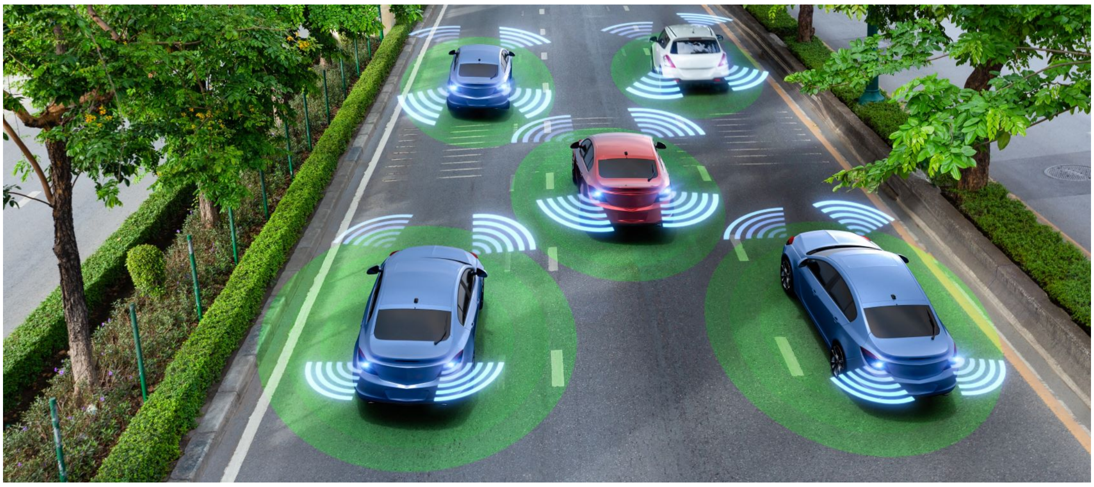

Impact of Autonomous Electric Vehicles on Power Systems

João Ricardo de Freitas Nunes

Thesis to obtain the Master of Science Degree in

Electrical and Computer Engineering

Supervisor: Dr Hugo Gabriel Valente Morais

Examination Committee

Chairperson: Prof. Célia Maria Santos Cardoso de Jesus
Supervisor: Dr Hugo Gabriel Valente Morais
Member of the Committee: Prof. Eduardo Manuel Godinho Rodrigues

June 2024

This work was created using LaTeX typesetting language
in the Overleaf environment (www.overleaf.com).

Declaration

I declare that this document is an original work of my own authorship and that it fulfills all the requirements of the Code of Conduct and Good Practices of the Universidade de Lisboa.

Acknowledgments

I would like to thank my beloved parents and godparents for their support, encouragement and caring throughout all these years. They stood by my side even in the hardest moments, believed and trusted in me, more than I could. I would also like to thank my younger brother for being a huge inspiration, a lighthearted boy from whom I learnt so much. Likewise, I want to express my profound gratitude to my safe place and best friend, Inês. Finally, I would like to give a word of appreciation to Professor Hugo Morais for all his guidance, patience, comprehension and sympathy throughout the whole execution of this thesis.

Abstract

The transportation sector is developing itself in two distinctive paths. On one side, Electric Vehicles (EVs) are emerging and have been rapidly expanding their market share for the past decade, generating an opportunity to decrease the direct fossil fuel dependency in the sector. On the other side, Autonomous Vehicles (AVs) are an announced revolution that will soon transform how the transport sector is seen. These two developments combined will reshape transportation and provide new horizons for science to intervene. This dissertation investigates the multifaceted impacts and opportunities of Autonomous Electric Vehicles (AEVs), particularly in energy integration, grid management and efficiency enhancement. By taking advantage of their autonomous capabilities, AEVs have the potential to serve as distributed energy storage units, facilitating greater integration of renewable energy sources and supporting overall energy efficiency. In this thesis, a mixed-integer linear programming algorithm is presented to demonstrate how managing a whole fleet of AEVs could benefit the energy sector regarding grid limitations and energy management through a regulated charging operation. Effective integration of AEVs into existing power systems requires a thorough understanding of their impacts and careful planning to optimize their benefits while mitigating potential drawbacks. The results of this project emphasise the need for a collaborative effort between stakeholders in the transportation and energy sectors to realize the full potential of this emerging technology.

Keywords

Autonomous electric vehicles; Public charging stations; Intelligent charging management.

Resumo

O setor automóvel tem se desenvolvido em dois prismas distintos. Por um lado, os veículos elétricos têm emergido rapidamente, aumentando imenso a sua cota de mercado na última década, criando a possibilidade de haver uma menor dependência direta de combustíveis fósseis no setor. Por outro lado, os veículos autónomos constituem uma revolução anunciada, que em breve transformará a forma como o setor é percecionado. Estes dois desenvolvimentos combinados irão redesenhar o sector automóvel e abrirão novos horizontes para a intervenção científica. Este artigo investiga os impactos e as oportunidades apresentadas pelos veículos elétricos autónomos, especialmente na integração energética, gestão de rede elétrica e melhoria da eficiência energética. Tirando partindo da capacidade autónoma destes veículos, estes podem ser vistos como unidades distribuídas de armazenamento de energia, facilitando uma maior integração de fontes de energia renovável e apoiando a eficiência energética geral. Neste artigo, é apresentado um algoritmo de programação misto-inteira linear que pretende demonstrar como gerir uma frota inteira de veículos elétricos autónomos, por forma a beneficiar o setor de energia em termos de limitações da rede e gerir energia por via de um carregamento regulado dos veículos. A integração eficaz destes veículos nos sistemas de energia existentes requer uma compreensão detalhada dos impactos e um planeamento cuidadoso para otimizar benefícios enquanto se mitiga possíveis desvantagens. Os resultados deste projeto enfatizam a necessidade de um esforço colaborativo entre as partes interessadas, nos setores de transporte e energia, no sentido de alcançar todo o potencial desta tecnologia emergente.

Palavras Chave

Veículos elétricos autónomos; Estações públicas de carregamento; Gestão inteligente de carregamento.

Contents

List of Figures

List of Tables

Acronyms

AEV Autonomous Electric Vehicles

AV Autonomous Vehicle

DICOPT Discrete an Continuous Optimizer

EV Electric Vehicles

GAMS General Algebraic Modelling System

GHG Green-House Gas

MINLP Mixed-Integer Nonlinear Programming

MIP Mixed-Integer Programming

NLP Nonlinear Programming

RES Renewable Energy Sources

SOC State of Charge

V2B Vehicle to Building

V2G Vehicle to Grid

V2H Vehicle to Home

V2X Vehicle to Everything

1

Introduction

Contents

1.1 Motivation

Electric Vehicles (EV) are changing the transport sector. Yet, another revolution can arrive soon. Autonomous Electric Vehicles (AEV) are emerging and are seen by several entities as a bright technology to be adopted soon [1].

AEVs can eventually work as an autonomous distributed energy storage, potentially allowing for greater integration of renewable energy sources and improved energy efficiency [2]. However, the future high-rated adoption of AEVs also presents challenges, such as power demand increase and the need for infrastructure upgrades [1]. It is essential for power systems to carefully consider the impacts of AEVs to integrate them and optimize their benefits effectively.

1.2 Objectives and Contributions

The goal of this master's thesis is to create a methodology that capitalizes on the impacts of AEVs on power systems in favour of the systems themselves. More precisely, this thesis aims to develop a control model that, on the one hand, considers the technical constraints of the distribution network and, on the other hand, optimizes the charging process of a fleet of AEVs. Considering network limitations, the proposed solutions will address congestion problems by managing the voltage at the distribution level. Within the scope projected, there are some points to be addressed.

- Is it possible to consider network constraints, such as voltage levels and grid congestion, in the AEVs management?
- Is it possible to apply the combination of price signal methods and network constraints in the AEVs management?
- What is the impact of AEVs on the operation of power systems and in the resolution of attended conditions?

1.3 Related Projects

The work carried out as part of this dissertation was developed under the scope of the following research project:

- Horizon Europe EV4EU – Electric Vehicles Management for carbon neutrality in Europe project, funded by the European Union under grant agreement no. 101056765. Views and opinions expressed are however those of the authors only and do not necessarily reflect those of the European

Union or CINEA. Neither the European Union nor the grating authority can be held responsible for them.

1.4 Outline

This document is structured as follows. The purpose and key contributions of this thesis are outlined in the current chapter. Chapter 2 presents the ongoing state of the automobile industry in terms of automation and electrification. Further on, it introduces the available and in-development EVs charging technologies, and also the charging and discharging methods being implemented so far.

Chapter 3 explores studies developed concerning the impact of EVs on power systems. It approaches congestion management, the impact of charging vehicles at peak demand hours, and how to avoid this problem. How EVs can cooperate in frequency and voltage regulation is also addressed. Finally, the way EVs can support a higher penetration of renewable energies is also approached.

Section 4 details the mathematical development of the algorithm to optimize the charging process for AEVs, considering key factors to ensure vehicles' charging efficiency and cost-effectiveness, and also exposes the environment in which the algorithm was developed. Chapter 5 reveals a series of Scenarios generated by the appliance of the algorithm and its nuances and also the results and explanations of those simulations attempt to manage a fleet of AEVs, according to the determined inputs and constraints. Finally, Chapter 6 presents the overall findings concerning the developed methodology, as the utilized system limitations and a perspective for future improvements.

2

Background

Contents

2.1 Autonomous Vehicles

Autonomous Vehicle (AV) are making their way to be entirely independent of human capacities to be driven safely. Equipped with onboard sensors and actuation networks supported by computational robustness and a great amount of stored data [2], AVs will play a key role in how mobility will be seen shortly. The massive adoption of this technology will bring social and economic benefits in the shape of fewer road accidents and fatalities, upgraded access to transportation, an exponential decrease in greenhouse gas emissions, congestion reduction, less space needed in urban areas and a capacity to cooperate in the energy management and storage, hugely important these days due to the increasing investment in renewable energy sources [1, 3].

Within this technology, six levels of driving automation were established, being Level 0 the non-existence of automation and Level 5 the correspondence to self-driving vehicles [4]. To fully accomplish all the benefits appointed above, Level 5 AVs have to dominate roads worldwide [2].

As of today, Tesla, for example, is only capable of commercializing vehicles with a Level 2 of automation [5]. Dedicating all its fleet to Electric Vehicles, Tesla ended 2021 with a 2.02% share in the U.S. light vehicle market according to Statista, which is still far from the 15.18% share of the market's leader General Motors [6]. Nevertheless, many other automobile manufacturers already have Level 2 models on the market, such as Escalade from Cadillac General Motors, BMW X5, or Volvo S90, all launched during the year 2022. Meanwhile, Mercedes-Benz launched the world's first completely certified Level 3 autonomous driving system [7], already available in Germany. This system can be used on 13.000 km of German highways and can go up to 60 km/h. Volkswagen partnered with Microsoft to speed up the automation of the German manufacturer's fleet [8] that has a 6.4% share of the global automotive market, only behind Toyota, the market leader, with 10.5%, as reported by Statista [9].

Despite these firm steps that are being taken towards total automation, practical application of fully autonomous vehicles, in a realistic context, showed that full automation is still not prepared to be commercialized due to safety issues related to urban environment complexity [3]. On top of that, there are a lot of concerns about how vehicles, with different levels of automation, will be able to share the road network.

Up to this point, predictions suggest that fully self-driving vehicles with, under specific constraints, automation level 4 will be available in many countries by 2030, despite being expensive and performance limited [10], leaving level 5 out of the projections for now. Nonetheless, forecasts indicate that self-driving taxis and micro-transient vehicles will be widely available by 2030. In São Francisco, California, a company called Cruise is already providing driver-less rides from 10 pm to 5:30 am [11]. In Japan, level 4 vehicles are now allowed to be used as public transportation and for delivery services from April 2023 [12].

2.2 Electric Vehicles

In the European Union, one-quarter of annual man-made Green-House Gas (GHG) emissions come exclusively from the transportation sector. This statistic includes aviation and excludes maritime shipping. Even so, 75% of those emissions are produced by road transport alone [3]. Having the European Commission aimed to decrease GHG emissions by at least 55% until 2030 to achieve climate neutrality by 2050 within its territory [13], it is now urgent to reduce and change transportation all over the continent.

That said, conventional vehicles with internal combustion engines and fuel tanks must be replaced by EV equipped with all-electric motors and batteries. EVs are not only less pollutant in terms of GHG emissions, but also more energy efficient. A gasoline-powered vehicle has an efficiency of 15% up to 35% and this means that around three-quarters of the fuel used to fill up the vehicle's tank corresponds to energy lost [14, 15]. However, an EV only loses 31% up to 35% of the energy used to charge its battery and due to the energy regenerated by the brakes, the efficiency of an EV can get to 90% [14,15].

So, a massive transition to EVs will not only reduce the amount of GHG emitted by road transport but will also, due to its energy efficiency, save tons of fuel from being wasted. During the past decade, there was a stable increase in EV registrations per year, in the EU. In 2010, there were only 600 EVs registered, and by the year 2020, there were more than a million units in circulation. By the end of 2021, this number almost doubled. Still, despite this respectable increase, these almost 2 million vehicles registered account for only 18% of the total number of new registrations and it still represents a deficient level of market penetration [16].

Globally speaking, in 2021, 16.5 million EVs were circulating worldwide, three times the amount reported in 2018. Nevertheless, it only represents 10% of the vehicles sold that year [17]. These percentages of EVs sold, either in Europe or worldwide, are conditioned by countries still in development, where EVs are still unattainable by mass-market consumers. On one hand, during 2021, China led the market selling 3.3 million EVs [17], in Norway, almost 90% of the vehicles sold were electric, followed by Iceland with more than 60%, Sweden with almost 50% and in Germany, the number falls to 30%, but it represents more than half a million EVs sold [16]. On the other hand, in countries like Brazil, India, or Indonesia less than 0.5% of car sales are electric [17].

2.3 Charging Technologies

Section 2.3 of the document addresses different technologies used for charging EVs. 2.3.1 discusses conductive charging, 2.3.2 examines wireless charging, and finally, 2.3.3 addresses the battery swapping method.

2.3.1 Conductive Charging

Conductive charging is the simplest and the most common charging technology, where the power supply connects physically with the battery. The evolution of the EVs penetration on the vehicle market is, despite not being the only relevant factor, strictly correlated with the ongoing growth of charging stations and street chargers installed. This was seen in Norway, where a study showed that charging infrastructure diffusion was able to increase EV ownership by 200% in five years [18].

This technology can be either unidirectional or bidirectional. Unidirectional charging only allows the EV to be charged from the grid and bidirectional permits the same as unidirectional and also allows the power to flow from the EV into the grid, building or house [15].

Conductive charging can also be divided into 3 charging levels according to the SAE J1772 standard, being Level 1 the slowest charging method where a wall outlet can be used to assess the EV at a 1.9kW peak power. It takes a lot of time to charge and it has a low impact on the power system due to its low power rating. Level 2 can go up to 19.2kW, consequently, it takes less time to charge than Level 1 and it needs dedicated supply equipment. Finally, Level 3 can reach 100kW and operate as a fast charger because it can take less than one hour to charge the EV. Although Level 3 has its positive points from the user's perspective, it can overload the distribution network equipment and a dedicated installation is extremely expensive [15].

2.3.2 Wireless Charging

Wireless Charging allows an EV to be charged without physically connecting the vehicle to the power supply. The technology can be either inductive or capacitive, it can work statically or dynamically and it can operate at different voltage levels [15, 19].

Inductive wireless charging involves using a transmitting coil on the power supply side and a receiving coil on the vehicle side, with power transfer occurring through electromagnetic induction. Capacitive wireless charging, which uses metal plates called capacitors instead of coils, is cheaper to install but has lower efficiency, requires a shorter distance between the power supply and the vehicle, and is only suitable for low-power applications. Inductive wireless charging is preferred due to its ability to work with both high and low power.

Static wireless charging involves parking a vehicle on a charging pad on the ground, eliminating the need for connectors and reducing the risk of maintenance issues and accidents. Dynamic wireless charging allows the charging of a vehicle while it is in motion, improving range, and safety, and reducing maintenance needs. Dynamic wireless charging can be implemented using inductive or capacitive systems, but inductive systems are preferred due to their ability to function at higher power and shorter ranges.

Wireless charging is still in development, so, a lot of studies on static and dynamic charging have been performed. In terms of stationary wireless systems, for example, Oak Ridge National Laboratory developed a prototype capable of working at 120kW, 88.5kHz with a 152 mm air gap and reaching a 95% efficiency in 2018 [20], WiTricity Corporation developed another system working at 11kW, 85kHz with a 150mm air gap and a 90% efficiency in 2019 [21]. Concerning dynamic charging systems, the Korean Advanced Institute of Science and Technology, for example, developed a system working at 62/100kW, 130/200mm air gap, reaching 75% efficiency [22] and the University of Auckland developed another system that works at 20kW, 15kHz with a 500mm air gap and an efficiency of 85% [23].

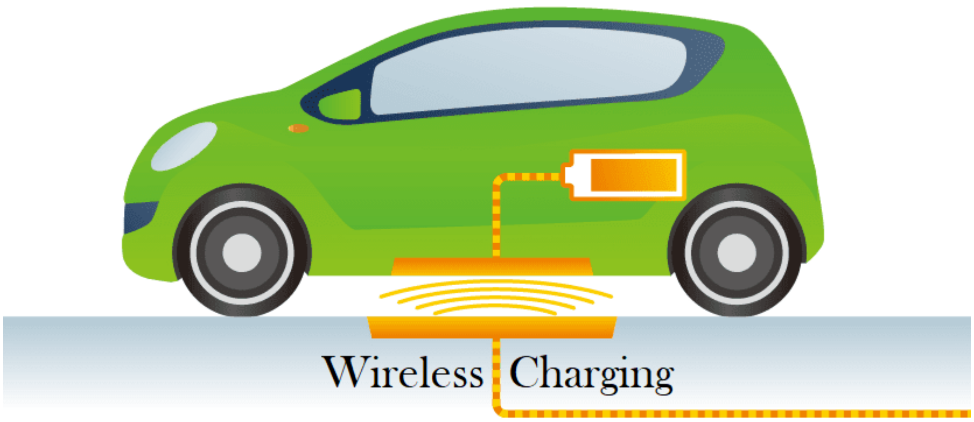

Figure 2.1: Wireless Charging illustration

2.3.3 Battery Swapping

A battery swapping station works as a charging station where an EV swaps its battery in a few minutes, replacing a used battery with a fully charged one [15, 24]. This structure requires space to stock and charge a considerable amount of batteries that can operate in a bidirectional way. In other words, the station schedules batteries to operate in Grid-to-Battery and also in Battery-to-Grid or Battery-to-Battery, if the batteries' energy exceeds its demand [24]. These batteries could be owned by the station and rented to the EV owner. Nevertheless, this system is limited by the uncertainty in the battery requisition and electricity price, by the high equipment cost, by the nonexistence of battery standardization, and by the station's large space demand [15, 24]. Although the Chinese EV manufacturer NIO is set to install 20 battery swapping stations in Germany and aims to have 120 all over Europe, by the end of 2023 [25]. The company claims to be able to swap batteries within 3 minutes [26].

2.4 Charging-Discharging Methods

Charging methods are divided into two categories, unidirectional and bidirectional methods [15]. Unidirectional charging means that the energy only flows from the grid to the vehicle, although in bidirectional charging the energy can flow both ways, from the grid to the vehicle and from the vehicle to the grid, home, or building.

2.4.1 Unidirectional Charging

Within Unidirectional charging, there are three main methods [15], uncontrolled, controlled, and delayed charging.

- Uncontrolled charging is the current most used way to charge an EV. The vehicle is connected to the grid at the maximum power rating possible until it is fully charged.
- In delayed charging, there is time control and no energy management. In other words, the vehicle is plugged in and programmed to start charging at a certain hour and from that point, it is charged at the maximum power rating until the battery is full.
- In controlled charging, both time and energy are managed. So, there is not only charging start control but also charging duration is managed through power control.

2.4.2 Bidirectional Charging

In bidirectional charging, there are also three different methods, Vehicle to Grid (V2G), Vehicle to Building (V2B), and Vehicle to Home (V2H) [15].

- V2G refers to the capability of having an EV working as an energy storage device that can provide power to the distribution network. To optimize the power system's reliability and efficiency, the EV should charge when the energy demand is lower than its generation and should supply energy into the grid when energy consumption is higher than its production.
- In V2B, the process is similar to V2G, but in this case, the vehicle is only connected to the building. The battery of the EV is charged at off-peak hours when the energy price is lower. Then supplies energy to the building in peak hours when the energy price is higher. This method is simpler since it is only building-connected, but it also provides less assistance to the power system.
- In V2H, the vehicle only communicates with the home without any connection to the grid, in a similar process when compared to the V2B method. The energy flows from the house to the vehicle and when it justifies, the EV supplies energy to the house. It can be used to reduce house

expenses with electricity services since the vehicle can be used to store energy when the electricity price is lower and to supply energy at peak hours. It can also be used to store local energy production surplus from photovoltaic panels or other kinds of small renewable energy sources.

3

Related Work

Contents

Since the purpose of this thesis is to understand how AEV can affect power systems, it is crucial to understand how the management of their connection to the grid can benefit utilities in terms of congestion management, voltage, reactive power, frequency regulation, and also how they can positively influence power quality in renewable energy dependent grids. Due to the lack of literature about AEVs' influence on power systems, this section is supported by studies regarding EVs' impact, since these papers' conclusions are still applicable to AEVs.

3.1 Congestion Management

Uncontrolled charging along with EV high penetration level is expected to create negative impacts on power systems that should be mitigated through power congestion management by incorporating the methods previously described [15]. Concerning the comprehension of the problem, numerous studies have been conducted to understand the real impact of charging vehicles at peak demand hours.

In [27], with an EV penetration rate of 30% and using uncontrolled charging, the peak demand increased by more than 50%. Another study presented in [28] approached the negative impact of uncontrolled charging on the Great Britain grid and how controlled charging can change it positively. For a 100% electric country fleet, uncontrolled charging would increase the peak demand by 8 GW at the transmission and generation level and create the need to upgrade 28% of the low voltage distribution networks. Although, it was also concluded that controlled charging could improve this scenario, reducing by 2 GW the increase at the peak demand and distribution networks would only need to be upgraded by 9%.

In the paper [29], delayed charging was applied and compared to the effect of uncontrolled charging in New Toshka City, Egypt. It was concluded that delayed charging can effectively reduce distribution network stress through voltage drop and power loss reduction when compared to uncontrolled charging. The authors in [30] also addressed the impact of uncontrolled charging in New Zealand's power system and, through a Monte Carlo modelling simulation, it was demonstrated how delayed and controlled charging can mitigate uncontrolled charging negative effect. It showed that without charging management, for instance in Auckland, peak demand could increase up to 31% while applying delayed and controlled methods, peak demand can increase by 9% at most, suspending any need to upgrade the network components.

In this other study [31], it was shown how V2G systems can reduce transmission congestion and increase grid stability in Germany. These results are even more important since it was proven that the German transmission network would not be capable of handling uncontrolled charging with a high EV penetration level. V2B strategy was used in a smart building microgrid concept, incorporating EVs, independent battery storage, and photovoltaic panels in several Universities in [32]. The study was able to achieve a significant peak load reduction, consequently diminishing the building's electricity bill and its necessary power rating subscription. Therefore, the study concluded that if more buildings had the possibility of having similar power management, it would diminish the stress in the distribution network and decrease the demand of the whole grid at the peak load.

Based on the studies cited in this paragraph, it is clear that uncontrolled charging of EVs can have negative impacts on power systems, including increased peak demand and the need for upgrades to transmission and distribution networks. However, these negative impacts can be mitigated through the use of controlled and delayed charging methods and through Vehicle to Everything (V2X) systems. These methods have been shown to effectively reduce stress on distribution networks and decrease the overall demand on the grid at peak load times. Power systems need the implementation of effective congestion management strategies, particularly as the penetration level of EVs increases, to avoid adverse impacts on the grid.

3.2 Frequency Regulation

In a power system, frequency is a constantly changing variable that allows the control between demand and production, and it should be kept at the nominal value of 50Hz or 60Hz [33]. The misalignment between demand and production affects the frequency value. This occurs due to permanent load variations and renewable energy production fluctuations hugely conditioned by weather behavior [15]. Through the past decades, frequency has been regulated at power plants using synchronous generators. In the near future, EVs will play an important role in frequency regulation since EVs batteries respond faster than normal generation units [29, 33].

Many studies were made to understand EVs' impact on frequency regulation. In [34], a control method that takes advantage of EVs operating in V2G in coordination with traditional generation, to manage load frequency is proposed. The concept was tested on the Great Britain power system and results showed that this method is capable of improving frequency regulation, consequently reducing power imbalance, and even proved to be capable of reducing power oscillations at the traditional generation level. To provide primary frequency control, a regulation method was proposed in [35], coordinating EV charging and discharging. An upper-level control system distributes the power management through smaller regions, diminishing frequency deviations in all controlled areas. The study [36] also showed how EVs can collaborate in load frequency control operating in a microgrid. Scheduling EV charging/discharging, the study proved that EVs can successfully contribute to a more stable frequency as well as minimize power losses from renewable energy sources.

All in all, it is safe to say that EVs can play a significant role in frequency regulation in power systems. Through the use of controlled charging and discharging, EVs can respond quickly to level demand

and production and by that assure a stable frequency. Coordinated control methods that involve EVs operating in V2G have been shown to be effective in improving frequency regulation and reducing power imbalances and oscillations. As such, EVs could potentially be used as a tool for frequency regulation in the future.

3.3 Voltage Regulation/Reactive Power Compensation

The voltage value has to be kept within stipulated limits at every stage of the power system [15]. At the distribution level, the voltage is high when the network is moderately loaded and it is low when the network is hugely loaded. Decentralized generation can make voltage exceed its upper limit, while long connections can make it harder to keep voltage above its lower limit. For this reason, it is important to have devices capable of regulating the voltage value, otherwise, this voltage instability can damage connected loads. To control voltage, active and reactive power must be controlled, being active power controllable by decentralized generators, energy storage systems, or EVs.

Numerous studies were made concerning voltage regulation and reactive power compensation that takes advantage of EVs availability. As so, a decentralized controlled charging method that regulates charging power having local voltage and battery state of charge in consideration was proposed in [37] and it was compared with uncontrolled charging. The method was capable of reducing voltage drop and improving its profile by manipulating charging power having voltage value as a reference. Therefore, when the voltage was at a normal value, the charging power was kept high, and when the voltage value was low, the charging power decreased or even stopped charging. This control system does not depend on a communication infrastructure that allows utility operators to communicate with EV chargers, making this system cheaper than those commonly proposed.

In [38], the particle swarm optimization algorithm was used to create a centralized smart charging and discharging control system, so it can flatten the load curve. The study was capable of satisfying its purpose and it was also able to reduce the voltage, flattening its profile when compared to uncontrolled charging. A bidirectional DC fast charging station with a new control topology, to minimize voltage drop when EVs are fast charging, is proposed in this paper [39]. A direct voltage control gives EV chargers the capacity to inject reactive power into the grid, regulating bus voltage and reducing power losses. In another study, it was proposed a multi-agent system to coordinate a distributed fleet of EVs and to provide reactive power compensation through a V2G system [40]. By this reactive power compensation, it was possible to improve the voltage profile and the paper concluded that, economically, this is a less expensive way of regulating the voltage value.

Overall, it is clear that voltage stability is important in power systems and that it can be maintained through the use of active and reactive power control. EVs and energy storage systems can be used as tools for voltage regulation and reactive power compensation, either through decentralized or centralized control methods. These methods can help reduce voltage drop and improve the voltage profile, as well as minimize power losses. Using EVs for voltage regulation and reactive power compensation can also be a cost-effective solution compared to other methods.

3.4 EVs coordination with Renewable Sources

As it was exposed before, uncontrolled charging can harm power systems. On the other hand, controlled charging can not only decrease the system imbalance but can also support renewable energy generation to mitigate its constant variations [15]. Renewable Energy Sources (RES), such as photovoltaic and wind generation, are intermittent due to their dependence on weather conditions which are hard to forecast. This leads to sudden fluctuations in these sources' output power, resulting in voltage fluctuations and consequently a quality decrease of the power in distribution systems, where these RES have a high rate of penetration.

To attenuate the intermittency of renewable energy sources' effect on power systems, several studies were developed. An interactive method that combines photovoltaic panels and EVs to minimize voltage imbalance and diminish power losses was proposed in [41]. This particular V2G strategy proved to be capable of achieving its objectives and consequently improving the energy efficiency of the grid. Relevant to notice, that this study did not consider battery degradation throughout its course. Author in [42] approaches the development of an efficient method to minimize voltage fluctuations at the distribution level, containing solar and wind generation. It takes advantage of a Gravitational Search Algorithm to optimize EVs' charging and discharging control to respond to those voltage oscillations generated by RES instability. The study results proved the effectiveness of the method and also proved to be capable of extending the lifespan of the batteries. Another similar study evaluates, throughout three different scenarios, the capacity of controlled charging to minimize voltage rapid variations created by photovoltaic energy generation [43]. These scenarios are used to stipulate the impact of three different levels of solar panels installed, based on the growing adoption of this renewable source. The paper proved its reliability in mitigating voltage fluctuation in low-voltage networks.

Another optimization process was proposed, within an isolated microgrid environment supported by wind and PV generation, to schedule EV charging, in [44]. In this paper a bi-level programming model is applied, being the upper level responsible for minimizing the microgrid's costs, while the lower one is for EV's charging cost maximum reduction, having a real-time pricing mechanism connecting these two levels. This method was able to flatten the load curve as well as reduce microgrid operating and EV charging costs. In [45], the aim was to increase RES' penetration, through the management of charging and discharging of EVs. A genetic algorithm was used to increase solar power installation gradually.

This strategy was employed by a segment of the Danish low-voltage grid and it was capable of ensuring a 50% increment of photovoltaic penetration.

Given these points, EVs can be used as a tool to support the integration of RES in power systems and to mitigate the negative impacts of their intermittent nature. Through optimization algorithms and control methods, EVs can also help reduce voltage fluctuations, power losses, and operating costs as well as flatten the load curve.

Table 3.1: Relevant topics, technologies, and methods mentioned in Section 3

Ref.	**Relevant Topics, Methods and Technologies**
[27]	Congestion management and uncontrolled charging
[28]	Congestion management, uncontrolled and controlled charging
[29]	Congestion management, frequency regulation, uncontrolled and delayed charging
[30]	Congestion management, uncontrolled, controlled and delayed charging
[31]	Congestion management, uncontrolled charging and V2G
[32]	Congestion management, V2B and RES penetration
[34]	Frequency regulation, controlled charging and V2G
[35]	Frequency regulation, controlled charging
[36]	Microgrid, frequency regulation, controlled charging and RES penetration
[37]	Voltage regulation, uncontrolled and controlled charging
[38]	Voltage regulation, uncontrolled and controlled charging
[39]	Voltage regulation, reactive power compensation and controlled charging
[40]	Reactive power compensation, V2G and voltage regulation
[41]	RES penetration, voltage regulation and V2G
[42]	Voltage regulation, RES penetration and controlled charging
[43]	Voltage regulation, controlled charging and RES penetration
[44]	Microgrid, RES penetration and scheduled charging
[45]	RES and controlled charging

4

Methodology

Contents

4.1 General description and assumptions

The presented system aims to manage and optimize the AEVs' charging process, given a range of chargers within a defined timeline. It was fundamental to consider a set of critical factors to develop this system. From the vehicle's perspective, it was relevant to evaluate the vehicle's battery capacity and the state of charge throughout the assessed period. On the charging stations side, it was imperative to consider each one maximum power, its availability, and also the charging price fluctuations, which can change according to the grid operation conditions.

Having the key factors defined, it was imperative to define a decision-making path, specifying a guideline for the algorithm's development. As seen in Figure 4.1, the first premise is to have an available vehicle, which is not being used or already charging. Secondly, the vehicle's State of Charge (SOC) must be evaluated to decide the necessity to charge. Afterwards, if there is a demand to charge, charging prices are examined to deduce the most financially convenient period to charge, within the chosen timeline. This procedure is aimed to be applied to a whole fleet simultaneously.

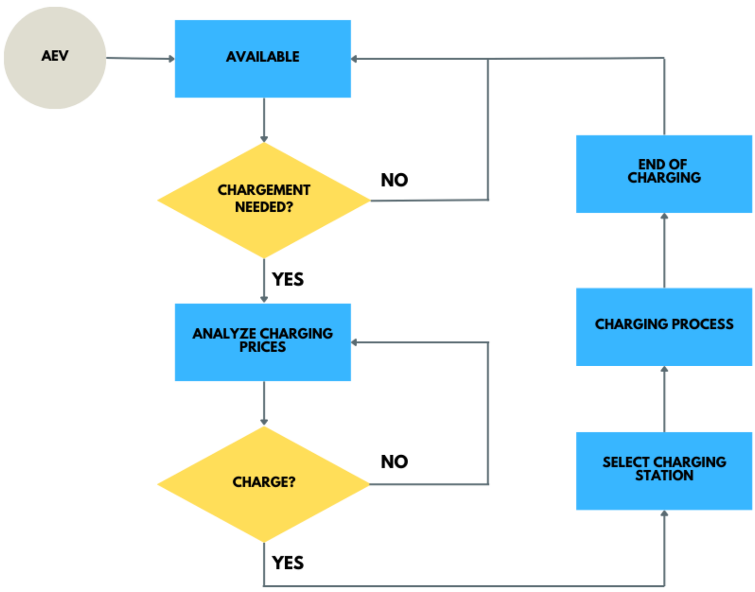

Figure 4.1: Algorithm's behaviour representative flowchart

Throughout the development of the algorithm, some assumptions were taken into account which are worth mentioning. All vehicles were considered to be AEVs, meaning they would all be at a level of autonomy that allows them to be driverless while moving from a parking lot to a charging station. Therefore, all chargers were assumed to be wireless, since the method can not rely on human help to connect the vehicle to the charger to keep its purpose and effectiveness. Also, the implementation of the algorithm depends on a centralized controller, where all key factors, both from the vehicles and charging stations, are weighted, so the decision-making process is optimised at the minimum cost possible.

The algorithm development intention described above is aligned with studies made throughout the past decade to optimize EVs charging operation, and the price signal strategy, which is based on fluctuating electricity costs, is one of the most common methods applied for this purpose. In [46], the impacts of EVs uncontrolled charging are compared with smart charging strategies that respond to dynamic price signals, demonstrating the usefulness of a fuzzy logic control system in handling uncertainties and oscillations in electricity price and grid conditions. The Author in [47] proposes a sophisticated price guidance mechanism using advanced predictive models, forecasting long-term electricity prices, and fractional-order control to provide a more subtle and versatile response to price signals. Another example of price signal applicability is presented in [48], where a cooperative interaction strategy for an EV network guided by price signal is studied, using a linear programming approach to minimize the costs and optimize the distribution of charging loads across the grid. EVs were coordinately charged based on price signals and the carrying capacity of the distribution network.

4.2 Mathematical Modulation

The developed algorithm seeks the optimized correlation between the amount of energy transmitted to the vehicles and the accumulated charging cost. Having this said, the adopted solution will always be the one that provides the most significant increment on the fleet's SOC for the smallish cost. The prominent inputs of the algorithm are, on the vehicle side, the initial state of charge $SOC_{initial(V,t=0)}$ and the vehicle's battery capacity $SOC_{min(V)}$ and, on the charger side, its maximum charging power $P_{chargemax(C,t)}$ and its charging cost $c_{charge(C,t)}$. For the decision-making process, it is also crucial to set the total number of vehicles N_V, the entire charging system N_C, and the whole considered timeline T, where each t is separated by a 15-minute gap. To obtain an algorithm that performs exactly as expected, it is crucial to define precise constraints to guide its behaviour.

$$P_{charge(V,C,t)} \leq P_{chargemax(C,t)} \cdot X_{(V,C,t)} \quad \forall V \in \{1, \ldots, N_V\}; \forall C \in \{1, \ldots, N_C\}; \forall t \in \{1, \ldots, T\} \tag{4.1}$$

$$\sum_{C=1}^{N_C} X_{(V,C,t)} \leq 1 \quad \forall V \in \{1, \ldots, N_V\}; \forall t \in \{1, \ldots, T\} \tag{4.2}$$

$$\sum_{V=1}^{N_V} X_{(V,C,t)} \leq 1 \quad \forall C \in \{1, \ldots, N_C\}; \forall t \in \{1, \ldots, T\} \tag{4.3}$$

The first defined constraint (4.1) aims to control the power transmitted from the chargers to the vehicles $P_{charge(V,C,t)}$, so it does not surpass the limit imposed by each charger $P_{chargemax(C,t)}$. On this equation, it is also introduced the $X_{(V,C,t)}$, which is a binary variable that handles the decision of which vehicle V connects to each charging station C on each period t. Equation (4.2) ensures that each V connects to only one charging station C, and following the same approach Equation (4.3) guarantees that each charging station C is exclusively connected to one vehicle V.

$$SOC_{(V,t=1)} = SOC_{initial(V,t=1)} + \sum_{C=1}^{N_C} P_{charge(V,C,t=1)} \quad \forall V \in \{1, \ldots, N_V\} \tag{4.4}$$

$$SOC_{(V,t>1)} = SOC_{(V,t-1)} + \sum_{C=1}^{N_C} P_{charge(V,C,t)} \quad \forall V \in \{1, \ldots, N_V\}; \forall t \in \{1, \ldots, T\} \tag{4.5}$$

$$SOC_{(V,t=T)} + SOC_{relax(V,t=T)} \geq SOC_{min(V)} \quad \forall V \in \{1, \ldots, N_V\} \tag{4.6}$$

Concerning the AEVs, the limitations are imposed by their batteries. The three constraints defined in Equations (4.4), (4.5) and (4.6) were built to manage the state of charge of all vehicles $SOC_{(V,t)}$ throughout the entire simulation process. In the first Equation (4.4), the vehicles' state of charge is updated by adding the energy transmitted on the first period, to their state of charge by the beginning of the simulation. In Equation (4.5), the objective and the updating process follow the same logic as the one in (4.4). Finally, the third constraint (4.6) was established to integrate a variable $SOC_{relax(V,t=T)}$ that could hold the value of the energy needed to fulfil the vehicles' battery capacity by the end of the simulation, in case of being impossible to have all vehicles charged at that point. Also, $SOC_{min(V)}$ holds each vehicle battery capacity, whose, in this frame, are the objective values for the charging process to be concluded.

$$Connect_{(V,C,t=1)} \geq X_{(V,C,t=1)} \quad \forall V \in \{1, \ldots, N_V\}; \forall C \in \{1, \ldots, N_C\} \tag{4.7}$$

$$Connect_{(V,C,t)} \geq X_{(V,C,t)} - X_{(V,C,t-1)} \quad \forall V \in \{1, \ldots, N_V\}; \forall C \in \{1, \ldots, N_C\}; \forall t \in \{1, \ldots, T\} \tag{4.8}$$

On the pair of Equations (4.7) and (4.8), another binary variable is included $Connect_{(V,C,t)}$. In this case, the aim is to hold, at each t, the number of new connections established between vehicles and chargers. This auxiliary variable purpose is related to the fact that in a practical environment, before the charging fee, there is a cost attached to the decision to move each vehicle V towards a charging station C, and energy is consumed to establish that connection. Therefore, by holding the number of new connections, this variable is used to prevent vehicles from an unrealistic behaviour, where AEVs keep changing the charging station to which they are connected, every when there is a slight charging price fluctuation.

$$f = \sum_{V=1}^{N_V} \sum_{C=1}^{N_C} \sum_{t=1}^{T} \left[P_{charge(V,C,t)} \cdot c_{charge(C,t)} + SOC_{relax(V,t=T)} \cdot K_1 + Connect_{(V,C,t)} \cdot K_2 \right] \tag{4.9}$$

Ultimately, the objective function presented in Equation (4.9) is integrated into the developed algorithm, working as a cost function that should be minimized. This function correlates the unitary charging cost with the charged power at each t. It also adds two penalties to the system. One for the unfulfilled vehicles' battery capacity $SOC_{relax(V,t=T)}$, and the other for the total number of new connections a vehicle establishes with a charger $Connect_{(V,C,t)}$, promoting the completion of a charging process in one single connection. In both cases, the variables are multiplied by a constant value K_1 and K_2 so their relative weight on the decision-making process can be manipulated.

4.3 Modulation Nuances

Posterior to the implementation of the algorithm described above, some modifications were applied, so it was possible to analyze, having this algorithm as a baseline, its response to a distinct behaviour from some, already mentioned, inputs and even new ones.

Firstly, maximum charging power $P_{chargemax(C,t)}$ was manipulated instead of staying static as it was in the first four simulations as it will be demonstrated in the following Chapter 5. As seen in Subsection 3.1, the manipulation of the maximum transmitted charging power is one way to deal with grid congestion. To give another example, in [49], a control strategy for managing charging stations' maximum power output was investigated. This involved the usage of bidirectional DC/DC converters to dynamically adapt the charging power based on grid conditions. The strategy aimed to align EV charging with grid demands, enhancing grid stability and efficiency. Therefore, throughout this thesis' algorithm development, the modulation of the maximum power available for each charging station became an interesting factor to explore, knowing that its management could benefit load distribution and even the integration of renewable energy sources.

Afterwards, the algorithm was subjected to some modifications focused on grid constraints, more precisely, the voltage variations at the charging station level. As observed in Subsection 3.3, voltage regulation can positively influence grid stability, and it could be achieved by controlling EVs charging process. As an additional instance, in [50], where a deep learning approach to coordinate EV charging scheduling and distribution network voltage control is studied, the authors aimed for a method that could stabilize the voltage in the distribution network while optimizing the charging schedule. So accordingly, in this thesis, voltage regulation was approached from two different perspectives.

The first voltage regulation strategy was to attach voltage oscillations at the charging station level to the charging cost $c_{charge(C,t)}$ throughout the defined timeline.

$$U_{charger(C,t)} \leq 1.05 \quad \forall C \in \{1, \ldots, N_C\}; \forall t \in \{1, \ldots, T\} \tag{4.10}$$

$$U_{charger(C,t)} \geq 0.95 \quad \forall C \in \{1, \ldots, N_C\}; \forall t \in \{1, \ldots, T\} \tag{4.11}$$

$$c_{charge(C,t)} = 1 + (1 - U_{charger(C,t)}) \quad \forall C \in \{1, \ldots, N_C\}; \forall t \in \{1, \ldots, T\} \tag{4.12}$$

It was important to define voltage variation limits for both voltage-related algorithm alterations. Following the IEEE standards [51], the constraints (4.10) and (4.11) were delineated, knowing that voltage should not deviate by more than +/- 5% of its nominal value under normal operating conditions. Having boundaries clarified, the Equation (4.12) defines the charging cost dependency from voltage variations in an inverse relation, so when having lower voltage values, which can occur due to high electricity demand, the charging cost is kept high, and when voltage values escalate beyond its nominal value, as in a low congested grid, the $c_{charge(C,t)}$ drops to promote charging in those periods. This nuance application to the algorithm aims to enable the correlation between a specific grid constraint and the price signal strategy in managing the considered AEVs fleet.

The other voltage-related adjustment was designed to ensure that voltage variations could directly influence the charging process. For this purpose, an electrical busbar was conceptualized on which each node would represent a charging station, with all stations connected in series. In these circumstances, the load introduced by the active charging station will influence the voltage level experienced by the other stations. Charging an AEV increases the current flow through the busbar, which causes a voltage drop on it due to its inherent resistance. Also, this series configuration means all charging stations share the same busbar impedance [52]. However, the charging activity at one station can change the impedance characteristics seen by the other stations, leading to variations in the voltage supplied.

$$U_{(bus,t)} = \sum_{V=1}^{N_V} \sum_{C=1}^{N_C} FS_{(bus,c)} \cdot P_{charge(V,C,t)} \quad bus \in \{1, \ldots, N_{bus}\}; \forall t \in \{1, \ldots, T\} \tag{4.13}$$

$$U_{ref(bus,t)} = 1 - U_{(bus,t)} \quad bus \in \{1, \ldots, N_{bus}\}; \forall t \in \{1, \ldots, T\} \tag{4.14}$$

$$U_{ref(bus,t)} \geq 0.95 \quad \forall bus \in \{1, \dots, N_{bus}\}; \forall t \in \{1, \dots, T\} \tag{4.15}$$

This voltage-related modification is ruled by these three Equations exposed above. On the first Equation (4.13), the voltage drop value $U_{(bus,t)}$ is linked to the charging power $P_{charge(V,C,t)}$ through the sensibility factor matrix $FS_{(bus,c)}$, which holds the charging stations' correlation element, acquired by the busbar inherent resistance and each station operational voltage. Furthermore, this is a square matrix due to the dimension equivalence between the bus and the charging stations C sets, therefore, the bus set guarantees the matrix necessary length to establish a correlation between every station. The Equations (4.14) and (4.15) ensure that the load applied by the charging power do not force a voltage deviation beyond its lower boundary for normal operating conditions. Finally, this nuance influence is added to the objective function, through the voltage drop $U_{(bus,t)}$, aiming to penalize the operational cost as much as the charging process impacts the voltage deviation. This transformation 4.16 adds another constant value K_3 so voltage variation has its adaptable weight on the algorithm decision-making.

$$f = \sum_{V,C,t,bus} \left[P_{charge(V,C,t)} \cdot c_{charge(C,t)} + SOC_{relax(V,t=T)} \cdot K_1 + Connect_{(V,C,t)} \cdot K_2 + U_{(bus,t)} \cdot K_3 \right] \tag{4.16}$$

4.4 Development Environment

The algorithm was developed using General Algebraic Modelling System (GAMS), a sophisticated system designed to mathematically address linear, non-linear, and mixed optimization problems in a fast, reliable, and platform-independent environment [53]. This platform allows the creation of flexible applications and models that can be easily adapted to new challenges. GAMS stands out from other modulation systems due to its distinctive modelling approach, which employs solvers to identify the optimal solution.

In this project, the adopted Discrete an Continuous Optimizer (DICOPT) solver, was chosen specifically for its suitability in handling problems with binary and linear variables and solving Mixed-Integer Nonlinear Programming (MINLP) problems. It employs a MINLP algorithm to address a series of Nonlinear Programming Nonlinear Programming (NLP) and Mixed-Integer Programming Mixed-Integer Programming (MIP) sub-problems within GAMS, the performance of the sub-solvers significantly influenced by the overall effectiveness of the solution.

Also, knowing that modern grids are anticipated to become increasingly complex with the integration of intelligent devices, the necessity for robust optimization tools becomes indispensable [54]. GAMS has emerged as a crucial asset for this purpose, due to its refined capacity to handle optimization challenges within large-scale systems [55]. Its versatility extends to various applications within the energy sector, including power-systems modelling, optimal power flow, load management, and integrated transmission-systems planning, making it the most accurate tool to use within this project's scope.

5

Implementation and results

Contents

5.1 Implementation description

The algorithm described in Chapter 4 was tested in different scenarios, each with a distinct intention and level of complexity. The purpose of these simulations is to provide clarity on how all key factors and inputs affect the decision-making process. Throughout these experiments, it was considered an 8-hour time period for all scenarios, and 12 hours for the final one. The maximum charging power, $P_{chargemax}$, was defined as around 12 kW for all considered chargers, based on output power from Tesla Wall Connector [56]. Lastly, all vehicles, despite having different initial states of charge, were considered to have a 40 kWh battery capacity to simplify the simulation process, a value defined considering an average EVs battery capacity estimation [57].

In the first Scenario 5.2.1, 6 vehicles and 3 charging points were considered. As the first and most simple case, its objective was only to show that the algorithm works and how it reacts to a simple oscillation in the charging price. Secondly, in Scenario 5.2.2, 9 vehicles and 2 chargers were taken into account. The main objective was to demonstrate the algorithm's performance when vehicles have significantly different distances from the charging stations. In Scenario 5.2.3, even more vehicles were integrated, 20 in total, and 5 charging points were considered. This case intends to display the algorithm response to a more complex situation regarding the number of vehicles and charging price variations. The fourth Scenario 5.2.4 added even more complexity to the problem by integrating 50 vehicles and 8 charging points.

To test different metrics, three other scenarios were developed. In the fifth one 5.2.5, the objective was to recreate a highly congested grid, in which the available maximum power was regulated. In this case, 40 vehicles and 8 chargers were considered. In the sixth Scenario 5.2.6, the purpose was to index the unitary price to voltage oscillations at the chargers level, conditioning the algorithm's decision-making to a grid constraint. In the seventh Scenario 5.2.7, the charging impact on voltage values at the charger level was integrated into the objective function, conditioning the charging process through its direct influence on the voltage at each charger. The final Scenario 5.2.8 combines the price signal methodology from the first experiments and the voltage manipulation executed in 5.2.7, within an extended vehicle and time frame.

Table 5.1: Scenarios' summary

Scenario	Nº of Vehicles	Nº of Chargers	Purpose
A	6	3	SOC/charging price relation
B	9	2	Vehicles/chargers distance impact
C	20	5	SOC/charging price relation
D	50	8	SOC/charging price relation
E	40	8	High grid congestion management
F	30	8	Index charging price to voltage oscillations
G	20	8	Controlled charging to regulate voltage
H	60	8	Charging prices & regulated voltage

5.2 Obtained results

5.2.1 Scenario A

The main purpose of Scenario A was to demonstrate a functioning algorithm within a simple approach. As such, it was relevant to visualize the vehicles' SOC evolving into its maximum capacity and its reaction to a charging price drop.

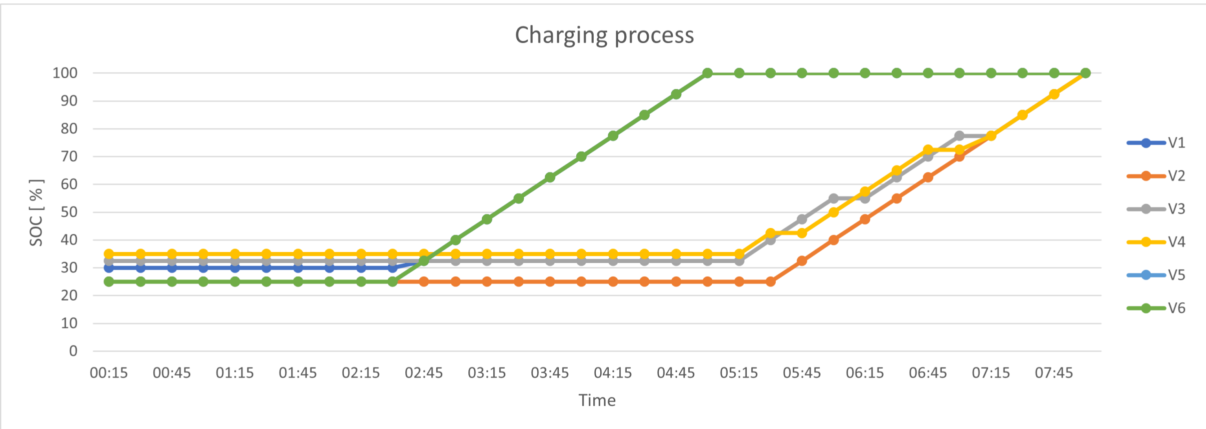

Figure 5.1: Charging process per vehicle through time

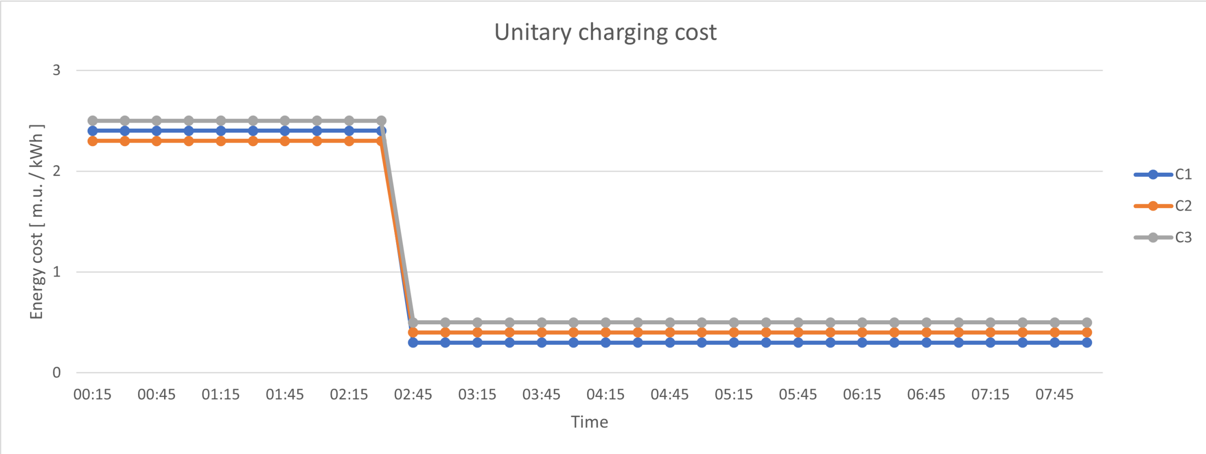

Figure 5.2: Unitary charging cost per charger through time

This first test succeeded in terms of getting into the vehicles' SOC maximum capacity as seen in Figure 5.1. Also, it was possible to visualize in Figure 5.2 that the chosen period for charging matches the most economically advantageous. Having that said, it is possible to affirm that the charging costs were minimized to their best in this Scenario, as intended.

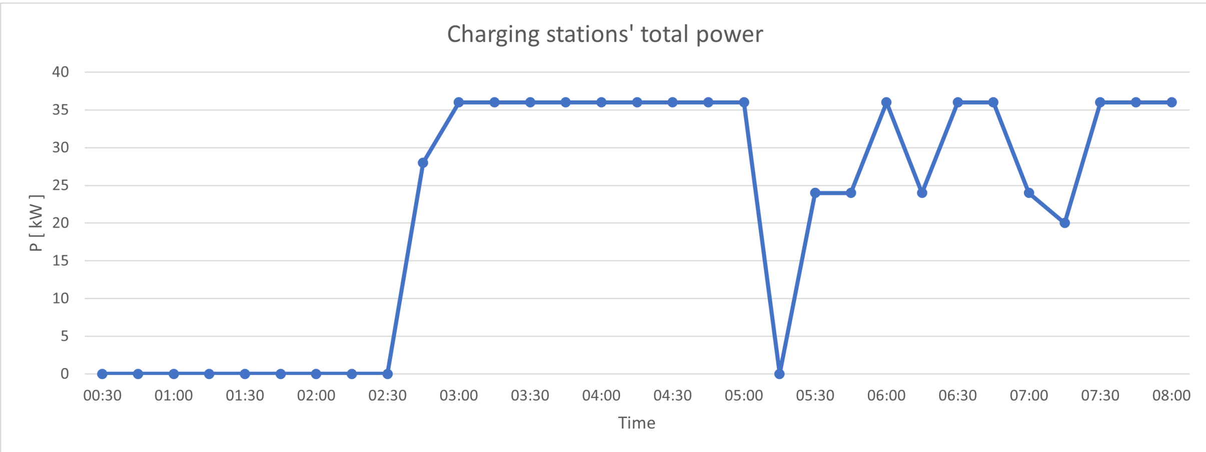

Figure 5.3: Total power injected by chargers through time

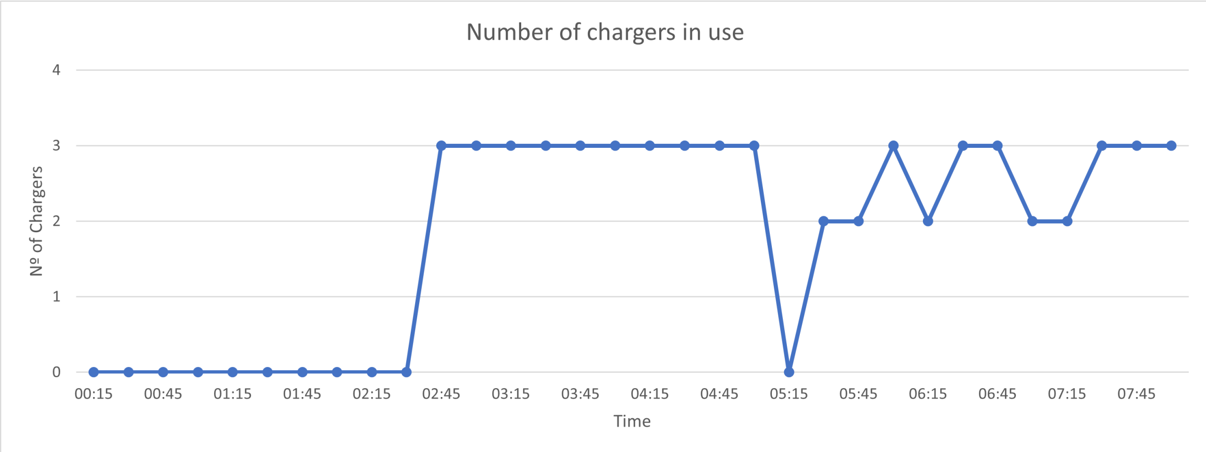

Figure 5.4: Number of chargers being used at each data point

The Figures 5.3 and 5.4 provide a more insightful perspective from this first Scenario. Considering the defined time range, the algorithm holds the charging process until the charging price drops, employing all chargers simultaneously at first, managing then the charging process until the end of the defined time range.

5.2.2 Scenario B

In this second test, it was imperative to demonstrate the impact of having vehicles positioned significantly far from the charging points. The illustration in Figure 5.5 intends to present the objective for this Scenario, where it is possible to identify two vehicles out of the radial preference for a connection. To complement the exposure of this differentiation, in Figure 5.2, it is possible to visualize the implemented penalization. In this case, it was applied the same charging costs from Scenario A (see Figure 5.2).

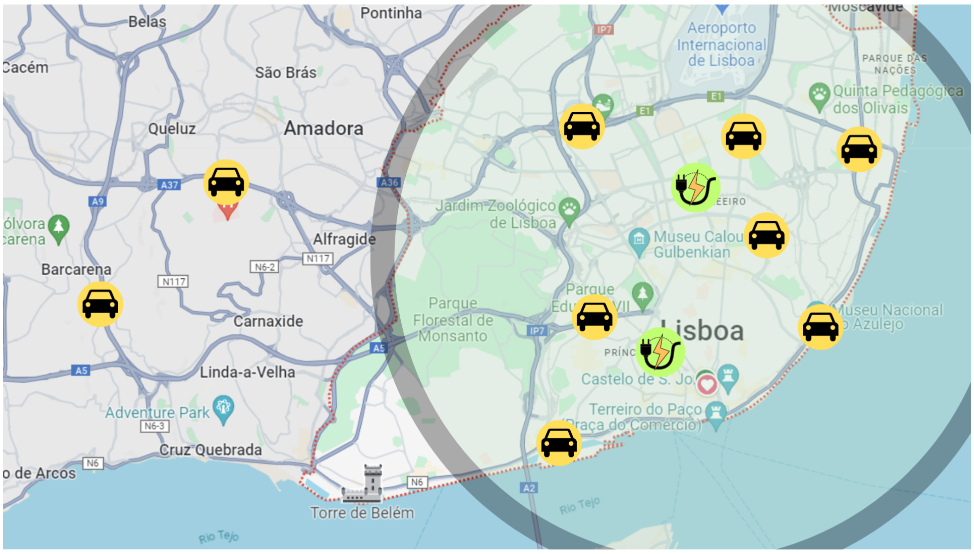

Figure 5.5: Illustration of charging station radial preferences

Table 5.2: Distance to charging points penalization factor

	V_1	V_2	V_3	V_4	V_5	V_6	V_7	V_8	V_9
C_1	10	10	10	90	80	10	10	10	10
C_2	10	10	10	90	80	10	10	10	10

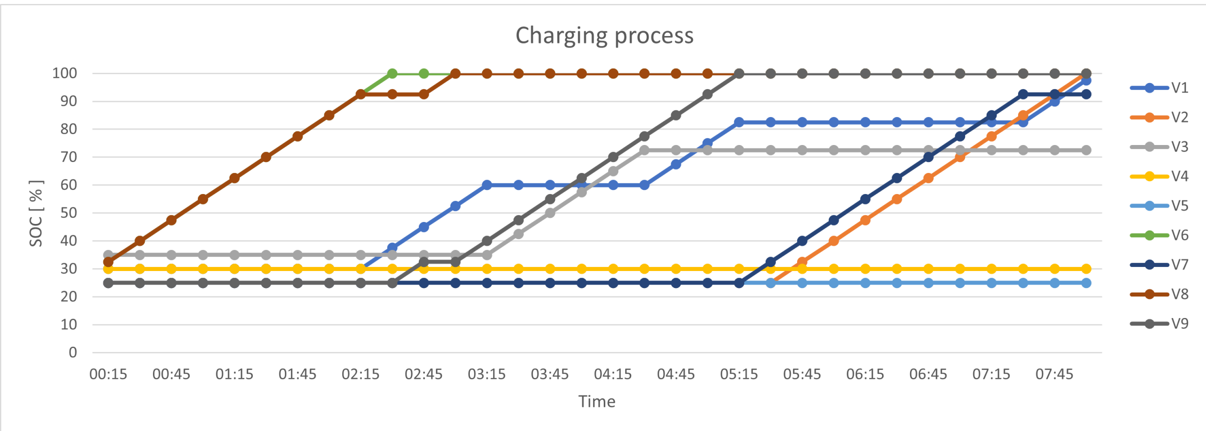

Figure 5.6: Charging process per vehicle through time

First of all, in this demonstration, it was crucial to dimension it so that having all vehicles fully charged wouldn't be possible, within the adopted time frame. As such, compared to the first Scenario, the number of vehicles was incremented and one charger was removed from the equation. This approach intends to put the algorithm in a position where it has to choose, from the vehicles available, those which will not be fully charged by the end of the test. As it can be seen in Figure 5.6, there are five vehicles which were not fully charged. From those, only two, vehicles 4 and 5, were not charged, precisely those with a higher penalization, as seen in Table 5.2, proving the functionality of the applied distance penalty.

5.2.3 Scenario C

In this third approach, the objective was to test the algorithm's robustness by challenging its response to an environment with a significant increment in the number of vehicles and charging points. Also, the charging costs presented in Figure 5.8 were manipulated so it was possible to identify, throughout the timeline, three distinctive periods: one where it is cheaper to charge, and two other more expensive periods in which there is only a slight difference between them. Pertinent to notice, this is the equivalent of time-of-use tariffs, widely used in EV public charging [58] or for home charging [59]. The appliance of these rates allows vehicle owners to manage their vehicle charging process according to lower charging prices. Our intention in these developments is to optimize these similar processes, by applying them to AEVs and consequently to automate the charging decision.

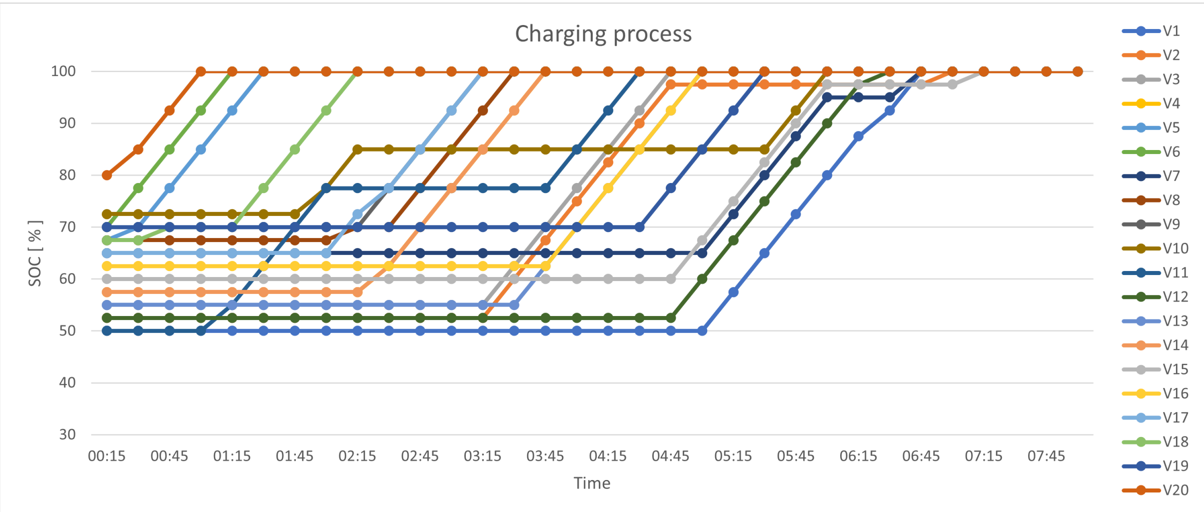

Figure 5.7: Charging process per vehicle through time

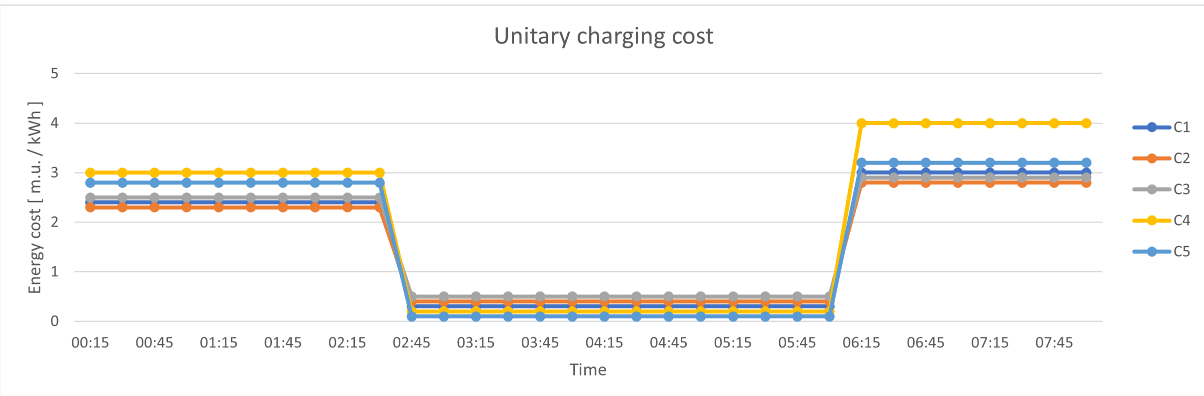

Figure 5.8: Unitary charging cost per charger through time

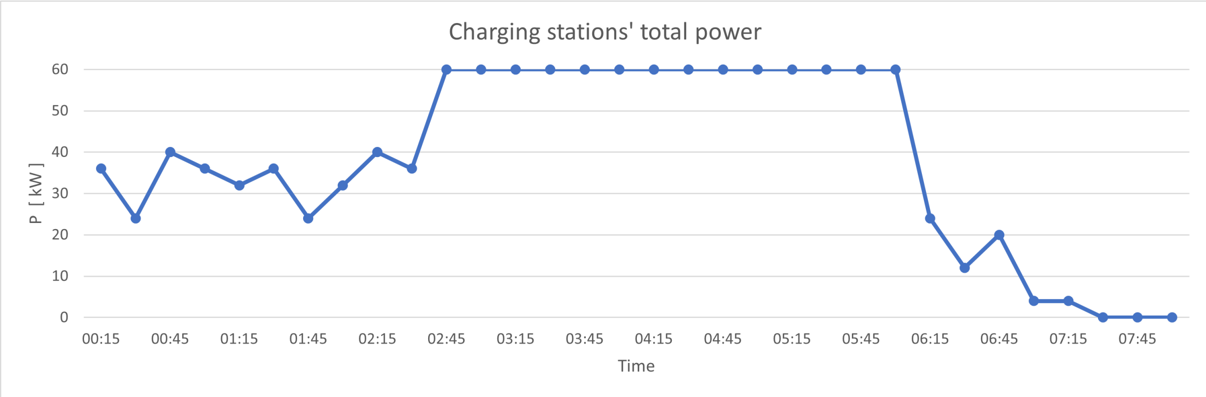

Figure 5.9: Total power injected by chargers through time

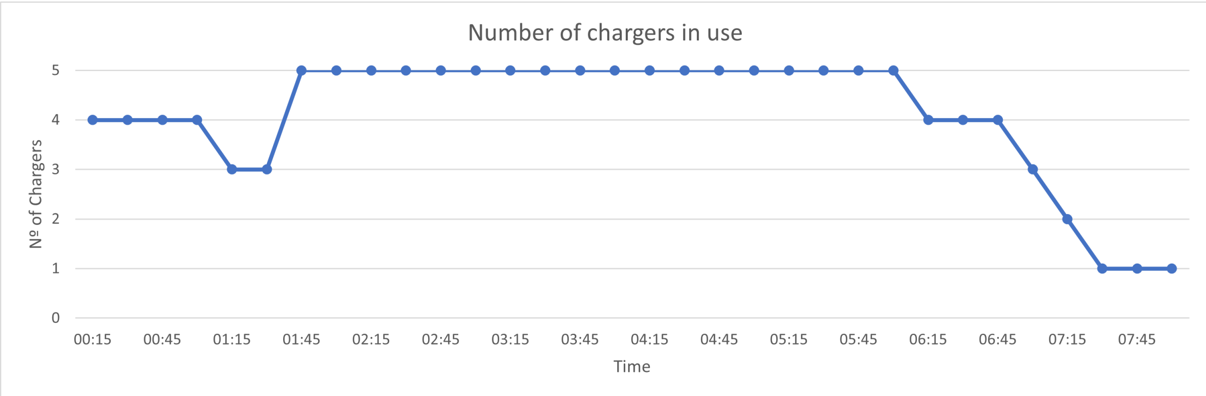

Figure 5.10: Number of chargers being used at each data point

Analysing the charging process of this Scenario, Figure 5.7, it is demonstrable that it succeeded in its purpose. All vehicles are fully charged by the end of the simulation, and it is also clear that the algorithm chose to fully charge right before the last third of the timeline, which was the most expensive one.

Since this demonstration was more dense in terms of vehicles accounted, another two metrics were displayed. In Figure 5.9, it is possible to visualize the total transmitted power from the charging points, and in Figure 5.10 the number of occupied chargers by each data point. In both, the considerations made above to this test are applied and reinforced, making clear the tendency to charge when charging costs are lower.

5.2.4 Scenario D

This fourth Scenario is aligned with the previous one in its objective. The algorithm's validity was tested by adding even more variables, in this case, by incorporating 50 vehicles and 8 chargers. The response to this Scenario is positively similar to the one in Subsection 5.2.3, with almost all vehicles being fully charged by the end of the experiment.

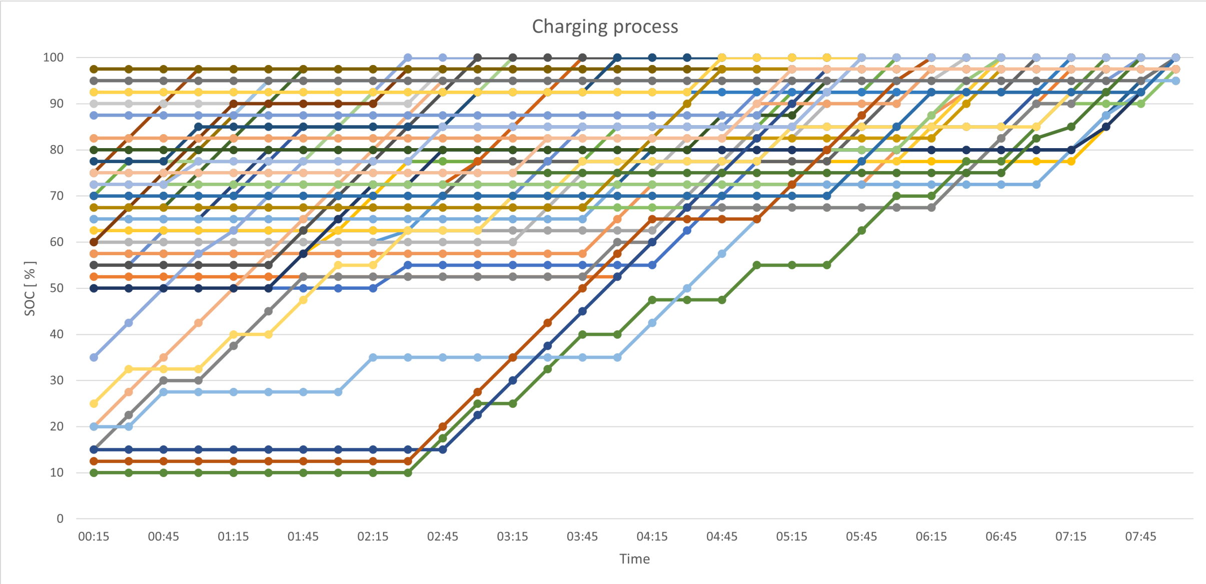

Figure 5.11: Charging process per vehicle through time

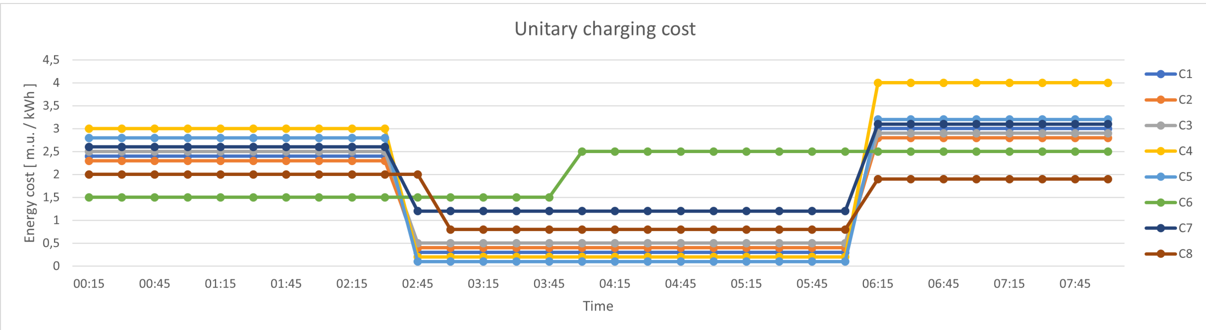

Figure 5.12: Unitary charging cost per charger through time

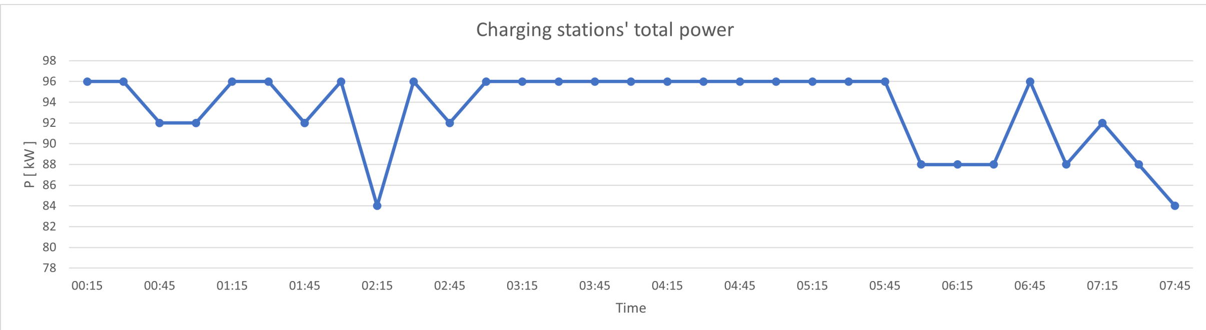

Figure 5.13: Total power injected by chargers through time

Analyzing the results of this Scenario, it is possible to conclude that the increment in vehicles and chargers didn't affect the algorithm's key points. The whole fleet was charged and the charging process occurred preferentially when prices were lower, as it is possible to confirm through Figures 5.12 and 5.13.

5.2.5 Scenario E

In this Scenario, the objective was to understand how the method would react to a congestion grid situation. To perform this, the maximum power per charger was controlled, lowering it to simulate a period of high electricity demand. In this case, it was considered 40 vehicles and 8 chargers. The unitary charging price for all chargers was not changed throughout the full experiment timeline, so every decision regarding the charging process was only influenced by the maximum power available.

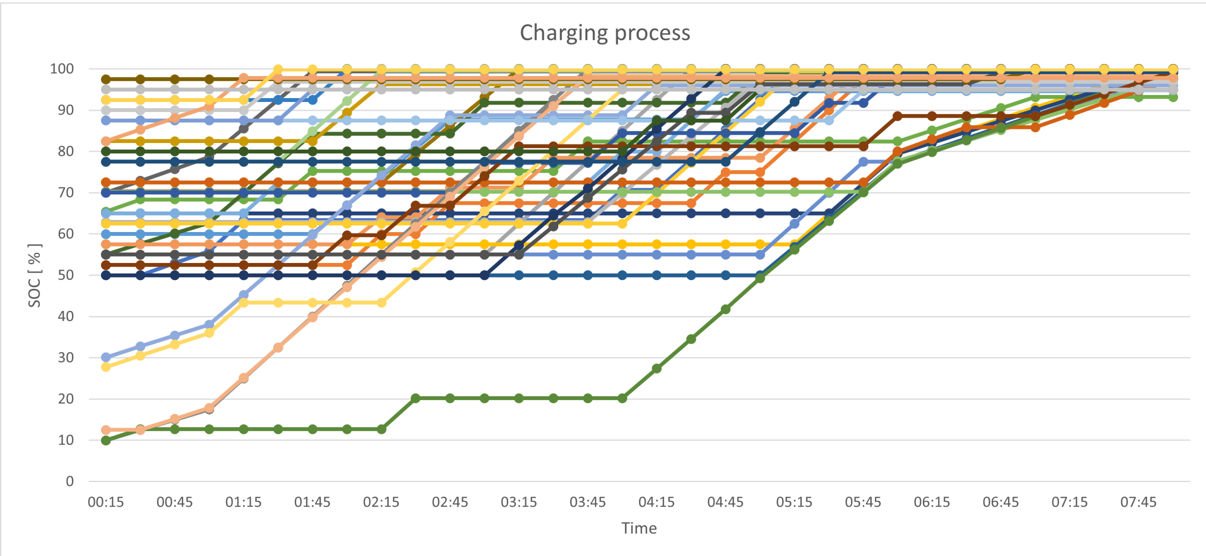

Figure 5.14: Charging process per vehicle through time

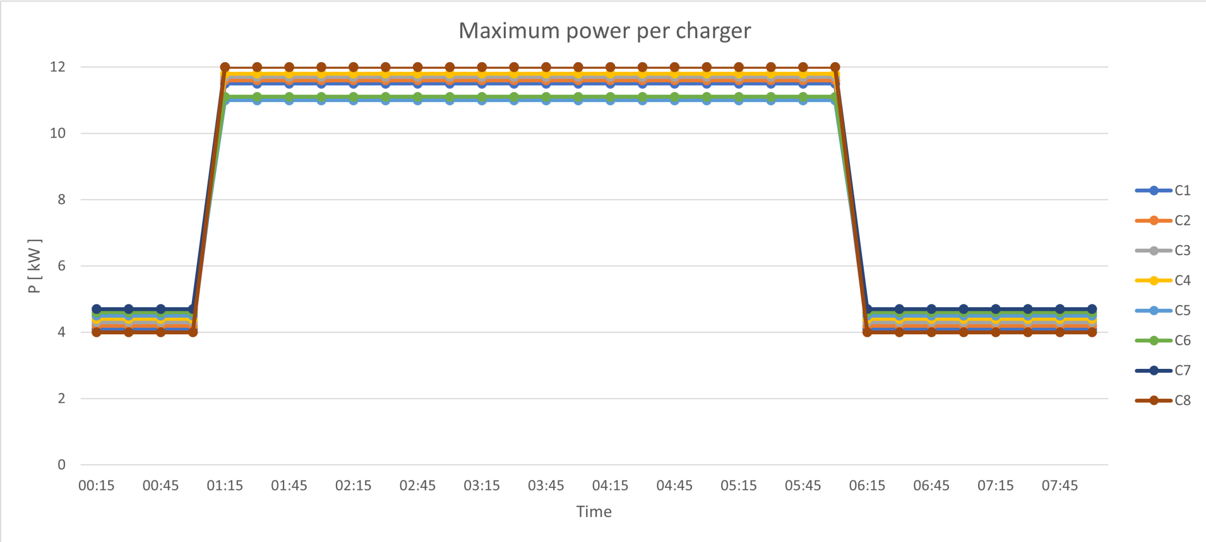

Figure 5.15: Maximum power per charger trough time

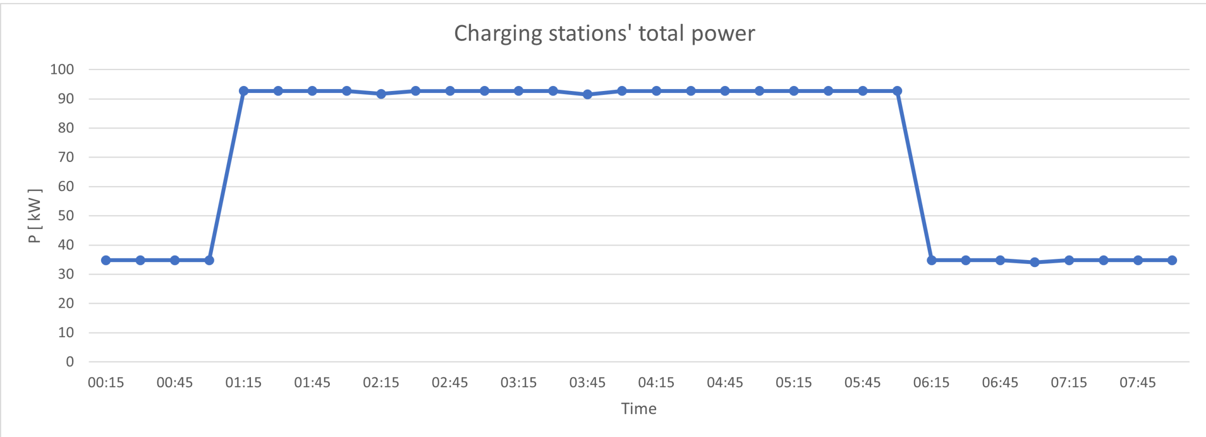

Figure 5.16: Total power injected by chargers through time

As seen in Figure 5.15, maximum power increases after the first hour of the experiment and it is kept high for 5 hours. In Figure 5.16, it is possible to confirm that there is a match between the period where the injected power was significantly higher, and the one with the most charging power availability, as intended.

5.2.6 Scenario F

In this experiment, 30 vehicles and 8 chargers were considered, and the key decision factor was once again the unitary charging cost at each data point. However, in this case, the price variations were indexed to voltage oscillations on each charger throughout the defined timeline.

The unitary charging cost was fixed at 1 monetary unit per kWh for a stable voltage value. It would get higher when the voltage drops, discouraging the charging process, and simulating a situation where the network is overloaded. On the other side, when the voltage increased, the price would fall, promoting charging and functioning as a case of low electricity demand.

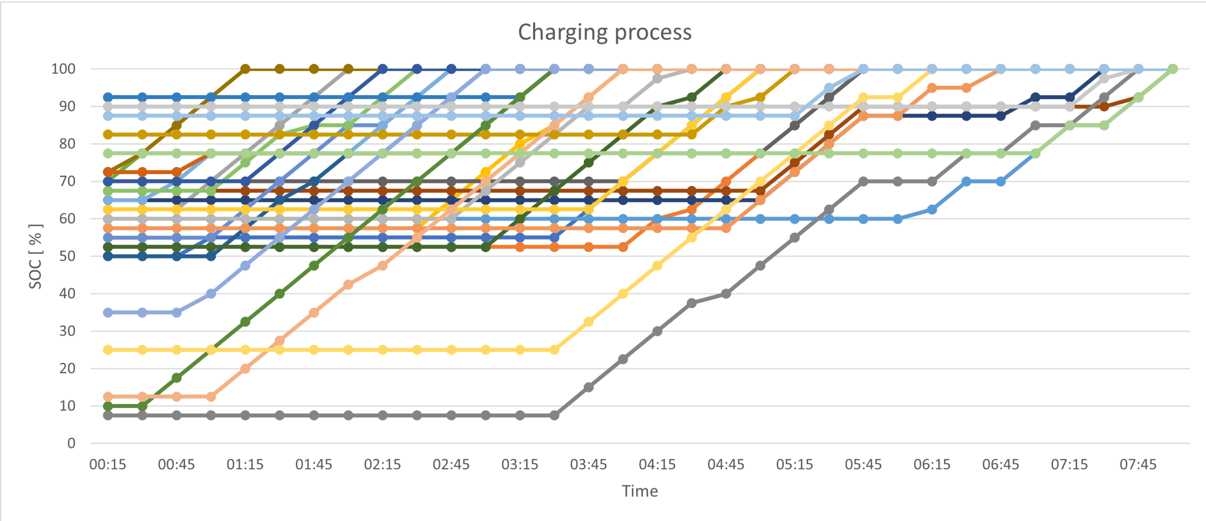

Figure 5.17: Charging process per vehicle through time

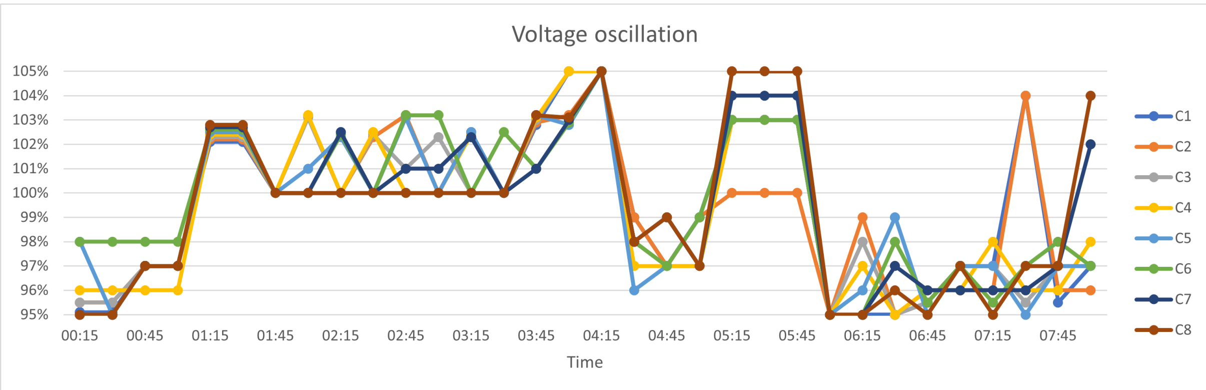

Figure 5.18: Voltage oscillations through time

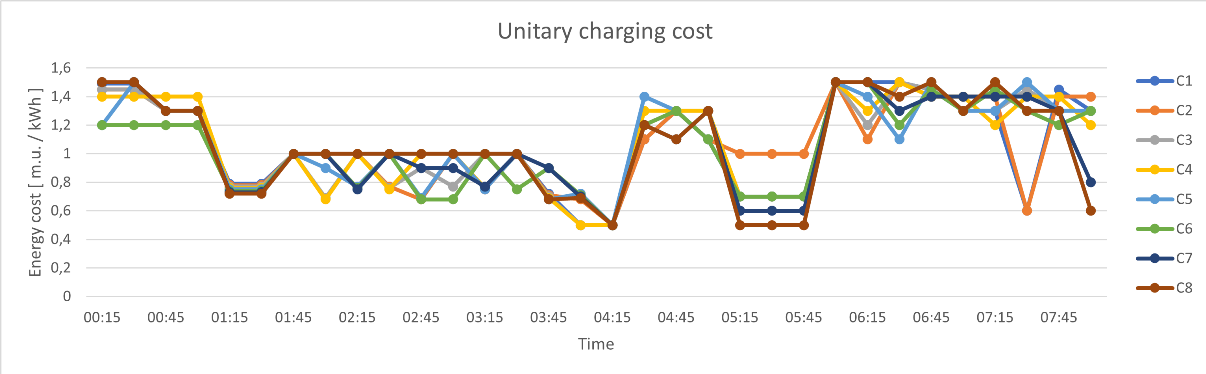

Figure 5.19: Indexed to voltage variations charging price

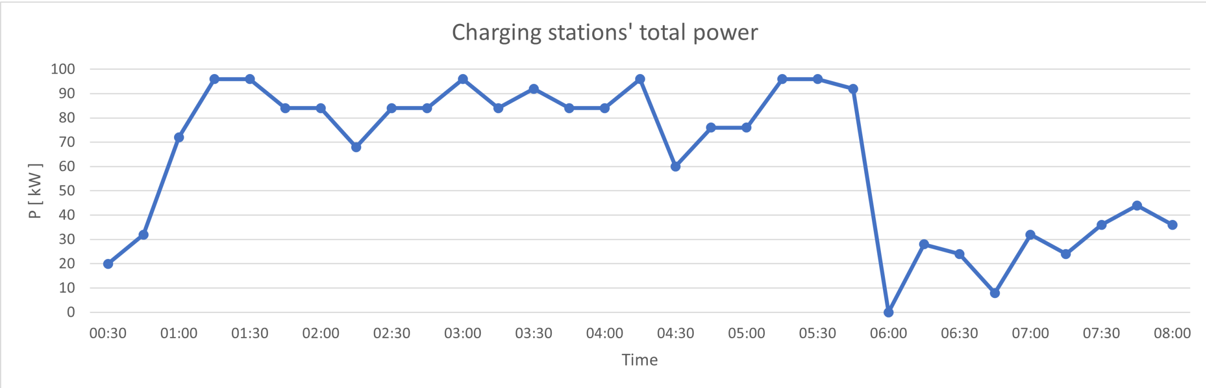

Figure 5.20: Total power injected by chargers through time

The voltage oscillated between +/- 5% around its normal value, which was considered to be 100%, as exposed in Figure 5.18, and the direct impact of those oscillations on the charging cost is reflected in Figure 5.19.

The experiment ran as expected and all vehicles were fully charged by the end of the defined timeline. By analyzing the voltage 5.19 and the unitary charging price 5.18 behaviours, it is possible to affirm that the algorithm behaved as expected, corresponding high voltage values to low prices, and vice-versa. Finally, in Figure 5.20, it is possible to acknowledge that the lower prices period equals a higher demand for charging as intended with this simulation.

5.2.7 Scenario G

In this scenario, the second voltage-related nuance was applied as described in Subsection 4.3. The objective was to pursue the charging impact on voltage at the charging station level. To attempt this topic, a busbar was conceptualized, as seen in Figure 5.21, aligning all chargers across its extension, being charger C_1 at the reference node, where the voltage is assumed to be stable. Knowing that voltage drop increases as much far as the charging process occurs from the reference node, the sensibility factor matrix (see Table 5.3) was estimated. It intends to reflect the charging impact from the charger in use on its and other chargers' voltage drop. This approach aimed to stimulate the nearest charging process to the reference node, so voltage oscillations, enabled by charging, are as slight as possible. For this analysis, all charging prices were kept at 1 monetary unit, removing their impact on the decision-making procedures.

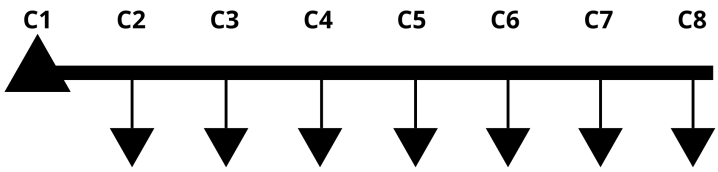

Figure 5.21: Charging stations aligned on a busbar

Table 5.3: Sensibility factor matrix

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
1	0	0	0	0	0	0	0	0
2	0	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
3	0	0.0001	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002
4	0	0.0001	0.0002	0.0003	0.0003	0.0003	0.0003	0.0003
5	0	0.0001	0.0002	0.0003	0.0004	0.0004	0.0004	0.0004
6	0	0.0001	0.0002	0.0003	0.0004	0.0005	0.0005	0.0005
7	0	0.0001	0.0002	0.0003	0.0004	0.0005	0.0006	0.0006
8	0	0.0001	0.0002	0.0003	0.0004	0.0005	0.0006	0.0007

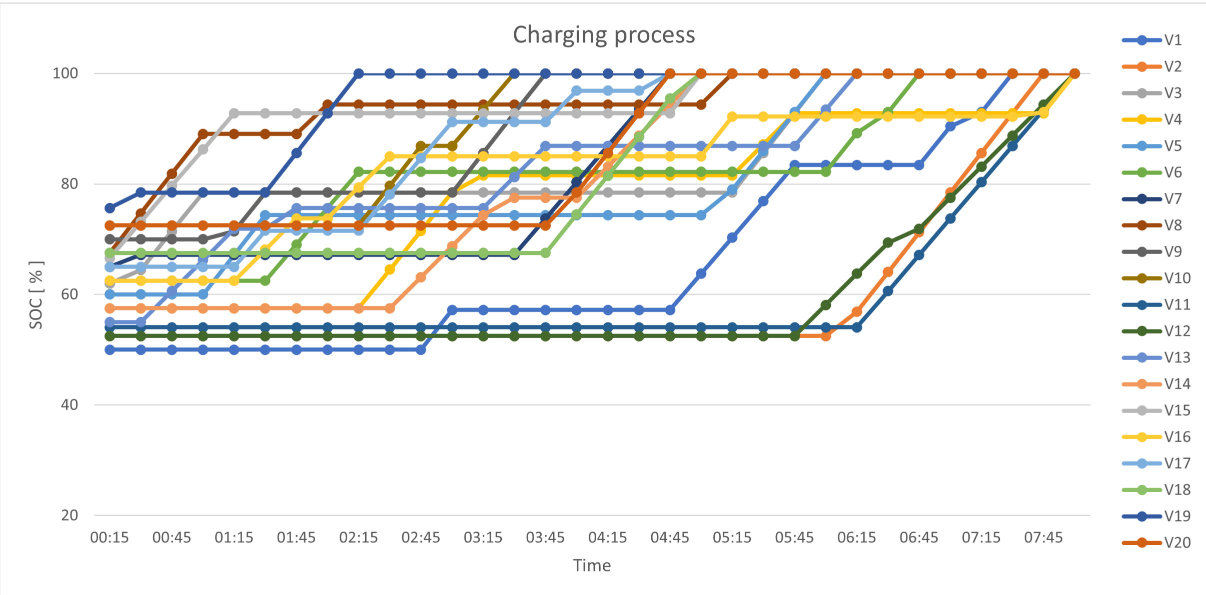

Figure 5.22: Charging process per vehicle through time

The developed experiment took 20 vehicles and 8 chargers into account. The Scenario proportionality was intentionally delineated to provide more charging points than needed to fulfil all AEVs batteries. By doing this, the algorithm is forced to choose within the available chargers, those whose charging impact is less harmful to voltage stability along the busbar. The charging process presented in Figure 5.22 demonstrates the algorithm's capability to fully charge all vehicles, as expected.

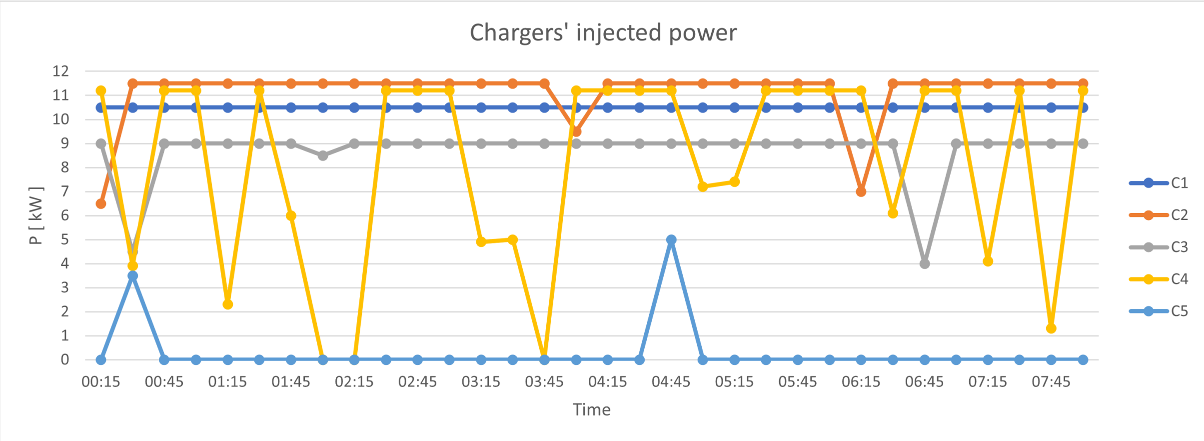

Figure 5.23: Injected power per charger through time

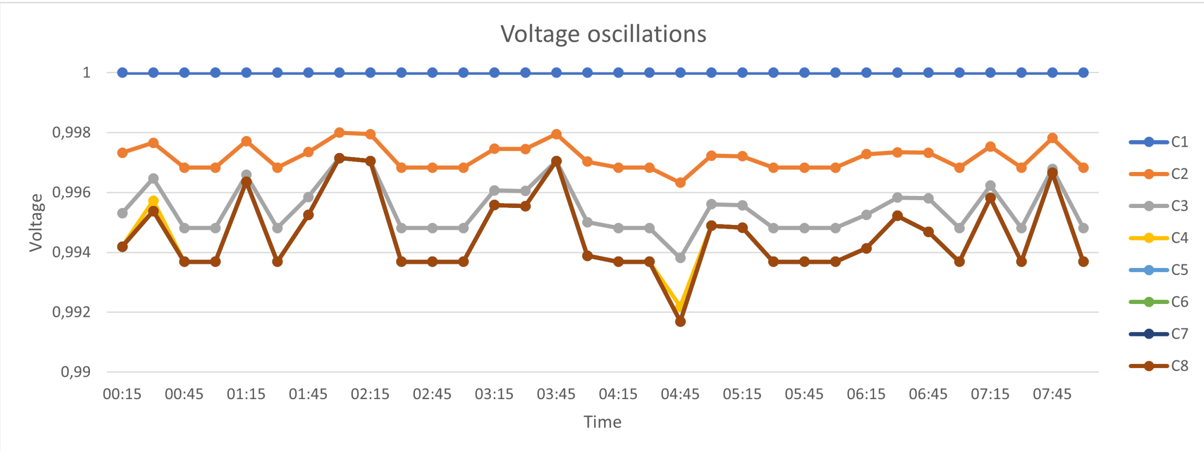

Figure 5.24: Voltage oscillations per charger through time

In Figure 5.23, it is possible to analyze the charging development per charger throughout the defined timeline. For this experiment, the maximum power of the chargers was adjusted to improve the visualization of the algorithm's decision-making, within a range of 9 kW to 12 kW. Therefore, the charging decision behaviour demonstrates a clear preference for the chargers C_1, C_2 and C_3, in this order, as these are those whose charging performance is more stable, proving the algorithm preference for those with the lowest impact on voltage oscillations, as seen in Figure 5.24. These results are unmistakable in proving the algorithm's capability to mitigate the charging impact on the grid, as long as it is supplied with voltage references and charging information concerning its effect on voltage levels.

5.2.8 Scenario H

In this last Scenario, the objective was to ultimately demonstrate the robustness of the algorithm developed, by challenging its performance with an extended time frame, 12 hours, an ample fleet of 60 vehicles, and most importantly, by combining the price signal methodology applied until the fifth Scenario 5.2.5 and voltage regulation from the previous one. The charging prices are described in the Figure 5.26. The conceptualized busbar 5.21 and its corresponding sensibility factor matrix (see Table 5.3) are the same as those used in the previous experiment.

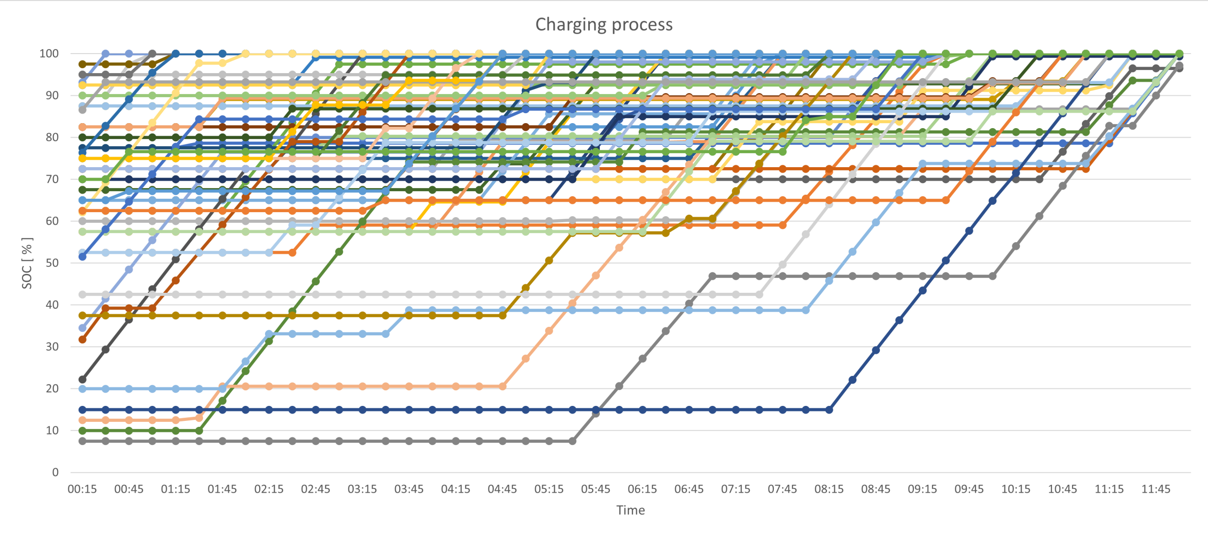

Figure 5.25: Charging process per vehicle through time

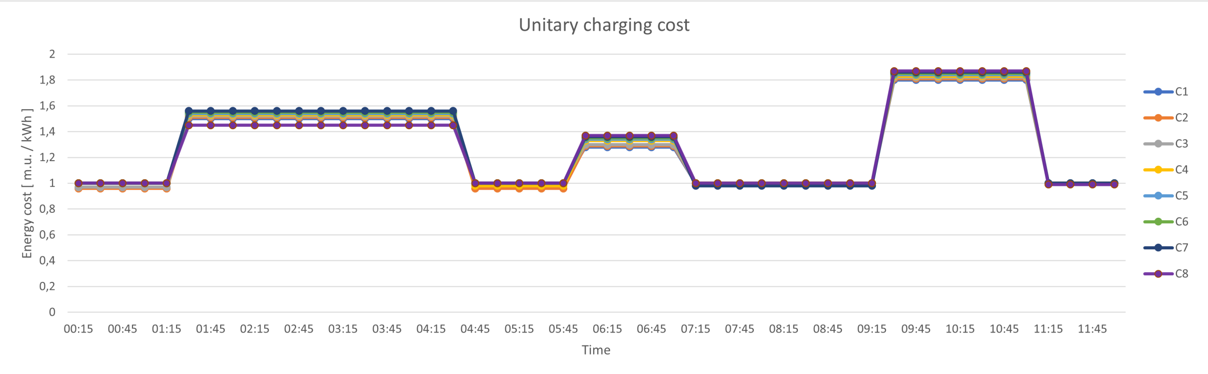

Figure 5.26: Unitary charging price per charger through time

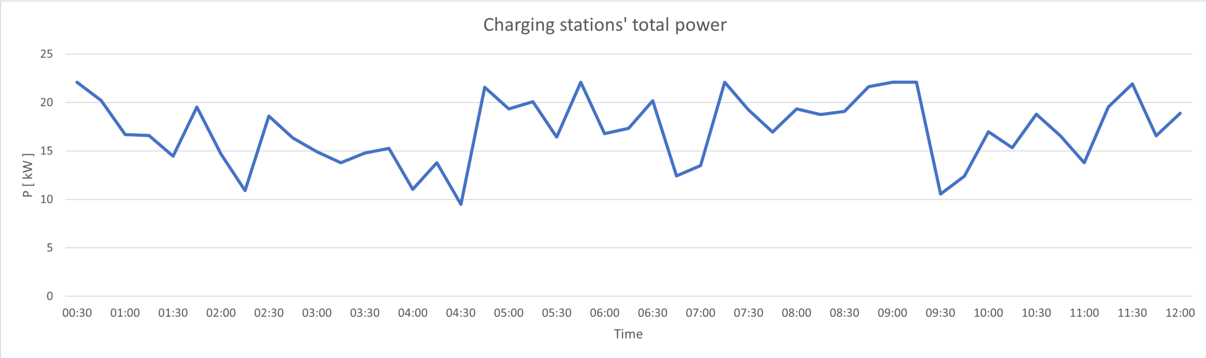

Figure 5.27: Total power injected by chargers through time

Firstly, in Figure 5.25, it is possible to visualize that this Scenario succeded in its main objective, to charge all vehicles within the defined data frame. Afterwards, it is important to understand if the algorithm's price signal dimension functioned as intended. By analysing the Figures 5.26 and 5.27, there is a clear pattern between them that can be envisioned. Higher charging prices correspond to a clear diminish in the total power injected by charging points and vice versa, proving the existence of an influence from charging costs on the charging decision.

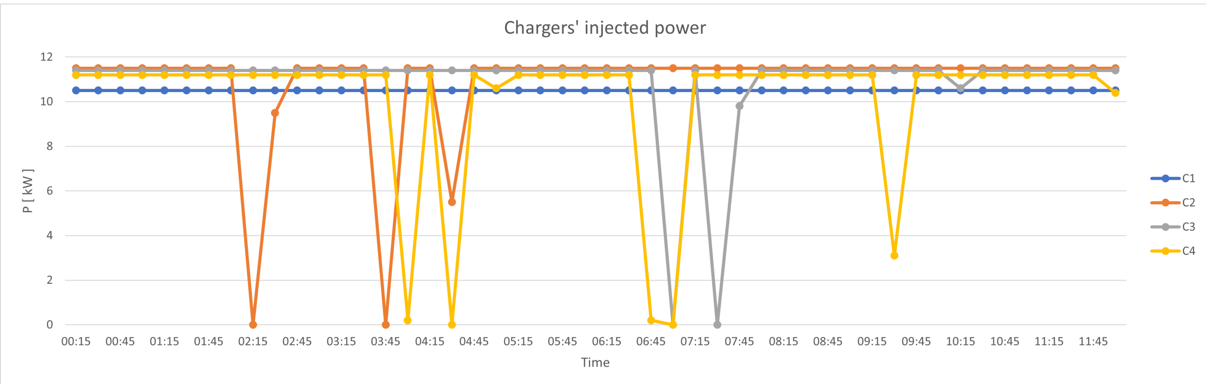

Figure 5.28: Injected power per charger through tim

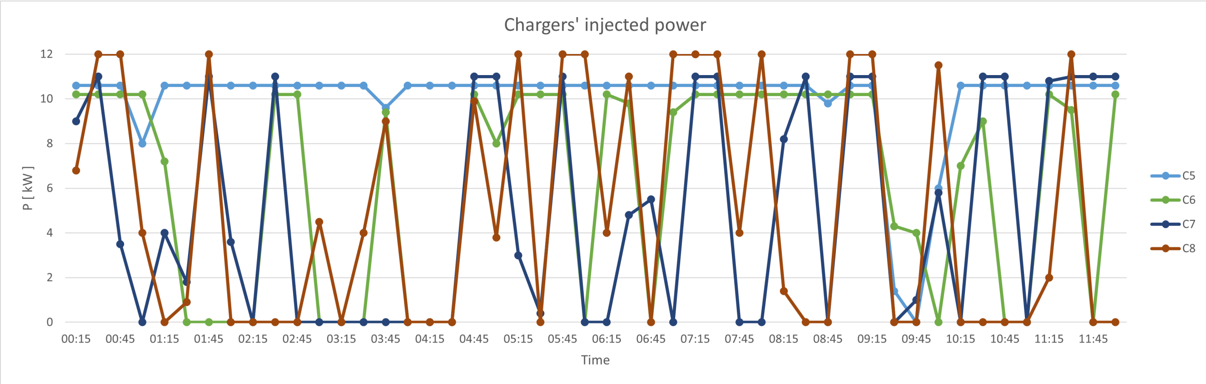

Figure 5.29: Injected power per charger through tim

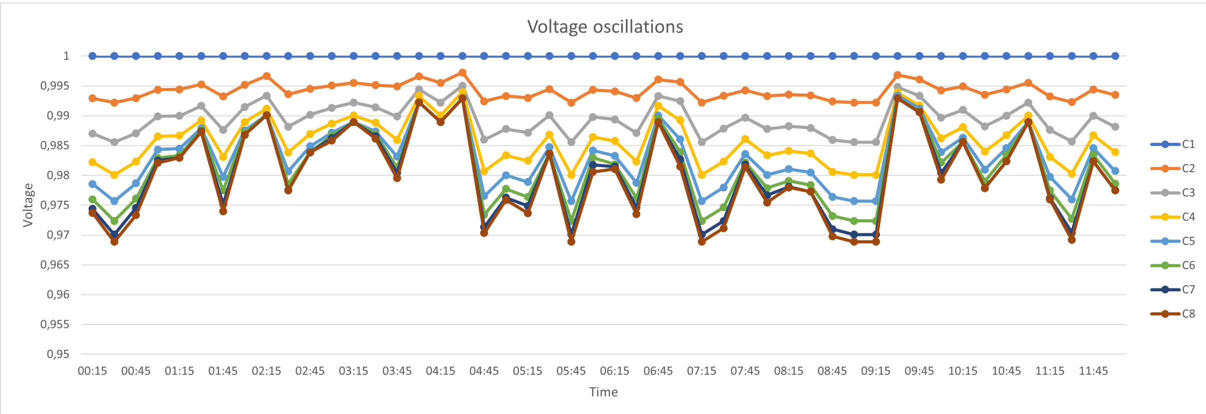

Figure 5.30: Voltage oscillations per charger through time

Lastly, Figures 5.28 and 5.29 demonstrate the injected power per charger throughout the timeline. This analysis was made through two different figures, so it could provide a better understanding of this scope. Following the environment defined by the busbar 5.21 and its corresponding sensibility factor matrix (see Table 5.3), the results shown by these figures prove the algorithm behaviour correctness by choosing to charge mostly where the charging process impacts the lowest the voltage intermittency at the charging station level.

Having proven the accurate behaviour from both dimensions of the algorithm decision-making, the price signal component and the charging impact on voltage, simultaneously, performing under a large scope of 60 vehicles and 12 hours, this Scenario demonstrates the significant capacity and robustness of the developed algorithm in terms of handling a noteworthy number of constraints and variables.

6

Conclusion

Contents

This chapter concludes the thesis by summarising conclusions and identifying points for future development and even limitations associated with the proposed solution and algorithm.

6.1 Conclusions

In this thesis, a vehicle charging management algorithm is proposed, which by taking advantage of autonomous electric vehicles' capabilities aims to make the charging process less costly to the vehicle owners, more energy efficient and less harmful to the energy grid. This mixed linear programming project was developed seeking the establishment of charging priorities by co-relating charging price oscillations, vehicles' SOC, the distance between AEVs and charging stations and finally, grid limitations, such as controlled chargers' maximum power simulating high grid congestion situations and controlled charging associated to voltage oscillations at chargers level.

The main objective of this framed work was to have a whole fleet charged by the end of each scenario and simulation, at the minimum possible cost while respecting all the imposed constraints. By assuming a state of full autonomy from the considered vehicles and only using wireless chargers, this project was developed under no restrictions due to human action.

Within the conceptualized environment, the algorithm proved its capability to handle a whole fleet minimizing its charging cost and following strictly all sets of constraints. Although the graphic results reflect the impact of each constraint on the decision-making process in each framed scenario, the system still has its limitations. When analyzing the implementation results in detail, it was possible to identify a few situations where the chosen charger, at some given data point, was not the most inexpensive when compared with other data points with a lower charging price which was not used. Those few isolated situations were possible to identify at the beginning of the simulations. However, as the number of constraints increased, it became harder to identify those opportunities for improved minimization. So, having this said, the results were valid and met the main objective of this scope, solving the minimization problem initially identified.

6.2 System Limitations and Future Work

Despite providing a robust mathematical problem-solver capacity, GAMS system may struggle with extremely large and complex models due to its solvers, processing and memory limitations. As more decision variables, constraints and non-linear relationships were added to the model, it became progressively less time-efficient in providing a solution. Therefore, the addition of complexity was counter-balanced with the diminishment of vehicles under analysis.

For future improvements and developments, it would be interesting to apply the whole complexity of the method under a platform with a higher amplitude of computational capability, so it could be applied to even more vehicles, chargers and data points. To the established method, might be interesting to incorporate a bidirectional charging variant, providing a more robust perspective of how these vehicles would be able to support grid and energy management. Finally, since all inputs used were delineated to serve the scope, a real-time system in which the algorithm could be tested will certainly deliver a more concise, applicable, real-framed perspective of its purpose.

GAMS might struggle with extremely large or highly complex models due to memory and processing limitations. Models with many decision variables, constraints, or non-linear relationships can sometimes be challenging to solve efficiently.

Bibliography

[1] J. Weiss, R. Hledik, R. Lueken, T. Lee, and W. Gorman, "The electrification accelerator: Understanding the implications of autonomous vehicles for electric utilities," *The Electricity Journal*, vol. 30, no. 10, pp. 50–57, 2017.

[2] A. A. Alkheir, M. Aloqaily, and H. T. Mouftah, "Connected and autonomous electric vehicles (caevs)," *IT professional*, vol. 20, no. 6, pp. 54–61, 2018.

[3] K. Anastasiadou, N. Gavanas, M. Pitsiava-Latinopoulou, and E. Bekiaris, "Infrastructure planning for autonomous electric vehicles, integrating safety and sustainability aspects: A multi-criteria analysis approach," *Energies*, vol. 14, no. 17, p. 5269, 2021.

[4] Society of Automotive Engineers, "Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles," 2021, https://www.sae.org/standards/content/j3016_202104/.

[5] David Silver, Forbes, "Tesla emails to the california dmv emphasize continued reliance on maps," 2021, https://www.forbes.com/sites/davidsilver/2021/03/09/tesla-emails-to-the-california-dmv-emphasize-continued-relia ?sh=6e63c84457e6.

[6] Statista, "Estimated u.s. market share held by selected automotive manufacturers in 2021," 2022, https://www.statista.com/statistics/249375/us-market-share-of-selected-automobile-manufacturers/.

[7] Mercedez-Benz Group, "First internationally valid system approval for conditionally automated driving," 2021, https://group.mercedes-benz.com/innovation/product-innovation/autonomous-driving/ system-approval-for-conditionally-automated-driving.html.

[8] Microsoft News Center, "Volkswagen group teams up with microsoft to accelerate the development of automated driving," 2021, https://news.microsoft.com/2021/02/10/volkswagen-group-teams-up-with-microsoft-to-accelerate-the-developmen

[9] Statista, “Global automotive market share in 2021, by brand,” 2022, https://www.statista.com/statistics/316786/global-market-share-of-the-leading-automakers/.

[10] Victoria Transport Policy Institute, “Autonomous vehicle implementation predictions: Implications for transport planning,” 2022, https://www.vtpi.org/avip.pdf.

[11] Forbes, “10 ai predictions for 2023,” 2022, https://www.forbes.com/sites/robtoews/2022/12/20/10-ai-predictions-for-2023/?sh=6b7a575ffab7.

[12] The Japan Times, “Japan approves use of highly autonomous ’level-4’ self-driving vehicles from april ’23,” 2022, https://www.japantimes.co.jp/news/2022/12/20/business/level-3-highly-autonomous-self-driving-vehicles/.

[13] European Commission, “Climate target plan 2030,” 2020, https://climate.ec.europa.eu/eu-action/european-green-deal/2030-climate-target-plan_en.

[14] Karin Kirk, Yale Climate Connections, “Electrifying transportation reduces emissions and saves massive amounts of energy,” 2022, https://yaleclimateconnections.org/2022/08/electrifying-transportation-reduces-emissions-and-saves-massive-amo

[15] M. Nour, J. P. Chaves-Ávila, G. Magdy, and Á. Sánchez-Miralles, “Review of positive and negative impacts of electric vehicles charging on electric power systems,” *Energies*, vol. 13, no. 18, p. 4675, 2020.

[16] European Environment Agency, “New registrations of electric vehicles in europe,” 2022, https://www.eea.europa.eu/ims/new-registrations-of-electric-vehicles.

[17] International Energy Agency, “Global ev outlook,” 2022, https://www.iea.org/reports/global-ev-outlook-2022/executive-summary.

[18] F. Schulz and J. Rode, “Public charging infrastructure and electric vehicles in norway,” *Energy Policy*, vol. 160, p. 112660, 2022.

[19] M. Amjad, M. Farooq-i Azam, Q. Ni, M. Dong, and E. A. Ansari, “Wireless charging systems for electric vehicles,” *Renewable and Sustainable Energy Reviews*, vol. 167, p. 112730, 2022.

[20] ORNL, “Ornl demonstrates 120-kilowatt wireless charging for vehicles,” 2018, https://www.ornl.gov/news/ornl-demonstrates-120-kilowatt-wireless-charging-vehicles.

[21] WiTricity Corporation, “Drive 11 evaluation system, wireless charging for ev phev platforms,” 2019, https://witricity.com/wp-content/uploads/2019/11/DRIVE_11_20191104-1.pdf.

[22] S. Li and C. C. Mi, "Wireless power transfer for electric vehicle applications," *IEEE Journal of Emerging and Selected Topics in Power Electronics*, vol. 3, no. 1, pp. 4–17, 2015.

[23] G. A. Covic and J. T. Boys, "Inductive power transfer," *Proceedings of the IEEE*, vol. 101, no. 6, pp. 1276–1289, 2013.

[24] M. R. Sarker, H. Pandžić, and M. A. Ortega-Vazquez, "Optimal operation and services scheduling for an electric vehicle battery swapping station," *IEEE transactions on power systems*, vol. 30, no. 2, pp. 901–910, 2014.

[25] REUTERS, "Nio to install 20 battery-swapping stations in enbw charging parks," 2022, https://www.reuters.com/business/autos-transportation/nio-install-20-battery-swapping-stations-enbw-charging-pa

[26] NIO, "An innovative smart power service solution," 2022, https://www.nio.com/nio-power.

[27] Z. Wang and R. Paranjape, "An evaluation of electric vehicle penetration under demand response in a multi-agent based simulation," in *2014 IEEE electrical power and energy conference*. IEEE, 2014, pp. 220–225.

[28] C. Crozier, T. Morstyn, and M. McCulloch, "The opportunity for smart charging to mitigate the impact of electric vehicles on transmission and distribution systems," *Applied Energy*, vol. 268, p. 114973, 2020.

[29] M. Nour, A. Ali, and C. Farkas, "Evaluation of electric vehicles charging impacts on a real low voltage grid," *Int. J. Power Eng. Energy*, vol. 9, no. 2, pp. 837–842, 2018.

[30] J. Su, T. Lie, and R. Zamora, "Modelling of large-scale electric vehicles charging demand: A new zealand case study," *Electric Power Systems Research*, vol. 167, pp. 171–182, 2019.

[31] P. Staudt, M. Schmidt, J. Gärttner, and C. Weinhardt, "A decentralized approach towards resolving transmission grid congestion in germany using vehicle-to-grid technology," *Applied energy*, vol. 230, pp. 1435–1446, 2018.

[32] H. Dagdougui, A. Ouammi, and L. A. Dessaint, "Peak load reduction in a smart building integrating microgrid and v2b-based demand response scheme," *IEEE Systems Journal*, vol. 13, no. 3, pp. 3274–3282, 2018.

[33] Z. A. Obaid, L. M. Cipcigan, L. Abrahim, and M. T. Muhssin, "Frequency control of future power systems: reviewing and evaluating challenges and new control methods," *Journal of Modern Power Systems and Clean Energy*, vol. 7, no. 1, pp. 9–25, 2019.

[34] H. Jia, X. Li, Y. Mu, C. Xu, Y. Jiang, X. Yu, J. Wu, and C. Dong, “Coordinated control for ev aggregators and power plants in frequency regulation considering time-varying delays,” *Applied Energy*, vol. 210, pp. 1363–1376, 2018.

[35] L. Wang and B. Chen, “Dual-level consensus-based frequency regulation using vehicle-to-grid service,” *Electric Power Systems Research*, vol. 167, pp. 261–276, 2019.

[36] M. Vahedipour-Dahraie, H. Rashidizaheh-Kermani, H. R. Najafi, A. Anvari-Moghaddam, and J. M. Guerrero, “Coordination of evs participation for load frequency control in isolated microgrids,” *Applied Sciences*, vol. 7, no. 6, p. 539, 2017.

[37] M. Nour, S. M. Said, H. Ramadan, A. Ali, and C. Farkas, “Control of electric vehicles charging without communication infrastructure,” in *2018 Twentieth International Middle East Power Systems Conference (MEPCON)*. IEEE, 2018, pp. 773–778.

[38] H. Ramadan, A. Ali, M. Nour, and C. Farkas, “Smart charging and discharging of plug-in electric vehicles for peak shaving and valley filling of the grid power,” in *2018 Twentieth International Middle East Power Systems Conference (MEPCON)*, 2018, pp. 735–739.

[39] J. Y. Yong, V. K. Ramachandaramurthy, K. M. Tan, and N. Mithulananthan, “Bi-directional electric vehicle fast charging station with novel reactive power compensation for voltage regulation,” *International Journal of Electrical Power & Energy Systems*, vol. 64, pp. 300–310, 2015.

[40] W. Zhang, O. Gandhi, H. Quan, C. D. Rodríguez-Gallegos, and D. Srinivasan, “A multi-agent based integrated volt-var optimization engine for fast vehicle-to-grid reactive power dispatch and electric vehicle coordination,” *Applied Energy*, vol. 229, pp. 96–110, 2018.

[41] E. Akhavan-Rezai, M. F. Shaaban, E. F. El-Saadany, and F. Karray, “Managing demand for plug-in electric vehicles in unbalanced lv systems with photovoltaics,” *IEEE Transactions on Industrial Informatics*, vol. 13, no. 3, pp. 1057–1067, 2017.

[42] A. Ali, D. Raisz, and K. Mahmoud, “Voltage fluctuation smoothing in distribution systems with res considering degradation and charging plan of ev batteries,” *Electric Power Systems Research*, vol. 176, p. 105933, 2019.

[43] N. Brinkel, M. Gerritsma, T. AlSkaif, I. Lampropoulos, A. van Voorden, H. Fidder, and W. van Sark, “Impact of rapid pv fluctuations on power quality in the low-voltage grid and mitigation strategies using electric vehicles,” *International Journal of Electrical Power & Energy Systems*, vol. 118, p. 105741, 2020.

[44] Y. Li and K. Li, “Incorporating demand response of electric vehicles in scheduling of isolated microgrids with renewables using a bi-level programming approach,” *IEEE Access*, vol. 7, pp. 116 256–116 266, 2019.

[45] R. Ahmadi Kordkheili, S. A. Pourmousavi, M. Savaghebi, J. M. Guerrero, and M. H. Nehrir, “Assessing the potential of plug-in electric vehicles in active distribution networks,” *Energies*, vol. 9, no. 1, p. 34, 2016.

[46] M. Nour, S. M. Said, A. Ali, and C. Farkas, “Smart charging of electric vehicles according to electricity price,” in *2019 International Conference on Innovative Trends in Computer Engineering (ITCE)*, 2019, pp. 432–437.

[47] L. Hu, Y. Cao, and L. Yin, “Fractional-order long-term price guidance mechanism based on bidirectional prediction with attention mechanism for electric vehicle charging,” *Energy*, vol. 293, p. 130639, 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360544224004110

[48] Z. Yang, B.-S. Chen, P.-L. Jin, Y. Yang, and W.-Q. Zhang, “Research on the cooperative interaction strategy of electric vehicle network based on price signal guidance,” in *2023 IEEE 6th International Electrical and Energy Conference (CIEEC)*, 2023, pp. 779–783.

[49] F. Barrero-González, M. I. Milanés-Montero, E. González-Romera, E. Romero-Cadaval, and C. Roncero-Clemente, “Control strategy for electric vehicle charging station power converters with active functions,” *Energies*, vol. 12, no. 20, 2019. [Online]. Available: https://www.mdpi.com/1996-1073/12/20/3971

[50] D. Liu, P. Zeng, S. Cui, and C. Song, “Deep reinforcement learning for charging scheduling of electric vehicles considering distribution network voltage stability,” *Sensors*, vol. 23, no. 3, 2023. [Online]. Available: https://www.mdpi.com/1424-8220/23/3/1618

[51] IEEE, “Ieee standard for interconnection and interoperability of distributed energy resources with associated electric power systems interfaces,” *IEEE Std 1547-2018 (Revision of IEEE Std 1547-2003)*, pp. 1–138, 2018.

[52] H. Morais, C. Paris, O. Carré, M. Carlier, and B. Bouzigon, “Levers optimization in short-term operational planning for real distribution systems,” 2019.

[53] GAMS, “System overview,” 2024, https://www.gams.com/products/gams/gams-language/.

[54] K. Mahmud, D. Soetanto, and G. E. Town, “5.6 energy management softwares and tools,” in *Comprehensive Energy Systems*, I. Dincer, Ed. Oxford: Elsevier, 2018, pp. 202–257. [Online]. Available: https://www.sciencedirect.com/science/article/pii/B9780128095973005186

[55] M. Daneshvar, B. Mohammadi-Ivatloo, and K. Zare, “Chapter 10 - an application of gams in simulating hybrid energy networks optimization problems,” in *Emerging Transactive Energy Technology for Future Modern Energy Networks*, M. Daneshvar, B. Mohammadi-Ivatloo, and K. Zare, Eds. Academic Press, 2023, pp. 149–181. [Online]. Available: https://www.sciencedirect.com/science/article/pii/B9780323911337000090

[56] Tesla, “Wall connector,” 2024, https://www.tesla.com/support/charging/wall-connector.

[57] E.ON, “Your guide to electric car battery capacity and lifespan,” 2023, https://www.eonnext.com/electric-vehicles/costs-and-benefits-of-electric-cars/battery-capacity-and-lifespan.

[58] MOBI.e, “Tariff structure,” 2024, https://www.mobie.pt/en/mobienetwork/tariff-structure.

[59] Green Energy Consumers, “Time of use rates,” 2024, https://www.greenenergyconsumers.org/drivegreen/timeofuserates.