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A Chance-Constrained Approach for Electric Vehicle Aggregator Participation in the Reserve Market

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Abstract

Increasing environmental concerns have led to changes in the power system, and the investment in distributed energy resources is in progress. However, the investment in renewable energy is usually associated to the intermittent behavior of the energy sources, like the sun, wind, waves, etc. In the last decade, Electric Vehicles (EV) have been continuously rising, and the trend is to play an important role in the power system. Thus, new relationships between EVs and market agents shall be addressed. Nowadays, EVs already have the ability to charge and discharge energy, known as Vehicle-to-Grid mode (V2G). This feature aided by proper algorithms, can contribute to the frequency and voltage support of the network. It all depends on the willingness of the vehicle owner to provide this type of services, always ensuring minimum State-Of-Charge (SOC) for the daily trips. Generally, the management of the electrical system is associated with high power levels, so EVs should be aggregated in order to be able to engage in this type of service. Thus, the concept of EV aggregator arises.

The EV aggregator concept entails joining several EVs together so they can actively participate in energy and ancillary services markets. This aggregator should gather all the information related to the fleet and relate to the market agents. Through operational algorithms, the EV aggregator should be able to achieve their goals benefiting all those involved.

This thesis proposes a optimization model for solving the EV aggregator problem, considering the uncertainty and risk associated to the EVs usage for reserve provision. The proposed model includes penalties in the event of a failure in the provision of upward or downward reserve. Therefore, stochastic and chance-constrained programming are used to handle the uncertainty of a small fleet of EVs and the risk behavior of the EV aggregator. Chance-constrained optimization through the deterministic equivalent (including Big-M and McCormcik relaxation methods) are applied in order to assess the risk of the EV aggregator decision. The proposed model is applied under the rules of the Frequency-Controlled Normal Operation Reserve (FCR-N) in East Denmark. It is implemented on a small fleet of 10 EVs from the Frederiskberg Forsyning utility company within the scope of the PARKER project. This methodology also presents two different probabilities of connecting the EVs to the network, considering different availability to provide the service, which may be related to poor connections.

Finally, the proposed model is validated and tested for different numbers of scenarios and different risk levels. Regarding the two methods discussed, Big-M and McCormick, they present very similar results when taking into account the aggregator's profit. The McCormick method presents a slightly better performance when the number of scenarios increases, which indicates its greater usefulness in large scale problems. However, it also presents the setback of requiring a greater computational effort. The probability functions also have a significant impact on the expected profit of the EV aggregator. An out-of-sample approach is also considered, assessing the outcomes of the aggregator's decision.

Resumo

As crescentes preocupações ambientais têm levado a alterações no sistema de energia, e por isso, é necessário haver investimento em recursos energéticos distribuídos. Contudo, o investimento nesta área está normalmente associado a energia solar, eólica, das ondas, etc. Na última década, os veículos elétricos têm-se desenvolvido e a tendência é que possam desempenhar um papel importante no sistema de energia. Por isso, é importante que sejam desenvolvidas novas relações entre os agentes de mercado e os EVs. Atualmente, os EVs já têm capacidade para carregar e descarregar energia (V2G). Esta funcionalidade, suportada pelos algoritmos certos pode contribuir para ajudar a rede elétrica a mitigar problemas de tensão e frequência. Tudo está dependente da disponibilidade dos proprietários dos EVs, sendo que a carga necessária para as suas viagens diárias será sempre assegurada. Geralmente, o controlo do sistema de energia está associado a elevados níveis de potência, por isso os EVs devem aglomerar-se para terem a possibilidade de prestar auxílio. Deste modo, nasce o conceito de agregador de EVs.

O conceito de agregador de EVs envolve associar vários EVs para que eles consigam mitigar problemas na rede, uma vez que já têm uma capacidade significativa. Este agregador deve reunir informação relativa a toda a frota e relacionar-se com os agentes de mercado. Através de algoritmos operacionais, o agregador de EVs deve atingir os seus objetivos e beneficiar todos os envolvidos. Esta tese propõe um novo modelo de otimização para resolver o problema que o agregador de EVs suscita para fornecer reserva, uma vez que há incerteza e risco associados. O modelo proposto inclui penalidades caso não seja fornecida reserva a subir e a descer. Assim, otimização estocástica e *chance-constrained* são utilizadas para tratar de incerteza e risco associados ao problema. Os métodos de relaxação *Big-M* e *McCormick* são aplicados de modo a analisar o risco que o agregador submete em mercado. O modelo é implementado numa pequena frota de 10 veículos da companhia Frederiskberg Forsyning, no âmbito do projeto PARKER. Esta metodologia também apresenta duas probabilidades diferentes da conexão do EV à rede, que representam diferentes disponibilidades para fornecer o serviço, que podem estar relacionadas com más conexões. Finalmente, o modelo proposto é validado e testado para diferentes números de cenários e diferentes níveis de risco. Relativamente as dois métodos analisados, *Big-M* e *McCormick*, os resultados apresentados são semelhantes, quando se tem em consideração o lucro do agregador. Para um maior número de cenários, o método *McCormick* apresenta uma ligeira melhor performance, o que é um indicador que esta método apresenta uma melhor resposta em problemas reais. Contudo, este método também exige um maior tempo computacional. As funções de probabilidade também apresentam um elevado impacto no lucro do agregador. São também gerados outros cenários para avaliar a resposta do agregador.

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António Sérgio Barbosa Faria

“Design is not how it looks like and feels like.
Design is how it works”

Steve Jobs

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Abbreviations

DSO	Distribution System Operator
EV	*Electric Vehicle*
EDV	Electric-Drive Vehicles
FCR-D	Frequency-Controlled Disturbance Reserve
FCR-N	Frequency-Controlled Normal Operation Reserve
GHG	Greenhouse Gas
GSM	Global System Management
LP	Linear Programming
MINLP	Mixed-Integer Nonlinear Programming
MIP	Mixed-Integer Programming
PHEV	Plug-in Hybrid Electric Vehicle
PSO	Particle Swarm Optimization
SO	System Operator
SOC	State of Charge
TSO	Transmission System Operator
V2G	Vehicle-to-Grid

Symbols

Parameters	
M	Big-M parameter
η_{Ch}	Charge efficiency
η_{Dch}	Discharge efficiency
π_{ω}	Probability of scenario ω
$\pi^{plugged}$	Probability of the vehicle be plugged to the grid in time Γ
λ	Prices and penalties
λ^{sp}	Energy spot price
Variables	
P	Power
r	Amount of reserve deployed in the second-stage
rev	Revenue
R	Amount of offered reserve in the first-stage
RLXD	Amount of power for missing offered downward reserve
RLXU	Amount of power for missing offered upward reserve
SOC	State-of-charge of the electric vehicle ev at the end of period t
X	Binary variable for charging/discharging selection
Y	Binary variable for offering in the market
Subscripts	
ω	Scenario index
Ch	Charge process
Dch	Discharge process
ev	Electric vehicle index
t	Period index
Superscripts	
DA	Day-ahead – first-stage
DW	Downward reserve
E	Energy
Forecast	Forecast estimation of EV's trip
Max	Upper bound limit
Min	Lower bound limit
pnlt	Penalty for missing the contracted reserve
RT	Real-time – second-stage
UP	Upward reserve

Chapter 1

Introduction

1.1 Context

In the face of increasing environmental and social concerns, sustainable development is imperative in every field in order to ensure that future generations are not compromised. Particularly in the area of energy where significant changes are already underway in developed and in developing countries, however, there is a long way to go, especially for the whole planet. The constant emissions of Greenhouse Gas (GHG) are one of the biggest scourges of today, which can be mitigated by investing in energy from renewable sources and energy efficiency measures.

According to a study by the European Environment Agency [1], in 2016, the transport sector accounted for 27% of GHG emissions. On the same year, emissions from transport increased by 26% compared to 1990, which dictates that they should decrease by 2/3 by 2050 in order to comply with the decrease defined in the *Transport White Paper* [2].

In this context, electric vehicles can play an important role as long as they are supported by an electric power system, essentially made up of clean energy. The technology of these vehicles is continuously evolving and they are now able to compete with vehicles that use fossil fuels. With the penetration of EVs there is also a decrease in external dependence on energy, hence there are several government supports to encourage the use of this type of transport.

Given the likelihood of high percentages of EV penetration in the future, it is also imperative to study the impacts it may imply on the electric power system. The concept of *Smart Grid* already encompasses the accentuated presence of EVs. Hence, the need to improve the infrastructure of the power system arises, in order to be prepared for this upcoming reality. Increases in load levels, congestion and voltage variations are expected, so it is mandatory to develop control and automation infrastructures. The charging of EVs should be scheduled smartly to avoid grid overloading during peak hours and to benefit from off-peak hours charging. When the charging schedule is not properly performed, many benefits that EVs can bring to the grid are being lost, namely if high GHG emission power plants are dispatched. If EVs work as flexible loads they can contribute to balancing power in the grid, as they have faster responses times and batteries can store energy cheaper than conventional methods. EVs can also act as a resource through V2G capability, injecting power back to the grid to mitigate voltage or frequency fluctuations.

Domestic consumers and EVs lack the capacity to enter the market directly. Therefore, a way for them to engage is to relate through aggregators. By then, they will be able to participate in the market with a significant level of power. Therefore, energy aggregators are concepts that are being implemented in various sectors, using technological advances. The role of the typical consumer has been changing over time, so the aggregators have the ability to create value that can benefit the entire power system. However, there are still many doubts and discussions around how to integrate these aggregators and who should benefit most from their integration.

As expected, the concept of aggregator arises in EVs as well. So, these aggregators are new market players who have to compete with each other and have the capability to attract new consumers. It is an agent that interacts with the System Operator (SO), controlling the charging process according to the momentary needs of the system. From the point of view of the system operator the aggregator is seen as a part of the control architecture. From the aggregator's point of view, it functions as a flexible load with storage capacity that can deliver energy at a lower price than that purchased or provide ancillary services.

The EV aggregator is responsible for gathering a set of information on the EVs' characteristics and on the users' characteristics. All this information is handled and from this point on the aggregator is available to interact with the different market agents. The EV aggregator must directly optimize the charging process of each EV. The EV aggregator uses operation management algorithms, in order to decrease forecast errors in the many uncertainties that this problem encompasses and to achieve the optimal bidding strategy. Regarding the main objective of the EV aggregator, it may vary and may be to increase its own profits, to benefit the network or to decrease GHG emissions. The option should be suitable and the profits should be applied to attract more customers.

1.2 Objetives

The power system's stability strongly depends of its ability to adapt and how it is managed. The increasing penetration of EVs can lead to small differences in the way energy is managed in the different markets of each country. As the role of the EV aggregator is still under development, it is important to exploit it so that its implementation achieves the best results and benefits to all those involved. Thus, the objectives of this thesis are:

- Analyze the state of the art in order to identify the already developed concepts of EVs aggregator and their applied problems;
- Adapt the strategic offering model for an EV aggregator participation in the reserve market proposed in [3], by applying chance-constrained programming. This modeling will allow the aggregator to have a trade-off between solution reliability and expected profit;
- Compare two different ways to apply chance-constrained: Big-M and McCormick methods;

- Exploring different probability distribution functions of EVs being connected to the grid, and ready or not to provide the service;

- Assessment of proposed approaches through a real case study, comprising the comparison of expected profit, offering strategy and computational effort.

1.3 Thesis Structure

This thesis is divided into 5 chapters, structured as follows:

- Chapter 1, the present one, depicts the contextualization of the problem and the main objectives to be achieved;

- Chapter 2 presents an overview of the EV aggregator, namely the different definitions and the application of this concept. It also presents the interactions between the different market agents and the aggregator. A brief reference to the electricity markets is introduced, focusing on ancillary optimization. Finally, an analysis is made of several existing control and optimization algorithms;

- Chapter 3 details the offering strategy problem, accounting for the relations between the market agents and the aggregator. The model proposed and implemented in this thesis are described. The mathematical formulation of the strategic offering problem with chance-constrained programming is presented. All the mathematical formulation for the reformulation of the equivalent deterministic problem through the Big-M and McCormick methods is exposed;

- Chapter 4 describes the realistic case study used to assess the proposed model. The performance of the proposed model is presented and analyzed;

- Chapter 5 gathers the most important conclusions and proposes some future work that can be developed in the area.

Chapter 2

EV Aggregator Overview

This chapter provides an overview of the EV aggregator concept. Different forms of interaction with the system will be analysed, as well as different options that the aggregator can offer for participating in the energy market. Some general concepts about the energy market will also be discussed, essentially concerning the reserve market. Finally, the existing literature will be reviewed, namely several algorithms that optimize the integration of EV aggregators in the power system.

2.1 EV Aggregator

EVs have storage and power capabilities with economic value, which can be aggregated, and therefore improve profits [4]. Current market rules, do not allow small-size power resources to participate in the market [5], which means that EV owners should look for aggregators.

The aggregator participates in short-term power market, namely day-ahead and real time, submitting forward regulation offers. The charging process is controlled by the aggregator according to the implemented algorithm, and in return, the EV owner receives attractive tariffs and shares the profits [6].

Another work [7] supports that EV aggregator works like an intermediary between the EVs and the SO, therefore, it needs to know every information on the EV, which can be provided in an online database. All that information, combined with historical data, should be enough to forecast with some certainty the available capacity at any point. This allows the aggregator participating in the market with high confidence levels, thus reducing penalties for energy not supplied.

Recent works [8] introduce the same concept, but aiming to maximize flexibility of EV's batteries. It does not not consider them as conventional loads but as mobile batteries, containing information about the owners behaviour. These batteries should be charged with slow/medium rates since it reduces their degradation, reduce power flow and increase charging duration which gives more flexibility to the SO. They also claim that EVs should be charged in different locals as smart households, buildings and parking lots, controlled by smart meters, allowing money savings to the EVs owners. Thus, EVs penetration, new business opportunities can be promoted and SO can increase system's efficiency, as well.

2.1.1 Vehicle-to-Grid

EVs can be seen as reliable energy sources, that can interact with the system or associated as an aggregator. The concept of Electric-Drive Vehicles (EDV) includes two different classes, namely: battery vehicles and hybrids. Hybrids also comprises plug-in and fuel-cell. All those EVs are equipped with power electronics allowing them to discharge energy into the grid, i.e., supporting frequency grid services. Specialists consider that EVs should play an important role in energy systems, whereas ancillary services appear as the most profitable one [9].

The V2G definition assumes that every EV, while parked, can provide ancillary services. To this end, it should be guaranteed: grid connection, control systems to communicate with the SO and have smart meters. Thus, the SO can require energy when needed [10]. EVs industry has been developed which means that it might play an important role in the power system, however its main purpose should not be left aside, ensure enough energy for the trips.

2.1.2 Distribution System Operator (DSO) and Transmission System Operator (TSO) Interaction and Electricity Market

The EV aggregator is seen by the DSO as an agent of the market, which can have a fundamental role on the grid operation when needed. To the TSO, aggregators are seen as possible source to provide ancillary services [11]. Thereby, the interaction between these three agents works as follows:

- In the beginning of each market session the aggregator buys electric energy to charge batteries;
- DSO validates and corrects, if necessary, aggregators offer, always concerning technical limits of the system. This correction should be seen as a revenue, leading to the inevitability of new ways of management and market rules.
- TSO defines the needs for the next hours or days. From now one, the aggregator makes its decision to participate or not in the market, having the possibility of profit through the adjustment of the charging tariff.

All this process requires communications systems between the three market agents, that should be bidirectional. The charging schedule and energy flow should be provided from the EV aggregator to the system operators (DSO and TSO), as discharging schedule and charging interruptions should be provided to the aggregators by the SOs [11]. Hereupon, are needed some mechanisms as [12]:

- A human interface capable of showing to the costumers, in real time, the power flow and information on maintenance and interruptions;

- Basic smart meters, to support SO management as well to aware the consumer about his consumption in every moment;
- Information storage, in order to maintain historical data to create consumption patterns and quality of service indicators;
- EV should be able to establish communications with the infrastructure in an autonomous way;
- Failure communication, as charging process will be dependent of communication infrastructures. In case a failure occurs the charging process must continue in a non-optimized way, ensuring EV owner's trip.

2.1.3 Economic Value of V2G

Financial opportunities of V2G vary according to the market, the EV type and other characteristics to provide the service. EVs can store energy, charge in valley hours and discharge in peak hours. It can also provide ancillary services, namely, upward and downward regulation and spinning reserve, always taking in account the impact it causes in the battery [9]. In Singapore, a study have showed that the storage capacity can improve around 50 MW only with a 2% EVs penetration, or more if the driver behaviour is known [13]. The same study states that V2G profit can be offered as encouragement to spread EVs penetration.

Another investigation [14] conducted in the California reserve market (CAISO), over a period of three years, shows the capabilities an aggregator can have. The results show that profits between US$150,000 and US$2.1 million can be achieved by providing upward and downward regulation.

2.2 Electricity Markets

The reformulation of the relation between producer and consumer identities led to the introduction of the electricity markets, whereas the concept pool market raised, which include short-term mechanisms aiming to balance the consumption and the production according to the offers made by the producers or the consumers. Usually, this kind of market works in the previous day to which it is implemented, being known as day-ahead market. The coordination of the technical operation is normally ensured by the TSO, involving the exchange of information with producers and market operators [15].

2.2.1 TSO

TSOs are entities that operate independently from other players in the market, such as generating companies, traders, suppliers, distributors and directly connected costumers. The TSO gives access to the grid to these players, who are obliged to comply with the rules it imposes. The security of the energy supply is also ensured by the TSO in order to ensure a good functioning of the system. In some countries the TSO is also responsible for grid infrastructure development and maintenance. As these processes entail high costs, usually the TSO is a monopoly. The TSO is in charge of transmitting the electrical power from the power plants to the regional or local distribution operators. One of the most important factors when it comes to energy transport is to ensure the reliability of the process, which is why the TSO are interconnected regionally or nationally. The roles of the TSO in the entire electricity market include managing the security of the power system in real time and coordination between generation and load.

All TSOs are required to maintain a continuous, second-by-second, balance between electricity supply from power stations and demand from consumers and also ensure the provision of reserves that will allow for sudden contingencies. This is achieved through an optimal economic dispatch, according to the load. Any abnormal event is handled through sophisticated communication and modelling systems [16].

2.2.2 Market Schemes

The market is assembled in different schemes, namely, baseload power, peak power, spinning reserve and regulation, which differ in control methods, response time, duration and prices [10]:

- Baseload power, is typical, sold in long term contracts and several studies have shown that it is not the best choice to the EV aggregator since it have low storage capacities, short average lifetime and high costs, being its advantages quick response and availability [17] [10].

- Peak power, is considered when high load levels are reached and, in general, is supported by generators with high capacity [10].

- Spinning reserve is related to the capacity of quick generation. Typically, in this service, the generators are connected and synchronized to the grid and are spinning in partial velocities, so that in case of abnormal events occur they can respond quickly. This service get revenue for the amount of time it is available, even if it is not used, which is ideal for EVs that are connected to the grid, regularly [10].

- Regulation, it is crucial for the electrical system to keep the voltage and frequency in its reference values, which implies that generation and loads are balanced. If the generation is higher than loads then the system frequency will raise, if load is higher than generation, frequency will decrease. All these aspects bring the inevitability of quick response generation or flexible loads ready to reduce or cut its consumption. Thus, upward reserve assumes the existence of generation units ready to increase the supplied power or loads ready to reduce its consumption. On the other hand, downward reserve assumes the existence of generation units ready to reduce its supplied power, or loads ready to increase its consumption [18].

2.2.3 Ancillary Services

It is important to balance demand and supply, in and near real time, even after markets have closed (gate closure). Therefore, it is important that this process is guaranteed at the lowest cost and ideally with environmental benefits, reducing the need to activate other energy sources. Usually, TSOs are responsible for contracting this type of service and should have the capacity to: black start, frequency response, fast reserve, provision of reactive power, among others. Access to these resources can come from various sources, and it is preferable to do so, as it increases TSO's flexibility. These sources can be generators, but also costumers who can change their operating patterns to help balance the system [19]. Typically, three frequency control types are considered:

- Primary control: it is an automatic control that quickly adjusts active power and load values, aiming to stabilize the frequency. Its main purpose is to level the frequency when a large generation or load outages occur [18] [20].
- Secondary control: adjusts active power to restore frequency and interchanges with other systems after an imbalance. As primary control limits and avoids frequency variations, secondary control restore the frequency value. Secondary control is not mandatory, therefore some systems dismiss it [18] [20].
- Tertiary control: usually is enabled by the TSO and concerns a manual adjust in the generation in order to balance primary and secondary reserves, and deal with interchange problems. It also works as a complement to the secondary control, in large generation or load outages [18] [20].

2.2.3.1 The Portuguese Case

Portugal is under the Continental Europe power system, and therefore, it follows the rules of this power system. In more detail, the frequency-control services are are commonly divided into three different reserves, namely primary reserve, secondary reserve and regulation reserve [21]:

- Primary reserve is a mandatory and unpaid system service provided by the generators in service and aims to automatically correct instantaneous imbalances between the production and consumption. The resulting power variation shall be replaced within 15 seconds in the event of disturbances that cause frequency deviations of less than 100 mHz and between 15 and 30 seconds for frequency deviations between 100 and 200 mHz.
- The proper operation of the electric power system, both from an economic point of view and in terms of guaranteeing supply and safety of operation in the short and medium term, requires a central regulator - frequency control. The achievement of these objectives shall be ensured, as long as the technical limitations are respected, against deviations resulting from random variations in consumption and against sudden imbalances between production and consumption caused by the loss of generating units or sporadic deviations in consumption. The Global System Management (GSM) is obliged to communicate to all market agents by 1 p.m. of each day the required secondary regulation reserve for each period of the following day. It is necessary to establish the proportions between the upward and downward reserve and the minimum secondary regulation band to be offered per offer. The communication of the offers available to provide this service must take place between 6:00 p.m. and 6:45 p.m..

- The proper operation of the electric power system, both from an economic point of view and in terms of guaranteeing supply and short and medium term operation safety requires an additional active power reserve which ensure that consumption is covered and that the system operates safely in the event of an incident that cause imbalances between generation and consumption, capable of depleting both primary and secondary reserves. Market agents shall be obliged to submit daily, within the limits of the the operation process an offer with the entire regulation reserve available, both upward and downward, for the next day. Immediately after the publication of the results of the secondary reserve, and until at 8:00 p.m. on the day prior to the date to which they refer, market agents shall provide to the GSM the information relating to the reserve regulation. The reserve regulation offers shall respect the maximum and minimum value limitations imposed by GSM following the technical validation previously performed. In the event of non-compliance with the amount of the contracted power, the deviations for a time period of 15 minutes shall be considered and these deviations shall be accounted for and must be the responsibility of the market agent that has not complied.

2.2.3.2 The Danish Case

Denmark is operating under the Continental Europe and Nordic power systems rules. Therefore, the provision of ancillary services in Denmark depends on the geographical position and is divided into DK1 (Continental Europe power system) and DK2 (Nordic power system). The operation of ancillary services in DK1 follows similar rules as Portugal, since it belongs to the Continental Europe power system. In the Nordic power system, ancillary services are operated and contracted following different rules. The main ancillary services to be delivered in DK2 are [22]:

- The frequency-controlled normal operation reserve (FCR-N) is designed to maintain the balance between production and consumption in order to keep the frequency close to 50 Hz. It consists of both upward and downward regulation and is provided by a symmetrical reserve where both regulation reserves are procured together. The normal reserve supply shall be activated each time the frequency deviates by +/- 100 mHz from the nominal value. It must be activated within a maximum of 150 seconds and should be supplied linearly. The supplier can submit hourly offers or block bids. Block bids submitted at the auction two days before the day of operation (D-2) may have a duration of up to six hours. Block bids submitted on the day before the operation day (D-1) may have a duration of up to three hours. The player determines the hours at which the block bid starts, however the block bid has to end on the same day of operation. Each bid has a minimum capacity of at least 0,3 MW and is always accepted in its entirely or not at all. For the availability payment to be effected, the capacity must in fact be available. This means that the availability payment is cancelled, and the player must cover any additional costs incurred in connection with cover purchases.

- Frequency-controlled disturbance reserve (FCR-D), exists to cover major system disturbances, so it needs to be fast for regulating the frequency following frequency drops resulting from the outage of major production units. It is an automatic upward regulation reserve provided by production or consumption facilities which respond to frequency deviations. This reserve activation is automatic in the event of drops to under 49.9 Hz and remains active until the balance has been restored or the manual reserve takes over the supply of power. FCR-D must be able to supply non-inverse power at frequencies between 49.9 and 49.5 Hz, supply 50% of the response within 5 seconds and supply the remaining 50% of the response within na additional 25 seconds. A delivery of this service can be made up from several production or consumption units with different characteristics which together can provide the service within the required response time. The procurement of this service is made at daily auctions where part is procured two days before the operation day (D-2) and part is procured one day before the operation day (D-1). As in FCR-N, the supplier can submit bids hourly or as block bids and each one must be entered for a minimum of 0.3 MW. Bids are always accepted in their entirely or not at all.

- Manual reserve, which are also procured in DK1, is a manual upward and downward regulation reserve activated by the control entre. The reserve relieves the FCR-N in the event of minor imbalances and ensures balance in the event of outages or restrictions affecting production facilities and interconnections. These reserves are put up for sale at daily auctions. Manual reserves are requested in DK1 and DK2 to meet the demand during individual hours. The manual reserve is used to restore system balance and should be supplied within 15 minutes after the activation. An auction is held once a day for each of the hours of the coming day of operation.

2.3 Optimization and Control Algorithms

In this section, it is intended to analyse algorithms regarding EVs integration and modelling, either individually or as an aggregator. Different approaches are considered by several authors, some give more prominence to the aggregator's point of view as maximizing the profit, minimizing the battery degradation, respecting minimum SOC levels, and other goals concerning the SO needs, as the voltage control, minimizing losses, operational costs and GHG emissions.

2.3.1 Strategic Offering

In [3] a model is proposed for the participation of an EV aggregator in the reserve market, namely the FCR-N in Denmark. The objective is to increase the aggregator's profit from participating in this type of service and takes into account possible penalties for noncompliance with the contracted reserve provision. The strategic participation is modeled as a two-stage stochastic program. The methodology studied considers both deterministic and stochastic approaches. This work also has the particularity of considering different probabilities of connecting the EV to the grid, so it may or may not be available to provide the service. The results show a better performance when the stochastic methods are considered. It also proves that grid connection can have a big impact on the aggregator's profit, so investments in this field can generate profits and bring greater flexibility to the aggregator.

Han [23] proposes a model to optimize charging variables to participate in reserve market, through dynamic programming techniques. He assumes that the energy required for the next trip is always above the current one, so charging is the only control element. Three variables are assumed: charging sequence, charging duration and charging rate. If the SOC is given as a point rather than as an interval, the charging duration problem is solved, and there is only one problem with two variables. When formulating this optimization, the capacity of the batteries and their weight were taken into account. Through the use of dynamic programming, optimal charging was achieved for all vehicles, which were verified in simulation. This study is a strategic approach for the V2G aggregator. Positive results were also achieved regarding the relationship between the SOC and the revenues achieved.

Kristoffersen [24] defines an optimal charging model for an EV aggregator to participate in the daily market of Nordpool, considering the driving patterns of the fleet and market prices fluctuation through linear and quadratic programming. The goal is to charge the EV at a lower price, and then sell it in V2G, if it pays off. Electricity costs, battery degradation and fuel costs are considered. The results mainly suggest that EVs provide most of the flexibility only through charging, and not by energy storing. It also points that charging process should occur during off-peak hours. However, with a high EV penetration rate, it may raise higher peak loads at this hours, which attenuates profits that the selling could bring.

In [25] the authors use an approach that involves fuzzy optimization in order to model the uncertainties forecasted that occur in the electricity market, mainly prices. The results show the benefits that the application of fuzzy algorithms can bring when compared to deterministic methods that do not consider the market uncertainties. The objective is to maximize the aggregator's revenue by participating in the regulation and spinning reserves market. Both models reduce peak load charging tariffs. Regarding expected revenues, these vary according to the expected SOC, but there is an agreement regarding the models with fuzzy algorithms, since the average profit is always 2 or 3 times higher than expected with the deterministic models.

In [26] author presents a mathematical model for optimal charging and discharging, for spinning reserve market participation. The authors state that EV owners should respect the EV aggregator and not disconnect the EV earlier than planned. To solve the MINLP problem is used a simulated annealing algorithm, in order to increase aggregator profit. The study concludes that low spinning reserve and higher market prices reduce aggregator profit.

In [27], the authors bring forward an optimal bidding strategy of an EV aggregator in day-ahead and reserve market, always considering the perfect forecast of day-ahead energy and regulation prices. It was identified key sources of uncertainty and included in the model which aimed to maximize the profit while providing reliable reserve levels. It concludes the aggregator has a preference for offering downward regulation instead of upward regulation. Costs of EV charging can became profits when the aggregator gets involved in the reserve market and the way the battery is charged is decisive to evaluate the true capability of the aggregator's market participation. Ortega-Vasquez [28] proposes a similar model, however, it compensates EV owners for battery degradation. It was implemented as a Mixed-Integer Programming (MIP) and guarantees to the system operating cost savings from its participation in reserve markets. The results prove the aggregator benefits from reserve more than the energy market as it obtains revenue for providing regulation without battery degradation. Furthermore, it affords a comparison with battery costs in the future, expected to decrease, which will raise aggregator's revenue and reduce system operating costs.

In [29] is investigated the design and performance of a system that would enable EV aggregator to participate in wholesale electricity markets including intraday and pay-as-bid reserve markets that require exact reserve delivery and have long operating intervals. The main goal is to maximize the reserve provision while making sure there are enough energy for the trips. It brings forward new ideas for achieving control of flexible loads with uncertain behaviour subject to restrictive rules, concluding that the more flexible markets became, the more profit aggregators can get through EV charging.

In [30], the flexibility of EV aggregator charging is studied in order to avoid forecasting errors. In this way, it is possible to participate in the reserve manual market. The aggregator has direct control over the EVs charging, however in this work it is not considered the V2G mode, the aggregator only provides reserve through the increase or decrease of the charging rate. The objective function is the minimization of the total cost divided in three components: cost of purchasing energy in the energy market, cost from charging EV with downward reserve and income from reducing the consumption (upward reserve). The results show that the participation of the aggregator in the reserve market may represent a reduction of its wholesale costs. The authors suggest that this cost reduction may help to attract new customers or increase the profit from retail activity.

In [31] it is proposed an risk-averse optimal bidding strategy of an EV aggregator in a frequency regulation market, under the rules of CAISO. The objective is to determine the optimal offer to be submitted in the market. The problem is formulated as Mixed-Integer Programming (MIP) and takes into account the uncertainties in the price of energy and frequency regulation. The objective function of this model also includes the degradation of the battery caused by the provision of the service. The objective of the proposed methodology is to maximize the aggregator's profits. The results prove that it is indeed possible to reduce battery degradation if the energy dispatch is optimal.

In [32] it is proposed that an EV aggregator participates in the reserve market. This formulation takes into account the uncertainty in the availability of EVs to provide the service. Optimum load and price levels are also developed. Comparisons are also made between unidirectional and bidirectional V2G. The results point to a slightly better performance of bidirectional V2G, however this also implies higher costs and consequently higher risks. Furthermore, with the prediction of EV saturation in the future, the authors recommend the use of unidirectional V2G.

2.3.2 EVs Energy Scheduling

In [33] the authors use a MIP, since linear and integer variables are introduced into the problem of EV charging coordination in an unbalanced distribution network. The formulation was applied to a distribution network, considering the limits in the magnitude of voltages and currents. It was also assumed that the batteries should be charged in a certain period of time, the energy required by the battery is known at the beginning of each period and that the EV had communication devices that allowed the DSO to control the battery SOC. Tests have shown that this model has a reduced error level and that approximations are acceptable, so the MIP can be applied to solve this type of problem.

In [34] stochastic and deterministic methods for optimizing hybrid vehicle charging plug-in are compared. The impacts that these extra loads imply on power losses and voltage deviations are analyzed. Both winter load profiles and summer load profiles for whole days divided into 15 minutes intervals are studied in the Belgian electrical system, and all loads are considered residential. Generally, the differences between the stochastic and deterministic losses are quite small, which means that load forecasting errors do not have much influence on the losses. It is possible to verify also a decrease of losses when the load is controlled, mainly due to the decrease of power required in peak hours.

Other authors focus their work on developing stochastic models to simulate the availability of EVs to provide services to the network [35]. Fluhr uses the Monte-Carlo method to create the probability distribution of the EV trip. The results show that EVs are parked more than 90% of the time, which makes it beneficial to build residential charging infrastructure. In [36] a technique for the sustainable integration of PHEVs is proposed, considering the most significant uncertainties. Robust optimization is used in order to evaluate the risk levels of the introduction of Plug-in Hybrid Electric Vehicles (PHEVs) in the transport sector. Others [37] use normal and Poisson distribution to determine the probability of charging times and initial battery states. This work, performs case studies to analyse intelligent charging algorithms for large amounts of PHEVs using Monte Carlo method.

Sundstrom and Binding [38] describe a model to minimize charging costs and achieve satisfactory SOC levels through deterministic methods. They compare linear and quadratic approximations to represent battery behaviour. The results indicate that linear approximation is sufficient when the focus is on optimizing the charging schedule. Battery limit violations are always less than 2% of their capacity when linear approximation is used, so the computational effort used by quadratic approximation is not justified.

In [39] a modified model of Particle Swarm Optimization (PSO) is presented to solve the problem that high penetration of distributed generation and EVs raises, with the possibility of V2G. The aim is to reduce operating costs. The optimization consists in the inclusion of mechanisms that adjust the speed limits during the search process, thereby becoming more independent. The authors argue that it has greater robustness, faster convergence and greater ability to deal with constraints when compared to the PSO, which gives it the ability to solve large-scale problems efficiently. A real network is the target of study. With the increase in penetration there is also a huge increase in computational execution time with with the deterministic method, which is a MINLP model. With 2000 EVs, the deterministic method took about 25 hours to obtain the solution, while the modified PSO presented a solution in 36 seconds, where the cost is only 1% higher than the deterministic method.

An information gap decision theory is proposed in [40] to manage revenue risk of the aggregator, due to the gap between the forecast and the real electricity prices. The model guarantees a profit for risk-averse decision makers and for risk-seeking decision makers, where travel behaviours are simulated using the Monte Carlo method. The decision maker can choose between robustness and opportunity functions based on the risk he is willing to take on the market.

2.3.3 Operation and Control of EVs in the Network

Sundstrom and Binding [41] describe basic aggregator's functions regarding optimization problems, considering grid constraints as voltages and power flow. An individual charging schedule is defined for each vehicle, in order to avoid distribution grid congestion. Two essential variables are considered, namely the forecast of minimum energy for the next trip and the moment it will happen. It is assumed that the information might be inaccurate, leading to prudent approaches, guaranteeing error margins. Linear programming is used to characterize SOC and to formulate the charging process, finding the optimal solution that minimizes battery charge. This model present disadvantages and limitations: error margins may not be the solution that minimizes cost, since high penalties will be applied; this method handles individual EV loads and does not act as an aggregator that could reduce forecasting errors; it is also necessary to predict arrival time, which introduces computational complexity [42].

Rotering and Ilic [43] propose and discuss the problem that EV charging can cause during peak hours, in particular, overloads. Two algorithms are analysed based on predicting future electricity costs and using dynamic programming to find the optimal solution for the EV owner. Both algorithms consider that the forecast is ideal for both the EV variables and the demand for reserve. The first optimizes charging time and energy flow, with the intention to reduce the daily cost of electricity without damaging the battery. The second also takes into account the support that the EV can give to the grid, always taking into consideration the technical constraints of the grid, by participating in ancillary services, namely in the secondary reserve market. The proposed models are implemented under the rules of CAISO. The results shows that smart charge timing reduces daily electricity costs for driving from \$0.43 to \$0.2. It also states that provision of regulating power improves PHEV economics.

2.3.4 Overview of Optimization and Control Algorithms

The table 2.1 summarises the information from the previous sections. The most important one was considered such as the problem that the authors intend to solve, the main objective of the optimization and the class on which the proposed methodology is based.

Table 2.1: Overview of state of the art studies.

Ref.	Problem	Objective	Problem Class
[3]	Strategic Offering	Maximize aggregator's profit	Stochastic and deterministic methods
[23]	Strategic Offering	Maximize aggregator's profit	Stochastic method
[24]	Strategic Offering	Minimize total operation costs	Analytical method
[25]	Strategic Offering	Maximize aggregator's profit	Stochastic method
[26]	Strategic Offering	Maximize aggregator's profit	Metaheuristic method
[27]	Strategic Offering	Maximize aggregator's profit and reliable reserve provision	Stochastic method
[28]	Strategic Offering	Maximize aggregator's profit without battery degradation	Stochastic method
[29]	Strategic Offering	Maximize reserve provision	Metaheuristic method
[30]	Strategic Offering	Minimization of the total cost	Analytical method
[31]	Strategic Offering	Maximize aggregator's profit	Stochastic method
[32]	Strategic Offering	Maximize aggregator's profit	Deterministic method
[33]	EVs Energy Scheduling	Minimize the energy cost of EV charging	Stochastic method
[34]	EVs Energy Scheduling	Minimize the power losses	Stochastic and deterministic methods
[35]	EVs Energy Scheduling	Define Evs availability	Stochastic method
[36]	EVs Energy Scheduling	Minimize the present value of the net electricity and emission costs	Deterministic method
[37]	EVs Energy Scheduling	Optimally allocate the power energy to PHEVs	Stochastic method
[38]	EVs Energy Scheduling	Minimize charging costs	Deterministic method
[39]	EVs Energy Scheduling	Minimize operation costs	Metaheuristic and deterministic method
[40]	EVs Energy Scheduling	Manage the revenue risk of the	Analytical method
[41]	Operation and Control of EVs in the Network	Avoid distribution grid congestion	Stochastic method
[43]	Strategic Offering, Evs Energy Scheduling, Operation and Control of Evs in the Network	Optimizing the charging time and energy flows; Maximize aggregator's profit	Analytical method

Chapter 3

EV Aggregator Market Model

This chapter details the strategic offering problem. The relationship between the aggregator and the market agents is assessed. It also describes the model proposed and implemented regarding the mathematical formulation of the problem with chance-constrained programming. In addition, it also exposes the reformulation of the problem by the deterministic equivalent through the Big-M and McCormick methods.

3.1 Architecture

An aggregator has the ability to control a set of EVs, i.e., it directly controls the charging patterns of EVs promoting smart charging. The vehicles only need an interface to provide information such as: SOC, EV type, power and battery capacity, charging characteristics and departure time. Thus, the energy required for the next trip is ensured within a time interval, giving to the EV aggregator the possibility to take control in the charging process during this period.

The TSO seeks to balance generation and load, and maintain frequency at nominal values, and EVs are a potential provider of these services as they are flexible and have quick response times. It would be a complex task if the TSO receives information from hundreds of thousands of vehicles, so communication should be bi-directional. As depicted in Figure 3.1: to make this relationship work, information must be exchanged between the aggregator and the EV. Thus, the EV should provide information on consumption, EV status, SOC, EV type, battery capacity, power capacity and charging characteristics. A communication between the aggregator and the TSO is also required, namely to inform about the balancing signal, seeling bid and market prices. Therefore, the aggregator is able to gather all this information and make its participation in the reserve market as effective as possible, increasing profits.

The TSO sends a signal of the reserve imbalance to the aggregator at each point in time, and the aggregator handles this information and distributes the necessary energy to the vehicles that are willing to provide the service in that period. Afterwards, the aggregator is able to predict the available energy to meet the TSO requirement, and therefore informing the TSO by offering in the market.

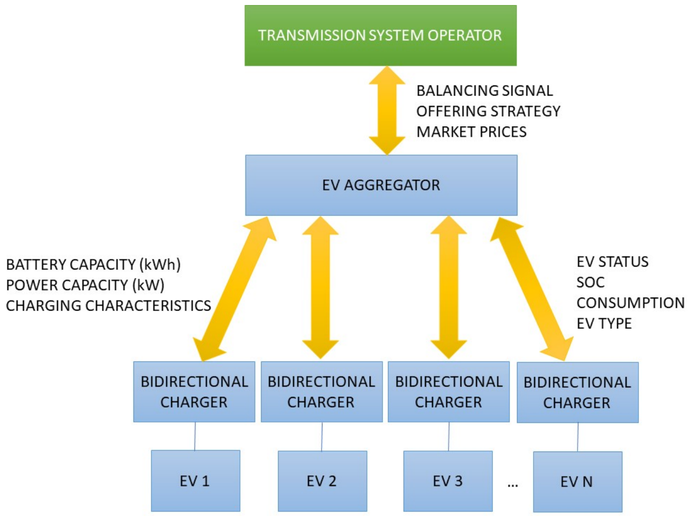

Figure 3.1: Schematic structure of EV participation in ancillary services.

The aggregator responds to TSO requests by participating in the ancillary services market. The TSO is responsible for the system services market and selects the best offers from aggregators. Thereafter, the aggregators activate the EVs so they can respond to the TSO signal. The bi-directional charging will allow the vehicles to adjust according to the aggregator requests imposed by the TSO, allowing them to provide upward and downward regulation. In return, the EV owner is economically compensated. The EVs owners' firm contract with the aggregator that offers better tariff. The aggregator works as an electricity retailer, representing EVs drivers in the electricity market, allowing to split the electricity price for this purpose and the inclusion of taxes from the government [42].

The aggregator aims to manage the fleet of EVs taking into account the individual needs of each vehicle, optimizing its bidding strategy in the reserve market. The aggregator operates as a price-taker, i.e. it accepts prevailing prices in the market and cannot influence or dictate its prices. This concept focuses on the needs of the aggregator, but it can also be extended and seen from the point of view of the EV individually.

It is important to consider that the main purpose of the EV remains to ensure the normal travel of users and only then to provide reserve services. Despite the evolution of the methods used to forecast drivers' behaviour and the existing databases, this prediction is always a complicated task and will remain subject to errors, so the only uncertainty of this problem is the energy trip. The SOC and the probability that the EV is plugged to the grid are considered parameters. In this way, it is possible to formulate the problem stochastically, since there is randomness present. In order to represent this randomness, a set of variables values are defined with a certain deviation, positive or negative, and then an equal probability is applied to them. In doing so, more possibilities will be covered and the response that the aggregator can provide will be better. This leads to the implementation of the chance-constrained approach, which is one of the ways of analyzing the risk of strategic offerings, considering uncertainty.

3.2 Offering Strategy Through Chance-Constrained Approach

One of the biggest current challenges is related to the resolution of large-scale problems, the chance-constrained method is one of the biggest approaches used in stochastic optimization problems, with a high uncertainty level. Essentially, it constrains a number of more unlikely scenarios, so that the decision-maker can choose the level of reliability and risk that wishes and considers to be adequate. Usually, this type of solution is robust, but in real dimension problems it can become difficult to solve. The usual formulation for this type of problem is as follows:

$$\min f(x,\xi) \tag{3.1}$$

s.t:

$$g(x,\xi) = 0 \tag{3.2}$$

$$h(x,\xi) \geq 0 \tag{3.3}$$

where x is the decision vector, ξ is the uncertainty vector, g represents the equality constraints and h the inequality constraints. Applying the chance-constrained method, the equality constraint is represented as [44]:

$$P(g(x,\xi) = 0) \geq 1 - \varepsilon \tag{3.4}$$

where ε represents the the risk to be defined by the decision-maker.

The chance-constrained programming is solved in several different ways. One of the solutions may involve reformulation and resolution by the equivalent deterministic problem. This problem can be derived through the Big-M method or through bilinear reformulation. Within the Big-M method, a binary variable is used indicating whether the associated scenario should be considered or may be violated, and thus the problem is converted into an MIP. Within the bilinear reformulation approach, the constraint becomes bilinear, which is a particular case of nonlinear constraints. Therefore, the McCormick relaxation method is used to relax the nonlinear constraint, turning it convex and linear [45].

3.2.1 Big-M Method

Equation 3.4 can be converted through the Big-M method as follows:

$$-Mz_{(t,\omega)} \leq g(x,\xi) \leq Mz_{(t,\omega)}, \forall\, t \in T; \forall \omega \in \Omega \tag{3.5}$$

$$\sum_{\omega}^{\Omega} \pi_{(t,\omega)} z_{(t,\omega)} \leq \varepsilon, z_{(t,\omega)} \in \{0,1\}, \forall\, t \in T \tag{3.6}$$

where $z_{(t,\omega)}$ represents the binary variable representing whether or not the scenario is active; M represents the Big-M parameter, which should be sufficiently large; ε represents the pre-defined risk, defined by the decision-maker.

3.2.2 McCormick Envelopes

The McCormick envelopes is a technique used to relax non-convex and non-linear functions using the boundaries of the variables. This relaxation can find solutions faster and with less computational effort, however the solution is not the optima of the original problem. It is important to choose a relaxation that has tightest bounds, in order to have limits that are closer to the ideal solution [46]. This relaxation consists of setting up four linear lines that create an approximate solution space to the function space, as depicted in figure 3.2.

Considering a bilinear function *w=xy*, then the relaxation of function w is given by:

$$w \geq x^L y + x y^L - x^L y^L \tag{3.7}$$

$$w \geq x^U y + x y^U - x^U y^U \tag{3.8}$$

$$w \leq x^U y + x y^L - x^U y^L \tag{3.9}$$

$$w \leq x y^U + x^L y - x^L y^U \tag{3.10}$$

where x^U and y^U are the upper bounds for x and y; x^L and y^L are the lower bounds for x and y, respectively. The equations 3.7 and 3.8 represent underestimators and 3.9 and 3.10 overestimators.

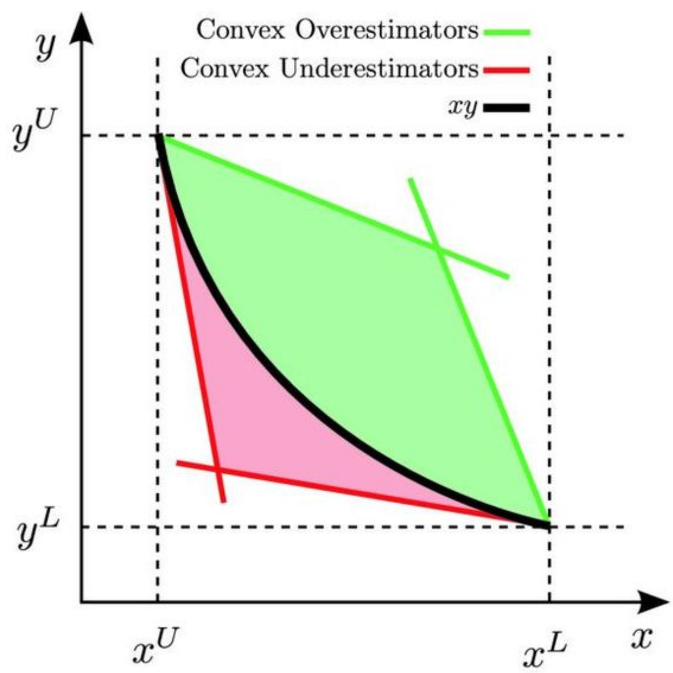

Figure 3.2: Representation of McCormick Envelopes.

3.3 Problem Description and Mathematical Formulation

This work focuses on the participation of an electric vehicle aggregator in the reserve market, namely in FCR-N in Eastern Denmark, according to the rules of the Nordic power system, where symmetric offering for upward and downward reserve is considered, as in [3]. This study considers the uncertainty in the energy trip and consequently in the SOC. It also features the particularity of modeling the probabilities of EVs being connected, but for some reason not being able to provide the service, for example due to misconnections or other reasons, and the probabilities being plugged-in and available to provide the service. The goal is to maximize the aggregator's profit by participating in the reserve market at day-ahead stage, taking into account that it can suffer penalties for energy not supplied in real-time stage.

The main objective is to maximize the profit EV aggregator gets by participating in the FCR-N. The strategic offering problem of the EV aggregator is modelled as a two-stage stochastic chance-constrained problem. The first-stage includes the optimal reserve bid to offer in the reserve market, and the second-stage models the activation of reserve and its associated imbalance costs. Thus, the objective function to be maximized is presented in 3.11, and combines the revenues at the day-ahead and real-time stages. The real-time stage considers the expected costs of failing to provide the service.

$$\max rev^{DA} + rev^{RT} \tag{3.11}$$

The day-ahead stage is given by the capacity payment λ of upward and downward reserve offered by the aggregator, in each time step t, as in 3.12

$$rev^{DA} = \sum_{t=1}^{T} \left(\lambda_t^{UP} R_t^{UP} + \lambda_t^{DW} R_t^{DW}\right) \tag{3.12}$$

Real-time stage remuneration takes into account revenues for service activation and penalties for reserve supply failures, both upward and downward, as can be seen in 3.13. It includes $RLXU$ and $RLXD$ variables that represent the amount of power that was not provided for the ω scenario of the Ω set, but was offered in the day-ahead. The discharge of energy is assumed zero, because this study does not consider the participation in the energy service.

$$\begin{aligned} rev^{RT} = \sum_{t=1}^{T}\sum_{\omega=1}^{\Omega} \pi_\omega \Bigg[& -\lambda_t^{UP,pnlt} RLXU_{(t,\omega)} - \lambda_t^{DW,pnlt} RLXD_{(t,\omega)} + \lambda_t^{sp} \sum_{ev=1}^{EV} (P^E_{Dch(ev,t,\omega)} \\ & - P^E_{Ch(ev,t,\omega)} + P^{UP}_{Dch(ev,t,\omega)} + P^{UP}_{Ch(ev,t,\omega)}) - P^{DW}_{Dch(ev,t,\omega)} - P^{DW}_{Ch(ev,t,\omega)}) \Bigg] \end{aligned} \tag{3.13}$$

The objective function is subject to several constraints related to technical limitations from the first-stage, second-stage and from the way aggregator can use each vehicle.

Equations 3.14 and 3.15 limit the upward and downward power that the aggregator can provide in the reserve service. This equation includes a binary variable stating whether the aggregator is willing to participate in the reserve market at each time step. It cannot be higher than the total capacity of the entire fleet or lower than a certain minimum.

$$P^{UP,Min}Y_t \leq R_t^{UP} \leq P^{UP,Max}Y_t, \forall t \in T \tag{3.14}$$

$$P^{DW,Min}Y_t \leq R_t^{DW} \leq P^{DW,Max}Y_t, \forall t \in T \tag{3.15}$$

3.16 requires that the aggregator's participation in the reserve market is symmetrical according to FCR-N rules, i.e., upward and downward bids must have both the same value.

$$R_t^{UP} = R_t^{DW}, \forall t \in T \tag{3.16}$$

The constraints 3.17 and 3.18 limit the the activation of reserve in the second-stage according to the offer made in the first-stage, for each t in any scenario.

$$r_{(t,\omega)}^{UP} \leq R_t^{UP}, \forall t \in T; \forall \omega \in \Omega \tag{3.17}$$

$$r_{(t,\omega)}^{DW} \leq R_t^{DW}, \forall t \in T; \forall \omega \in \Omega \tag{3.18}$$

The balance between the system's needs and the availability of the aggregator to supply the contracted upward and downward reserve is presented in equation 3.19. The value of the system needs can be positive or negative and is dependent on the aggregator's willingness to provide the service at each time. The RLXU and RLXD variables represent the relaxation of the balancing equation, in cases the power available in the EVs being insufficient to provide what aggregator have promised at the day-ahead stage.

$$Pr\left(\Delta SI_{(t,\omega)} Y_t = r_{(t,\omega)}^{DW} - r_{(t,\omega)}^{UP} + RLXD_{(t,\omega)} - RLXU_{(t,\omega)}, \forall t \in T; \forall \omega \in \Omega \right) \geq 1 - \varepsilon \tag{3.19}$$

The equations 3.20 and 3.21 consider the availability of each vehicle for the activation of the upward and downward reserve in each period t and scenario ω. The activation of the EVs can lead to either increase or decrease the actual charging and discharging power of the EVs battery.

$$r_{(t,\omega)}^{UP} = \sum_{ev=1}^{EV} \pi_{(ev,t)}^{plugged} \left(P_{Dch(ev,t,\omega)}^{UP} + P_{Ch(ev,t,\omega)}^{UP} \right), \forall\, t \in T; \forall \omega \in \Omega \tag{3.20}$$

$$r_{(t,\omega)}^{DW} = \sum_{ev=1}^{EV} \pi_{(ev,t)}^{plugged} \left(P_{Dch(ev,t,\omega)}^{DW} + P_{Ch(ev,t,\omega)}^{DW} \right), \forall\, t \in T; \forall \omega \in \Omega \tag{3.21}$$

Equations 3.22 and 3.25 denote that each vehicle may not reduce its charging power in upward service if it is not charging in the power service, nor reduce its discharging power if it is not discharging in the power service. Equations 3.23 and 3.24 indicate that each vehicle has an upper charging and discharging limit, according to its characteristics. It also states that the charging and discharging ability of the EVs cannot occur at the same period t. That is, the EV cannot charge and discharge in the same period, and this is controlled by the binary variable X.

$$P^{E}_{Ch(ev,t,\omega)} \geq P^{UP}_{Ch(ev,t,\omega)}, \forall t \in T; \forall \omega \in \Omega; \forall ev \in EV \tag{3.22}$$

$$P^{E}_{Ch(ev,t,\omega)} + P^{DW}_{Ch(ev,t,\omega)} \leq P^{Max}_{Ch(ev,t)} \left(1 - X_{(ev,t,\omega)}\right), \forall t \in T; \forall \omega \in \Omega; \forall ev \in EV \tag{3.23}$$

$$P^{E}_{Dch(ev,t,\omega)} + P^{UP}_{Dch(ev,t,\omega)} \leq P^{Max}_{Dch(ev,t)} X_{(ev,t,\omega)}, \forall t \in T; \forall \omega \in \Omega; \forall ev \in EV \tag{3.24}$$

$$P^{E}_{Dch(ev,t,\omega)} \geq P^{DW}_{Dch(ev,t,\omega)} \forall t \in T; \forall \omega \in \Omega; \forall ev \in EV \tag{3.25}$$

In addition, the SOC of each vehicle is determined in 3.26. In this equation the previous SOC, the energy of each trip and its participation in the reserve market is taken into account for each ω scenario and each t time interval, accounting for the charging and discharging efficiency.

$$\begin{aligned} Pr(SOC_{(ev,t,\omega)} = SOC_{(ev,t-1,\omega)} - E_{Trip(ev,t,\omega)} + \Delta t \eta_{Ch(ev)} \left(P^{E}_{Ch(ev,t,\omega)} - P^{UP}_{Ch(ev,t,\omega)} + P^{DW}_{Ch(ev,t,\omega)}\right) \\ - \frac{\Delta t}{\eta_{Dch(ev)}} (P^{E}_{Dch(ev,t,\omega)} - P^{UP}_{Dch(ev,t,\omega)} + P^{DW}_{Dch(ev,t,\omega)})) \leq 1 - \varepsilon, \forall t \in T; \forall \omega \in \Omega; \forall ev \in EV \end{aligned} \tag{3.26}$$

In 3.27 the upper and lower battery limits for each EV are set.

$$SOC^{Min}_{(ev,t)} \leq SOC_{(ev,t,\omega)} \leq SOC^{Max}_{(ev,t)}, \forall t \in T; \forall \omega \in \Omega; \forall ev \in EV \tag{3.27}$$

The constraint 3.28, illustrates the stochastic process that represents the energy for the trip of each vehicle, and represents the only uncertainty in this model.

$$E_{Trip(ev,t,\omega)} = E^{Forecast}_{Trip(ev,t)} + \Delta E_{Trip(ev,t,\omega)}, \forall t \in T; \forall \omega \in \Omega; \forall ev \in EV \tag{3.28}$$

The equation 3.29 states that at the end of the simulated day the SOC of each vehicle must be between 65 and 85% of the maximum SOC in order to ensure driving needs or market participation in the next hour of the following day.

$$0.65 SOC^{Max}_{(ev,t)} \leq SOC_{(ev,t,\omega)} \leq 0.85 SOC^{Max}_{(ev,t)}, \forall t \rightarrow end; \forall \omega \in \Omega; \forall ev \in EV \tag{3.29}$$

3.4 Bilinear Reformulation of the Chance-Constrained Problem

The reformulation of the chance-constrained problem through the deterministic equivalent can be performed through the Big-M and McCormick approaches, as explained in the section 3.2. Through the Big-M method, one can introduces a binary variable to the chance-constrained equations 3.19 and 3.26. Therefore, both 3.19 and 3.26 can be reformulated as follows [45]:

$$-Mz_{(t,\omega)} \leq -\Delta SI_{(t,\omega)}Y_t + r^{DW}_{(t,\omega)} - r^{UP}_{(t,\omega)} + RLXD_{(t,\omega)} - RLXU_{(t,\omega)} \leq Mz_{(t,\omega)}, \forall\, t \in T; \forall \omega \in \Omega \tag{3.30}$$

$$\begin{aligned} -Mz_{(t,\omega)} \leq\; & -SOC_{(ev,t,\omega)} + SOC_{(ev,t-1,\omega)} - E_{Trip(ev,t,\omega)} + \Delta\, t\eta_{Ch(ev)} \Big(P^{E}_{Ch(ev,t,\omega)} - P^{UP}_{Ch(ev,t,\omega)} \\ & + P^{DW}_{Dch(ev,t,\omega)}\Big) - \frac{\Delta t}{\eta_{Dch(ev)}} (P^{E}_{Dch(ev,t,\omega)} - P^{UP}_{Dch(ev,t,\omega)} + P^{DW}_{Dch(ev,t,\omega)}) \leq Mz_{(t,\omega)}, \\ & \forall t \in T; \forall \omega \in \Omega; \forall ev \in EV \end{aligned} \tag{3.31}$$

$$\sum_{\omega}^{\Omega} \pi_{(t,\omega)} z_{(t,\omega)} \leq \varepsilon, z_{(t,\omega)} \in \{0,1\}, \forall\, t \in T \tag{3.32}$$

where z represents the binary variable. When z=0, the constraints 3.19 and 3.26 assume their original form. When z=1, the same constraints are ignored, meaning that can be violated. For good performance of this relaxation method, the Big-M parameter (M) should be large enough [45]. Equation 3.33 is able to constrain the number of scenarios in which z will take the value 1, based on the control parameter ε defined by the decision-maker. The use of the Big-M method is usually associated with issues such as determining the M-parameter value, without compromising the validity of the constraints. Usually it is also associated with a decrease in computational efficiency, being linked to long times of computational effort.

Another approach of reformulating the chance-constrained problem is through the bilinear reformulation [45]. Thus, equation 3.19 can be reformulated through

$$(-\Delta SI_{(t,\omega)}Y_t + r^{DW}_{(t,\omega)} - r^{UP}_{(t,\omega)} + RLXD_{(t,\omega)} - RLXU_{(t,\omega)})(1 - z_{(t,\omega)}) = 0, \forall\, t \in T; \forall \omega \in \Omega \tag{3.33}$$

$$\sum_{\omega}^{\Omega} \pi_{(t,\omega)} z_{(t,\omega)} \leq \varepsilon, z_{(t,\omega)} \in \{0,1\}, \forall\, t \in T \tag{3.34}$$

Here, the same logic is applied as for the Big-M method. When z=0 the restrictions 3.19 and 3.26 take their original form. When z=1 all constraint is multiplied by zero, thus becoming an non-responsive scenario.

This reformulation makes the problem nonlinear, since equation 3.33 is a bilinear equation. The bilinear equation can be linearized through the McCormick envelopes [46], where it is possible to convert it back into an MIP. Therefore, equation 3.33 can be rewritten as:

$$\begin{aligned} & (-\Delta SI_{(t,\omega)}Y_t + \Delta SI_{(t,\omega)}\tilde{Y}_t) + r^{DW}_{(t,\omega)} - r^{\tilde{DW}}_{(t,\omega)} - r^{UP}_{(t,\omega)} + r^{\tilde{UP}}_{(t,\omega)} + RLXD_{(t,\omega)} \\ & - RLX\tilde{D}_{(t,\omega)} - RLXU_{(t,\omega)} + RLX\tilde{U}_{(t,\omega)} = 0, \forall\, t \in T; \forall \omega \in \Omega \end{aligned} \tag{3.35}$$

where,

$$\tilde{Y}_t = Y_t z_{(t,\omega)} \tag{3.36}$$

$$r^{\tilde{DW}}_{(t,\omega)} = r^{DW}_{(t,\omega)} z_{(t,\omega)} \tag{3.37}$$

$$r^{\tilde{UP}}_{(t,\omega)} = r^{UP}_{(t,\omega)} z_{(t,\omega)}; \tag{3.38}$$

$$RLX\tilde{D}_{(t,\omega)} = RLXD_{(t,\omega)} z_{(t,\omega)}; \tag{3.39}$$

$$RLX\tilde{U}_{(t,\omega)} = RLXU_{(t,\omega)} z_{(t,\omega)}; \tag{3.40}$$

Each of the equations 3.36, 3.37, 3.38, 3.39 and 3.40 is linearized as in equations 3.7, 3.8, 3.9 and 3.10:

- Equation 3.36 is replaced by:

$$\tilde{Y}_t \geq 0 \tag{3.41}$$

$$\tilde{Y}_t \geq Y^{max} z_{(t,\omega)} + Y_t z^{max} - Y^{max} z^{max} \tag{3.42}$$

$$\tilde{Y}_t \leq Y^{max} z_{(t,\omega)} \tag{3.43}$$

$$\tilde{Y}_t \leq Y_t \tag{3.44}$$

- Equation 3.37 is replaced by:

$$r^{\tilde{DW}}_{(t,\omega)} \geq r^{DW,min} z_{(t,\omega)} \tag{3.45}$$

$$r^{\tilde{DW}}_{(t,\omega)} \geq r^{DW,max} z_{(t,\omega)} + r^{DW}_{(t,\omega)} - r^{DW,max} \tag{3.46}$$

$$r^{\tilde{DW}}_{(t,\omega)} \leq r^{DW,max} z_{(t,\omega)} \tag{3.47}$$

$$r^{\tilde{DW}}_{(t,\omega)} \leq r^{DW}_{(t,\omega)} + r^{DW,min} z_{(t,\omega)} - r^{DW,min} \tag{3.48}$$

- Equation 3.38 is replaced by:

$$r^{\tilde{UP}}_{(t,\omega)} \geq r^{UP,min} z_{(t,\omega)} \tag{3.49}$$

$$r^{\tilde{UP}}_{(t,\omega)} \geq r^{UP,max} z_{(t,\omega)} + r^{UP}_{(t,\omega)} - r^{UP,max} \tag{3.50}$$

$$r^{\tilde{UP}}_{(t,\omega)} \leq r^{UP,max} z_{(t,\omega)} \tag{3.51}$$

$$r^{\tilde{UP}}_{(t,\omega)} \leq r^{UP}_{(t,\omega)} + r^{UP,min} z_{(t,\omega)} - r^{UP,min} \tag{3.52}$$

- Equation 3.39 is replaced by:

$$RLX\tilde{D}_{(t,\omega)} \geq RLXD^{min}_{(t,\omega)} z_{(t,\omega)} \tag{3.53}$$

$$RLX\tilde{D}_{(t,\omega)} \geq RLXD^{max} z_{(t,\omega)} + RLXD_{(t,\omega)} - RLXD^{max} \tag{3.54}$$

$$RLX\tilde{D}^{UP}_{(t,\omega)} \leq RLXD^{max} z_{(t,\omega)} \tag{3.55}$$

$$RLX\tilde{D}_{(t,\omega)} \leq RLXD_{(t,\omega)} + RLXD^{min} z_{(t,\omega)} - RLXD^{min} \tag{3.56}$$

- Equation 3.40 is replaced by:

$$RLX\tilde{U}_{(t,\omega)} \geq RLXU^{min}_{(t,\omega)} z_{(t,\omega)} \tag{3.57}$$

$$RLX\tilde{U}_{(t,\omega)} \geq RLXU^{max} z_{(t,\omega)} + RLXU_{(t,\omega)} - RLXU^{max} \tag{3.58}$$

$$RLX\tilde{U}_{(t,\omega)} \leq RLXU^{max} z_{(t,\omega)} \tag{3.59}$$

$$RLX\tilde{U}_{(t,\omega)} \leq RLXU_{(t,\omega)} + RLXU^{min} z_{(t,\omega)} - RLXU^{min} \tag{3.60}$$

Chapter 4

Case Study

This chapter presents the analysis of the methodology proposed in chapter 3. The aim is to analyze the behavior of the proposed model considering a wide range of cases. These cases comprise a set of simplified and complex studies covering different scenarios for the aggregator.

4.1 Data Description

The case study is based on a real case, comprising the fleet of EVs from the Frederiskberg Forsyning utility company within the scope of the PARKER project [47]. 10 EVs were considered, namely Nissan e-NV200 vans. 10 ENEL V2G charging units were used to charge and discharge the EVs. Each ENEL charging unit has a capacity of 10kW, with a total sum of 100 kW, which already allows the participation of the aggregator in the reserve market.

Further information of the EVs is shown in the table 4.1.

Table 4.1: Electric vehicles characteristics.

Battery capacity (kWh)	21
Minimun SOC level (kW)	6.3
Maximum charge/discharge (kW)	10
Minimum charge/discharge (kW)	0
EV charge/discharge efficiency (%)	88

It is worth mentioning that the minimum SOC of each battery, for any period, was defined as 30% of its maximum capacity. The SOC of the last period for each EV of one-day simulation is used as the previous state for the next day simulation, guaranteeing the continuity of the results.

In the table 4.2, it is possible to find information regarding market prices for energy, upward and downward reserve, as well as upward and downward deficit penalties. These data were obtained from Energinet.dk website [48] and are for the period from 1 to 31 January 2017 in East Denmark. The penalties for lack of contracted reserves were assumed to be 100 times higher than the upward and downward reserve prices. The figure 4.1 depicts these prices for the first week.

Table 4.2: Upward and downward offers characteristics.

Electric Vehicle Aggregator	**Min**	**Mean**	**Max**
Power offer limits (kW)	40	-	100
Upward price (€/kW)	3.7	46.1	221.5
Downward price (€/kW)	3.7	40.4	108.5
Spot price (€/kW)	-6.3	33.9	117.1
Upward deficit penalty (€/kWh)	370	461	2215
Downward deficit penalty (€/kWh)	370	404	1085

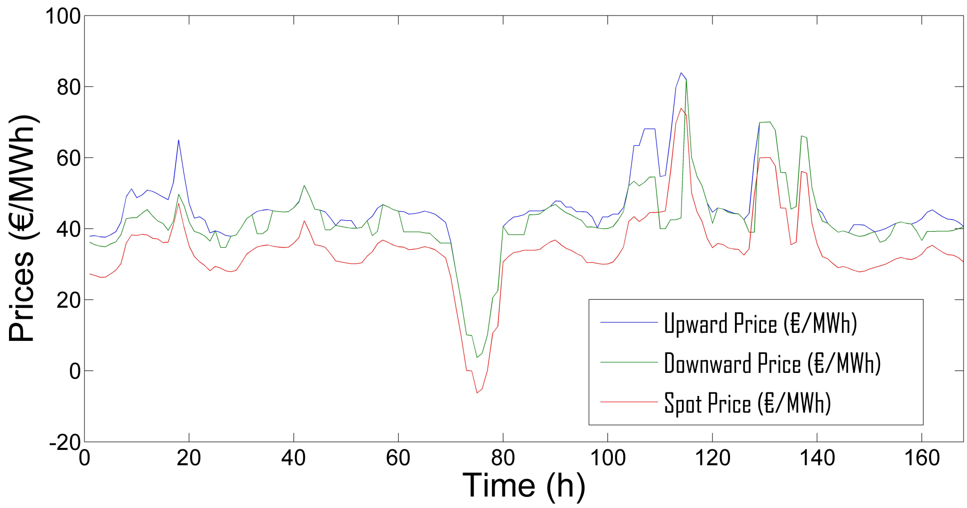

Figure 4.1: Market Prices considered for one week.

In this study, two distinct probabilities are considered for the connection to the grid by the EVs. One represents the probability that the vehicle is connected to the grid, but may not be available to provide the service, $\pi^{plugged}$. The other, $\pi^{available}$, represents the probability of the vehicle being connected to the grid and ready to provide the service. Figure 4.2 illustrates the distribution of these probabilities for the first week.

The TSO imbalance signal is the expected amount of power that the EV aggregator must provide in each period in a given scenario. This signal is based on a normal distribution and includes information on four months of upward and downward reserve provision, capturing the needs trend in the Danish system. In figure 4.3 it is possible to observe this signal for a period of one week. Regarding the parameter presented in equation 3.28, $\Delta E_{Trip(ev,t,\omega)}$, representing EV trip deviation of each scenario, was also based on a normal random distribution.

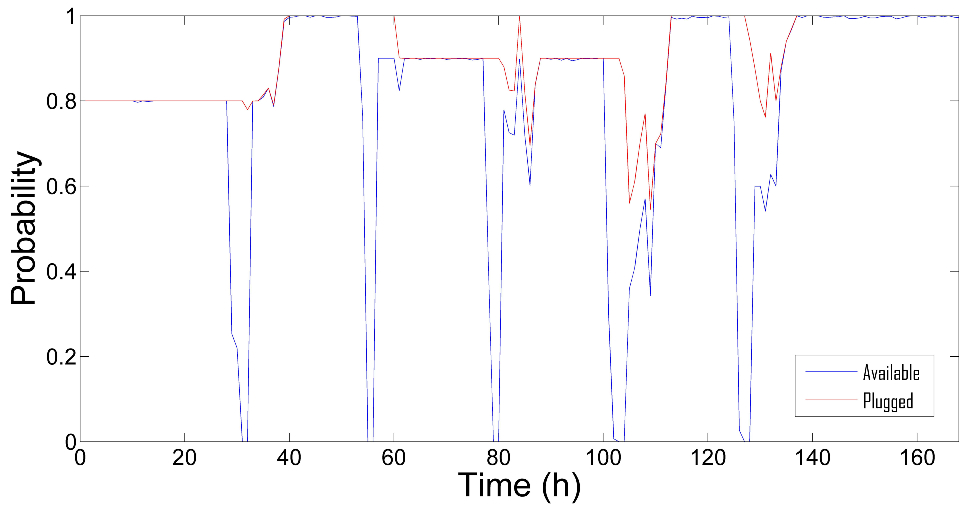

Figure 4.2: Available probability vs. Plugged probability for one week.

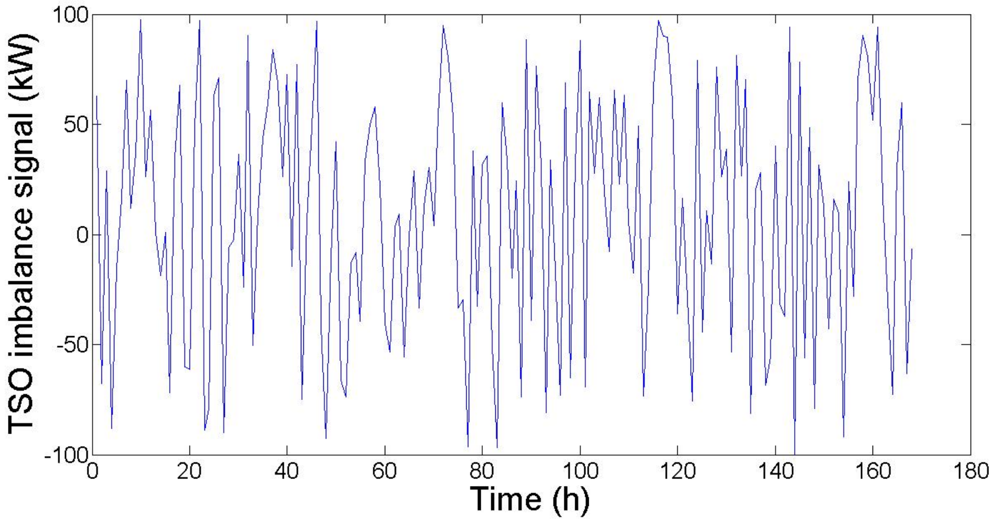

Figure 4.3: TSO imbalance signal for one scenario

4.2 Computational Tools

In order to apply the proposed models two computational tools were essentially used: MATrix LABoratory (MATLAB) and General Algebraic Modeling System (GAMS).

MATLAB is a powerful numerical computing language. This software integrates computing, visualization and programming in a user-friendly environment, given that the problems and solutions presented are in familiar mathematical notation [49].

Within the scope of this thesis, MATLAB is used to handle the input data of the model, and therefore connect it to GAMS.

GAMS is a high-level modeling system for mathematical optimization and programming. The results, after the GAMS optimization, are sent to MATLAB where the data is also processed for further analysis.

Although via MATLAB it is possible to perform the optimizations of the presented models, GAMS was chosen as optimization tool, because of its advantages in solving optimization problems using stochastic methods compared with MATLAB. In the GAMS software, the CPLEX solver has been used to solve the proposed MIP problem. In figure 4.4, is depicted the information exchange between MATLAB and GAMS.

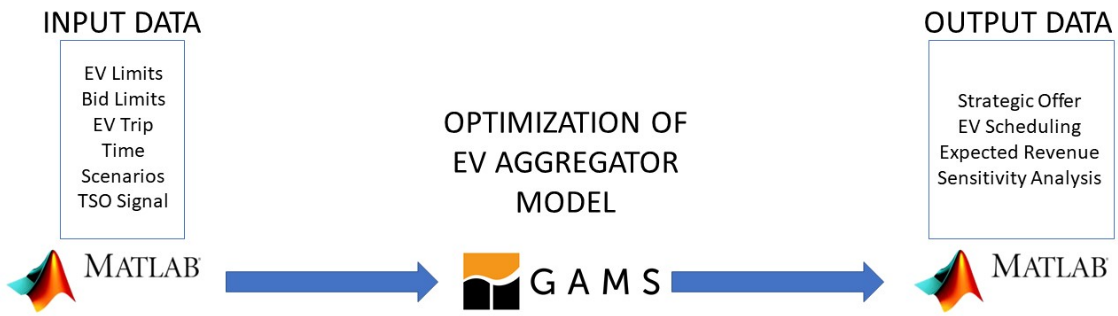

Figure 4.4: MATLAB/GAMS information exchange.

In MIP problems solving, with integer variables, CPLEX uses the branch and bound algorithm that solves series of Linear Programming (LP) subproblems. The single MIP generates many other small problems, even if the problem is small it can become computationally intensive and require large amounts of physical memory. CPLEX can also offer the solving of an MIP in parallel in a distributed computing environment that harnesses the power of multiple computers or of multiple nodes inside a single computer to achieve better performance.

GAMS/CPLEX also uses the following options [50]:

- Option IterLim=x; Responsible for setting the limit number of iterations. The algorithm will stop and pass the current solution to GAMS. CPLEX handles the iteration limit for MIP problems differently than some other GAMS solvers. For MIP problems, controlling the length of the solution run by limiting the execution time (ResLim) is preferable.

- Option ResLim = x; Sets the time limit in seconds. The algorithm will terminate and pass on the current solution to GAMS.
- Option OptCA = x; Absolute optimality criterion for a MIP problem. The OptCA option asks CPLEX to stop when

  $$|BP - BF| < OptCA$$

  where BF is the objective function value of the current best integer solution while BP is the best possible integer solution.
- Option OptCR = x; Relative optimality criterion for a MIP problem. Notice that CPLEX uses a different definition than GAMS normally uses. The OptCR option asks CPLEX to stop when

  $$(|BP - BF|)/(1.0e - 10 + |BF|) < OptCR$$

  where BF is the objective function value of the current best integer solution while BP is the best possible integer solution. The GAMS definition is:

  $$(|BP - BF|)/(|BP|) < OptCR$$

Furthermore, GAMS also provides a model status code regarding the reached solution. These codes can be seen in the table A.1

It is important to note that are only accepted solutions with the model status codes 1, 2 and 8.

4.3 Big-M vs. McCormick

In this section, it is intended to analyze the performance of the Big-M and McCormick methods, considering the expected profit and computational effort.

4.3.1 Expected Profit Analysis

Here, are compared the profit that the aggregator expects to achieve under different scenarios number ω and different pre-defined risk ε. Only one-day simulation and only plugged probability were considered. For all simulations, it is defined the parameter M=1000, which is a sufficiently large number.

Firstly, it is meant to analyze the expected profit under Big-M method applied to two different chance-constraints, namely the TSO balance and SOC balance constraints. So, applying equations 3.30, 3.31 and 3.33 to the problem, the following results were obtained:

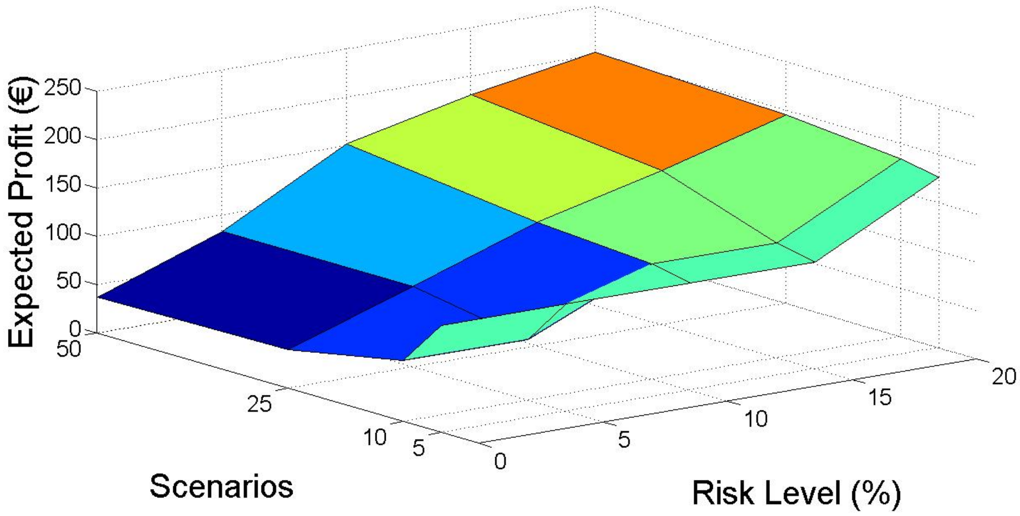

Figure 4.5: Expected profit by scenarios and risk level for the Big-M method applied to the TSO balance constraint.

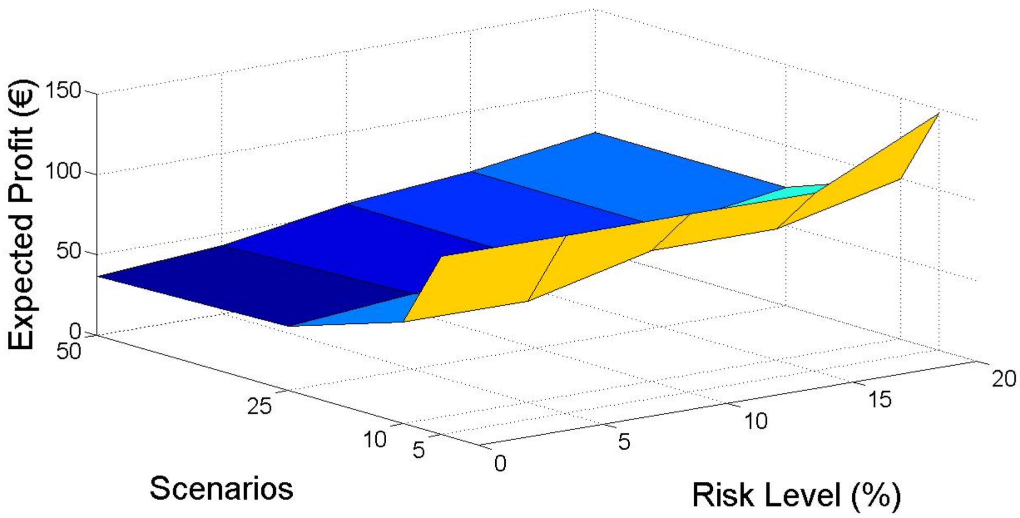

Figure 4.6: Expected profit by scenarios and risk level for the Big-M method applied to the SOC constraint.

In general one can see that, Big-M method applied to the balance between system needs and the availability of the aggregator to provide the contracted reserve (Figure 4.5) has higher expected profits than when applied to the SOC equation (Figure 4.6). The difference between these values tends to increase in proportion to the pre-defined risk and the number of scenarios.

For the same number of scenarios and for 0% of risk level (ε=0%) the objective function takes the same values, according to the scenario, regardless of the constraint used. This is due to the fact that the constraint is not yet active and the worst case scenarios are not being violated, so the problem is being solved without risk of violating any scenario. There are cases where ε is not large enough to remove scenarios, as happens under 5 scenarios where only with 20% of risk level (ε=20%) the first scenario is violated. Except for these cases, the TSO constraint always presents better expected results for the aggregator. When comparing the application of the method in the TSO constraint to that of the SOC, the following is verified for 50 scenarios (ω=50):

- For 5% risk level (ε=5%), the expected profit decreased 48%;
- For 10% risk level (ε=10%), the expected profit decreased 64%;
- For 15% risk level (ε=15%), the expected profit decreased 65%;
- For 20% risk level (ε=20%), the expected profit decreased 64%;

This downward trend is also true for all other numbers of scenarios, so when the aggregator looks for more flexibility in making the decision, it should decide to choose the TSO constraint, as it is the one that will ensure the highest profits.

Applying the McCormick method to the TSO constraint, equations the results obtained were:

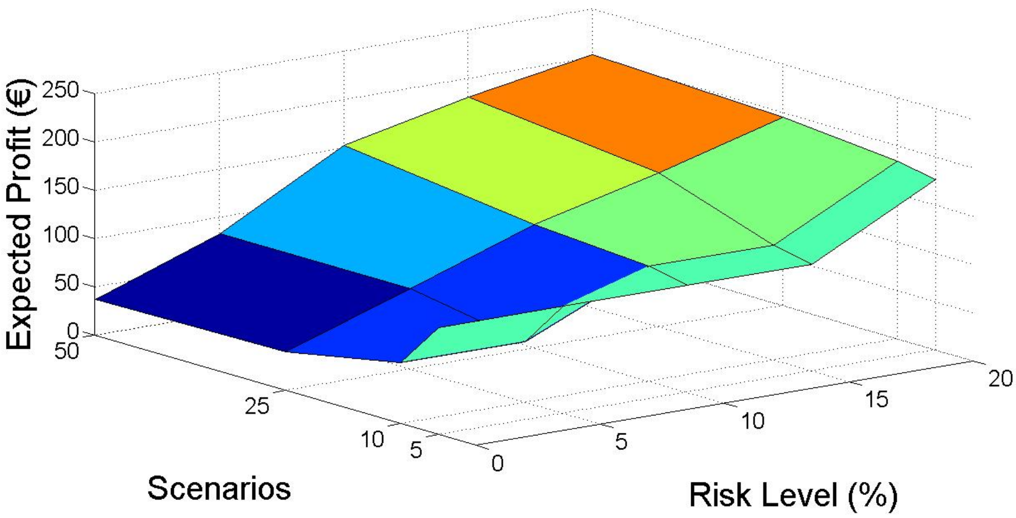

Figure 4.7: Expected profit by scenarios and risk level for the McCormick method applied to the TSO balance constraint.

When comparing the Big-M with McCormick methods, regarding the TSO constraint, the results obtained are very similar. In fact, the follow happened:

For 5 scenarios (ω=5):

- For 0%, 5%, 10% and 15% risk level (ε=0%, ε=5%, ε=10% and ε=15%) no differences were noted, since no scenarios are violated yet;
- For 20% risk level (ε=20%) the expected profit of the McCormick method is 0.0026% lower than the Big-M method.

For 10 scenarios (ω=10), no differences are verified, the two methods present the same expected profit.

For 25 scenarios (ω=25):

- For 0% and 5% risk level (ε=0% and ε=5%) no differences were noted;
- For 10% and 15% risk level (ε=10% and ε=15%) the expected profit of the McCormick method is 0.0001% higher than the Big-M method;
- For 20% risk level (ε=20%) no differences were noted.

For 50 scenarios (ω=50):

- For 0% risk level (ε=0%) no differences were noted;
- For 5% risk level (ε=5%) the expected profit of the McCormick method is 0.015% lower than the Big-M method;
- For 10% risk level (ε=10%) the expected profit of the McCormick method is 0.1143% higher than the Big-M method;
- For 15% risk level (ε=15%) the expected profit of the McCormick method is 0.1018% higher than the Big-M method;
- For 20% risk-level (ε=20%) the expected profit of McCormick method is 0.0293% lower than the Big-M method;

In general the McCormick method presents a better performance, since there are more cases where it presents a higher expected profit and in the cases where that happens this increase is much higher than the cases in which the Big-M method performs better. The biggest differences are also found for the largest number of scenarios, which may indicate that the McCormick method may be a more effective solution to real dimension problems.

4.3.2 Computational Effort

In this kind of problem, in which the time that the aggregator has to submit a proposal is an important factor, it is critical that a solution should be found even if it is not the optimal one.

To do so, algorithm runtime limits have been defined. The IterLim option was limited to 2 hours for the Big-M method and limited to 4 hours for the McCormick method. The McCormick method requires more computational processing time, since it involves a linearization of bilinear terms. Each bilinear term is linearized through 4 constraints, hence the increase in computational effort. Also the absolute and relative optimality criterion were limited to $1E^{-10}$ (OptCA=$1E^{-10}$ and OptCR=$1E^{-10}$).

By observing the tables 4.3 and 4.4 it is possible to conclude that only for 5 scenarios the algorithm is able to find the optimal solution (Model Status Code=1), while for all other scenario numbers the time limit is reached, meaning that GAMS was not able to find the optimal solution, but an integer solution is obtained (Model Status Code=8).

Table 4.3: Computational effort under Big-M method (s).

		TSO			
		ω			
		5	10	25	50
ε	0%	6,53	7202,43	7203,06	7218,46
	5%	7,36	7201,81	7202,86	7219,88
	10%	7,15	7214,18	7202,27	7213,63
	15%	7,25	7259,65	7202,35	7209,05
	20%	30,53	7200,94	7202,23	7226,61

Table 4.4: Computational effort under McCormick method (s).

		TSO			
		ω			
		5	10	25	50
ε	0%	5,71	14401,59	14402,68	14444,97
	5%	5,57	14402,47	14404,09	14407,13
	10%	6,00	14403,76	14402,97	14411,76
	15%	5,74	14403,32	14402,32	14429,15
	20%	32,43	14402,56	14402,51	14426,79

Looking now at the tables 4.5 and 4.6, which represent the methods behavior for one-week simulation, it is possible to observe that for 50 scenarios (ω=50) and 0% risk level (ε=0%) GAMS finds three optimal solutions. For day 7, the McCormick method finds a solution that takes 45% longer than with the Big-M method. However, on the day 6, the McCormick method can also find the optimal solution, which does not occur under the Big-M method.

Table 4.5: Computational effort for one-week simulation under Big-M method and 50 scenarios (s).

		ε				
		0%	5%	10%	15%	20%
Day	1	7208,90	7206,31	7213,12	7206,86	7214,65
	2	7244,00	7209,02	7209,58	7213,57	7203,83
	3	7240,44	7221,58	7206,98	7230,87	7213,26
	4	7238,27	7212,60	7215,08	7213,54	7213,95
	5	7223,92	7208,90	7205,63	7203,20	7206,08
	6	7248,17	7240,84	7215,16	7214,99	7215,17
	7	73,64	7256,63	7251,67	7251,04	7265,19

Table 4.6: Computational effort for one-week simulation under McCormick method and 50 scenarios (s).

		ε				
		0%	5%	10%	15%	20%
Day	1	14428,99	14413,40	14421,02	14410,20	14412,05
	2	14415,49	14409,69	14405,97	14409,67	14417,00
	3	14463,35	14503,47	14439,93	14449,62	14452,46
	4	14540,09	14433,59	14427,91	14413,24	14448,27
	5	14496,52	14411,51	14410,08	14408,04	14405,53
	6	615,72	14435,73	14439,13	14423,79	14417,33
	7	106,54	14481,22	14477,09	14507,27	14510,87

4.3.3 Best and Worst Case Scenarios

In the tables 4.7 and 4.8, it is possible to find the best and worst case scenarios for each studied method.

Table 4.7: Best and worst case scenarios under Big-M method.

			TSO			
			ω			
			5	10	25	50
ε	0%	min	79,91	-34,81	-194,18	-158,42
		max	135,09	105,60	107,64	121,98
	5%	min	79,91	-34,81	-47,87	-203,03
		max	135,09	105,60	171,37	180,93
	10%	min	79,91	28,44	0,47	-13,50
		max	135,09	169,21	188,19	208,38
	15%	min	79,91	28,44	71,50	69,14
		max	135,09	169,21	207,85	208,38
	20%	min	171,21	131,20	147,88	171,21
		max	208,38	208,37	208,39	208,38

Observing the table 4.7 one would expect that when the number of scenarios holds and the pre-defined risk increases, the maximum value would remain constant and the minimum value would increase, because the worst case scenario would be neglected. However, this is not the reality in all cases, since a computational time limit was established due to the aggregator's demand to be able to find the offer to submit in the market in appropriate time. In some cases this temporal limitation forces the algorithm to stop before the optimal solution being achieved, and therefore returns the best solution found until that moment, which is feasible but not the optimal. In this cases, integer solutions were found (Model status code=8). Analyzing the example of 50 scenarios (ω=50), for 0% and 20% risk level (ε=0% and ε=20%) the minimum value with the superior pre-defined risk is higher, which should not be verified. This is due to the fact that the method performs different relaxation and as the optimal solution was not found, these values present such inconsistency.

Table 4.8: Best and worst case scenarios under McCormick method.

			TSO			
			ω			
			5	10	25	50
ε	0%	min	79,91	-34,81	-194,18	-158,42
		max	135,09	105,60	107,64	121,98
	5%	min	79,91	-34,81	-47,87	-203,03
		max	135,09	105,60	171,37	180,93
	10%	min	79,91	28,44	0,47	-13,50
		max	135,09	169,21	188,19	208,38
	15%	min	79,91	28,44	71,50	69,14
		max	135,09	169,21	207,85	208,38
	20%	min	126,73	131,20	147,88	177,18
		max	201,11	208,37	208,39	208,38

Comparing tables 4.7 and 4.8 it can be noticed that the two methods often have the same maximum and minimum values. The biggest difference is for 5 scenarios (ω=5) and 20% risk level (ε=20%), where the minimum value under the McCormick method is 35% lower and the maximum value is 4% lower, which means that for 5 scenarios the Big-M method is tightening the objective function values. On the other hand, for 50 scenarios (ω=50) and 20% risk level (ε=20%), under the McCormick method the values are tighter, the minimum value is 3% higher, which again reinforces the effectiveness of this method for larger problems.

4.4 Available and Plugged Probabilities Impact

In this section the aim is to analyze the impact that a possible failure in the connection of vehicles to the network may affect the expected aggregator's profit. For this purpose, the Available probability pattern in the figure 4.2 was used in the Big-M method. The results obtained were as follows:

Comparing the figure 4.8 with the 4.5, the following differences are observed:

- For 5 scenarios (ω=5): no differences were noted.
- For 10 scenarios (ω=10):
  - For 0% and 5% risk level (ε=0% and ε=5%) no differences were noted;
  - For 10% and 15% risk level (ε=10% and ε=15%) the expected profit decreased 0.14%;
  - For 20% risk level (ε=20%) the expected profit decreased 0.03%.
- For 25 scenarios (ω=25):
  - For 0% risk level (ε=0%) no differences were noted;
  - For 5% risk level (ε=5%) the expected profit decreased 0.29%;
  - For 10% risk level (ε=10%) the expected profit decreased 0.23%;

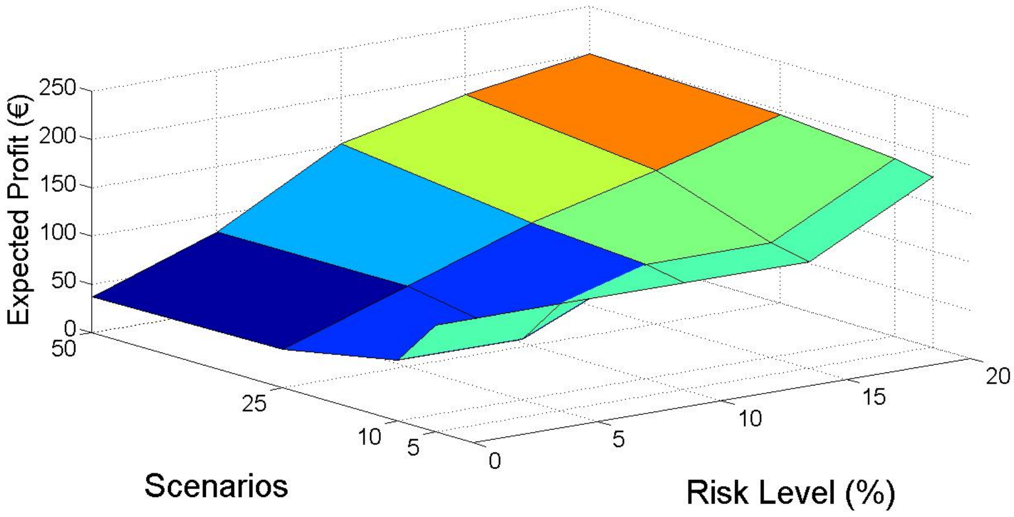

Figure 4.8: Expected profit by scenarios and risk level for the Big-M method applied to the TSO balance constraint under available probability

- For 15% risk level (ε=15%) the expected profit decreased 0.13%;
- For 20% risk level (ε=20%) the expected profit decreased 0.01%.

- For 50 scenarios (ω=50):
  - For 0% risk level (ε=0%) no differences were noted;
  - For 5% risk level (ε=5%) the expected profit decreased 0.59%;
  - For 10% risk level (ε=10%) the expected profit decreased 0.28%;
  - For 15% risk level (ε=15%) the expected profit decreased 0.23%;
  - For 20% risk level (ε=20%) the expected profit decreased 0.56%.

It is now possible to realize how the probability of vehicles being connected to the grid can influence the profit expected by the aggregator. Since these values only cover one day, in the long term they can imply a lot of associated costs, which leads to the conclusion that improvements in the connections between the EVs and the grid can improve the flexibility of the aggregator.

4.5 One-week Simulation Results

For one-week simulation and 50 scenarios, it is intended to analyze in more detail the performance of the aggregator regarding the contracted reserve and reserve activation, as well as expected inflow, costs and revenue, from different perspectives.

The Forecast simulation is exactly the same as all the simulations that have been performed so far, intending to represent a reserve prediction of the market needs taking into account their need and response from the aggregator.

The Deployed simulation represents the hour-ahead simulation based on potential realization scenarios and constrained by the forecast simulation results, i.e., a deterministic optimization per realization scenario. After the forecast performed previously, it is assumed that the contracted reserve is considered a parameter, which means that its values are considered fixed and no relaxations are made. From this point on, new scenarios with the same distribution are generated, leading to a different scheduling of EVs and other variables. The aggregator does not have the deployed information before making its decision. To do this analyze, the McCormick method and plugged probability were chosen.

Table 4.9: Cumulative results of one-week simulation under the McCormick method.

	ε									
	0%		5%		10%		15%		20%	
	Forecast	Deployed	Forecast	Deployed	Forecast	Deployed	Forecast	Deployed	Forecast	Deployed
Contracted Upward reserve (kW)	14100,00	14100,00	15400,00	15400,00	16200,00	16200,00	16400,00	16400,00	16600,00	16600,00
Contracted Downward reserve (kW)	14100,00	14100,00	15400,00	15400,00	16200,00	16200,00	16400,00	16400,00	16600,00	16600,00
Upward activation (kWh)	3620,54	3398,83	3639,02	3721,88	3324,09	3887,68	3008,75	3936,01	2540,96	3985,20
Downward activation (kWh)	3567,49	3417,70	3696,57	3721,14	3568,49	3931,80	3457,19	3977,05	3233,69	4023,36
Upward deficit - RLXU (kWh)	29,26	176,03	24,85	192,09	14,98	214,98	8,35	220,67	2,42	225,09
Downward deficit - RLXD (kWh)	28,11	28,67	23,82	40,47	12,47	53,65	8,36	58,53	4,43	67,70
Expected inflow (€)	1206,01	1206,01	1324,26	1324,26	1398,40	1398,40	1416,76	1416,76	1441,14	1441,14
Expected costs (€)	233,13	829,35	205,99	959,41	120,40	1125,80	71,26	1175,17	27,76	1254,78
Expected revenue (€)	972,88	376,66	1118,27	364,85	1277,99	272,60	1345,50	241,59	1413,38	186,36

The table 4.9 shows that the contracted reserve increases as ε increases, since the worst case scenarios are excluded and there is the possibility of a better scheduling by the EVs to participate in the reserve market. The values of the upward and downward reserve are equal for the same ε because the market under consideration is symmetrical. It is possible to verify that the expected inflow is equal, for the same value of ε, whether it is Forecast or Deployed. The expected costs are related to the deficit of supplied reserve.

Regarding expected revenue for the forecast, as predicted, it increases as the ε increases, since the worst case scenarios are neglected. For Deployed, there is an opposite effect, i.e., the expected revenue decreases as the ε increases. This is due to the imposed contracted reserve value, which is fixed forcing the aggregator to comply and to adapt to this value for new scenarios. This sometimes leads leads to a slight increase in the value of relaxation variables (RLXU and RLXD), which have a negative influence on expected profit since the penalty considered here is 100 times higher than the upward and downward balancing power prices, respectively. For the Forecast, one can also note that:

- when the risk level (ε) varies from 0% to 5%, the expected profit increases 15%;
- when the risk level (ε) varies from 5% to 10%, the expected profit increases 14%;
- when the risk level (ε) varies from 10% to 15%, the expected profit increases 5%;
- when the risk level (ε) varies from 15% to 20%, the expected profit increases 5%;

For the Deployed:

- when the risk level (ε) varies from 0% to 5%, the expected profit decreases 3%;
- when the risk level (ε) varies from 5% to 10%, the expected profit decreases 25%;
- when the risk level (ε) varies from 10% to 15%, the expected profit decreases 11%;
- when the risk level (ε) varies from 15% to 20%, the expected profit decreases 23%;

This information can also be useful to the aggregator because it establishes a trade-off regarding the decision to be made.

4.5.1 Expected Costs of Risk

Typically, in this type of problem, the main objective is to maximize the expected profit. However, the objective function is related to costs, and a reduction of this value can lead to an increase in expected revenue. Risk exists in every field and is inevitable, so it is important for the aggregator to quantify the existing risk and then be able to minimize or manage it. The aggregator must accept responsibility for the attitude it has taken towards the risk.

Thus, it was calculated the costs that the neglected scenarios present, that is, the costs that they represent for the aggregator when the binary variable $z_{(t,\omega)}$ is active.

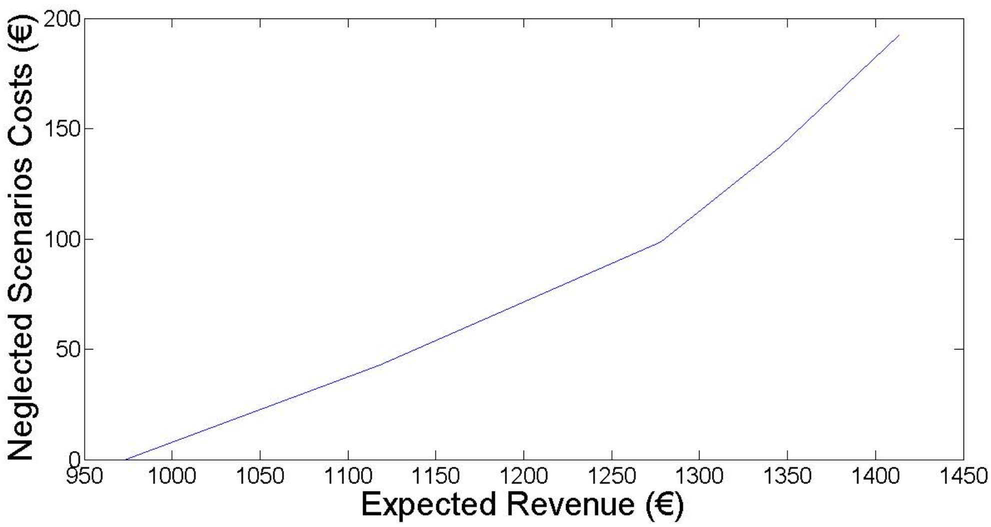

Figure 4.9: Neglected scenarios expected costs vs. Expected revenue.

Analyzing the figure 4.9, one can see that the costs of neglected scenarios increase along with the expected revenue. As expected revenue increases with the pre-defined risk, as predicted, these costs are increasing steadily. When the expected profit is higher than 1300€ the slope becomes even more accentuated, highlighting the ever-increasing costs that the aggregator is subject to. The more scenarios the aggregator ignores, the greater will be the expected revenue in Forecast.

However, if these ignored scenarios occur, they entail higher costs. Therefore, it is important that the decision maker takes into account this trade-off between expected revenue and the potential costs of neglected scenarios.

Chapter 5

Conclusion and Future Work

5.1 General Contributions

In the near future, EVs will change the current paradigm of energy markets, as they will play a key role, especially, in ancillary services. Ancillary services are important to maintain and control the stability of power systems. The most effective way for EVs to participate in this type of service is through aggregators. These aggregators collect the most important and necessary information and then relate to the TSO in order to optimize the offer made in the market. This offer can have different objectives such as improving the profit of the aggregator, improving the profit of each individual EV, providing the best service to the network, reducing the emission of GHG, etc.

This dissertation focuses on modeling the strategic offering of an EV aggregator, aiming to maximizes aggregator's profit. To this end, a two-stage stochastic model with chance constrained programming was proposed to tackle the EV aggregator's problem. The proposed approach allows the aggregator to assess and submit their offers in the market under appropriate risk awareness.

This model contemplates the particularity of considering different probability functions of the EV being connected to the grid (namely, available and plugged probability function), in order to analyze the impact that a proper or poor connection can represent on the expected profit. The uncertainty of the problem is related to the energy trip of the EVs, which depends on the driving patterns and consequently usage of the EV. In addition, uncertainty related to the TSO actual needs is also considered and modeled. The model is implemented under the rules of the FCN-R service, in Eastern Denmark, within the scope of the PARKER project, where symmetric offering for upward and downward reserve is considered.

The chance-constrained problem has been implemented following the deterministic equivalent way, which may requires the use of relaxation methods. In this particular, the Big-M and the McCormick methods has been introduced, formulated and compared. The introduction of a binary variable and an M parameter allows the problem to be reformulated through the Big-M method. The McCormick method is used to derive the linear part of the mixed integer bilinear formulation.

This methodology was tested on the basis of real information, comprising the fleet of EVs from Frederiskberg Forsyning utility company, within the scope of the PARKER [47] project. The total fleet power is 100 kW. The market prices used were from East Denmark for January 2017. This work also considers different probabilities of connecting EVs to the grid. The models were tested and validated in the GAMS and MATLAB software.

The proposed methodology shows interesting results when analyzing the differences achieved under the Big-M and McCormick methods. In fact, the results present several similarities for most of the number of scenarios considered. For a low number of scenarios, the results are similar in both methods. However, when the number of scenarios increases, the differences start to become evident, which leads us to believe that for larger and real situations the proposed model under the McCormick relaxation method presents a better solution for the aggregator when it comes to the expected profit.

Another consideration to take into account, in this type of problems that involve that involve close time-lines, is the computational effort. In this case, appropriate computational time limits has been established in the optimization software, ensuring feasible solutions. More precisely, the solutions found may not be the global optimum, but rather a local optimum. During the simulation process, it was found that the McCormick method took longer to converge and find a solution than the Big-M method, so different time limits were set for both methods.

Regarding the use of different probability functions of the EV connection to the grid, the results show a slight difference for one-day simulation. In the case of long period simulations, namely one week, the probability of EVs being connected to the grid, whether or not they may be available to provide the service, shows higher expected profits, up to 19%. This probability also impacts the scaling of contracted power, as well as the activation of upward and downward reserve.

It was concluded that the contracted and activated reserve increases in accordance with the risk level. On the contrary, the penalties are decreasing, since the scenarios that present higher cost to the aggregator are being neglected. New scenarios were also generated to assess the aggregator's response in hour-ahead. For this case, the results show that as the risk increases, the expected profit tends to decrease, since a significant percentage of scenarios that may occur were neglected.

Lastly, this work contributes to optimizing the participation of EV aggregators in the reserve market. However, there is a different perspective that is analyzed using two different methods. This perspective aims to assess the risk that the aggregator should submit in the market, i.e. to give the aggregator the appropriate tools to reach the most appropriate decision. Thus, it is expected that it will be able to meet its primary objective - to maximize profits.

5.2 Future Work

During the development of this work, new ideas have emerged that may enhance the further development of this kind of projects, namely:

- Benders decomposition can be introduced to handle the complexity of the two-stage model. In fact, it can reduce the computational effort of the by splitting the problem in master and several slave instances related to the high number of scenarios;

- The application of metaheuristics to solve this problem. The metaheuristics are based on optimization processes found in nature and their characteristics allow to present solutions close to the optimum in very competitive computational times;
- Extend the problem to a larger number of vehicles and scenarios, to realize the impact that the proposed models may imply in real world, which would require powerful computational tools;
- Extend to other markets with other characteristics and where the demand for upward and downward reserve is not symmetrical, like in the Portuguese ancillary services market;
- Adapt the model to include multiple objectives, such as the individual benefit of each EV owner, the provision of the best service to the grid and the reduction of GHG emissions.

Appendix A

Appendix

Table A.1: GAMS model status codes.

Model Status Code	Description
1	Optimal
2	Locally Optimal
3	Unbounded
4	Infeasible
5	Locally Infeasible
6	Intermediate Infeasible
7	Intermediate Nonoptimal
8	Integer Solution
9	Intermediate Non-Integer
10	Integer Infeasible
11	Licensing Problems - No Solution
12	Error Unknown
13	Error No Solution
14	No Solution Returned
15	Solved Unique
16	Solved
17	Solved Singular
18	Unbounded - No Solution
19	Infeasible - No Solution

Table A.2: Cumulative results of one-week simulation under Big-M method-Plugged probability

	ε									
	0%		5%		10%		15%		20%	
	Forecast	Deployed	Forecast	Deployed	Forecast	Deployed	Forecast	Deployed	Forecast	Deployed
Contracted Upward reserve (kW)	14100,00	14100,00	15400,00	15400,00	16200,00	16200,00	16400,00	16400,00	16600,00	16600,00
Contracted Downward reserve (kW)	14100,00	14100,00	15400,00	15400,00	16200,00	16200,00	16400,00	16400,00	16600,00	16600,00
Upward activation (kWh)	3622,21	3398,83	3645,57	3721,88	3323,79	3887,68	2987,80	3936,01	2539,41	3980,41
Downward activation (kWh)	3569,16	3417,70	3684,07	3721,14	3551,20	3931,80	3458,59	3977,05	3253,40	4018,57
Upward deficit - RLXU (kWh)	29,26	176,03	24,52	192,09	15,02	214,98	8,38	220,67	2,45	225,09
Downward deficit - RLXD (kWh)	28,11	28,67	24,18	40,47	12,45	53,65	8,43	58,53	4,51	67,70
Expected inflow (€)	1206,01	1206,01	1324,26	1324,26	1398,40	1398,40	1416,76	1416,76	1441,14	1441,14
Expected costs (€)	233,13	829,35	205,99	959,41	120,49	1125,80	71,81	1175,17	28,24	1254,78
Expected revenue (€)	972,88	376,66	1118,27	364,85	1277,91	272,60	1344,94	241,59	1412,90	186,36

Table A.3: Cumulative results of one-week simulation under Big-M method-Available probability

	ε									
	0%		5%		10%		15%		20%	
	Forecast	Deployed	Forecast	Deployed	Forecast	Deployed	Forecast	Deployed	Forecast	Deployed
Contracted Upward reserve (kW)	12100,00	12100,00	13200,00	13200,00	13800,00	13800,00	14100,00	14100,00	14600,00	14600,00
Contracted Downward reserve (kW)	12100,00	12100,00	13200,00	13200,00	13800,00	13800,00	14100,00	14100,00	14600,00	14600,00
Upward activation (kWh)	3087,55	2910,62	3109,38	3174,96	2922,57	3311,03	2590,70	3381,83	2244,19	3506,32
Downward activation (kWh)	3060,47	2964,66	3155,34	3232,37	3099,12	3366,89	2942,24	3430,88	2834,28	3531,01
Upward deficit - RLXU (kWh)	25,88	158,33	22,54	172,37	12,53	181,86	7,33	193,62	5,90	215,01
Downward deficit - RLXD (kWh)	26,12	27,06	21,94	37,13	10,20	44,89	8,08	50,23	6,15	67,02
Expected inflow (€)	1026,46	1026,46	1123,19	1123,19	1172,55	1172,55	1204,20	1204,20	1260,67	1260,67
Expected costs (€)	206,05	733,82	182,80	842,35	90,79	914,93	64,30	1009,70	56,49	1225,48
Expected revenue (€)	820,41	292,64	940,39	280,84	1081,76	257,63	1139,90	194,50	1204,18	35,19

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