ALTA SCUOLA POLITECNICA
POLITECNICO DI MILANO | POLITECNICO DI TORINO

MULTIDISCIPLINARY PROJECT

FINAL REPORT

OASIS

Optimal Allocation and Sizing of Infrastructures for charging electric vehicles basing on predictive Simulations.

www.asp-poli.it

POLITECNICO DI MILANO
Piazza Leonardo da Vinci, 32 - 20133 Milano
info-mi@asp-poli.it

POLITECNICO DI TORINO
Corso Duca degli Abruzzi, 24 - 10129 Torino
asp@polito.it

ALTA SCUOLA POLITECNICA
POLITECNICO DI MILANO | POLITECNICO DI TORINO

ALTA SCUOLA POLITECNICA

MULTIDISCIPLINARY PROJECT

FINAL REPORT

OASIS

Alessandro Amato, Mechanical Engineering, Politecnico di Milano

Signature_______________________

Filippo Cipriani, Mathematical Engineering, Politecnico di Milano

Signature_______________________

Gabriele Corbo, Mathematical Engineering, Politecnico di Milano

Signature_______________________

Michelangelo Giuffrida, Mechatronic Engineering, Politecnico di Torino

Signature_______________________

Riccardo Rosi, Mechanical Engineering, Politecnico di Milano

Signature_______________________

Aurelio Zizzo, Mathematical Engineering, Politecnico di Torino

Signature_______________________

Paolo Timis, Mechatronic Engineering, Politecnico di Torino

Signature_______________________

Principal Academic Tutor

Prof.ssa Michela Longo, Department of Energy, Politecnico di Milano

Other Academic Tutors

Prof. Andrea Mazza, Department of Energy, Politecnico di Torino

External Tutor(s)

Paolo Ciliento, Atlante

Francesca Mapelli, Atlante

Marco De Donno, Atlante

Abstract

This report describes the development of the OASIS project, conducted by students of the Alta Scuola Politecnica in collaboration with Atlante. The project aims to provide a systematic and efficient approach to the deployment of charging stations, thereby facilitating the transition towards a sustainable transportation system that relies on EVs. By efficiently allocating charging stations, this project seeks to enhance the accessibility and reliability of EV charging infrastructure, making it convenient and easy for EV users to charge their vehicles while also minimizing the impact on the environment. This project is a research initiative whose goal is to implement a decisional algorithm able to optimally locate and size electric vehicle charging stations. The work is divided into two phases; the first phase involves conducting a comprehensive literature review to explore the existing research on similar projects and to identify any gaps in the current knowledge; the second phase consists of implementing an algorithm to optimize the allocation of EV charging stations based on various factors such as location, usage patterns, demand, and supply, and developing an economic model to assess the profitability of the proposed solution. The algorithm has been tested on different cities, on which it achieves an optimal performance both for the sizing and allocation tasks. The results show that the model identifies locations with a correct balance between the different parameters and it attain high levels of station saturation and Return on Investment, proving the financial robustness of the project. Overall, the OASIS Project has the potential to transform the EV charging industry, making it more sustainable, efficient, and accessible for everyone.

Contents

1. Executive Summary

Issue, Goal and Requirements
Road transportation is one of the major factors responsible for air pollution and carbon emissions, exerting a substantial environmental impact on ecosystems and climate. The emerging paradigm in the mobility sector addresses this issue by pushing for the transition towards electric vehicles (EVs), to replace fossil fuel-based systems with clean energy sources. Accordingly, governments are promoting electrification, introducing policies to favour the usage of EVs and the deployment of the charging infrastructure. Within this paradigm, the OASIS project contribute is the development of a technological tool to support the design of an efficient charging network: the essential goal is to implement a decisional algorithm able to optimally locate and size EV charging stations.

The primary stakeholder of the project is Atlante, a NHOA's global business line dedicated to build the first EV fast-charging network enabled by renewables and energy storage in Southern Europe. The company set some requirements to be met by the algorithm. To begin with, the algorithm must be easy-to-use, automated and interpretable, so that Atlante's employees can efficiently interact with it and take decisions based on its outputs. From an economic point of view, instead, the solution of the optimization model must lead to a maximization of the revenues for Atlante in the long term.

Methodology
After a review of the solutions proposed in the literature regarding the optimal location and sizing of EV charging stations, the methodology chosen for the project is an approach based on the use of the Geographic Information System (GIS), a system able to analyse and map geospatial data. This method stands out when dealing with geographical tasks, due to its ability to connect data to maps, integrating location data with all types of descriptive information, and its capacity of immediate and interpretable visualization of results.

The core idea behind the solution is to segment the area of interest into a grid of hexagonal cells and to assign to each cell a score representing its suitability for the installation of charging stations. The decisional algorithm will then find the optimal locations, i.e., those ones with the highest score and satisfying a set of technical constraints. In parallel, an economic analysis is performed to size the charging network. The optimal number of charging stations is determined by evaluating the ratio between the estimated daily energy demand and the average energy output of a charger.

Data Collection
The input data used to construct the algorithm have been chosen based on the state-of-the-art and the guidance provided by Atlante. They are used for the formulation of the objective function, i.e., the function that the algorithm aims to maximize or minimize, and can be divided into four groups:

1. <u>Traffic data</u>: For the given area of interest, information about traffic was embedded in a set of point coordinates equipped with a measure of the average annual traffic. For each cell, the average annual traffic is calculated taking the mean of the average annual traffic of the points within that cell. Furthermore, a congestion index is assigned to each cell, computed considering the difference between the average travel

time in and out the cell, with and without traffic. The algorithm prioritizes locations with high traffic levels.

2. Points of interest (POIs): Information about POIs has been gathered from OpenStreetMap, an open-source geographical database. POIs have been clustered depending on their type (e.g., "Food and drinks") and a weight has been assigned to each cluster depending on their importance. Cells with a lower mean distance from POIs will receive a higher score in the objective function.

3. Costs and revenues data: These data were exploited to define the economics of the optimization model and to determine the profitability of the designed charging network, which must be maximized. They include technical specifications, such as the penetration rate, i.e., the ratio between EVs and all vehicles, or the utilization rate of a charging station, and costs, such as the cost of electric energy, or maintenance costs.

4. Existing EV charging stations: An analysis of the existing charging infrastructure is necessary to detect those areas not sufficiently covered by charging services and to understand what competitors are doing. Using the open-source database OpenChargeMap, it is possible to get access to detailed information about charging stations in various cities, such as hours of operation and the types of charging ports available at each station.

A subtle step before the testing phase was the creation of an open-source dataset, containing all the listed information for various cities. Despite the numerous difficulties, mainly concerning the poor availability of the required data, a test set of 6 cities has been obtained: Madrid, Rotterdam, Utrecht, Hamburg, London and Toronto. The criteria for the selection of a city were to have sufficient traffic points and POIs data and at least 150 existing charging stations.

Results
The results obtained in the testing phase show that the proposed solution achieves an optimal performance, fulfilling the company's requirements. The algorithm identifies locations with a correct balance between the different parameters. As an example, despite the multitude of POIs and the high traffic levels, the number of charging stations located in the city centres is limited, due to the presence of an already existing charging infrastructure. Consequently, the algorithm is able to detect high-potential peripheral points, such as trafficked highways and boulevards. On the economic side, the charging networks designed by the optimization model attain excellent performances in terms of station saturation and Return on Investment in the long term, proving the financial robustness of the project.

The proposed algorithm is designed to be flexible, thus future improvements can be easily implemented. A more comprehensive scoring model might be developed introducing new parameters, such as demographic information and data about the residual power of the electric grid, since it can be exploited for charging without overloading the grid. A further step might be to refine the economics of the algorithm, differentiating installation and land costs based on the area and considering the price fluctuations of energy.

2. Introduction

2.1. Importance of EVs and Charging network

In the 2021-2022 the EIB Climate survey stated that 67% of European car buyers said they would buy a hybrid or an electric vehicle, an interest almost doubled with respect to what reported in early 2021. This interest in electric vehicle adoption is not only limited to Europe, in fact, a survey from Consumer Reports shown that 71% of American expressed interest in an EV as their next vehicle [1]; this trend is not to be intended as a result of commercial dynamics only, but more like a dynamic fueled by governments and institutions. The Sixth Assessment Report (ARS) of the United Nations (UN) Intergovernmental Panel on Climate Change (IPCC) released in 2023 its Climate Change Synthesis Report for Policymakers; a report that recognizes the close linkages between climate change adaptation, mitigation, ecosystem health, human well-being, and sustainable development, and reflects the increasing diversity of actors involved in climate action. This report, when dealing with Current Mitigation Progress, Gaps and Challenges, stated that [2]:
"From 2010 to 2019 there have been sustained decreases in the unit costs of solar energy (85%), wind energy (55%), and lithium-ion batteries (85%), and large increases in their deployment, e.g., 10× for solar and 100× for electric vehicles (EVs), varying widely across regions. The mix of policy instruments that reduced costs and stimulated adoption includes public R&D, funding for demonstration and pilot projects, and demand-pull instruments such as deployment subsidies to attain scale. Maintaining emission-intensive systems may, in some regions and sectors, be more expensive than transitioning to low emission systems."
Furthermore, *"Electric vehicles powered by low-GHG emissions electricity have large potential to reduce land-based transport GHG emissions, on a life cycle basis (high confidence). Advances in battery technologies could facilitate the electrification of heavy-duty trucks and compliment conventional electric rail systems (medium confidence). The environmental footprint of battery production and growing concerns about critical minerals can be addressed by material and supply diversification strategies, energy and material efficiency improvements, and circular material flows."*.
It is clear how vehicle electrification is a key technology in tackling climate change thus being a technical issue of global importance supported by governments and institutions; in this context, there is a particular aspect that constraints the spread of electric vehicles: the charging infrastructure. An analysis conducted by PwC [3] in 2013 considered the availability (as well as perception of availability) of electric vehicle charging stations plays a crucial role in the diffusion of EVs; even though the vast majority of EV owners will do the recharging at home the ability to find public charging stations is among the concerns most cited; a more recent study done by Deloitte [4] in 2020 shows that this issue still plays a relevant part in this dynamic.

2020 Global Auto Consumer Study												
	FRANCE		GERMANY		ITALY		UK		CHINA		US	
In your opinion, what is the greatest concern regarding all battery-powered electric vehicles?	2018	2020	2018	2020	2018	2020	2018	2020	2018	2020	2018	2020
Driving range	31%	28%	35%	33%	4%	27%	26%	22%	25%	22%	24%	25%
Cost/price premium	32%	22%	22%	15%	19%	13%	24%	16%	9%	12%	26%	18%
Time required to charge	11%	15%	11%	14%	18%	16%	13%	16%	12%	15%	10%	14%
Lack of electric vehicle charging infrastructure	16%	22%	20%	25%	44%	32%	22%	33%	18%	20%	22%	29%
Safety concerns with battery technology	4%	11%	5%	10%	7%	10%	6%	12%	22%	31%	8%	13%
Others	6%	2%	7%	3%	8%	2%	9%	1%	14%	0%	10%	1%
Total	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Sample size	1,083	1,266	1,287	3,002	1,048	1,274	965	1,264	1,606	3,019	1,513	3,006

Figure 1: Consumer priorities for EV adoption, 2018 and 2020

In Figure 1 it is shown the consumer priorities for EV adoption in 2018 and 2020, in this period shifts in consumer attitudes towards EVs happened. Except in China cost/price premium have diminish in every country; although being the top concern in Germany and France the driving distance in 2020 was less cited with respect to 2018; elsewhere, the lack of charging stations has become the top concern for costumers. This statistic reflects the proneness of the market towards EVs that are more and more considered as a viable option. Still referring to [4] it is expected that some barriers will be completely removed in the near future: in fact, EVs' driving range currently can be compared with internal combustion engines; the price difference if considering the total costs of ownership is shrinking; also, the variety of EV models is increasing.

2.2. The OASIS project

These considerations make clear that the big constraint to EVs diffusion, currently and in the near future, is the charging infrastructure; in this scenario the mission of the OASIS project stands out. The OASIS project relates with the Optimal Allocation and Sizing of Infrastructures for charging electric vehicles basing on predictive Simulations. This project was carried out in collaboration with Atlante i.e., NHOA's Global Business Line dedicated to build the first Fastcharging Network enabled by renewables, energy storage and 100% grid-integrated. The role of the OASIS project is to provide Atlante with a tool able to support the development of a fast-charging station network in Southern Europe; able to maximize EV needs coverage, providing a top costumer experience as well as leading to a feasible business plan. To carry out the activity several aspects and variables had to be included such as: traffic data, viability plans, transmission and distribution, power flows, grid capacity and congestions, proximity to logistic districts or large recreational areas, distribution of population and economic wealth. All those data were supposed to be fed to the optimization model to find the optimal location and size of a new charging station. The optimization model gives the possibility to evaluate different scenarios through behavioral models; in order to identify hot areas where to install charging infrastructures in the provision of changing in demand.

2.3. Synergies with other teams

Although all projects of Alta Scuola Politecnica are related to innovation and sustainability, the project "eHome-solutions" is the more closely linked with the OASIS Project; in fact, the external institution involved in this project i.e. Free2Move eSolution is a joint venture between Stellantis and NHOA.
Among the targets of the team eHome-Solution there is the development and testing of algorithms employed in response/demand of energy forecast and energy consumption optimization in household environment. Considering that the focus lies in the residential aspect of energy management it was not possible to include eHome-Solutions' achievements in the Oasis project; however, as a next step it is reasonable to consider the algorithms previously cited in grid applications related with EVs fast charging.
Another project whose targets show affinity with OASIS is "Santa Barbara 4.0", carried out by the team SB4. Santa Barbara 4.0 aims at evaluating and integrating into existing buildings and urban areas trends such as: renewable energy sources, energy efficiency, electric vehicle integration and storage. It is clear that while OASIS project deals with realizing a fast charging network, SB4's findings can be eventually deployed to provide a methodology to integrate charging stations into urban and residential scenarios; making sure that aspects not exhaustively covered by OASIS (e.g. environmental and architectural) are evaluated.

2.4. Methodologies and Phases of work

The OASIS team is composed by four Mechanical/Mechatronic Engineers and three Mathematical Engineers, tackling a problem in the field of strategic optimization and data analysis but closely linked to the energy sector. The lack of Energy Engineers led to the way the team organized in the first phase of the project: the analysis of the state of the art. Mathematical Engineers studied the Existing Solutions for Optimal Electric Vehicle Charger Allocation; the rest of the group, due to its industrial background, focused on Energy, Infrastructure and Advanced Opportunities like Vehicle to Grid (V2G). This subdivision aimed at valorising Mathematical skills within the group while making up for the lack of Energy competences; the knowledge acquired was then shared with the rest of the team. Even during the state of the art, meetings with company and Academic tutors were scheduled in order to keep the advancement of the project on track.
With the knowledge acquired from the state of the art, the project proceeded with finding sources of different type of data: traffic points, EV charging stations, points of interest, streets, and cost/revenues data. In this phase the OASIS team together with its tutors collaborated in order to gather information and metrics for data evaluation; leading parallelly to the first implementation of the model. This first implementation was done considering the city of Madrid, due to its urban complexity, availability of data and alignment with the geographic target of the company.
Insightful meetings with Atlante led to the necessity of new factors to be included in the model such as traffic flux and information regarding road/street morphology; opening new challenges related to data acquisition, engineering, and analysis. Finally, the optimization

was done for different European cities including a detailed economic analysis as well.
Overall, the methodology of work of the OASIS team was meant to proficiently highlight the vertical skills of its components while at the same time filling the gaps due to the lack of Energy and Management Engineers; resembling the scenario that may occur in the future professional life. With recurrent meetings all the member of the group were updated with the activities carried out parallelly, in order to get an organic view of the state of the project.
Additionally, the in-presence schools of Alta Scuola Politecnica together with the time spent also beyond this project allowed to build a friendly and respectful environment within the team, easing the capability of delivering results.

3. Users' Requirements

3.1. OASIS Stakeholders Identification

Being the OASIS project primarily focused on the algorithm development, it is challenging yet essential to clarify its stakeholders and closest partners. The transition in the transportation sector is expanding quickly and it is continuously pushing towards an increasing adoption of electric vehicles over ICE vehicles. In fact, a number of enterprises are contributing to such a goal, generating a vast network of competing and collaborating realities. The understanding of the available resources, as well as the presence of existing competitors, is crucial for the development of the decisional algorithm. The latter is intended to exploit at best such resources and bring competitive advantage over competitors at the same time.

The team has been working together with Atlante, whose main objective is to deploy an efficient network of fast charging infrastructure, particularly focusing on southern European territories of Italy, France, Spain and Portugal. The optimal allocation algorithm serves Atlante as a primary tool to achieve its strategic objectives, contributing to the success of the company and simultaneously to the electric transportation transition. Atlante was born from the investments of NHOA Energy, which is within the first 5 top players worldwide in energy storage. Additionally, NHOA has also collaborated with Stellantis Group to form Free2Move eSolutions, which is a joint venture developing innovative technologies for electric mobility. As an instance, eSolutions has designed a considerable number of wallboxes for domestic recharging, as well as other infrastructure and components for public recharging on the road. Further than that, the company is creating and studying the largest V2G system in the world, located in Mirafiori. Considering its expertise in hardware solutions for electric mobility, it acts as a sister company to Atlante, taking up the role of its primary tech partner and components provider.
Once clarified Atlante's background, it is still of crucial importance to comprehend that the project has a broader scope nonetheless, which is affected by public institutions, and which affects the end users (EV users) in turn. The regulations imposed by public institutions may in some cases be favourable to the deployment of the charging stations (thanks to favourable policies and funding), however they may also constraint the positioning of certain stations due to space availability or limited traffic areas. Similarly, the end users' needs must be taken into account when pursuing the optimal allocation of the charging stations, prioritising convenient locations near Points of Interest (POIs) of the city, as well as parking spots and proximity to their commuting routes. From a broader point of view, there are even more categories that would indirectly be affected by the project and its outcomes. To mention a few, the EV/ICE car industries would respectively benefit and be damaged by the realisation of an efficient recharging network. The more efficient it would be, the quicker the adoption of EV would be over the ICE vehicles, changing the ICE users' perspective and future choices.

For these reasons, the OASIS stakeholders can be eventually classified in three main tiers:

- The primary group is formed by those who directly interact with the design of the algorithm (Atlante)

- The second one clusters all the entities which benefit from the design (eSolutions, NHOA, EV users. . .)
- Lastly, a third category is identified to gather all the ones that are indirectly affected (positively or negatively) by the outcomes of the project (car industries, ICE users. . .)

The classification mentioned above is visually represented and summarized in Figure [2].

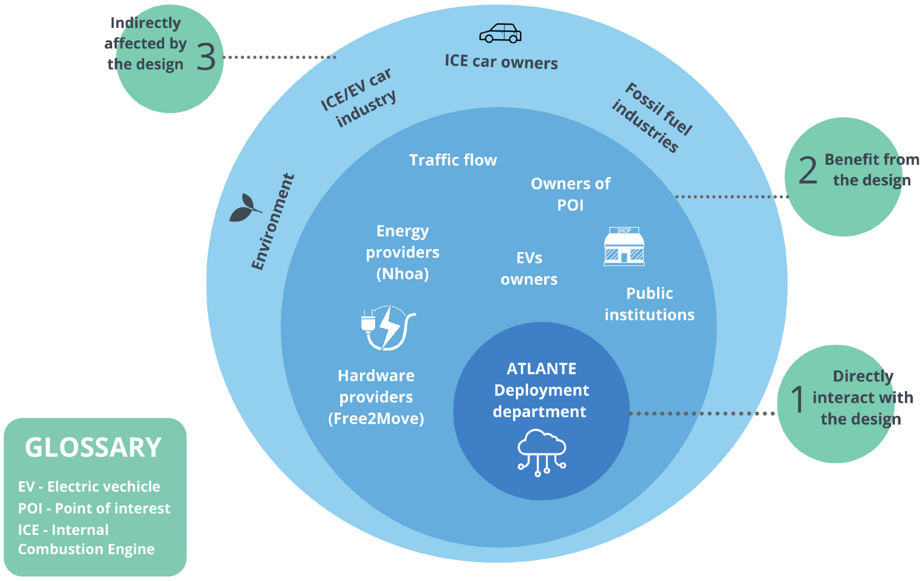


Figure 2: OASIS project stakeholders' classification

The multitude of stakeholders involved unfolds an intricate web of relationships within one another. Such dynamics are key aspects for the growth of the company and are crucial to identify the boundaries within which the project can evolve. To better understand these relationships, the following chart [3] was constructed to frame them directly and more clearly. The left side of the diagram depicts the origin and affiliates of the partner company, as it was previously described. All of these entities share common interests and provide significant contribution to Atlante's industrial progression. Despite these synergies, some conflicts arise among the other stakeholders' tiers. As an instance, the EV industry can benefit from the diffusion of charging stations and the reduction of range anxiety, which are factors that discourage potential customers from buying internal combustion engine vehicles in the end. This would result in a loss of market share and revenues for the ICE automotive industry, which might resist the electric mobility transition, that is regulated by public institutions (e.g. by trying to influence them to delay the zero carbon emissions goals and reduce public funding for electric mobility projects). This way, the two businesses generate antagonising relations. Similar conflicts are present between the environmental protection enterprises and the fossil fuels extraction industries, which would also be negatively affected by the transition. Furthermore, even the EV users (who are Atlante's main customers) might have conflicting interests with the team's partners. In particular, they wish to have ultra-fast charging and (possibly) oversized stations to avoid long waiting times, but on the other hand NHOA has to take into account grid expansion costs and grid load management issues. Similarly, the more chargers Atlante installs, the higher the initial investment costs it has to bear, meaning this requires trade-offs implementation from the decision making algorithm's perspective as well.

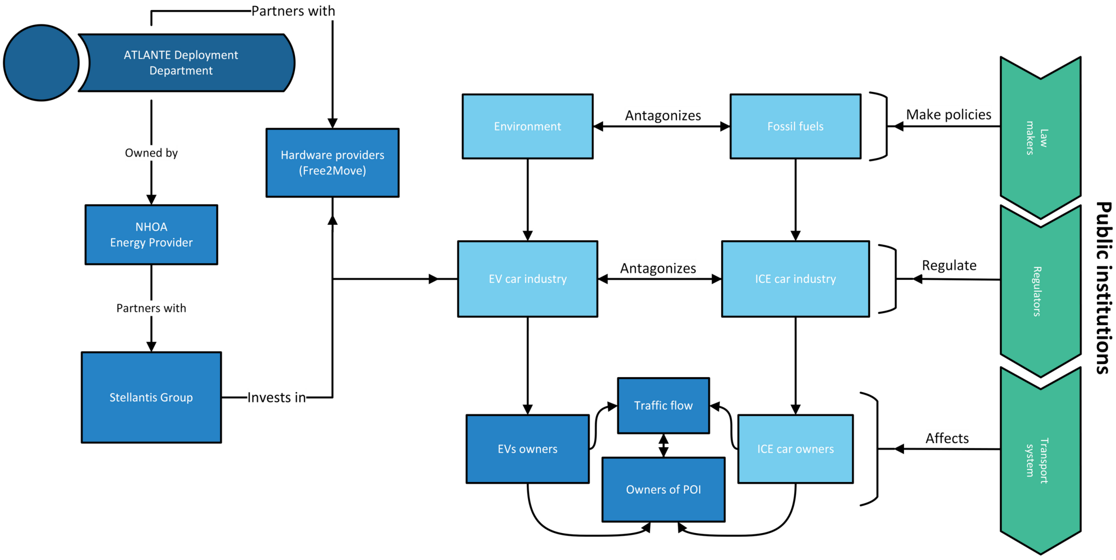


Figure 3: OASIS project stakeholders' relationships diagram

3.2. Framing the users' needs and requirements

Due to the presence of this abundance of entities involved in the realisation of the project and its outcomes, a comprehensive collection of their needs is fundamental. Indeed, the latter would then translate into technical or operative requirements for the software development. To this purpose, a further classification has been created to better detail the process. More specifically:

- The *Technical Stakeholders* predominantly include the members of Atlante's deployment department, which have direct interaction with the software as part of their job
- *Business Stakeholders* are composed of Atlante's business managers (who consider the economic feasibility of the firm), as well as NHOA's Electricity division, which not only is a primary reference company for the team, but also aim to preserve their own interests (grid infrastructure management)
- *Impact Stakeholders* that consist of social and political organisations, public entities, and the European mobility departments, which all take interest in the electric transition, in the impact on the environment and in the transportation sector evolving within their nations, or cities to a smaller scale.
- *Functional Stakeholders* cover all those indirectly affected individuals as the end EV users

Each and every category has its own needs, and those can be classified accordingly to their nature in turn. Note that the need's nature does not always have a direct correspondence to each stakeholder category (e.g. business stakeholders might have both financial and technical related needs). It is worth to mention that, in the end, the majority of all needs (independently of their nature) eventually translate to software requirements for the development team. In conclusion, the needs' nature can be of four types related to: Technical implementation, Finance and Economics, Social and Political, and Mobility.

Technical Implementation
Being the OASIS team primarily an algorithm provider, the greatest focus is fully devoted to Atlante, the infrastructure management company that will make use of our software to allocate and size the charging stations. Because the company has monitored and supervised the whole development cycle of the project, there have been multiple occasions of discussion regarding their needs during the subsequent usage of the software, the goals to pursue, and how those translated into specifications for the algorithm itself.

To begin with, the project kicked off with the definition of the main tasks to accomplish, then, as time passed, further adjustments and more needs emerged. Aside from the main structuring of the model (which will be described later), the user needs have been highlighted in terms of what are the necessary elements to include for a favourable software-user experience. It has emerged that Atlante's deployment department members find it crucial for the algorithm to be easy-to-use, provide meaningful explanation of the results and, not less importantly, to be automated to the greatest extent possible. This means that the software is required to be user-friendly, must avoid repetitive input operations, moreover the results obtained must accurate and yet easily interpretable at the same time. From a technical point of view, this translates into a software capable of running successive and iterative operations without the need of excessive manual inputs from the user. Additionally, the development phase must dedicate great care in programming the results to be presented in relevant graphs as well as the overall User Interface, both being understandable at a glance. To account for all these needs, the team eventually implemented a Python Web-App allowing the user to easily choose which city to analyse, evaluate, and obtain results from, all given a single input.

As previously mentioned, the technical implementation needs are moved not only by the technical stakeholders. Indeed, NHOA electric division members (despite being part of the Business Stakeholders category) also need to somehow interact with the optimal allocation model. Being their activities related to energy storage and distribution, a number of employees need to make interpretable and data-driven decisions, generated by the algorithm itself. In short, this requires providing a proper training for the interpretation and potential usage of the software in the long run as well.

Finance and Economics
As a part of the intended outcomes of the project, the software has been realised so that it is able to evaluate the economic feasibility and cost/revenues of the optimally chosen deployment locations (the process of such evaluation will be described in the next chapters). This has been done to tackle a variety of stakeholders' needs, which, also in this case, have been easily gathered through direct interaction with the industrial partners. To begin with, Atlante needs to maintain the investors trust, thereby this requires deriving comprehensive reports of the obtained results, which must be interpretable and meaningful for their interests. Further than that, the company shares a common interest with NHOA

Energy, which is seeking to improve financial revenues of their companies. Thus, to achieve sustainable economic outcomes, the optimisation model needed to be accurate and efficient, meaning the team firstly focused on:

- determining to the greatest detail all the potential parameters to consider and their weight in the evaluation of each location (traffic flow, POIs, sociodemographic distribution. . .)
- gathering as much data as possible concerning those previously defined parameters
- framing the economic model based on relevant data (energy cost, maintenance costs, expected revenues, usage rates...)

Of note, is that the phase of data collection is in truth much more challenging than one might believe. Not only data must be reliable (i.e. from a certified source), but must also be as complete as possible (should not exclude any road or existing charging point) and possibly be open source, for improved economic feasibility.
To embrace NHOA's needs as well, the algorithm should additionally consider the proximity of currently existing electric grid infrastructure in the optimal location positioning, with the purpose of minimising expansion costs. To this end, the team has had the possibility to gather the necessary data related to the expansion costs thanks to direct collaboration with partners through Atlante, and eventually include this analysis in the economic model.
Furthermore, as a shared interest for favourable revenues, it is desirable that the charging stations are placed nearby busier roads, so to deliver the services of NHOA and Atlante to the greatest number of customers possible. Last but not least, despite not having a direct influence on the design of the optimisation model, POIs' owners gladly benefit from the positioning of charging stations near their activity. A parking spot with allowed charging close to a restaurant would possibly attract more customers, in some cases, just for the presence of the possibility to recharge. Indeed, the evaluation of proximity to POIs has been meticulously implemented into the model, addressing both the EV users and the owners' needs.

Social, Political & Mobility
Social and political demands, as well as the ones related to everyday mobility issues are predominantly coming from Impact and Functional stakeholders. Bear in mind that, in this case, the team has not had the chance for direct interactions with the above groups. To fully grasp their needs and impact on the project development, extensive research has been performed, seeking for existing interviews. Indeed, the electric mobility transition, the impact of EV charging station placement, the adoption of such technologies and their business opportunities, have been publicly discussed during these present years. This can be observed from a number of interviews arranged with politicians (as the United States' secretary of Transport, the Piedmont region president in Italy or European Council members), with enterprises' CEOs (Stellantis, NHOA) or with Chief Commercial Officers of companies promoting and selling EV (which have reported their users' needs).

Despite the project intends to solve real issues (like range anxiety for EV users) or to contribute to reducing environmental pollution generated by the transportation sector, it is crucial to evaluate unintended negative effects on society, mobility patterns, as well as grid infrastructure balance. Such topics are of enormous importance, so much so that they are widely discussed internally to all countries' public institutions. As an instance, Thomas Massie, member of US House of Transportation Representatives, stated that [[5]]: "According to Joe Biden's policy by 2030 approx. 50% of cars in the USA should be electric, reaching 100% in 2035. According to the US department of energy this will lead to an energy consumption of 25 times as much as the refrigerator, in an average American household; or equivalently, 4 times the consumption of air conditioning. This massive energy consumption will lead to blackouts and inconvenience, since those goals were set considering political science instead of engineering." Indeed, part of the initial phase of the project focused specifically on gathering knowledge related to the above described issues, driven by the responsibilities that engineers have when playing such a crucial role in this sector. Further than that, misplaced or unbalanced distribution of EV charging station might redirect traffic flows, possibly generating congested roads and traffic jams in specific areas. Each city's mobility councillor needs this to be avoided, which requires the model to strategically place charging stations on frequently chosen and larger roads, rather than deviating traffic flow to smaller and tighter city streets. Nonetheless, each chosen location must comply with the current local territory urban policies, meaning that the optimisation model also requires input data related to such policies constraints. At the same time, the sizing of the charging stations and optimal placement is a key aspect for the end EV users, which wish for a capillary charging network that simultaneously keeps waiting times as short as possible.

In conclusion, Figure 4 is reported to visually summarize the above-described process and classifications on the whole. In particular, a prior stakeholder analysis has been performed to shape the scope of the project and how its outcomes might affect the industrial partners and society. Gathering all their needs eventually allowed to understand the shared interests and peculiar necessities, eventually translating each one into a project requirement in order to find optimal solutions and tackle them all.

	Needs	Stakeholders	Requirements
Technical implementation	1. Easy to update tool 2. Interpretable and data-driven decisions 3. Few manual operations required 4. Maintain a balanced electric grid load	1. Atlante Deployment Department Employee 2. Nhoa Electricity Division Manager 3. Atlante Deployment Department Employee 4. Nhoa Electricity Division Manager	1. The algorithm requires constant regular support and an update schedule 2. The employee must be properly trained about how to use the software 3. The software must be automated, user-friendly and require no manual adjustments at each iteration 4. Presence of energy storage system
Finance and economics	1. Mantain investors trust 2. Keep grid expansion related costs low 3. Keep installation cost low 4. Improve financial revenues 5. Augment POI's traffic	1. Atlante Deployment Department Employee 2. Nhoa Electricity Division Manager 3. Atlante Business Department Manager 4. Nhoa Electricity Division Manager, Atlante Business Department Manager 5. POI owners.	1. The algorithm must produce interpretable results 2. Algorithm must take into account current grid 3. Algorithm has to consider land prices as a scoring parameter 4. To allocate charging stations, the algortihm has to focus on busier roads 5. Decisional model must evaluate POI position in the optimization problem
Social and political	1. Comply with local territories urban policies 2. Follow regulators environmental protection laws 3. Reduce range anxiety 4. Promote diffusion of EV	1. City mobility councillor 2. European Council member 3. Electric Vehicle owner 4. European Council member, EV car industry	1. Algorithm must take into account urban policies constrains into the optimization problem. 2. The decisional model developed must reduce pollution 3./4. Take into account long routes traffic and increase the available infrastructure
Mobility	1. Keep waiting times in charging station low 2. Capillarity of the stations network 3. Redirect traffic in order to enhance mobility	1. Electric Vehicle owner 2. Electric Vehicle owner 3. City mobility councillor	1. Algorithm has to take into account charging time in the sizing of the charging station 2. Maximize the number of charging station 3. Traffic is to be used as an input data, predicting the impact charger placement may have on it

Figure 4: OASIS project stakeholders' needs and requirements

4. State of the Art

The analysis of the state of the art included various aspects that were crucial in framing the problem as well as finding possible lines of action; therefore, the focus was on the optimization model, the infrastructure, and the Vehicle to Grid (V2G) technology.
The research on the optimization model provided insights and trends through existing solutions, while the study of the infrastructure allowed for understanding energy aspects, filling the gaps due to the lack of energy engineers in the group; finally, the evaluation of the V2G technology provided information regarding future developments.

4.1. Benchmark analysis

This section is focused on answering the following four pivotal research questions:

1. **Exploration of Existing Solutions for Optimal Electric Vehicle Charger Allocation:**
   The investigation delved into an in-depth analysis of the current landscape of solutions aimed at achieving the optimal allocation of electric vehicle chargers. By analyzing a range of existing approaches and methodologies, the aim is to uncover the diverse possible strategies that have been developed to address this challenge.

2. **Direction of Research Trends Over Recent Years:**
   Another key focal point of the project revolved around the examination of the direction that the research have pointed in recent years. By tracing the evolution of various research directions, it is possible to understand a potential convergence or divergence in the optimal method within this dynamic field.

3. **Primary Inputs used in Charger Allocation Strategies:**
   Central to the investigation was the exploration of the primary inputs that play a pivotal role in shaping the formulation of effective charger allocation strategies. Through an analysis of different research papers it was possible to understand which are the most useful inputs parameters to use in this type of problems.

4. **Emergence of Projects and Research Groups in the Field:**
   A noteworthy aspect of this area of research was the identification and examination of projects and research groups that have concentrated their efforts in the electric vehicle charger allocation.

4.1.1. Existing solutions

GIS-based approach
The problem of the optimal allocation of EV charging stations has been widely discussed in the literature and different methodologies have been proposed. The most popular approach involves the use of the Geographic Information System (GIS). GIS is a system that can create, manage, analyse, and map any type of data. It relies on spatial data, which includes information tied to specific geographic locations. This can range from simple coordinates (latitude and longitude) to complex spatial geometries that represent features such as roads, buildings, and natural resources. In addition to spatial data, GIS incorporates attribute data, which provides additional information about the features or locations being represented. Attribute data can include attributes like population, temperature, land use,

and more. Through GIS it is possible to link integrate and overlay all these types of data on a single map to relate and compare different types of information. This helps users understand patterns, relationships, and geographic context. The benefits include improved communication and efficiency, as well as better management and decision-making processes.

The paper [6] presents a geospatial analysis of electric vehicle charging infrastructure allocation, within a city and a region, based on GIS tools. Specifically, the aim of the proposed methodology is to provide optimal locations of EV within a spatially extended region. Two different cases were identified: placement in a city network and placement in a regional or national network (rural roads and highways).

- The approach at city level is based on a set of collected geospatial data that are edited to be transformed into raster layers. A map is created with square cells of size 100x100 m. This calculated map indicates the optimal city areas where EV charging infrastructure could be placed according to specific scoring levels. The final location should consider space limitations and the maximum acceptable distance from the electricity network. The input data used in this case are residential statistics, position of parking areas, electric power distribution network, public transport stations, distribution of points of interest.
- The regional/national level analysis aims to allocate EV infrastructure every x km, where x should be large enough to ensure that no electric vehicle remain without adequate charge on the road. Charging stations on highways must be placed in already built areas (rest areas, gas stations, etc.) since the cost and time to construct new areas is high. The required input data for the regional level allocation mainly concern information about the road network and distribution of service areas.

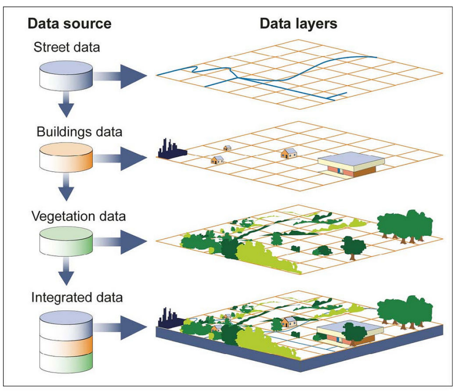
As to the final results, for a city and a regional network, the methodology identifies high-potential areas for the installation of charging stations. In contrast, for a highway network the methodology provides explicitly the suggested locations: the charging stations should preferably be placed in already built areas, gas stations or rest areas, to minimize additional investment costs.

In [7] the use of GIS is combined with a Multi-criteria Decision Analysis (MCDA) to address the EVCS site selection. Across many of the revised papers, Analytic Hierarchy Process (AHP) is a recurrent and broadly applied MCDA method. It emerges as a technique to determine the weights of criteria and priorities of alternatives in a structured manner based on pairwise comparison This methodology conceptualizes a decision-making problem through the lens of a hierarchy, encompassing criteria, sub-criteria, and alternatives. The decision-maker expresses their preferences with regards to the selected set of criteria, thus contributing to a structured and informed decision-making process. In the paper, a four-step solution approach is developed for the problem. The first step consists in the determination of 15 criteria of evaluation of a location which cover three dimensions, environment, urbanity and economics. In the second step, based on the previously identified criteria an availability score is assigned to each EV charging station site. The third step consists in prioritizing the criteria using Analytic Hierarchy Process (AHP), a broadly applied multi-criteria decision-making method to determine the weights of criteria and priorities of alternatives in a structured manner based on pairwise comparison. Finally, all the potential sites are ranked.

Finally, another paper that, similarly to the previous one, follows a GIS-based approach together with a MCDA is [8]. This paper seeks to support local governments in the implementation of their public charging infrastructure for electric vehicles in terms of size and placement. In the initial phase, the paper estimates the demand for charging based on four different scenarios projecting EV adoption and public charging trends in 2030. The second step involves conducting a geospatial analysis of the study area, taking into account both supply and demand criteria to assess the desirability of each location on a grid map. Supply criteria encompass factors related to the availability of infrastructure, while demand criteria are categorized into three aspects: residential, commercial, and recreational. The prioritization of these demand criteria is determined through input from the municipality using the AHP to align with its strategic objectives. Following the creation of a suitability index map, a k-means clustering algorithm is applied to ensure comprehensive geographical coverage of the charging network. Ultimately, the recommended charging stations from each scenario are assigned to the highest-ranking locations, establishing a municipal public charging network.

On the basis or the analyzed papers, the following common framework has been identified for adopting a GIS-based approach:

1. **Formation of a Grid of Cells, starting with the layer with the largest spatial extent:**
   The first step entails the creation of a grid of cells, with the process initiated by working with the layer that spans the most extensive spatial area.
2. **Generation of Buffered Layers Corresponding to Each of the Different Data Types:**
   Buffered layers are fashioned for each distinct data type under consideration.
3. **Integration of Every Buffered Layer into the Initial Grid:**
   The buffered layers are integrated with the original grid structure.
4. **Normalization of Cell Values:**
   A pivotal stage involves the normalization of values attributed to individual cells.
5. **Derivation of the Final Score through Layer Overlay:**
   The conclusive scores are arrived at through a process that involves the superimposition of the various layers, resulting in a comprehensive evaluation.



Source: GAO.

Figure 5: GIS-based approach

Graph approach

Another prevailing strategy for achieving optimal allocation revolves around a graph-based framework. This approach involves the creation of a graph originating from a collection of potential nodes, interconnected through routes and links.

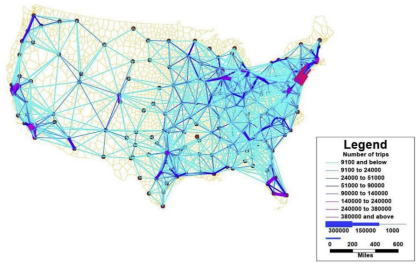


Figure 6: Graph based approach

The overarching goal might involve minimizing the number of elements while factoring in the constraint of having one element per route. Alternatively, an approach might aim to maximize the flow of traffic within the graph.
The specific constraints to be considered naturally hinge upon the available input data. A few illustrative examples encompass cost, material availability, geographical factors, and coverage requirements. The successful application of this approach hinges on tailoring the constraints to align with the underlying dataset.

Other approaches

Moreover, there exists some other approaches less used to perform such allocations. For instance, the Improved Whale Optimization Algorithm stands out as an alternative approach. This technique draws inspiration from the hunting behavior of whales, adapting their social behavior and exploration strategies into an optimization algorithm. It aims to locate optimal solutions through a combination of exploration and exploitation.
Another option is the application of a Genetic Algorithm, a heuristic optimization approach inspired by the process of natural selection. In this context, solutions are treated as individual "genomes", subjected to selection, crossover, and mutation operations to iteratively improve their fitness. Genetic Algorithms are particularly useful for combinatorial optimization problems, seeking optimal solutions by mimicking evolutionary processes.
Furthermore, the utilization of a GeoSpatial model using Kriging prediction and clustering offers a distinctive avenue. Kriging is a geostatistical interpolation technique that estimates values at unobserved locations based on nearby observations. When coupled with clustering methods, it can assist in grouping spatially related data points, aiding in the identification of trends and patterns within the dataset.
Each of these approaches provides a unique lens through which to approach the challenge of optimal allocations, catering to specific problem domains and characteristics.

4.1.2. Research direction

For what concerns the evolution in the research it is possible to affirm that convergence on a single approach has not been reached. In a large literature review conducted by Pagany [9], there were no predominant strategies to optimally allocate recharging stations.
The text discusses the pivotal role of electric mobility (e-mobility) in the transition towards more sustainable energy systems, particularly within the transportation sector. It underscores the growing global interest in electric vehicles (EVs) as a promising alternative

to traditional fossil-fueled vehicles. However, for EV adoption to reach its full potential, the establishment of an efficient charging infrastructure is paramount. The text highlights the importance of strategically locating charging stations (CS) to ensure widespread access and usability for EV users. Determining the right locations for these stations is a complex task, involving considerations such as demand density and trip length. To address this challenge, various methodologies for CS localization have emerged in recent years.
The key contribution of the text is the proposal of a classification scheme for these localization methodologies. This scheme helps categorize them based on their underlying modeling theories and practical applications. Furthermore, the text delves into the nuances of spatial location planning for charging stations, examining the criteria used for their selection and the analytical processes employed. Additionally, the text points out a lack of comprehensive empirical data on EV traffic behavior, which poses a significant challenge in accurately planning and deploying charging infrastructure.
In conclusion, the text offers a comprehensive overview of the importance of e-mobility and the critical role of charging infrastructure in this transition. It introduces a classification approach to understand the various localization methodologies and highlights the need for more comprehensive research to address the evolving challenges and opportunities in the field of electric mobility.
Such paper was important to answer the research direction question. Indeed, in the main part of the article, the author principally analyzes existing research, attempting to discern patterns, trends, and prevailing approaches. The article sheds light on the absence of any prominent strategies that have universally dominated the field, reflecting the dynamic nature of this evolving domain.
From the results presented in the article is clear that the evolution of the research is still stuck on a dualism between graphs and grid approaches. The choice of which method utilize often depends on the constraints and input parameters of the problem.

4.1.3. Input parameters

As previously mentioned, the potential input parameters to be considered within the optimization model are diverse and can be categorized into three primary groups. These comprehend *Users' data*, which entails parameters associated with the influence of individuals. This includes demographic information, such as age and income, as well as geo-location data.
The second category pertains to *Destinations' data*, encompassing crucial details about Points of Interest (POI) and charging stations. This set of parameters plays a pivotal role in shaping the allocation strategy, as it involves identifying high-traffic areas, popular destinations, and charging infrastructure distribution.
Lastly, the third set encompasses *Routes data*, a facet predominantly influenced by infrastructure and traffic variables. Examples of pertinent parameters within this category encompass infrastructure costs, the likelihood of utilizing a recharge station, the required charging capacity, and the imposition of constraints on route distribution.
Further examples of Routes data could encompass the financial implications of utilizing specific infrastructure, indicating the cost-effectiveness of utilizing various charging stations. Likewise, considering the probability of recharging station usage aids in devising strategies that cater to user preferences. Meanwhile, incorporating charging capacity requirements facilitates efficient resource allocation, ensuring that stations cater to varying charging needs.

Additionally, constraining route distribution serves as a mechanism to regulate traffic flow and station utilization. This could involve ensuring equitable station access across different regions or managing peak demand periods effectively.
By synthesizing these diverse input parameters across the three main categories, the optimization model endeavors to strike a balance between user needs, destination dynamics, and route intricacies, culminating in an effective and tailored solution for electric vehicle charging station allocation.

4.1.4. Existing projects

The final research question of the benchmark analysis aimed to understand which companies or group projects are specialized in the research field. Unfortunately, the availability of such information is quite limited, and only one study was identified: the research titled *"Optimal locations of U.S. fast charging stations for long-distance trip completion by battery electric vehicles"*[10].
This study examines the approach developed by Tesla and classifies it as a graph-based method. The text discusses the challenges Tesla encountered in promoting battery electric vehicles (BEVs) due to environmental and energy concerns. It highlights two main issues: a lack of fast recharging infrastructure and limitations on the range of BEVs, which hinder their adoption and usage.
To address these challenges, the paper proposes a solution using U.S. long-distance travel data. The goal is to strategically place charging stations across the United States to maximize the completion of long-distance trips using BEVs. Different scenarios are considered, varying the number of charging stations from 50 to 250 and the all-electric range (AER) of the vehicles from 60 to 250 miles (97 to 402 km). The problem is formulated as a mixed integer program, and a modified flow-refueling location model (FRLM) is used in conjunction with a branch-and-bound algorithm to find solutions. The results of this analysis indicate that the percentage of trips completed with a 60-mile AER varies from 31% to 65% as the number of charging stations increases from 50 to 250. The study suggests that BEVs with at least a 100-mile range (161 km) are likely needed to address long-distance travel concerns for the majority of U.S. households.
In summary, the research offers an effective method to determine the optimal number and locations of fast charging stations under different conditions. The approach described as a FRLM is indeed a graph approach and aims to facilitate better planning and the development of more sustainable transportation systems.
To conclude, despite the restricted information encountered, this study sheds light on Tesla's strategy for optimally placing fast charging stations in the U.S. to support battery electric vehicles on long-distance trips.

4.2. Infrastructure

The evaluation of electric vehicle charging's impact on the grid is of considerable importance as highlighted by ENTSO-E's (European Network of Transmission System Operators for Electricity) deep analysis [11]. The convergence of EVs as a dual-purpose resource underscores their potential in addressing transport sector decarbonization and enhancing energy system flexibility. To maximize these benefits, a harmonious fusion of EVs with grid infrastructure is crucial. The integration of intelligent charging systems and vehicle-to-grid technology stands as a pivotal step towards achieving these advantages. Emphasizing the substantial role of EVs in the broader energy landscape, there is a discernible trend towards embracing electric mobility, especially given the ongoing advancements in EV models. However, the challenge lies in bridging the gap in charging infrastructure, coupled with the implementation of effective smart charging mechanisms. The EV charging process effectively serves as a bridge connecting transportation and energy domains, underscoring its pivotal role. Unregulated charging practices pose the risk of imposing peak power demand on the grid, which controlled management seeks to mitigate. Through scheduled charging, power profile optimization, and market-based mechanisms, the grid-related challenges can be effectively managed, paving the way for new opportunities. Smart EV charging not only aligns with the seamless integration of renewable energy sources, grid stability, and cost efficiency but also leads to emissions reduction. Moreover, it enhances overall system management while offering tangible benefits to EV users in the form of cost savings, dependable services, and contributions to sustainable transportation paradigms.The infrastructure analysis was performed with the aim of assessing the impact of different charging topology on existing grids. Then, using existing case studies as reference, possible solutions to reduce this effect were analysed, such as active integration.

4.2.1. Grid organization

Existing electric grids can be divided into two main groups: rural and urban. The main differences rely on power limits and distribution areas: the former group covers large areas with limited power density (in general it's based on HV lines, while distribution network is poorly capillary and limited in power), while the latter focus on concentrated areas with high users' density (so it relies on MV/LV lines extensively distributed). Base curves allow to analyse and predict power requirements during the day, assessing dependency on time, day and season. In general, we can identify the main power peak between 3 p.m. and 8 p.m. but each specific case can differ[12].

4.2.2. Charging infrastructure and standards

The landscape of electric vehicle (EV) charging technologies is diverse, encompassing wired conductive methods that ensure power levels, safety, and vehicle interoperability. Inductive non-wired solutions are explored for highway use, while battery swap systems find relevance in specialized contexts like car races or fleet applications. Alternating Current (AC) infrastructures rely on onboard chargers and are limited by vehicle size and cost, whereas Direct Current (DC) setups leverage off-board power electronics for higher charging capacities, reaching up to 350 kW. The trend now favors DC charging, which is becoming standard across EVs, while AC charging is typically kept below 22 kW.

The growing adoption of EVs in Europe correlates with an increase in charging infrastructure. Over the past four years, public charging points more than doubled, surpassing 200,000 units. Of these, around 90% are "normal chargers" with up to 22 kW capacity, and the remaining 10% are "fast chargers" offering 50 kW or more. Leading in charging infrastructure expansion are countries like the Netherlands, France, and Germany[11].

The vehicle-to-public charging point ratio emerges as a key parameter, with the Alternative Fuels Infrastructure Directive suggesting an average of one charging point per 10 cars. This approach balances charger availability and investment returns for Charging Operators. However, the ratio's applicability varies based on factors like population density and desired charging strategies, with a lower ratio allowing for more extended vehicle connection and flexibility services.

4.2.3. Grid impact

Considering different charging strategies, it's clear they can significantly affect the power grid. Simultaneously, network characteristics, such as urban versus rural grids, connected loads, grid topology, and operational attributes, can introduce unique challenges. For a comprehensive assessment of impact, targeted analyses of grid segments become essential. However, certain common elements emerge, facilitating a general overview of potential grid concerns across various use cases.

Reflecting upon the considered use cases, three primary conclusions emerge [11]. Firstly, widespread slow charging may engender elevated power demands owing to simultaneity effects. This scenario is particularly pronounced during instances of numerous additional loads connected to low voltage (LV) lines, notably during evening peak periods, and could potentially lead to overloads on Secondary Substations or LV lines themselves. The subsequent part underscores how the implementation of smart charging effectively mitigates this predicament. Secondly, instances requiring momentary high-power connections necessitate the installation of fresh, dedicated substations alongside connection lines, thereby incurring supplementary expenses and time investments. Lastly, when the charging infrastructure caters to buses and trucks, substantial additional megawatts could be imperative. In such a scenario, the potential installation of new lines or even primary substations might be requisite. Robust collaboration between charging and grid operators is strongly advised to ascertain optimal location and technical solutions.

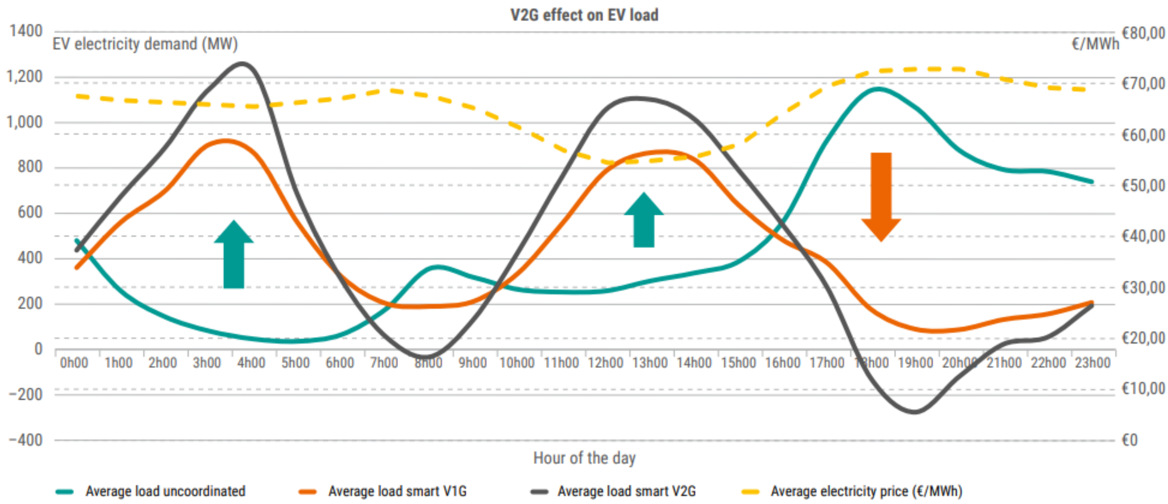


Figure 7: Grid impact for different conditions

In light of these considerations, distinct clusters emerge, categorized as slow/medium charging and fast/ultra-fast charging. These clusters exhibit divergent impacts on infrastructure, power requisites, and charging duration. While private and public charging on streets and parking areas typically involve low power, extended connection times, and minimal impact on energy supply, high-power chargers may necessitate augmented medium voltage (MV) lines to accommodate heightened loads, thereby mandating supplementary investments. It is noteworthy that only slower chargers are amenable to active integration approaches such as Vehicle-to-Grid (V1G) or Vehicle-to-Grid (V2G), as these may conflict with the goals of fast-charging strategies.

4.2.4. Californian Demonstration Site (CAISO)

Quantifying and deciphering EV charging patterns is a first crucial step to make a meaningful evaluation of the impact of electric vehicles on the distribution grids. The paper [13] uses statistical analysis to shape such patterns, based on real-world charging data collected from a demonstration project based in Los Angeles, CA. Despite considering a small amount of EVs (17), UCLA examined their charging patterns across the chargers deployed on campus for over a year, for a total of 19.617 charging events. It has emerged that the energy transfer in 90% of those charging events required less than 12 kWh. At the same time, it has been observed that 67% of events occurred with a plug-in time of less than 4 hours, whereas 87% were below 7 hours. Essentially, it frequently happens that users leave their vehicles parked and plugged longer than the time needed for a full charge, which leads to assume there would indeed be great benefits in introducing active smart charging. Further than that, the paper derives important conclusions regarding the overall impact of EV charging on the total load distribution, simulating increasing penetration rate (PR) starting from the data obtained on site.

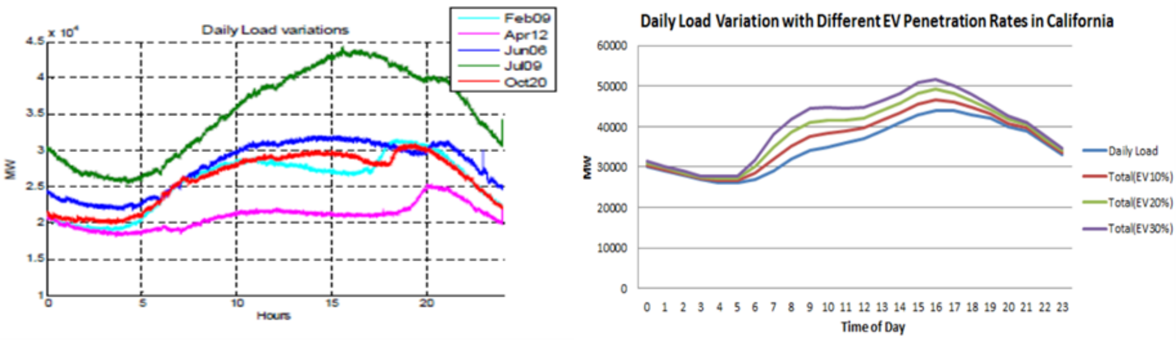


Figure 8: Daily Load Variation by CAISO and simulation at increasing PR

Figure 8 clearly shows that the increasing percentage of population using and charging EVs would eventually have the potential to considerably increase the grid load. Not only that, but by reporting CAISO load curves, it can be seen how they are greatly affected by seasonality, meaning the impact of EVs would be even more considerable during summer months, due to the stressed state of the electric infrastructure.

4.2.5. Finnish Smart Charging

Based on an actual case area located in Southern Finland (Lappeenranta city), the effect of smart charging has been simulated to verify the effects on grid load variations [14]. The low-voltage grid in the area is made of two substations with about 400 kW of peak annual power in total. Starting from real traffic flows measurements of the area, estimating average travelling distances and battery capacities, the optimised model of smart charging involves charging all vehicles when the grid load is at lower amplitudes. The algorithm also requires input data concerning plug-in times and the power limits mentioned above. Thanks to all those data, the simulation is capable of maintaining the grid load below the highest peak at base value, even when a 100% penetration rate is considered. This way, the paper highlights how it is possible to make a step further to a simple charging event delay, reaching optimised charging when the base load exhibits its lowest values, thus allowing to reduce the transmission fees paid by the end user.

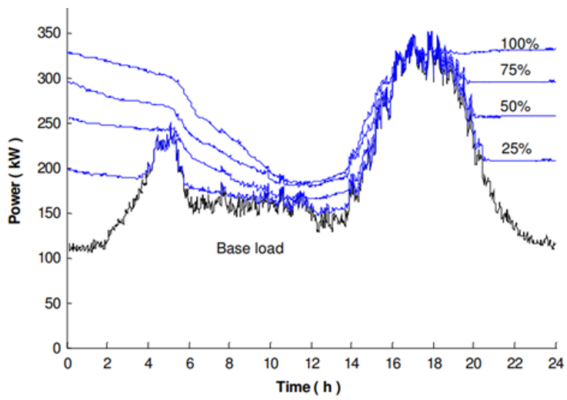


Figure 9: Base Load control with Smart Charging at increasing PR

4.2.6. Simulation of Italian Grid Topology

Although smart charging seems promising, a major downside is present, indeed it is not always desirable to slow down the charging process, and least of all to delay it. Therefore, would the existing distribution lines be able to manage the increasing demand in those cases? The paper [15] focuses on the potential issues related to power overloading of the distribution lines, especially considering the different kinds of grid topology in various areas. By simulating the typical Italian travelling habits on a statistical basis, the specific impact of charging on real networks is studied. The urban, rural, and commercial networks cases are considered by assessing the impact of both slow and fast charging methods. While slow charging is applied only to urban and rural areas at nighttime, fast charging occurs at daytime and closer to POIs. The commercial network is also examining the installation effect of super-fast charging stations (i.e. up to 150 kW). All topology are simulated at increasing penetration rate, specifically at 20%, 40%, 60% and finally 80% PR.
The analysis conveys that:

- For the *Urban Areas*, the voltage drop generated is not exceeding the nominal minimum values. However, for the worst-case scenario (at 80% PR), the transformers overcome their 150% peak capacity threshold, meaning that they would surely be damaged and require upsizing. On the other hand, introducing smart charging techniques (which involve photovoltaic energy usage during the day), allow keeping the voltage profiles and load curves below their respective limits.

- *Rural Areas* are generally less burdened; thus, the MV/LV transformers are capable of sustaining up to 80% penetration rate without producing significant criticalities (reaching a maximum of 128% loading peak). Not only that, but the situation is even more stable when implementing PV support. Hence it can be concluded that the rural network is robust and possibly oversized, ready to withstand the massive penetration of EVs in the future.

- The last set of simulations involve the installation of ultra-fast charging infrastructure into *Commercial Areas*. Note that this type of chargers can be installed either in LV or, more commonly, in MV, which is the solution adopted by the author as well. The results indicate that the voltage drop is limited in magnitude, assuring working conditions within the technical standards.

It would be reasonable to assume that these trends would generally remain the same when investigating different seasons' base load curves. However, from the considerations made previously, it is important to bear in mind that potential critical situations might occur especially during summer months, requiring further studies to this end.

Figure 10: Urban (left) and Rural (right) networks' transformers loading trends

4.3. V2G application opportunities

4.3.1. Overview

Vehicle-to-Grid (V2G) technology is a groundbreaking innovation that allows electric vehicles to not only draw power from the grid but also feed excess energy back to the grid when required. As the demand for electric vehicles (EVs) continues to grow, V2G has the potential to revolutionize the charging infrastructure market. In this relation, we will explore the future impact of V2G technology on the EV charging station market and we will try to answer to three main questions:

- Do exist countries that allow the use of V2G to provide service to the final customer?
- Are there well-established remuneration schemes for those who offer their car to sustain these services?
- What is the state of the art that emerges from the current projects?

In analyzing these points, the focus has been on Italy, with the aim of better understanding how it is collocated with the other European countries.
Looking at the current reports about the last and most important projects the V2G-dependent services appear to be in their early stage. In fact, if the V2G technology itself is quite mature, its actual application to provide services (Firm Frequency response, Arbitrage, TRIAD, Demand Turn Up, Short Term Operating Reserve etc) must be tested

on a larger scale and more data about their performances must be collected. This inequality between the Technology Readness Level of the service with respect to the technology make quite difficult to directly introduce this services to the grid and consequently their impact can just be estimated [16]. As it emerges from this study, directly introducing V2G would create more benefit for the DSO than for the car owner. In addition an easier solution like the V1G(smart charger) would cover the majority(up tp 80%) of the saving given by the V2G. Instead, in the case where the abovementioned service would be available, this percentage may vary a lot depending on the plugin-time and on the market price of the service provided to the grid, making the range going from 40% to 10%, but this last case is the more optimistic one concerning the FFR selling price and the plugin-time, reaching the 75% of a day.

4.3.2. Technical and Regulatory barriers in Europe

Technical and regulatory issues is what stops the diffusion of V2G, although encouraging pilot programs [17]. Technical issues relate with topics such as battery degradation, charger efficiency and aggregation [18]; according to a study conducted by PwC[19] and covering Sweden, Netherlands, France and Germany,some regulatory issues, are:

- the definition of the storing activity from a tax point of view, to avoid a double fee (one for charging and the other for discharging operations);
- the lack of coordination between the smart charging initiatives and DSO;
- the low incentives for large-scale expansion of the services (the non-linear cost of capacities is not taken into account yet in the incentives, that is larger capacities cost much more than the lower ones and they are not repaid in the short term by incentives).

In Italy, both the energy dispatching market and regulation are in development. Projects like the Drossone are accelerating the current regulation's evolution. These changes must be technically safe and respect the technological neutrality principle. Therefore, the national organization ARERA (after a consultation with TERNA) has not allowed reducing the minimum power for the UVAM under 0.2 MW yet(the mentioned limits is cited in [20]). It would have made it possible for small aggregation of the car to participate in the market. By comparing the current stage of diffusion with Roger's curve of adoption[21], it results evident how only innovators have lent themselves to the pilot programs, consequently the remunerations schemes are not meaningful and they are based on refunds for the storing services provided by the user's car. In the future, In the future, as emerges from a study [16] of a UK non-profit organization (CENEX), there could be significant advantages for those who make their car available for V2G services and revenue will be best of all related to FFR, STOR and DTU services. Those services shown the best performance taking into account profitability for the final user and technical properties, such as: readiness for DSR, technical requirements, service stackability etc.

Nonetheless, to have much higher revenue than the simple V1G, the rate of diffusion and the percentage of daily time spent connected to the grid have to grow significantly. Overall, despite its importance in the future energy consumption balance, investment in V2G may not produce considerable income in the short term for the DSOs, but the evolution of such technology can be crucial for supporting the development of a sustainable energy market.

5. The Solution

After carefully evaluating various approaches to the project, it was collectively decided that a GIS-based approach would be the most efficient and effective method to achieve the project's goals. With this decision, it was started the research and the data gathering process.
In the upcoming section, it will be presented the results obtained working on the city of Madrid, the first one taken into consideration. Madrid serves as an ideal case study due to its urban complexity. Through this analysis, the aim is to demonstrate the practical application of the methodologies discussed earlier.

Figure 11: Madrid map

5.1. Data pipeline

To begin with, it was crucial to identify the necessary data that would be required for the GIS-based approach. After carefully reviewing various publicly available sources, there were identified the most relevant, authoritative and reliable data sets for the project. This involved going through a vast amount of data, including maps, satellite imagery, demographic data, land-use data, and infrastructure data, among others.
Once that the necessary data were compiled, it was time to begin to process it to make it usable within the system. Furthermore, it was essential to ensure that the data met the relevant quality standards and was fit for the intended purpose of the project.

5.1.1. Traffic points

The first step was to retrieve the data related to the traffic, which turned out to be the hardest to uncover. A long research led to the retrieval of the traffic behaviour in specific points in 40 cities on the site UTD19 (Understanding traffic capacity of urban networks) [22]. The pre-processing consisted in a aggregation of the measurements and a merge with the points coordinates. This process resulted in obtaining the traffic daily mean in each

point of the cities.
Once obtained the traffic daily mean for each point in the cities, the next step was to create a grid on a map over the area of interest. For each grid cell, the average traffic mean for all the points within that cell was calculated.
The resulting grid gave good understanding of the relative traffic levels across different areas of the city.
To visualize the scores and highlight areas with high traffic levels, it was decided to color the grid cells on a map using a gradient from light blue to dark blue, with the first indicating low traffic levels and last indicating high traffic levels. This allowed to easily identify areas with high traffic levels and prioritize them for further analysis and potential interventions to improve traffic flow. Subsequently in the report the grid cell is analyzed with more attention, showing the results of the described procedure in the Figure 16.

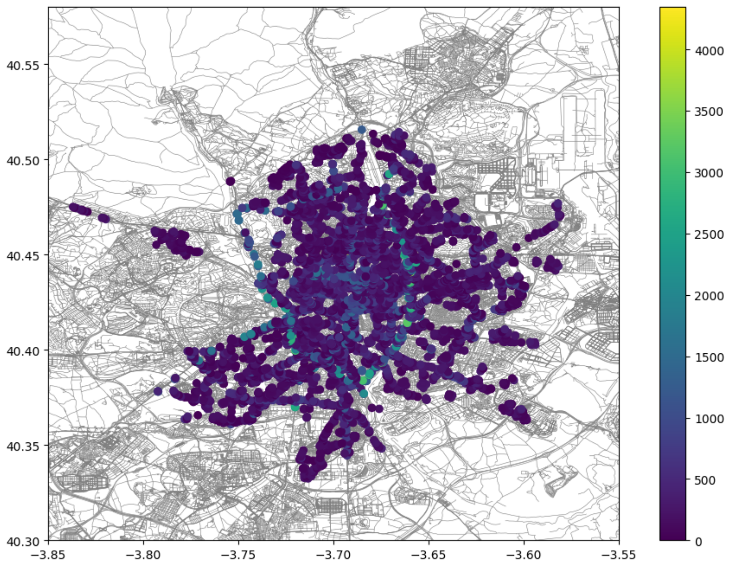


Figure 12: Madrid distribution of traffic points

The distribution of the traffic points in Madrid is depicted in Figure 12. It is important to note that the axes' unit measurements are latitude and longitude, respectively, and that the values of the traffic in the legend relate to the measurement of the average daily number of cars passing from each traffic point.

5.1.2. EV charging stations

The next step was to retrieve the location of the EV charging stations.
After realizing that the data retrieved from OpenStreetMap were not sufficient for the project's needs, it was decided to turn to OpenChargeMap for locating EV charging stations.
OpenChargeMap provides a more comprehensive and detailed database of charging stations in various cities. To access this information, was developed a code that could retrieve the JSON files associated with EV chargers' locations from the OpenChargeMap GitHub repository.
The code was designed to analyze each piece of information connected to the chargers and add it to a CSV file to make it easier to navigate. By doing so, it was possible to retrieve and store useful information about EV charging stations such as their exact location,

hours of operation, and the types of charging ports available at each station.
The process of retrieving this information was crucial in helping create a spatial database of EV charging stations in various cities. By knowing the exact location of these stations, it was possible to develop a plan to optimize routes and facilitate charging for EV users in those cities.
It was decided to focus only on the cities in which were present the traffic points data, the POI (Points of interest) data (described later) and with more than 150 EV chargers. Such constraints implied the reduction to 6 cities that will be analyzed: Manchester, Madrid, Rotterdam, Utrecht, Hamburg and London.

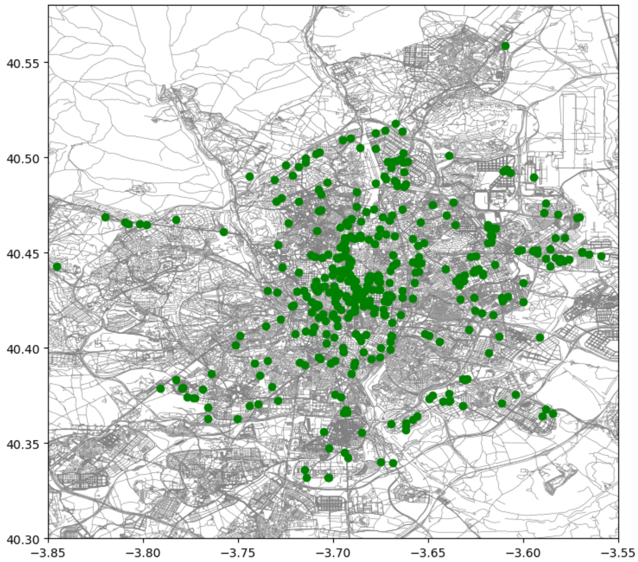


Figure 13: Madrid distribution of existing EV charging stations

5.1.3. Points of interest and streets

An important step was retrieving the street configuration and the points of interest data from OpenStreetMap on the 6 cities considered. It was decided to assign each type of POI in a cluster and give to such cluster a value that will influence the importance of such class.
Following a productive meeting with Atlante, a table containing the clusters and scores that typically form an integral part of their projects was graciously provided.

Category	Cluster score
Food	0.29
Retail	0.27
Leisure	0.17
Tourism	0.14
Finance	0.08
Health	0.02
Education	0.02

Table 1: Distribution of Categories

Table 1 serves as a valuable resource that encapsulates the essential framework upon which Atlante's projects are built. The shared clusters and corresponding scores offer insights into the prioritization and categorization criteria that guide their decision-making processes.
To assign values to the POI clusters, it was first necessary to identify the different types of POIs that exist in each city. The task was accomplished by manually inspecting the data from OpenStreetMap and creating a list of all the different POI types that were found.
Once a comprehensive list of POI types was detailed, similar POIs were grouped together in the clusters defined in the table 1. For example, all types of restaurants, cafes, and bars were grouped together into the *Food* cluster. In the Tables A.8, A.9 and A.10 of Appendix A it is possible to see how each clusters has been created with every POI category assigned to one of the seven clusters.
This allowed to easily compare the importance of different clusters across cities and make recommendations based on the data.
As can be noticed, the higher the importance of a cluster is, the higher the weight assigned. Indeed, such weights will be used as multiplier coefficient in a formula to compute a weighted distance of a possible parking spot to all the POIs. The obtained value will be low for the spots near to a lot of influential POIs and high otherwise. It will be used as multiplier in the objective function of the optimization model in order to take into consideration also the distance from the most important POIs. Specifically, in order to make bigger the objective function when the weigthed distance is little, the distance was scaled in the interval $[0, 1]$ using a MinMaxScaler and inserted through the term $1 - D_j$, with D_j representing such scaled distance. Figure 14 shows the distribution of the seven POI's clusters in the city of Madrid. Food cluster is portrayed by red dots, while health is depicted by orange ones. It is noticeable that there are more health structures towards the city's northeast. Then light blue, mainly located in the center, correspond to Tourism cluster, dark blue to Leisure and green to Education. Finally, pink represents Retail cluster and yellow the Finance one.

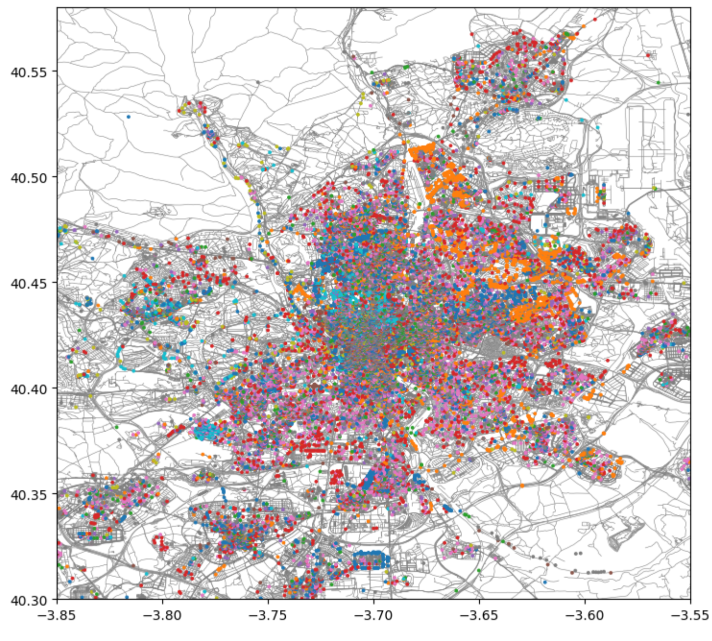


Figure 14: Madrid distribution of POIs

5.1.4. Costs and revenues data

This study employs Life Cycle Cost (LCC) analysis to evaluate the economic feasibility of Electric Vehicles Charger Stations (EVCSs), with a focus on the infrastructure necessary for EV adoption. Implementing a cost and revenues structure is an essential step for any business to understand its financial standing and to make informed decisions for its operations. To this end, relevant data from reputable sources such as [23] and [24] have been retrieved and studied them to develop a comprehensive understanding of the EV charging services' financials. In addition, a wide portion of data come from the collaboration with Atlante company that shared their know-how on the main economic parameters involved.
Some of the data retrieved include the maximum charging rate in kW (defined by Atlante charging station hardware), the average battery capacity of an EV in kWh the average energy transferred in a charging session, and the average charging efficiency [25].
Time value of money is considered through discounting, allowing costs and benefits across different time frames to be equated to present values. The cumulative present value (CPV) encapsulates the total present values of current and future costs related to the EV infrastructure. For the aim of this analysis an interest rate of 5,5% has been used, according to current rates: this value should also be updated in case of sudden changes in the market.
Penetration rate (PR), defined as the ratio between EVs and all vehicles, and catch rate (CR), defined as the ratio between EV users affiliated to Atlante's services among all EV users, represent two important parameters with relatively high level of variability. For the aim of this project indeed, progression proxy values were used, as a reference for future planning, as shown in table 2.

	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032
PR	2,00%	3%	4%	5%	6%	8%	10%	12%	14%	16%
CR	2,00%	2,5%	3,0%	3,5%	4,0%	4,5%	5,0%	5,5%	6,0%	7,0%

Table 2: Proxy progression values for PR and CR

For the aim of this analysis, the accurate determination of the utilization rate is of paramount importance in developing affordable results. In scenarios where charging patterns exhibit discontinuous loading throughout the day, using a correct average value that considers the discontinuous loading pattern is crucial because it captures the dynamic nature of the charging station's activity. According to [26] the load curve for charging stations follows a Gaussian distribution, starting a 5 AM with peak usage typically occurring between 2 PM and 3 PM, as shown in figure 15.

By calculating the area under the Gaussian load curve, which effectively represents the total energy demand throughout the day, it becomes possible to derive the equivalent full-load working hours of the charging station. This metric offers a more accurate reflection of the station's effective operational duration, accounting for the varying intensity of demand. Consequently, when comparing these equivalent full-load working hours to the total 24 hours in a day, the resulting utilization rate (UR) provides an insightful measure of how effectively the charging station is being utilized. The resulting UR obtained is about 31%, for an average daily usage at full-load of 7.5 hours.

This approach takes into consideration the temporal discontinuity of the loading pattern,

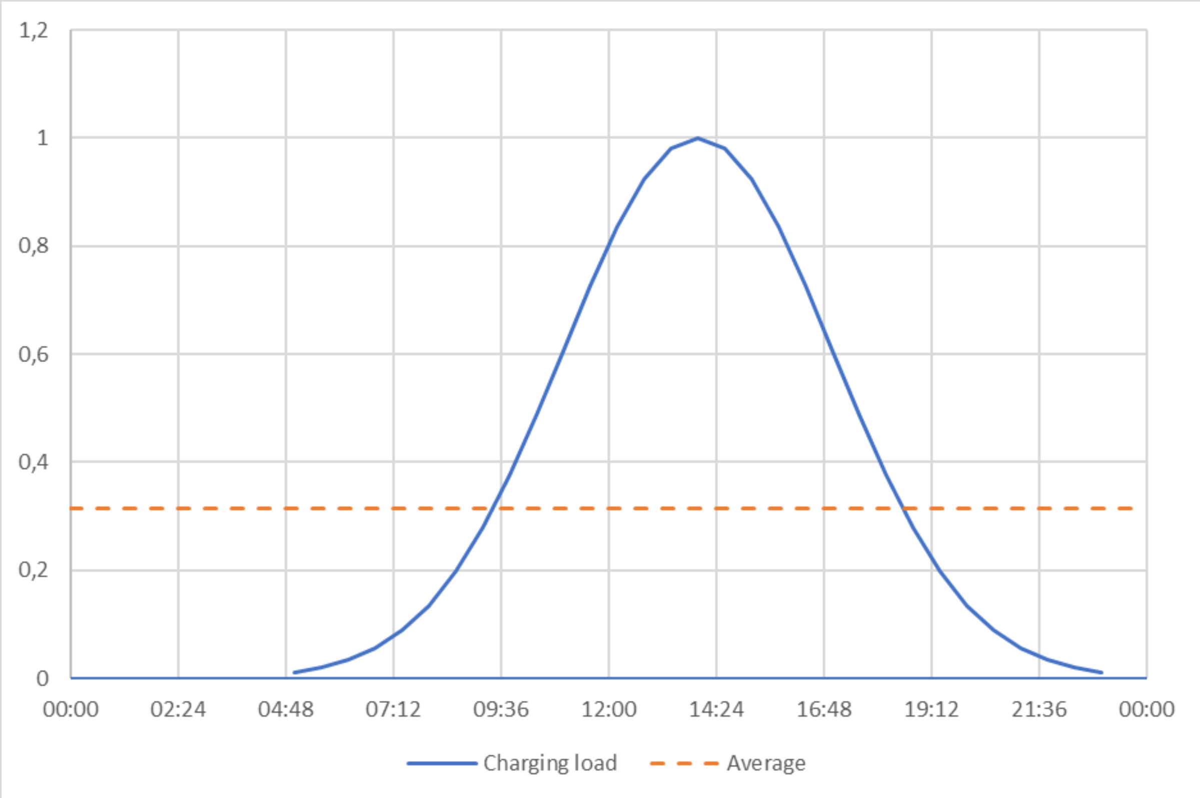


Figure 15: Daily utilization rate of a charging station

thus providing a correct average value which ensures that the utilization rate metric offers a clearer, more nuanced perspective on the charging station's operational efficiency and effectiveness. In addition, possible downtimes due to maintenance are assumed to be programmed in low load periods, reducing the any possible lost sale or inefficiency. Furthermore, additional relevant cost data were retrieved, such as:

- The acquisition cost per each fast charging station in euros, according to Atlante experience and analyzed references [24]. This cost demonstrate variability stemming from technological advancements, logistical considerations, regulatory changes, and regional factors.

- The costs associated with the creation and management of a new Point of Discharge (PoD) due to the the Transmission System Operator (TSO), related to factors such as the location, capacity, regulatory environment, and specific technical requirements. For the aim of this analysis those costs have been distinguished between initial costs (energy management cost, power fee and distance fee) and operational cost (annual power fee and annual energy management cost).

- The cost of electric energy in euros per kWh [11]: note that this value exhibits variability due to contractual arrangements, socioeconomic influences, policy shifts, and weather conditions. Regular updates of this cost value are essential to ensure accurate assessments and informed decision-making in those types of analyses.

- The average revenue generated by selling electric energy in euros per kWh [27]. The revenue generated by charging stations under TSOs exhibits considerable variability driven by factors like contractual agreements, local policies, market competitiveness, and promotional incentives. To ensure precise evaluations and effective decision-making in the energy sector, it is essential to regularly update these revenue values.

These cost data are essential in determining the profitability of EV charging services and in devising effective pricing models that attract users while maintaining profitability. By carefully studying and analyzing those relevant data, it is possible to develop informed decisions that optimize provided services, while maximizing profitability.

Input Data

			min	*avg*	*max*
Lifetime	n	[yr]		10	
Acquisition Cost	AC	[€/station]	30000	45000	60000
Energy management Cost	EMC	[€/PoD]		26	
Power fee	PF	[€/kW]		59	
Distance fee	DF	[€/PoD]		536	
Vehicle Capacity	C_{EV}	[kWh]		50	
Energy Cost	C_{elec}	[€/kWh]		0,21	
Annual Maintenance Cost	AMC_i	[€/(station*yr)]		500	
Annual power fee	APF_i	[€/(kW*yr)]		46	
Annual energy management cost	$AEMC_i$	[€/yr]		1113	
Profit Margin	c	[%]		100,00%	
Selling Price	P_{EV}	[€/kWh]		0,6	
Charging Efficiency	η_c	[%]		90%	
Interest rate	r	[%]		5,50%	
Penetration rate	PR	[%]		*see table 2*	
Catch rate	CR	[%]		*see table 2*	
Utilization rate	UR	[%]		31%	
Working hours	W_h	[h]		7,5	
Charging power	C_{pow}	[kW]		150	
Average EV charging percentage	ΔSOC	[%]		50%	

Table 3: Input data used for economic analysis

5.2. Grid creation

After gathering all the necessary information, it was crucial to create a grid system that would be helpful to analyze the city's features, such as population distribution, transportation infrastructure, and land usage. The team spent a considerable amount of time researching various grid patterns and evaluating their suitability for the project's specific needs.

Through careful consideration, it was decided that hexagonal cells offered the most advantages. Unlike traditional square grids, hexagons permitted to avoid right angles and provided more natural boundaries for analysis. Additionally, the use of hexagons allowed for a more accurate representation of interconnected areas within the city, while still providing a uniform shape for each cell. Hexagonal grids also suffer less distortion over large areas and offer more straightforward neighbor-finding techniques[28].

However, it was evident that each city has unique characteristics, and therefore the hexagonal cells were designed with varying dimensions according to the specific features of each town.

The decision was reached to align the dimensions of the hexagon with the H8 resolution, a parameter commonly employed in the context of working with this particular type of data. H8 is a resolution framework often utilized when dealing with geographical and spatial data. It signifies a specific level of grid resolution that assists in representing complex geographic features with a balanced trade-off between detail and computation efficiency, guaranteeing an equilibrium between granularity and manageability. The average hexagon area of the H8 framework, calculated at the equator, is 0.737327598 km^2. The sizes of the hexagons for each city might be found by converting to their respective coordinate systems.

By employing such a systematic method, it was possible to enhance the understanding of the city and provide a more comprehensive understanding of its unique features, which ultimately would aid in making informed decisions for urban planning and development.

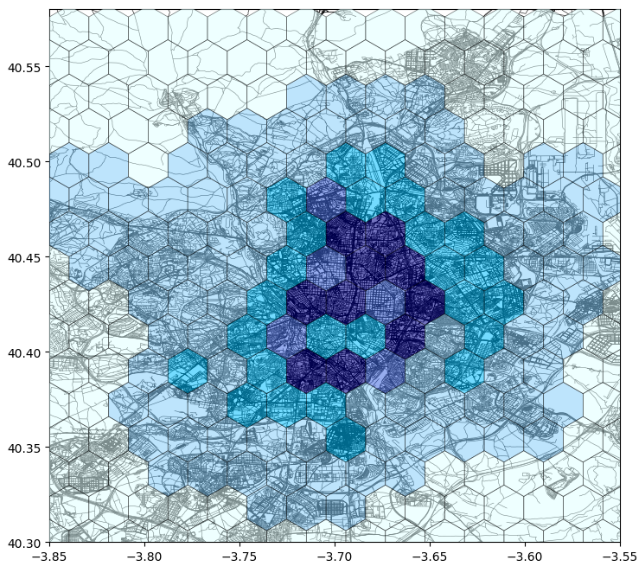


Figure 16: Madrid traffic distribution on the grid cell

As said above, using a gradient of light blue to dark blue, Figure 16 depicts the distribution of traffic points in the grid, with the light showing low traffic levels and the dark indicating high traffic levels.

5.3. Optimization model

The successive step was the definition of an optimization model for selecting car parks for charging stations in a given area.

$$\Pr(x_j) = \max \sum_{j=1}^{J} (dr_j \cdot x_j)(1 - D_j) \quad , j = 1, 2, \ldots, J. \tag{1}$$

Using as constraints:

$$\sum_{j=1}^{J} x_j = N, \tag{2}$$

$$\sum_{i \in \text{neigh}_j \cup \{j\}} x_i \leq 1 \quad \text{for } j = 1, 2, \ldots, J, \tag{3}$$

$$dr_j = d_j - \sum_{z=1}^{Z} d_{jz}, \tag{4}$$

$$D_j = \text{MinMaxScaler}(\sum_{l=1}^{L} dp_{jl} \cdot \lambda_l), \tag{5}$$

$$x_j \geq 0. \tag{6}$$

Symbol Glossary
J = number of cells,
L = number of POIs,
x_j = binary variable whether car park j is selected for a charging station,
neigh_j = set of all the neighbors of the grid cell j,
dr_j = remaining demand in grid cell j,
d_j = charging demand of an EV in grid cell j,
d_{jz} = charging demand of an EV in grid cell j already being met by existing station z,
D_j = sum of the distances of the centroids from the POIs (scaled in the interval $[0, 1]$),
dp_{jl} = distance of the centroid j from the POI l,
λ_l = weight of each POI l, based on its cluster.

The objective is to maximize the probability that a charging station in the selected car parks would meet the remaining demand for charging in the corresponding grid cell, while minimizing the distance of the car parks from the points of interest (POIs).
The decision variable x_j takes binary values to represent whether a charging station is selected for car park j. The first constraint ensures that the total number of car parks selected for charging is equal to a fixed value N. The second constraint limits the selection of charging stations in neighboring car parks to avoid overcrowding. The third constraint calculates the remaining charging demand for each cell at the end of the selection process. The fourth constraint calculates the distance of the selected car parks from the POIs and scales it to the interval $[0, 1]$ using MinMaxScaler. Finally, the last constraint ensures that the decision variable takes non-negative values.
Overall, this model aims to identify the optimal set of car parks for charging stations that would meet the demand for charging while minimizing the impact on the surrounding areas.

5.4. Innovative Approach

Following the initial implementation of the model, a series of discussions with Atlante revealed several limitations that warranted attention and refinement.

Among the constraints encountered, a significant one was closely associated with the nature of the collected data, particularly concerning the estimation of the demand variable, denoted as d_j. The estimation process relied on the utilization of traffic data points extracted from the UTD19 dataset, which provided an annual average traffic value for each specific location. While this singular value does serve as an initial estimator for the demand, its simplicity falls short of providing a comprehensive understanding of the intricate dynamics governing traffic patterns in the area. To achieve a more holistic representation of the actual demand based on the traffic data, several additional factors must be incorporated:

- Viewing Traffic as a Flux: The conceptualization of traffic as a flux is essential. Within a given area, a high-traffic location—characterized by a substantial volume of vehicles passing through—must not be solely evaluated by its overall traffic count. Equally important are the inward and outward fluxes, where a high-traffic point with balanced inflow and outflow demands different considerations compared to a location with inbound flux exceeding the outbound counterpart.

- Road and Street Network Morphology: The feasibility of accommodating the demand for charging stations hinges on the configuration of the road and street network. The accessibility and layout of these roadways fundamentally dictate the capacity of a charging station to effectively serve the demand.

However, the endeavor of comprehensively studying traffic as fluxes within the framework of a road network introduces multifaceted complexities, which manifest from various vantage points and operational contexts:

1. Data Acquisition Challenges: Such an approach necessitates significantly larger volumes of data, coupled with heightened data quality requirements. The acquisition of such enriched data proves considerably more arduous, often entailing elevated costs.

2. Data Engineering Complexities: Upon securing this enriched data, the ensuing workflow and transformations mandated to integrate it into the model escalate to a notably higher order of complexity.

3. Data Analysis and Interpretability: Noteworthy is the present model's simplicity, both in terms of its structure and the ease of hyperparameter tuning. Integrating the augmented data would engender a considerably more intricate model. While the enhanced model's accuracy would mitigate bias, it would concurrently accentuate its susceptibility to the selection of hyperparameters, consequently amplifying variance. Moreover, the heightened complexity would engender interpretability challenges.

Evidently, the direct pursuit of raw traffic flux data within road networks is an impractical endeavor both temporally and within the project's scope. In light of these constraints, the exploration for viable alternatives that encapsulate the information inherent in traffic fluxes was directed toward street routing services.

5.4.1. Routing services

The intricacies of estimating demand for electric vehicle charging stations within a dynamic urban environment necessitate a strategic and multifaceted approach. In the pursuit of accurate demand estimation, the utilization of routing services as a surrogate to directly incorporating raw traffic flux data emerged as an innovative and promising avenue. This section offers an in-depth exploration of diverse routing services, highlighting the considerations and deliberations that led to the choice of Google Maps.

Routing services, renowned for their comprehensive route planning and navigation capabilities, presented themselves as a compelling means to indirectly access the complex intricacies of traffic flows.

This investigation encompassed a selection of prominent routing service providers, each distinguished by unique attributes and data sources. Among these, the following stood out:

- RoutingPy: An adaptable Python library tailored for routing applications, empowering with the flexibility to fine-tune routing algorithms and leverage the wealth of data from OpenStreetMap.
- OpenRouteService: A versatile platform offering open access to geospatial and routing services, harnessing the extensive information within OpenStreetMap for robust route planning.
- TomTom: A heavyweight in navigation and mapping solutions, offering a rich repository of traffic-related data that holds promise for accurate demand estimations.
- Google Maps: Renowned for its navigational prowess, Google Maps boasts a seamless fusion of real-time traffic updates, comprehensive mapping data, and user-friendly integration.

Amidst the array of options, the selection of the most suitable routing service hinged upon a meticulous analysis of parameters crucial to the demand estimation objectives. These parameters encompassed the quality and granularity of traffic data, coverage of road networks, frequency of real-time updates, ease of integration, and computational efficiency. After a thorough evaluation, Google Maps emerged as the most optimal choice for several compelling reasons:

1. Holistic Data Integration: Google Maps harmonizes an expansive range of historical and real-time traffic information from diverse sources, rendering it adept at capturing the intricate nuances of traffic patterns in urban environments.
2. Global Road Network Coverage: The service offers an extensive global road network, aligning with the study area's complex road infrastructure and ensuring comprehensive coverage.
3. Time Adaptability: With its traffic updates, Google Maps equips the demand estimation model to flexibly adjust to the dynamic ebb and flow of traffic conditions and the different time estimations.
4. API accessibility: The service's user-friendly Application Programming Interface streamlines the integration process, minimizing complexity and enhancing usability within the framework.

5. Cost efficiency: Google Maps' routing algorithms exhibit robust scalability and computational efficiency, well-suited to demand estimation requirements, ensuring timely and accurate outcomes.

Google Maps and TomTom were the only ones that allowed for time adaptability, but Google Maps stood out as the most promising candidate due to ease of use and cost efficiency for scalability. Google Maps API *Directions* was chosen, with a cost of 0,004 USD per 1000 requests and 5000 free requests per month.

5.4.2. Congestion Index

A systematic workflow was devised, centered around the Google Maps API for routing. This approach entails calculating the time required to travel between adjacent hexagons, effectively quantifying the flow and movement patterns in the urban landscape.

To elaborate, the employed methodology involves the following steps:

- API Requests from/to single hexagons: The process is initiated by leveraging the Google Maps API for routing calculations. Specifically, the travel time between the centroids of a given hexagon and the centroids of its neighboring hexagons is computed in two conditions: one in which it is asked not to take into account traffic for determining travel time, and one in which it is asked to incorporate traffic into prediction.
- Outgoing/Inflowing flux proxy calculation from/to single hexagon: For each adjacent hexagon, the in/out flux proxy from/to the centroids is determined by subtracting the travel time without traffic to the travel time in congested conditions. This assessment effectively quantifies the additional flow due to traffic, keeping into account the surplus travel time due to traffic and not simple routing.

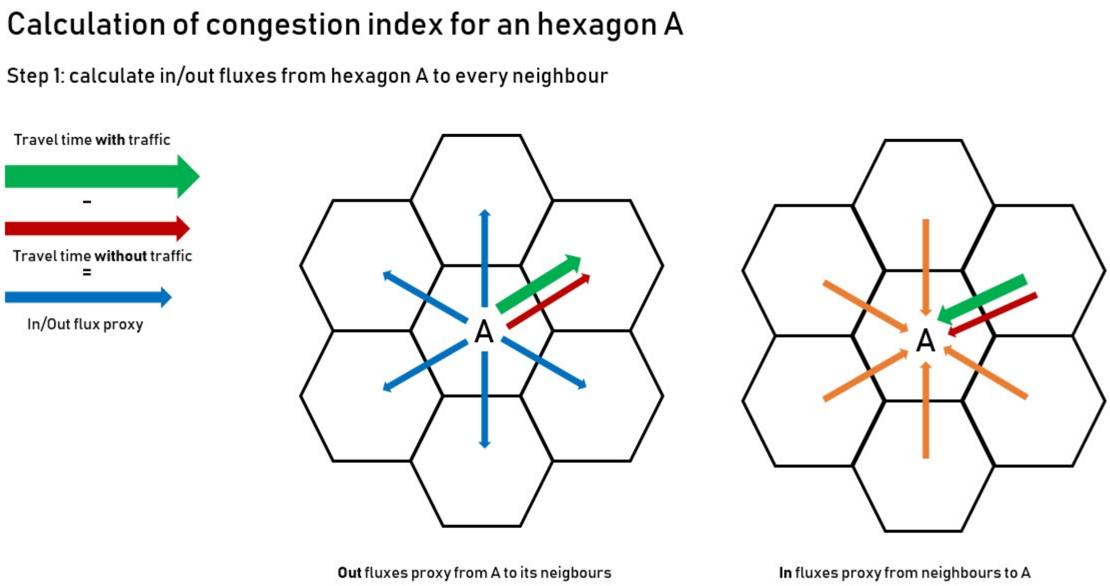


Figure 17: The first two steps of procedure

- Total Time Calculation: By aggregating the travel times for the six adjacent hexagons, two total proxies for each hexagon are generated —one representing surplus travel time due to traffic flow in and out.

- Congestion Index Formulation: A distinctive "congestion index" was conceived for each hexagon. This index, is calculated by summing all the in-proxies and subtracting the sum of all the out-proxies of the hexagon.

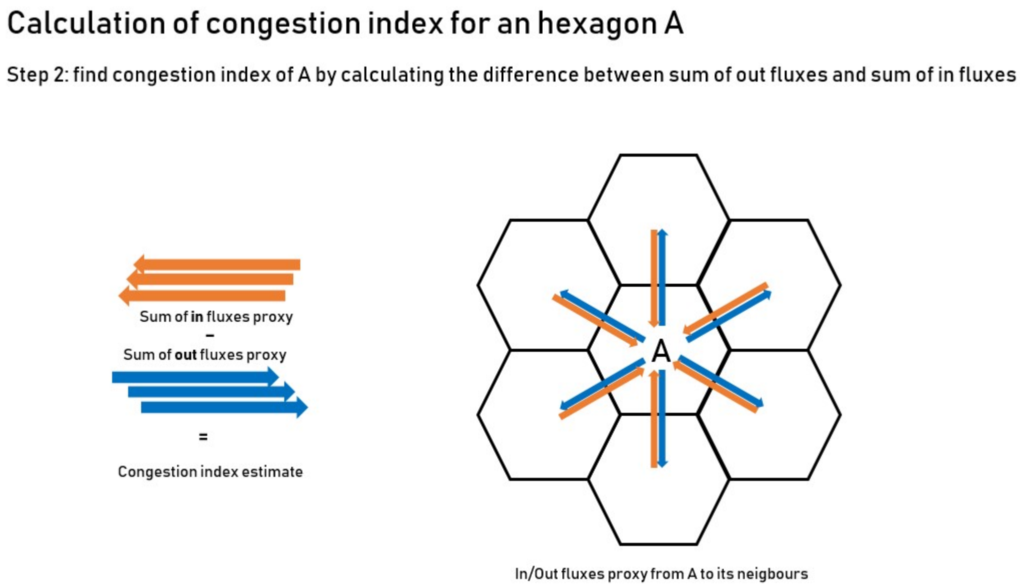


Figure 18: The last two steps of the procedure

Note that in step 1, when traffic is incorporated into prediction, several requests are made to the Google Maps API to estimate travel time with traffic in different work time hours of the day. The travel time with traffic used in the next steps is the average of all the requests.

The congestion index is thus a single value correlated with the amount of traffic flux remaining *in* the hexagon: the higher the value, the higher the inbound traffic - relative to the outbound one - in the hexagon area.

It is efficiently computed with simple API requests and can be easily integrated into the model due to its simple numerical structure. Although summing up the complex traffic dynamics in a single value is an oversimplification and introduces some bias, it is a cost-efficient estimator that takes marginally into account all the valuable factors indicated to have a better understanding of the movement patterns (streets morphology, directioned traffic) while overcoming the challenges that would arise by treating more complex data.

The index can be normalized using min-max scaling, and can be used in the objective function in two ways:

1. Serving as a multiplicative coefficient, if normalized, to pointwise traffic estimate in the objective function, effectively accentuating these contributions beyond singular

traffic values.

$$d_j = c_j \cdot t_j \tag{7}$$

2. Serving as demand estimator in a convex linear combination with the singular traffic values used in the original model.

$$d_j = \eta \cdot t_j + (1 - \eta) \cdot c_j \tag{8}$$

η is a tuning hyperparameter, t_j is the pointwise traffic estimator and c_j the congestion index for hexagon j. d_j is the demand estimated for the hexagon in the objective function.

The subsequent subsections present results derived from employing the first approach. The absence of hyperparameter tuning (η) in the multiplicative approach contributed to this preference, along with other numerical stability factors to be explained in the relevant section.

As an alternate avenue to calculate the congestion index, it was contemplated utilizing the ratio between the in and out proxies instead of the difference to establish a dimensionless "congestion index". However, empirical findings suggest that this approach yields results nearly equivalent to the initial method, affirming the robustness of the chosen framework.

5.5. Madrid Results

As already noted in the previous subsection, the following results are produced using a model with a multiplicative factor approach of the congestion index. Indeed, the multiplicative factor's intrinsic ability to amplify the impact of the congestion index is a key strength. By multiplying the congestion index with a separate factor, the resulting combined metric inherently emphasizes the influence of congestion more profoundly. This amplified emphasis facilitates a sharper delineation between high-congestion and low-congestion areas. Moreover, the multiplicative factor approach maintains a higher degree of sensitivity to fluctuations in the congestion index. Since the impact of the congestion index is directly proportional to the multiplicative factor, even minor changes in congestion levels are more perceptible in the final metric.
The optimal allocation of six EV charging stations in the city of Madrid, obtained by the algorithm, can be observed in Figure 19.

The first finding that stands out has to do with how the detected hexagonal zones are distributed spatially; it is interesting to note that they do not all reside in the city centre. This occurrence can be linked to a number of interconnected variables.
Firstly, the constraints that dictates that stations cannot be situated in close proximity to one another. Furthermore, the complex layout of these hexagonal zones is intricately connected to the interrelationship between elements like the current levels of demand satisfaction and the congestion index. A careful analysis of these hexagonal zones reveals a striking pattern: several of them include wide highways and large boulevards. Even though these major roads may not have a high punctual traffic density, the congestion index acts as a more accurate indicator and offers useful information about how frequently congestion episodes occur. It becomes clear as a result that these highways frequently experience heavy traffic loads. The near-fulfillment of demand in the city centre provides another strong case for the distribution of these hexagonal zones distant from it. In fact, it is possible to see that the current EV charging stations are currently mostly situated

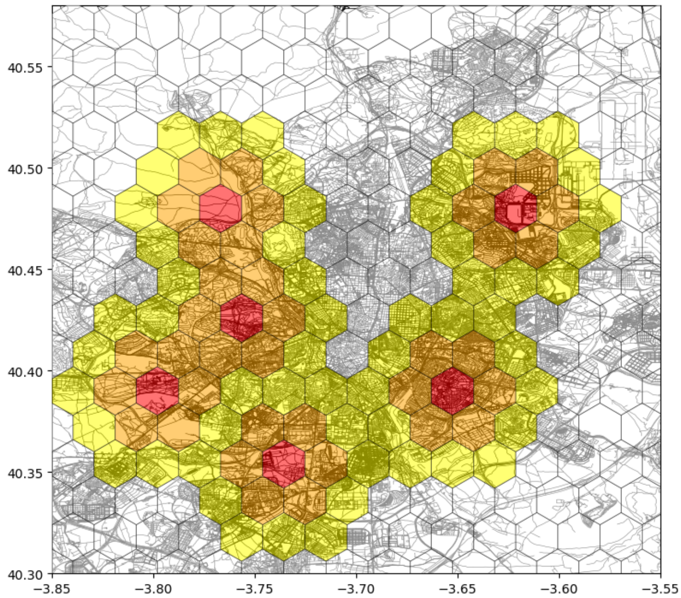


Figure 19: Optimal locations of the EV chargers in the city of Madrid

on the streets in the city centre.
In light of this findings, allocating stations along the city's main avenues, even though they are not in the center, seems like a wise course of action. By avoiding an excessive concentration of resources in a region where demand is mostly met, this strategy still maintains effective service coverage for the population.

Finally, it is important to underline that the algorithm in question operates within a semiautomatic framework. The used approach enables the identification of optimal hexagonal zones for the placement of stations. However, it falls short of pointing the precise coordinates along the road network where these stations should be built.
Consequently, a subsequent manual intervention becomes necessary, with the role of investigating the factors that govern the practicability and scope of a given road, like the viability, accessibility and dimensions.

5.6. Economic Analysis

5.6.1. Methodology

The proposed methodology involves a two-phase approach: first, an optimization phase (section 5.3) based on a scoring function that accounts for relevant factors such as traffic and distance to key attractions; second, a financial analysis phase that addresses the station sizing based on projected traffic volume. This phases decoupling ensures a comprehensive and balanced decision-making process, integrating both spatial and economic considerations. The study highlights that a purely spatial approach can result in sub-optimal solutions neglecting the financial aspect, while an exclusive financial focus may overlook strategic placement.
By harmonizing economic analysis with location optimization, Atlante can pinpoint ideal charging station sites and tailor its capacities to accommodate projected EV traffic, thereby fostering the growth of sustainable transportation networks. This holistic approach not only advances the understanding of EV charging station placement but also contributes to the broader goal of converting the current circulating car fleet from ICEs to EVs.
Economic analysis comprises two distinct yet complementary steps. The former unfolds within the Python code, meticulously designed to leverage fixed parameters and generate essential economic metrics such as Return on Investment (ROI) and the Breakeven Point (BEP). Notably, this initial Python phase sidesteps the intricacies of discount rates, focusing results on the first 6 optimal positions identified by the algorithm, as a preliminary analysis. The second phase unfolds within an Excel environment, affording a dynamic platform to validate the sensitivity analysis across a spectrum of parameters. This part of the endeavour corroborates the results gleaned from the optimization algorithm (in term of average daily traffic moving through hexagons), exploring the robustness of different strategies, through comprehensive exploration of parameter variations.
The rationale underlying the decoupling of the preliminary analysis lies in the comprehensive nature of the optimization algorithm. This algorithm, encompassing a wide spectrum of parameters, extends beyond the realm of traffic considerations alone. Rather, it incorporates various factors contributing to the overall attractiveness of a charging station location, transcending the confines of expected economic returns. While recognizing that the behavior of individuals might remain unaltered post-deployment (an assumption made for simplification), it is imperative to acknowledge that the traffic parameter retains a decisive role in influencing economic revenue. Consequently, the primary objective of the preliminary analysis centers on the determination of the broad economic feasibility of the identified key points. This preliminary evaluation serves as an indicator of the general economic attractiveness of potential charging station locations. Once a suitable location is identified, a more comprehensive economic analysis (Techno-Economic Analysis) can be embarked upon. This analysis seeks to define the optimal sizing of the charging station and the associated finance, effectively navigating the delicate balance between expected revenue and associated costs. This intricate trade-off is evaluated against diverse sets of input parameter values, thus refining the charging station design and providing a robust foundation for informed decision-making.

5.6.2. Preliminary Analysis

The preliminary analysis involves conducting a comprehensive yet synthetic economic evaluation of the output results derived from the optimization process. The primary objective is to gain insight into the anticipated general economic income that these stations can generate. This phase specifically focuses on a financial analysis of Capital Expenditures (CAPEX) and Operating Expenses (OPEX), without considering cash flow actualization or proxy values progression.
CAPEX refers to the initial investment required to establish the charging stations, encompassing equipment, installation, labor, permits, and taxes. OPEX includes the ongoing operational costs, such as electricity expenses, maintenance, and monitoring systems. Both CAPEX and OPEX are essential metrics for assessing the feasibility and viability of any project.
From these parameters, two critical indicators are derived: the breakeven point and the expected return on investment (ROI). The breakeven point indicates the point at which total costs match total revenue, signifying the stage where investment is recovered. On the other hand, ROI quantifies the percentage of return gained on the investment over a certain period, providing insights into the project's profitability. These parameters play a pivotal role in decision-making processes, enabling informed judgments on project viability and potential economic gains.

5.6.3. Techno-Economic Analysis

The Techno-Economic Analysis (TEA) developed is based on Life Cycle Cost Analysis (LCCA), providing a comprehensive lens through which the economic viability of EV charging stations can be gauged. LCCA, a pivotal facet of TEA, hinges on assessing the total costs of a technology over its lifespan, thus serving as a touchstone to evaluate the feasibility of novel innovations. In the specific context of EVs, LCCA takes center stage to examine the infrastructure required for EV adoption.

Notably, LCCA does more than merely quantifying costs; it unravels the intricate web of components that dominate expenses, thereby exerting profound influence on overall feasibility. This diagnostic approach facilitates manufacturers, researchers, and policymakers in refining strategies to improve the economic prospects of EV charging stations. By dissecting the elements of acquisition costs, operation costs, maintenance costs, and revenue streams, LCCA offers a integrated financial panorama.

Integral to this analysis is the consideration of the time value of money, achieved through discounting, which converts future costs and benefits into present values. The cumulative present value (CPV) encapsulates the entirety of current and future costs, culminating in a comprehensive assessment of the station's financial landscape. Moreover, by incorporating selling revenues from electricity, LCCA goes beyond expenses to embrace revenue dynamics, further enriching the analytical canvas.

By using a suitable discount interest rate, which represents the change in the value of money over a specific time period, the process converts the costs and benefits experienced at various points in time into the present. The present value (PV_i) of costs incurred in year i, with future value (FV_i), can be presented as follows, given a discount interest rate of r:

$$PV_i = \frac{FV_i}{(1+r)^i} \tag{9}$$

The cumulative present value (CPV) include all present values of all past, present, and future costs related to the stations:

$$CPV = \sum_{i=1}^{n} \frac{FV_i}{(1+r)^i} \tag{10}$$

The acquisition cost (AC), operating cost (OC_i), maintenance cost (MC_i), and selling revenue (SR_i) from the sales of electricity, in various years i throughout its assumed n effective years, are taken into account for the analysis.

- Acquisition cost encompasses expenses related to procuring equipment and the associated installation, which covers labor, materials, permits, and taxes. This cost category assumes that all the expenses associated with acquiring the necessary resources are settled through a single, upfront payment, without resorting to borrowing. This lump sum payment approach ensures that the acquisition costs remain unaffected by fluctuations in interest rates. It is important to note that these costs are incurred at the project's outset, providing a clear and definitive basis for financial evaluation.

- Operating costs represent all those annual expenses related to electric energy cost and electrical supply contracts. Fuel cost $FC_{EV,i}$ for charging the EV in year i is dependent on the number of EVs charged $n_{EV,i}$, their capacity C_{EV}, and the per unit electricity cost C_{elec}.

  $$FC_{EV,i} = E_{EV} \times C_{elec} \times n_{EV,i} \tag{11}$$

  The amount of energy required E_{EV} for a one-time charge of the C_{EV}-capacity battery due to ΔSOC, with charger efficiency η_c

  $$E_{EV} = \frac{C_{EV}}{\eta_c} (\Delta SOC) \tag{12}$$

  While the number of EVs charged $n_{EV,i}$ in year i, depends on average yearly traffic AT_i, penetration rate PR_i, catch rate CR_i as:

  $$n_{EV,i} = AT_i \times PR_i \times CR_i \tag{13}$$

  For every charging spot it is required to develop a new electrical supply contracts with annual fees EF_i based on energy management and maximum power available. Then the discounted total operation cost $OC_{total,EV}$ of operating an electric charging station for EVs over its useful life is given by

  $$OC_{total,EV} = \sum_{i=1}^{n} \frac{FC_{EV,i} + EF_i}{(1+r)^i} \tag{14}$$

- Maintenance costs have been analyzed by means of a internal research developed with Atlante: as for acquisition cost, they are the result of the know-how the company developed during years. Given that MC_i represents the annual maintenance cost in year i, the discounted total maintenance cost MC_{total} over the useful life of the stations is simply given by

  $$MC_{\text{total}} = \sum_{i=1}^{n} \frac{MC_i}{(1+r)^i} \tag{15}$$

- Selling revenue are the result of the charging process and the sales on electric energy. Revenue for year i $R_{EV,i}$ depends on the selling price per kWh P_{EV}, the number of EVs charged $n_{EV,i}$ and the average energy sold in each charging session E_{EV}.

$$\begin{aligned} R_{EV,i} &= E_{EV} \times P_{EV} \times n_{EV,i} \\ R_{\text{total}} &= \sum_{i=1}^{n} \frac{R_{EV,i}}{(1+r)^i} \end{aligned} \tag{16}$$

The LCC of the stations encompasses the cumulative discounted worth of acquisition, operation, and maintenance expenses, subtracting the revenue obtained from selling electricity or fossil fuel. From a business standpoint, positive LCC values would not justify investing in a venture, as investors anticipate returns on their investment and effort. A diminished LCC value signifies a more enticing business prospect. When deliberating whether to invest in constructing an electric charging station for EVs, the investor's preference leans toward the option with the lower LCC value. This metric aids in gauging the economic feasibility and competitiveness of the investment.

$$LCC = AC + OC_{\text{total}} + MC_{\text{total}} - R_{\text{total}} \tag{17}$$

The Payback Period (PP) and Discounted Payback Period (DPP) emerge as critical quantitative measures, lending insight into the temporal dynamics of capital recovery and the effects of time value of money. The PP, denoting the interval required for the return of initial investment, gauges the speed of capital recoupment through the division of investment by net annual income. Conversely, the DPP extends this analysis by incorporating the nuanced influence of discount interest rates, reflecting the pragmatic appreciation of the devaluation of future cash flows. Computed as the quotient of initial investment and the discounted net annual income, DPP presents a refined perspective that harmonizes financial sustainability with the intricate fabric of temporal financial adjustments. These metrics, emblematic of fiscal prudence, furnish decision-makers with quantifiable data points to orchestrate judicious investment strategies in the dynamic theater of resource allocation, optimizing the balance between upfront costs and enduring profitability.

$$\begin{aligned} PP &= \frac{AC}{\sum_{i=1}^{n} (R_i - OC_i - MC_i)} \\ DPP &= \frac{AC}{R_{\text{total}} - OC_{\text{total}} - MC_{\text{total}}} \end{aligned} \tag{18}$$

5.6.4. Sizing

The sizing methodology employed in this study involves projecting a 10-year horizon into the future. The objective is to anticipate the charging station's optimal capacity, ensuring it reaches maximum saturation while avoiding any missed sales opportunities. By considering the projected growth in electric vehicle adoption and associated traffic patterns over this timeframe, the sizing process seeks to strike a balance between accommodating future demand and avoiding over-provisioning, thus aligning with the principle of resource optimization for sustained economic viability.

The decoupling of the optimization phase from economic analysis in the strategic siting of charging stations is a pivotal practice, conferring multifaceted benefits. This separation acknowledges that a single location's economic viability hinges on the nuanced interplay

between sizing and saturation thresholds. The resultant potential for economic advantage or disadvantage underscores the necessity of this bifurcated approach.
By orchestrating this separation, the misdesign of infrastructure is thwarted, a dual triumph of prudent investment and maximized returns. This solution inherently provides a greater margin of error, reducing the risk of economic losses. For instance, in the event of border-line PoD where n stations could be not enough to face future trends so $n + 1$ stations seems to be needed, it is important to notice the effect shown on figure 20. The resulting graph indeed, represents a saw-tooth pattern, in which every time the additional traffic require an additional station, the saturation drops and the LCC increase. This particular behaviour is related to acquisition cost weight on the LCC, and will be deeper analyzed on next section. It is remarkably to notice that the effect reduces while the traffic increases, since increasing the charging stations number reduces costs are more evenly distributed.

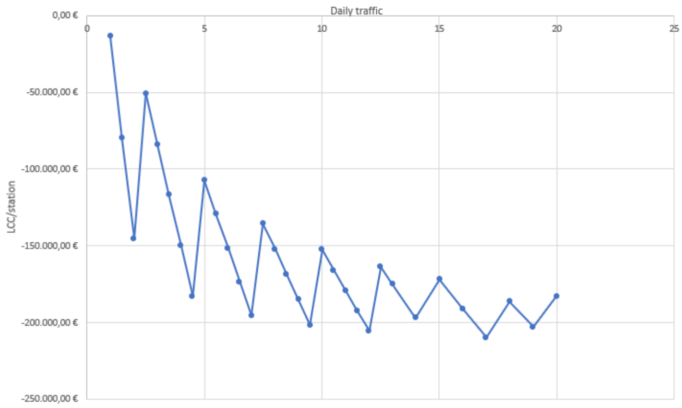


Figure 20: Life Cycle Cost per station

The adoption of an additional station would drastically increase LCC per station, increasing DPP and reducing saturation. This event would result in a non correct optimization of the economic capital utilization that should have been employed for alternative more retributive investments. Not by chance, embracing this paradigm also bolsters resilience against parameters variability, mitigating economic risk. A higher margin ensues, cushioning potential setbacks stemming from inaccuracies.
Starting from the average energy sold in each charging station E_{EV}, the charging power P_{charge} and the effective working hours W_h (obtained in section 5.1.4), it is possible to define the average number of EV chargable in a year.

$$EV_{cap} = \frac{P_{charge} \times W_h \times 365}{E_{EV}} \tag{19}$$

Then the number of needed charging stations n_{CS} depends on the number of EVs to be charged $n_{EV,10}$ in year 2033 and the EV that can be charged by a station in a year:

$$n_{CS} = \left\lceil \frac{n_{EV,10}}{EV_{cap}} \right\rceil \tag{20}$$

However, it is incumbent to temper ambition with prudence. Ensuring that the saturation threshold during the design phase does not exceed 97.5% becomes imperative. This limitation prevents the charging spot from being undersized in the face of expected electric vehicle diffusion, safeguarding against lost sales in the future. As a result the previous equation becomes:

$$n_{CS} = \left\lceil \frac{n_{EV,10}}{0.975 \times EV_{cap}} \right\rceil \tag{21}$$

In summation, the decoupling of optimization and economic analysis stands as a linchpin strategy. Its dynamic influence on charging station location not only mitigates financial pitfalls but also aligns infrastructure with evolving market dynamics, facilitating sustainable success.

The sizing phase for EV charging stations in the proposed process cannot be entirely automated due to the inherent complexity of incorporating a wide range of parameters beyond traffic, resulting in decisions being based on attractiveness rather than on expected economic returns, as previously discussed. Consequently, this phase necessitates a data-driven approach, wherein the operator plays an essential role in manually adjusting and intervening in borderline scenarios to ensure accurate outcomes. This manual correction ensures that the chosen locations align with economic feasibility and practicality. To further enhance comprehension of the economic dynamics within the environment and gain deeper insights into the process, a sensitivity analysis is introduced in the subsequent sections. This analysis serves as a substitute, enabling a more comprehensive grasp of the intricate economic interactions in the system. By exploring the sensitivity of various parameters and their impact on the economic aspects, a clearer understanding is established, enhancing the decision-making process and facilitating optimal station sizing.

5.6.5. Economic results on Madrid

The main output from the Python code needed for the economic analysis consist on the list of most *interesting* hexagons, ordered according to the objective function, associated with the average daily traffic as shown in table 4.

# exagon	$centroid_x$	$centroid_y$	daily traffic
37	-3,798	40,390	3306
71	-3,756	40,426	10200
74	-3,767	40,480	3313
83	-3,736	40,354	7278
149	-3,653	40,390	12899
186	-3,621	40,480	3925

Table 4: First 6 hexagons ordered by descending objective function on Madrid

Focusing on economic analysis for the most heavily trafficked hexagons among the six strategically significant ones holds notable significance. This approach allows to delve into the potential impact of high demand scenarios on the anticipated revenue streams and discounted payback periods. By evaluating these economic metrics within the context of the busiest areas, it is possible to gain insights into the financial feasibility of EV charging station deployment in locations where the potential for user adoption and revenue generation is at its peak.

As a result, hexagon number 149 was chosen as example for the economic analysis, since

		1	2	3	4	5	6	7	8	9	10	
		2023	2024	2025	2026	2027	2028	2029	2030	2031	2032	
Penetration rate	[%]	2,00%	3%	4%	5%	6%	8%	10%	12%	14%	16%	
Catch rate	[%]	2,00%	2,5%	3,0%	3,5%	4,0%	4,5%	5,0%	5,5%	6,0%	7,0%	
Reduction coeff	[%]	0,04%	0,08%	0,12%	0,18%	0,24%	0,36%	0,50%	0,66%	0,84%	1,12%	
Daily demand, $n_{EV,i}$	[EV/day]	5,16	9,67	15,48	22,57	30,96	46,44	64,50	85,13	108,35	144,47	
No. of charging spot	[]	4										
Saturation		3%	6%	10%	14%	19%	29%	40%	52%	67%	89%	$\sum$
OC_i	[k€/yr]	40K€	49K€	62K€	77K€	95K€	128K€	166K€	210K€	260K€	336K€	1.423K€
$OC_{PV,i}$	[k€/yr]	38K€	44K€	53K€	62K€	73K€	93K€	114K€	137K€	160K€	197K€	971K€
MC_i	[k€/yr]	2,0K€	2,0K€	2,0K€	2,0K€	2,0K€	2,0K€	2,0K€	2,0K€	2,0K€	2,0K€	20K€
$MC_{PV,i}$	[k€/yr]	1,9K€	1,8K€	1,7K€	1,6K€	1,5K€	1,5K€	1,4K€	1,3K€	1,2K€	1,2K€	15K€
R_i	[k€/yr]	28K€	53K€	85K€	124K€	169K€	254K€	353K€	466K€	593K€	791K€	2.917K€
$R_{PV,i}$	[k€/yr]	27K€	48K€	72K€	100K€	130K€	184K€	243K€	304K€	366K€	463K€	1.936K€

Table 5: Economic annual projection for exagon number 149

it represents the most trafficked hexagon among the chosen ones. In table 5 the economic projections for this hexagon are shown, considering the effect of rate discount. In particular, while OC_i, MC_i and R_i represent the actual economic value of the i_{th} year; OC_{PV}, MC_{PV} and R_{PV} represent the present discounted value, considering the current value of those future cash flows. This process allows to compare cash flows happened in different historical periods, as already introduced in equation 9. In addition, according to equation 21, the number of station is obtained from average daily traffic expected in 2032, maintaining a maximum saturation in that period of 97,5%.
Calculating precedent cumulative economic values represent a critical step in deriving the LCC of this project, shedding light on its financial feasibility. It is important to recall that the LCC, being associated with costs, has a unique interpretation; a negative LCC signifies positive income for the company. In this specific case, analyzing the LCC of EV charging station deployment provides valuable insights.
With a high station saturation value of 89%, the rapid recovery of the initial investment becomes evident – in approximately 2 years and 4 months, as indicated by a DPP of 2.3 years. This swift recovery timeframe underscores the financial robustness of the project. Moreover, the LCC per station, an amalgamation of costs and revenues over 10 years, stands at an impressive figure of around 180 k€. This value highlights the comprehensive financial impact, demonstrating that the investment encompasses both expenditure and potential income.
Further elucidating the financial prospects, the Return on Investment (ROI) metric deserves attention. Over the 10-year period, the calculated ROI reaches an impressive 340%. This metric portrays the remarkable gain in comparison to the initial investment, emphasizing the project's lucrative nature.

Acquisition Cost - AC	[€]	215.511 €
Operating Cost - OC_{total}	[€]	970.555 €
Maintenance Cost - MC_{total}	[€]	15.075 €
Revenue - R_{total}	[€]	1.936.272 €
Life Cycle Cost - LCC	[€]	-735.130 €
Payback Period - PP	[yr]	1,462
Discounted Payback Period - DPP	[yr]	2,267
LCC per station	[€/station]	-183.782 €
Return On Investment - ROI_{10}	[]	341%

Table 6: Life Cycle Cost for # 149 exagon

5.6.6. Sensitivity analysis

It is important to note that the presented sensitivity analysis serves as a tailored guide specifically designed for the city of Madrid. As urban landscapes, infrastructure, and consumer behaviors vary across different cities, the sensitivity analysis framework may need to be re-engineered for each unique context. While the underlying principles and methodologies remain valuable, customization is essential to account for distinct factors that influence the economic dynamics of EV charging station deployment. Future projects in other cities could benefit from adapting and refining the sensitivity analysis to align with the specific attributes and dynamics of each urban environment, ensuring accurate insights and well-informed decision-making processes.

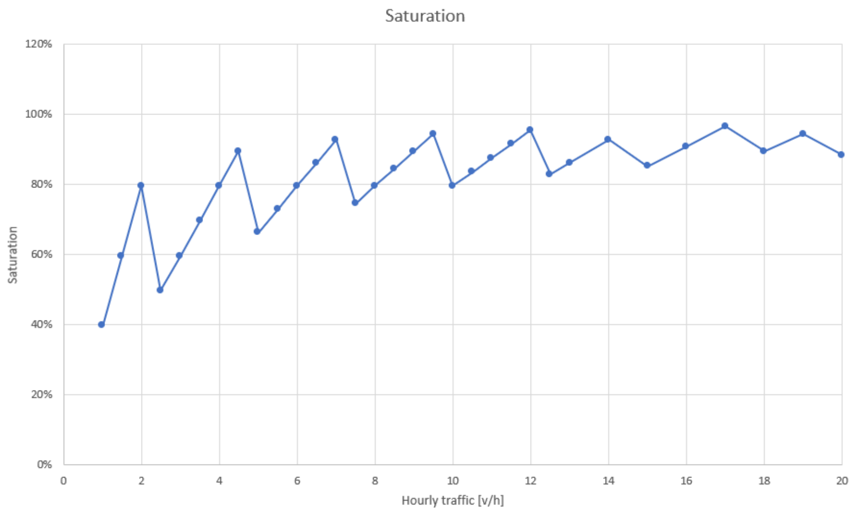


Figure 21: Sensitivity analysis on saturation varying traffic

The sensitivity analysis conducted on Madrid's EV environment reveals a distinctive sawtooth-like behavior as explained in section 5.6.4. This pattern arises due to discreetly increasing acquisition costs tied to expanding the number of stations, which in turn is distributed more favorably among highly saturated stations. Consequently, this phenomenon necessitates cautious sizing of discharge points to prevent lost sales. This effect not only impacts the LCC per station but also influences the overall LCC of the discharge point. Examining various traffic scenarios shown on table 7, two possibilities arise. For instances with average traffic between 4.5 and 5 vehicles/h, adding a station both parameters increase, rendering the expansion of stations unfavorable. Conversely, in cases such as hourly traffic between 14 and 15 vehicles/h, adding a station, despite the rise in LCC per station, the overall LCC diminishes. Here, the decision must compare the yield of this specific point with alternative investments to ascertain profitability. It is crucial to note that such analyses extend beyond individual points, encompassing inter-PoD comparisons. After performing economic evaluations on selected PoDs, the order of investments realization among them should be guided by the anticipated LCC per station for optimal outcomes.

Hourly traffic	# of stations	DPP	Saturation	LCC/station	LCC
1	1	8,03	40%	-13.345 €	-13.345 €
1,5	1	4,06	60%	-79.394 €	-79.394 €
2	1	2,72	79%	-145.442 €	-145.442 €
2,5	2	5,15	50%	-50.846 €	-101.692 €
3	2	3,92	60%	-83.870 €	-167.741 €
3,5	2	3,16	70%	-116.895 €	-233.789 €
4	2	2,65	79%	-149.919 €	-299.838 €
4,5	2	2,28	89%	-182.943 €	-365.887 €
5	3	3,34	66%	-107.379 €	-322.136 €
5,5	3	2,94	73%	-129.395 €	-388.185 €
6	3	2,63	79%	-151.411 €	-454.233 €
6,5	3	2,37	86%	-173.427 €	-520.282 €
7	3	2,16	93%	-195.444 €	-586.331 €
7,5	4	2,84	74%	-135.645 €	-542.580 €
8	4	2,61	79%	-152.157 €	-608.629 €
8,5	4	2,42	84%	-168.669 €	-674.678 €
9	4	2,25	89%	-185.182 €	-740.726 €
9,5	4	2,11	94%	-201.694 €	-806.775 €
10	5	2,61	79%	-152.605 €	-763.025 €
10,5	5	2,45	83%	-165.815 €	-829.073 €
11	5	2,31	87%	-179.024 €	-895.122 €
11,5	5	2,19	91%	-192.234 €	-961.170 €
12	5	2,08	95%	-205.444 €	-1.027.219 €
12,5	6	2,47	83%	-163.911 €	-983.469 €
13	6	2,35	86%	-174.920 €	-1.049.517 €
14	6	2,15	93%	-196.936 €	-1.181.614 €
15	7	2,38	85%	-171.988 €	-1.203.913 €
16	7	2,20	91%	-190.859 €	-1.336.010 €
17	7	2,04	96%	-209.730 €	-1.468.107 €
18	8	2,24	89%	-186.301 €	-1.490.405 €
19	8	2,10	94%	-202.813 €	-1.622.502 €
20	9	2,27	88%	-182.756 €	-1.644.801 €

Table 7: Sensitivity analysis on traffic

5.7. Results on the other considered cities

5.7.1. Manchester

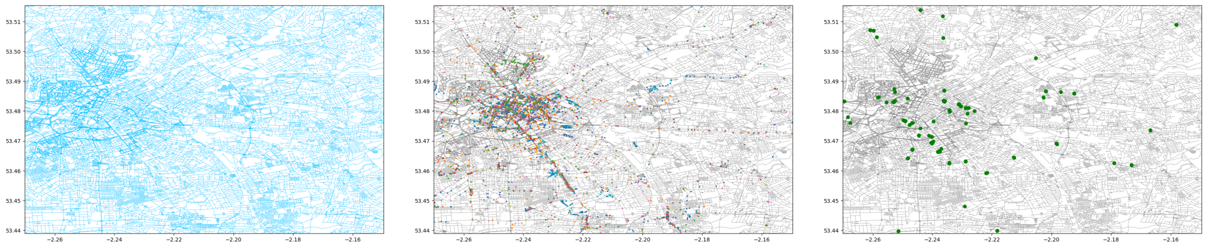


Figure 22: Manchester map, POIs and existing charging stations

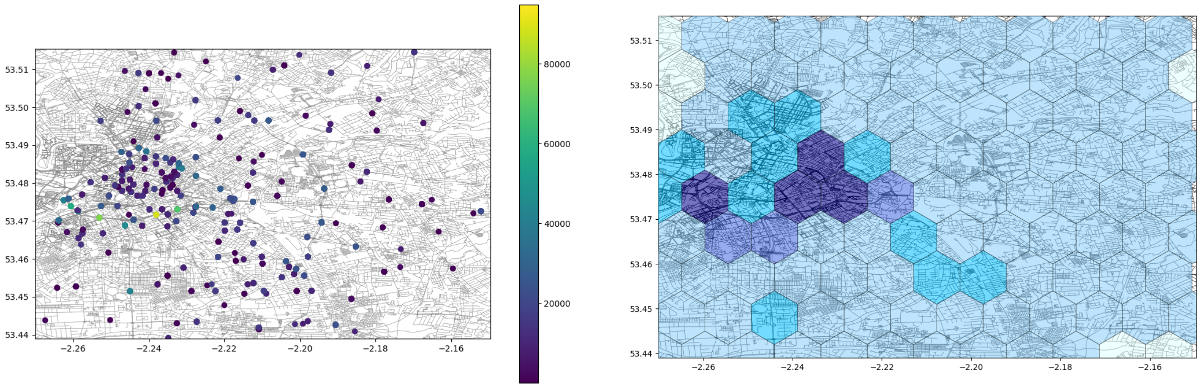


Figure 23: Manchester traffic points and grid cell with traffic distribution

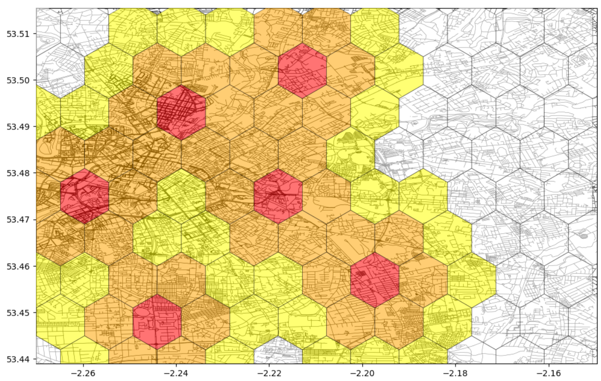


Figure 24: Manchester solution

The optimal distribution of resources in Manchester resembles the one of Madrid. Just like in Madrid, only two out of the six highlighted hexagons are located in Manchester's city center. The rest cover key routes leading to the downtown.
Additionally, it is worth specifying that since these punctual traffic points are collected from another site, Manchester's traffic points have completely different scales and measurements than those of the other cities. In fact, whereas traffic points of other cities measure average daily number of cars passing from there, in Manchester the data refers to annual averages.

5.7.2. London

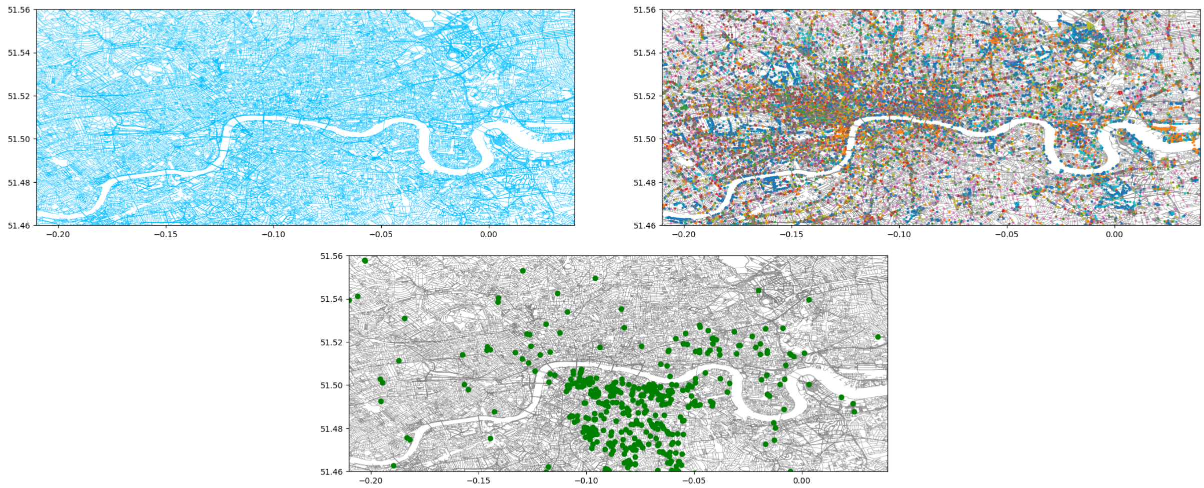


Figure 25: London map, POIs and existing charging stations

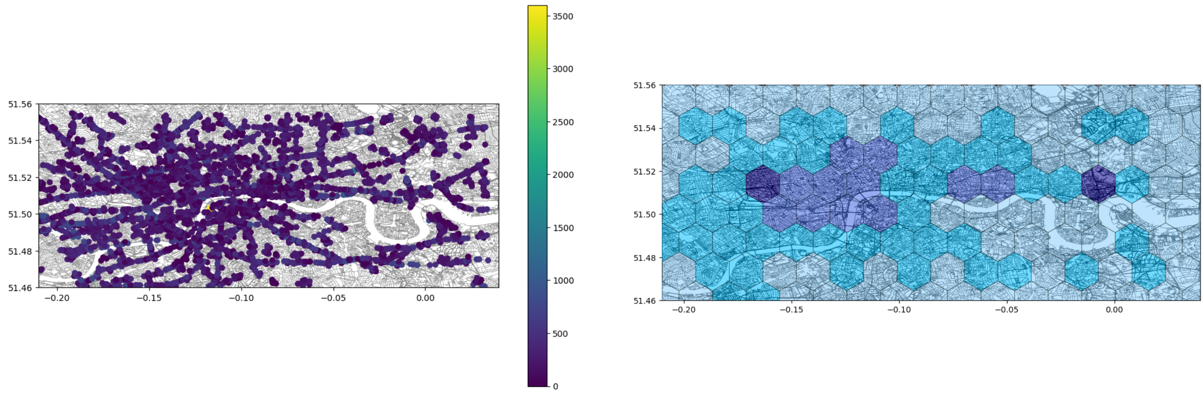


Figure 26: London traffic points and grid cell with traffic distribution

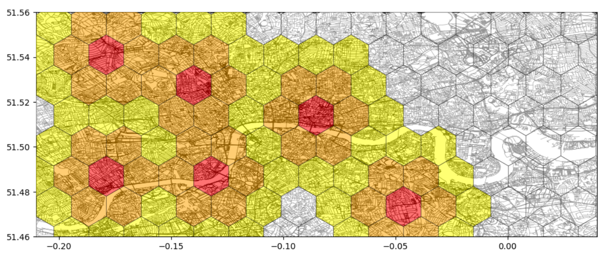


Figure 27: London solution

The results from the English capital are fairly comparable to those from the other cities as they follow the same trend. Furthermore, it is even clearer to understand in this instance how the hexagonal zones are allocated while avoiding the areas with a high demand that have already been met.
It is also interesting to observe how distance from the points of interest impacts allocation in this scenario, given that there are no hexagons allocated on the right side of the city, where there are way less POIs.

5.7.3. Utrecht

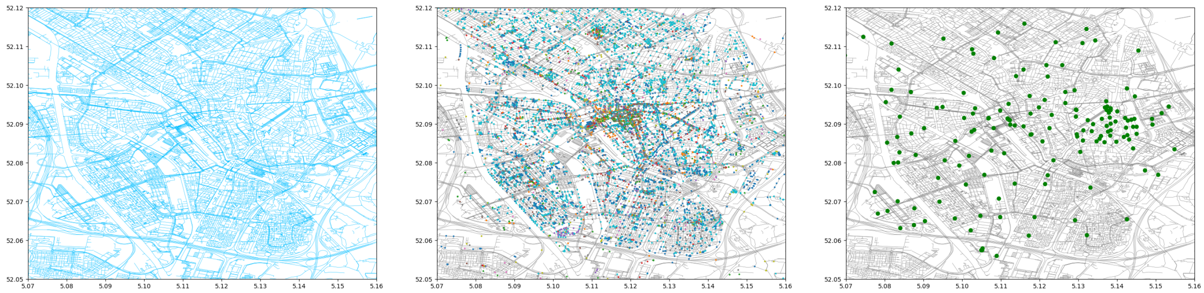


Figure 28: Utrecht map, POIs and existing charging stations

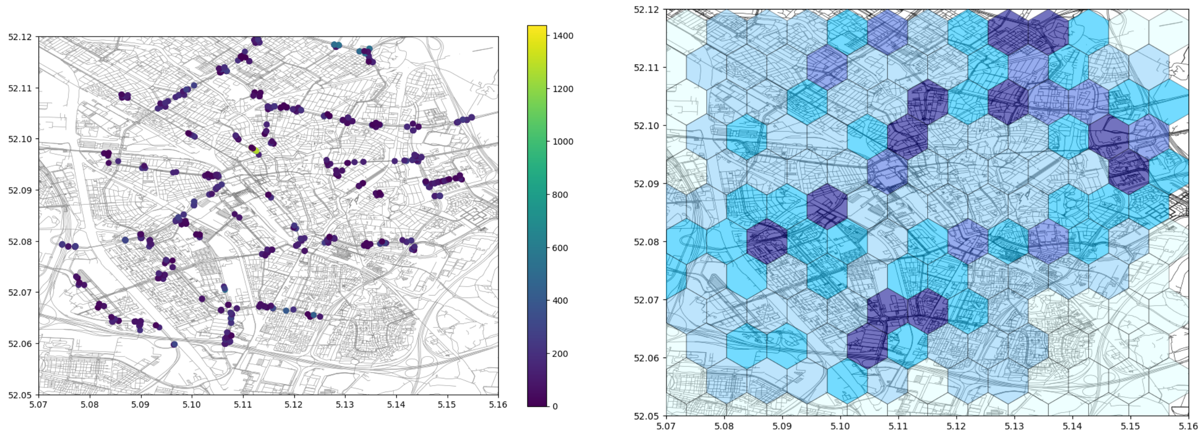


Figure 29: Utrecht traffic points and grid cell with traffic distribution

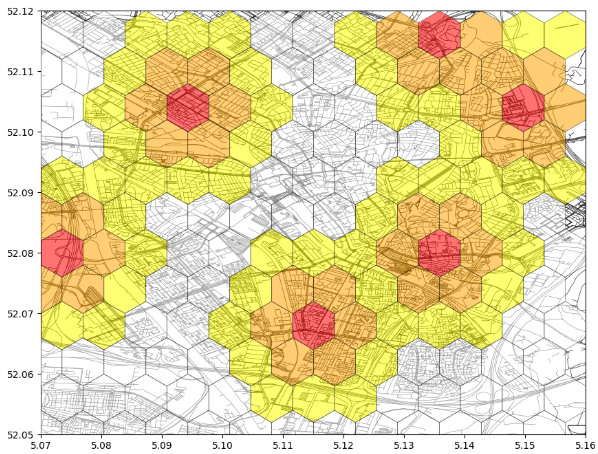


Figure 30: Utrecht solution

Even Utrecht exhibits the same trends as the other cities, focusing mostly on areas with broad roadways.

5.7.4. Rotterdam

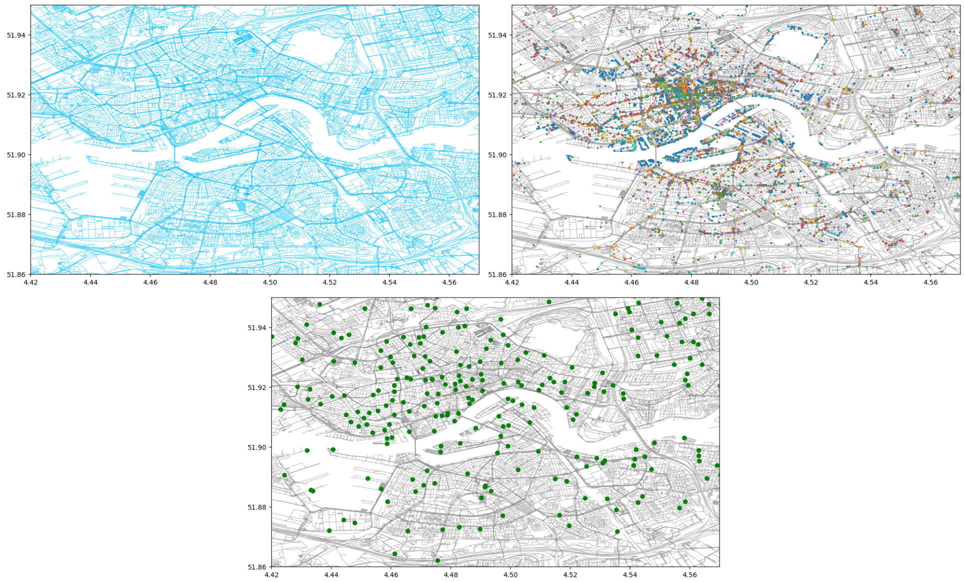


Figure 31: Rotterdam map, POIs and existing charging stations

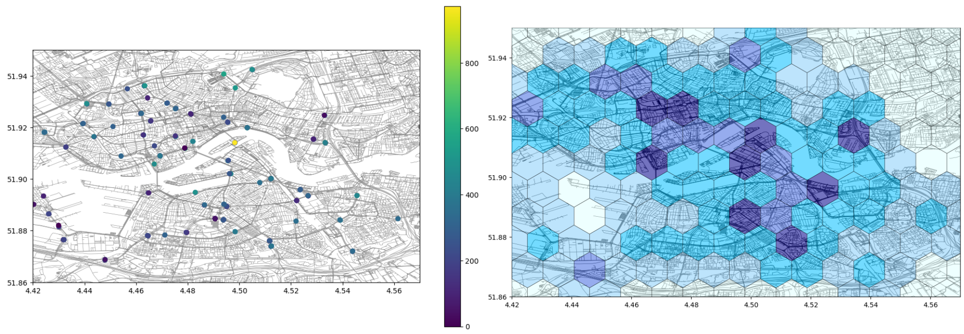


Figure 32: Rotterdam traffic points and grid cell with traffic distribution

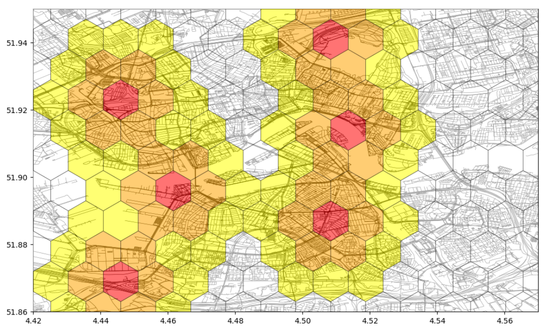


Figure 33: Rotterdam solution

As they follow the same pattern, the outcomes from the Dutch port city are fairly similar to those from the other cities.
As in the London example, considering that there are no hexagons allocated on the right side of the city, where there are far fewer POIs, it is fascinating to study how proximity to the points of interest affects allocation in this case.

5.7.5. Hamburg

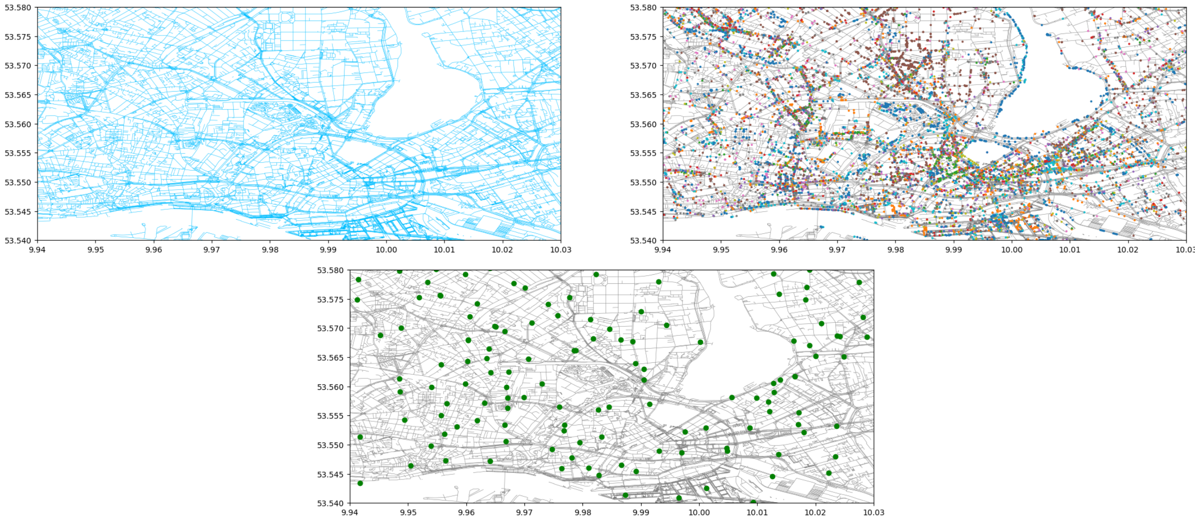


Figure 34: Hamburg map, POIs and existing charging stations

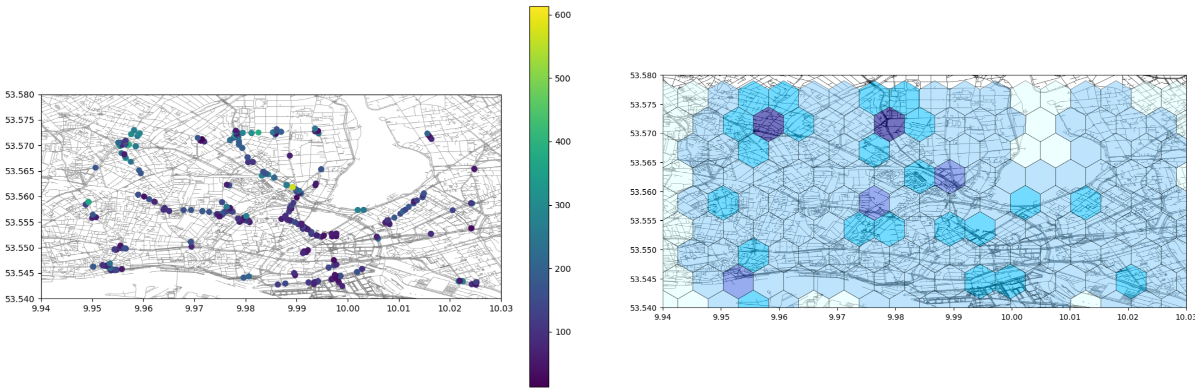


Figure 35: Hamburg traffic points and grid cell with traffic distribution

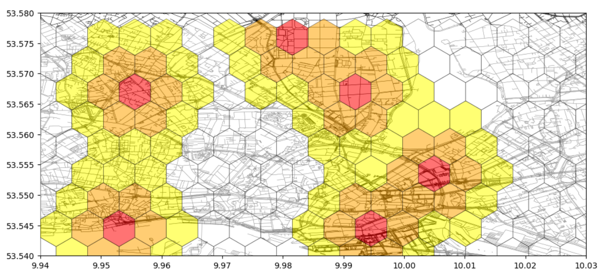


Figure 36: Hamburg solution

Even the Hamburg case adheres similarly to the pattern of the other examples. It is interesting to note that in this particular scenario, two hexagons are situated next to the river, where there is an important presence of points of interest, and areas that can be seen as node for several principal roads. This layout emphasises the role of geographic characteristics in affecting how these hexagonal zones are arranged, highlighting the complex interaction between urban planning and the surrounding environment.

5.8. Web App

In the last step of the project, attention switched to designing a user-friendly interface that could effectively depict the successful outcomes. This interface was meticulously designed to seamlessly translate complex results into easily comprehensible visualizations, enhancing the overall user experience.
To accomplish this, the web app contains the following functionalities:

1. **User Input:** Users start by providing the name of one of the six cities analyzed and the desired number of zones they wish to allocate within the city limits. This input is the foundation for generating the hexagon zones.

2. **City's Features Visualization:** Given a city, the web application displays a selection area with a city's map, points of interest, available charging stations, and traffic points. Users can choose one of these four plots and print it larger to better analyse the city's features.

3. **Algorithmic Allocation:** The core functionality of the app lies in its proprietary algorithm that determines the optimal placement and configuration of hexagonal zones within the city. The algorithm developed uses the input data and the techniques described to generate the optimal solution.

4. **Result Visualization:** To visualize the solution of the optimization algorithm it was created a user-friendly interface that translates the algorithm's results into a visually engaging map. The map showcases the allocated hexagon zones, each clearly demarcated and color-coded for easy identification. Users can explore the city's new zoning layout and gain insights into the spatial distribution of different zones.

For convenience, a visual representation of the web app's layout has been included in the Appendix A. This supplementary section features a collection of screens that effectively showcase the arrangement and design of various elements within the application. Figure A.37 and A.38 of Appendix A depict the design and layout of the Web App developed.

6. Conclusion

6.1. Problem approach

A problem such as optimally placing of charging stations for electric vehicles hides a wide number of opportunities and challenges. In this regard, Oasis project view has gone beyond a mere allocation of resources, subject to certain constraints. That is because, at the moment, electric vehicles are considered a key element in the transition towards a greener energy source. As a consequence, this radical change represents a breaking point with respect to the past (strongly dependent on fossil fuels) and a chance to revisit the whole concept of mobility. In addition, the electric grid infrastructure should be able to sustain an additional burden that may create the need to invest a large amount of money. With the aim of acquiring a suitable knowledge of the opportunities connected with this transition process, an initial phase was dedicated to study both the state of the current infrastructure and the future one, related to forecasts about the penetration rate of the EVs in society. In particular, different papers concerning prediction models of the EVs' diffusion, and their impact on the grid have been examined. From the analyzed papers, it emerged that major concerns are connected to three aspects mainly:

- the influence of slow chargers on the power demands during peak hours, which should be considered as an extra-request concerning the current one, where EV's penetration rate is still low;
- the installation of high-power chargers, to cope with the need to charge the vehicle quickly(fast chargers), may request the augmentation of medium voltage (MV) lines;
- looking even further into the future, the necessity to keep into account also heavier transportation means, such as trucks or buses, that would need high-power charging stations to charge them in an amount of reasonable time.

In particular, as exposed in [29], in Italy this power overloading may be completely unsustainable with current transformers, best of all if the urban area is considered in a scenario with a high penetration rate. Hence the role of the vehicle in the grid ecosystem and its possibility to become a dual-purpose source has been addressed. The research focused on current cutting-edge grid services connected to the grid: an unmissable opportunity to solve both the problem of the limited infrastructure (best of all concerning the energy storage and the peaks in energy consumption) and the opportunity for car owners to receive a fee. From the study of Cenex[16] the potential of V2G to actively provide service to the grid (DTU, STOR, FFR) is clearly highlighted, but tightly dependent on the plug-in time per day and the market price of the services provided to the grid. Nonetheless, the profitability for the owners, accepting a continuous degradation of the battery and a reduction of the car disposal, for a modest fee, could be a false move in a phase where these services must be better tested on a large scale, and car owners, in countries like Italy, show extreme resistance against the electric transition. By contrast, Smart Charging (often indicated as V1G) appears to be a suitable transient solution. It allows to save money to the final user just by regulating the charging time and speed, contributing to reducing peak consumption. It is still a passive solution, but its savings reach 80% of the V2G one, considering savings as income and up to 40% of the total V2G income when actively provided services are considered, but the plugin time is low. Last, but not least, it is important to remember that active services can be provided just when the plug-in time is consistent, of course, and not the case of fast-chargers, which represent the core business of Atlante.

Although not always directly involved, the built knowledge has led to an open-minded approach. The design phase of the "solution" was guided by a forward-thinking vision: to be sustainable and efficient, the capability of building a dynamic solution, able to anticipate instead of pursue, should have been the baseline.

Passing from the infrastructural aspects to the algorithm-related ones, the dilemma consisted of choosing between a GIS-based and a graph-based one. In the absence of models in which theoretical choices were motivated/validated, a GIS-based one was preferred due to its previous adoption by the founder company (Atlante) and its simplicity in being visualized and refined, overlaying different data on a single map to extract useful information from them.

As it is known, to produce numerical values from a model data are needed and they have an economic value, consequently whoever owns them usually is not prone to share them or simply cannot (in the case of a profit organization, like Motus-E[30]). Therefore, the parameters that could be involved in the optimization model and the available data were tightly related and thus the development of a mathematical model became a subordinate task. Thanks and due to this, the adopted approach showed its full potential: once a new typology of data is found, a new layer in the map is added and related information are extracted to be kept into account in the optimization, as constraint or as part of the cost function. Another key advantage was related to the possibility of visualizing the different data and it proved to be useful to understand if they presented inconsistencies. In addition, every intermediate result, related for example to grid creation or traffic proxy estimation was directly plotted on the map to check if the used formula produced results coherent with the known trend, i.e. in the central area of the studied town. At this point, the project concentrated on the creation of a *toy model* in cities where data were available, and in the attempt to make the algorithm adaptable in each case the same type of data were provided as input.

Establishing a data pipeline to collect and transform into numerical value the needed information was crucial to make the algorithm scalable. To start with, for each point of the city, a value indicating the mean traffic was computed with data from OpenStreetMap and it would be used as the first proxy for the traffic estimate near a certain point (better defined later). Secondly, it was important to have as data the location of the current EV charging station, which position and number already satisfies a certain part of the demand (and in certain cases, also more than that because currently not every EV charger is optimally located). To have an interesting scenario, just cities with more than 150 EV charges were chosen and the set was reduced to the previous mentioned six. Last, but not least, the POIs have been extracted from OpenStreetMap and their position acquired an important role in the optimization process: if people spend a certain amount of time in a certain POI, consequently, it would be advisable to put the EV chargers as close as possible to this it, offering in this way an attracting service to people and maximizing the utilization time of the chargers. To this end, a different weight was assigned to different POIs, depending on the cluster to which they were considered part of, because the time spent in a certain POI was considered correlated to the type of activity done there.

A map discretization, necessary to pass from layer data to a specific indexes/coefficients, was applied. As suggested by the company and by some readings[28], a hexagonal grid was adopted. To be precise, an H8 resolution was chosen with appropriate consideration given to the trade-off between the level of detail and computational efficiency. It ensures that there exists a balance between granularity and manageability.

For what concern the optimization algorithm itself, the cost function was built with the purpose of of maximizing the likelihood that a charging station located within the chosen car parks would encounter the residual charging demand in the corresponding grid cell, whilst simultaneously minimizing the distance between the car parks and the points of interest. Some constraints were added mainly about:

- maximum number of parking slots (site) chosen;
- avoidance of adjacent car parks as selected one;
- minimum value of the remaining charging demand for each cell at the end of the selection process.

A new approach was applied to quantify the traffic flow and improve the fairness of the used index. The main reason was that this datum was punctual and not representative of the main direction followed by the traffic or of the time the traffic was stacked at that specific point. Several additional factors must be taken into account to achieve a more complete representation of the actual demand based on the traffic data. In the innovative adopted perspective, traffic is seen as *flux*. In this way, the focus was moved towards the time spent by traffic in a certain area. The more congested the area, the more time the vehicle spends there. To compute a significant index, first, a lot of effort was spent in finding a tool to estimate these traffic fluxes and Google Maps proved to be the best compromise. A proxy of the flux in the hexagon was computed by considering for each hexagon the difference between the traffic time from it towards its six neighbor centroids(and vice versa) in case of congested traffic and without traffic. Consequently, two proxies were extracted: one representative of the additional time due to traffic flow congestion inbound and the other for the outbound one. Finally, a congestion index was computed by summing for each hexagon all the inbound traffic time proxies and subtracting the outbound ones.

To finally realize a project, its economic feasibility is at the base. To evaluate it, a Life Cycle Cost analysis was conducted. Both technical and economic aspects were involved and some assumptions on the value of certain parameters was necessary (i.e. penetration rate or cath rate) in this regard, the team closely collaborated with Atlante company which shared its proxy and/or other estimates coming from experience for the parameters to be used in the optimization model. A Gaussian distribution was assumed for the load curve, producing an average full-power daily load of 7.5 hours. Other parameters introduced in the model were related to the acquisition cost (cost for each physical charging station), the PoD cost, the cost of the electric energy (to be constantly updated), and the average revenue generated for a sold kWh of energy. All these factors are completely parameterized and easy to change by the company operators.

6.2. Discussion of the results

6.2.1. Optimal placement

The initial city utilized as input for the toy model was Madrid. After evaluating the results, the primary emphasis of the study revolves around the organization of hexagonal zones created for electric vehicle (EV) charging stations. Notably, these zones do not exclusively align with the city's center due to several contributing factors. Certain constraints necessitate a minimum distance between stations, and the layout of these zones is contingent upon variables like demand fulfillment and traffic congestion. Many of these zones encompass major roadways, which, while not consistently congested, experience periodic congestion events that validate the placement of charging stations. The current high supply of stations in the city center supports the identification of optimal locations, extending the distribution of stations beyond the city center. Consequently, positioning stations along prominent avenues, albeit outside the center, ensures efficient service coverage. Considering road suitability, accessibility, and dimensional factors, human intervention is necessary for exact station placement, even though the algorithm can identify ideal zones.

Finally, the team strived to meet the needs of users searching for an intuitive and friendly interface with a tailored web application. Key features of this app include user input for city selection and zone allocation, visualization of various city features, an algorithm essential for optimal zone placement, and an interactive map for presenting results. The aim was to enhance user engagement and provide clarity in comprehending how different zones in the chosen city would be spatially distributed.

6.2.2. Financial analysis

The economic analysis comprises two distinctive yet complementary steps. In the initial phase, conducted using Python, key economic metrics such as Return on Investment (ROI) and the Breakeven Point (BEP) are calculated for the first 10 optimal station positions. The subsequent phase, carried out in Excel, serves to validate the sensitivity of results to various parameters and explores the robustness of different strategies through parameter variations. Considerations beyond traffic are taken into account by the optimization algorithm, making the separation of analyses necessary. Despite assuming no change in individual behavior after deployment, the algorithm is affected greatly by traffic parameters, leading to economic revenue implications. As such, the preliminary analysis is used to evaluate the economic practicality of the identified key points, providing insight into their overall allure. Undertaking a Techno-Economic Analysis is necessary once an appropriate site is found. This analysis assists in establishing the perfect station sizing and financial details. An equilibrium between probable revenue and expenditures is reached by taking into account various input parameters. This technique polishes station design and sets a firm groundwork for educated choices. The preliminary analysis primarily focuses on evaluating Capital Expenditures (CAPEX) and Operating Expenses (OPEX) without cash flow actualization. CAPEX encompasses initial investments such as equipment, installation, labor, permits, and taxes, while OPEX covers ongoing operational costs, including electricity, maintenance, and monitoring. From these parameters, crucial financial indicators are derived, including the breakeven point, which signals when costs align with revenue, and ROI, quantifying the return on investment over a specific period. These metrics play a pivotal role in guiding decision-making, allowing for the assessment of project viability and potential profitability. The economic analysis hones in on hexagons with the highest traffic volumes, offering insights into the financial feasibility of deploying EV charging stations in locations with the greatest user adoption and revenue generation potential. Hexagon number 149, representing the most heavily trafficked hexagon among the chosen ones, serves as an illustrative example. Key economic values for each year, along with their present discounted values, are computed, enabling comparisons across different time periods. The determination of the number of stations hinges on the expected average daily traffic in 2032, with a maximum saturation rate capped at 97.5%. Calculating cumulative economic values is integral to deriving the Life Cycle Cost (LCC), offering insights into financial feasibility. A negative LCC implies positive income, a favorable outcome for EV charging station deployment. With a station saturation rate of 89%, the rapid recoupment of the initial investment becomes evident, occurring in approximately 2 years and 4 months, as indicated by a DPP of 2.3 years. This swift recovery underscores the financial robustness of the project. Furthermore, the LCC per station, an amalgamation of costs and revenues over a 10-year period, stands at an impressive figure of approximately 180,000 €, underscoring the comprehensive financial impact, encompassing both expenditure and potential income. The Return on Investment (ROI) metric further accentuates the positive financial outlook. Over the 10-year timeframe, the calculated ROI reaches an impressive 340%, highlighting substantial gains compared to the initial investment and affirming the project's profitability. Last but not least, a sensitivity analysis was presented, which is tailored to Madrid's unique context but can be adapted for different cities. It reveals cost patterns, emphasizing cautious station sizing to prevent lost sales. Results vary with traffic scenarios; while adding stations may be unfavorable with average traffic, it can reduce overall costs in high-traffic scenarios. Decisions should consider not only individual stations but also inter-point comparisons for optimal investment sequencing. Customizing such analyses for specific urban contexts is crucial for accurate insights and informed decision-making in EV charging station deployment in different cities.

6.3. Future developments

The algorithm, as currently organized, is open to further developments. As said, some of the principles guiding it were flexibility and dynamism. Consequently, though it represents a sufficient baseline, it is far from being a definitive product. During the time spent on the developments, different possible improvements have been discussed, and, considering the available time, some of them have been left as guidelines for future works. These ideas have been divided into two main categories: one related to the algorithm(optimization model and data collected) and one to the economic aspects. From what will emerge, these guidelines for further developments can be seen in part as advice for the company to improve the algorithm, but also as suggestions for institutions, like local municipalities or government entities, which, representing *super partes* players, may more easily collect the needed data and use them, on the contrary, to better route incentives and policy towards the achievements of social common purposes instead of private ones.

6.3.1. Optimization model and input data

These two sides of the project have been considered together because, as said, every constraint added to the optimization model is often connected to new data that must be found:

- the most important one is related to the **residual power** of the electric grid with respect to its total capacity. Its importance was highlighted also in the article [15]. Different parts of the city have different residual power that can be exploited without overloading the grid. Consequently, the proximity of a hexagon to a less stressed area (commercial, rural), should favor it as the optimal one. As a starting point, a possible solution may distinguish the area of the city as urban, rural, and commercial, assigning to them a different multiplicative coefficient. A more refined one, instead, should have the for each area the residual capacity, favoring the ones with higher ones in the placement.

- the scoring model may take into account much more information. For example, **population** density would be an index that encourages the placement in more populated areas for logical reasons. In addition, the different coefficients such as penetration or catch rate could be refined taking into account both the current **sociological index and trend**. An area where wealthier people are concentrated would probably show a higher penetration rate than one with less wealthy people. Another factor to be kept into account is **people's habits**: an area known for its relevant technological and social development(such as the one near an innovation district) may be more sensitive to climate-related issues and may anticipate the adoption of an electric vehicle if compared with the early majority of the population.
- starting from an example, the concept of requested dynamism wants to be stressed. **Habits** of people change over time and, locally, the placement of electric chargers may stimulate the spreading of new points of interest that can entertain people during downtimes. This reciprocal influence is quite difficult to be forecast and modelized, but at least its existence must be remarked on to create awareness of how complex and interconnected is the studied scenario.
- not all the areas inside a hexagon are exploitable. A possible solution would consist of a further layer to be added to the GIS model, to **take into account also prohibited areas** (i.e. protected sites or ZTL) to be apriori excluded from the possible locations for the chergers.
- in the placement algorithm, to choose the place where the EV charger(s) must be located, **other parameters about the specific site should be known and related to the charger requirements**. For example, by considering an amount of $12m^3$ for chargers, some sites would be excluded if the space is not enough compared to the number of chargers to be installed.
- the algorithm just suggests a hexagon to the operator using it. The actual choice of the position into the hexagon of the street or the precise land is left free. With more information about the **economic side** (as will discussed later), this arbitrariness could be further reduced towards "the most" optimal choice.
- an other useful feature, in this context, would be an **inner-hexagon analysis** to further reduce the search space inside the hexagon. For example, it would be useful to consider more granularly the shape of existing parks and their precise location in the neighborhood, aiming to guarantee a suitable compromise between **user experience** and **architectural integration**. Of course these two last aspects would be extremely complex to be quantified.
- the **text estimated average range of EV may be corrected depending on the considered city characteristics**. Some parameters influencing the range may be the driving speed, elevation, weather, and road surface, as done in [31].
- the congestion index has been defined ad a multiplicative coefficient. Nonetheless, as discussed in 5.4.2, it may be defined as convex linear combination with puntual traffic flow value.

6.3.2. Economic aspects

The economic aspects of an installation are crucial for its profitability and consequently for the business of the company. From a project perspective, it was born just as an appendix but its importance constantly arises also as selection criteria. Therefore the following improvements should be applied:

- in **the installation cost and the land cost must be further differentiated depending on the area** and the purpose(i.e. private or public) indicated on the town plan, which would greatly influence the amount to invest. In addition, possible **incentives** for the placement in a specific area (i.e. innovation district) must be kept into account.
- the **objective function does not consider any economic factor** at the moment. The economic evaluation of the profitability of the chosen site is just made a posteriori. It follows that, once the economic/financial analysis is improved, it can be introduced in the optimization process to reach a less suboptimal compromise between economic and technical requirements.
- As discussed, **energy cost** is variable, consequently it would be advisable to take it from an authoritative source and thus automate this operation. This operation can be extended to other parameters like the penetration rate or the selling price per kWh.

A. Appendix

A.1. Table

POI	Cluster	Weight
Bar Convenience Greengrocer Cafe Restaurant Fast food Supermarket Bakery Butcher Market place Food court Ice rink Pub Kiosk Beverages Vending parking	Food	0.29
Artwork Hairdresser Bookshop Bicycle shop Furniture shop Toy shop Beauty shop Telephone Mobile phone shop Clothes Sports shop Stationery Department store Jeweller Video shop Travel agent Shoe shop Bicycle rental Laundry Car dealership Florist Car rental Computer shop Gift shop	Retail	0.27

Table 8: POI Clusters with Weights

POI	Cluster	Weight
Playground Park Dog Park Cinema Nightclub Town Hall Swimming Pool Mall Shelter Outdoor Shop Arts Centre Golf Course Fire Station Courthouse Fort Chalet Nursing Home Theme Park Water Tower Community Centre Pitch Attraction Theatre Track	Leisure	0.17
Hotel Monument Fountain Post Office Memorial Observation Tower Tourist Info Viewpoint Ruins Castle Wayside Cross Picnic Site Museum Battlefield Embassy Guesthouse Hostel Archaeological Tower Motel Windmill Water Mill Car Sharing Wayside Shrine	Tourism	0.14

Table 9: POI Clusters with Weights

POI	**Cluster**	**Weight**
Bank ATM	Finance	0.08
Pharmacy Dentist Hospital Clinic Sports Centre Veterinary Chemist Doctors	Health	0.02
Kindergarten School College University Library	Education	0.02

Table 10: POI Clusters with Weights

A.2. Web App

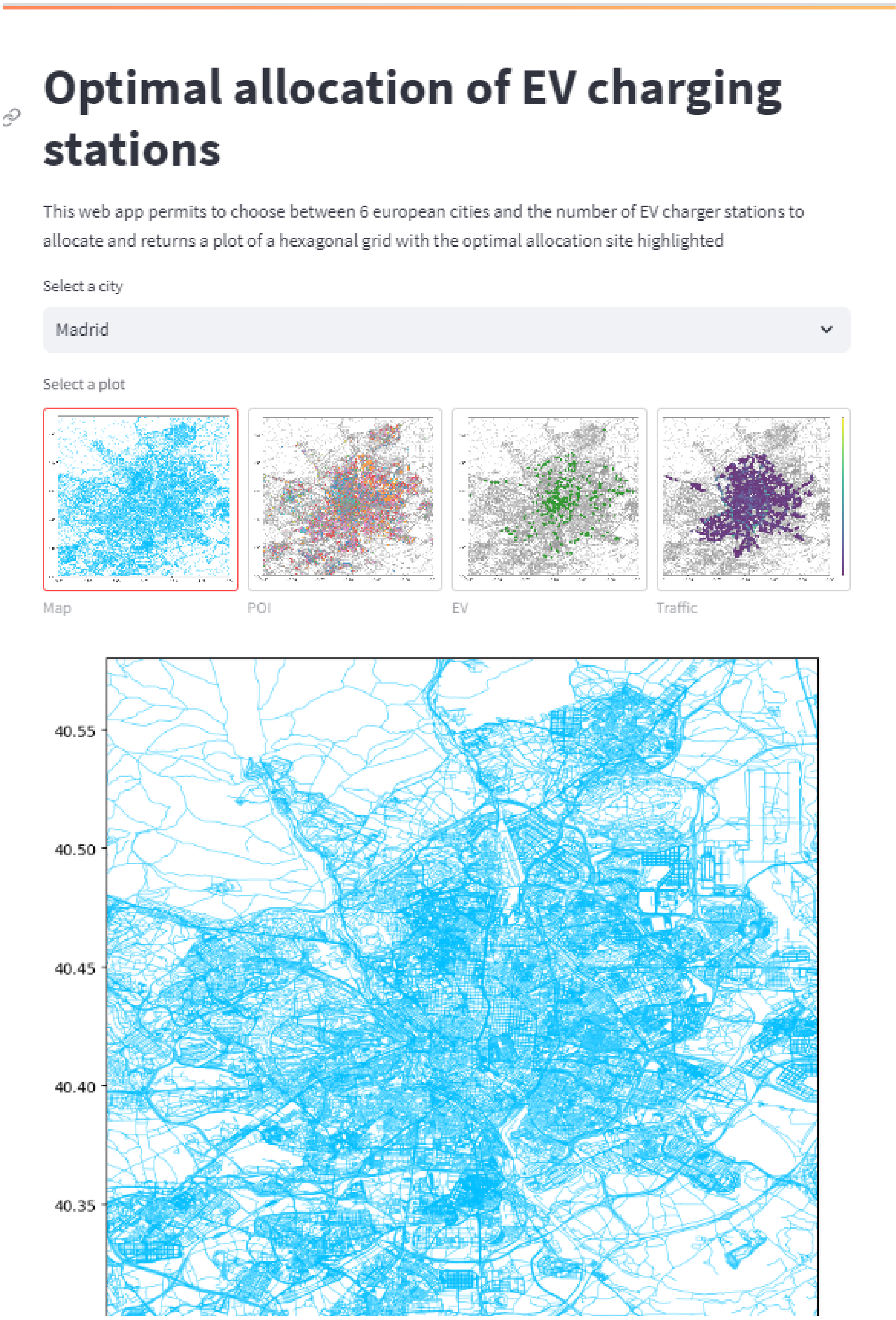


Figure 37: Web App illustration

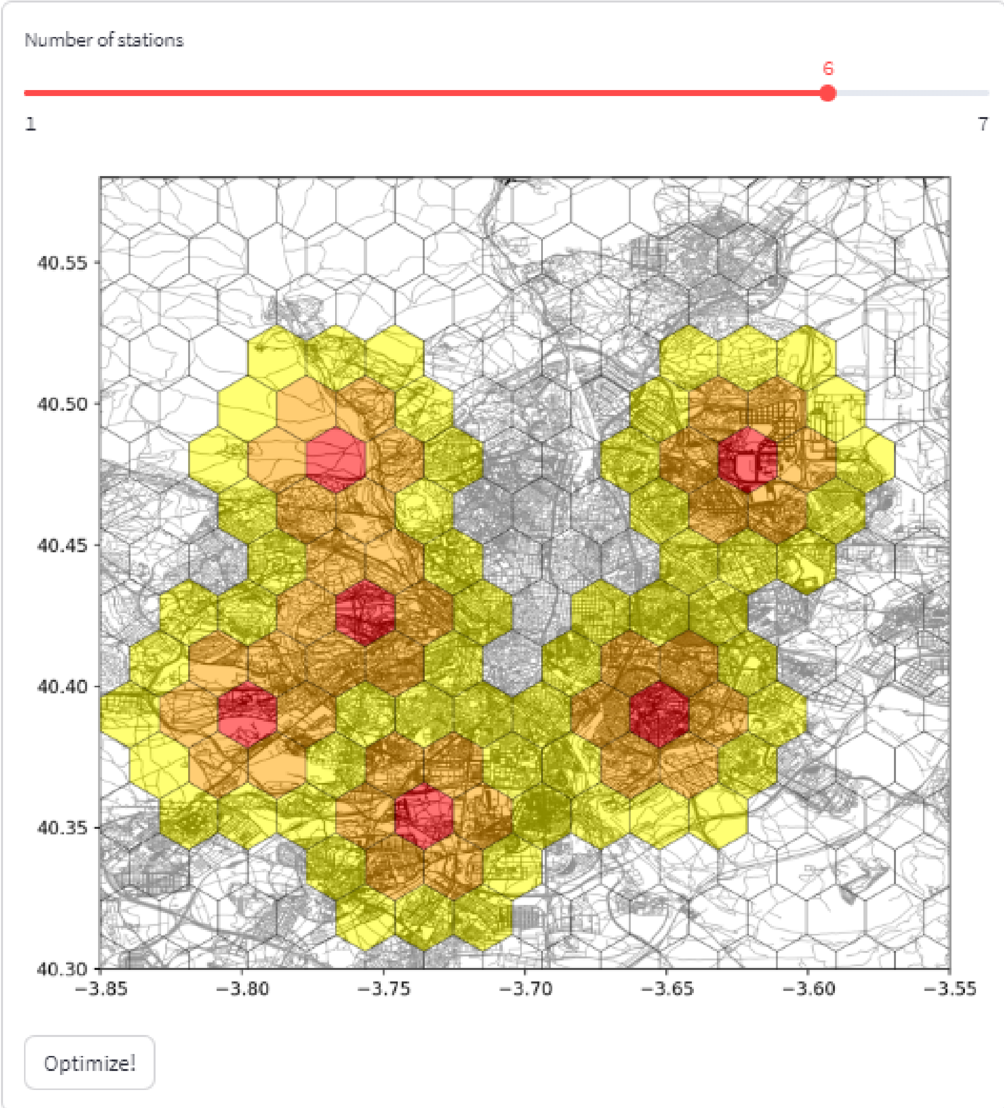


Figure 38: Web App illustration

References

[1] Siemens. *Vehicle Electrification: Electrify the future of automotive.* 2023. URL: https://static.sw.cdn.siemens.com/siemens-disw-assets/public/MMM9n8aaG6q7DdMf1eYXN/en-US/TAC_900.016_GBL_EBK_The%20Value%20of%20Vehicle%20Electrification.pdf.

[2] José Romero Hoesung Lee. 'CLIMATE CHANGE 2023 Synthesis Report, Summary for Policymakers'. In: *IPCC Intergovernamental Panel on Climate Change* ().

[3] PwC. *State of the Plug-in Electric Vehicle Market.* 2013. URL: https://www.pwc.com/gx/en/automotive/industry-publications-and-thought-leadership/assets/pwc-ec-state-of-pev-market-final.pdf.

[4] Deloitte. *Electric vehicles, Setting a course for 2030.* 2020. URL: https://www2.deloitte.com/content/dam/insights/us/articles/22869-electric-vehicles/DI_Electric-Vehicles.pdf.

[5] Massie Thomas. *Rep. of US House of Transportation on EV transition.* Forbes News. 2022. URL: https://youtu.be/avi9iBC8opU.

[6] Dimitrios Gkatzoflias et al. 'Optimal allocation of electric vehicle charging infrastructure in cities and regions: the new technical research report of the Joint Research Centre of the European Commission, the European Commission's in-house science service'. In: (2016).

[7] Mehmet Erbaş et al. 'Optimal siting of electric vehicle charging stations: A GIS-based fuzzy Multi-Criteria Decision Analysis'. In: *Energy* 163 (2018), pp. 1017–1031.

[8] Ali Khalife, Tu-Anh Fay and Dietmar Göhlich. 'Optimizing Public Charging: An Integrated Approach Based on GIS and Multi-Criteria Decision Analysis'. In: *World Electric Vehicle Journal* 13.8 (2022), p. 131.

[9] Raphaela Pagany, Luis Ramirez Camargo and Wolfgang Dorner. 'A review of spatial localization methodologies for the electric vehicle charging infrastructure'. In: *International Journal of Sustainable Transportation* 13.6 (2019), pp. 433–449.

[10] Yawei He, Kara M Kockelman and Kenneth A Perrine. 'Optimal locations of US fast charging stations for long-distance trip completion by battery electric vehicles'. In: *Journal of cleaner production* 214 (2019), pp. 452–461.

[11] ENTSO-E. 'Electric Vehicle Integration into Power Grids'. In: (2021).

[12] Elia group. 'Accelerating to net-zero: redefining energy and mobility'. In: (2022).

[13] Zeming Jiang et al. 'Statistical analysis of Electric Vehicles charging, station usage and impact on the grid'. In: *2016 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT).* 2016, pp. 1–5.

[14] Ville Tikka et al. 'Case study of the load demand of electric vehicle charging and optimal charging schemes in an urban area'. In: *2012 3rd IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe).* 2012, pp. 1–7.

[15] Enrico Mancini et al. 'Assessment of the Impact of Electric Vehicles on the Design and Effectiveness of Electric Distribution Grid with Distributed Generation'. In: *Applied Sciences* 10.15 (2020).

[16] Cenex. 'Understanding the True Value of V2G, an analysis of the customers and value streams for V2G in the UK.' In: (2019).

[17] Everoze & EVC Consult commisioned by UK Power Networks. 'V2G Global Roadtrip: around the world in 50 projects'. In: (2019).

[18] Sovacool Noel Zarazua de Rubens. 'The Technical Challenges to V2G. In: Vehicle-to-Grid, Energy, Climate and the Environment'. In: (2019).

[19] PwC. 'Regulatory barriers for Smart Charging of EVs and second life use of EV batteries'. In: (2020).

[20] Daniel Murfet. *Orientamenti relativi alla partecipazione dei veicoli elettrici al mercato per il servizio di dispacciamento, per il tramite delle infrastrutture di ricarica dotate di tecnologia Vehicle to Grid*. https://www.arera.it/allegati/docs/20/201-20.pdf. Accessed: 25-03-2023.

[21] Wikipedia. *Diffusion of innovations — Wikipedia, The Free Encyclopedia*. http://en.wikipedia.org/w/index.php?title=Diffusion%20of%20innovations&oldid=1161425904. [Online; accessed 25-August-2023]. 2023.

[22] Lorder Allister. *UTD19*. 2020. URL: https://www.research-collection.ethz.ch/handle/20.500.11850/437802.

[23] Paul Gilchrist. *RETURN ON INVESTMENT (ROI) ON ELECTRIC VEHICLE CHARGERS*. 2022. URL: https://www.electricvehiclechargers.net/ev-charger-roi-return-on-investment-electric-vehicle-charger/.

[24] New West Technologies. *Costs Associated With Non-Residential Electric Vehicle Supply Equipment*. 2019. URL: https://afdc.energy.gov/files/u/publication/evse_cost_report_2015.pdf.

[25] 'Electric vehicles standards, charging infrastructure, and impact on grid integration: A technological review'. In: *Renewable and Sustainable Energy Reviews* 120 (2020), p. 109618. ISSN: 1364-0321. DOI: https://doi.org/10.1016/j.rser.2019.109618.

[26] Zeming Jiang et al. 'Analysis of electric vehicle charging impact on the electric power grid: Based on smart grid regional demonstration project — Los Angeles'. In: *2016 IEEE PES Transmission & Distribution Conference and Exposition-Latin America (PES T&D-LA)*. 2016, pp. 1–5. DOI: 10.1109/TDC-LA.2016.7805675.

[27] Chargeprice. *EV charging fees*. 2023. URL: https://www.chargeprice.app/.

[28] ArcGIS Pro 3.1. *Why hexagons?* 2022. URL: https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-statistics/h-whyhexagons.htm.

[29] Enrico Mancini et al. 'Different Penetration of Electric Vehicles and Impact on Developments in the Electric Grid'. In: *2020 IEEE Vehicle Power and Propulsion Conference (VPPC)*. 2020, pp. 1–5. DOI: 10.1109/VPPC49601.2020.9330914.

[30] *Motus-E*. https://www.motus-e.org/. [Online; accessed 25-August-2023]. 2023.

[31] *Chargetrip*. https://chargetrip.com/. [Online; accessed 25-August-2023]. 2023.

[32] Miguel Campaña, Esteban Inga and Jorge Cárdenas. 'Optimal sizing of electric vehicle charging stations considering urban traffic flow for smart cities'. In: *Energies* 14.16 (2021), p. 4933.

[33] Zeming Jiang et al. 'Statistical analysis of Electric Vehicles charging, station usage and impact on the grid'. In: *2016 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT)*. 2016, pp. 1–5. DOI: 10.1109/ISGT.2016.7781228.

[34] Germana Trentadue et al. 'Evaluation of Fast Charging Efficiency under Extreme Temperatures'. In: *Energies* 11.8 (2018). ISSN: 1996-1073. DOI: 10.3390/en11081937. URL: https://www.mdpi.com/1996-1073/11/8/1937.