BESS for this particular case. The reason for that is the energy cost of BESS which is not there in EVA because the EVA does not own the storage in EVs case. The optimal points for BESS using 70.38 million \$ as investment cost are 185.4 MW and 175.7 MWh for power and energy capacity respectively.

Table 4-7 EVA versus BESS optimal decision for the first case.

Line	Investment cost (Millions\$)	Optimal Power Capacity (MW)	Optimal Energy Capacity (MWh)	Energy Storage Payoff (Millions\$)	EV Aggregator Payoff (Millions\$)
1($\gamma = 0.2$)	23.46	61.8	58.6	34.31	109.3
2($\gamma = 0.4$)	46.92	123.6	117.2	68.63	218.6
3($\gamma = 0.6$)	70.38	185.4	175.7	102.94	327.9
4($\gamma = 0.8$)	93.84	247.3	234.3	137.26	437.2
5($\gamma = 1$)	117.3	309.1	292.9	171.57	546.9

For the second case where EVs are not available between the two trips, table 4-8 summarizes the results. Still, the EVA results in higher profits than the BESS. For line 3, BESS investment is less by 47 % from EVA. We can see that the gap between the two investments is reduced in the second case, however, still EVA provides a higher payoff.

Table 4-8 EVA versus BESS optimal decision for the second case.

Line	Investment cost (Millions\$)	Optimal Power Capacity (MW)	Optimal Energy Capacity (MWh)	Energy Storage Payoff (Millions\$)	EV Aggregator Payoff (Millions\$)
1($\gamma = 0.2$)	19.55	51.5	48.8	28.6	53.23
2($\gamma = 0.4$)	39.11	103	97.6	57.2	106.46
3($\gamma = 0.6$)	58.66	154.5	146.5	85.8	159.70
4($\gamma = 0.8$)	78.21	206.1	195.3	114.4	212.92
5($\gamma = 1$)	97.76	257.6	244.1	143	266.15

4.5.2 EV versus BESS with DN

As seen from the results of EVA (3500 EVs) and BESS (all buses are available) (summarized in table 4-9) when DN is included, the BESS profits are higher than EVA for line 1, 2 and 3($\gamma = 0.2, 0.4, 0.6$). The EVA resulted in higher profits in lines 4 and 5 ($\gamma = 0.8, 1$) where the slope of the relation between β and the number of EVs participated in the regulation is high as in figure 3-6. Although BESS in some cases results in higher profits, still the investment cost of BESS is much higher than EVA and that due to the cost of the battery. In the BESS investment the investor owns the battery storage system, however, in the EVA the battery is owned by the EV owner and the investor only own the bi-directional chargers.

Table 4-9 EVA (3500 EVs) profits and investment cost along with BESS (NA=20).

Line	Investment cost (Millions\$)	EV Aggregator Payoff (Millions\$)
1($\gamma = 0.2$)	0.978	2.60
2($\gamma = 0.4$)	1.560	4.65
3($\gamma = 0.6$)	2.1	6.10
4($\gamma = 0.8$)	2.35	7.25
5($\gamma = 1$)	2.93	8.17
BESS	5.47	6.51

As seen also from the results of the previous section, increase the number of EVs or changing the locations where EVs are available in the distribution could change the optimal profits and results in higher payoff comparing to BESS. EVA investment is riskier than BESS because changing the relation between β and the number of EVs participated could change the optimal decision and this relation is hard to be estimated by the aggregator, so for more risk taker investor EV investment could be a good choice.

CHAPTER 5

BESS FUZZY OPTIMIZATION

In this chapter, the fuzzy linear program (FLP) is used to handle the uncertainties of inaccurate AS price forecasts in the BESS model. To verify its effectiveness, the proposed FLP-based optimization is compared with its deterministic counterpart.

5.1 Fuzzy Model for BESS Sizing

Consider the following general form for an optimization model:

$$\text{Maximize } f(x, y, z)$$

Subject to

$$g_j(x, y, z) \leq 0 \quad j = 1, \dots, n \quad (5-1)$$

$$g_j(x, y) \leq 0$$

$$j = n + 1, \dots, N \quad g_j(x, \zeta, \xi) \leq 0 \quad j = 1, \dots, m \quad (5-2)$$

Where x , y and z here are vectors of decision variables, certain parameters, and uncertain parameters respectively. The constraint $g_j(x, y)$ is crisp, or certain, because it is not a function of uncertain parameters. However, $f(x, y, z)$ and $g_j(x, y, z)$ are two functions that depend on the uncertain parameters.

The uncertainty of z in the case of deterministic optimization, is neglected and historical data is used to estimate, or forecast, these parameters. In the case of fuzzy optimization, the fuzzy model can handle these uncertain parameters efficiently without

increasing the size of the problem significantly. The objective function and any constraints that are functions of uncertain parameters are represented by membership or satisfaction functions. Each satisfaction function represents how close the objective or constraint to the optimal solution[47]. Therefore, instead of optimizing the objective function, f , directly, the satisfaction levels are optimized as shown below:

Maximize

$$\lambda = \min\{\mu_f, \mu_{g_1}, \dots, \mu_{g_n}\} \quad (5-3)$$

Subject to

$$g_j(x, y) \leq 0 \quad j = n + 1, \dots, N \quad (5-4)$$

where μ_f and μ_{g_i} are the membership functions of the objective and uncertain constraints, respectively. The value of each satisfaction function can range from 0 to 1.

5.2 Fuzzy Formulation

The uncertain parameters considered here include the energy and AS prices ($\sigma^U, \sigma^D, \sigma^R$, and σ^E). That is, these prices are forecasted but the forecasts are not accurate. Mean absolute parentage error (MAPE) is used to estimate the error and based on that the aggregate satisfaction will vary between 0 and 1. Five satisfaction functions are developed; one related to the objective function and the other four related to the four price uncertainties.

The fuzzy set of the objective function (profit) as defined in (4-1) is:

$$\widetilde{TP} = \{[TP, \mu_{TP}], \quad 0 \leq TP \leq \overline{TP}\} \quad (5-5)$$

The profit satisfaction function is defined in (5-6). This can be represented as an inequality fuzzy constraint as shown in (5-7) and (5-8). Figure 5-1 shows the graphical representation of objective membership function.

$$\mu_{TP} = \begin{cases} 0, & TP \leq 0 \\ \frac{TP}{\overline{TP}}, & 0 < TP \leq \overline{TP} \\ 1, & TP > \overline{TP} \end{cases} \quad (5-6)$$

$$\lambda \leq \mu_{TP} = \frac{TP}{\overline{TP}} \quad (5-7)$$

$$\lambda * \overline{TP} \leq TP \quad (5-8)$$

$\overline{TP}$ is a decision maker's parameter that can be defined in a way related to the optimal profits obtained from the deterministic optimization.

The fuzzy model and the membership function for the regulation up prices σ^U are represented in (5-9) and (5-10) respectively and graphically shown in figure 5-1.

$$\widetilde{\sigma^U} = \{[\sigma^U, \mu_{\sigma^U}], \quad \underline{\sigma^U} \leq \sigma^U \leq \overline{\sigma^U}\} \quad (5-9)$$

$$\mu_{\sigma^U} = \begin{cases} 0, & \sigma^U \geq \overline{\sigma^U} \\ \frac{\overline{\sigma^U} - \sigma^U}{\overline{\sigma^U} - \underline{\sigma^U}}, & \underline{\sigma^U} \leq \sigma^U \leq \overline{\sigma^U} \\ 1, & \sigma^U \leq \underline{\sigma^U} \end{cases} \quad (5-10)$$

where $\overline{\sigma^U}$ and $\underline{\sigma^U}$ are the maximum and minimum expectation of the price that can be decided based on the MAPE:

$$\overline{\sigma^U} = \sigma^U * (1 + MAPE) \quad (5-11)$$

$$\underline{\sigma^U} = \sigma^U * (1 - MAPE) \quad (5-12)$$

Similarly, the fuzzy models and membership functions for the regulation down σ^D and reserve prices σ^R will follow the same graphical representation as regulation up prices σ^U and they can be represented as:

$$\widetilde{\sigma^D} = \{[\sigma^D, \mu_{\sigma^D}], \quad \underline{\sigma^D} \leq \sigma^D \leq \overline{\sigma^D}\} \quad (5-13)$$

$$\mu_{\sigma^D} = \begin{cases} 0 & \sigma^D \geq \overline{\sigma^D} \\ \frac{\overline{\sigma^D} - \sigma^D}{\overline{\sigma^D} - \underline{\sigma^D}}, & \underline{\sigma^D} \leq \sigma^D \leq \overline{\sigma^D} \\ 1, & \sigma^D \leq \underline{\sigma^D} \end{cases} \quad (5-14)$$

$$\widetilde{\sigma^R} = \{[\sigma^R, \mu_{\sigma^R}], \quad \underline{\sigma^R} \leq \sigma^R \leq \overline{\sigma^R}\} \quad (5-15)$$

$$\mu_{\sigma^R} = \begin{cases} 0 & \sigma^R \geq \overline{\sigma^R} \\ \frac{\overline{\sigma^R} - \sigma^R}{\overline{\sigma^R} - \underline{\sigma^R}}, & \underline{\sigma^R} \leq \sigma^R \leq \overline{\sigma^R} \\ 1, & \sigma^R \leq \underline{\sigma^R} \end{cases} \quad (5-16)$$

The maximum and minimum expected limits are calculated the same way as σ^R using MAPE.

The energy prices σ^E are transferred into the fuzzy set defined in (5-17) and (5-18). As noted from figure 5-1, the membership function is developed in an opposite manner from the AS prices due to the expectation that the actual prices of energy will be higher than the forecasted prices.

$$\widetilde{\sigma^E} = \{[\sigma^E, \mu_{\sigma^E}], \underline{\sigma^E} \leq \sigma^E \leq \overline{\sigma^E}\} \quad (5-17)$$

$$\mu_{\sigma^E} = \begin{cases} 0 & \sigma^E \geq \overline{\sigma^E} \\ \frac{\overline{\sigma^E} - \sigma^E}{\overline{\sigma^E} - \underline{\sigma^E}}, & \underline{\sigma^E} \leq \sigma^E \leq \overline{\sigma^E} \\ 1, & \sigma^E \leq \underline{\sigma^E} \end{cases} \quad (5-18)$$

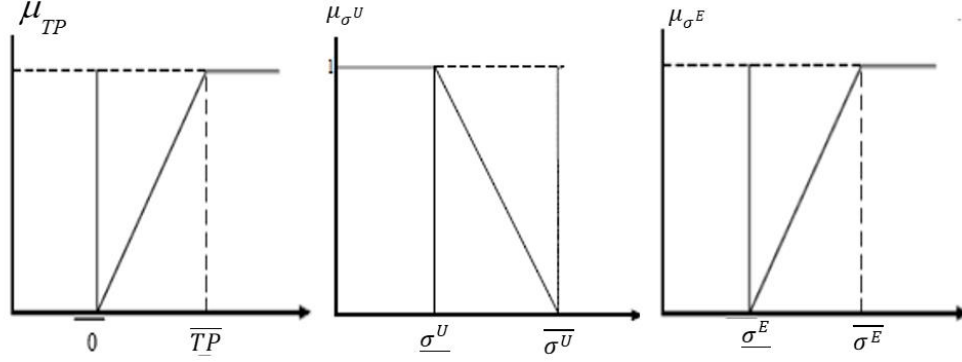


Figure 5-1 The fuzzy membership function for the expected profit, regulation up and energy prices.

5.3 The Complete Fuzzy Model

The main objective of the BESS investor is to maximize the total profits by participating in AS markets. The uncertainties in the AS and energy prices and their effects on the other decision variables are handled using the fuzzy concepts by introducing the membership functions as explained before. All the fuzzy membership functions are converted to fuzzy inequality constraints as follows:

$$\lambda * \overline{TP} \leq TP \quad (5-19)$$

$$\lambda * (\overline{\sigma^U} - \underline{\sigma^U}) \leq \overline{\sigma^U} - \sigma^U \quad (5-20)$$

$$\lambda * (\overline{\sigma^D} - \underline{\sigma^D}) \leq \overline{\sigma^D} - \sigma^D \quad (5-21)$$

$$\lambda * (\overline{\sigma^R} - \underline{\sigma^R}) \leq \overline{\sigma^R} - \sigma^R \quad (5-22)$$

$$\lambda * (\overline{\sigma^E} - \underline{\sigma^E}) \leq \overline{\sigma^E} - \sigma^E \quad (5-23)$$

Therefore, the full fuzzy optimization model is:

Maximize

$$\lambda = \min\{\mu_{TP}, \mu_{\sigma^U}, \mu_{\sigma^D}, \mu_{\sigma^R}, \mu_{\sigma^E}\}$$

Subject to

Fuzzy constraints (5-19)-(5-23), and deterministic constraints (4-2)-(4-19).

5.4 Case Study

The main purpose of this case study is to investigate the effectiveness of the fuzzy logic programming (FLP)-based planning model for BESS and to compare it to that of the benchmark deterministic planning model. The project's life span is assumed to be 12 years. The discount rate is 5%. An initial investment budget of \$10 million is assumed. This investment cost is to be spent mainly in acquiring power and energy capacities. All other costs, e.g. installation and maintenance, are embedded in the cost of power and energy capacities. The power and energy capacities prices are 190 \$/kW and 200 \$/kWh respectively. The efficiency of battery charging/discharging is taken as 90%, each way.

The data for market prices of the regulation up/down, reserves, and energy, in addition to the ancillary services deployment signals are taken from the Electric Reliability Council of Texas (ERCOT) market information [60].

For the fuzzy optimization part, the membership function for each price is defined based on the forecasted price and the MAPE of the forecast. Table 5-1 summarizes the

MAPE for each of the prices, which is obtained from the historical data. To define the profits membership function, the profit's maximum limit $\overline{TP}$ needs to be defined. In the base case, $\overline{TP}$ is set to be 10% greater than the expected profits obtained from the benchmark deterministic optimization.

Table 5-1 The values of fuzzy parameters.

Parameters	MAPE
Regulation up prices σ^U	8.3 %
Regulation down prices σ^D	9.5 %
Reserve prices σ^R	7 %
Energy prices σ^E	15 %

5.5 Results and Discussion

For comparison, the deterministic and fuzzy-based algorithms are run and results are obtained using GAMS. The comparison is carried out based on the expected profits and realized profits obtained from each algorithm.

5.5.1 Deterministic Versus Fuzzy Expected Results

The optimally expected profits of the deterministic and fuzzy optimization are obtained along with the optimal power and energy capacities. By expected profits, we mean the value of TP as obtained from evaluating (4-1) during the optimization. Table 5-2 summarizes the results of each approach.

Note that the expected profits of the fuzzy approach are less than those of the deterministic approach. This just indicates that in the case where price forecasts are precise, the deterministic approach is better. In fact, this result is expected. It is also noteworthy that fuzzy and deterministic approaches give rise to different optimal power and energy capacities.

Table 5-2 Comparison between fuzzy and deterministic optimization.

	Optimal Power Capacity (kW)	Optimal Energy Capacity (kWh)	Expected Profits (Millions\$)
Fuzzy	23148.3	28009.1	12.47
Deterministic	24166.5	27041.8	15.51

it is worth to mention that the introduced fuzzy optimization affects the operation schedules of the BESS during the day.

Figure 5-2 and figure 5-3 show the BESS preferred operating point and regulation up capacities during a sample day. These results indicate that taking forecast uncertainties into account can impact how the BESS bids its capacities. For example, at 3 PM, the fuzzy regulation up bid is nonzero. However, the deterministic bid is zero during this specific hour.

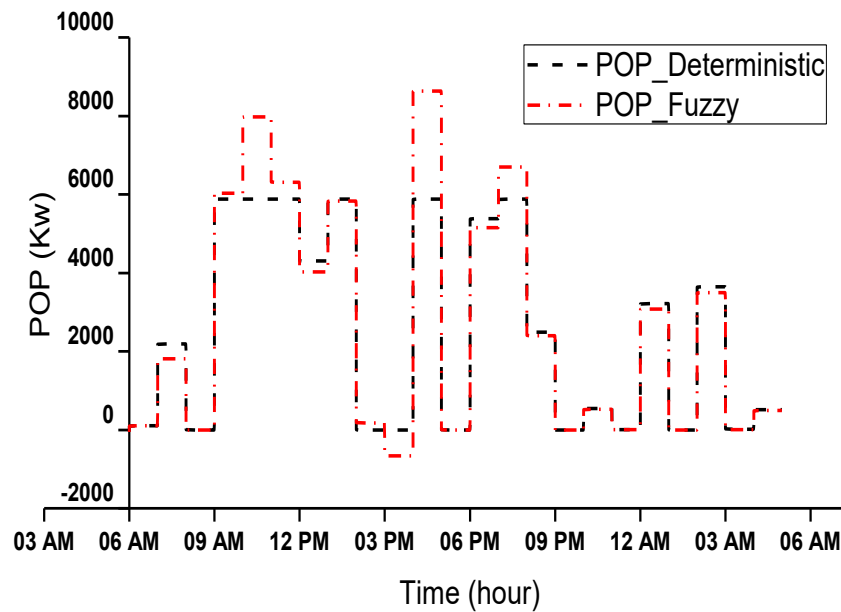


Figure 5-2 Preferred operating point (POP) bids for a sample day

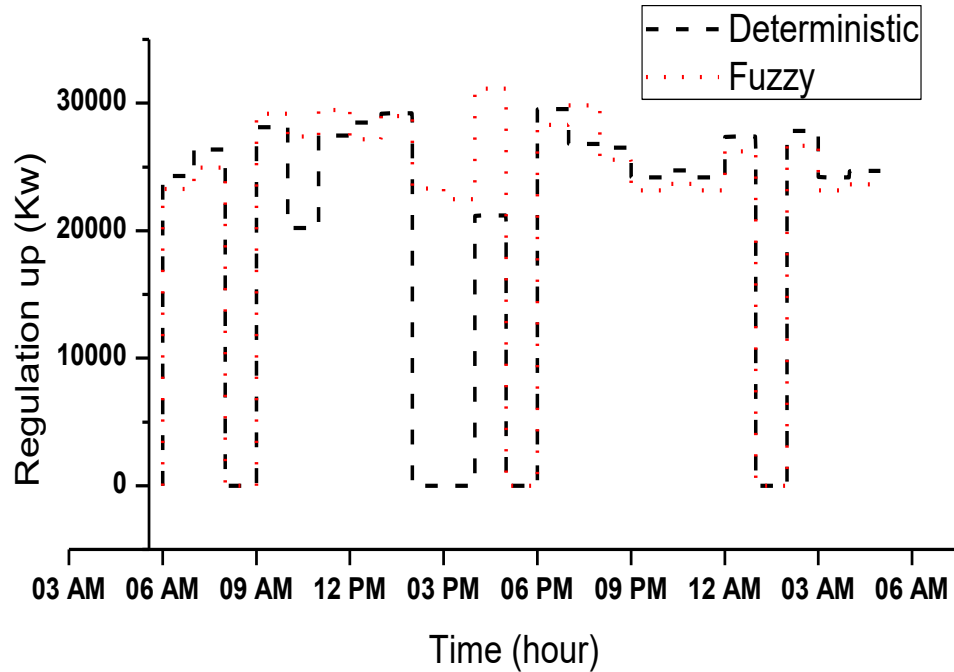


Figure 5-3 Regulation up capacity bids for a sample day

5.5.2 Realized Profits

For both deterministic and fuzzy approaches, the forecasted data has been used and biddings for the POP and AS capacities are assumed to have been decided. However, in real time, the realized prices could deviate from the forecasted prices. For this reason, the bids from each approach are used along with the real historical data of each day, and the realized profits for each day are obtained. Then, the project's realized profits are determined. In other words, the project's realized profits are obtained by evaluating (4-1) using the optimal bids for each approach and the real historical price data. The project's expected profits are obtained by evaluating (4-1) using the optimal bids for each approach and the forecasted prices.

Table 5-3 summarizes the profits results of both approaches. Evidently, the fuzzy approach results in higher realized profits than the deterministic counterpart. This is one of

the most important results of this research. Also, note that the expected profits and realized profits are further apart in the deterministic case. That is, the fuzzy approach is more capable of predicting the project's actual profits than the deterministic approach.

Table 5-3 Expected and realized profits

Line	Expected Profits (Million \$)	Realized Profits (Million \$)
Fuzzy	12.47	13.50
Deterministic	15.51	13.06

5.5.3 Sensitivity Analysis

The effects of changing the maximum limits of the acceptable profit $\overline{TP}$ is investigated. Four maximum limits are considered: 10, 30, 50, and 80%. As seen from table 5-4, the maximum realized profit is obtained when $\overline{TP}$ is 10% of the deterministic profits. As this percentage increases, the fuzzy realized profits start to decrease and the optimal power and energy capacities start to approach those of the deterministic case.

The power (MP) and energy (MC) capacities from each approach (deterministic and fuzzy) are also tested. Those values are set as obtained from the planning models using historical data of a specific year, as explained above. Then, daily operational optimization using price data for 90 days of the next year. In this case, the data used for planning optimization and the data used for operational optimization are different. As seen in table 5-5, using the power and energy capacities obtained from the fuzzy planning model gives rise to higher operational profits. This verifies the robustness of the fuzzy model.

Table 5-4 The sensitivity of profits to maximum limits.

Line	Expected Profits (Millions\$)	Realized Profits (Millions\$)	Optimal Power Capacity (kW)	Optimal Energy Capacity (kWh)
Deterministic	15.51	13.06	24166.5	27041.8
Fuzzy 10 %	12.47	13.50	23148.3	28009.1
Fuzzy 30 %	12.82	13.48	23254.9	27907.8
Fuzzy 50 %	13.27	13.39	23439.3	27732.6
Fuzzy 80 %	13.91	13.29	23698.7	27486.2

Table 5-5 Operational profits for 90 days

	Power Capacity (kW)	Energy Capacity (kWh)	Operational Profits (\$)
Fuzzy	23148.36	28009.1	721275.7
Deterministic	24166.53	27041.8	713498.3

CHAPTER 6

CONCLUSION AND RECOMMENDATIONS

In this work, two investment options are studied to bid regulation and reserve capacities to the ancillary services market. The first option is to use the batteries of the EVs in the fleet that is organized by what is called EV aggregator (EVA). EVA will make profits from charging the EVs in the fleet and participating in the ancillary services market. The second option is to by battery energy storage (BESS) with certain power and energy capacities and uses them to bid to the market. The most important parameter that was optimized in the case of EVA is the charging tariff. In the case of BESS, the best power and energy capacity is the most important parameter.

The linear planning models for BESS and EV aggregator for market-based evaluation are developed and integrated with the linear model of an unbalanced distribution network to optimize the long-term profits for an investor willing to use BESS or EVs to participate in ancillary services markets. The used model showed different profits between including and ignoring the distribution network. In the case of ignoring DN, the EVA showed better profits compared to the BESS investment and that due to the high energy storage cost which is included in the prepaid investment cost of the BESS and ignored in the case of EVA because the batteries are owned by the EVs owners. In the case of including DN, both investments show comparable results with the preference of BESS investment in deciding the best location and capacity of the power and energy capacities in the different buses, not like EVA where the distribution of the EVs is predetermined

based on the availability of them in the distribution network. In addition, invest in EVs contains a lot of risk and uncertainty that are hard to predict by the investor like EVs elasticity with the energy tariff which makes BESS investment better if less risk is desired. The results show the effectiveness of the linear model in determining the BESS network constraints compared with the nonlinear model and that also proves the currency of the proposed linear power flow.

Moreover, fuzzy optimization is used to optimize the long-term profits for an investor willing to use BESS for participating in ancillary services markets. The proposed fuzzy approach considers the uncertainties related to the AS and energy prices. The main advantage of fuzzy optimization is that it can model the impact of uncertain parameters while not increasing the optimization problem significantly. The results show the effectiveness of the proposed fuzzy model in determining the BESS capacities that maximize the project's profits. It is also able to predict the realized profits more accurately than its deterministic counterpart.

Future work could focus on applying Fuzzy optimization to the system including the distribution network uncertainties. Also, more enhancement could be done to the fuzzy model by considering the uncertainties of deployment signals and finding the best maximum and minimum limit for the fuzzy constraints that could lead to better optimal result compare to the deterministic model. In addition, considering renewable resources like wind and solar and integrating them with the unbalanced distribution model can be a good addition to this work. Final the studied network model was tested in 13 bus system, so applying the model in a bigger system could approve the efficiency of the model.

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APPENDIX

IEEE 13-bus distribution test feeder:

References [61] and [62] provides full details about the system. Figure 0-1 shows the system connected phases. As we can see if the main feeder buses 650 and 632 are excluded, 20 phase locations are available to locate BESS. All lines in the system have line thermal capacity of 700 kVA except the main line that connects bus 632 with 671 which has thermal limit of 1400 kVA.

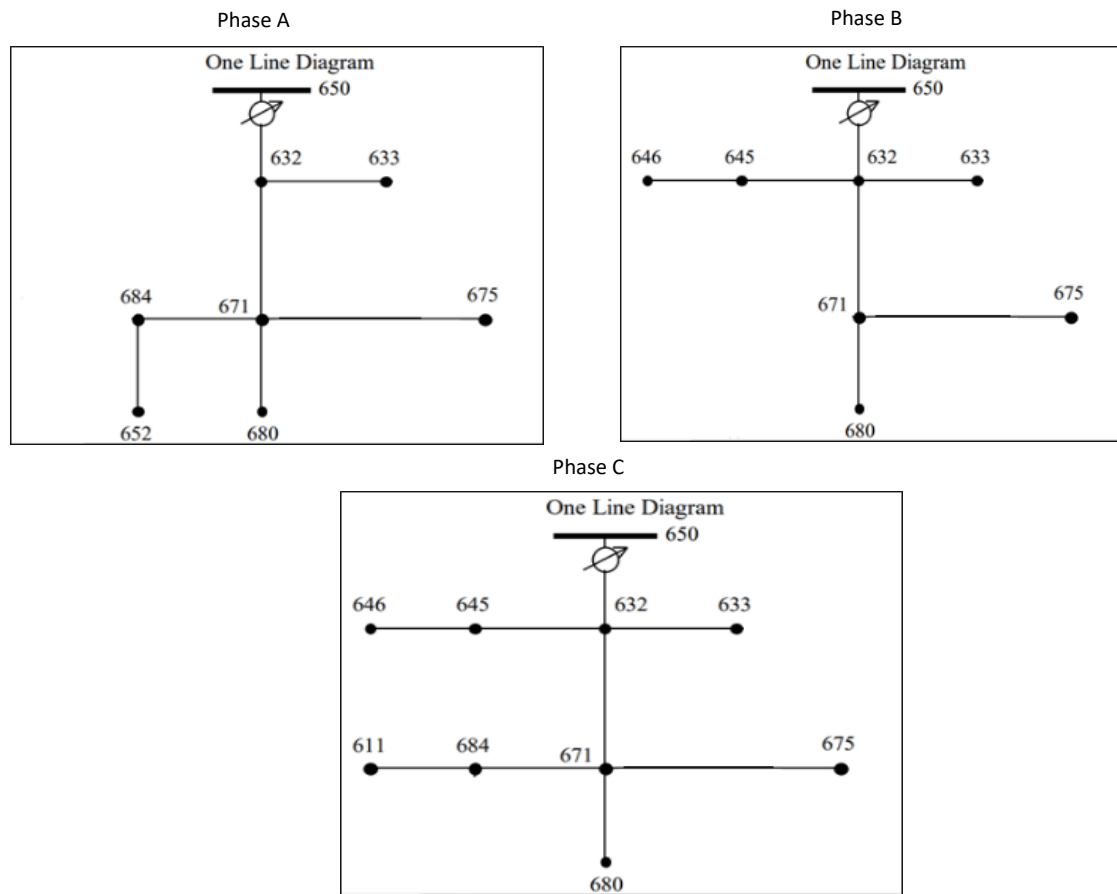


Figure 0-1 IEEE 13-bus distribution test feeder phases

Table 0-1 Overhead line configuration data

Config.	Phasing	Phase	Neutral	Spacing
		ACSR	ACSR	ID
601	B A C N	556,500 26/7	4/0 6/1	500
602	C A B N	4/0 6/1	4/0 6/1	500
603	C B N	1/0	1/0	505
604	A C N	1/0	1/0	505
605	C N	1/0	1/0	510

Table 0-2 Underground line configuration data

Config.	Phasing	Cable	Neutral	Space ID
606	A B C N	250,000 AA, CN	None	515
607	A N	1/0 AA, TS	1/0 Cu	520

Table 0-3 Line segment data

Node A	Node B	Length(ft.)	Config.
632	645	500	603
632	633	500	602
633	634	0	XFM-1
645	646	300	603
650	632	2000	601
684	652	800	607
632	671	2000	601
671	684	300	604
671	680	1000	601
671	692	0	Switch
684	611	300	605
692	675	500	606

Table 0-4 Transformer data

	kVA	kV-high	kV-low	R - %	X - %
Substation:	5,000	115 - D	4.16 Gr. Y	1	8
XFM -1	500	4.16 – Gr.W	0.48 – Gr.W	1.1	2

Table 0-5 Capacitor data

Node	Ph-A	Ph-B	Ph-C
	kVAr	kVAr	kVAr
675	200	200	200
611			100
Total	200	200	300

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1. Ammar Muqbel, Jafar Mohamed, A. T. Al-Awami, “Sizing and Siting of a Battery Energy Storage System in a distribution network to Participate in Ancillary Services Markets” to be submitted as a journal paper.

2. Ammar Muqbel, Abubakr Elsayed, M. A. Abido, "Optimal sizing and location of solar capacity in an electrical network using lightning search algorithm" submitted as a journal paper in Electrical Power Components and Systems.
3. Ammar Muqbel, A. Aldik, A. T. Al-Awami, and F. Alismail, "Fuzzy Optimization-based Sizing of a Battery Energy Storage System for Participating in Ancillary Services Markets," IEEE IAS Annual Meeting 2018.
4. A. T. Al-Awami, N. A. Amleh and A. M. Muqbel, "Optimal Demand Response Bidding and Pricing Mechanism With Fuzzy Optimization: Application for a Virtual Power Plant," in IEEE Transactions on Industry Applications, vol. 53, no. 5, pp. 5051-5061, Sept.-Oct. 2017.
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