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Assessing the challenges and opportunities of electric mobility through the optimization of carsharing considering demand uncertainty

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Leonardo de Arruda Bitencourt

Assessing the challenges and opportunities of electric mobility through the optimization of carsharing considering demand uncertainty

Thesis submitted to the Graduate Program in Electrical Engineering of the Federal University of Juiz de Fora as a partial requirement for obtaining a Doctor's degree in Electrical Engineering. Concentration area: Electric Power Systems

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ABSTRACT

Although electric vehicle (EV) sales have been increasing over the years, worldwide EV adoption is still low. The key factors influencing this are the EV high acquisition cost and the reduced charging infrastructure. Therefore, traditional business models may not be adequate for a region and stagnate EV diffusion. Thus, designing innovative business models can be crucial to accelerate the transition to electric mobility. However, the increase in EV charging may come with drawbacks for the DSO. A possible way to mitigate those problems is to implement dynamic tariffs. Therefore, the objective of this thesis is twofold. First, to discuss the application of business models for EV adoption and charging stations (CSs) worldwide. Then, it highlights the challenges and opportunities for some business model options. Second, to assess the profitability of an e-carsharing company based on distribution local marginal price (DLMP) and vehicle-to-grid (V2G) that cooperates with the DSO through a two-stage stochastic model. The AC optimal power flow (ACOPF) is modelled using second-order cone programming (SOCP) linearized by the global polyhedral approximation. The IEEE 33 bus test system and a real Kernel distribution for the EV rental demands are used in four planning cases. The results indicate that planning disregarding the power grid perspective is the most profitable solution, but the operation may not be possible in real applications due to the high-power flows via V2G. Finally, the e-carsharing planning considering the DSO perspective increased the charging cost by 0.24% but also reduced the DLMP peak, peak demand and cable reinforcement cost by 1.5%, 5.1%, and 66%, respectively. The technical benefits brought to the DSO by the e-carsharing company could be turned into public policies and benefit both agents, increasing profit and mitigating negative impacts.

Keywords: 1. Electric Vehicle. 2. Shared mobility. 3. Distribution Power System. 4. V2G. 5. Business models.

RESUMO

Embora as vendas de veículos elétricos (VEs) tenham aumentado ao longo dos anos, a adoção mundial de VEs ainda é baixa. Os principais fatores que influenciam isso são o alto custo de aquisição do VE e a infraestrutura de recarga reduzida. Portanto, os modelos de negócios tradicionais podem não ser adequados para uma determinada região e estagnar a difusão de VEs. Assim, projetar modelos de negócios inovadores pode ser crucial para acelerar a transição para a mobilidade elétrica. No entanto, o aumento no carregamento de VEs pode trazer desvantagens para o operador do sistema de distribuição. Uma possível forma de mitigar esses problemas é pela implementação de tarifas dinâmicas. O objetivo desta tese é duplo. Primeiro, é discutir a aplicação de modelos de negócios para adoção de VEs e eletropostos em todo o mundo. Em seguida, são destacados os desafios e oportunidades para algumas opções de modelos de negócios. Em segundo lugar, é avaliar a rentabilidade de uma empresa de compartilhamento de VEs (e-carsharing) com base no preço marginal local de distribuição e Vehicle-to-Grid (V2G) que coopera com o operador do sistema de distribuição por meio de um modelo estocástico de dois estágios. O fluxo de potência ótimo AC é modelado usando programação de cone de segunda ordem linearizada pela aproximação poliédrica global. São utilizados o sistema de teste IEEE 33 barras e uma distribuição real de Kernel para as demandas de aluguel de VE em quatro casos de planejamento. Os resultados indicam que o planejamento desconsiderando a perspectiva da rede elétrica é o mais rentável, mas a operação pode não ser possível em aplicações reais devido aos altos fluxos de potência do V2G. Por fim, o planejamento da e-carsharing considerando a perspectiva operador do sistema aumentou o custo de carregamento em 0.24%, mas também reduziu o pico do DLMP, pico de demanda e custo de reforço de cabos em 1.5%, 5.1% e 66%, respectivamente. Os benefícios técnicos trazidos ao operador do sistema de distribuição pela companhia de e-carsharing podem ser transformados em políticas públicas e beneficiar ambos os agentes, aumentando o lucro e mitigando impactos negativos.

Palavras-chave: 1. Veículo Elétrico. 2. Mobilidade Compartilhada. 3. Sistema de Distribuição. 4. V2G. 5. Modelos de negócios.

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LIST OF ACRONYMS

ACOPF	Alternate Current Optimal Power Flow
BEV	Battery Electric Vehicle
BFM	Branch Flow Model
CPO	Charging Point Operator
CS	Charging Station
DCOPF	Direct Current Optimal Power Flow
DER	Distributed Energy Resource
DLMP	Distribution Locational Marginal Pricing
DSO	Distribution System Operator
EAAS	Energy as a Service
EV	Electric Vehicle
HEV	Hybrid Electric Vehicle
ICE	Internal Combustion Engine
IEA	International Energy Agency
LMP	Locational Marginal Pricing
MILP	Mixed-Integer Linear Programming
MPS	Mobility Service Providers
OEM	Original Equipment Manufacturer
PDF	Probability Density Function
PHEV	Plug-in Hybrid Electric Vehicle
RFID	Radio-Frequency Identification
RTP	Real Time Pricing
SEV	Shared Electric Vehicle
SoC	State-of-charge
SOCP	Second-Cone Order Programming
TOU	Time-of-Use
TSO	Transmission System Operator
V2G	Vehicle-to-Grid

LIST OF SYMBOLS

Sets

$\omega \in \Omega_\omega$	Set of scenarios
$\epsilon \in \Omega_\epsilon$	Set of EVs
$\rho, i, j \in \Omega_\rho$	Set of position and buses
$\delta \in \Omega_\delta$	Set of rental demands
$t \in \Omega_t$	Set of periods in short-term (hours)
$y \in \Omega_y$	Set of periods in long-term (years)
$c \in \Omega_c$	Set of types of cables
$S(j)$	Set of tail buses of branches whose head bus is$j$

Parameters

$p^i_{\rho,\epsilon}$	Initial positions of vehicles
SoC^i_ϵ	Initial vehicle state-of-charge
$\zeta^e_{t,\rho}$	Energy tariff
ζ^r	Vehicle rental tariff
ζ^{rl}	Vehicle relocation tariff
ζ^g	Energy price at slack bus
E^b	Vehicle battery energy
eff_{cha}	Charger efficiency
P^c	Maximum charging/discharging power
p_ω	Scenario probability
p^{ev}	Vehicle purchase price
p^{cs}	Charging station installation price
p^{ch}	Charger price
p^{Cr}_c	Cable c price
B_y	Budget at year y
Ch^{max}_ρ	Maximum number of chargers in position ρ
Ch^{min}_ρ	Minimum number of chargers in position ρ
$D^O_{t,\delta,\rho,y,\omega}$	Rental demand origin in position ρ at time t
$D^D_{t,\delta,\rho,y,\omega}$	Rental demand destination to position ρ at time t
$D^d_{\delta,y,\omega}$	Rental demand trip duration
d_r	Electric vehicle energy consumption due to movement
$P^d_{t,i,y}$	Active power demand at bus i in period t
$Q^d_{t,i,y}$	Reactive power demand at bus i in period t
$r_{i,j,y}$	Resistance of branch (i, j)
$x_{i,j,y}$	Reactance of branch (i, j)
v^{max}	Maximum voltage
v^{min}	Minimum voltage
$I^{max}_{i,j,y}$	Maximum current of branch (i, j) at year y
I^{Cr}_c	Cable c capacity

First-stage Variables

$CS_{\rho,y}$	{0,1}	Charging stations position at year y
$E_{\epsilon,y}$	{0,1}	Vehicles purchased at year y
$Ch_{\rho,y}$	$\mathbb{Z}$	Number of charges in position ρ at year y
$x_{i,j,c,y}^{Cr}$	{0,1}	Cable reinforcement of branch (i, j) at year y

Second Stage Variables

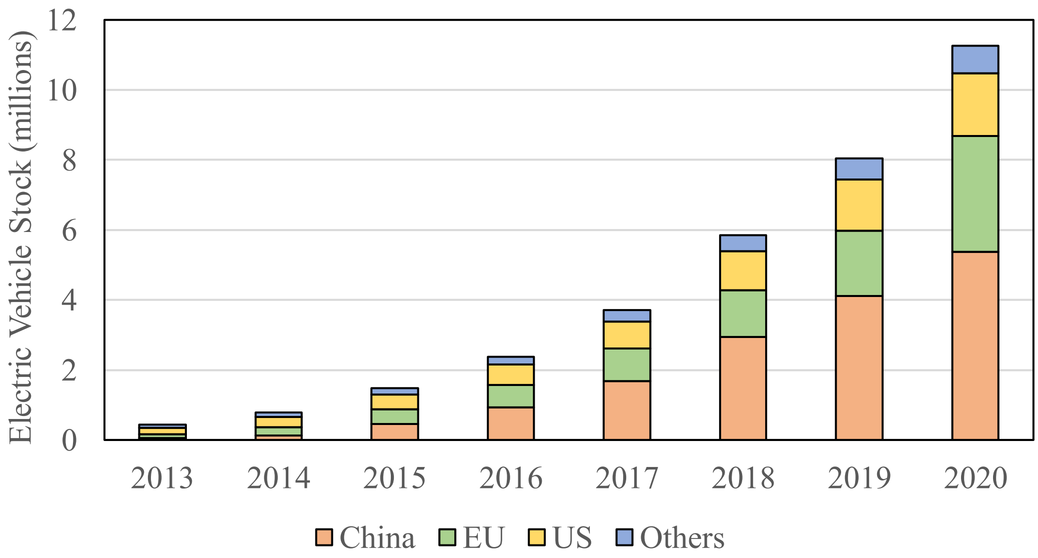
$ev_{\delta,\epsilon,y,\omega}^{r}$	{0,1}	Accepted demand δ by vehicle ϵ
$ev_{t,\rho,\epsilon,y,\omega}^{cha}$	[-1,1]	Vehicle charging power when connected
$ev_{t,\rho,\epsilon,y,\omega}^{d}$	{0,1}	Vehicle who departure for relocation
$ev_{t,\rho,\epsilon,y,\omega}^{a}$	{0,1}	Vehicle who arrived from relocation
$ev_{t,\rho,\epsilon,y,\omega}^{con}$	{0,1}	Vehicle connection status on the power grid
$ev_{t,\epsilon,y,\omega}^{mov}$	{0,1}	Vehicle movement status
$SoC_{t,\epsilon,y,\omega}$	$\mathbb{R}^+$	Vehicle state-of-charge
$P_{t,\rho,y,\omega}^{ev}$	$\mathbb{R}$	Total charging power at position ρ
$P_{i,j,t,y,\omega}$	$\mathbb{R}$	Active power injected at the head bus of branch (i,j) in period t
$Q_{i,j,t,y,\omega}$	$\mathbb{R}$	Reactive power injected at the head bus of branch (i,j) in period t
$v_{i,t,y,\omega}$	$\mathbb{R}^+$	Squared voltage magnitude at bus i in period t
$l_{i,j,t,y,\omega}$	$\mathbb{R}^+$	Squared current in branch (i,j) in period t
$P_{t,i,y,\omega}^{g}$	$\mathbb{R}^+$	Active power generation at bus i in period t
$Q_{t,i,y,\omega}^{g}$	$\mathbb{R}^+$	Reactive power generation at bus i in period t

SUMMARY

1. INTRODUCTION

The global electric vehicle (EV) fleet has been increasing in recent years, as reported in (IEA, 2021), which indicates that the EV stock reached 10 million vehicles in 2020, as shown in Figure 1. However, the global EV market share is still low, approximately 1% (IEA, 2020). Innovative sustainable technologies often face more barriers to increase market penetration, whereas current business models may not be adequate to break these barriers (LIAO *et al.*, 2019). The main barriers to EV adoption are the high acquisition cost, limited charging infrastructure, range anxiety, and high charging time. Therefore, designing new business models may be decisive in increasing EV adoption.

Figure 1 – World Electric Vehicle Stock

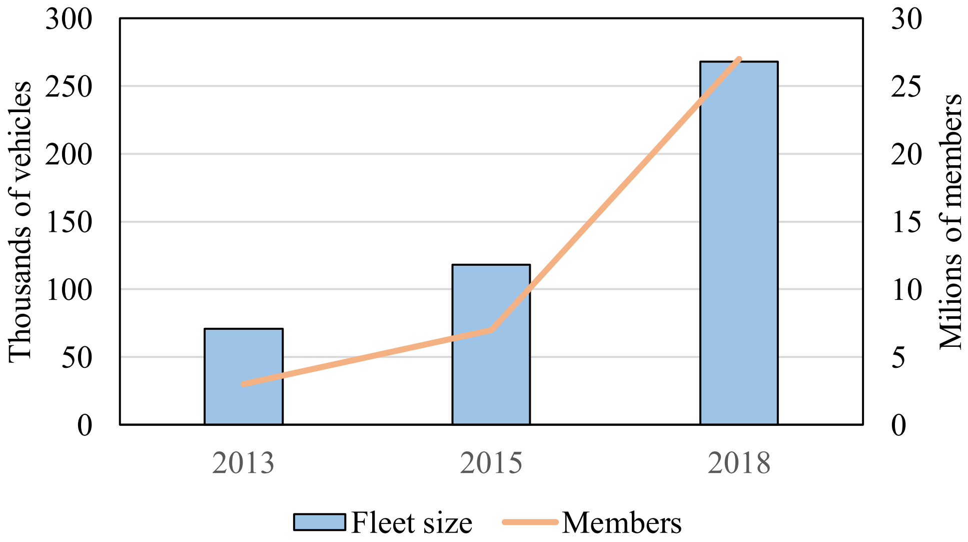


Source: Adapted from (IEA, 2021)

Business models can be generalized as simplified representations of the value proposition, value creation and delivery, and value capture elements (GEISSDOERFER; VLADIMIROVA; EVANS, 2018). A value proposition is a simple statement that summarizes why a customer would choose a product or service. Value creation is the process of turning labor and resources into something that meets the customer's needs. Value delivery refers to the costs and profit associated with the value delivered. Finally, value capture is retaining some percentage of the value provided in every transaction. For example, a company may adopt different strategies that offer a cheap/expensive product or service (related to profit margin) to capture more/fewer customers, respectively. The interactions between these elements are within an organizational unit. In the electric mobility context, business models range from access to electric vehicles and charging infrastructure to the generation of energy for charging and payment methods (SAN ROMÁN *et al.*, 2011).

The most traditional business model for EV adoption is total vehicle acquisition. While the EV price is already competitive with conventional vehicles in some European countries, the United States and China, this is still a distant reality in Latin America and other countries (CÁRDENAS; BONILLA; BRUSA, 2021). Hence, it is important to rethink other ways to accelerate the EV transition. Leasing is a common business model that can be extended to EVs. In parallel, the sharing economy is another growing business model, especially concerning shared mobility, known as carsharing (LUNA *et al.*, 2020). Figure 2 shows the increase in the number of members and the fleet of shared vehicles in the world between 2013 and 2018. This type of service is offered by some companies, such as Zipcar, Car2Go, and Didi (CAR2GO, 2022; DIDI, 2022; ZIPCAR, 2022). There are three types of operating systems for e-carsharing[1] companies: round-trip, one-way, and free-floating. The first requires users to return vehicles to the station of origin. The one-way system allows users to return vehicles to any company station. Finally, the last system allows users to return the vehicle anywhere (HUA *et al.*, 2019; HUANG, KAI; AN; CORREIA, 2020; XIE *et al.*, 2020).

Figure 2 – Carsharing fleet size and members



Source: Adapted from (STOLLE *et al.*, 2020)

[1] A carsharing company that owns only EVs.

Shared mobility can bring opportunities for agents who decide to operate in this new business model. E-carsharing company (shared mobility companies that use EVs) could be run by pure players and its objective would be to maximize its profit by rentals. Although, others agents could have additional objectives. EV manufacturers could also run a e-carsharing and improve people's perception of the company, as they offer the use of cutting-edge technology at an affordable price for the final costumer, especially by preventing them from a high capital expenditure. In addition, they can captivate potential buyers (final users of the e-carsharing) for both conventional vehicles and EVs.

From the point of view of energy companies, Distribution system operators (DSOs) running this business can identify places where e-carsharing stations bring benefits to the power grid without jeopardizing the service to the customers. Moreover, power utilities running a e-carsharing can provide energy and ancillary services to the grid through EV charging optimization (PASTOR *et al.*, 2018).

Despite the perspective of different agents, the e-carsharing service running by a pure player depends on some factors to guarantee its profitability, such as the size of the city, the local population density, moving traffic, parking situation, population demographics, agreement with the administration, and demand uncertainty (STOLLE *et al.*, 2020). Thus, to increase the development of e-carsharing, it is important to evaluate other ways to guarantee the company's profitability.

Typically, leasing refers to long-term rentals, such as months and years, while renting refers to shorter rental periods, such as days and weeks. Although there are differences in the term of contracts for rental or leasing, we consider both as equivalent business model. Thus, both leasing and rental have been used interchangeably throughout this text. Finally, another potential cheaper business model than the acquisition of an EV is the retrofit. In this model, the main components of the conventional vehicle are replaced to transform it into an electric vehicle. However, more studies assessing the feasibility of this business model is needed.

Regarding charging infrastructure, a research shows that most charging station (CS) deployment is performed by pure-player operators, oil and gas utilities, and equipment manufacturers in the United States, Europe, and China, respectively (ECKHOUSE; STRINGER; HODGES, 2019). However, these agents have lower investment risk, as there is already a charging demand in those regions. The implementation of charging infrastructure in countries with low EV penetration is a risky business for investors, given that charging demand is practically nonexistent. This leads to an important dilemma, where one does not know which EV or the charging infrastructure should come first. Although a disputable question, the lack of infrastructure is a deterrent to the increase in EV sales. However, agents that decide to invest in this business have more space to innovate and detain most of the early market.

Historically, the first charging services emerged as a means of attracting customers to another business (e.g., markets, malls, restaurants, etc.) (CHEN, TIANJIN *et al.*, 2020). Those services traditionally charge EVs connecting them to the power grid through cables. The variety of wired chargers available allows different charging times, which range from 10 minutes to 8 hours, depending on the battery size and the charging type (LAMONACA; RYAN, 2022). Indeed, countries with low EV penetration can use past experiences to develop a charging infrastructure. Moreover, those countries can make a technological leap and invest in other charging technologies that are becoming viable, such as wireless charging and battery swaps (LIMB *et al.*, 2019; REVANKAR; KALKHAMBKAR, 2021). These technologies have gained attention more recently to further reduce charging time and increase convenience. However, due to the high cost, the wired power supply is still preferred.

Therefore, with the high cost of acquisition and the high risk of investing in charging infrastructure, leasing and sharing-based business models (both for EV adoption and charging) seem to be promising options (SUBRAMANI, 2015). Shifting high investment costs from EV users to a company can accelerate the electric mobility transition. This development will require coordination between the private sector and public entities through subsidies, regulations, and public policies.

For EVs to be truly zero carbon emissions, the energy generated to charge them must also be clean (DOLUWEERA *et al.*, 2020; KAMIYA; AXSEN; CRAWFORD, 2019). Different from other countries, Latin American countries are in a rapid transition toward clean energy due to the high participation of renewable resources in their energy matrix. However, this transition can be accelerated through distributed energy resources (DERs). Thus, CSs powered by solar panels could compose a business model for clients with environmental awareness (CALISE *et al.*, 2019). In addition, DER is a good option for the DSO to overcome the impacts of EV charging, such as undervoltage and cable overload.

Another business model option is Vehicle-to-Grid (V2G), which defines a system capable of bidirectionally controlling the power flow between the power grid and EVs (ADRENE BRIONES *et al.*, 2012; LIN, XIANGNING *et al.*, 2014). V2G can attenuate peaks and fill valleys of energy consumption and provide support to the power grid through ancillary services, such as voltage and frequency control (BAI *et al.*, 2015; DRUDE; PEREIRA JUNIOR; RÜTHER, 2014; LIU *et al.*, 2015; TAN; RAMACHANDARAMURTHY; YONG, 2016). It is noteworthy that constant battery charging and discharging in V2G can decrease the battery lifetime (HABIB; KAMRAN; RASHID, 2015; KEMPTON; TOMIĆ, 2005). In this way, charging stations (CSs) can manage energy through a smart grid, charging EVs during low consumption times and supplying energy through EVs to the power grid during high consumption times (A. RAHMAN *et al.*, 2015; HADDADIAN *et al.*, 2015; LAMEDICA *et al.*, 2015; NOEL; MCCORMACK, 2014).

The implementation of V2G requires price signals, such as time of use (TOU) or real-time pricing (RTP). Although these techniques reflect the power grid's state in time (load variation), they do not have information on nodal load. A technique that considers the nodal load and time variation of consumption widely applied in transmission systems is the local marginal price (LMP). In addition, LMP can be decomposed into three components: the marginal cost of energy, losses, and congestion (LI, RUOYANG; WU; OREN, 2014; YUAN; HESAMZADEH; BIGGAR, 2018).

Another recent trend is related to the concept of Energy as a Service (EAAS), which defines a business model where customers pay for an energy service without having to make any investment in infrastructure or generation (e.g., diesel or solar) (INGALALLI; KAMALASADAN, 2021). Through V2G, the e-carsharing company can help the DSO reduce peak consumption and postpone investments in network reinforcement. However, in places where EVs are not yet widespread, the DSO needs to wait for EVs to reach higher penetrations to have a reliable service. Thus, the e-carsharing business model can play an important role in accelerating the sustainable energy transition. Moreover, the DSO can enjoy the benefits of V2G without necessarily expecting high EV penetration. Finally, the V2G provided by e-carsharing companies can be more reliable than those of individual users, as they can guarantee the energy supply through pre-established agreements.

The CS siting and sizing problem can be treated as an optimization problem, given the series of complexities presented to define its business model (charger type, charging type, energy tariff, position, capacity, etc.). Generally, the objective of the CS operator is to maximize its profit while minimizing the investment cost. Thus, to define the CS's position, it is necessary to understand the region's charging demand to choose a location that meets the maximum number of customers and avoid oversizing its capacity. In the shared mobility context, the EV charging time differs from that of private EVs. Unlike CSs for private EVs, where clients want to charge as soon as possible, in this case, the e-carsharing operator has more control over the EV charging time (FALABRETTI; GULOTTA, 2022). In addition, for an e-carsharing business model, there are still additional variables, such as the EV fleet size. To define the EV fleet size, one must know the total profit per EV, which can be summarized as the sum of three parts: rental profit, charging costs, and relocation costs. Relocation is a mechanism used to obtain vehicles where there is demand. The relocation can be carried out by the operator (operator-based) or by the user (user-based) through a price incentive (HUANG, KAI *et al.*, 2020; QIN *et al.*, 2022). The total profit per EV could be an approximated parameter, but in this case, the optimization problem can rely on the e-carsharing operation decisions to obtain the profit more accurately. However, to avoid biased planning, the e-carsharing optimization problem must consider uncertainties in rental demand.

The insertion of a large EV fleet can cause, or exacerbate, problems in the distribution power grid. In fact, the price signal (such as TOU or RTP) is a mechanism to shift EV charging to off-peak times. However, such a mechanism may not be a sufficient condition to guarantee the operation of the power grid, especially regarding cables' and transformers' overload. Thus, it is important to consider the DSO perspective in e-carsharing planning through power flow. Works involving planning (even CSs or DERs) usually use the direct current optimal power flow (DCOPF) as simplified modeling, which facilitates implementation and reduces computational time (DING; TENG; *et al.*, 2020). However, such simplification could bring inaccurate results that could affect long-term decisions, such as the optimal position of CSs (LARRAHONDO *et al.*, 2021). In its complete formulation, the alternate current optimal power flow (ACOPF) accurately reflects the optimal values of the operating variables (bus voltage, cable currents, losses, etc.). However, the model is non-linear, which increases the computational time, making it often intractable for large-scale problems. Recently, the second-order cone programming (SOCP) formulation, together with the branch flow model (BFM), has emerged as an option to reduce the computational time of the ACOPF but without losing accuracy (NICK *et al.*, 2018). The basic idea is to transform the nonlinearity of the problem into a quadratic one, which is simpler to solve. However, solving both the e-carsharing problem and ACOPF with the SOCP formulation is difficult because of not only the non-convexity, but also their intrinsic numeric instability due to the constraint (XIE *et al.*, 2020). This problem can be avoided with linearization techniques, which are well known in the literature, such as Big-M, piecewise linearization and the polyhedral global approximation (LIN, MING-HUA *et al.*, 2013; WU; TIAN; ZHANG, 2017). The main advantage of a linearized model is related to the efficiency of available linear optimization solvers, considering the computational time. This is an important factor to make tractable models in shorter terms operation.

Based on these considerations, two optimization models fit the problem: two-stage stochastic programming and robust optimization. A stochastic program is an optimization problem in which some or all of the parameters of the problem are uncertain but follow known probability distributions. This structure contrasts with deterministic optimization, in which all parameters of the problem are known exactly. The objective of stochastic programming is to find a decision that optimizes some criteria chosen by the decision-maker and adequately takes into account the uncertainty of the problem parameters (SHAPIRO; DENTCHEVA; RUSZCZYŃSKI, 2009). Furthermore, the basic idea of two-stage stochastic programming is that decisions must be based on data available at the time the decisions are made and cannot depend on future observations. On the other hand, robust optimization is a field of optimization theory that addresses optimization problems in which a certain measure of robustness is sought against the uncertainty that can be represented as deterministic variability in the value of the parameters of the problem itself and/or its solution (BERTSIMAS; SIM, 2004). In other words, stochastic optimization finds an optimal solution based on a risk associated with the realization of the scenarios, while robust optimization finds the optimal solution relying on the realization of the worst case of uncertain parameters.

1.1 AIMS AND OBJECTIVES

Understanding the strengths and weaknesses of each business model is vital to avoiding pitfalls and accelerating the transition to electric mobility. Thus, the objectives of this thesis are twofold. First, is to present a discussion regarding business models for EV adoption and CS infrastructure. For this, a critical analysis based on a robust literature review of EV adoption and CS business models it presented. The business models are categorized as traditional and innovative. Traditional models are those that are already widespread worldwide, while innovative models are in the research phase or isolated applications. Moreover, a discussion of the role of each agent involved in electric mobility (public administrators, regulators, energy suppliers, operators, and EV users) and the different charging technologies is presented. The successful application of a particular business model depends on the characteristics of the region. To understand the best way to accelerate the electric mobility transition, challenges and opportunities for new business models are presented.

The second objective is to assess how different operation decisions and agents' perspectives (such as the DSO[2]) affect the long-term planning and profit of an e-carsharing company, a mathematical model is proposed. The DSO perspective is modeled as an AC optimal power flow (ACOPF), formulated by second-order cone programming (SOCP) linearized by the global polyhedral approximation. Since demand uncertainties can affect the profit of an e-carsharing company, scenarios based on kernel distribution from real data are considered. Therefore, the problem is formulated with two-stage stochastic programming as a siting and sizing problem. The first-stage variables are the position of CSs, the number of chargers per CS, and the size of the EV fleet. The second-stage variables refer to both the operation of the company's EVs (rental, charging, and relocation) and the power grid. The TOU and RTP tariffs are widely used in the literature. To date, these types of tariffs have a good application for private EVs, which tend to have stricter origins and destinations. Although these tariffs reflect the state of the network, they are the same for an entire concession area (assuming a regulated market). Thus, distribution locational marginal pricing (DLMP) has a good application in the context of shared mobility. Hence, EVs on constant trips can take advantage of cheaper prices in different parts of the city and reduce charging costs.

Specifically, this work contributes to the literature in the following ways:

- This thesis presents a critical analysis based on a robust literature review of EV adoption and CS business models.

- Raises a discussion on the feasibility of cooperation between an e-carsharing company and the DSO. The design of this joint planning business model can be a win–win situation for both agents. The company can increase profitability, while the DSO can mitigate the impact on the power grid with V2G;

- Design a two-stage stochastic DLMP-based model that considers both DSO and e-carsharing operating constraints under EV rental demand uncertainty;

- Solve the ACOPF with a SOCP formulation linearized by the global polyhedral approximation in the shared mobility context.

[2] It is assumed a regulated market, that is, customers cannot choose their energy supplier. Thus, the power utility is also the system operator.

1.2 THESIS STRUCTURE

Regarding the structure of the thesis, Section 2 presents the literature review, which encompasses the EV adoption business models, EV charging stations business models, and some thoughts from the author about the business models for EV adoption and charging stations. Section 3 presents the stochastic problem formulation, which is divided into an objective function and first-stage and second-stage constraints. Section 4 presents the case study, with information about the e-carsharing company and the distribution network. In Section 5, the results are discussed, and the main conclusions are developed in Section 6.

1.3 RELATED PUBLICATIONS

1.3.1 Published Papers

BITENCOURT, LEONARDO; ABUD, TIAGO P.; DIAS, BRUNO; BORBA, BRUNO S. M. C.; MACIEL, RENAN S.; QUIRÓS-TORTÓS, JAIRO. Optimal Location of EV Charging Stations in a Neighborhood considering Multi-Objective Approach. *Electric Power Systems Research*, 2021.

BITENCOURT, LEONARDO; DIAS, BRUNO; ABUD, TIAGO; BORBA, BRUNO; FORTES, MARCIO; MACIEL, RENAN S. Electric Vehicles Charging Optimization Considering EVs and Load Uncertainties. In: *2019 IEEE Milan PowerTech*, 2019, Milan. 2019 IEEE Milan PowerTech, 2019. p. 1.

BITENCOURT, LEONARDO DE A.; BORBA, BRUNO S. M. C.; DIAS, BRUNO H.; MACIEL, RENAN S.; DIAS, DANIEL H. N.; OLIVEIRA, LEONARDO W. Electric Vehicles Charging Optimization to Improve the Insertion Considering the Brazilian Regulatory Framework. *Energy Storage*, v. 1, p. e76, 2019.

1.3.2 Papers Submitted to Journals

BITENCOURT, LEONARDO; DIAS, BRUNO; SOARES, TIAGO; BORBA, BRUNO S. M. C.; QUIRÓS-TORTÓS, JAIRO. Understanding business models for the adoption of electric vehicles and charging stations: Challenges and opportunities in Latin America. *IEEE Access*, 2022.

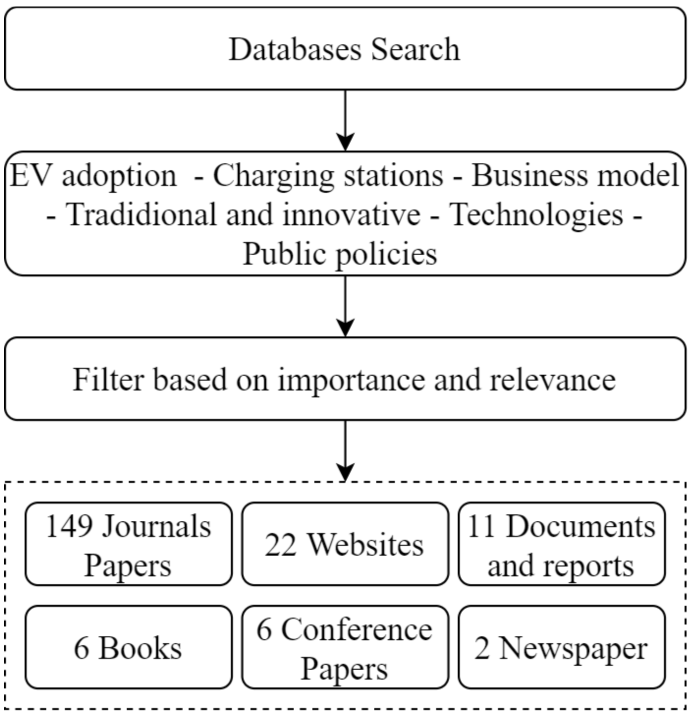
BITENCOURT, LEONARDO; DIAS, BRUNO; SOARES, TIAGO; BORBA, BRUNO S. M. C.; QUIRÓS-TORTÓS, JAIRO. e-Carsharing Siting and Sizing DLMP-based Under-Demand Uncertainty. *Applied Energy*, 2022.

2. LITERATURE REVIEW

This section provides a literature review of EV adoption business models and CS business models, which are categorized as traditional and innovative. In addition, a brief discussion of light-duty electric vehicle technologies is presented, along with the main agents involved in electric vehicle charging. A categorization of recent literature on the siting and sizing of charging stations and e-carsharing is also presented. Finally, a discussion of the challenges and opportunities for different business models is presented at the end of the section.

The flowchart with the methodology to select the research literature is presented in Figure 3. The main databases used were Science Direct, IEEE Xplore, Engineering Village, and Google Scholar. The objective was to find a wide option of literature that addressed the main business models regarding EV adoption and charging stations. Most of the discussions are in journal papers among the selected literature. Websites are usually associated with companies that provide services, while documents and reports are usually from government research. Finally, 74% of the selected literature is between 2018 and 2022, indicating a recent relevance on the topic.

Figure 3 – Literature selection flowchart.

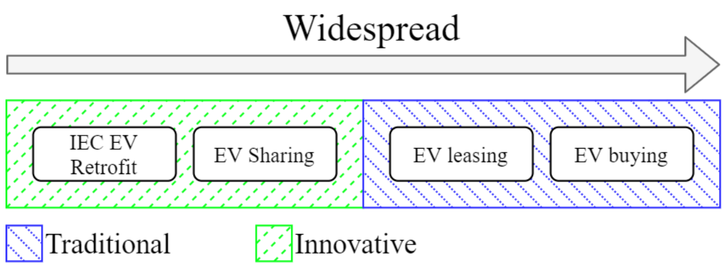


Source: Author

2.1 EV ADOPTION BUSINESS MODEL

A suitable definition of business models in the context of EV adoption is presented in (SAN ROMÁN *et al.*, 2011), which describes the business model as "how a product or service is provided, including perceived value creation of a certain product for a final customer. It is internal to one single agent and usually easy to assess by spending strategic thoughts on opportunities and threats". Thus, business models focused on EV adoption must consider factors such as access duration and cost, payment method for access (one-time payment, monthly fee, hourly tariff, etc.), and operation and maintenance costs. In this way, four main business models for EV adoption in the literature were identified, which are classified as (i) buying, (ii) leasing, (iii) sharing, and (iv) retrofitting. These models are classified as traditional or innovative depending on their level of deployment and replication. Traditional models are considered widespread and consolidated models, while innovative models are those that are in the design or testing phase, implemented in some parts of the world. Figure 4 shows that EV adoption business models are organized according to their widespread nature and innovation.

Figure 4 – EV adoption business models.



Source: Author

The main agents involved in the EV adoption process are manufacturers, retailers, fleet operators, final users, and the government (LUO, CHUNLIN *et al.*, 2014; YU *et al.*, 2021). Manufacturers are responsible for building EVs, while retailers (dealers) buy vehicles from manufacturers to resell them to end-users. Final users can also have access to EVs through rental platforms (leasing or sharing) operated by third parties (fleet operators). Last, the government has a fundamental role in EV proliferation through incentive policies, which can be classified as direct and indirect.

Direct incentives are financial, such as reduction in purchase tax, reduction in annual license tax, carbon taxation, and increase in internal combustion engine (ICE) vehicle taxes. Moreover, indirect incentives are related to benefits for EV users, such as access to exclusive lanes, reduction of tolls, and parking spots. Research on the effectiveness of public policies to increase EV penetration is growing. Several studies indicate that tax subsidies on purchases can accelerate the spread of EVs (HARDMAN *et al.*, 2017; LÉVAY; DROSSINOS; THIEL, 2017; SHAFIEI *et al.*, 2018). Evidence from Europe shows that an incentive of €1,000 in EV purchases would increase sales shares on average by an approximately 5–7% relative increase in a given sales share (MÜNZEL *et al.*, 2019). On the other hand, the carbon tax policy in the transport sector may be an unpopular measure because it affects the less wealthy more than the richest, leading to greater social inequality (JAGERS; HAMMAR, 2009). Furthermore, indirect policies also have a positive correlation with EV sales (HARDMAN, 2019). Colombia, Chile, Costa Rica, and Panama already have national strategies or plans for electric mobility, while Argentina, Brazil, Mexico, and Paraguay are in the process of formulating and launching their strategies (UNEP, 2020).

Despite policies having a fundamental role in EV proliferation, governments should phase out incentives to reduce the burden on the public budget (HE, HAONAN *et al.*, 2021; MA *et al.*, 2021). However, this transition must be carefully evaluated to avoid negatively impacting vehicle sales. China reduced subsidies and introduced a dual credit policy in 2017, similar to the zero-emission vehicle and carbon cap policies. Although EV sales decreased by 4% in 2019, this policy shifts the responsibility for EV long-term adoption to automakers (YU *et al.*, 2021).

2.1.1 EV technology

The main light-duty EV technologies are hybrid electric vehicles (HEVs), plug-in electric vehicles (PHEVs), and battery electric vehicles (BEVs). HEVs have an electric motor and an internal combustion engine to propel. The HEV battery, which cannot connect to the external power grid, is charged by the ICE or by regenerative braking. PHEVs are similar to HEVs, but they can connect the battery to the power grid to charge. Furthermore, the BEV uses only an electric motor to propel, and it can connect in the power grid to charge. HEVs have been important in the past to foster the development of EVs. However, because they use an ICE and do not provide access to the battery, they are only a step toward the full development of EVs (LI, ZHENHE; KHAJEPOUR; SONG, 2019). One of the reports from the US Department of Energy shows that HEV market share decreased while PHEV and BEV technologies increased in the country (U.S. DEPARTMENT OF ENERGY, 2021). Additionally, the price of batteries has a significant impact on the EV price. Evidence shows that battery capacity is a greater barrier than vehicle cost in the Chilean context (URRUTIA-MOSQUERA; FÁBREGA, 2021). According to the International Energy Agency (IEA), the weighted average cost of automotive batteries declined 13% in 2020 from 2019, reaching US$ 137/kWh at the pack level (IEA, 2021). It has been estimated that the threshold for an EV to be truly cost-comparable to an ICE vehicle is US$100/kWh (KNUPFER *et al.*, 2017). However, despite recent battery prices dropping, this process will slow down in the medium term (approximately 10 years) (HSIEH *et al.*, 2019).

2.1.2 Traditional business models

The most traditional EV adoption business model is the one in which consumers buy the vehicle. The main advantage of this model is that the user has total ownership of the vehicle, giving him/her the freedom to use it at any time. However, the high acquisition cost limits most people from adopting this type of model (METAIS *et al.*, 2022). The payback for EVs is approximately 10 years in some European countries. However, EVs are already cheaper than ICE vehicles in some countries, such as Denmark and Spain (COSTA *et al.*, 2021). Furthermore, despite the reduced operating costs, the batteries need to be replaced if the user stays with the same car for some years (ALHARBI; BHATTACHARYA; KAZERANI, 2019).

Another traditional business model is car leasing. This option is cheaper for users who cannot (or do not wish to) bear the total cost of the vehicle. Leasing has grown in popularity, now accounting for nearly 27% of all new car sales. However, regarding EVs, 80% are leased (BLOOMBERG, 2018). With EV leasing, users can (i) have faster access to new technology upgrades, (ii) avoid dealing with rapid EV and battery degradation, (iii) have more government incentives, and (iv) earn loyalty bonuses offered by rental companies. However, vehicle availability is restricted to rental company fleet availability (LANE *et al.*, 2018). For instance, the website electrek presents the EV leasing plans offered by dealers in the US (ELECTREK, 2021). Customers can choose subscriptions that vary from 24 to 42 months. The current cheapest subscription fee is for Hyundai Ioniq, US$ 8,064 for 36 months (US$ 224 per month), while the current price is US$ 33,245 (approximately 75% savings) (ELECTREK, 2021; HYUNDAI, 2021). In Europe, France and Germany raised EV subsidies to €9,000 and €7,000, respectively, to increase adoption. Drivers can lease an EV for €39 a month in Germany, while customers can lease the Renault Zoe for €79 a month in France (AUTOMOTIVE NEWS EUROPE, 2020).

2.1.3 Innovative business models

Vehicle sharing has been increasing in recent years (GONG *et al.*, 2019). Its proposal, unlike leasing, is to be a faster and for short periods rental. Shared vehicles also have business models and can be classified as round-trip, one-way, and free-floating[3] (TART *et al.*, 2018). The round-trip system requires users to return vehicles to the same station of departure. The one-way system allows users to return vehicles to any company station. Finally, the free-floating system allows users to return the vehicle anywhere (HUA *et al.*, 2019; HUANG, KAI; AN; CORREIA, 2020; XIE *et al.*, 2020). The shared electric vehicle (SEV) proposal is from a vehicle sharing company that only owns EVs. In this case, in addition to the general considerations for this type of business model (fleet capacity, station positioning, vehicle relocation, etc.), decision-makers need to take into account other aspects related to EVs, such as the number of chargers per station and vehicle battery capacity. Some companies use this business model in Latin America, but only with bicycles and scooters, such as Urbano, AWTO, and Itau (TORO; VAN DER KROGT; FLORES, 2019). This business model is dependent on both the transport network and the electricity network. In this way, some authors study the planning of SEVs considering the perspective of the power grid operator (WANG, SHU *et al.*, 2020a). In addition, as SEV companies have a large energy capacity, they may be able to participate in the energy market or provide ancillary services (XIE *et al.*, 2020). Furthermore, electric taxis have similar challenges as SEVs (MANRÍQUEZ *et al.*, 2020; MORRO-MELLO *et al.*, 2019; PAN, AIQIANG *et al.*, 2019).

The retrofitting of internal combustion to EVs (ICE to EV retrofitting) is a potential transitional solution to the widespread adoption of EVs. Adaptation consists of replacing components, such as the combustion engine, exhaust system, and fuel tank, for the electric motor, controller, batteries, and inverter. A few small companies offer this type of service, such as Zeletric and Green Shed Conversions (GREEN SHED CONVERSIONS, 2021; ZELECTRIC, 2021). In Germany, for example, retrofit prices cost approximately 8,000 euros for light-duty vehicles. In addition, the country has regulations and processes to approve adapted vehicles for use on public roads (HOEFT, 2021). Few previous studies have investigated the retrofitting of ICE to EVs. Most studies in the literature focus on the practical application of vehicle component replacement (AGGARWAL; CHAWLA, 2021;

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[3] Some organizations operating within those business models can be cited: car2go, Zipcar, DriveNow, Autolib, Bluetorino, Bluecity, Juuve, Partago, Ubeeqo, Cambio, Greenwheels, Io Guido, Dégage, Drivy, CarAmigo (TART *et al.*, 2018).

EMBRANDIRI; ISA; AREHLI, 2011; KALEG; HAPID; KURNIA, 2015). On the other hand, some authors investigate the feasibility of converting conventional vehicles into EVs (GABRIEL-BUENAVENTURA; AZZOPARDI, 2015; HOEFT, 2021). Recently, Silva and Urbanetz Junior converted an ICE vehicle into an EV in Brazil (SILVA; URBANETZ JUNIOR, 2019). The results of several tests indicate that the converted vehicle reached an average travelling cost of 0.16 R$/km, assuming a price for the energy of 0.63 R$/kWh. However, there is not enough evidence to show whether the conversion is economically feasible. Nevertheless, ICE to EV retrofitting still needs further investigation, especially in assessing the feasibility of this business model.

2.2 EV Charging Business Model

The lack of efficient public charging infrastructure is one of the main problems in EV adoption (YOO; CHOI; SHEU, 2021). Understanding the strengths and weaknesses of various charging technologies, service provision, tariffs, and payment methods is vital for proper business model design. Furthermore, the deployment and operation of CSs require the participation of several agents. Thus, the main elements for setting a business model for CSs are presented in this section.

2.2.1 Agents

To develop the charging infrastructure, the interaction between different agents is necessary, such as public administrators, regulators, energy suppliers, and operators. Public administration and regulators can elaborate laws and standardization regarding charging stations. There is a wide variety of EVs on the market, and CSs must be capable of charging them all. Countries where there is greater adoption of EVs are already in motion on this topic (DE LA PARRA; CHEN; YU, 2013; GREAKER, 2021). Therefore, the government has an important role in ensuring the development of technology through incentive policies (BITENCOURT, LEONARDO; ABUD; SANTOS; *et al.*, 2021). Seven programs aiming to develop public CSs were launched in the US between 2009 and 2017 (CONSONI *et al.*, 2018). Public policies to increase charging infrastructure were also effective in the Chinese market. The country had 88,476 slow charge stations and 52,778 fast-charge stations in 2017 (CONSONI *et al.*, 2018; QIAN; GRISOLÍA; SOOPRAMANIEN, 2019). In addition, the Chinese government has set a target to install 12,000 charging stations and 4.8 million charging points (500,000 public and 4.3 million private) by 2020. Despite not having been reached, the numbers have been growing every year (HU *et al.*, 2021). In the Netherlands, policies aimed at charging infrastructure also had a high impact on EV sales (MEA, 2017). In addition to free charging at public stations, a subsidy of 1,450 € is offered for the installation of home chargers (ACEA, 2019). To enable long trips, Chile, Mexico, Brazil, and Argentina built 1200 km, 620 km, 434 km, and 212 km charging corridors, respectively (UNEP, 2020). However, the total number of chargers is still small compared with the other nations.

The energy supplier is the agent that sells energy to the final consumer[4]. The energy purchased at the distribution level depends on the country's market structure, which can be regulated or deregulated. However, this topic will not be addressed in this thesis. Public CSs can be considered service providers (AFSHAR *et al.*, 2021). Thus, the energy cost is at the price of the service. It is noteworthy that with the evolution of new business models, CSs can reduce their dependence on external generation through DER (solar and wind) (AHMAD; KHALID; PANIGRAHI, 2021; EKREN; HAKAN CANBAZ; GÜVEL, 2021; FATHABADI, 2017). Several authors have investigated CS business models focused on solar-powered generation. Ye *et al.* (2015) show that this business model is viable in China, but due to the high initial cost and land usage, combining it with SEV might be a better option to ensure its feasibility. Moreover, Fang *et al.* (2019) investigate the public–private partnership to promote solar generation in CSs. The results show that with a proper subsidy policy and pricing strategy, this business model can be effective.

The DSO is the regulated agent that operates the distribution network. In addition, in early markets, the DSO, which is also the power utility, can install and act as a station operator. For example, Tata Power, an Indian power utility, recently installed over 1,000 charging points in 40 cities across India (TATA POWER, 2022). The DSO is also concerned about how EV charging will affect distribution network expansion planning. Heymann *et al.* (2019) show that traditional approaches to allocating DERs in distribution networks underestimate the impact of EV adoption. Thus, traditional approaches might result in strong underinvestment in capacity expansion during EV early uptake. It is noteworthy that with the development of smart grids, CSs can help DSOs reduce the negative impacts of EV charging through vehicle to-grid (V2G) (GÖNÜL; DUMAN; GÜLER, 2021; SOVACOOL *et al.*, 2020).

The charging impacts that a single EV has on the distribution network can be negligible. However, with the increase in the number of vehicles, the charging impacts also

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[4] The energy is delivered to the final consumer by the TSO and DSO. The TSO aspects will not be covered in this work. For more information, see (CODANI; PEREZ; PETIT, 2016; CROZIER; MORSTYN; MCCULLOCH, 2020; GUNKEL *et al.*, 2020).

increase. Coordinating EV charging is a task generally assigned to the aggregator in the literature. The aggregator can, through charging management, bring economic gains for both EV users and the DSO (DING; LU; *et al.*, 2020; RAHMAN *et al.*, 2016). Bitencourt *et al.* (2017) show that charging coordination by an aggregator can alleviate the distribution transformer peak demand, while decentralized charging can create new peak consumption. It is noteworthy that the aggregator can be the charging point operator (CPO), managing the charging of its various CSs, or a third party that manages the charging of EVs in a community.

Moreover, the EV user is the final agent in the charging infrastructure value chain, which has different charging profile types. Hence, the EV user chooses the CS that better meets his/her demand at a given moment (proximity, lower charging cost, fast charging, etc.). Finally, the CPO is the agent that operates and maintains the CS. In more developed markets, where there is competition, different CPOs compete to capture the users' demands. To illustrate, Laha *et al.* (2019) study the EV charging problem considering several CSs competing against each other using game theory. The EV user selects the closest CS with the lowest charging cost. Due to the selfishness of the players (CPOs), the authors also investigate the so-called Price of Anarchy. In addition to the technical attributions (operation, maintenance, and installation), the CPO also addresses the pricing of the service provided. Figure 5 summarizes the main agents involved in the EV charging process.

Figure 5 – Agents involved in the EV charging process.

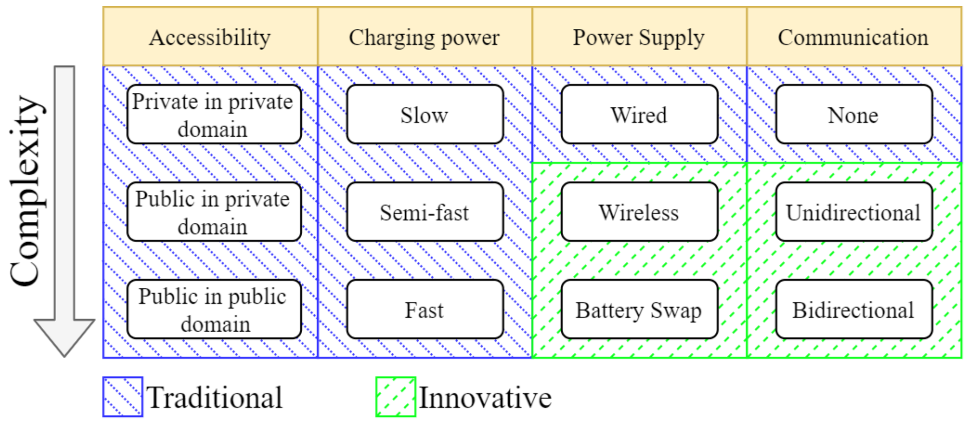
Source: Author

2.2.2 Electric vehicle charging technology

The main aspects related to CS infrastructure technology can be summarized into four topics: accessibility, charging power, power supply, and communication. In this thesis, those aspects are organized according to their complexity for mass implementation and innovation in Figure 6. It is noteworthy that there is a set of combinations of CS infrastructure aspects within the topics presented that could lead to different business models. A similar approach was made in (MADINA; ZAMORA; ZABALA, 2016).

In the CS station context, users need some level of accessibility to the charging point. However, due to different locations, different designs need to be adapted. Thus, charging infrastructure accessibility can be classified into three main segments: private in the private domain, public in the private domain, and public in the public domain (EURELECTRIC, 2010). In private domains, users need some level of permission to access the charging point, while in public domains, access depends only on the availability of the charging point. Private accessibility in the private domain could be a house where you must have the owner's authorization to use their charger. Moreover, public accessibility in private domains is a place that can be freely accessed, but it is privately owned, such as shopping malls, office buildings, private parking lots, etc. Finally, public accessibility in the public domain includes locations owned by municipalities, including roads, streets, public parking lots, etc. The complexity of accessibility can be related to installation and operating costs (e.g., type and quantity of chargers, cables, specialized workforce, etc.), standardization, and electrical installation reinforcement.

Figure 6 – Charging station infrastructure main aspects.



Source: Author

As the EV charging time is still high, different charging power solutions have been developed to meet the different charging demands. There are three main types of charging power: slow, semi fast, and fast. As all of them already have widespread solutions, they can be classified as traditional. However, the installation complexity also increases as the charging power increases. The slow charger is the simplest in terms of installation, usually associated with residential charging. This type of charging is approximately 3.6 kW AC power and takes between 8 h and 12 h, depending on the EV battery (CHEN, JIE *et al.*, 2022; ZHOU, KAILE *et al.*, 2020). The semi fast charger has applications in both residential and public places. The charging is between 7.2 kW–22 kW AC power and takes between 2 h–5 h to charge the EV (ILLMANN; KLUGE, 2020). Fast chargers are usually installed in public domains (by specialized parking lots), given the high cost of installation. The DC charging power varies from 50 kW to 350 kW and can take up to 10 minutes to fully charge the EV (BRÄUNL *et al.*, 2020; TU *et al.*, 2019).

Another point related to the CSs is regarding the energy supply. The traditional model uses power cables. However, in addition to connection problems due to a large number of equipment manufacturers, cables can be potentially dangerous on rainy days and can cause sparks at the time of connection/disconnection. Therefore, wireless charging is considered an innovative option to avoid such problems (MACHURA; LI, 2019; NIU *et al.*, 2019). Wireless charging can be stationary, semi-dynamic, and dynamic. Stationary devices work like traditional chargers, in which the vehicle stays parked while charging but without the need to connect cables. Semi-dynamic charging, on the other hand, has applications at bus stops, taxis, and traffic signals and can supply energy to vehicles that make a brief stop. Finally, dynamic charging charges the EV while it is in movement. The main advantages of on-road wireless charging are as follows: (i) EV batteries can be smaller; (ii) the need for a large number of fast chargers is reduced; (iii) charger usage is increased, justifying the high investment cost; and (iv) long trips are enabled. However, this application requires building large corridors on roads and highways. Several studies have been conducted in the literature assessing the technical and economic feasibility of wireless technology (GARCÍA-VÁZQUEZ *et al.*, 2017; JANG, 2018; JEONG; JANG; KUM, 2015). Recently, the company ElectReon has completed the deployment of its dynamic wireless charging system on a 1.65 km public road in Gotland, Sweden. Tests showed that the battery charged even on the road with snow and ice (RADU, 2021). A project with the Solano Transportation Authority and Momentum Dynamics Corporation will deploy a 300 kW automatic wireless fast charging infrastructure at seven strategic points in California (CORPORATION MOMENTUM DYNAMICS, 2021). Despite the implementation of some projects, little is discussed in the literature regarding the possible business models related to this technology, such as in (GILL *et al.*, 2014).

Battery swaps are another innovative method of EV charging. The principle of the battery swap station is to be fast charging, similar to gas stations, but without demanding high power from the distribution network (FENG *et al.*, 2020; WANG, HAIFENG *et al.*, 2021). Thus, it is possible to avoid the costs of reinforcing the network. However, there are difficulties with this technology. Similar to cable connection issues, manufacturers would also have to comply with standards to ensure battery connectivity in any vehicle. There is also concern about battery ownership. New EV users will require a battery with the same power capacity as the swapped one. Therefore, the CPO of the battery swap station needs to ensure that the battery will deliver an amount of energy within limits established by a standard. Such factors imply the cost of this type of station, which has a high investment (battery purchase) and maintenance (battery replacement to ensure quality) cost (AHMAD *et al.*, 2020). The authors in (LIDICKER; LIPMAN; WILLIAMS, 2011) analyzed the feasibility of a subscription-based battery swap station, considering different parameters. Analyses suggest that the station is only profitable with high gas prices. A real case of a battery swapping station was the Better Place in Israel. The company was founded in 2007 but went bankrupt in 2013. The lack of government subsidies, adhesion of automakers, and positive word of mouth from customers were some of the shortcomings that led to the end of the enterprise (GUNTHER, 2013). In contrast, battery swap stations for scooters are growing in India, where the battery price is approximately 30%–40% of the total vehicle price. Hence, this business model may continue to be relevant for a price-sensitive market such as India (PHILIP, 2021).

Finally, communication allows for external management of battery charge. In the traditional method, no communication is used[5], and the vehicle starts charging as soon as it connects to the network. Unidirectional and bidirectional communications are more advanced methods that control the charge[6] of the battery and even power injection into the network, known as vehicle-to-grid (BAI *et al.*, 2015; DRUDE; PEREIRA JUNIOR; RÜTHER, 2014; LIU *et al.*, 2015; TAN; RAMACHANDARAMURTHY; YONG, 2016).

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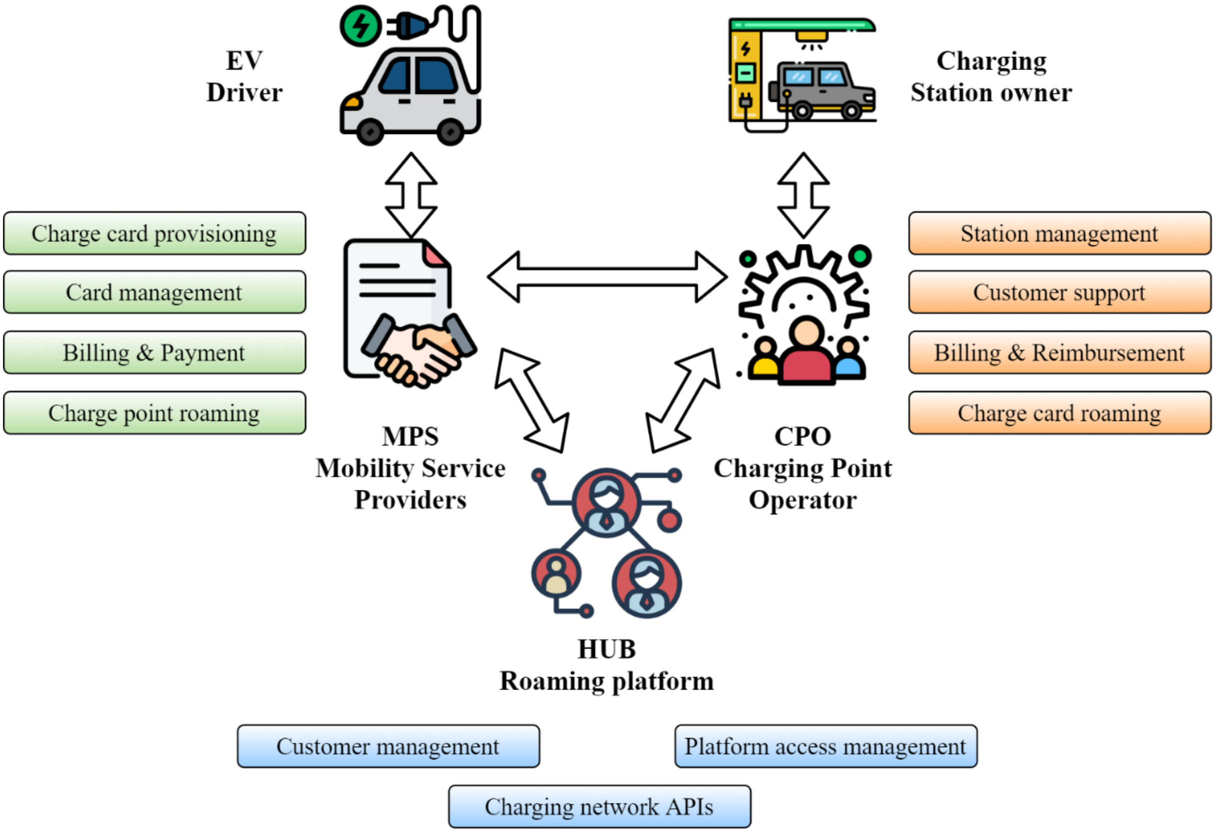
[5] Known as uncoordinated charging or dumb charging.
[6] Known as coordinated charging or smart charging.

2.2.3 *Charging station services*

Historically, there have been three roles in public EV charging services (KRUG; KNOBLINGER; BAUER, 2020): charge point operators, mobility service providers (MSPs), and e-rooming platforms. The CPOs run and maintain the CS, but they do not necessarily need to own the charging infrastructure. Their tasks can be separated into technical (deployment, operation, maintenance) and financial CPOs (marketing, pricing), and both parts can be fulfilled by different entities. A high number of small and regional players are active in this field. MSPs offer service contracts to end customers and provide an interface for the user to access the charging infrastructure. Today, practical access to charging is mainly through radio-frequency identification (RFID) cards and apps. Historically, automotive original equipment manufacturers (OEMs) were front-runners in enabling long-distance e-mobility for their EV customers. However, as this is a software-intense business, many small, innovative IT start-ups have entered and now directly compete with OEMs (e.g., NewMotion, Plugsurfing, Virta) (NEWMOTION, 2022; PLUGSURFING, 2022; VIRTA, 2022). Finally, eRoaming platforms act as aggregators of the two other roles, connecting CPOs and MSPs. Currently, the market is divided between just a few platforms. Aggregators such as Hubject and Gireve were put in place by energy and automotive companies (GIREVE, 2022; HUBJECT, 2022). Their key success factor is offering MSPs and CPOs access to as many partners as possible. Figure 7 summarizes the agents and their respective roles in EV charging customer service.

Figure 7 – Agents in EV charging customer service.



Source: Author

According to (KRUG; KNOBLINGER; BAUER, 2020), the key success factor for MSPs is diversification to offer the end customer easy access to as many charging points as possible. MSPs must either have the most intelligent energy services or offer charging as part of integrated mobility platforms. For eRoaming platforms, authors consider that it will be extremely difficult to remain in the game. Their core business models will most likely be taken over by CPO aggregators. Hence, they must come up with new solutions, for example, the plug & charge solution.

CPOs are currently the most active players along with the public EV charging service. CPOs may offer customized solutions and operate them as full-service providers after deployment (KRUG; KNOBLINGER; BAUER, 2020). Because the network of charging points is wide-meshed in most markets, growth potential still comes from improved geographical coverage [54]. In addition, CPOs must secure the most attractive charging locations, expanding their networks by aggregating smaller players, especially for fast charging services. In future markets, CPOs can offer more services to customers, especially with the evolution of 5G (MAHMUD *et al.*, 2018).

From a private CPO perspective, the main concern is to ensure the high utilization of chargers to validate the investment. In contrast, from the DSO perspective, the main concerns about EV charging are the negative impacts on the power grid. The impacts of uncoordinated EV charging can bring new challenges to the DSO, such as overloads in transformers and low voltages. In this way, coordinated charging and V2G can reduce those impacts with peak shaving (MEHTA *et al.*, 2019) and bring some benefits, such as ancillary services and postponing investments in the grid (MORADIJOZ; PARSA MOGHADDAM; HAGHIFAM, 2018; MOZAFFARI *et al.*, 2020). However, it is important to understand the user's charging demand to evaluate the applications of coordinated charge and V2G. The usage of a type of charger depends on the user's charging demand at a given time, which may vary according to day-to-day events. In this way, users who demand fast charging want to spend the shortest possible time charging. Thus, there is no applicability of coordinated charging or V2G in fast chargers. On the other hand, users who charge their EVs at work or in places where they usually spend a lot of time (shopping, office buildings, supermarkets, etc.), are more susceptible to accept these types of charging. In this case, slow and semi fast chargers are more suitable, as there is no priority in the charging time (CHEN, HUIMIAO *et al.*, 2019; EHSAN; YANG, 2020).

With the development of smart meters and chargers, V2G is becoming more viable. Some projects are being developed around the world. According to the V2G Hub website (V2G HUB, 2022), ninety-eight projects related to V2G have already been started since 2009. Although 57.3% of the projects are proof of concept, 20.2% are already in the small-scale commercial trial phase. Among the services provided are time-shifting, frequency response, and DSO services. Figure 8 presents a map with the V2G projects listed on the V2G Hub website. To exemplify one of these projects, in 2021, the Advanced Australian V2G Project retrofitted an EV van to bidirectionally control the power flow and implemented onboard metering capabilities to turn the EV into a potential energy wallet (AEVA, 2021). Despite not being listed on the website, Chile, in a public-private partnership with Nissan LEAF, launched the first V2G project in Latin America in 2019. The system featured an Enel X bidirectional charger and a 3 kW photovoltaic system (NISSAN, 2019).

Figure 8 – V2G projects across the globe.

Source: Adapted from (V2G HUB, 2022)

2.3 CHARGING STATIONS OPTIMIZATION PROBLEM

The CS siting and sizing problem is generally approached as an optimization problem, which contains three main aspects: technical, economic, and mobility. The technical aspects are generally related to minimizing the impacts that the CS can bring to the power grid or maintaining it at standard levels, such as overload of transformers and cables, low voltage, power losses, etc. (CUI; WENG; TAN, 2019). However, technical aspects can also be part of the objective function, such as power losses (DE QUEVEDO; MUNOZ-DELGADO; CONTRERAS, 2019; WANG, SHU *et al.*, 2020a). Economic aspects are normally in objective functions. objectives are associated with maximizing the profits of the CS operator or minimizing investments in reinforcement in the power grid to support the load due to EV charging (LUO, LIZI *et al.*, 2018; MAO; TAN; WANG, 2020). Moreover, economic aspects are normally associated with maximizing CPO profits or minimizing investments in reinforcing the power grid (LUO, LIZI *et al.*, 2018; MAO; TAN; WANG, 2020). Economic aspects can also be a problem constraint, such as limiting the investment to a certain budget. It is important to highlight that the technical objectives can be transformed into economics, as done in (BANOL ARIAS *et al.*, 2018). Finally, mobility aspects are related to the mobility of both EVs and their users. Some examples of mobility aspects include minimizing the distance a user must walk from the CS to his/her destination, vehicle flow inroads, range anxiety, and trip loss (BITENCOURT, LEONARDO; ABUD; DIAS; *et al.*, 2021; PAN, LONG *et al.*, 2020; WANG, YUE *et al.*, 2018). An overview of the recent literature regarding siting and sizing problems is given in Table 1, which is organized according to the aspects considered in the objective function.

Table 1 – Summary of siting and sizing papers

Reference	Profit	Mobility preferences	Network operation costs	Investment costs
(HUANG, KAI; AN; CORREIA, 2020; HUANG, YANTAO; KOCKELMAN, 2020; MEHTA *et al.*, 2019; XIE *et al.*, 2020; ZHANG, YONGMIN *et al.*, 2019)	✓			
(MAO; TAN; WANG, 2020; MORADIJOZ; PARSA MOGHADDAM; HAGHIFAM, 2018; MOZAFFARI *et al.*, 2020)	✓		✓	✓
(ANDRADE; OCHOA; FREITAS, 2020; MANRÍQUEZ *et al.*, 2020; WANG, SHU *et al.*, 2018)		✓	✓	✓
(WANG, SHU *et al.*, 2020a; ZHANG, YUE *et al.*, 2019)		✓	✓	
(GONG *et al.*, 2019; HE, JIA *et al.*, 2018; PAGANI *et al.*, 2019; PAN, LONG *et al.*, 2020; WANG, YUE *et al.*, 2018)		✓		
(AGHAPOUR *et al.*, 2020; BANOL ARIAS *et al.*, 2018; BARINGO; BOFFINO; OGGIONI, 2020; CHEN, HUIMIAO *et al.*, 2019; CUI; WENG; TAN, 2019; DE QUEVEDO; MUNOZ-DELGADO; CONTRERAS, 2019; HUANG, PEI *et al.*, 2019; KONG *et al.*, 2019; LUO, LIZI *et al.*, 2018, 2020; PAN, AIQIANG *et al.*, 2019; REN *et al.*, 2019; WANG, XIAOLIN; NIE; CHENG, 2020; ZHOU, BO *et al.*, 2020)			✓	✓
(ALJANAD *et al.*, 2018)			✓	
(ERBAŞ *et al.*, 2018; HASHEMIAN; LATIFY; YOUSEFI, 2020; HUA *et al.*, 2019; JOCHEM; SZIMBA; REUTER-OPPERMANN, 2019; WANG, XU *et al.*, 2019; ZHANG, HONGCAI; MOURA; HU; QI; *et al.*, 2018; ZHANG, HONGCAI; MOURA; HU; SONG, 2018)				✓

Source: Author

2.3.1 Solution methods

The optimization problem relies on the perspective of one or more agents. In general, the authors are based on the CPO, DSO, and EV user perspectives. When the objective of these agents is conflicting, the problem can be handled as a multi-objective problem. Otherwise, it is treated as a mono-objective. Mono-objective problems are usually solved using mathematical programming techniques, such as mixed-integer linear programming (MILP) (HASHEMIAN; LATIFY; YOUSEFI, 2020; WANG, XU *et al.*, 2019; ZHANG, HONGCAI; MOURA; HU; SONG, 2018), mixed-integer second-cone order programming (MISCOP) (LUO, LIZI *et al.*, 2020; ZHANG, HONGCAI; MOURA; HU; QI; *et al.*, 2018), and convex optimization (CUI; WENG; TAN, 2019; ZHANG, YONGMIN *et al.*, 2019). Mathematical programming has advanced in recent years, making it possible to reach optimal solutions for complex problems in a tractable time. However, mathematical programming still fails to converge on highly complex and large-scale problems. Thus, heuristic and meta-heuristic techniques, such as genetic algorithm (GA) (HUANG, PEI *et al.*, 2019; REN *et al.*, 2019), particle swarm optimization (PSO) (ZHANG, YUE *et al.*, 2019), and multi-objective evolutionary algorithm based on decomposition (MOEA/D) (WANG, SHU *et al.*, 2018), are still used to solve these types of problems. In addition, meta-heuristics are a good tool for solving multi-objective problems.

On the other hand, some authors find optimal solutions to the CS siting and sizing problem via simulation. Pagani *et al.* (2019) developed a novel agent-based simulation framework coupled with a detailed geo-referenced digital model of the built infrastructure. The authors create more than 2500 scenarios of the transition to electric mobility in a mid-size city in Switzerland. Andrade *et al.* (2020) propose a scalable methodology that integrates high-resolution traffic flow and multi-phase electrical simulations to find the number, locations, and sizes of fast charging stations (FCSs) at the lowest societal cost considering the uncertainties in driving patterns. Finally, Erbaş *et al.* (2018) use the fuzzy analytical hierarchical process (AHP) and technique for order preference by similarity to ideal solution (TOPSIS) based on geographic information system (GIS) as a decision-making tool to choose the optimal EV CS location.

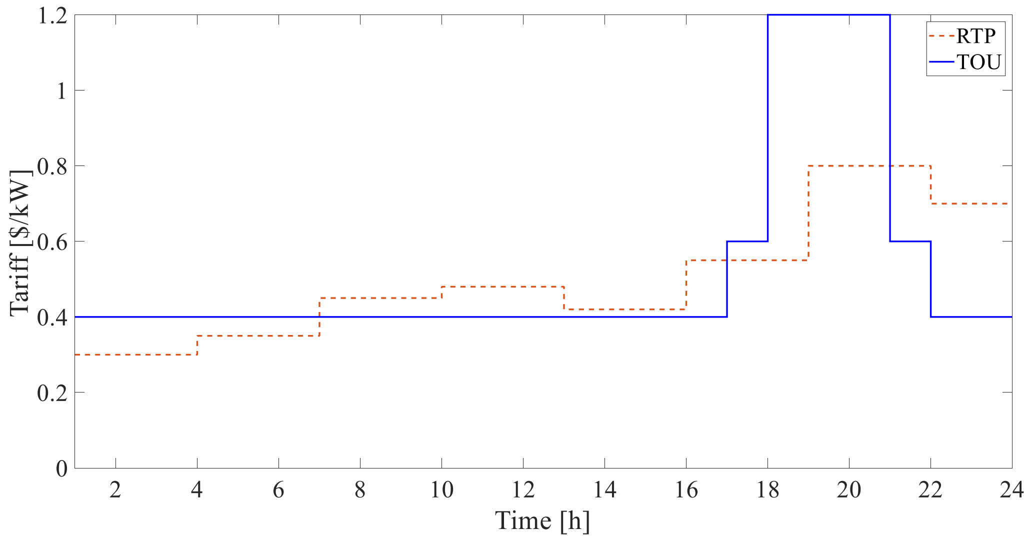
2.3.2 EV charging tariffs

The energy tariff is the most common parameter used in the literature to control EV charging. Energy tariffs can encourage load shifting to periods of low demand and alleviate the power grid. In addition, it is possible to postpone investment with power grid reinforcement due to the load increase.

The simplest form of tariff is the flat rate, in which the price of energy is the same at all periods. This tariff would not help the DSO alleviate the load due to EV charging, as there is no incentive to charge during off-peak hours. For this, it is necessary to define energy tariffs that vary over time, such as time of use (TOU) and real-time pricing (RTP). The TOU tariff has different values according to the time of day and normally has two tariff values, peak and off-peak, and eventually has an intermediate tariff. In some cases, this tariff is applied for an entire year; in others, it changes seasonally (NICOLSON; FELL; HUEBNER, 2018). However, the incentive to adjust demand given by the TOU tariff can end up creating new power peaks, causing voltage drops and transformers overload (BITENCOURT, LEONARDO DE A. *et al.*, 2017). Therefore, due to these potential shortcomings of TOU tariffs, several RTP tariff schemes have been defined, which dynamically adjust prices based on load instead of using fixed prices differentiated in time and therefore may be more effective in terms of changing consumer behavior (SAHRIATZADEH; NIRBHAVANE; SRIVASTAVA, 2012). Figure 9 presents an example of the TOU and RTP tariff schemes. A properly designed RTP tariff can result in a three-way solution: a flat load demand increases robustness and reduces power grid generation costs; lower generation cost leads to a lower wholesale market price, which in turn increases retailers' profit; and users can reduce their electricity bills by taking advantage of lower tariffs at off-peak time intervals (MOUFTAH; EROL-KANTARCI, 2016). However, the energy consumption of consumers must be elastic in relation to the energy tariff for such results to be achieved.

Moreover, a price mechanism widely used in transmission networks is local marginal pricing (LMP), which accounts for cable congestion in tariffs (BOHN; CARAMANIS; SCHWEPPE, 1984). With the increase in distributed generation, this concept has been extended to the distribution system (named distribution local marginal pricing - DLMP). Besides the power congestion issues, DLMP can reflect the losses and voltage stability in the tariff due to load or generation (PAPAVASILIOU, 2018). The DLMP was used as a price signal for EV aggregators to manage line congestion (HUANG, SHAOJUN *et al.*, 2015; LI, RUOYANG; WU; OREN, 2014). However, these authors consider private EVs with a preset origin and destination. In this way, vehicles cannot take advantage of lower energy prices in other buses, given that their movement is a fixed parameter. Finally, the DLMP is considered to optimize the siting and sizing of distributed generation (NEMATSHAHI; RAJABI MASHHADI, 2019), which can be extended to CSs.

Figure 9 – TOU and RTP tariff examples.



Source: Author

2.3.3 Power grid and transportation network

The main concerns about EVs are the charging time and its impacts on the power grid and battery autonomy. In this sense, researchers are investigating how the power grid and transportation network can affect the position and size of CSs. Some authors consider aspects related only to the transport network. It is noteworthy that most studies consider planning at the state or national level in this case. Since the focus of these studies is to ensure EV autonomy over long distances, it is expected that the power grid will adapt to meet the demand. He *et al.* (2018) proposed a bilevel programming model considering the driving range of EVs to find the optimal locations of CSs. The results indicate that the EV's driving range has a great influence on the optimal CS locations. The minimum number of FCS along the European highway network is estimated by Jochem *et al.* (2019). The authors applied a flow-refueling location model in combination with a comprehensive data set of passenger car trips in Europe to estimate the FCS's future profitability. Huan and Kockelman (2020) optimized the FCS location across a congested city's network subject to stochastic demand for charging under a user-equilibrium traffic assignment.

On the other hand, some authors optimize the location and capacity of CSs considering only the power grid. Unlike planning at the state or national level, studies that consider the electrical grid generally focus on smaller areas, such as cities. Furthermore, optimization involving a large electrical network (considering its operation) can make the problem intractable. In the work from de Quevedo *et al.* (2019), a multistage distribution expansion planning model is presented where investments in distribution network assets are jointly considered. The authors in (ALJANAD *et al.*, 2018) discuss a generalized methodology to assess the optimal placement when installing the CS in the distribution network. Wang *et al.* 2020) perform a comprehensive cost analysis to obtain the optimal planning scheme, considering the variation in EV penetration, charging preference, and customer damage cost. The economics and stability of the planned distribution system are assessed with real-world travel records. Finally, an adaptive robust optimization (ARO) approach is proposed by Baringo *et al.* (2020) for the expansion planning problem of a distribution system involving CSs for EVs. The problem is formulated under the perspective of a central planner that minimizes both investment and DSO costs.

However, with the increase in the discussion about the future of smart grids and systems integration, researchers are investigating the effects of the CSs location considering both electrical and transportation networks. Notably, the context of this application is very specific. The use of both networks can be applied to controlled fleets, such as buses, taxis, and corporate and government fleets. Shared vehicles can also fit into this application, but user privacy must be considered. Thus, real data usually contain only the trips' departure and arrival. Aghapour *et al.* (2020) addressed the optimal sizing and allocation of FCS in a distribution network to minimize the annual investment cost, as well as the energy losses. A stochastic framework is developed based on the queuing theory (QT) to model the EV's charging demand, and the user equilibrium-based traffic assignment model (UETAM) is used to model the traffic flow. Zhou *et al.* (2020) establish a bilevel programming model to address the FCS planning issues in electrified transportation networks with the consideration of uncertain charging demands. Kong *et al.* (2019) study a novel location planning method of FCS to achieve the overall optimization of operators, drivers, vehicles, traffic conditions, and the power grid. The authors used dynamic real-time data for optimal planning instead of statistical data.

2.3.4 e-carsharing siting and sizing

The usage pattern is an important aspect to characterize the operation of e-carsharing since its travelling time is longer than that of an EV owned by a single person. Some authors assess different carsharing systems, such as one-way and round trips (SMET, 2021; YOON; CHERRY; JONES, 2017). One-way systems are the most widely deployed, giving good convenience for both users and operators. Other authors investigate the optimal tariff and price discount for profit maximization (LI, YAN *et al.*, 2021; ZHANG, SI *et al.*, 2022). Finally, some authors study different relocation mechanisms, such as operator-based and user-based mechanisms (HUANG, KAI *et al.*, 2020; QIN *et al.*, 2022). Operator-based relocation is easier to implement, but user-based relocation with dynamic tariffs can achieve higher profits and fewer relocation costs (XU; MENG; LIU, 2018). All these operation topics could lead to different decisions, which affect the e-carsharing profit.

Therefore, it is important to consider e-carsharing operation decisions in long-term planning. However, unlike carsharing, long-term planning for e-carsharing involves additional complications, such as CS building and EV autonomy. Thus, some authors have investigated CS siting and sizing with EV fleet sizing planning for a one-way e-carsharing business model (HUA *et al.*, 2019; HUANG, KAI; AN; CORREIA, 2020). To address a larger-scale problem, these authors simplify the EV energy aspect and do not consider the power grid. Such analysis can be beneficial for planning large areas (municipal and state), as it addresses a reduced amount of data and constraints. However, it can lead to high investment costs in power grid reinforcement. Moreover, some authors focus on small regions and investigate the impacts of shared EV charging on the power grid, but without any type of service provision by e-carsharing, such as V2G (FAN *et al.*, 2019; WANG, SHU *et al.*, 2020b). In addition, those authors do not investigate how the integration of e-carsharing with the DSO affects the company's profit.

The recent literature shows that few authors analyze the interaction between shared EVs and the DSO. Furthermore, the operational characteristics of an e-carsharing company are not considered in DSO or power utility expansion planning. Another point that needs to be researched is how other services, such as V2G, affect the company's profitability. Finally, most authors deal with the problem as deterministic. The demand uncertainty is of major importance in this context, impacting the daily operation of e-carsharing and consequently its profitability.

2.4 DISCUSSION OF THE CHALLENGES AND OPPORTUNITIES RELATED TO ELECTRIC VEHICLES AND CHARGING STATIONS

Innovative business models can change the paradigm of electric mobility. Agents can take advantage of early technology to obtain market share. However, there are still old and new challenges to overcome. Thus, this chapter discusses the opportunities and challenges regarding the adoption of EVs and CSs and proposes different business models for EV charging.

2.4.1 Challenges

EVs are reaching the breakeven of having prices similar to those of conventional vehicles in some countries of Europe and the US. Even so, diffusion is low as the charging infrastructure is still restricted. Thus, the electric mobility sector is currently facing a dilemma. People do not buy EVs because there is not enough charging infrastructure available. In contrast, investors do not build CSs, as there are not enough EVs to guarantee the return on investment. Therefore, who should act first? In this way, the government has a fundamental role in incentives, through public policies, for both EV adoption and charging infrastructure. Subsidy policies can be more effective in countries where the price of EVs is still high. However, it is necessary to develop the charging infrastructure to keep up with the growth of the EV fleet. Furthermore, since ICE vehicles have been consolidated in the market for decades, policies can also be discouraging for ICE vehicle users. Price increases proportional to vehicle gas emissions and increases in fossil fuel prices are some examples. However, these mechanisms must be carefully studied to avoid harming economically vulnerable populations.

In countries where EV prices are still high, the first “massive” EV adoption might be through leasing and innovative models (sharing and retrofitting). Thus, investigating the feasibility of ICE retrofitting may be a more viable solution for populations with less purchasing power to make a faster transition to EV adoption. Furthermore, governments can use their regulatory expertise in natural gas-adapted cars to elaborate a framework for retrofitting ICEs to EVs (HAO *et al.*, 2016). However, precautions must be taken regarding the effects that profound structural changes can have on vehicle safety (MAZUMDER *et al.*, 2012). On the other hand, the shared electric mobility service depends on some factors to guarantee its profitability, such as the size of the city, the local population density, moving traffic, parking situation, population demographics, and agreement with the public administration (STOLLE *et al.*, 2020). Thus, to increase the development of shared EVs, it is important to evaluate other ways to guarantee a company's profitability.

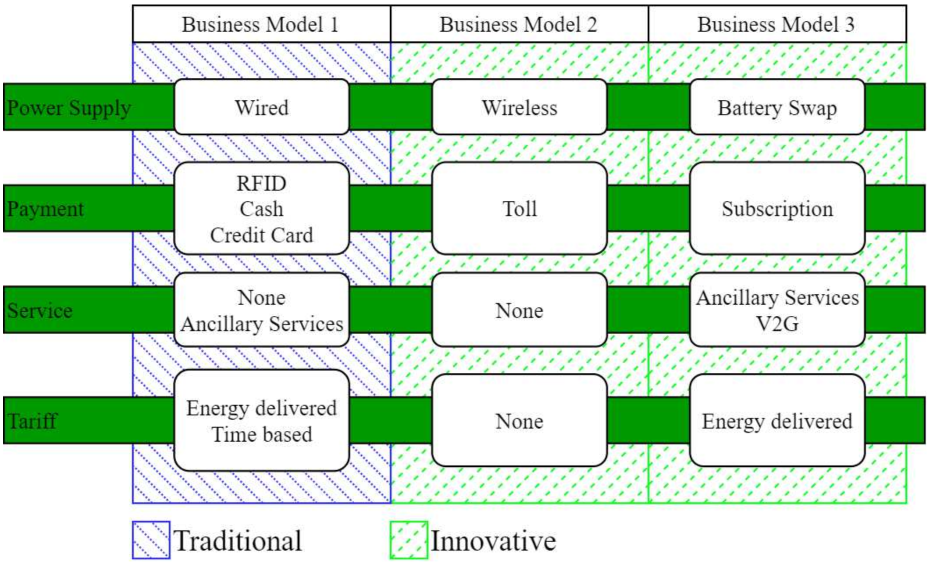
2.4.2 Opportunities

The sharing economy is a promising business model, as new generations are more aware of reducing the consumption of the planet's resources. In particular, shared electric mobility can bring opportunities for agents who decide to operate in this new business model. For automakers, vehicle purchase costs can be reduced because they do not need to negotiate with dealerships. Automakers can also improve people's perception of the company, offering cutting-edge technology at an affordable price. In addition, the company can captivate potential buyers. Finally, automakers can sell used EVs to renew the company's fleet and recover part of the investment. On the other hand, DSOs running this business can identify places where CSs bring benefits to the power grid without jeopardizing the service to customers.

The present work describes CS opportunities into three main business models, as shown in Figure 10. Each model is defined according to its power supply, payment method, additional service, and pricing method. It should be noted that each model has advantages, disadvantages, and applicability. In model 1, traditional chargers are used, which transfer energy through cables. As a well-known business model, it is more likely to be implemented in early EV markets. The infrastructure for this model is also relatively cheap for slow and semi fast chargers. With the development of the market and smart meters, CSs under this model can provide services for DSOs, such as ancillary services. However, a large number of EVs must be connected to the CS. Therefore, if this business model is operated by an aggregator that controls a community's EV fleet, EV users can participate in the energy market. It is worth noting that participants need to be informed that this can lead to premature battery degradation, so EV owners must perform a trade-off analysis between cost savings and battery degradation.

Model 2 is intended for on-road charging EVs (dynamic wireless), enabling long trips. In early markets, this model has synergy with exclusive lane policies, giving one more advantage for EV users. As the EV fleet increases, the most suitable form of payment in this model is the toll for highway usage. As the user pays a fixed amount, there is no charge for energy consumption or time of use. However, this business model can affect non-EV users. Ideally, tolls should be differentiated by vehicle type (EV and non-EV), but this can be difficult to apply. Moreover, this business model is only intended to meet the EV charging demand; hence, no additional services are provided to the DSO. However, this model involves major infrastructure for both the transport network and the power grid. Therefore, it is more suitable to be operated by the DSO since the only operation requirement will be the energy delivery itself. The amounts received for EV charging can be divided proportionally between the agents involved (DSO, public administration, and transport agency).

Figure 10 – Charging station business models.



Source: Author

Finally, Model 3 is a business model that aims to fast charge the EV while giving the CPO more freedom to operate battery charging. In this way, the CPO can obtain economic gains with charging optimization and even participate in the energy market. In addition, this model has synergy with DERs and SEVs, as the operator can control the battery charging time. Moreover, if the CS is operated by the DSO, battery charging can be controlled to reduce impacts on the power grid. This model can also help to increase EV adoption since the battery price is the most expensive part of the vehicle. However, this cost is transferred to the CS owner. Thus, to make this model viable, it is important to have subsidies from the government, adherence from automakers, and advertisements for customers. In addition, the most appropriate pricing scheme involves a subscription (fixed cost) plus a variable cost, depending on the amount of energy delivered. The subscription can be interpreted as the fixed operational costs to swap the battery.

3. METHODOLOGY

According to the evidence presented in the previous section, the e-carsharing business model is promising for users who cannot (or do not wish) afford an EV. However, this model faces some difficulties that may affect its viability, such as the size of the city, the local population density, moving traffic, parking situation, population demographics, agreement with the public administration, and demand uncertainty. For this work, only the uncertainty in rental demand will be considered, given the ease of implementation.

A sufficiently large EV fleet can cause problems for the power grid, such as cable and transformer overload. However, such a problem can be avoided with properly designed energy tariffs, which shift EV charging to off-peak periods. Moreover, V2G can also reduce peak demand and help to postpone investments in network reinforcement. Thus, to provide more opportunity for e-carsharing to increase profit, V2G is also considered in its operation.

E-carsharing could carry out its planning without considering the power grid constraints. In fact, it is the obligation of the local power utility (assuming a regulated market) to provide energy to a customer connected to the power grid. However, the power flows generated by the large number of EVs, even considering the energy tariffs, could cause problems in the power grid. In this sense, this work considers the perspective of the DSO through the constraints of the ACOPF, aiming to minimize the grid's operating and cable reinforcement costs.

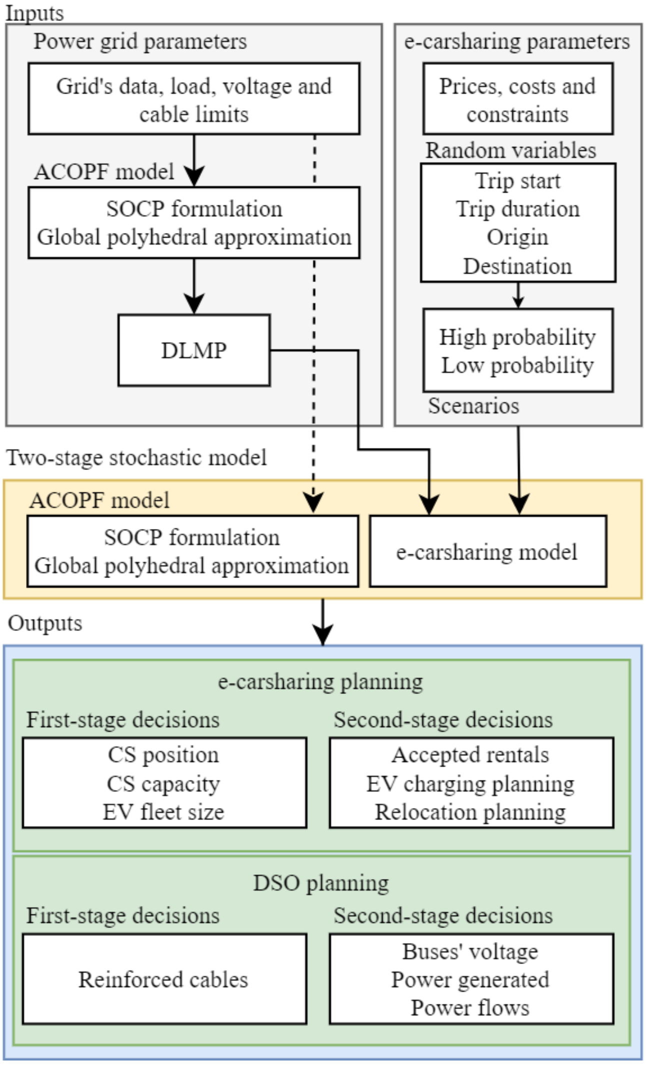
Thus, the second objective of this work is to assess how different e-carsharing operation decisions and DSO perspectives affect the planning of both agents. In addition, agents are expected to be willing to accept a certain level of risk in decision making, despite the Expected Value of Perfect Information (EVPI[7]) not being calculated in this work. For this, two decision levels are considered. The first refers to long-term decision variables, while the second is based on daily operation decisions, which encompass demand uncertainty. Hence, a two-stage stochastic programming model is proposed as a solution method.

Figure 11 summarizes the proposed methodology in a flowchart, presenting the model and the inputs as the output variables. First, the input data are set, which are defined in two groups: e-carsharing inputs and power grid inputs. The e-carsharing input data include random variables, the scenario creation, and the parameters of the company, such as prices, costs, and constraints (technical and financial). The second group of input data is related to the power grid through its parameters, such as grid data, load, voltage limits, and cable capacity. In addition, the power grid's ACOPF is calculated without any EV. Thus, the DLMP of the energy marginal cost is obtained, which is used as an energy tariff in the two-stage stochastic model. The ACOPF is formulated using the SOCP relaxation and further linearized using the global

[7] EVPI is the price that one would be willing to pay in order to gain access to perfect information. For example, in a given problem the calculated EVPI is $100 and someone charges $99 for perfect information about the future. That information would return $1 in profit. On the other hand, if the cost of information is $101, buying that information would loss $1.

polyhedral formulation. Finally, both problems (ACOPF and joint planning) are cast as a mixed-integer linear programming (MILP) formulation.

Figure 11 – Proposed methodology flowchart.



Source: Author

The two-stage stochastic model has first-stage and second-stage variables, known as "here and now" and "wait and see", respectively. In summary, the first-stage variables are chosen before the realization of the uncertainty in the second stage. In the context of e-carsharing siting and sizing, the rental demand (including its uncertainty) affects the company's daily operation decisions (for example, the charging time). Consequently, operating decisions affect long-term decisions, such as the optimal location and capacity of CSs as well as the EV fleet size. On the other hand, in the context of the DSO, the load affects its operational decisions. It is noteworthy that in this thesis, load uncertainty is not considered. Rental demand uncertainty is reflected in EV charging, which in turn is reflected in the operational decisions of the power grid. Finally, these decisions also affect the DSO's long-term planning, such as cable reinforcement. Thus, one can ponder, through the analysis of output variables, how different operation decisions affect long-term planning and, consequently, the profit and costs of these two agents.

3.1 INPUTS

The model considers a set of Ω_y years and Ω_t time intervals in the planning. The decisions of the first stage refer to years, while the decisions of the second stage refer to daily (or weekly) operation. Moreover, a set of Ω_ρ positions, Ω_ϵ EVs, and Ω_δ rental demands are also considered. The set of rental demands Ω_δ contains three pieces of information: origin (from), destination (to), and trip duration. It is important to highlight that ρ, i, and j all refer to positions. However, to facilitate, ρ is used in the e-carsharing model, while i and j are used in the DSO model. The set of cables Ω_c contains a list of available cables for replacement, with their price and capacity. Finally, the model has a set of scenarios Ω_ω with p_ω probabilities.

3.1.1 e-carsharing inputs

The input data are divided into two groups: e-carsharing inputs and power grid inputs. E-carsharing has costs that, if not properly estimated, can make the business unfeasible. However, it is assumed that such analysis was previously performed by the decision-maker. Thus, the focus is not to investigate whether the deployment of e-carsharing is feasible but to assess how decisions affect its profit. For this, the prices referring to the first-stage variables are the charging station installation price (p^{cs}), charger price (p^{ch}), and EV purchase price (p^{ev}). It was adopted in this thesis that the budget available through e-carsharing is limited to B_y per year. B_1 can be interpreted as the initial budget, and B_2, B_3, B_4... is the available budget for the following years. Note that if the company disposes only of the initial budget (B_1), B_2, B_3, B_4... must be set to zero.

Moreover, to calculate the operational revenue, one must know the prices involved. The prices considered are rental tariff (ζ^r), energy tariff ($\zeta^e_{t,\rho}$), and relocation tariff (ζ^{rl}), which are used to calculate rental profit, charging cost, and relocation cost, respectively. Note that rental and relocation tariffs are considered as fixed prices, while the energy tariff is a function of time and position due to DLMP-based tariffs. Although the electricity tariff is an input for e-carsharing, it is calculated using the ACOPF model. Tariffs can highly influence the outcome of the model. For example, if the relocation tariff is too high, the optimal decision might be to not meet as many demands as possible. On the other hand, if the energy tariff is too high at a certain location, EVs can take advantage of their high mobility to charge in places where energy is cheaper.

The following parameters are related to the technical aspects of e-carsharing: EV battery capacity (E^b), EV energy consumption due to movement (d_r), maximum charging/discharger power of the charger (P^c), charger efficiency (eff_{cha}), and maximum (Ch_ρ^{max}) and minimum (Ch_ρ^{min}) number of chargers per position ρ. For those parameters, some considerations were made. First, all EVs are the same; thus, their battery capacity and energy consumption due to movement (in [kWh/km] or [kWh/h], assuming a constant velocity) are the same. Second, all chargers are the same, equipped with V2G technology, and their efficiency is the same for charging and discharging. Third, CSs do not have infinite capacity, and their minimum and maximum capacities are defined by Ch_ρ^{min} and Ch_ρ^{max}, respectively, for each position. This could be interpreted as a space limitation given the low availability in high-density urban centers.

Moreover, $p_{\rho,\epsilon}^i$ and SoC_ϵ^i are the initial position of EVs and the initial state-of-charge[8] (SoC) of EVs, respectively. Note that those parameters are not a function of the scenario. Although these parameters serve as the basis for completing a daily operation cycle, they could be defined as problem variables, thus resulting in the optimal initial position and the initial SoC regardless of the scenario to maximize profit. However, due to simplicity, it was decided to adopt these parameters as fixed values.

Furthermore, the scenario creation is defined by a set of data that includes the rental demand origin in position ρ at time t ($D_{t,\delta,\rho,y,\omega}^O$), the rental demand destination to position ρ at time t ($D_{t,\delta,\rho,y,\omega}^D$), and the rental demand trip duration ($D_{\delta,y,\omega}^d$). Note that $D_{t,\delta,\rho,y,\omega}^O$ and $D_{t,\delta,\rho,y,\omega}^D$ are functions of time and thus already include the trip start time and end time, respectively. The problem considers that e-carsharing operates in a one-way system. More precisely, customers can rent a vehicle for a tariff ζ^r at its origin and drop it off at its destination. As the work considers the e-carsharing siting and sizing problem, the proposed model is based on the trip schedule. In other words, users schedule a trip a day before, and the operator selects which trips to accept or not. Based on this, the model defines which positions to install the CSs ($CS_{\rho,y}$), how many chargers to install in each CS ($Ch_{\rho,y}$), and how many EVs to purchase ($E_{\epsilon,y}$).

[8] State-of-charge is the amount of energy in a battery at a given time. It can be represented in terms of energy or percentage of its total capacity.

However, there is another approach that focuses on the deviation of each scenario from a forecast, known as day-ahead, which is not considered in this study. The demand data used in this work do not have the drivers' path, as it violates the privacy agreement. Thus, the transportation network is not considered in this work.

Finally, the rental demand contains uncertainty; thus, the scenario probability (p_{ω}) must be defined. Note that the probability realization of all scenarios must sum one. For this work, only two scenarios are considered, one with a high probability and the other with a low probability. This simplification is considered due to the high computational effort that a large number of scenarios bring. In addition, it is expected that the high probability scenario represents a normal daily demand, while the low probability scenario represents reduced daily demand arising from some event, such as a pandemic. In this sense, one can investigate whether e-carsharing takes advantage of idle EVs to provide more energy to the grid in low-demand periods. This shift in the operation mode (from EV rental to energy selling) could help the company maintain its profit (or at least reduce losses) and avoid bankruptcy. It is important to highlight that the number of scenarios could be increased if there were simplifications in the power grid model (from ACOPF for DCOPF). However, it is necessary to evaluate which simplifications (number of scenarios or electrical grid model) bring more risk to the model results, which is beyond the scope of this work.

3.1.2 DSO inputs

The second group of input data is related to the power grid parameters and its operation, through ACOPF, without any EV. The branch data parameters contain the resistance ($r_{i,j,y}$) and reactance ($x_{i,j,y}$) from bus i to bus j, respectively. Note that the parameters are a function of the year y. This model was chosen to consider any changes in the network in the following years, such as scheduled cable reinforcement or reconfiguration. Moreover, $P_{t,i,y}^{d}$ and $Q_{t,i,y}^{d}$ are the active and reactive power demand at bus i at time t, respectively. As previously mentioned, uncertainty in the load was not considered. Thus, $P_{t,i,y}^{d}$ and $Q_{t,i,y}^{d}$ are not a function of the scenarios ω.

The following parameters are related to power grid operation limits. v^{max} and v^{min} are the maximum and minimum voltage limits for all buses, respectively. $I_{i,j,y}^{max}$ is the maximum current limit of branch (i,j). Note that $I_{i,j,y}^{max}$ is a function of the year, according to the possible changes that may occur in the power grid in the following years. In addition, it is possible to set different limits for each cable in the power grid. In real cases, cables closer to the beginning of the grid tend to have a higher capacity, as they need to support higher power flows than those closer to the end of the grid[9].

The energy price at slack bus ζ^g is given in \$/MVA. In this study, a radial distribution system with a single generation source is considered. Moreover, p_c^{Cr} and I_c^{Cr} are the cable c price and its capacity, respectively. Thus, based on these parameters, the DLMP of the energy marginal cost is obtained through linearized ACOPF, which is used as an input in the two-stage stochastic model.

3.2 Two-Stage Stochastic Problem Formulation

The second objective of this work is to assess how different e-carsharing operation decisions, under demand uncertainty, and DSO perspectives affect the planning and profit of both agents. For this, a two-stage stochastic formulation is proposed. The ACOPF, which is naturally nonlinear, is modelled through the BFM and SOCP, which convert the nonlinear problem into quadratic. Furthermore, it is linearized by the polyhedral global approximation. The final model is cast as mixed-integer linear programming. In this section, the variables, objective function, and constraints that define the proposed model are presented.

3.2.1 Variables

The first-stage variables related to e-carsharing are $CS_{\rho,y}$, $E_{\epsilon,y}$, and $Ch_{\rho,y}$. $CS_{\rho,y}$ is the binary decision if the company will or will not install the CS in position ρ at year y. $Ch_{\rho,y}$ is the number of chargers that will be installed in position ρ at year y. Thus, $Ch_{\rho,y}$ is a positive integer variable. Moreover, queues are not modelled in this work, and each spot contains a charger; thus, the capacity of CS is given by the number of its chargers. Finally, $E_{\epsilon,y}$ is the binary decision if the company will or will not by EV ϵ at year y. Note that since the initial position of EVs ($p_{\rho,\epsilon}^i$) and initial SoC (SoC_ϵ^i) are random, ideally, ϵ should be as large as possible to give flexibility to the problem. However, this increases the problem size, which would lead to a higher computational time.

The second-stage variables related to e-carsharing are, $ev_{\delta,\epsilon,y,\omega}^r$, $ev_{t,\rho,\epsilon,y,\omega}^{cha}$, $ev_{t,\rho,\epsilon,y,\omega}^d$, $ev_{t,\rho,\epsilon,y,\omega}^a$, $ev_{t,\rho,\epsilon,y,\omega}^{con}$, $ev_{t,\epsilon,y,\omega}^{mov}$, $SoC_{t,\epsilon,y,\omega}$, and $P_{t,\rho,y,\omega}^{ev}$. $ev_{\delta,\epsilon,y,\omega}^r$ is the binary

[9] In general, distribution networks are radial.

decision if the demand δ at year y and scenario ω will or will not be accepted by the operator and allocated to EV ϵ. $ev^{cha}_{t,\rho,\epsilon,y,\omega}$ is the EV ϵ charging power at position ρ, time t, year y, and scenario ω. The charging power is [pu]; hence, the variable is between -1 and 1 when V2G is considered and between 0 and 1 when not. $ev^{d}_{t,\rho,\epsilon,y,\omega}$ and $ev^{a}_{t,\rho,\epsilon,y,\omega}$ are the binary decisions if EV ϵ will depart/arrive for/from relocation at position ρ, time t, year y, and scenario ω, respectively. $ev^{con}_{t,\rho,\epsilon,y,\omega}$ is the binary decision if EV ϵ will connect in position ρ at time t, year y, and scenario ω. $ev^{mov}_{t,\epsilon,y,\omega}$ is the binary decision if EV ϵ is moving, given an accepted demand, at time t, year y, and scenario ω. $SoC_{t,\epsilon,y,\omega}$ is the state-of-charge of EV ϵ at time t, year y, and scenario ω. The SoC can be noted in two ways in terms of energy or percentage. The latter was chosen for this work. Finally, $P^{ev}_{t,\rho,y,\omega}$ is the total EV charging power at position ρ, time t, year y, and scenario ω.

The first stage variable related to the DSO is the cable reinforcement $x^{Cr}_{i,j,y}$. For this model, cables are not allowed to downgrade; thus, this variable is binary. The second-stage variables related to the DSO are $P_{i,j,t,y,\omega}$, $Q_{i,j,t,y,\omega}$, $v_{i,t,y,\omega}$, $l_{i,j,t,y,\omega}$, $P^{g}_{t,i,y,\omega}$ and $Q^{g}_{t,i,y,\omega}$. $P_{i,j,t,y,\omega}$ and $Q_{i,j,t,y,\omega}$ are real variables and represent the amount of active and reactive power injected at the head bus of branch (i,j) in period t, year y, and scenario ω, respectively. $v_{i,t,y,\omega}$ is the squared voltage magnitude at bus i, period t, year y, and scenario ω. $l_{i,j,t,y,\omega}$ is the squared current of branch (i,j) at period t, year y and scenario ω. Note that to obtain the voltage and current, one needs to take the square root of $v_{i,t,y,\omega}$ and $l_{i,j,t,y,\omega}$, respectively. Ultimately, they are real positive variables. Finally, $P^{g}_{t,i,y,\omega}$ and $Q^{g}_{t,i,y,\omega}$ are the amount of active and reactive generated at bus i, period t, year y, and scenario ω. Since the substation (main energy source) is not allowed to absorb energy, $P^{g}_{t,i,y,\omega}$ and $Q^{g}_{t,i,y,\omega}$ are real positives.

3.2.2 Objective Function

Two main objective functions are modelled in this work, as shown in Equation (1a) and Equation (1b). In this first one, only the interests of the e-carsharing operator are considered. Hence, the first main objective is to maximize profit from vehicle rental (obf_{rental}) and minimize EV charging costs (obf_{cha}) and relocation costs (obf_{relo}), respectively. The second main objective considers only the perspective of the DSO, which aims to minimize the investment in cable reinforcement (obf_{Irein}) and the cost of energy generation (obf_{ecost}).

Finally, the joint decision-making between the e-carsharing operator and the DSO is given by $OF_{ecar} + OF_{DSO}$.

Moreover, the e-carsharing first-stage variables are not represented in the objective function. It is expected that the company has a budget at its disposal to achieve its goals. To maximize profit, the model needs to invest in CSs, chargers, and EVs. Hence, only constraints for the first-stage variables are needed. In the following, the objective functions that define the main objective functions are presented.

$$OF_{ecar} = obf_{rental} - obf_{cha} - obf_{relo} \tag{1a}$$

$$OF_{DSO} = -obf_{Irein} - obf_{ecost} \tag{1b}$$

3.2.2.1 e-carsharing objective function

The e-carsharing objective function is divided into three parts related to the company's daily operational decisions. Therefore, to adjust the temporal coupling with the long-term decisions, they are multiplied by the number of days in a year. In addition, they are also multiplied by the probability of realization of each scenario, as they represent the second stage decisions. Equation (2a) gives the rental profit due to a given trip acceptance ($ev^{r}_{t,\delta,\epsilon,y,\omega}$) and its duration ($D^{d}_{\delta,t,y,\omega}$). $ev^{r}_{t,\delta,\epsilon,y,\omega}$ is a binary variable, which means that a trip can or cannot be accepted by the operator and allocated to an EV.

The EV charging cost is given by Equation (2b), where $ev^{cha}_{t,\rho,\epsilon,y,\omega}$ is the EV charging power, P^{c} is the maximum charger power and $\zeta^{e}_{t,\rho}$ is the energy tariff. The energy tariff ($\zeta^{e}_{t,\rho}$) is the DLMP regarding the time and position obtained from the ACOPF without EV. $ev^{cha}_{t,\rho,\epsilon,y,\omega}$ is given in [pu], which means that it varies between 0 and 1 when V2G is not considered and between -1 and 1 when V2G is considered.

Equation (2c) shows the operator-based relocation cost of the vehicles, where $ev^{d}_{t,\rho,\epsilon,y,\omega}$ and ζ^{rl} are the vehicles that depart for relocation and the relocation tariff, respectively. It is worth mentioning that without relocation, more vehicles are needed to meet the demand. Thus, if the relocation tariff is a reasonable price, the company can increase profit and meet demand. The relocation duration time is simplified as a 1-time interval for any position at any time, which is represented as a binary variable.

$$obf_{rental} = 365 \sum_{\Omega_\omega} p_\omega \sum_{\Omega_y} \sum_{\Omega_\delta} \sum_{\Omega_\epsilon} ev^{r}_{\delta,\epsilon,y,\omega} D^{d}_{\delta,y,\omega} \zeta^{r} \tag{2a}$$

$$obf_{cha} = 365 \sum_{\Omega_\omega} p_\omega \sum_{\Omega_y} \sum_{\Omega_t} \sum_{\Omega_\rho} \sum_{\Omega_\epsilon} ev_{t,\rho,\epsilon,y,\omega}^{cha} P^c \zeta_{t,\rho}^{e} \tag{2b}$$

$$obf_{relo} = 365 \sum_{\Omega_\omega} p_\omega \sum_{\Omega_y} \sum_{\Omega_t} \sum_{\Omega_\rho} \sum_{\Omega_\epsilon} ev_{t,\rho,\epsilon,y,\omega}^{d} \zeta^{rl} \tag{2c}$$

3.2.2.2 DSO objective function

The DSO's objective function is divided into two parts related to its first- and second-stage decisions. The first part, given by Equation (2d), represents the investment cost in cable reinforcement, where $x_{i,j,c,y}^{Cr}$ is the decision if a cable needs reinforcement or not, and p_c^{Cr} is the reinforcement price. Note that branch (i,j) is reinforced by cable c in a set of cables Ω_c. Moreover, p_c^{Cr} is divided by two to remove double counting. In real cases, old cables are replaced by new cables, which can lead to additional costs. However, to simplify the modelling, it was adopted that all involved costs are included in p_c^{Cr}. In addition, it was considered that all cables have the same length, one kilometer. On a grid on the edge of operation, a sufficiently large EV fleet can cause problems, even using energy tariffs to shift charging to off-peak periods. Furthermore, if the investment is unavoidable, either because of a large EV fleet or a load increase, V2G may be able to reduce this cost.

Equation (2e) gives the dispatch cost from the primary energy source, where $P_{t,\rho,y,\omega}^{g}$ and ζ^g are the active power generated at the slack bus and the energy price, respectively. Similar to the e-carsharing objective function, the dispatch cost is multiplied by the number of days in the year and the probability of the scenario realization p_ω.

$$obf_{Irein} = \sum_{\Omega_y} \sum_{\Omega_i} \sum_{\Omega_j} \sum_{\Omega_c} x_{i,j,c,y}^{Cr} \, p_c^{Cr}/2 \tag{2d}$$

$$obf_{ecost} = 365 \sum_{\Omega_\omega} p_\omega \sum_{\Omega_y} \sum_{\Omega_t} \sum_{\Omega_\rho} P_{t,\rho,y,\omega}^{g} \zeta^g \tag{2e}$$

3.2.3 First Stage constraints: e-carsharing siting and sizing

The e-carsharing first-stage constraints refer to the investment cost in CSs, chargers, and the EV fleet. The CS installation cost considers all the costs involved in CS construction (land purchase, earthworks, electrical installation, infrastructure construction, etc.), except for the cost of the chargers. The cost of the charger could be included in the CS installation cost.

However, this modelling allows limiting the number of chargers given that each CS may have different physical space limitations.

$$\sum_{\Omega_\rho}\left(CS_{\rho,y}p^{cs} + Ch_{\rho,y}p^{ch}\right) + \sum_{\Omega_\epsilon} E_{\epsilon,y}\, p^{ev} \leq \sum_{\varphi=1}^{y} B_\varphi \tag{3a}$$

$$CS_{\rho,y} \geq CS_{\rho,y-1} \tag{3b}$$

$$Ch_{\rho,y} \geq Ch_{\rho,y-1} \tag{3c}$$

$$E_{\epsilon,y} \geq E_{\epsilon,y-1} \tag{3d}$$

$$Ch_\rho^{min} CS_{\rho,y} \leq Ch_{\rho,y} \leq Ch_\rho^{max} CS_{\rho,y} \tag{3e}$$

Equation (3a) is the generalized form of the e-carsharing financial balance. The general idea of the equation is that the expenses of year y (left side) must be less than the budget available at year y plus the remaining amount invested from previous years (right side). For example, once an EV (or CS) is purchased, it does not need to be purchased again in the following years. Finally, note that for $y = 1$, Equation (3a) shows that the total expenses must be less than the initial budget (B_1) only. In addition, the interest rate over the years is disregarded.

As rental demand is uncertain, it can vary significantly from year to year. Thus, the first-stage optimal variables may differ for each year due to the e-carsharing operation. Hence, Equation (3b), Equation (3c), and Equation (3d) are non-anticipativity constraints, which prevent the model from removing the CSs, chargers, and EVs once installed/bought, respectively. Note that if $y = 1$, Equation (3b), Equation (3c), and Equation (3d) indicate that $CS_{\rho,y}$, $Ch_{\rho,y}$, and $E_{\epsilon,y}$, respectively, must only be an integer.

The space availability in urban areas can be a limiting factor in planning. In this sense, Equation (3e) limits the chargers to be installed only where CS was installed. In addition, the number of chargers is limited to a minimum (Ch_ρ^{min}) and maximum (Ch_ρ^{max}) amount, which depends on the position ρ.

Finally, a financial constraint (on cable reinforcement) was not considered for the DSO, such as Equation (3a), for the e-carsharing company. It is assumed that the DSO has an unlimited budget at its disposal and will use all available resources to keep the network operational. Since the objective is to minimize the cable reinforcement cost, the minimum will be used to upgrade the cables. On the other hand, the objective of e-carsharing is to maximize its profit disregarding the investment cost. If no constraint such as Equation (3a) were set, the company would spend the maximum possible to meet 100% of demand and profit with charging optimization.

3.2.4 First-stage constraints: cable reinforcement

The DSO first-stage constraints refer to the cable capacity that will be chosen for the reinforcement. Equation (4a) indicates that only one type of cable can be chosen for reinforcement if the branch needs it. Equation (4b) indicates that if the cable of a branch (i, j) is reinforced, its equivalent (j, i) must also be reinforced. From these equations, the model chooses, within a set of cables, the one that best suits the branch.

$$\sum_{\Omega_c} x_{i,j,c,y}^{Cr} \leq 1 \tag{4a}$$

$$x_{i,j,c,y}^{Cr} = x_{j,i,c,y}^{Cr} \tag{4b}$$

3.2.5 Second Stage constraints: e-carsharing operation

This section presents the operating constraints of e-carsharing, which are related to EV rental, relocation, and charging. The set of Equations (5) referring to the daily operation of e-carsharing (second stage) also presents the year index. Thus, in addition to the first-stage variable linkage, the model can also execute the operation according to parameters that could change annually, such as total rental demand or energy demand.

3.2.5.1 e-carsharing operation: rental and relocation

The balance of EVs connected to the CS ($ev_{t,\rho,\epsilon,y,\omega}^{con}$) is presented in Equation (5a). The term $\sum_{\Omega_\delta} ev_{\delta,\epsilon,y,\omega}^{r} D_{t,\delta,\rho,y,\omega}^{D}$ are all the accepted demands that arrive at destination ρ at time t, while the term $\sum_{\Omega_\delta} ev_{\delta,\epsilon,y,\omega}^{r} D_{t,\delta,\rho,y,\omega}^{O}$ is all the accepted demands that depart from destination ρ at time t. Moreover, the vehicles arriving ($ev_{t,\rho,\epsilon,y,\omega}^{a}$) and departing ($ev_{t,\rho,\epsilon,y,\omega}^{d}$) from relocation are added and subtracted in Equation (5a), respectively.

Equation (5b) defines the initial position of EVs ($p_{\rho,\epsilon}^{i}$) at the beginning of the day ($t = t_{in}$) only if $CS_{\rho,y}$ has been installed in the first stage. Similarly, Equation (5c) indicates that EVs must finish the day ($t = t_{end}$) in the same initial position to complete an operation cycle. It is worth noting that the EV's initial position could be a first-stage optimization variable. Thus, the e-carsharing operator could identify the best initial position to maximize profit in all scenarios. However, to simplify, a random initial position was assigned to the EVs.

$$ev^{con}_{t,\rho,\epsilon,y,\omega} = ev^{con}_{t-1,\rho,\epsilon,y,\omega} + \sum_{\Omega_\delta} ev^{r}_{\delta,\epsilon,y,\omega} D^{D}_{t,\delta,\rho,y,\omega} - \sum_{\Omega_\delta} ev^{r}_{\delta,\epsilon,y,\omega} D^{O}_{t,\delta,\rho,y,\omega} + ev^{a}_{t,\rho,\epsilon,y,\omega} - ev^{d}_{t,\rho,\epsilon,y,\omega} \quad (5a)$$

$$ev^{con}_{t_{in},\rho,\epsilon,y,\omega} = p^{i}_{\rho,\epsilon} CS_{\rho,y} \quad (5b)$$

$$ev^{con}_{t_{end},\rho,\epsilon,y,\omega} = p^{i}_{\rho,\epsilon} CS_{\rho,y} \quad (5c)$$

Equation (5d) shows that a rental demand δ from/to position ρ can only be accepted by the operator ($ev^{r}_{\delta,\epsilon,y,\omega}$) if the CS at position ρ has been built in the first stage. Equation (5e) defines the number of EVs connected ($\sum_{\Omega_\epsilon} ev^{con}_{t,\rho,\epsilon,y,\omega}$) in the CS as less than or equal to the number of chargers in the station ($Ch_{\rho,y}$). It is worth mentioning that all spots have a charger, which can connect only one EV each time. Therefore, the CS capacity is equal to the number of chargers. Equation (5f) defines that each rental demand must only be accepted once and by one EV. Equation (5g) defines that if purchased in the first stage, a vehicle must be either moving ($ev^{mov}_{t,\epsilon,y,\omega}$), connected ($ev^{con}_{t,\rho,\epsilon,y,\omega}$), or relocating ($ev^{d}_{t,\rho,\epsilon,y,\omega} + ev^{a}_{t,\rho,\epsilon,y,\omega}$). The relocation duration time is simplified as a 1-time interval for any position, as indicated in Equation (5h).

$$ev^{r}_{\delta,\epsilon,y,\omega} \leq CS_{\rho,y} \quad (5d)$$

$$\sum_{\Omega_\epsilon} ev^{con}_{t,\rho,\epsilon,y,\omega} \leq Ch_{\rho,y} \quad (5e)$$

$$\sum_{\Omega_\epsilon} ev^{r}_{\delta,\epsilon,y,\omega} \leq 1 \quad (5f)$$

$$ev^{mov}_{t,\epsilon,y,\omega} + \sum_{\Omega_\rho} \left(ev^{con}_{t,\rho,\epsilon,y,\omega} + ev^{d}_{t,\rho,\epsilon,y,\omega} + ev^{a}_{t,\rho,\epsilon,y,\omega} \right) = E_{\epsilon,y} \quad (5g)$$

$$\sum_{\Omega_\rho} ev^{d}_{t,\rho,\epsilon,y,\omega} = \sum_{\Omega_\rho} ev^{a}_{t+1,\rho,\epsilon,y,\omega} \quad (5h)$$

3.2.5.2 e-carsharing operation: EV charging

The SoC of an EV battery is defined in Equation (5i). The battery energy consumption (d_r) is constant for both rental and relocation. Note that the charging power ($ev^{cha}_{t,\rho,\epsilon,y,\omega}$) varies from -1 to 1 when V2G is considered and from 0 to 1 when V2G is not considered. Using a single variable for vehicle charging makes it easier in terms of implementation and computational effort. On the other hand, it has drawbacks due to simplification, such as the use of charger efficiency for both charging and discharging. Equations (5j) and (5k) impose equal operating states in the SoC at the beginning ($t = t_{in}$) and the end ($t = t_{end}$) of each day to complete a daily cycle. Equation (5k) is relaxed with $\geq$, but it holds at SoC_{ϵ}^{i} to reduce the charging cost. The total charging power of each CS at position ρ ($P_{t,\rho,y,\omega}^{ev}$) is presented in Equation (5l). Finally, Equation (5m) defines that an EV can only charge if it is connected. Note that to disable V2G, the lower limit must be set to zero instead of $-ev_{t,\rho,\epsilon,y,\omega}^{con}$.

$$SoC_{t,\epsilon,y,\omega} = SoC_{t-1,\epsilon,y,\omega} - \left(ev_{t,\epsilon,y,\omega}^{mov} + \sum_{\Omega_\rho} ev_{t,\rho,\epsilon,y,\omega}^{d} \right) \frac{d_r}{E^b} + \sum_{\Omega_\rho} \frac{ev_{t,\rho,\epsilon,y,\omega}^{cha} P^c eff_{cha}}{E^b} \tag{5i}$$

$$SoC_{t_{in},\epsilon,y,\omega} = SoC_{\epsilon}^{i} \tag{5j}$$

$$SoC_{t_{end},\epsilon,y,\omega} \geq SoC_{\epsilon}^{i} \tag{5k}$$

$$P_{t,\rho,y,\omega}^{ev} = \sum_{\Omega_\epsilon} ev_{t,\rho,\epsilon,y,\omega}^{cha} P^c eff_{cha} \tag{5l}$$

$$-ev_{t,\rho,\epsilon,y,\omega}^{con} \leq ev_{t,\rho,\epsilon,y,\omega}^{cha} \leq ev_{t,\rho,\epsilon,y,\omega}^{con} \tag{5m}$$

3.2.6 Second Stage constraints: ACOPF

This section presents the set of constraints related to the operation of the power grid. The constraints of an ACOPF are complex, nonlinear, and nonconvex. The BFM with the SOCP formulation is used to relax the original problem. Finally, the global polyhedral approximation is used to linearize the problem. Thus, the problem reads as follows.

Equations (6a) and (6b) present the balance of active and reactive power, while Equation (6c) presents the current limit of the branch. Note that if $\sum_{\Omega_c} x_{i,j,c,y}^{Cr} = 0$, the cable remains the same; otherwise, it is replaced by a new cable with I_c^{Cr} capacity. The DLMP is given by the dual variable[10] associated with the active power balance (Equation (6a)). The voltage calculation at each bus is given by Equation (6d), and its limits are presented in Equation (6e). Finally, Equation (6f) is a nonconvex equality that defines the branch flow at the head bus of each branch. Although the BFM guarantees the same voltages and power flows as the traditional AC power flow, the problem is more computationally tractable when Equation (6f)

[10] In this context, the dual variable of Equation (5a) can be interpreted as the marginal cost of energy generation at slack bus.

is linearized (WEI *et al.*, 2020). Thus, replacing $=$ for $\leq$, the second-order cone equation becomes convex, given by the canonical form of Equation (6g). It was proven in (HUANG, SHAOJUN *et al.*, 2016) that in distribution systems, Equation (6g) holds in the optimal solution under some mild conditions.

$$P_{i,j,t,y,\omega} - r_{i,j,y} l_{i,j,t,y,\omega} + P^{g}_{t,i,y,\omega} - P^{d}_{t,i,y} - P^{ev}_{t,\rho,y,\omega} = \sum_{k \in S(j)} P_{j,k,t,y,\omega} : \zeta^{e}_{t,\rho} \tag{6a}$$

$$Q_{i,j,t,y,\omega} - x_{i,j,y} l_{i,j,t,y,\omega} + Q^{g}_{t,i,y,\omega} - Q^{d}_{t,i,y} = \sum_{k \in S(j)} Q_{j,k,t,y,\omega} \tag{6b}$$

$$0 \leq l_{i,j,t,y,\omega} \leq \left(I^{max}_{i,j,y}\right)^2 \left(1 - \sum_{\Omega_c} x^{Cr}_{i,j,c,y}\right) + \sum_{\Omega_c} (I^{Cr}_{c})^2 x^{Cr}_{i,j,c,y} \tag{6c}$$

$$v_{j,t,y,\omega} = v_{i,t,y,\omega} - 2\left(r_{i,j,y} P_{i,j,t,y,\omega} + x_{i,j,y} Q_{i,j,t,y,\omega}\right) + \left(r^2_{i,j,y} + x^2_{i,j,y}\right) l_{i,j,t,y,\omega} \tag{6d}$$

$$\left(v^{min}\right)^2 \leq v_{j,t,y,\omega} \leq (v^{max})^2 \tag{6e}$$

$$l_{i,j,t,y,\omega} v_{i,t,y,\omega} = P^2_{i,j,t,y,\omega} + Q^2_{i,j,t,y,\omega} \tag{6f}$$

$$\left\| \begin{matrix} 2P_{i,j,t,y,\omega} \\ 2Q_{i,j,t,y,\omega} \\ l_{i,j,t,y,\omega} - v_{i,t,y,\omega} \end{matrix} \right\| \leq l_{i,j,t,y,\omega} + v_{i,t,y,\omega} \tag{6g}$$

The polyhedral global approximation is developed for second-order cone equations in the form of $\sqrt{x_1^2 + x_2^2} \leq x_3$ (BEN-TAL; NEMIROVSKI, 2001). Thus, Equation (6g) is decomposed into Equation (6h) and Equation (6i). Applying the technique of (BEN-TAL; NEMIROVSKI, 2001) in Equation (6h) and Equation (6i), one can obtain the set of linear constraints of Equation (6j) and Equation (6k), where $\xi^1_{i,j,\varkappa,t,y,\omega}$, $\eta^1_{i,j,\varkappa,t,y,\omega}$, $\xi^2_{i,j,\varkappa,t,y,\omega}$, $\eta^2_{i,j,\varkappa,t,y,\omega}$, and φ are auxiliary variables and $\varkappa$ is a positive integer, which is used to adjust the approximation accuracy. According to (BEN-TAL; NEMIROVSKI, 2001), if (5g) is satisfied, then Equation (6j) and Equation (6k) must hold. Thus, Equation (6g) can be replaced by Equation (6j) and Equation (6k).

$$\sqrt{(2P_{i,j,t,y,\omega})^2 + (2Q_{i,j,t,y,\omega})^2} \leq W_{i,j,t,y,\omega} \tag{6h}$$

$$\sqrt{(W_{i,j,t,y,\omega})^2 + (l_{i,j,t,y,\omega} - v_{i,t,y,\omega})^2} \leq l_{i,j,t,y,\omega} + v_{i,t,y,\omega} \tag{6i}$$

$$\begin{cases} \xi^1_{i,j,0,t,y,\omega} \geq 2P_{i,j,t,y,\omega}, \xi^1_{i,j,0,t,y,\omega} \geq -2P_{i,j,t,y,\omega} \\ \eta^1_{i,j,0,t,y,\omega} \geq 2Q_{i,j,t,y,\omega}, \eta^1_{i,j,0,t,y,\omega} \geq -2Q_{i,j,t,y,\omega} \end{cases} \tag{6j}$$

$$\begin{cases} \xi^1_{i,j,\varphi,t,y,\omega} = \cos\left(\frac{\pi}{2^{\varphi+1}}\right)\xi^1_{i,j,\varphi-1,t,y,\omega} + \sin\left(\frac{\pi}{2^{\varphi+1}}\right)\eta^1_{i,j,\varphi-1,t,y,\omega} \\ \eta^1_{i,j,\varphi t,y,\omega} \geq -\sin\left(\frac{\pi}{2^{\varphi+1}}\right)\xi^1_{i,j,\varphi-1t,y,\omega} + \cos\left(\frac{\pi}{2^{\varphi+1}}\right)\eta^1_{i,j,\varphi-1,t,y,\omega} \\ \eta^1_{i,j,\varphi,t,y,\omega} \geq +\sin\left(\frac{\pi}{2^{\varphi+1}}\right)\xi^1_{i,j,\varphi-1,t,y,\omega} - \cos\left(\frac{\pi}{2^{\varphi+1}}\right)\eta^1_{i,j,\varphi-1,t,y,\omega} \end{cases}$$

$\varphi = 1, \ldots, \varkappa$

$$\begin{cases} \xi^1_{i,j,\varkappa,t,y,\omega} \leq W_{i,j,t,y,\omega} \\ \eta^1_{i,j,\varkappa,t,y,\omega} \leq \tan\left(\frac{\pi}{2^{\varkappa+1}}\right)\xi^1_{i,j,\varkappa,t,y,\omega} \end{cases}$$

$$\begin{cases} \xi^2_{i,j,0,t,y,\omega} \geq W_{i,j,t,y,\omega}, \xi^2_{i,j,0,t,y,\omega} \geq -W_{i,j,t,y,\omega} \\ \eta^2_{i,j,0,t,y,\omega} \geq l_{i,j,t,y,\omega} - v_{i,t,y,\omega}, \eta^2_{i,j,0,t,y,\omega} \geq -\left(l_{i,j,t,y,\omega} - v_{i,t,y,\omega}\right) \end{cases}$$

$$\begin{cases} \xi^2_{i,j,\varphi,t,y,\omega} = \cos\left(\frac{\pi}{2^{\varphi+1}}\right)\xi^2_{i,j,\varphi-1,t,y,\omega} + \sin\left(\frac{\pi}{2^{\varphi+1}}\right)\eta^2_{i,j,\varphi-1,t,y,\omega} \\ \eta^2_{i,j,\varphi t,y,\omega} \geq -\sin\left(\frac{\pi}{2^{\varphi+1}}\right)\xi^2_{i,j,\varphi-1t,y,\omega} + \cos\left(\frac{\pi}{2^{\varphi+1}}\right)\eta^2_{i,j,\varphi-1,t,y,\omega} \\ \eta^2_{i,j,\varphi,t,y,\omega} \geq +\sin\left(\frac{\pi}{2^{\varphi+1}}\right)\xi^2_{i,j,\varphi-1,t,y,\omega} - \cos\left(\frac{\pi}{2^{\varphi+1}}\right)\eta^2_{i,j,\varphi-1,t,y,\omega} \end{cases} \tag{6k}$$

$\varphi = 1, \ldots, \varkappa$

$$\begin{cases} \xi^2_{i,j,\varkappa,t,y,\omega} \leq l_{i,j,t,y,\omega} + v_{i,t,y,\omega} \\ \eta^2_{i,j,\varkappa,t,y,\omega} \leq \tan\left(\frac{\pi}{2^{\varkappa+1}}\right)\xi^2_{i,j,\varkappa,t,y,\omega} \end{cases}$$

4. CASE STUDY

A benchmark case, namely the base case, and four scenarios are proposed for the case study, denoted Cases 1A, 1B, 2A, and 2B. The base case objective, given by Equation (6a)[11], is to obtain the DLMP from the power grid disregarding EVs, which will be used as an energy tariff in Cases A and B. In addition, other power grid variables are also obtained, such as total power losses, cable currents, and bus voltages.

In Case 1A, e-carsharing planning is carried out only with EV charging optimization, without considering the V2G and power grid constraints. Case 1B is similar to 1A but with V2G. Cases 1A and 1B problem formulations are given by Equation (6b), with the optimality gap set as 0.1%. Case 2A contains the power grid constraints, but without V2G. Finally, Case 2B considers V2G and the power grid constraints. Cases 2A and 2B problem

[11] Maximizing an objective function is equal to minimizing its negative.

formulations are given by Equation (6c), with the optimality gap also set as 0.1%. Table 2 presents a summary of the main aspects of each case.

$$\min(-OF_{DSO}) \quad \textbf{\textit{s.t.}}\ (6a) – (6e), \text{ and } (6j) – (6k) \tag{7a}$$

$$\max(OF_{ecar}) \quad \textbf{\textit{s.t.}}\ (4), \text{ and } (5) \tag{7b}$$

$$\max(OF_{ecar} + OF_{DSO}) \quad \textbf{\textit{s.t.}}\ (4), (5), (6a) – (6e), \text{ and } (6j) – (6k) \tag{7c}$$

Table 2 – Case Studies Summary

	Optimization without V2G	Optimization with V2G	Power Grid
Base Case			✓
Case 1A	✓		
Case 1B		✓	
Case 2A	✓		✓
Case 2B		✓	✓

Source: Author

The model is developed in MATLAB R2020a and GAMS using the CPLEX solver (GAMS, 2022) on a 16 GB RAM, Intel(R) i7-4790 processor, clocking at 3.6 GHz. Due to high computational time, it is considered to be only one year for the planning horizon ($\Omega_y = 1$), 24 hours with a 1-hour time period, and two scenarios. The scenarios are defined as low and high rental demand, with a total of 20 and 40 daily trips and 20% and 80% probability, respectively.

4.1 E-CARSHARING PARAMETERS

It is assumed that all EVs are the same, as are the chargers. The rental tariff and relocation cost are constant, while the energy tariff is based on the DLMP from the grid without any EV (Base Case). Although e-carsharing does not actively participate in the formation of the DLMP, it is expected that its use, given the company's load flexibility, will be economically more attractive than the flat rate. Table 3 summarizes the parameters for the e-carsharing model (DANPING *et al.*, 2020; KOBASHI *et al.*, 2020). Moreover, it is assumed that the maximum (Ch_p^{max}) and minimum (Ch_p^{min}) number of chargers are 10 and 1 for all positions, respectively.

The authors in (ALENCAR *et al.*, 2021) provide a real database with 644,511 vehicle rental trips over five months. The data contain the trip start time ($trip_{start}$), trip duration ($trip_d$), and date of the trip, among other data. An algorithm was developed to treat this database, as shown in Table 4. The algorithm extracts the trip start time probability density function (PDF) based on the kernel distribution (ROSENBLATT, 1956) to generate scenarios.

As the analysis of the operation in this study is for one day, the average probability density function of the week was used.

Table 3 – Summary of e-carsharing parameters

Parameter	Value
Electric vehicle price [$]	30,000
Charging station price [$]	100,000
Charger price [$]	1,000
Initial budget [$]	3,000,000
Rental tariff [$/h]	4
Relocation cost [$/h]	2
Charging power [kW]	7.2
EV battery [kW]	40
EV energy consumption due to movement [kWh/h][12]	4.4
Charger efficiency [%]	95

Source: Author

Table 4 – Algorithm for scenario generation

Scenario generation Algorithm

Input data
Collects the parameter $trip_{start}$
Selects the base time: week or day
Treat the parameters according to the selected base time

Estimate the Kernel distribution based on $trip_{start}$
$\hat{f}_h(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x-x_i}{h}\right)$

Defines the number of demands δ
for each year y
  for each scenario ω
    for each demand δ
      Defines the origin/destination based on uniform integer distribution within the set Ω_p
      Defines the $trip_{start}$ based on Kernel distribution $\hat{f}_h(x)$
      Defines the $trip_d$ based on uniform integer distribution within [1,2]
 $trip_{end} = trip_{start} + trip_d$
    end for
  end for
end for

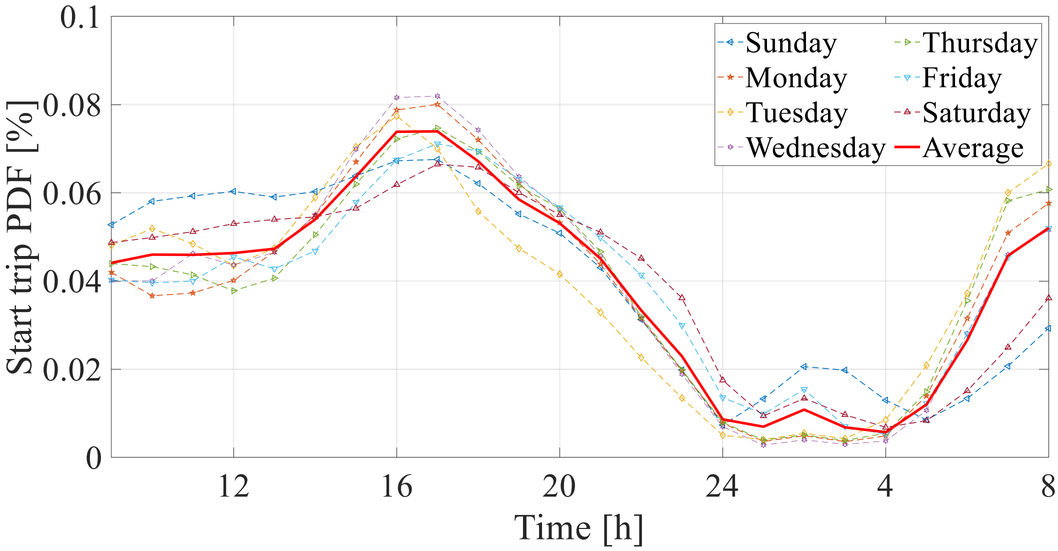
Source: Author

The origin and destination are randomly generated through a uniform integer distribution contained in the set of positions Ω_p. It is noteworthy that position 1 was removed, as the substation space is reserved and does not support a load.

[12] It is considered an autonomy of 300 km and a constant velocity of 33 km/h.

Although the database contains information about the duration of trips, on average, they last less than 1 hour. The problem is with an interval of 1 h; thus, such behavior would not be captured. In this sense, the trip duration is defined as a uniform integer distribution of one or two hours. Finally, with the trip start time and its duration, it is possible to define the end time of the trip. It should be noted that if the start of the trip is 24 hours, the end of the trip is shifted to the beginning of the day. As a result of the algorithm, a start trip time PDF is established, as shown in Figure 12. Moreover, Table 5 and Table 6 present the information generated for scenarios 1 and 2, respectively. It is noteworthy that for real cases, an in-depth study is needed to understand the region's demand.

Figure 12 – Carsharing start trip probability density function.



Source: Author

Table 5 – Demand from scenario 1

From	To	Start time [h]	Trip duration [h]	End time [h]
29	13	6	1	7
25	4	7	2	9
27	18	7	1	8
32	11	7	1	8
2	28	7	2	9
3	7	8	2	10
8	20	9	2	11
12	16	9	2	11
3	18	10	1	11
7	21	11	2	13
4	5	13	1	14
3	31	14	2	16
33	11	16	1	17
33	19	17	2	19
14	6	18	1	19
16	26	18	2	20
15	8	19	2	21
31	33	19	2	21
5	7	19	1	20
12	30	24	1	1

Source: Author

Table 6 – Demand from scenario 2

From	To	Start time [h]	Trip duration [h]	End time [h]
11	21	1	2	3
14	21	4	1	5
27	17	6	2	8
19	7	6	1	7
20	25	7	1	8
15	24	7	2	9
26	24	7	1	8
10	30	7	2	9
19	12	7	1	8
25	33	8	2	10
18	4	8	1	9
6	6	8	1	9
21	33	8	1	9
4	31	9	2	11
26	8	11	1	12
5	11	11	1	12
10	14	11	1	12
19	9	13	2	15
31	7	13	1	14
21	12	13	1	14
15	22	14	2	16
6	4	15	1	16
6	7	15	1	16
12	12	15	1	16
12	22	16	2	18

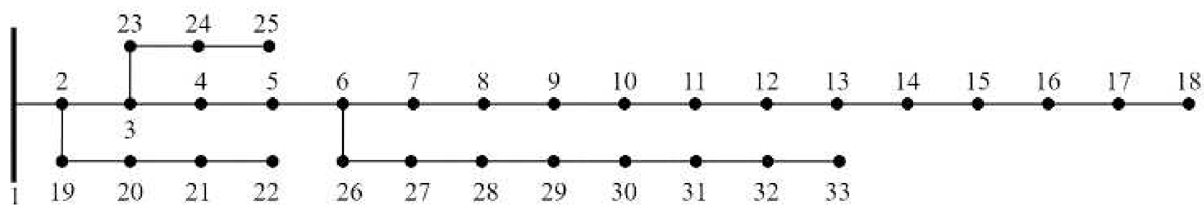
From	To	Start time [h]	Trip duration [h]	End time [h]
23	21	16	2	18
5	5	16	2	18
15	22	16	1	17
29	13	16	2	18
4	13	17	1	18
18	5	17	2	19
13	8	18	1	19
14	7	18	2	20
16	15	18	1	19
23	15	19	1	20
23	14	19	2	21
11	18	21	2	23
17	6	22	2	24
14	10	23	1	24
21	3	23	1	24

Source: Author

4.2 IEEE 33 Bus Test System

The 33-bus IEEE system is used as the power grid, whose topology is shown in Figure 13. Table 7 presents the bus data of the system. The total load is 3.715 MW, of which 1.135 MW are among buses 6 to 18, 0.36 MW are among buses 19 to 22, 0.93 MW are among buses 23 to 25 and 0.92 MW are among buses 26 to 33. Table 8 presents the branch data of the system. Different cable capacities are defined to let the network close its operating limit. In this way, it is possible to identify the benefits of V2G, especially in postponing cable reinforcement investments. The energy price at slack bus (1) ζ^g is set to \$20/MWh. The voltage lower and upper bounds are set to 0.95 and 1.05 pu, respectively. The voltage and power bases are 12.66 kV and 1 MVA, respectively. Finally, all loads have the same shape, as shown in Figure 14 for both active and reactive power.

Figure 13 – IEEE 33 bus system.



Source: Author

Table 7 – IEEE 33 bus system data

Bus	P [kW]	Q [kVar]	Bus	P [kW]	Q [kVar]	Bus	P [kW]	Q [kVar]
1	0	0	12	60	35	23	90	50
2	100	60	13	60	35	24	420	200
3	90	40	14	120	80	25	420	200
4	120	80	15	60	10	26	60	25
5	60	30	16	60	20	27	60	25
6	60	20	17	60	20	28	60	20
7	200	100	18	90	40	29	120	70
8	200	100	19	90	40	30	200	600
9	60	20	20	90	40	31	150	70
10	60	20	21	90	40	32	210	100
11	45	30	22	90	40	33	60	4

Source: Adapted from (VITA, 2017)

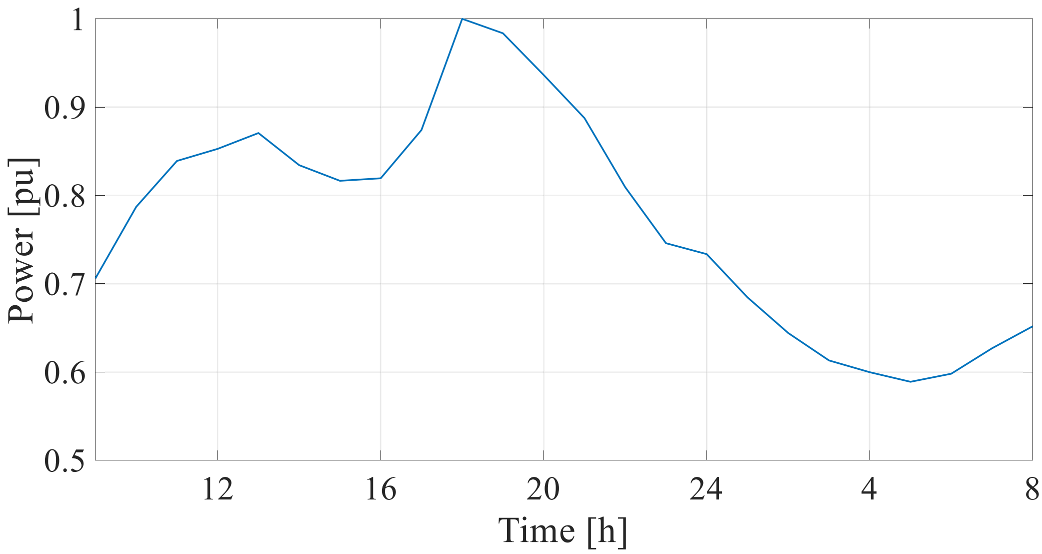
Table 8 – IEEE 33 bus system branch data

Branch	From bus	To bus	R [Ω]	X [Ω]	Capacity [A]
Branch-1	1	2	0.0922	0.0470	350
Branch-2	2	3	0.4930	0.2511	320
Branch-3	3	4	0.3660	0.1864	250
Branch-4	4	5	0.3811	0.1941	250
Branch-5	5	6	0.8190	0.7070	250
Branch-6	6	7	0.1872	0.6188	100
Branch-7	7	8	0.7114	0.2351	100
Branch-8	8	9	1.0300	0.7400	100
Branch-9	9	10	1.0440	0.7400	100
Branch-10	10	11	0.1966	0.0650	100
Branch-11	11	12	0.3744	0.1298	100
Branch-12	12	13	1.4680	1.1550	100
Branch-13	13	14	0.5416	0.7129	100
Branch-14	14	15	0.5910	0.5260	100
Branch-15	15	16	0.7463	0.5450	100
Branch-16	16	17	1.2890	1.7210	100
Branch-17	17	18	0.7320	0.5740	100
Branch-18	2	19	0.1640	0.1565	50
Branch-19	19	20	1.5042	13.554	50
Branch-20	20	21	0.4095	0.4784	50
Branch-21	21	22	0.7089	0.9373	50
Branch-22	3	23	0.4512	0.3083	100
Branch-23	23	24	0.8980	0.7091	100
Branch-24	24	25	0.8960	0.7011	100
Branch-25	6	26	0.2030	0.1034	110
Branch-26	26	27	0.2842	0.1447	110
Branch-27	27	28	1.0590	0.9337	110

Branch	From bus	To bus	R [Ω]	X [Ω]	Capacity [A]
Branch-28	28	29	0.8042	0.7006	110
Branch-29	29	30	0.5075	0.2585	110
Branch-30	30	31	0.9744	0.963	110
Branch-31	31	32	0.3105	0.3619	110
Branch-32	32	33	0.3410	0.5302	110

Source: Adapted from (VITA, 2017)

Figure 14 – Demand Loadshape.



Source: Author

Moreover, a set of four candidate types of cables for reinforcement is considered in this work, as shown in Table 9 (FALAGHI *et al.*, 2011). Note that the cable's capacity and price from Table 9 are I_c^{Cr} and p_c^{Cr} parameters, respectively. All costs associated with the cable reinforcement, such as staff dispatch and load shed, are included in the cost of the cable. The idea of giving different prices for different capacities is to assess the benefits of V2G in postponing the reinforcement or at least reducing the capacity needed. It is worth mentioning that, for simplicity, the resistance ($r_{i,j,y}$) and reactance ($x_{i,j,y}$) of the new cable are the same as the old cable.

Table 9 – Set of cables for reinforcement

Capacity [A]	Price [$]
400	100,000
350	70,000
150	50,000
100	30,000

Source: Author

5. RESULTS

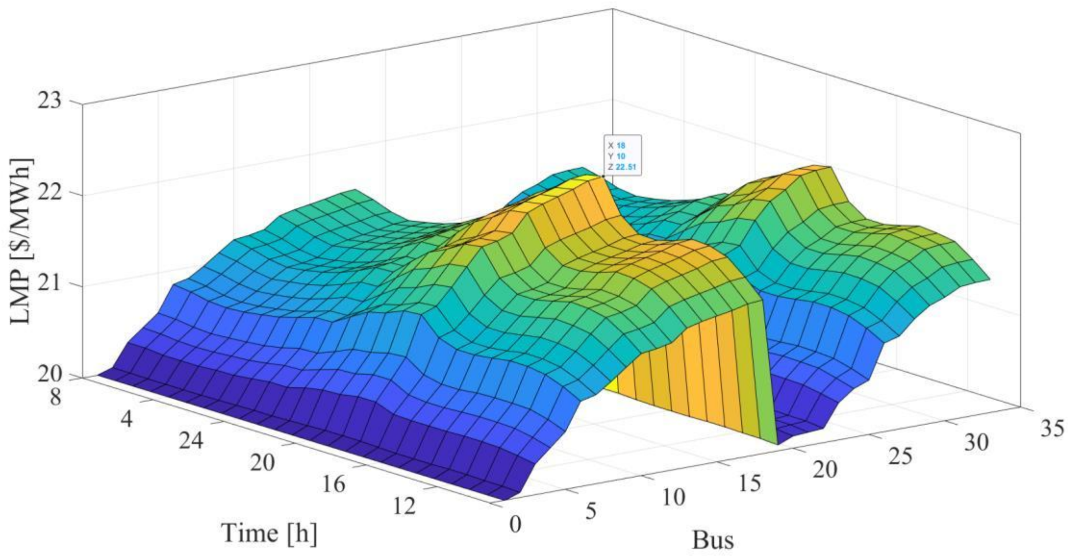
5.1 OVERVIEW

The total losses in the Base Case are 2.5 MW for one operation day. As the cable capacities were carefully modelled for the power grid to operate at its limit, no cable needed to be reinforced ($\sum_{\Omega_c} x_{i,j,c,y}^{Cr} = 0$). Figure 15 shows the DLMP of the system without any EVs. As expected, the DLMP peak occurs at the time of peak load, 18:00. Furthermore, it is located on the electrically furthest bus from substation (bus 18). Similarly, the minimum voltage occurs at the same time and position, with a magnitude of 0.9683 pu. Note that the substation voltage (bus 1) was set to the maximum value, 1.05 pu, as shown in Figure 16. As the power grid does not have capacitor banks, it is necessary for the grid to maintain voltage limits, especially at the furthest buses.

The main decision variables' results are presented in Table 10. The rental profit is the same in all cases. The case with V2G and no power grid constraints (Case 1B) is the one with the highest profit, given that there is no limit to the company's interaction with the power grid. Moreover, when power grid constraints are considered (Case 2B), the company's profit decreases compared with Case 1B. Cases 1A and 2A present the same behavior. It is worth mentioning that the V2G and power grid constraints (Case 2B) changed the decisions in the first stage, increasing the number of chargers. This only happened to meet the power grid constraints because the meeting demand remained the same. This indicates that the company's mode of operation could affect the siting and sizing of CSs according to the agent planning perspective. Moreover, the relocation mechanism was most used as a way to maximize profit in Cases 2A and 2B, given the power grid constraints. However, this is only possible if there is a trade-off between relocation and charging costs.

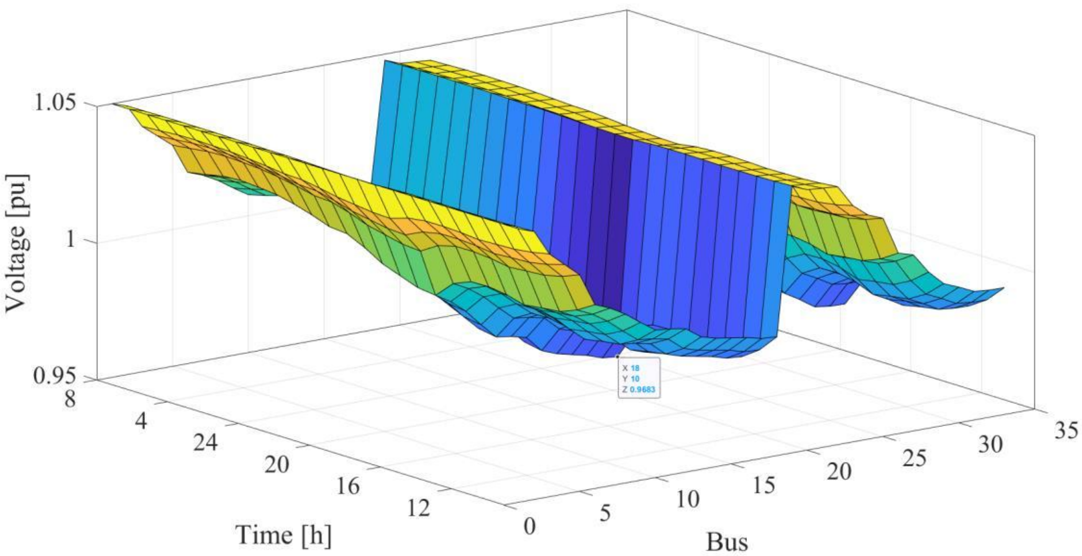
One can note that a CS was installed in almost every position (32 in total). Since the cable's length are one kilometer, it can be interpreted that users must walk at maximum 500 meters to reach a station. User's preferences and behavior can be considered in the model in future improvements to achieve not only maximum profit but also add quality in the service.

Figure 15 – DLMP in the Base Case.



Source: Author

Figure 16 – Voltage in the Base Case.



Source: Author

Regarding the scenarios, the demand was not met in either scenario or case due to the budget limit of the first stage. It is also noted that the total daily losses in the case with V2G are slightly lower than in the case without V2G, which highlights its benefits for the DSO.

Finally, the profits in decreasing order are Case 1B > Case 2B > Case 1A > Case 2A. Case 1B was expected to present the highest profit, given that there are no constraints for power injection into the grid. On the other hand, Case 2A was also expected to present the lowest profit, since there is no flexibility of V2G and there are power grid constraints. However, Cases 1A and 2B have a less straightforward interpretation. If the power grid is operating close to its limit, the power flows will be more limited, preventing EVs from injecting more energy into the grid, leading to a higher charging cost. Although Case 1A does not have V2G, its profit may be higher due to fewer constraints.

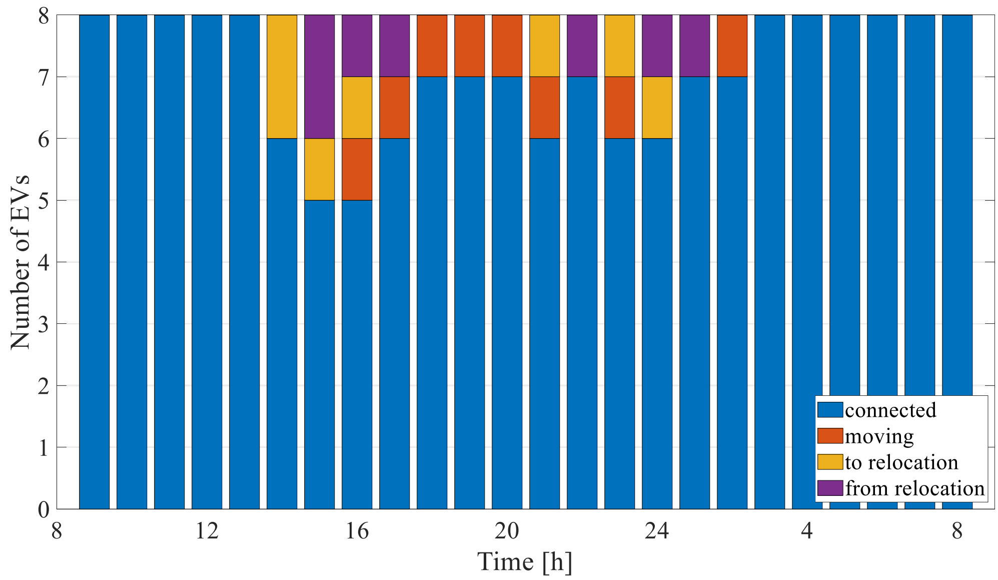
Table 10 – Decisions Summary

	Case 1A		Case 1B		Case 2A		Case 2B	
Total profit [$]	39,477		39,500		39,476		39,497	
Total rental profit [$]	52,268		52,268		52,268		52,268	
Total charging cost [$]	1,257		1,234		1,258		1,237	
Total relocation cost [$]	11,534		11,534		11,534		11,534	
First stage decisions								
Number of charging stations	27		27		27		27	
Number of chargers	29		29		29		29	
Number of electric vehicles	8		8		8		8	
Total acquisition cost [$]	2,969,000		2,969,000		2,969,000		2,969,000	
Second stage decisions								
	Scenarios							
	1	2	1	2	1	2	1	2
Meeting demand [%]	45	70	45	70	45	70	45	70
Total daily losses [MW]	-	-	-	-	2.91	3.67	2.89	3.65
Simulation time [s]	7		4		870		1.239	

Source: Author

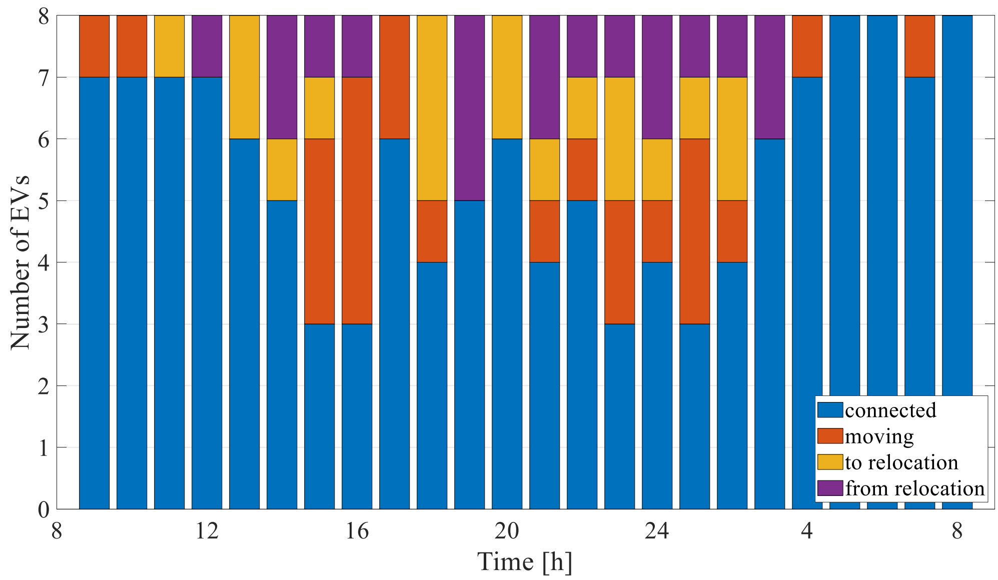
The rental profit and relocation cost are the same in all cases, while only the EV charging cost differs. In this sense, Figure 17 and Figure 18 show the EVs' status in scenarios 1 and 2, respectively. Note that in scenario 1, most vehicles are simultaneously connected. On the other hand, in scenario 2, the EVs present a more status diversity, meeting demands and relocating more. This was expected, as the rental demand is higher. However, there are at least 3 EVs connected at peak times in scenario 2. In addition, the demand is not completely met for both scenarios. As there is no investment cost minimization and demand maximization in the objective function, the model finds that it is more profitable to buy more EVs and leave them parked for possible relocation or energy sale at peak hours (when V2G is considered) than install more CSs to meet more demand. In summary, the unmet demands are the least profitable for the model, given the budget limit. Finally, although the EV status is the same in all cases, the connection status (the blue one) does not provide information about the charge/discharge of the EVs, needing further investigation.

Figure 17 – EV status in scenario 1.



Source: Author

Figure 18 – EV status in scenario 2.

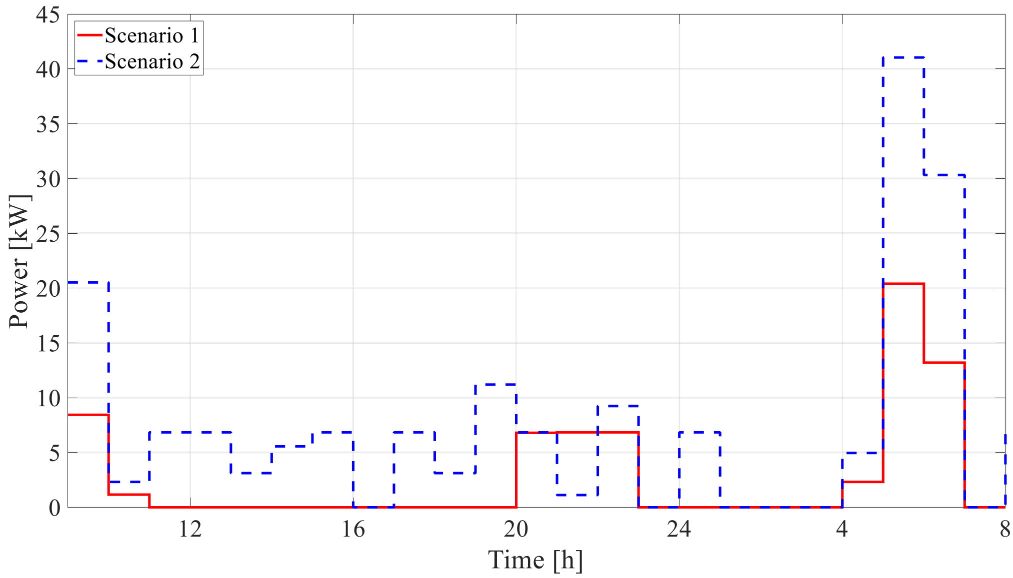


Source: Author

5.1.1 EV Charging and Power Grid Impact

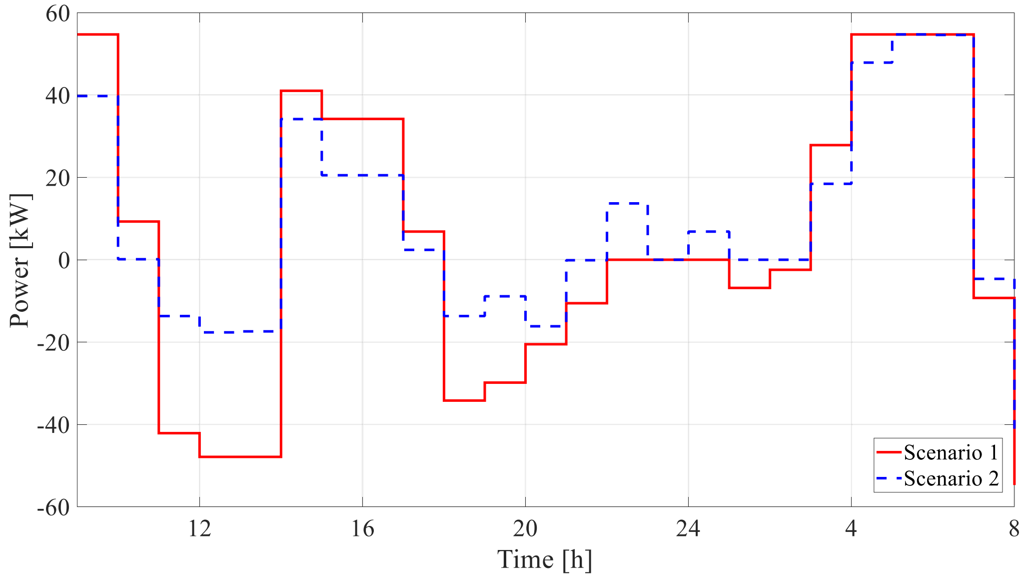
A comparison of the total EV charging load between both scenarios in Case 1A is presented in Figure 19. It can be noted that the EV charging power in scenario 2 is higher than that in scenario 1. The demand in scenario 2 is higher than that in Scenario 1; thus, the EV discharge due to movement is higher. On the other hand, Figure 20 shows the comparison of the total EV charging load of both scenarios in Case 1B. As the number of EVs is the same for both scenarios (first stage variable), it is expected that the EV fleet is oversized for the low-demand scenario, which is less likely to happen. One can note that the power injection in scenario 1 is greater than that in scenario 2. Due to low rental demand, EVs in scenario 1 can take advantage of idle time to inject more energy into the grid when the tariff is higher. On the other hand, EVs in scenario 2 have more rental demand, which leaves less time for EVs to profit from V2G.

Figure 19 – EV Charging power in Case 1A.



Source: Author

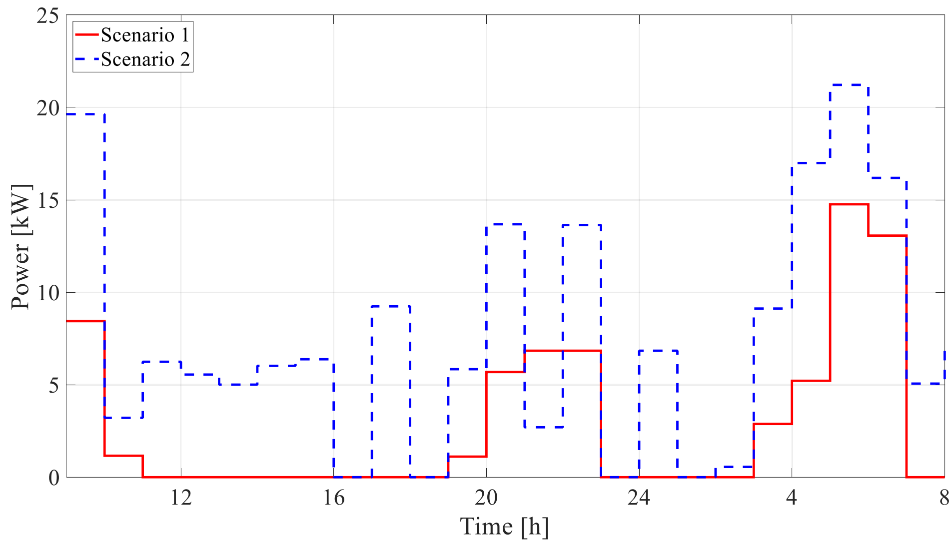
Figure 20 – EV Charging power in Case 1B.



Source: Author

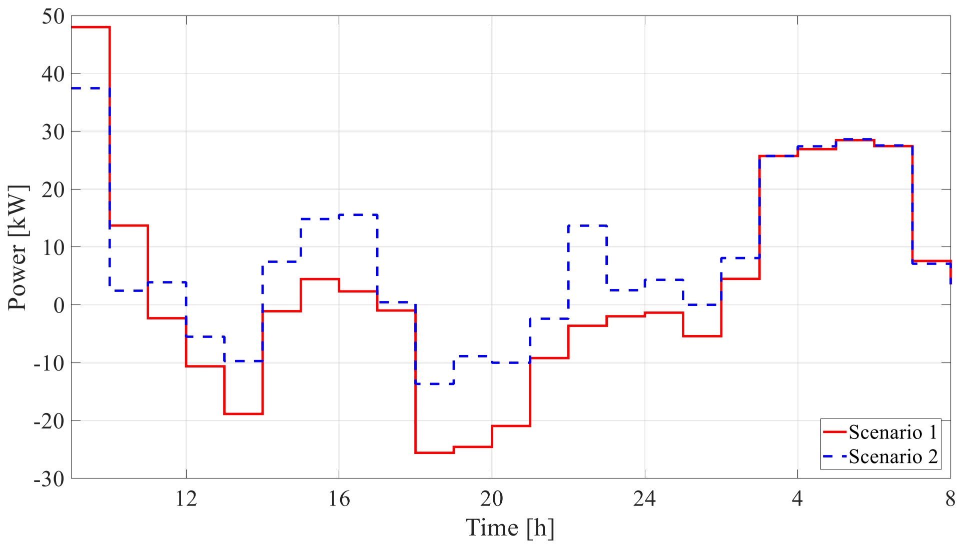
Figure 21 and Figure 22 show the total EV charging load between Cases 2A and 2B in both scenarios, respectively. The behavior is similar to Cases 1A and 1B, but the power amplitude is smaller due to grid constraints. Moreover, one can notice that in the cases without V2G (Cases 1A and 2A), the interaction with the power grid is greater in the high-demand scenario. In cases with V2G (Cases 1B and 2B), the interaction with the power grid is greater in the low demand scenario. This shows how EVs can take advantage of low-demand scenarios to increase profit, while most of the profit comes from vehicle rentals in high-demand scenarios.

Figure 21 – EV Charging power in Case 2A.



Source: Author

Figure 22 – EV Charging power in Case 2B.

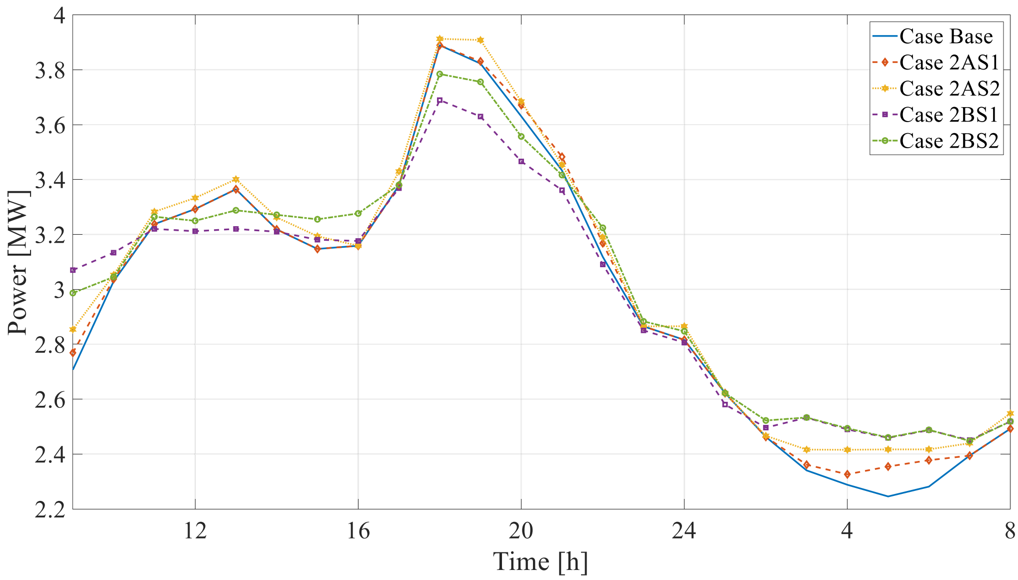


Source: Author

It can be noted that the charging power in scenario 2 is higher than that in scenario 1. The charging power peaks are more accentuated (positive and negative) in cases where there are no power grid constraints. On the other hand, with the power grid constraints, the total load curve is smoother. In this way, if the e-carsharing operator is coordinated with the DSO, a coordinated charge with V2G can be used to postpone investments in network reinforcement and still keep meeting the rental demand.

Figure 23 presents the power on the slack bus in Cases 2A and 2B with scenarios 1 and 2 (S1 and S2). Most of the EV charges are concentrated at night in Case 2A when rental demand and energy tariffs are low. In this case, the EV charging optimization benefits are smaller for the DSO. As in this case study, few trips are being considered, and the intensity of vehicle use is small compared to the battery capacity, so the total discharge throughout the day is low. Thus, the charging demand is also low. Despite the rental demand during the day (8 h~24 h), some parked EVs take advantage of the high DLMP to discharge into the grid, reducing the substation demand (slack bus) in Case 2B. On the other hand, this discharge during the day is compensated at night, when the EVs charge (with more intensity than Case 2A).

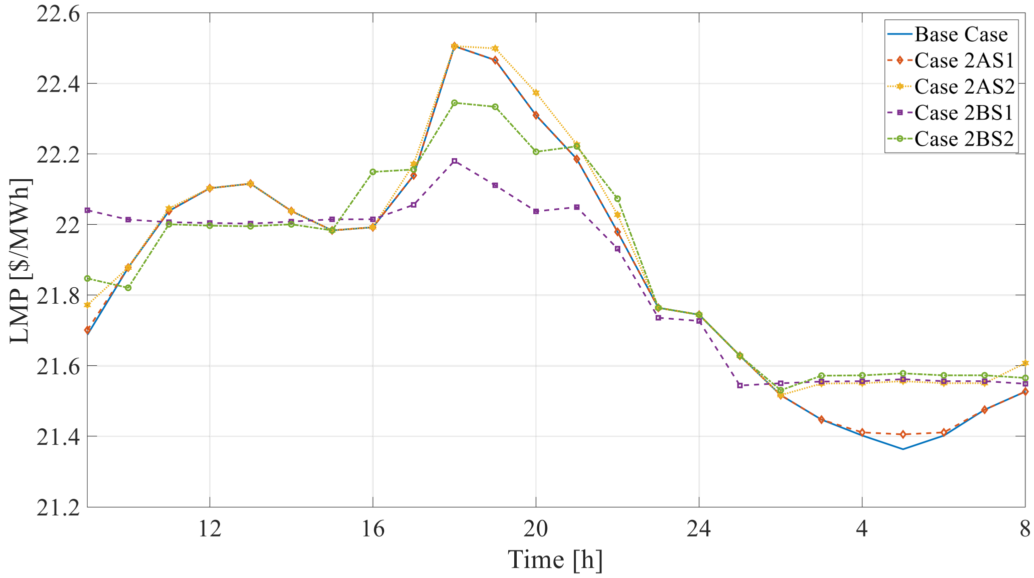
Figure 23 – Power at Slack Bus.



Source: Author

Figure 24 shows the DLMP at bus 18 (farthest from the substation). Note that the DLMP change is very small in Case 2A, while there is a greater variation in Case 2B for both scenarios. This behavior is repeated in all the system buses, as shown in the summary in Table 11. Although the average DLMP remained constant, the maximum and minimum DLMP decreased in Case 2B compared to Base Case and Case 2A. This reinforces the idea of the benefits of coordinated planning of both agents.

Figure 24 – Distribution Local Marginal Price at bus 18.



Source: Author

Table 11 – DLMP Summary

		Min			Average	Max		
		Bus	Time [h]	DLMP [$/MWh]	DLMP [$/MWh]	Bus	Time [h]	DLMP [$/MWh]
Base Case		1	[1,24]	20.00	21.06	18	18	22.51
Case 2A	S1	1	[1,24]	20.00	21.06	18	18	22.51
	S2	1	[1,24]	20.00	21.09	18	18	22.51
Case 2B	S1	1	18	19.95	21.05	18	18	22.18
	S2	1	[1,24]	20.00	21.08	18	18	22.35

Source: Author

On the other hand, if the e-carsharing company operates using a flat tariff, its charging cost would remain the same regardless of the time of day. This could lead to a further increase in the DLMP at peak consumption times, as there would be no incentive to charge during off-peak times. Furthermore, a relatively large EV fleet (not only e-carsharing but also EV taxis) charging at the same time at a single CS can significantly influence the DLMP. Thus, energy costs would be passed on to all consumers in that region, even those who do not use e-carsharing.

Therefore, V2G increased the company's profit (not as much as in case 1B), reduced the total system losses, reduced the DLMP, and flattened the substation demand. Although the difference between the profits of Cases 2A and 2B is relatively low, this may indicate that cooperation between agents is beneficial. However, if the company took a selfish stance and proceeded with Case 2B planning to maximize profit, the DSO may not be able to operate as planned. Thus, there may be a blackout due to the unexpected increase in load or even load shedding if considering a smart grid with control. Both situations are disadvantageous for the e-carsharing company and the DSO, which highlights the importance of cooperation between them. It is necessary to assess the benefits that V2G brings to DSO expansion planning.

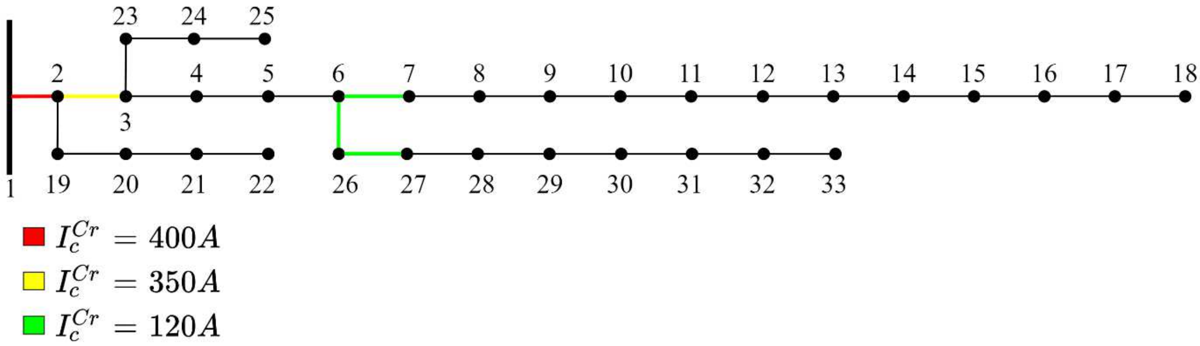
Moreover, the difference between the profits of cases considering V2G and not considering V2G is relatively small. This is mainly due to the energy tariff being cheap (between \$.2/kWh and \$.22/kWh) in comparison to the rental tariff (\$4/h). In places where the energy tariff is higher, the differences could be more expressive. In addition, the disadvantages of V2G (battery degradation and expensive chargers), which were not modeled, may make this operating mode unfeasible for the company. In this sense, it is necessary to evaluate other benefits that V2G can bring, in addition to the operation, for the DSO, such as cable investment cost reduction in the expansion planning.

5.2 Sensitivity Analysis 1: Load Increase

The objective of this section is to present a sensitivity analysis regarding the power grid load increase. For this, the load was increased by 10%. Thus, it is expected that there will be an investment in cable reinforcement by the DSO to make the power grid operation feasible. The load increase only caused problems in the power grid during the peak hour, 18 h. To meet this new load, Branch-1, Branch-2, Branch-6, Branch-25, and Branch-26 were replaced with 400 A, 350 A, 120 A, 120 A, and 120 A, respectively, which cost \$290,000. Figure 25 shows, with the color scale in Ampere [A], the new cable of each branch that needed reinforcement. Note that the reinforced branches are the ones that need to support more load when the cable sections change. For example, between branches 5 and 7, the cable capacity reduces from 250 A to 100 A.

In addition, the DLMP has a small difference regarding the Base Case, as shown in the Figure 26. This was expected since the marginal energy generation cost increased due to the additional load. The voltage maintains its minimum value at 18:00 and bus 18, but with a reduced magnitude, 0.9594 pu, as shown in the Figure 27. Finally, the total daily losses are 3.0 MWh.

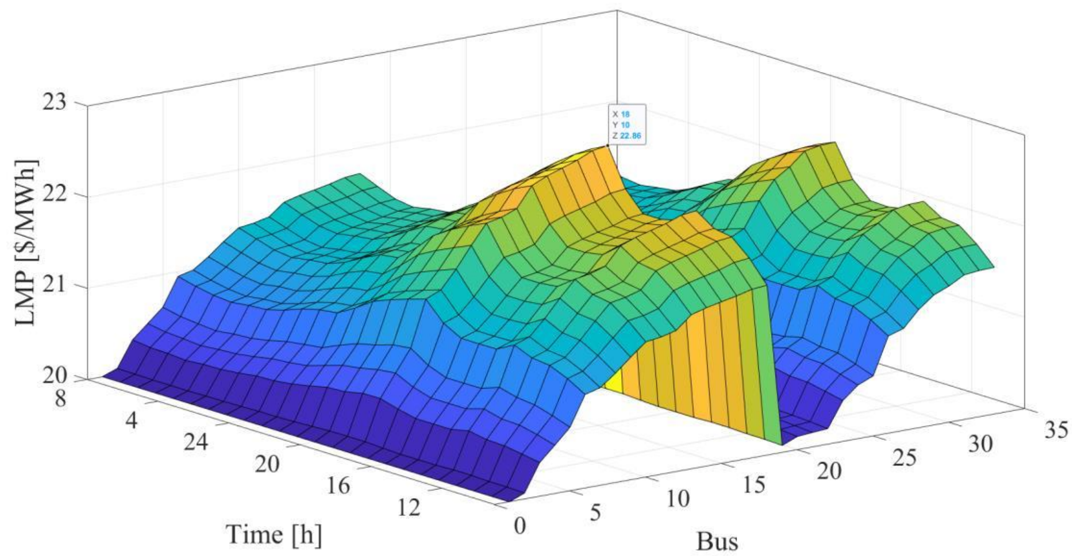
Figure 25 – Cable reinforcement in Base Case with a 110% load increase.



Source: Author

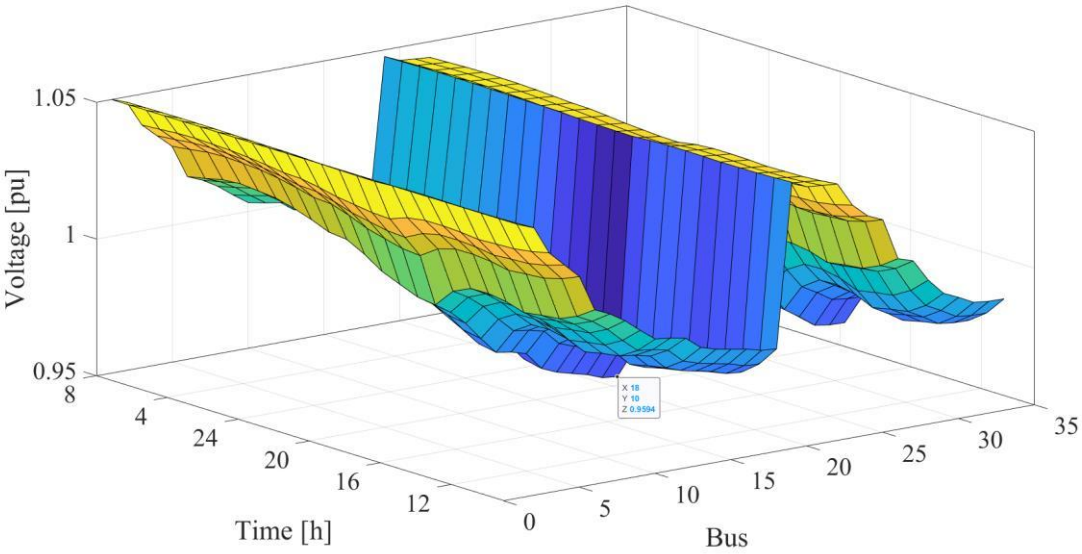
As the focus of this section is the analysis of the interaction between e-carsharing and the DSO, only Cases 2A and 2B are analyzed. Table 12 shows the decision summary for a 110% load increase for both cases. Different from the normal load case, Case 2B presented lower rental profit, charging cost, relocation cost, and meeting demand. In addition, more EVs were purchased in Case 2B. These values are aligned with the reinforcement cost of the power grid, in which Case 2A presented the same cost as the Base Case, \$290,000, while Case 2B has a reduced cost, \$100,000. Finally, the power losses in Case 2B were higher than those in the normal load of the same Case due to the load increase.

Figure 26 – DLMP in the Base Case with a 110% load increase.



Source: Author

Figure 27 – Voltage in the Base Case with a 110% load increase.



Source: Author

This shows how V2G can reduce the reinforcement cost, while charging optimization without V2G did not bring any benefit to the DSO. Figure 28 shows the reinforced cables in Case 2A, with a 110% load increase. As previously stated, optimized charging without V2G did not postpone investment in cable reinforcement. On the other hand, only Branch-1 needed to be reinforced, as shown in Figure 29. Moreover, 9 EVs with V2G were not enough to supply the load increase.

It is noteworthy that the maximum current (at 18 h) in Branch-1 of Case 2A is 378 A (same as in the Base Case), while in Case 2B, the maximum current is 362 A. However, as the only option of the model is a 400 A cable, this one was selected as a reinforcement. However, if there was a cable option with a lower capacity available (therefore cheaper), V2G would reduce the unavoidable reinforcement cost.

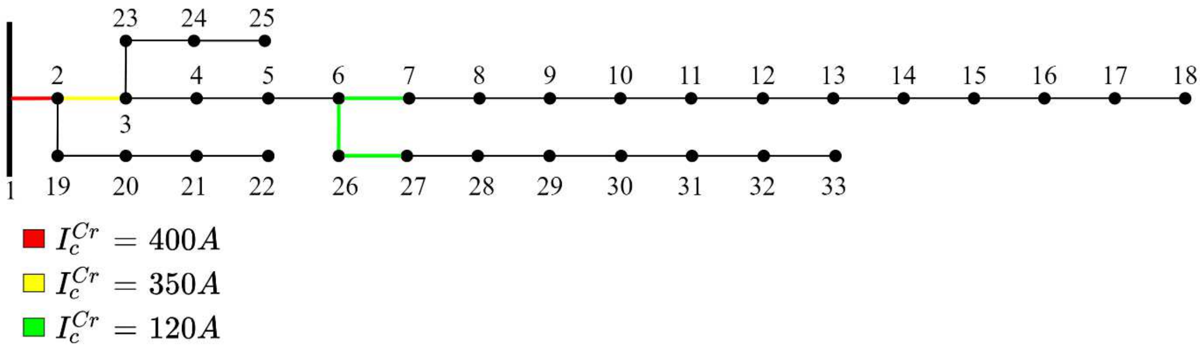
Despite reducing the reinforcement cost, the profit in Case 2B was lower ($37,659) compared with the same case with the normal load ($39,497). This shows that the Case 2B decision was also affected by the DSO to avoid increasing its costs. Hence, such a set of decisions favored the DSO to the detriment of the e-carsharing profit, which, in addition to EV charging operation, also affected its meeting demand and EV fleet size. This is because the decision is being taken jointly. However, the decisions that most impact the objective function have priority, regardless of the agent's perspective. As the DSO has higher associated costs in the model, decisions tend to favor it, as the results indicate. Thus, it is necessary to carry out an analysis that ponders the decisions of both agents.

Table 12 – Decisions Summary with a 110% load increase

	Case 2A		Case 2B	
Total profit [$]	39,472		37,659	
Total rental profit [$]	52,268		49,640	
Total charging cost [$]	1,262		1,177	
Total relocation cost [$]	11,534		10,804	
Reinforcement cost [$]	290,000		100,000	
First stage decisions				
Number of charging stations	27		27	
Number of chargers	29		29	
Number of electric vehicles	8		9	
Total acquisition cost	2,969,000		2,999,000	
Second stage decisions				
	Scenarios			
	1	2	1	2
Meeting demand [%]	45.0	70.0	40.0	65.0
Total daily losses [MW]	3.46	4.22	3.41	4.16
Simulation time [s]	1,104		2,366	

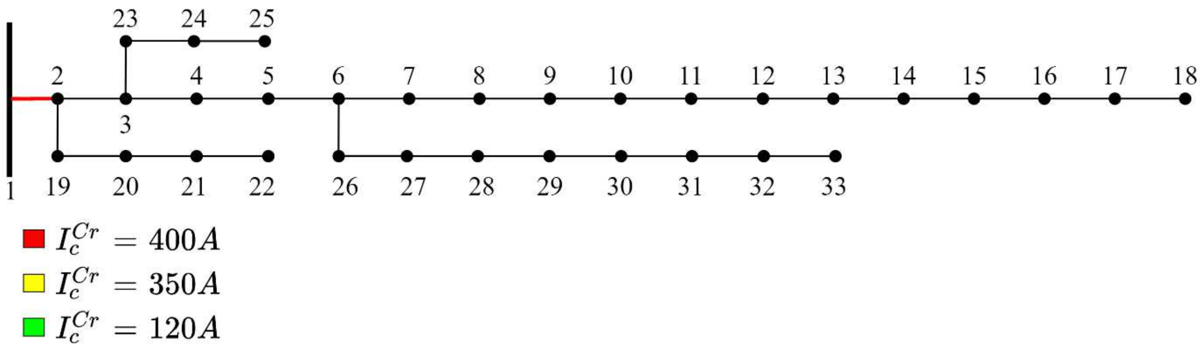
Source: Author

Figure 28 – Cable reinforcement in Case 2A with a 110% load increase.



Source: Author

Figure 29 – Cable reinforcement in Case 2B with a 110% load increase.



Source: Author

5.3 Sensitivity Analysis 2: Multi-Objective Approach

This section shows an analysis considering different weights for the perspectives of e-carsharing and DSO in a multi-objective approach. For this, a new objective function is used, as shown in Equation (8a), in which α and β are the weights of the objective functions. α and β are positive integers, between 0 and 1, and must sum one, as shown in Equation (8b). It is noteworthy that for this analysis, the 110% load increase is still considered. Finally, for this analysis, only Case 2B is considered.

$$OF_{MO} = OF_{ecar}\alpha + OF_{DSO}\beta \quad (8a)$$

$$\alpha + \beta = 1 \quad (8b)$$

Table 13 presents the decision summary in the multi-objective approach. $\alpha = 1$ indicates that the entire decision is made by e-carsharing. Thus, what is observed is that Case 2B becomes Case 1B, in which there are no power grid constraints. Hence, the generation costs and cable reinforcement costs are completely neglected. This leads to a total cost for the DSO of approximately 3.86 M$, of which 3.20 M$ is to reinforce cables.

On the other hand, when $\alpha = 0$ (therefore $\beta = 1$), the entire decision is made by the DSO. In this case, the EVs are similar to the assets of the DSO and serve exclusively to reduce the generation costs and grid expansion costs.

Table 13 – Decisions summary in the multi-objective approach

α	e-carsharing				DSO		
	Total profit [$]	Rental profit [$]	Charging cost [$]	Relocation cost [$]	Total cost [$]	Generation cost [$]	Reinforcement cost [$]
1	**39,500**	52,268	1,234	11,534	**3,861,092**	661,092	3,200,000
0.9	**37,661**	49,640	1,175	10,804	**682,339**	582,339	100,000
0.8	**37,660**	49,640	1,176	10,804	**682,334**	582,334	100,000
0.7	**37,660**	49,640	1,176	10,804	**682,332**	582,332	100,000
0.6	**37,659**	49,640	1,177	10,804	**682,332**	582,332	100,000
0.5	**37,659**	49,640	1,177	10,804	**682,331**	582,331	100,000
0.4	**37,137**	47,304	1,115	9,052	**681,905**	581,905	100,000
0.3	**36,587**	46,136	1,081	8,468	**681,672**	581,672	100,000
0.2	**32,652**	40,296	928	6,716	**680,625**	580,625	100,000
0.1	**1,730**	3,212	22	1,460	**674,446**	574,446	100,000
0	**1,731**	3,212	21	1,460	**674,443**	574,443	100,000

Source: Author

Values between $0 < \alpha < 1$ represent the weighted perspectives of each agent. Note that at $\alpha = 0.9$, there is a 97% reduction in the cost of reinforcing cables compared to $\alpha = 1$, while the reduction in e-carsharing profit is approximately 5%. For $0 \leq \alpha \leq 0.9$, the cable reinforcement costs are the same, which is the minimum value ($100,000). This is the maximum reduction, given the available EV fleet. For $0 < \alpha \leq 0.4$, the DSO's decision affects not only EV charging but also the e-carsharing rental and relocation operation. However, this does not bring any gain in terms of cable reinforcement cost reduction for the DSO, only generation cost reduction. Moreover, based on the decision of $\alpha = 0.9$, the DSO cost reduction is low, reaching a maximum of 1.16%. On the other hand, the e-carsharing profit reduction is significant for $\alpha \leq 0.2$. Hence, a decision with a low impact on the DSO can drastically affect the e-carsharing revenue. Thus, if both agents are willing to make a fair agreement, the decisions that bring the best trade-off are in $0.5 \leq \alpha \leq 0.9$.

Remarkably, one can realize that the order of magnitude of DSO costs is greater than e-carsharing revenue. This is a problem for multi-objective optimization, as the differences in objective magnitudes can be so large that even the weights are not able to balance the decisions. This is apparently to be the case, as there is no smooth reduction in the cost of reinforcing cables. Even with 90% of the decision under the control of e-carsharing, the cost of reinforcing cables is as low as possible, even compared to the base case value ($290,000). To address this problem, the objective functions need to be on the same order of magnitude, which can be achieved by converting them into pu. However, this analysis is not within the scope of the work. Ultimately, the main findings are as follows:

- Under normal load, there is a low difference between e-carsharing profit with and without V2G. Therefore, there is a low incentive to use V2G given the additional costs.
- Under normal load with V2G, e-carsharing can increase its profit in scenarios of low rental demand.
- Under increased load without V2G, there is no change in e-carsharing profit. However, there is no benefit to the DSO.
- Under increased load with V2G, there is a low reduction in profit of the e-carsharing and a high reduction in DSO cost.

In this sense, public policies could be designed to encourage companies with controlled EV fleets to use V2G to help postpone the investment in cable reinforcement in distribution networks. E-carsharing could offer a more reliable power supply than EV users or private EV aggregators as they have control of their fleet. In addition, it is easier for large companies, such as those in the energy market, to make bilateral contracts with companies than with EV users. Finally, e-carsharing operators can help in the energy market, operating as an energy source in low rental demand and high tariffs times. Although the cable reinforcement reduction benefits for e-carsharing are not computed in the model, the results show that, for this case study, using V2G would be advantageous for both agents. Furthermore, policies would need to be designed in such a way as not to divert the social function of e-carsharing. If the incentive were large enough, the most profitable operation would be to let the EVs operate as stationary batteries.

6. CONCLUSIONS

The high acquisition cost and reduced charging infrastructure are some of the reasons for the low EV adoption. In addition, as the EV charging time is still high, different business models are needed to meet users' charging demands. In this way, the contribution of this thesis is twofold. First, a discussion of possible models for EV adoption and CS business models were presented. The main findings are as follows:

- Public policies may be decisive for the implementation of business models in early markets. However, the proper application of public policies must consider the specificities of the region. Thus, it is possible to direct investments in order to meet user preferences (for example, invest in residential charging instead of public charging or vice-versa). Finally, some business models may transfer the costs to other agents, leading to the importance of subsidies from the government.

- Countries with low EV penetration can take advantage of less costly business models for the user (leasing and sharing) to accelerate EV adoption.

- The coordination of different agents can be beneficial for creating an environment with different business models, especially in the development of large-scale charging infrastructure.

- Countries with low EV penetration can make a technological leap and invest in new technologies, such as on-road wireless charging and battery swaps. Thus, charger usage is increased, and the power grid demand is reduced. To properly allocate the costs and drive the policies, a better analysis of the trade-offs of these technologies in the country context is needed.

With distribution networks moving toward smart grids, it is important to find solutions that better meet the demands of all agents (manufacturers, DSOs, CPOs, and EV users). In other words, solutions that are economically attractive to investors and operators have a low impact on the distribution network and satisfy EV users' demands. Counting on the experience of Europe and the United States, different countries can understand the solutions that better fit their context and avoid pitfalls already highlighted. Finally, in the academic context, it is necessary to encourage researchers to develop more comprehensive models. The development of techniques capable of handling large problems in a feasible computational effort is vital in this process.

Moreover, the recent literature shows that previous works do not consider both the operational characteristics of an e-carsharing company and the DSO in carsharing planning. Other aspects that could help sustain the profitability of e-carsharing planning are also neglected, such as V2G and DLMP. Thus, in the second contribution, this work proposes a model for siting and sizing CSs and the EV fleet of an e-carsharing company under demand uncertainty. The ACOPF was modeled using SOCP relaxation and linearized by the polyhedral global approximation. For this, two-stage stochastic programming was used to model the problem. Four cases were proposed to assess the company's profitability in different EV charging situations and agents' planning perspectives.

The results indicate that planning considering V2G and ignoring the power grid constraints is the most profitable but by a small amount (0.06%). However, in a real application, there is a probability of this case not occurring, since the power grid may not be able to cope with high power flows due to V2G. Thus, e-carsharing designers should consider an analysis of the power grid for proper design to limit potential problems. On the other hand, coordinated planning with the DSO increased the charging cost by 0.24% while reducing the DLMP peak and peak demand by approximately 1.5% and 5.1%, respectively. The power losses were also lower than the case without V2G, approximately 0.7%. Furthermore, the realization of this scenario is more plausible in real applications, as the operation is within the limits of the power grid.

Moreover, two sensitivity analyses were proposed to evaluate decisions under a scenario of load increase. The main findings show that due to the high cost, DSO decisions prevail over e-carsharing. However, in fair trade, a reduction of approximately 5% in e-carsharing profit can equate to a reduction of approximately 66% in grid reinforcement with V2G.

Although they were not included in this work, the benefits that e-carsharing brought to the DSO (at the expense of profit) could be converted into financial compensation. Thus, public policies could be designed to incentivize controlled EV fleet operators (such as e-carsharing) to provide services to the DSO. Hence, e-carsharing could work as a power grid buffer in periods of low rental demand, making its profit more sustainable.

6.1 Future Improvements

Despite dealing with demand uncertainty, this thesis considered only two scenarios and a small number of daily trips due to the high computational effort. Another simplification considered is the travel time and the route of the users. As the model is for car rental, it is important to maintain users' privacy. However, applications in which routes are also controlled (such as taxis and buses), considering the transport network, can influence the optimization results. Finally, future improvements can encompass user's preference, such as maximum walking distance between charging stations.

Therefore, future improvements to reduce computational time involve improving the model through decomposition techniques, such as Bender's decomposition or dynamic programming. In addition, the model can also be adapted for applications with controlled routes, considering the transport network, traffic, and Dijkstra's algorithm.

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APPENDIX

All codes are available at:
https://drive.google.com/drive/u/1/folders/0ADHKKCf5hxmgUk9PVA