EFFICIENT MODEL FOR ELECTRIC VEHICLE CHARGER INSTALLATION ON A NON-URBAN HIGHWAY: THE CASE OF BR-386, BRAZIL

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MASTER'S DISSERTATION IN TRANSPORTATION

FACULTY OF TECHNOLOGY

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TIAGO DE OLIVEIRA MAFRA TEIXEIRA

DEDICATION

To God, who by His grace saved this poor sinner;
To my parents, Lúcio and Lígia, for being the foundation of my past, present, and future;
To my grandmother, Adília, for all her prayers and her immense love;
To my Paiá for always being my second mother;
To Aunt Denise for her constant support throughout all phases of my life.

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First, I thank God for granting me this opportunity that many people dream of having, and especially for choosing me and saving me, even though I didn't deserve it or wasn't the most capable. Without that, I wouldn't be here today. To Him all honor and glory.

To the best parents anyone could ask for, Lúcio and Lígia, for their constant support throughout all the years of my life and for always showing me the right path, according to God's will. I am certain that this achievement of mine was a dream you both longed for. If I am who I am today, it is entirely because of you. I love you very much.

I thank my grandmother, Adília, for always believing in me and showing me, from a very young age, that education is our only opportunity. To my Paiá, my second mother, for her constant support amidst laughter, shouts, and kisses. In the way that only we know how. To Aunt Denise, for always being present throughout my life, helping me and showing me other ways of thinking and seeing.

To my uncles, aunts, cousins, relatives, and friends at UMP, thank you so much for your prayers and companionship throughout this master's program and for what is to come.

I thank my advisor and friend, Professor Reinaldo, for guiding me since my undergraduate studies and for always motivating me to take the next step in my academic career, whether in the master's or doctoral program to come. Thank you so much for the advice, work, and patience during all these years. See you in the USA.

To the professors of the PPGT, my sincere thanks for all the classes, lectures, and new ways of acquiring knowledge that I learned. You were a part of this too.

Finally, I thank the PPGT secretary, Camila, for being a blessing all these years, always helping me and showing me how to move forward in the master's program, even when I was slow to understand many times.

"Commit your way to the Lord; trust in him, and he will act." Psalm 37:5

ABSTRACT

This study aimed to find optimal points to place electric vehicle chargers (EVCs) for electric vehicles (EVs) on the non-urban highway BR-386, part of the MOTIVA ViaSul concession. This work applied a Genetic Algorithm (GA) model combined with the Geographic Information System (GIS) to determine the optimal locations of the charging station. The work was implemented in three stages. The first stage was the acquisition and cleaning of the database because the data was obtained from several different sources. The second stage was the implementation of the GA model. This phase used the applied data, including traffic flow (both in 2025 and an estimate for 2030), electrical energy infrastructure and EV specifications. The third stage was the application of different scenarios to obtain the optimal solution for the model. The model found two optimal locations for EV charger allocation, besides to the ideal number of chargers, the average queue length size, and the utilization percentage of the chargers depending on the scenario, either the 2025 one or the 2030 scenario.

Keywords: Electric Vehicle Charging, Optimization, Genetic Algorithm, Geographic Information System

RESUMO

Este estudo teve como objetivo encontrar pontos ótimos para posicionar carregadores de veículos elétricos (CVEs) para veículos elétricos (VEs) na rodovia não urbana BR-386, parte da concessão da MOTIVA ViaSul. Este trabalho aplicou um modelo de Algoritmo Genético (AG) combinado com o Sistema de Informação Geográfica (SIG) para determinar os locais ótimos da estação de recarga. O trabalho foi implementado em três etapas. A primeira etapa foi a aquisição e limpeza do banco de dados, pois os dados foram obtidos de diversas fontes diferentes. A segunda etapa foi a implementação do modelo de AG. Esta fase utilizou os dados aplicados, incluindo o fluxo de tráfego (tanto em 2025 quanto uma estimativa para 2030), infraestrutura de energia elétrica e especificações de VEs. A terceira etapa foi a aplicação de diferentes cenários para obter a solução ótima para o modelo. O modelo encontrou dois locais ótimos para alocação de carregadores de VEs, além do número ideal de carregadores, o tamanho médio da fila e a porcentagem de utilização dos carregadores dependendo do cenário, seja o de 2025 ou o de 2030.

Palavras-chave: Carregamento de Veículos Elétricos, Otimização, Algoritmo Genético, Sistema de Informação Geográfica

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LIST OF SYMBOLS, NAMES AND ABREVIATIONS

ARIMA	AutoRegressive Integrated Moving Average
BEV	Battery Electric Vehicle
CI	Confidence Interval
EV	Electric Vehicle
EVC	Electric Vehicle Charger
FCEV	Fuel Cell Electric Vehicle
FIFO	First In, First Out
GA	Genetic Algorithm
GIS	Geographic Information System
HEV	Hybrid Electric Vehicle
MCDA	Multi-Criteria Decision Analysis
NPV	Net Present Value
ONS	National Electrical System Operator (*Operador Nacional do Sistema Elétrico*)
QPP	Quadratic Polynomial Projection
PHEV	Plug-in Hybrid Electric Vehicle
PSO	Particle Swarm Optimization
PNCT	National Traffic Control Plan (*Plano Nacional de Contagem de Tráfego*)
RS	Rio Grande do Sul

1 INTRODUCTION

The use of fossil fuels is the main source of the vehicle transportation worldwide (HUANG *et al.*, 2018). Nowadays, however, this utilization is turning into a questionable and negative subject because of the effects on Earth (KARNAUSKAS *et al.*, 2020). Therefore, the limited and expensive amount of fossil fuels available, makes that the search for the new and the renewable sources or vehicle transportation occurs in almost all of the countries (KALGHATGI *et al.*, 2018). Even though Brazil's energetic sources mainly come from renewable sources, this urge for replacing fossil fuels is a government proposition (LIMA *et al.*, 2020; OLIVEIRA *et al.*, 2022).

One of the many solutions for this replacement is the use of electric vehicles (EV), avoiding the fossil fuels industry (SUDJOKO *et al.*, 2021). Currently, the EV in Brazil corresponds to only 0,64% of the total vehicles being used, being a total of 397,789 of the 61,803,369 cars (BRAZIL, 2022; BRAZILIAN ELECTRIC VEHICLE ASSOCIATION, 2024). That occurs because of the many difficulties faced in Brazil, such as greater social inequality, public security and transportation problems, besides the lack of logistic support once the developing countries do not have the same level of expertise when compared to developed ones (COSTA *et al.*, 2018). Moreover, the average Brazilian needs to spend 65.81 times of the minimum wage to buy the cheapest EV available, while only 46.50 times of the minimum wage to buy the cheapest fossil fuel available car (BRAZIL, 2024; RENAULT, 2024; CITROËN, 2024). It must also be said that in Brazil, only 29.6% of the population have access to a car, whereas 30.9% of the population use public transportation (BRAZILIAN CONFEDERATION OF TRANSPORT, 2024).

Brazil has a total of 1.720.909,00 km of highways connecting the country, because the most used transportation method is still the highway system (BRAZILIAN CONFEDERATION OF TRANSPORT, 2022). This study is going to focus on the southern part of the country, especially in the state of Rio Grande do Sul (RS), in the highway BR-386, concession MOTIVA ViaSul, connecting the city of Canoas with the city of Caraizinho, with a total of 266 km of extension. This is because it is a research project developed in collaboration with MOTIVA ViaSul.

Looking at the experience of other countries, it can be a natural process to substitute fossil fuels cars for the EV in some decades (HOLECHEK *et al.*, 2022). One of the most challenging needs is the implementation of Electric Vehicle Charging (EVC) stations to deal with the demand of the EV fleet (DEB *et al.*, 2018). Currently, in Brazil there are about 11,000 EVC, most of them only located in the urban area, and most frequently located close or inside shopping malls (BRAZILIAN ASSOCIATION OF ELECTRIC VEHICLES, 2024). This EVC number may be insufficient for the market growth of EV in the coming years in urban areas (VELANDIA VARGAS *et al.*, 2020).

It is known that the faster the EVC, the higher the installation costs (GNANN *et al.*, 2018). Having those two categories, cost and charging time, being the most decisive when it comes to implement the EV in a highway, this study takes this into account to decide the optimal locations to install the EVCs (MAHDAVIAN *et al.*, 2021).

The Brazilian logistics is then made through the non-urban highways, and the vehicles carrying the goods are mainly fossil fuels based. The switch to an electric fleet can reduce the goods final price for the end consumer because of the lower transportation emissions and costs (ALP *et al.*, 2022).

Since Brazil has long highways, in order to implement the EVs, including more EVC allows longer trips (NOEL *et al.*, 2019). The research question of this study is then to determine where are the possible optimal locations for the EVCs, taking into account the maximum number of vehicles to be charged, the traffic flow, the queuing time, to optimize the installation of EVCs in a non-urban highway, particularly in the BR-386, concession MOTIVA ViaSul.

The main objective of this study is to propose and evaluate scenarios for the placement of EVC stations along the BR-386 highway, in the segment between Canoas and Carazinho, by applying a genetic algorithm to determine optimal station locations. For the localization, a Geographic Information Systems (GIS) approach is also used.

The genetic algorithm was chosen because it is widely used in similar location-allocation problems, particularly in highway contexts where a large number of variables and constraints must be considered (ZHOU *et al*., 2022; KROL & GRZEGORZ SIERPINSKI, 2021; CHOI *et* *al.*, 2024; LI *et al.*, 2021; AKBARI *et al.*, 2018; CHUNYAN SHUAI *et al.*, 2024; TURAN *et al.*, 2021; YENİGÜN *et al.*, 2024; PINTO *et al.*, 2024).

A Geographic Information Systems (GIS) is an effective analysis tool to enhance the optimization and finding the best location for the EVC (BANEGAS & MAMKHEZRI, 2021). In addition, Python is used to create the numeric problem itself, with all the conditions and boundary conditions necessary to simulate the real world. And also, the use of Python is to create visually all the scenarios that were tested and to give a real representation of the problem.

The specific objectives of this study include two main ones: First to analyze the growth of the EVs in Brazil worldwide and in the BR 386 scenario. This analysis is important to understand the difference between Brazil and other developed and developing countries about the implementation of the EV and the EVC. Moreover, it is important to forecast the future for the EVs in Brazil besides looking at what other countries have done to mitigate the downsides of the change of fossil fuels to EVs.

The second objective is to formulate a decision-making model capable of determining the optimal type and quantity of EV charging stations along highways. This involves constructing low-growth, baseline, and high-growth scenarios derived from historical PNCT time series, and assessing each scenario in terms of average queue length, utilization levels, economic viability, and geographic siting performance throughout the entire study period. Therefore, the model aims to aid the decision makers to install the EVCs efficiently.

After the development, modeling, and calibration of the genetic algorithm, the model identified two locations as optimal for the installation of charging stations along the BR 386 MOTIVA ViaSul concession. In addition, the optimal number of chargers for each year and for each of the proposed growth scenarios was determined.

This study is structured into three main phases, as illustrated in Figure 1.1. The first phase consists of a literature review, focusing on the evolution of electric vehicles and charging infrastructure, as well as the theoretical foundations relevant to optimization in similar contexts, which is presented in Chapter 2. The second phase describes the data, methodological procedures, and the modeling framework adopted for this research, which is presented in Chapters 3 and 4. Finally, the third phase presents and evaluates the results of the proposed model, including the identification of possible charging station locations and scenario outcomes, which is presented in Chapters 5, 6, and 7.

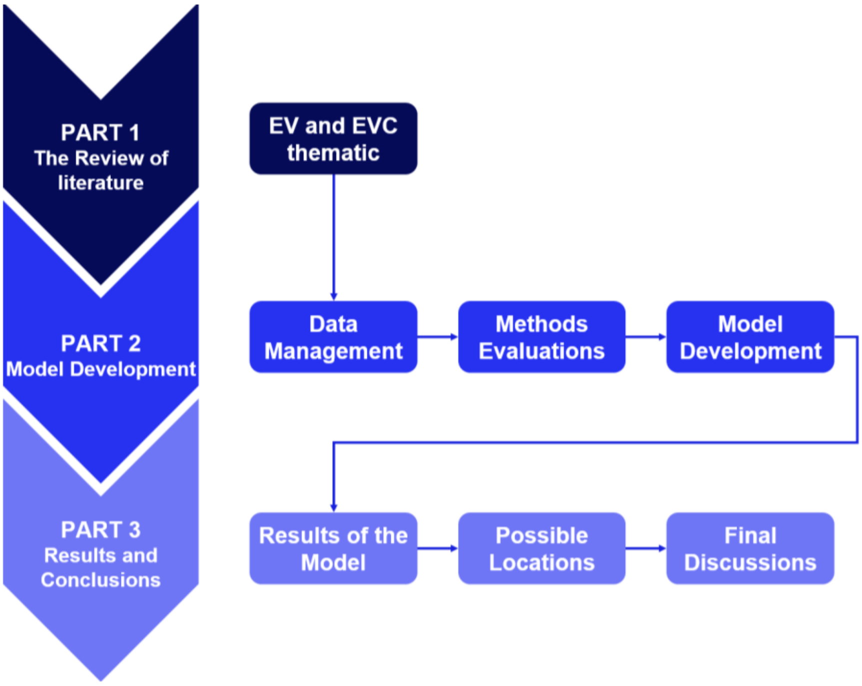

Figure 1.1 Study Structure

2 LITERATURE REVIEW AND THE APPLIED METHOD

In this section, a literature review about the most important topics related to this study is presented. A background of the EV, the EVCs and their technology are shown besides a description of the GIS. The implemented mathematical proposition for the optimal locations of the EVCs is presented, as well as the applied method used in this study.

2.1 EVOLUTION OF THE EVS IN THE WORLD

It is considered an Electric Vehicle (EV) those cars being propelled partially or fully by electric engines (RUAN & SONG, 2019). There is still no consensus of the first appearance of the EV in the world, but many say that it was about 1828, when a Hungarian named A´nyos Jedlik, invented a small-scale model car powered by an electric motor (CHAN, 2013). However, widespread use, and consequently commercialization, began only almost 170 years after the first prototype was made by Ányos Jedlik, by the year 2000 (BARBOSA *et al.*, 2022). The delay between these dates was necessary due to the advance of EV technology, like any other conceptual design coming to the real world (SUN *et al.*, 2019).

The "green idea" related to the EV is to decrease the use of fossil fuels engines, because besides being harmful to the atmosphere it also causes damage to its recycling process (LELIEVELD *et al.*, 2019). Another benefit for the EV is that the fossil fuels are finite, and with the large demand for its utilization, about 102 Mb/d (million barrels per day), some projections estimate that it will last about 50 years, if nothing new is found and the demand continues to rise at this accelerated rate (U.S. ENERGY INFORMATION ADMINISTRATION, 2025; KALGHATGI, 2018).

Nevertheless, it does not mean that the switch to EV will happen in a few months or even years, due to its technology challenges including a smaller range anxiety, more charging infrastructure and the decrease in the battery cost (LEE & CLARK, 2018; KUMAR & ALOK, 2020). One of the many challenges faced to the EV implementation is the phenomenon known as range anxiety, being a very influential factor to decide or not to purchase an EV (NOEL *et al.*, 2019). Range anxiety is the fear of running out of electricity before reaching other EVC (NEUBAUER & WOOD, 2014). The anxiety is amplified by the lack of EVCs in the highways.

Possible solutions can be devised to overcome the range anxiety. A possible solution is to increase the EV autonomy in a non-urban scenario, making for instance, the EV range going from 200 km to 500 km per charge. Another possible solution is to provide more charging infrastructure, EVC (PEVEC *et al.*, 2019). The first mentioned solution is more technology dependent, and the second one is more economic dependent. Nowadays, there are different types of cars considered as EV.

The first vehicle type, the Battery Electric Vehicles (BEVs), was developed as early as 1828 with the creation of an electric driven motor consuming electricity as a way of transportation (FARAZ *et al.*, 2020). However, it was only from 1960 to 1990 that the EV invention was popularized and developed to the stage as it is known today. By the year 2005, the company Tesla was responsible for the main EV development and the spread of the market in the USA and in the rest of the world (LONG *et al.*, 2019). One of the main differences of the BEVs and the other EVs is that the BEV is the only one fueled only by electric power (KÖNIG *et al.*, 2021). Therefore, there is no need for a combustion engine because the only engine needed in the car is the battery one (LIU *et al.*, 2021). Another benefit is the zero CO2 emissions since there is no fossil fuel being used (KAWAMOTO *et al.*, 2019). In order to charge the BEVs faster, a Plug-in Charging is used, having about a 100 km to 600 km of electric range, as an important factor to control the range anxiety (DAS *et al.*, 2019). The Figure 2.1 shows a representation of a BEV car.

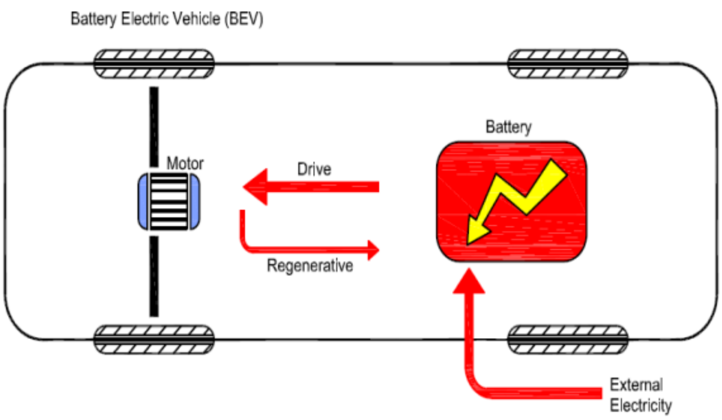

Figure 2.1 The Architecture and Components of BEV
Source: HARIKRISHNAN *et al.*, 2023.

The second vehicle type is the Plug-in Hybrid Electric Vehicles (PHEVs). The PHEV was first developed by 2002 to 2005 aiming to merge the BEV and the fossil fuel cars, having the option to recharge their battery via external power source besides the onboard electric generator (SINGH *et al.*, 2020). Moreover, the PHEV decreases the operation cost and the emission of harmful pollutants (PLÖTZ *et al.*, 2021). Usually, the people want to be more ecologically responsible, lowering their pollution, but do not want to have all the constraints, difficulties and range anxiety of a BEV (ADNAN *et al.*, 2018). It has about 30 km up to 100 km of electric range solely on the battery, and then the internal combustion engine will take over. The Figure 2.2 shows the PHEV car.

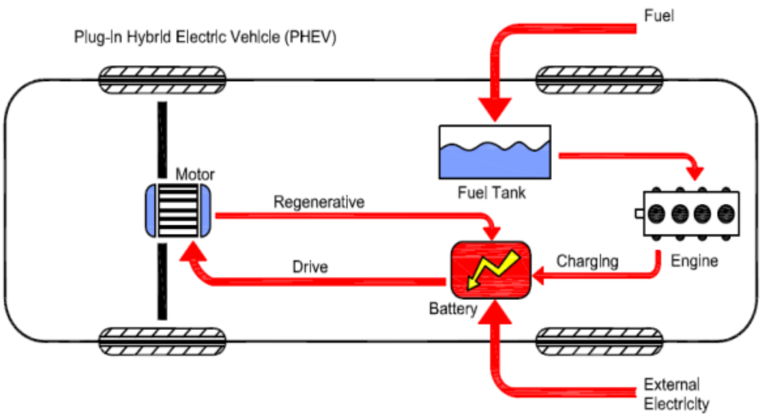

Figure 2.2 The Architecture and Components of PHEV
Source: HARIKRISHNAN *et al.*, 2023.

The third vehicle type, Hybrid Electric Vehicles (HEVs), was first developed in 1898 by Dr. Ferdinand Porsche, using an internal combustion engine to generate power to the traction electric motor (EHSANI *et al.*, 2021). Nowadays, after the creation of the Toyota Prius, almost every other auto manufacturer has introduced HEV automobile (ORECCHINI *et al.*, 2020). The difference between HEV and PHEV is that the HEV does not charge the battery externally (DENTON, 2020). The HEV works by using internal combustion engines and electric batteries, being recharged by the braking energy, which is normally wasted in other types of vehicles (RAHMANI & LOUREIRO, 2018). When the battery uses the braking energy the vehicle autonomy is only 5 km to 10 km, but the mentioned autonomy depends on the scenario, mainly if there is traffic jams (ZHUANG *et al.*, 2020). The CO2 emissions are not as low as previous electric vehicle types because of the short electric range of HEVs and the requirement to use only the breaking for charging (SINGH *et al.*, 2019). The Figure 2.3 shows the representation of an HEV car.

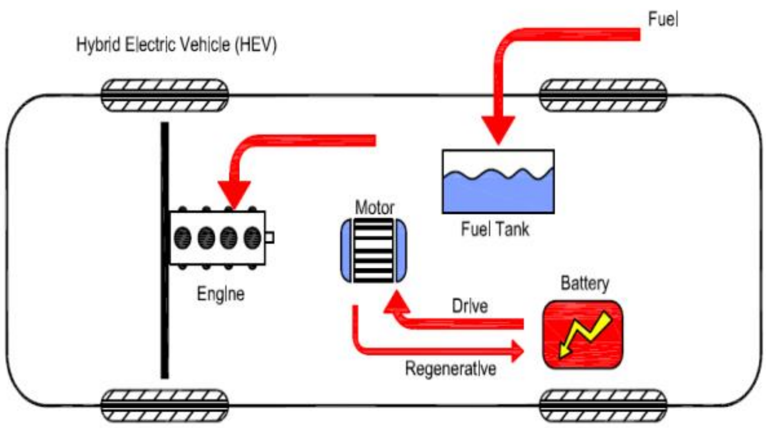

Figure 2.3 The Architecture and Components of HEV
Source: HARIKRISHNAN *et al.*, 2023.

The fourth vehicle type, Fuel Cell Electric Vehicles (FCEVs) is the latest type and features the best technology being considered the nonpolluting transport, if it excludes the recharge of the batteries on electric power stations (PENG *et al.*, 2022). The idea of the FCEVs is the conversion of fuel cells. Fuel cells are electrochemical devices converting the chemical energy from a reaction into electrical energy, with hydrogen serving as the fuel (MUTHUKUMAR *et al.*, 2020). The electric range is by far the most important feature of a FCEV, providing up to 700 km of autonomy (PRAMUANJAROENKIJ & KAKAÇ, 2022). The Figure 2.4 shows the representation of a FCEV car.

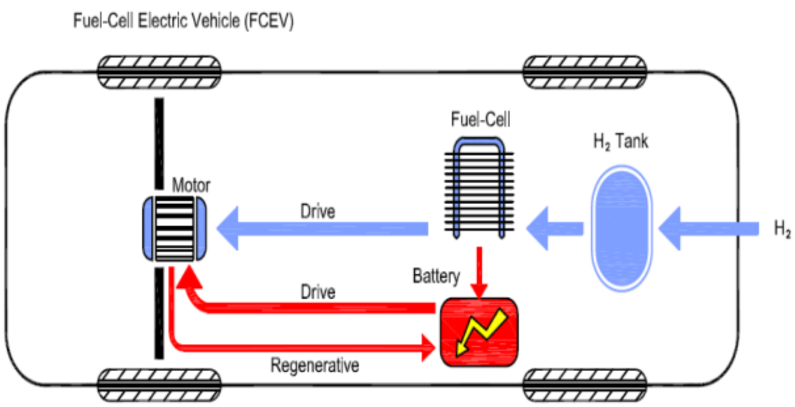

Figure 2.4 The Architecture and Components of FCEV
Source: HARIKRISHNAN *et al.*, 2023.

Table 2.1 summarizes the four different types EVs, presenting their characteristics and distinctions to support a clearer understanding of their technical and operational differences.

Table 2.1 Characteristics of EVs Type

VEHICLE TYPE	ENERGY SOURCE	ELECTRIC RANGE	ADDITIONAL FUEL	PLUG-IN CHARGING	CO2 EMISSIONS
Battery Electric Vehicles (BEVs)	Only electric battery	High (100-600 km)	None	Yes	Zero
Plug-in Hybrid Electric Vehicles (PHEVs)	Battery + combustion engine	Medium (30-100 km)	Gasoline or diesel	Yes	Low
Hybrid Electric Vehicles (HEVs)	Battery + combustion engine	Low (5-10 km)	Gasoline or diesel	No	Moderate
Fuel Cell Electric Vehicles (FCEVs)	Hydrogen fuel cell	High (300-700 km)	Hydrogen	No	Zero

This study applies the Battery Electric Vehicles (BEVs) because they are the ones requiring strictly Plug-in Charging to operate. Therefore, the BEVs will directly benefit from the construction and installation of the EVC in the highway.

2.2 EVOLUTION OF THE EVC IN THE WORLD

Electric Vehicle Charging (EVC) recharges the batteries of the BEVs and PHEVs. The place where the EVCs are installed can increase or decrease the range anxiety (XU *et al.,* 2020). It is also important to evaluate the waiting time to charge the car with the waiting time to fill it up, observing how many more kilometers will be required to recharge the car (GNANN *et al.*, 2018; SINGH *et al.*, 2020). The competition between EVs and fuel cars was unbalanced due to the cost disparity and the significant time difference in refueling times, because, while an average fuel car can be refueled in approximately five minutes, early EVs required up to 15 hours to fully charge (WISHART, 2014; COLLIN *et al.*, 2019).

An important issue related to the EVs is the high consumption of electricity to charge them (MURATORI *et al.*, 2019). The EVC can normally charge 5 kWh up to 50 kWh, implying a waiting time of 11 hours to 30 minutes (HEMAVATHI & SHINISHA, 2022). The mentioned EV required time varies between 132 to 6 times slower than the filling of a regular fossil fuel-based car to the EVCs. Furthermore, the flow of electricity must be considered. Nowadays, with the new and improved technology, there are basically four types of EVC being used worldwide:

Slow or normal charger: Up to 7.4 kilowatts (kW) of power and can take up to six to 12 hours to charge a vehicle. Not recommended for highways, where time to fuel needs to be as fast as possible.

Semi-fast charger: Up to 22 kilowatts (kW) of power taking up to two to six hours to charge a vehicle. It is also not recommended for highways due to the time to charge the EV.

Fast charger: Up to 100 kilowatts (kW) of power and lasting up to an hour and half to 30 minutes to charge a vehicle. It is recommended and mostly used on highways, even though the time is still high, when compared to a normal 5 minutes to fuel a normal vehicle.

Ultra-fast charger: Minimum of 150 kilowatts (kW) of power charging a vehicle in less than 30 minutes. It is recommended and mostly used on busier highways that need to charge their EV at the fastest time. Figure 2.5 shows an Ultra-fast charger.

Figure 2.5 Typically Ultra-Fast Charger
Source: SIEMENS, 2025.

To normalize all the possible outcomes, the Ultra-fast charger is the one to be applied in this research.

2.3 OPTIMIZATION METHOD

There are different approaches to analyze and to obtain the optimal localization for the same problem (ZHANG *et al.*, 2020). It depends on the subject of study, data analysis, theory and the criteria besides the expected outputs of the model (ZHOU *et al*. 2025). Moreover, it is important to find the global solution for the problem (KONG *et al.*, 2019). Some researchers have applied the weighted multi criteria location optimization methods, genetic algorithms or even particle swarm optimization methods (CSISZÁR *et al.*, 2020; YENİGÜN *et al.*, 2024). It must also be mentioned that the artificial intelligence has also been used to obtain the optimal solution for localization problem (JANOWICZ *et al.*, 2019).

The multi-criteria location optimization method has already been applied to separate the decision making into variables making a ponderation of the most important variables, according to the model (FENG *et al.,* 2021). The multi-criteria method has been applied in the localization problems and in a wide scope of other problems including healthcare, energy sector, production, supply chain management, transportation and finance/economics (TAHERDOOST & MADANCHIAN, 2023). It has been applied because it has the ability to obtain the exact global solution of the model (MUKHAMETZYANOV & PAMUČAR, 2018). Nevertheless, the system lacks to obtain a specific global solution for the problem when there are many variables, taking a much longer time to obtain the optimal solution (DUGGER *et al.*, 2022).

The metaheuristic method, including the genetic algorithms (GA), has also been applied to solve both constrained and unconstrained optimization problems being already used to biological evolution processes (KATOCH *et al.*, 2020). It is a population-based search algorithm applying the concept of survival of the fittest or the strongest producing new populations by the iterative use of genetic operators on individuals present in the population (MICHALEWICZ, 1996). The chromosome representation, selection, crossover, mutation, and fitness function computation are the key elements of the GA (PAPAZOGLOU & BISKAS, 2023). One of the main limitations for the application of the GA in the optimization problems is it cannot guarantee to obtain the global solution because of the way how the populations are created. Nevertheless, it is able to obtain a reasonably close solution for the global one (AZIZ *et al.*, 2023). An example of the GA algorithm is shown in Figure 2.6.

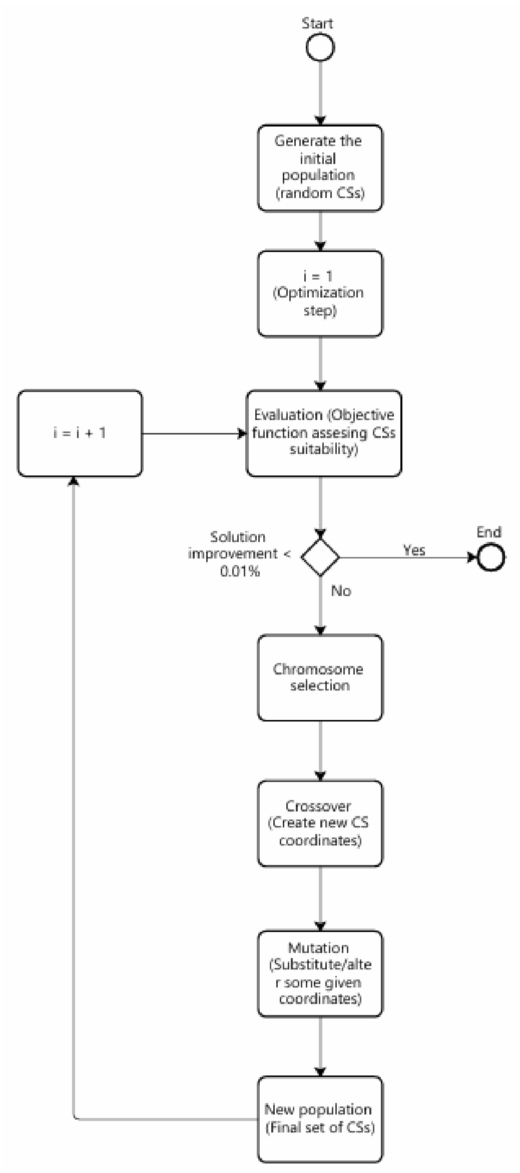

Figure 2.6 Genetic Algorithm Flowchart

Finally, another algorithm applied is the particle swarm optimization (PSO) making use of probability, by transition rules to make parallel searches of the solution hyperspace without explicit assumption of derivative information (KENNEDY & EBERHART, 1995). When implementing a PSO, a group of particles explores the problem space having movement influenced by both individual history and the trajectory of the swarm. Each particle shares then its best position with the other ones, incorporating random perturbations, and, after updating all their positions in an iteration, the process continues, refining the search near the perceived optimum (HOUSSEIN *et al.*, 2021). The PSO has the same limitations as the GA, once it does not guarantee to obtain the global solution, reaching solutions closer or near the global one.

This study applies the GA location optimization method because of the large number of variables to optimize the installation of the EVCs on specific kilometers of the BR-386, the studied highway in this project.

2.4 GEOGRAPHIC INFORMATION SYSTEM (GIS)

The Geographic Information System (GIS) is a concept, used in some software, making it possible to analyze the input dataset, linking it to a location on the earth's surface. Defining a GIS can be done by either explaining what it can do by looking at the components. Both are important to really understand a GIS and use it optimally (ALI, 2019).

One of the main GIS applications is that the model can be a combination of GIS and spatial analysis tools applying Multi-Criteria Decision Analysis (MCDA) methods, or even GA methods to achieve a better spatial decision by integrating multiple criteria from various spatial data sources (KAZEMI & AKINCI, 2018).

Therefore, the main benefit when implementing a GIS is that it will be trained to obtain a better solution, tied to a location on the earth's surface. Thus, it is through the GIS application that all points, coordinates and locations will be implemented in the model.

2.5 THE APPLIED METHOD

This study includes three different phases. The first one is the acquisition and cleaning of the input database. The data is obtained by multiple locations and sources:

Length of BR-386 highway (km): MOTIVA Via Sul.

Traffic flow: PNCT and DETRANRS.

Electrical energy infrastructure: ONS.

EV specification: SENATRAN

The main objective of this phase is to clean the dataset, checking for missing information. Useful information including traffic flow, traffic by period of the day, the car model, the length of the highway and the electrical energy infrastructure is given as input for the model.

The second phase is the implementation of the GA to obtain the location of the charging stations. The third phase is the creation of different scenarios for better understanding of the possible solution for the model. The best solution is achieved at this phase, fitting the solution and the other parameters, including the queueing time and the time to fully charge an EV. The idea is to create scenarios to enable the decision makers to install efficiently the EVCs.

3 THE DATA OVERVIEW

The main goal of this stage is to gather the data, preparing it for the model. The data analyzed is presented in Figure 3.1. The next sections describes the dataset showing the results from the implemented Python program on the data and show the result in the Python program.

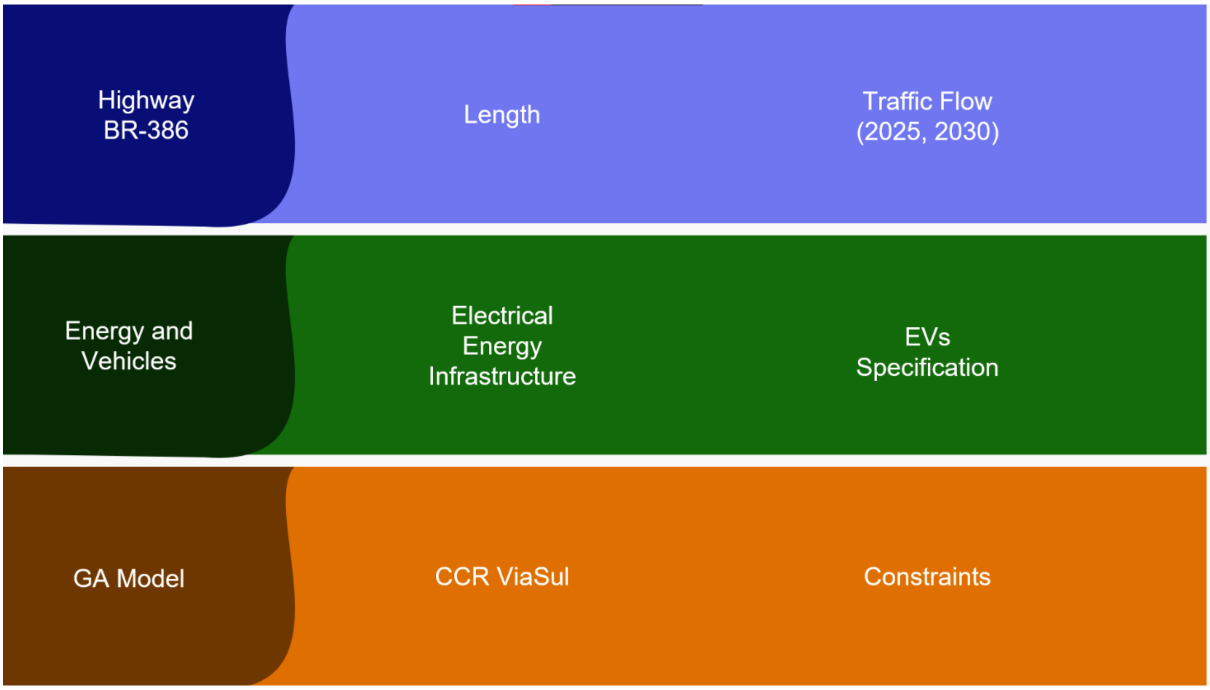

Figure 3.1 Data Overview Diagram

3.1 THE LENGTH OF BR-386 HIGHWAY (KM)

The first important task is to locate and plot the BR-386 highway. The gathered information was that the BR-386 by the MOTIVA ViaSul has a length of 266 km. Its starting point is in the city of Caraizinho, and its finishing point is in the city of Canoas (MOTIVA, 2025). Therefore, the next step was to plot this map using the Python script and the OpenStreeMap. Figure 3.2 shows all the highways that MOTIVA operates near the BR-386. Figure 3.3 has a detailed plot of BR-386 in the full size and Figure 3.4 has a detailed plot of the BR-386 belonging to the concession of the MOTIVA ViaSul, being the case study of this dissertation. A more detailed view of Figure 3.3 will be provided to present the optimal locations, including further parameters.

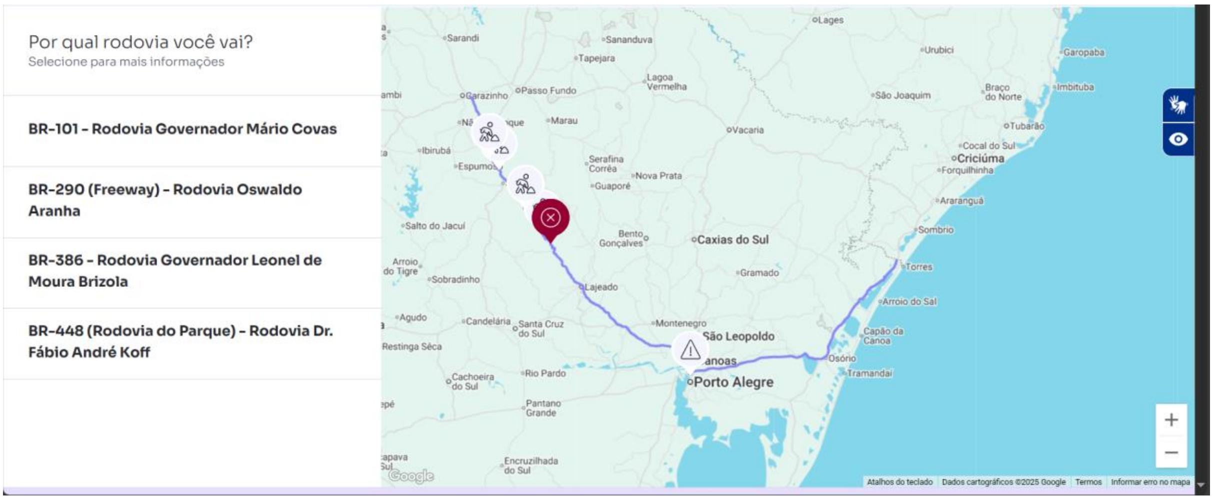

Figure 3.2 MOTIVA's Website
Source: MOTIVA, 2025.

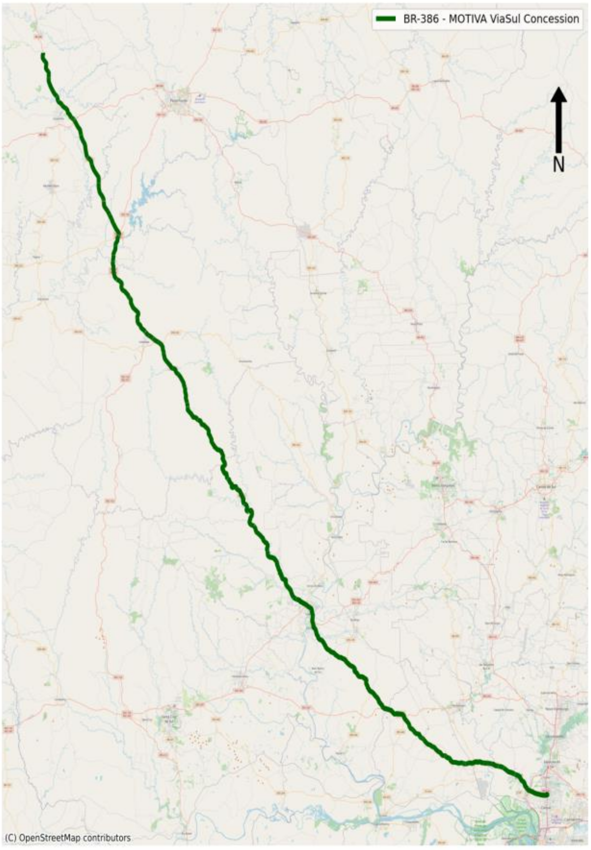

Figure 3.3 BR-386 Full Size
Source: MOTIVA, 2025.

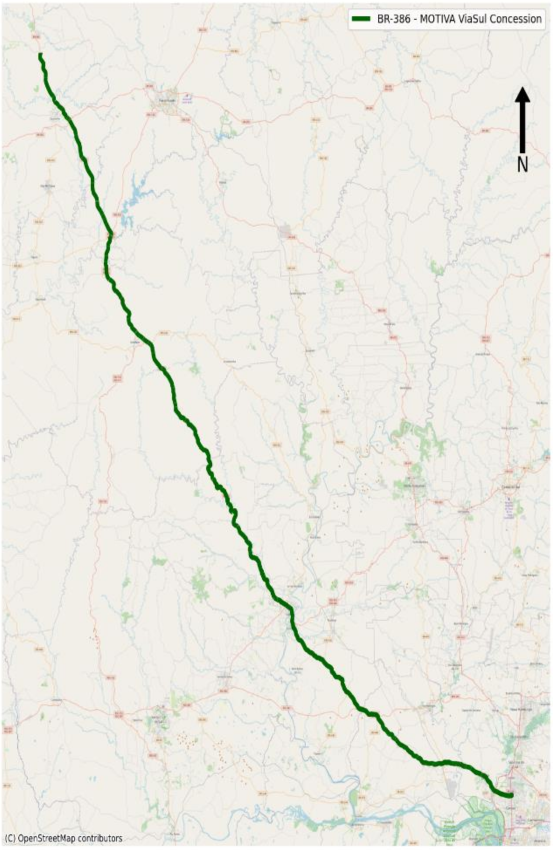

Figure 3.4 BR-386 MOTIVA ViaSul
Source: MOTIVA, 2025.

3.2 TRAFFIC FLOW (2025)

The traffic flow was calculated by the average measurement from the data collected in two different locations within the BR-386 highway, the kilometer 422-6 and the kilometer 362-8. This data was obtained through the PNCT (National Traffic Control Plan) being compiled from the 2024 measurements at these two specific kilometer locations (PNCT, 2025).

Firstly, the annual average daily traffic from passenger cars in both locations was consolidated. Afterwards, there was a count of how many days there was in the data for every location. Finally, the flow of cars was evaluated by an average. It was considered that the evaluated average did not vary along the time. The expected traffic flow is yearly was then evaluated. The percentages of the EVs was obtained from the data of the DETRAN-RS (RS State Department of Transit) and the EVs represent approximately 0.13% of the fleet in circulation in RS, as shown in Table 3.1. (DETRAN-RS, 2025).

Table 3.1 Traffic Flow Percentage 2025

CATEGORY	QUANTITY IN RS	PERCENTAGE OF FLEET
EVs	5,918	0.13%
All vehicles	4,627,979	100%

Source: DETRAN-RS, 2025.

Finally, the traffic flow of EVs in the highway BR-386, annually, was calculated being displayed in Table 3.2.

Table 3.2 Traffic Flow Analysis 2025

SECTION	CARS OBSERVED	DAYS OBSERVED	NUMBER OF CARS	NUMBER OF CARS PER DAY	NUMBER OF EVS PER DAY
422-6	5,538	231	2,061,019	8,922	-
362-8	5,536	334	2,132,332	6,384	-
Combined				**15,306**	**19.57**

Source: DETRAN-RS, 2025.

The Number of the EVs per year were used in the Python implemented program being changed in sensitivity tests to figure out the impact in the optimal location solution.

The daily number of EVs is evaluated by multiplying the Combined Total Number of Cars per Day to the Percentage of EV in the fleet. It was obtained the number of 20 EVs per day.

3.3 TRAFFIC FLOW FORECAST (2030)

The forecasts were made to the number of EVs in the period from 2025 to 2030. The data used was also from DETRAN-RS. The forecasts were implemented by three different methods, including the Linear Projection, a Quadratic Polynomial Projection and an Autoregressive Integrated Moving Average (ARIMA) method.

Linear Projection is mainly used for time series forecasting. Even though there are other more complex approaches, the studies have shown that the performance of complex models for the forecasting are often similar to the simpler linear models (ZENG *et al.*, 2023; LI *et al.*, 2023).

Quadratic Polynomial Projection (QPP) is another method used to forecast once it has a better fit quality with fewer iterations, for instance (ALRIDHA, 2023). The QPP has advantages since it is a polynomial of degree two.

ARIMA Projection is based on the assumption of stationarity of a series using a high number of past observations to predict the future values of the EVs (BAHUGUNA *et al.*, 2025).

The results of the 3 projections, both for all vehicles and for EVs, are presented in Table 3.3 to Table 3.6 and Figure 3.5 to Figure 3.12.

3.3.1 Linear Projection

The average yearly increase was calculated by taking the difference between consecutive historical data points and computing the mean of these differences. This value represents the typical growth per period. Then, starting from the most recent observed sales value, this average increase was added cumulatively to generate projected values for each year in the forecast horizon. Thus, the projection assumes that the rate of change remains constant over time, producing a linear continuation of the historical growth pattern as shown in Table 3.3 and Figure 3.5 and Figure 3.6.

Table 3.3 Linear Projection 2026-2030

YEAR	EVS	ALL VEHICLES
2026	23,725	4,810,490
2027	27,668	4,892,048
2028	31,611	4,973,606
2029	35,554	5,055,164
2030	39,498	5,136,722

Source: DETRAN-RS, 2025.

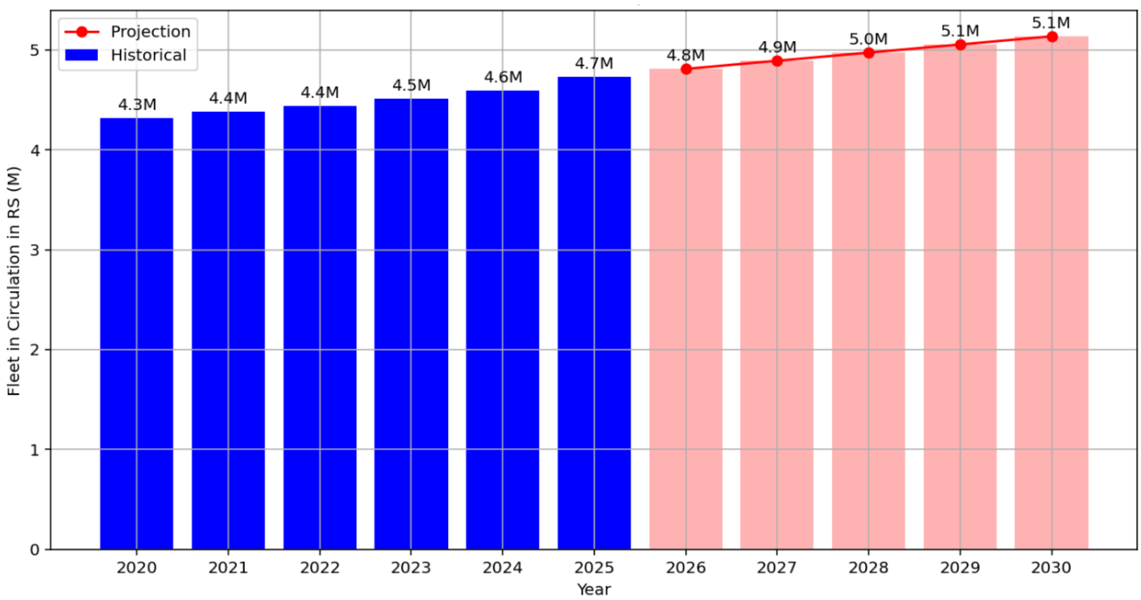

Figure 3.5 Linear All Vehicles Fleet Projection 2026-2030
Source: DETRAN-RS, 2025.

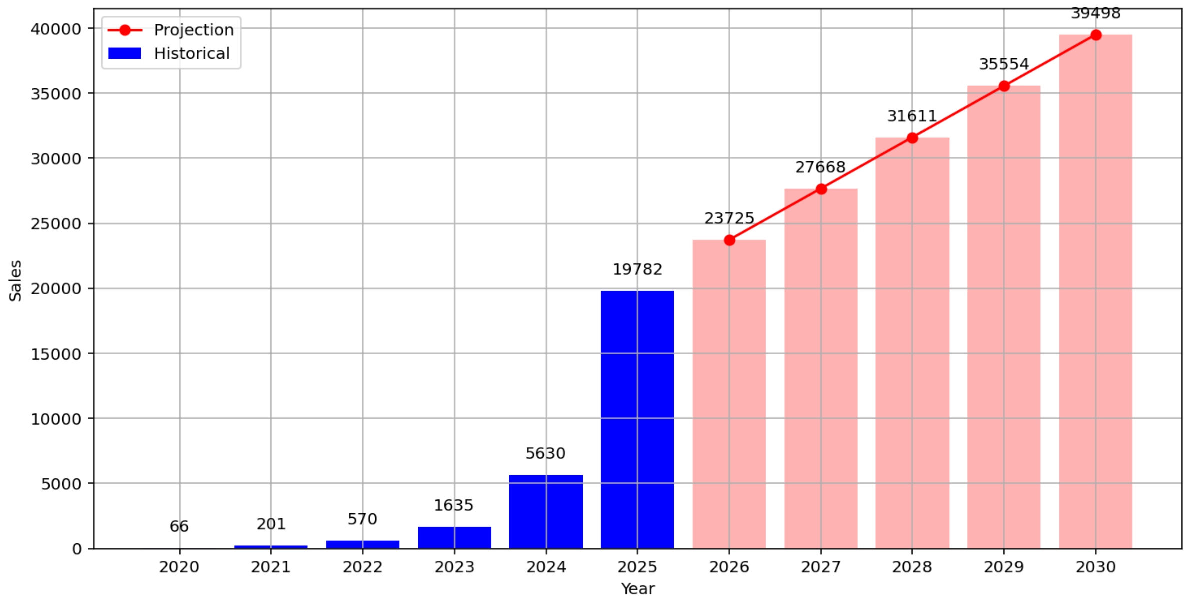

Figure 3.6 Linear EVs Fleet Projection 2026-2030
Source: DETRAN-RS, 2025.

3.3.2 Quadratic Polynomial Projection

For the polynomial projection, a second-degree polynomial was fitted to the historical data using least-squares regression. Then, this function was evaluated at each of the future years to generate the projected values. Unlike the linear projection, which assumes a constant rate of change, the polynomial projection allows the growth rate to increase or decrease over time, resulting in a curved trend that follows the pattern observed in the historical data pattern as shown in Table 3.4 and Figure 3.7 and Figure 3.8.

Table 3.4 Quadratic Polynomial Projection 2026-2030

YEAR	EVS	ALL VEHICLES
2026	30,338	4,850,020
2027	45,735	4,996,173
2028	64,152	5,159,252
2029	85,591	5,339,257
2030	110,050	5,536,186

Source: DETRAN-RS, 2025.

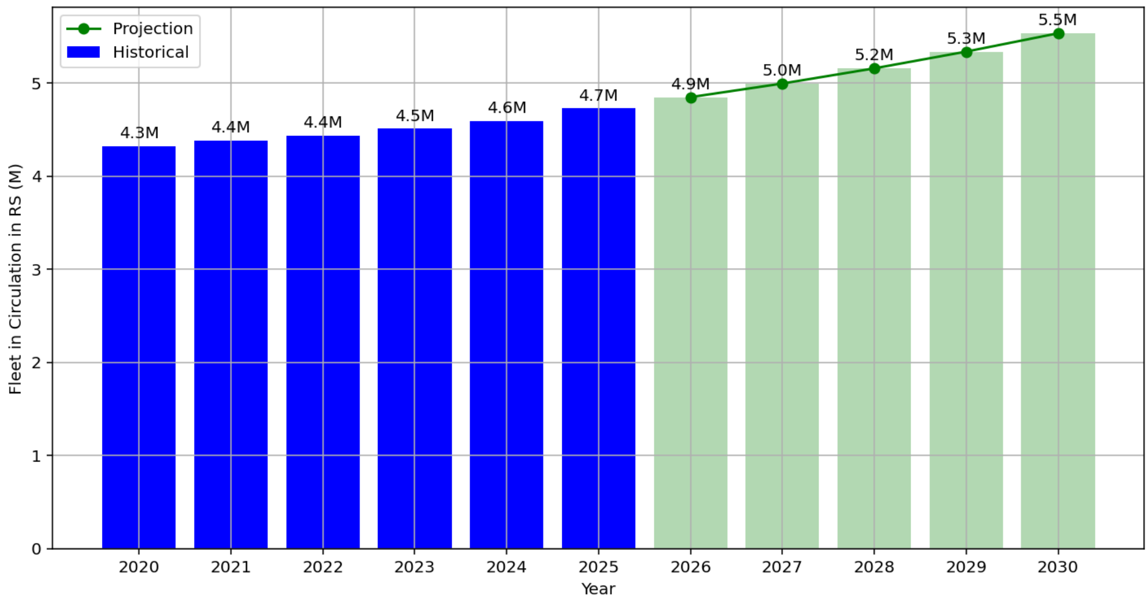

Figure 3.7 Quadratic Polynomial All Vehicles Fleet Projection 2026-2030
Source: DETRAN-RS, 2025.

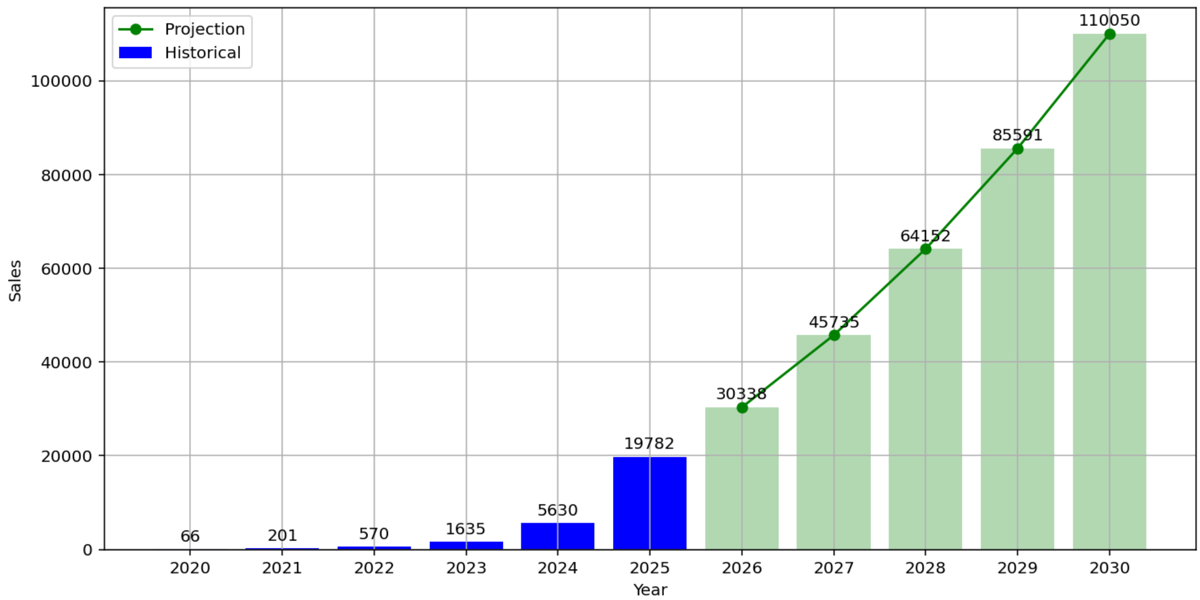

Figure 3.8 Quadratic Polynomial EVs Fleet Projection 2026-2030
Source: DETRAN-RS, 2025.

3.3.3 ARIMA Projection

For the ARIMA projection, a time-series model was fitted to the historical sales data using an ARIMA(2,1,1) specification. This model incorporates autoregressive terms to account for dependence on past values and a moving-average term to capture short-term fluctuations. As a result, the projection reflects both the underlying trend and the temporal correlation structure present in the historical data as shown in Table 3.5 and Figure 3.9 and Figure 3.10.

Table 3.5 ARIMA Projection 2026-2030

YEAR	EVS	ALL VEHICLES
2026	48,213	4,837,934
2027	90,258	4,934,731
2028	145,004	5,012,738
2029	211,313	5,083,206
2030	287,847	5,138,851

Source: DETRAN-RS, 2025.

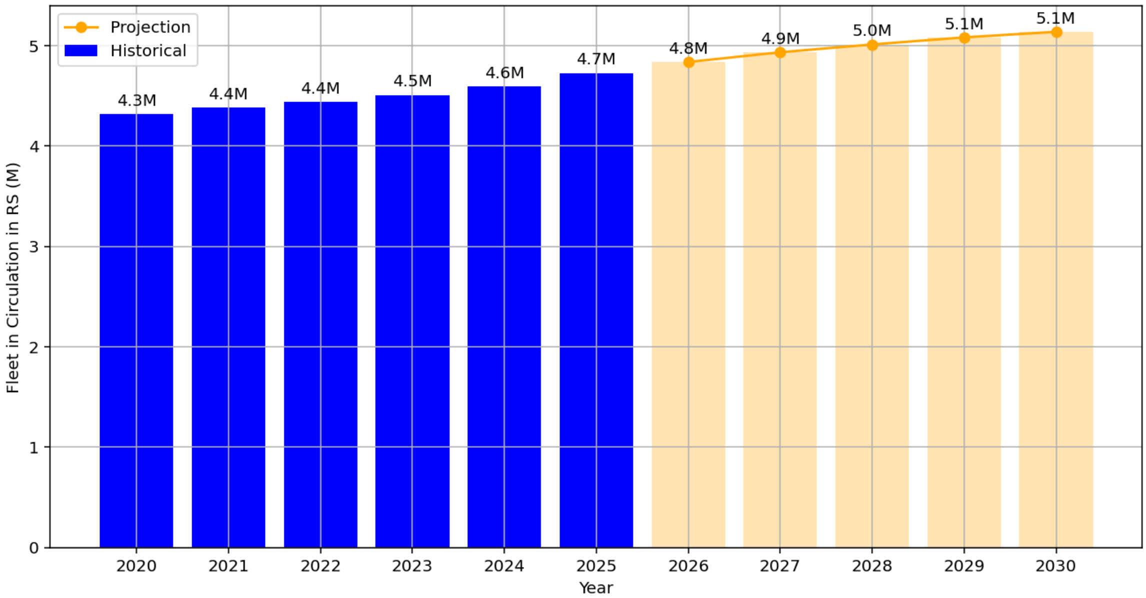

Figure 3.9 ARIMA All Vehicles Fleet Projection 2026-2030
Source: DETRAN-RS, 2025.

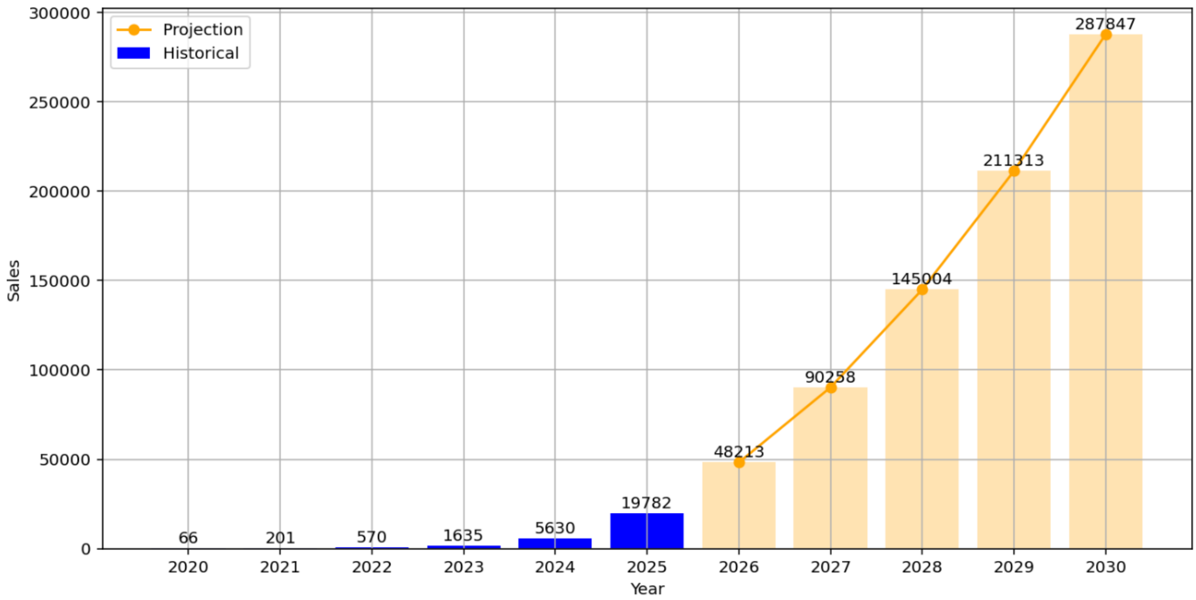

Figure 3.10 ARIMA EVs Fleet Projection 2026-2030
Source: DETRAN-RS, 2025.

3.3.4 Projection Comparison

Based on the three projections developed, Table 3.6, Figure 3.11 and Figure 3.12 were created to compare the three forecasting approaches analyzed in this study.

Table 3.6 Comparison 2026-2030

YEAR	LINEAR EVS	QUADRATIC EVS	ARIMA EVS	LINEAR ALL VEHICLES	QUADRATIC ALL VEHICLES	ARIMA ALL VEHICLES
2026	23,725	30,338	48,213	4,810,490	4,850,020	4,837,934
2027	27,668	45,735	90,258	4,892,048	4,996,173	4,934,731
2028	31,611	64,152	145,004	4,973,606	5,159,252	5,012,738
2029	35,554	85,591	211,313	5,055,164	5,339,257	5,083,206
2030	39,498	110,050	287,847	5,136,722	5,536,186	5,138,851

Source: DETRAN-RS, 2025.

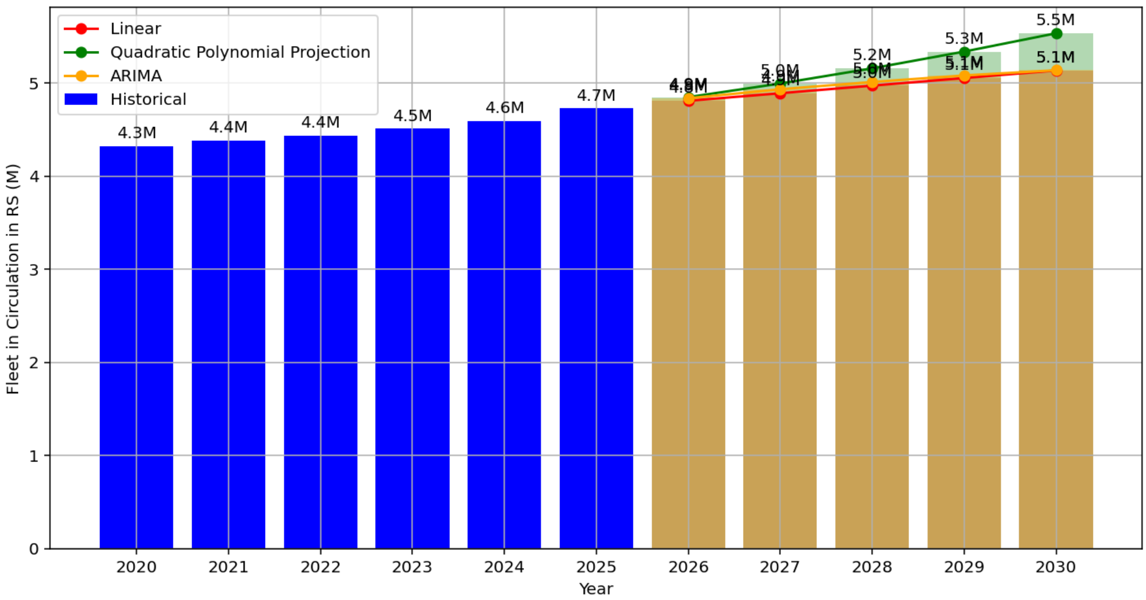

Figure 3.11 Comparison of All Vehicles Fleet Projection 2026-2030
Source: DETRAN-RS, 2025.

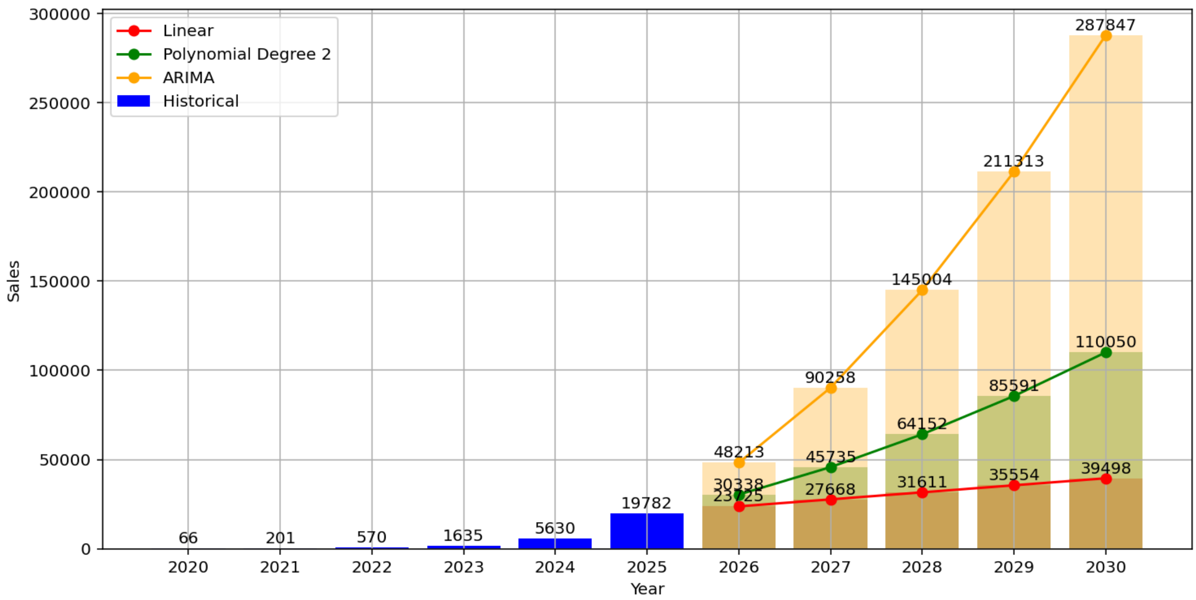

Figure 3.12 Comparison of EVs Fleet Projection 2026-2030
Source: DETRAN-RS, 2025.

For this study, the Linear Projection and the ARIMA Projection were not the chosen method because of their results. The Linear requires the data to have a constant growth, not considering all the other variables that can occur, which led to estimates below expectations. The ARIMA technique is usually applied when there is a large data compiled for the forecast to be more accurate. Usually, with five years of data, its accuracy decreases, and the values are not the most reliable ones, resulting in estimates above the expected ones. The Quadratic Polynomial Projection has its challenges, mainly because it can overestimate the future EV values, but it is the best fitting method when analyzing the growth acceleration of the EV numbers. Thus, the Quadratic Polynomial method is the applied method in this research.

The total evaluated number of all vehicles for 2030 is 5,536,186 and the number of calculated EVs is 110,050. The EVs will then represent approximately 2% of the fleet in circulation in RS, as shown in Table 3.7.

Table 3.7 Traffic Flow Percentage 2030

CATEGORY	QUANTITY IN RS	PERCENTAGE OF FLEET
EV	110,050	2%
All vehicles	5,536,186	100%

Source: DETRAN-RS, 2025.

Finally, the traffic flow of EVs, for the BR-386 in 2030 has been displayed in Table 3.8.

Table 3.8 Traffic Flow Analysis 2030

SECTION	CARS OBSERVED	DAYS OBSERVED	NUMBER OF CARS	NUMBER OF CAR PER DAY	COMBINED NUMBER OF EVS PER DAY
422-6	6,608	231	2,465,479	10,673	-
362-8	6,622	334	2,550,787	7,637	-
Combined				**18,310**	**366.2**

Source: DETRAN-RS, 2025.

The daily number of EVs is calculated by the same way described as the traffic flow of 2025. This number is expected to be about 367 EVs per day.

A Confidence Interval (CI) of 95% for the year 2030 was also calculated by using the OLS theory. The results are shown in Figure 3.13 and Figure 3.14 and in Table 3.9 and Table 3.10.

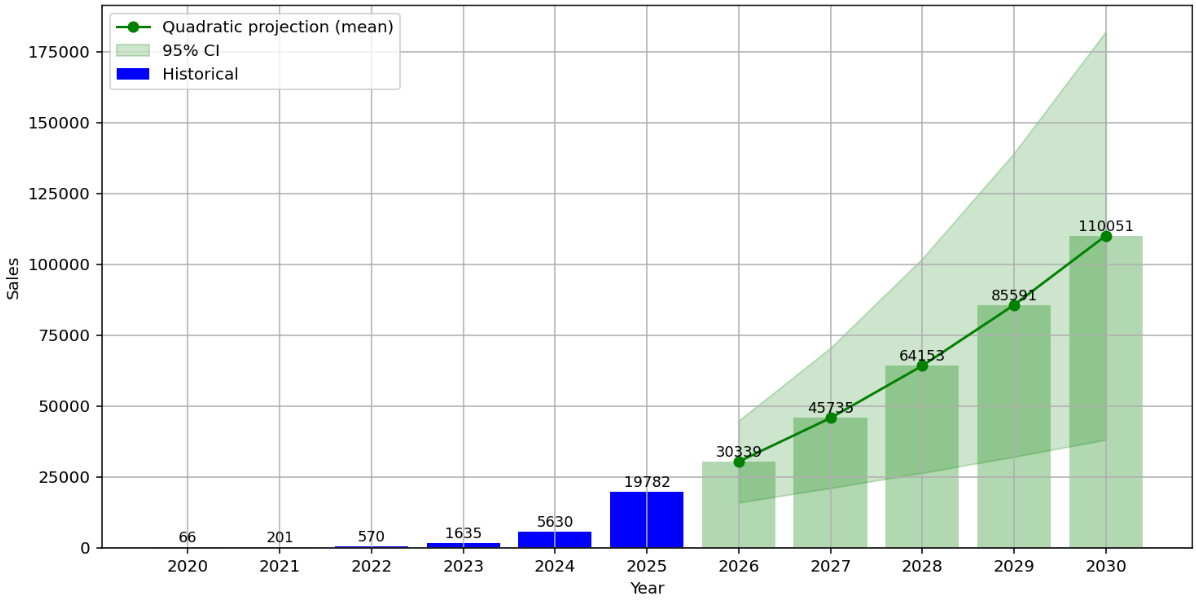

Figure 3.13 CI Quadratic Polynomial EVs Fleet Projection 2026-2030
Source: DETRAN-RS, 2025.

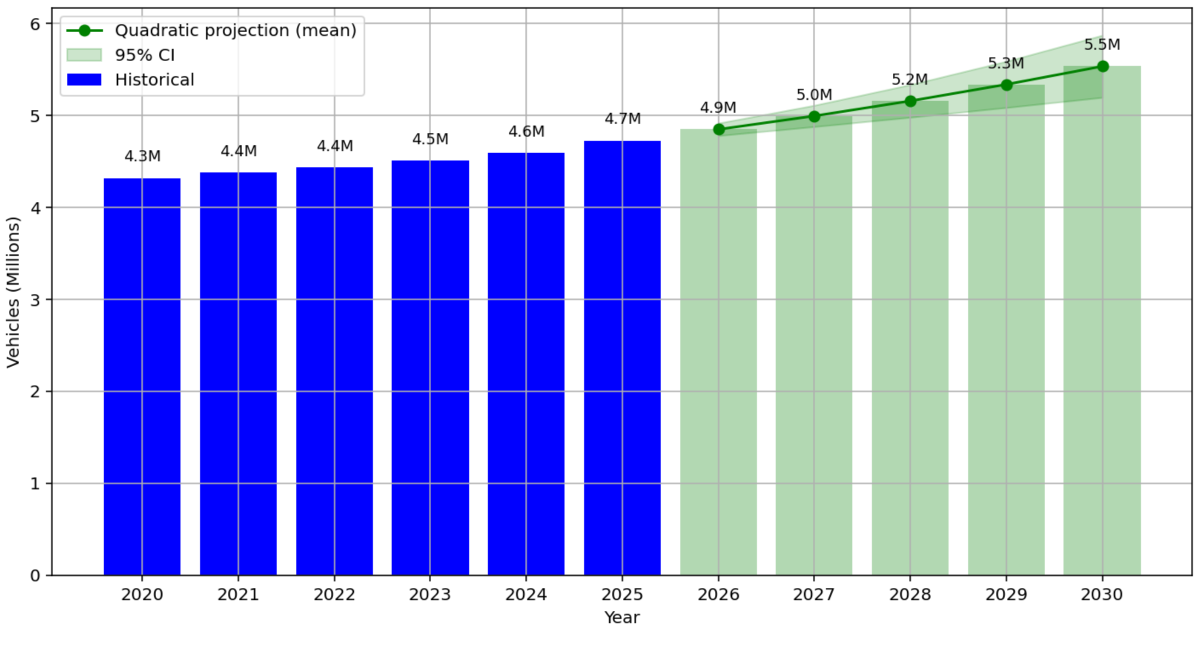

Figure 3.14 CI Quadratic Polynomial All Vehicles Fleet Projection 2026-2030
Source: DETRAN-RS, 2025.

Table 3.9 Confidence Interval EVs 2026-2030

YEAR	EVS	95% CONFIDENCE INTERVAL ±
2026	30,339	14,438
2027	45,735	24,708
2028	64,153	37,777
2029	85,591	53,550
2030	110,051	71,996

Source: DETRAN-RS, 2025.

Table 3.10 Confidence Interval All Vehicles 2026-2030

YEAR	ALL VEHICLES	95% CONFIDENCE INTERVAL ±
2026	4,850,021	67,842
2027	4,996,175	116,099
2028	5,159,254	177,508
2029	5,339,259	251,626
2030	5,536,189	338,300

Source: DETRAN-RS, 2025.

To determine what would happen to the ideal number of chargers in 2030, a two-scenario analysis was created as well as a baseline scenario.

The low-growth scenario and the high-growth scenario, making it possible to analyze the minimum and maximum percentage of EVs that can be expected in 2030, and consequently the number of EVs per day, respectively.

For the low-growth scenario, the total evaluated number of the 95% IC of all vehicles for 2030 is 5,874,489 and the number of calculated EVs is 38,055. The EVs will then represent approximately 0.65% of the fleet, as shown in Table 3.11.

Table 3.11 Low-Growth Percentage 2030

CATEGORY	QUANTITY IN RS	PERCENTAGE OF FLEET
EV	38,055	0.65%
All vehicles	5,874,489	100%

Source: DETRAN-RS, 2025.

The traffic flow of EVs, for the low-growth scenario in 2030 has been displayed in Table 3.12.

Table 3.12 Low-Growth Analysis 2030

SECTION	CARS OBSERVED	DAYS OBSERVED	NUMBER OF CARS	NUMBER OF CAR PER DAY	COMBINED NUMBER OF EVS PER DAY
422-6	7.012	231	2.616.138	11.325	-
362-8	7.027	334	2.706.659	8.104	-
Combined				**19.429**	**125,9**

Source: DETRAN-RS, 2025.

The daily number of EVs for the low-growth scenario is expected to be about 126 EVs per day.

For the high-growth scenario, the total evaluated number of the 95% IC of all vehicles for 2030 is 5,197,889 and the number of calculated EVs is 182,047. The EVs will then represent approximately 3.5% of the fleet, as shown in Table 3.13.

Table 3.13 High-Growth Percentage 2030

CATEGORY	QUANTITY IN RS	PERCENTAGE OF FLEET
EV	182,047	3.5%
All vehicles	5,197,889	100%

Source: DETRAN-RS, 2025.

The traffic flow of EVs, for the high-growth scenario in 2030 has been displayed in Table 3.14.

Table 3.14 High-Growth Analysis 2030

SECTION	CARS OBSERVED	DAYS OBSERVED	NUMBER OF CARS	NUMBER OF CAR PER DAY	COMBINED NUMBER OF EVS PER DAY
422-6	6.204	231	2.314.822	10.021	-
362-8	6.218	334	2.394.917	7.170	-
Combined				**17.191**	**602,1**

Source: DETRAN-RS, 2025.

The daily number of EVs for the high-growth scenario is expected to be about 603 EVs per day.

3.4 THE ELECTRICAL ENERGY INFRASTRUCTURE

It is important to analyze about the electricity demand of an EVC. Firstly, all the Substations and Power Plants in the region were determined by the data extracted from the SIN Maps and the ONS (National Electrical System Operator) (ONS, 2025).

The Table 3.15 shows the location of the existing electric Substations and Power Plants.

Table 3.15 Substations and Power Plants Coordinates

TYPE	LATITUDE	LONGITUDE
Substation	-29.877750	-51.107592
Substation	-29.266667	-51.191667
Substation	-29.141389	-51.157500
Substation	-29.132500	-51.191667
Substation	-29.165833	-51.122778
Substation	-29.649473	-52.806648
Substation	-29.951944	-51.621111
Substation	-29.970506	-51.597058
Substation	-29.891389	-51.177778
Substation	-29.947222	-51.190833
Substation	-29.877083	-51.146886
Substation	-29.146425	-51.148083

Continuation of Table 3.15 Substations and Power Plants Coordinates

TYPE	LATITUDE	LONGITUDE
Substation	-29.059167	-51.280278
Substation	-29.218611	-51.323889
Substation	-29.237222	-51.511944
Substation	-29.465564	-51.984503
Substation	-29.431389	-51.916000
Substation	-29.039444	-51.534167
Substation	-28.805278	-51.612222
Substation	-30.008333	-51.140556
Substation	-29.971111	-51.195833
Substation	-29.823206	-51.343779
Substation	-29.869167	-51.388056
Substation	-29.719722	-51.151389
Substation	-29.719722	-51.151667
Substation	-29.712500	-52.547222
Substation	-28.283333	-52.428611
Substation	-29.633611	-52.155278
Substation	-29.181225	-51.474756
Substation	-28.541291	-52.094986
Power Plant	-29.008333	-51.379167
Power Plant	-29.016667	-51.500000
Power Plant	-29.050000	-51.666667
Power Plant	-29.982500	-51.761667
Power Plant	-29.876389	-51.146944

Source: ONS, 2025.

The locations presented in Table 3.8 allowed to draw the Figure 3.15 and also Figure 3.16 having a 75 km of radius around the Power Plants and the Substations because this radius is enough to supply any EVC in the area and can be more economically viable (ZHOU *et al.*, 2022). This distance will also be a parameter in the simulation.

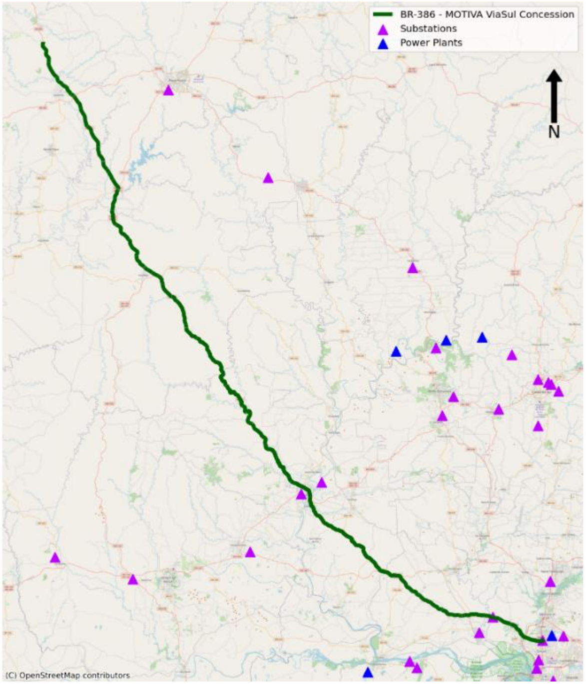

Figure 3.15 BR-386 with Substations and Power Plants
Source: ONS, 2025.

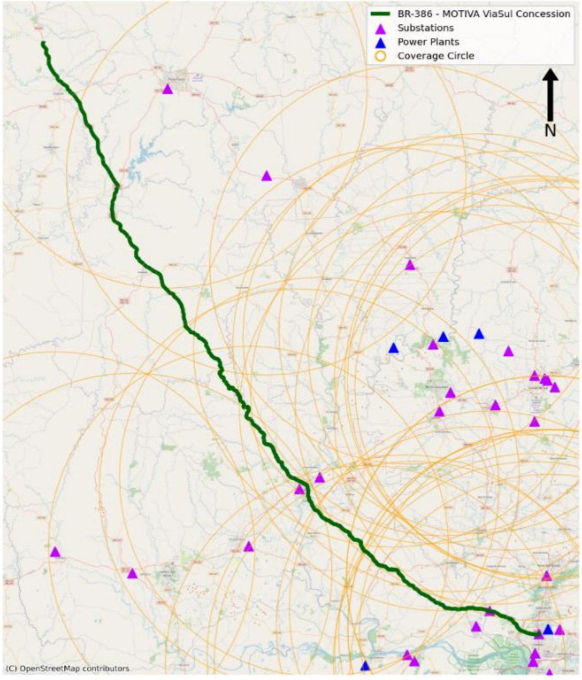

Figure 3.16 BR-386 with Substations' and Power Plants' radius
Source: ONS, 2025.

Secondly, it is important to measure the energy needed for an EVC to work with a high capacity of utilization. It is important because the EVC has a different average power (kW). The best charger for highways is the Ultra-fast charger. For this study, his average power (kW) was defined as being 150 kW. This number is sufficient by the large number of Substations and Power Plants nearby the BR-386 highway. However, their distance to the optimal point will also be considered, for simulation and boundary conditions purposes in this study.

3.5 EVS SPECIFICATION

It is important to determine the model of the EVs to be considered in this study, since a vast number of EVs have different battery sizes, and, consequently, different autonomy and recharge waiting time. The accumulated data since 2015 gathered from SENATRAN show which model is the most used allowing the possibility to calculate the autonomy and the capacity of the battery (SENATRAN, 2025). Table 3.16 was then obtained showing the dominant brands in the EVs market in RS.

Table 3.16 Brands Analysis

MANUFACTURER	QUANTITY	PERCENTAGE (%)
BYD	4,275	61.05%
GWM	520	7.43%
VOLVO	479	6.84%
JAC	431	6.16%
RENAULT	278	3.97%
BMW	238	3.40%
CHERY	110	1.57%
MINI	108	1.54%
PORSCHE	99	1.41%
AUDI	84	1.20%
PEUGEOT	78	1.11%
NISSAN	59	0.84%
MERCEDES-BENZ	41	0.59%
CHEVROLET	39	0.56%
FIAT	34	0.49%
TESLA	31	0.44%
FORD	26	0.37%
ZEEKR	24	0.34%
JAGUAR	17	0.24%
GMC	6	0.09%
HYUNDAI	5	0.07%
NETA	5	0.07%
DONGFENG	3	0.04%
GURGEL	3	0.04%
KIA	3	0.04%
HITECH	2	0.03%

Source: SENATRAN, 2025.

Since most of the EVs are manufactured by BYD, a second analysis was made to determine which BYD are the most used ones (BYD, 2025). Table 3.17 presents the main used BYD models.

Table 3.17 Analysis of BYD EVs Models

MODEL	AUTONOMY (KM)	BATTERY CAPACITY (KW)	QUANTITY	PERCENTAGE (%)
DOLPHIN MINI GS5EV	280	38	1,171	27.69%
DOLPHIN GS 180EV	291	44.9	1,098	25.96%
DOLPHIN MINI GS EV	280	38	668	15.80%
DOLPHIN PLUS 310EV	427	60.5	515	12.18%
SEAL AWD GS 590EV	372	82.5	356	8.42%
YUAN PLUS GL 310EV	294	60.48	314	7.42%
YUAN PRO GS 290EV	250	45	107	2.53%

Source: BYD, 2025.

Furthermore, a weighted average for the BYD models was calculated, resulting in an Autonomy of 309 km and a Battery Capacity of 48 kW to be used in this study.

The average time to charge these models was also evaluated, considering the Ultra-fast charger of 150 kW. The time was calculated for charge between 25% and 100% of the battery's capacity. The data compiled is shown in Table 3.18.

Table 3.18 Analysis of Charging Time of BYD EVs

MODEL	BATTERY CAPACITY (KW)	ENERGY TO ADD (KW)	IDEAL TIME (MIN)	QUANTITY	PERCENTAGE (%)
DOLPHIN MINI GS5EV	38.00	28.50	11.4	1,171	27.69%
DOLPHIN GS 180EV	44.90	33.68	13.5	1,098	25.96%
DOLPHIN MINI GS EV	38.00	28.50	11.4	668	15.80%
DOLPHIN PLUS 310EV	60.50	45.38	18.2	515	12.18%
SEAL AWD GS 590EV	82.50	61.88	24.8	356	8.42%
YUAN PLUS GL 310EV	60.48	45.36	18.1	314	7.42%
YUAN PRO GS 290EV	45.00	33.75	13.5	107	2.53%

Source: BYD, 2025.

Finally, in the weighted average, the time resulted in 14,45 minutes to charge the EVs.

3.6 CONSTRUCTION OF THE GA MODEL

This study aims to find the optimal location for the EVC, using the GIS-based approach. Therefore, the expected result of the GA model will be a set of coordinates that will be plotted in the map showing the location of the EVCs. The boundary conditions of this model have factors including the autonomy and the time to charge the EVs, the battery capacity and the location of the Power Plants among other factors.

3.6.1 Boundary Conditions

The delimitation of the BR-386 to only plot the MOTIVA concession was made by consulting the OpenStreetMap via Overpass API, showing a rectangle where the system finds the name “BR-386”. After having all the elements that were connected to “BR-386”, the script interconnected these points of interest resulting in one line, via LineString. Afterwards, there are the boundaries of the studied area, since the MOTIVA is the highway to be analyzed, specifying the geographic coordinates of Canoas (-51.1839, -29.9122) and Carazinho (-52.7360, -28.2896) was made.

The average autonomy of the EVs utilized in this study is about 309 km. However, to prevent the possible range anxiety of not having enough battery capacity to finish the trip, because not every EV will have their battery at 100% before entering into the highway and the energy consumption tends to be higher on highways due to sustained higher speeds and less regenerative braking (LAKSHMI & GUDIPALLI, 2023). Thus, a 25% reduction in autonomy is imposed in this study. The autonomy used in this study is then of 230 km.

The EVC requires a lot of energy to charge EVs. The radius of 75 km around the energy is the coverage circle within which the energy supply is met, and the necessary energy support is ensured, as shown in Figure 3.12 (ZHOU *et al.*, 2022).

The average battery capacity applied in this study is about 50 kW. The considered battery capacity is important to determine the number of ideal chargers in the EVC.

The total number of EVs per year in 2025 is about 7,144. For 2030, however, this number is about 113,663. This boundary condition gives the amount of EV needed to be charged besides being an important factor to determine the utilization, the standby time and the queuing time for the BR-386 considered in this research.

The average time to charge the EVs, from 25% or the battery capacity to 100%, is about 14.45 minutes assuming a constant 150 kW Ultra-fast charger. Although this time is a reasonable estimator, it will be penalized with about 50% increase because the charging can slow down when the battery is at 70% or 80% of its capacity (KOSTOPOULOS *et al.*, 2020). Consequently, the time increases to about 22 minutes.

As the annual average daily traffic flow is 7,144 it results in a daily flow of 20 EVs. Thus, this study assumes that the total number of chargers in each EVC will depend on the number of EVCs to be installed in the highway.

The arrival pattern of the EV must then be determined. The ARENA Input Analyzer was used. The input to the ARENA includes the daily flow of EVs data during the year 2024 collected in the kilometer 422-6 and kilometer 362-8 of the highway.

The fitting for the data was then implemented considering the EV percentage of 0.13% of the fleet. Results are shown in Figure 3.17 to Figure 3.20.

```
        Distribution Summary

Distribution:   Normal
Expression:     NORM(1.45e+004, 3.87e+003)
Square Error:   0.011910

Chi Square Test
  Number of intervals   = 11
  Degrees of freedom    = 8
  Test Statistic        = 53.8
  Corresponding p-value < 0.005

Kolmogorov-Smirnov Test
  Test Statistic        = 0.077
  Corresponding p-value = 0.0376

        Data Summary

Number of Data Points   = 335
Min Data Value          = 2.47e+003
Max Data Value          = 2.86e+004
Sample Mean             = 1.45e+004
Sample Std Dev          = 3.88e+003

        Histogram Summary

Histogram Range         = 2.47e+003 to 2.86e+004
Number of Intervals     = 18
```

Figure 3.17 Distribution Summary of All Vehicles
Source: PNCT, 2025.

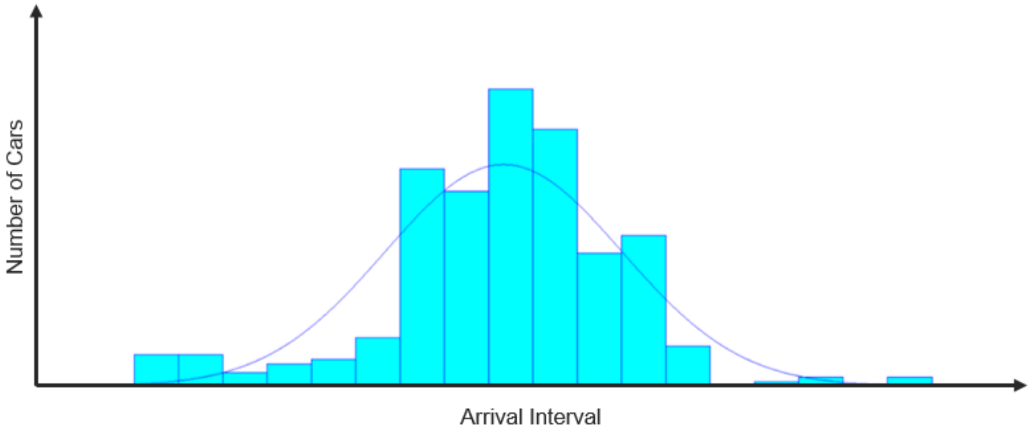

Figure 3.18 Graphical Representation of All Vehicle Results
Source: PNCT, 2025.

```
        Distribution Summary

Distribution:   Normal
Expression:     NORM(18.6, 4.95)
Square Error:   0.014256

Chi Square Test
  Number of intervals   = 11
  Degrees of freedom    = 8
  Test Statistic        = 59.2
  Corresponding p-value < 0.005

Kolmogorov-Smirnov Test
  Test Statistic        = 0.0778
  Corresponding p-value = 0.0343

        Data Summary

Number of Data Points   = 335
Min Data Value          = 3.16
Max Data Value          = 36.5
Sample Mean             = 18.6
Sample Std Dev          = 4.96

        Histogram Summary

Histogram Range         = 3 to 37
Number of Intervals     = 18
```

Figure 3.19 Distribution Summary of EVs
Source: PNCT, 2025.

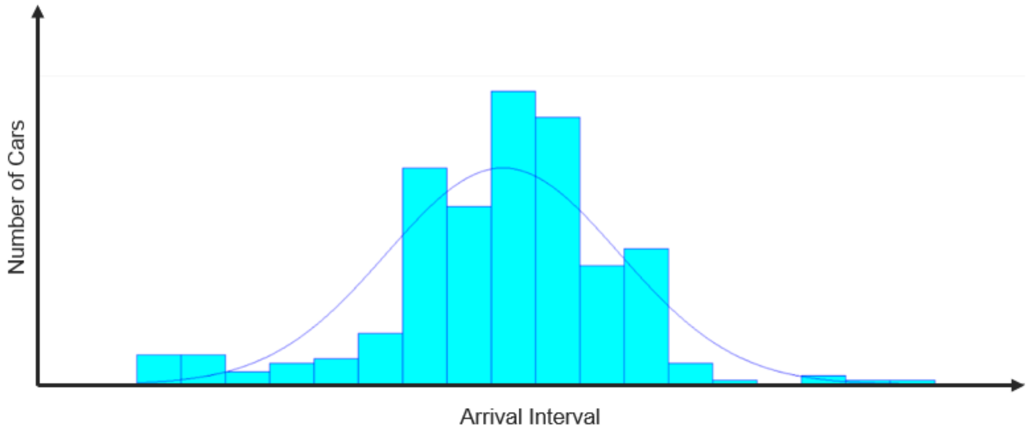

Figure 3.20 Graphical Representation of EVs Results
Source: PNCT, 2025.

The evaluated arrival distribution of EVs was determined as being a Poisson, having a rate (lambda) of 20 in 2025.

An analysis was then made varying the assuming evaluated arrival distribution. At this phase, the time to charge, the daily traffic flow and the time average arrival distribution were considered important factors. Figure 3.21 presents the average utilization of the chargers, depending on the number of chargers.

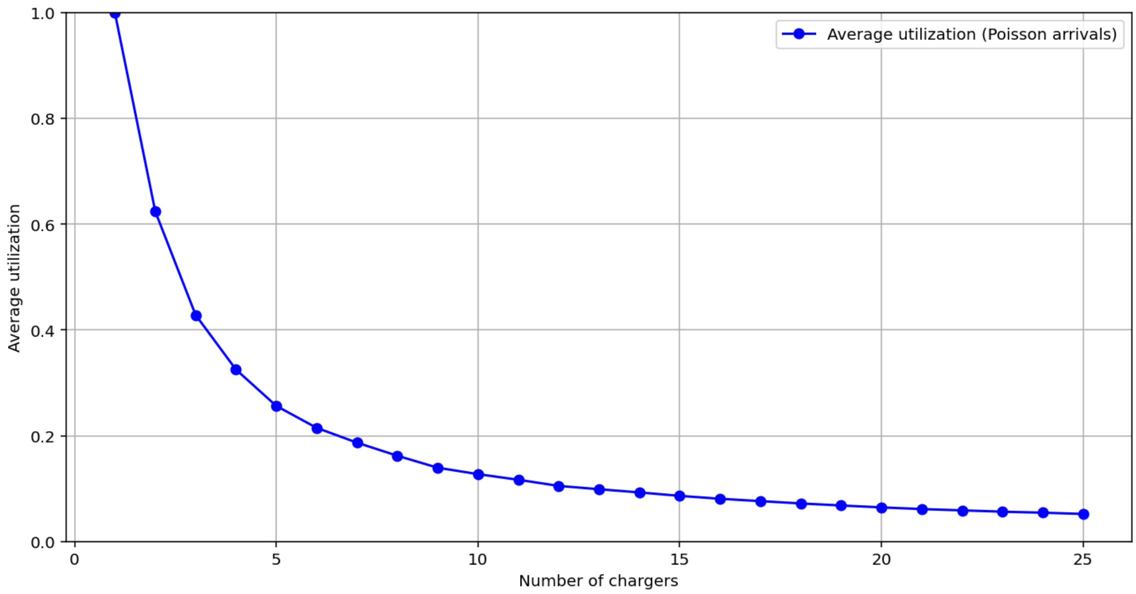

Figure 3.21 Charger Utilization by Number of Chargers, 2025
Source: PNCT, 2025.

The ideal number of chargers had then to be evaluated. The utilization percentage of the chargers was fixed at 50% or lower and the average queuing time for the EVs to be charged was calculated. As a result, Figure 3.22 was created.

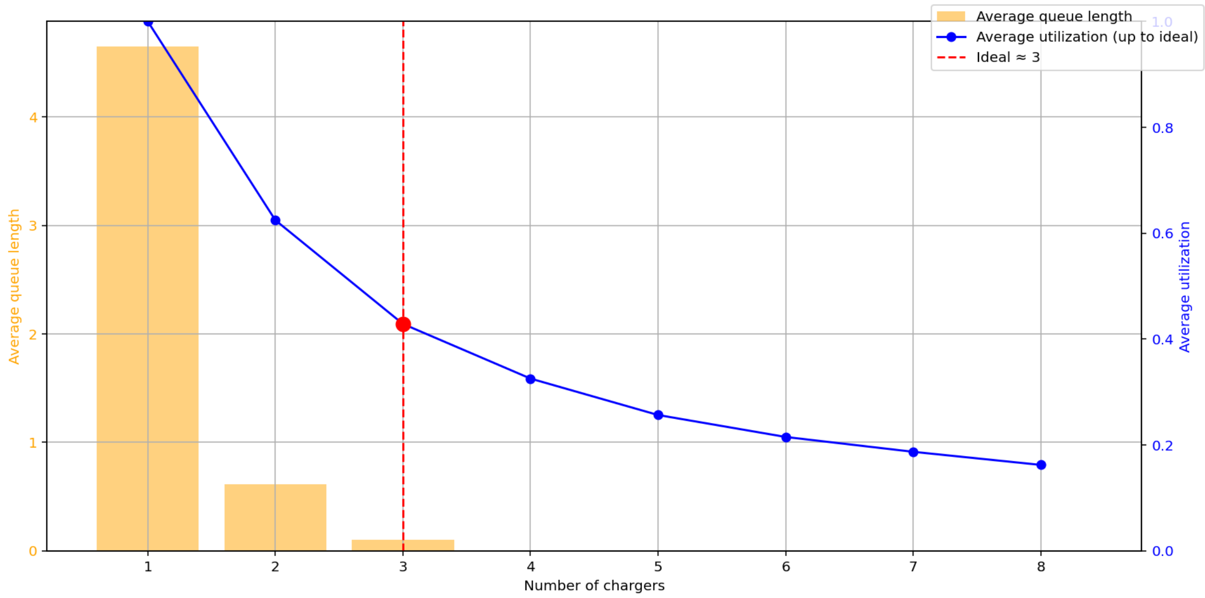

Figure 3.22 Ideal Chargers, Utilization, and EV Queuing, 2025
Source: PNCT, 2025.

Considering the 2025 EVs demand, with only one charger, the queue would be about 5 vehicles, and the utilization of the charger would be 100%, being not considered a viable result. The queue would decreases to 1 vehicle, installing two chargers in the EVC, and the utilization would decrease to 62.45%. However, the optimal number of chargers obtained is three chargers because the queue would be numerically zero and the utilization only 42.85%. Table 3.19 shows the result.

Table 3.19 EVC Utilization and Average Queue, 2025

NUMBER OF CHARGERS	UTILIZATION	AVERAGE QUEUE (VEHICLES)
1	100%	4.65
2	62.45 %	0.61
3	42.85%	0.10

Source: PNCT, 2025.

Finally, it was simulated what would happen if the entire flow of vehicles, in this case 20 EVs for 2025, arrived at the EVCs at once. Figure 3.23 and Figure 3.24 show the result for this case.

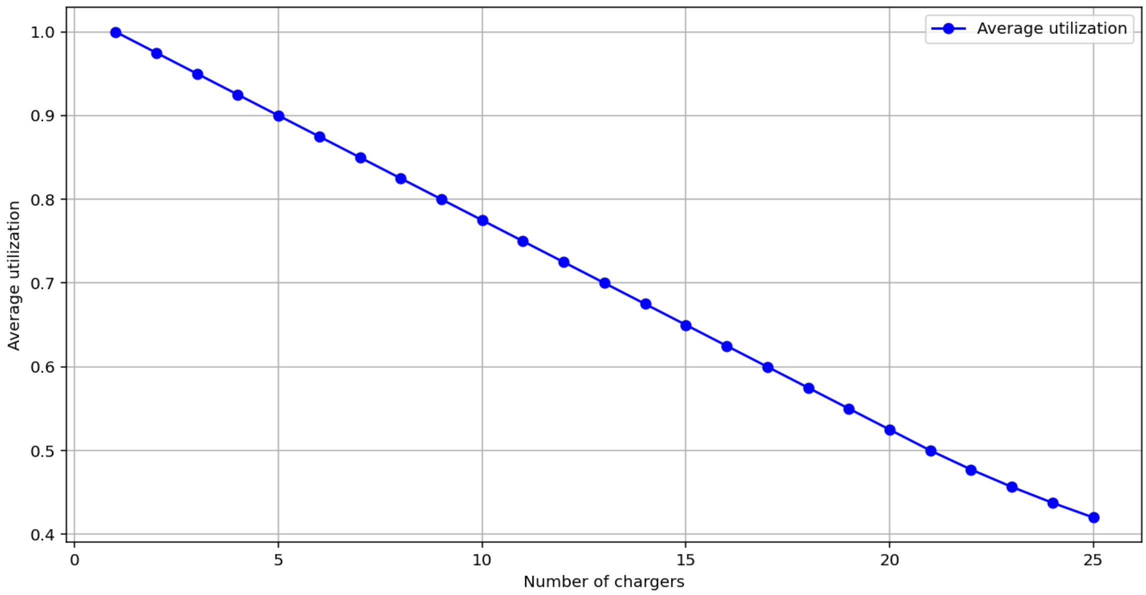

Figure 3.23 Charger Utilization by Number of Chargers – Arriving at Once, 2025
Source: PNCT, 2025.

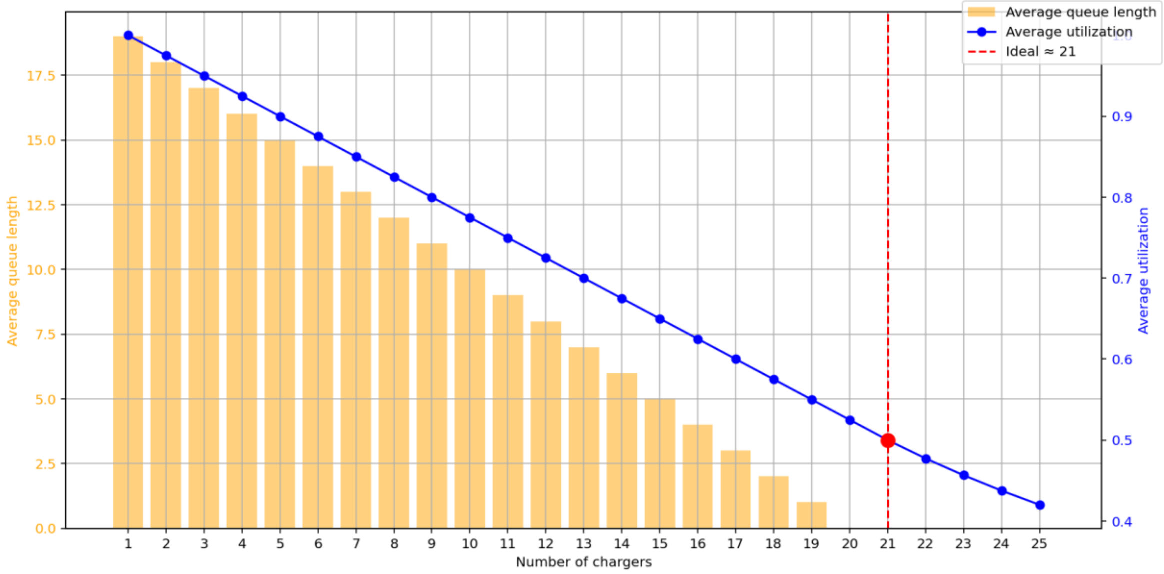

Figure 3.24 Ideal Chargers, Utilization, and EV Queuing – Arriving at Once, 2025
Source: PNCT, 2025.

When all cars arrive at the same time for the 2025 scenario, the queue length and the average utilization of the chargers are almost a decreasing straight line when the number of chargers increase. Therefore, the optimal number of chargers would be 21 chargers once the queue length is zero vehicles, and the utilization equal or lower than 50%. It is interesting to note that the total number of chargers is the number of the flow of vehicles, 20 EVs, plus one ensuring no queue length. Table 3.20, Figure 3.24 and Figure 3.25 present the results for 2030.

Table 3.20 EVC Utilization and Average Queue – Arriving at Once, 2025

NUMBER OF CHARGERS	UTILIZATION	AVERAGE QUEUE (VEHICLES)
1	100.00%	19.00
2	97.50%	18.00
3	95.00%	17.00
4	92.50%	16.00
5	90.00%	15.00
6	87.50%	14.00
7	85.00%	13.00
8	82.50%	12.00
9	80.00%	11.00
10	77.50%	10.00
11	75.00%	9.00
12	72.50%	8.00
13	70.00%	7.00
14	67.50%	6.00
15	65.00%	5.00
16	62.50%	4.00
17	60.00%	3.00
18	57.50%	2.00
19	55.00%	1.00
20	52.50%	0.00
21	50.00%	0.00

Source: PNCT, 2025.

The same study was conducted including the traffic flow expectation of 367 in 2030, as shown in Figure 3.25 and Figure 3.26.

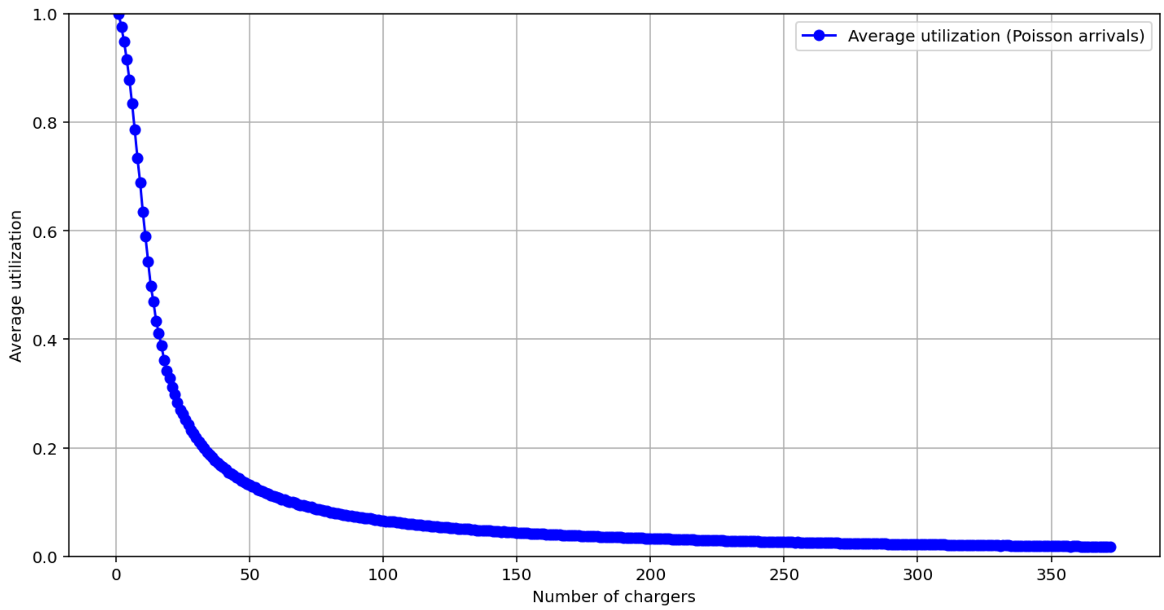

Figure 3.25 Charger Utilization by Number of Chargers, 2030
Source: PNCT, 2025.

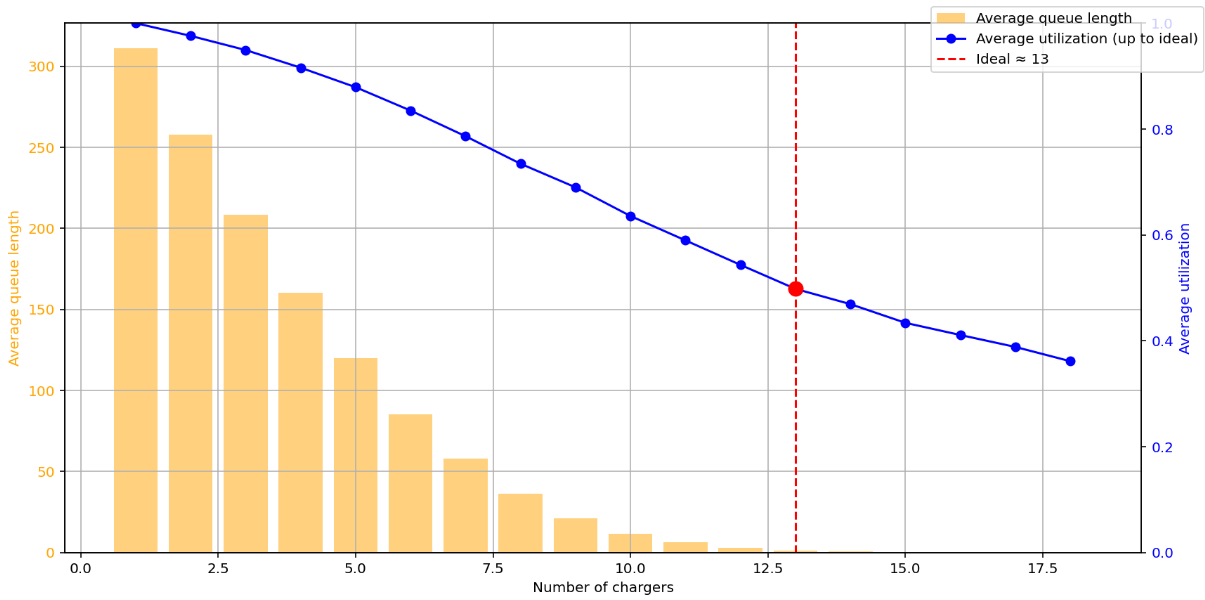

Figure 3.26 Ideal Chargers, Utilization, and EV Queuing, 2030
Source: PNCT, 2025.

It was then found that, for the 2030 demand, when varying from 1 to 10 chargers the queue varies from 311 to 12 vehicles and the utilization of the charger varies from 100% to 63.56%, making the total waiting time unfeasible, because even for 10 vehicles their waiting time would be 264 minutes, or 4.4 hours, and the chargers utilization would still be very high, possibly leading to future maintenance problems (HSU *et al.*, 2023). When there are 11 or 12 chargers, the average queue length would be shorter, less than 7 vehicles. Nevertheless, the waiting time would be 154 minutes, a refueling time much longer than the average of 4 minutes for a combustion car, not even considering the necessity to have an internet connection, to access the mobile application, and the potential waste of time trying to find it on a highway. Therefore, the optimal number of chargers is considered to be 13 chargers because the queue length would be around 1 car and the charger's utilization only 49.80%. Table 3.21 presents the results.

Table 3.21 EVC Utilization and Average Queue, 2030

NUMBER OF CHARGERS	UTILIZATION	AVERAGE QUEUE (VEHICLES)
1	100.00%	311.08
2	97.60%	257.88
3	94.92%	208.26
4	91.59%	160.42
5	87.90%	119.96
6	83.48%	85.11
7	78.64%	57.93
8	73.44%	36.11
9	68.98%	21.20
10	63.56%	11.57
11	58.96%	6.28
12	54.33%	2.81
13	49.80%	0.92

Source: PNCT, 2025.

It was then simulated what would happen if the entire flow of vehicles, in this case 367 EVs for 2030 arrived at the EVCs at once. Figure 3.27 and Figure 3.28 show the result for this case.

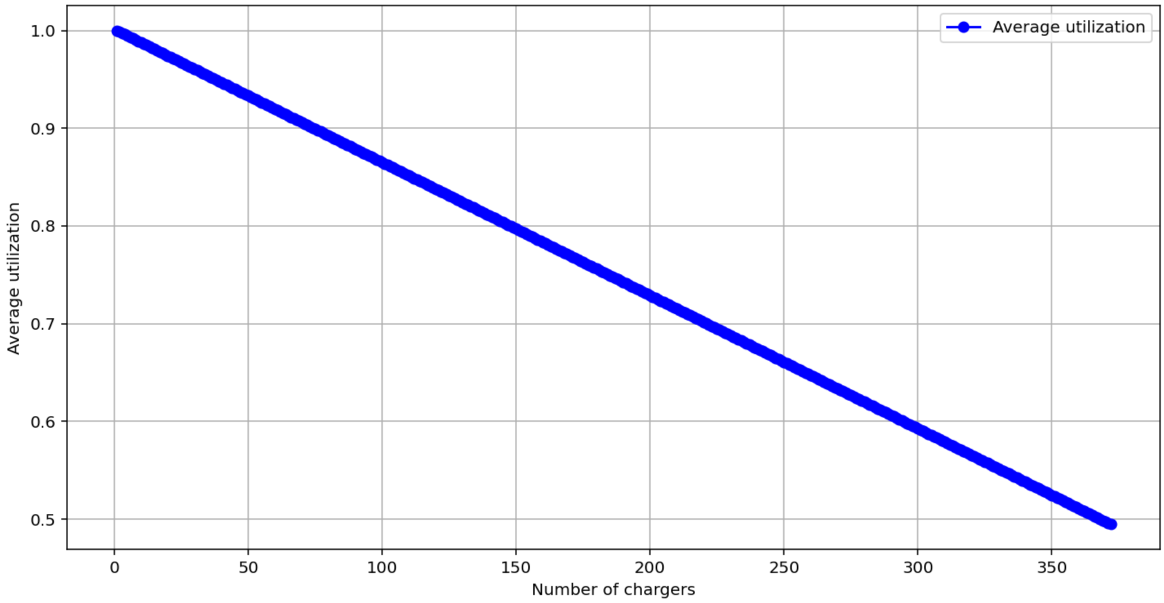

Figure 3.27 Charger Utilization by Number of Chargers – Arriving at Once, 2030
Source: PNCT, 2025.

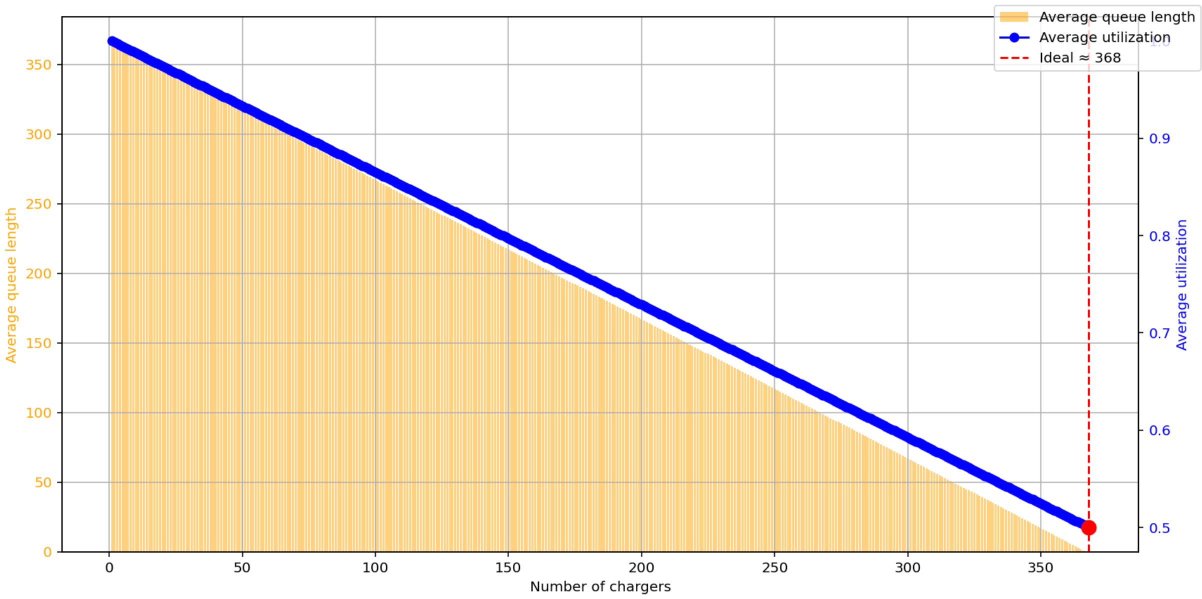

Figure 3.28 Ideal Chargers, Utilization, and EV Queuing – Arriving at Once, 2030
Source: PNCT, 2025.

Similar to the 2025 scenario, the curve graphs obtained for the 2030 scenario has the same shape with the utilization of the chargers and the queuing length decreasing when the chargers increase, as it is expected. Thus, the optimal number of chargers would be 368 chargers because the utilization would be about 50%. Table 3.22 shows the compiled result for this case.

Table 3.22 EVC Utilization and Average Queue – Arriving at Once, 2030

NUMBER OF CHARGERS	UTILIZATION	AVERAGE QUEUE (VEHICLES)
1	100.00%	366.00
2	99.86%	365.00
3	99.73%	364.00
18	97.68%	349.00
33	95.64%	334.00
108	85.42%	259.00
123	83.38%	244.00
303	58.86%	64.00
318	56.81%	49.00
333	54.77%	34.00
348	52.72%	19.00
349	52.59%	18.00
364	50.54%	3.00
365	50.41%	2.00
366	50.27%	1.00
367	50.14%	0.00
368	50.00%	0.00

Source: PNCT, 2025.

The low-growth scenario and the high-growth scenario for the 2030 year were also created. For the low-growth scenario an ideal number of 6 chargers was found, as shown in Figure 3.29 and in Table 3.23. For the high-growth scenario an ideal number of 20 chargers was found, as shown in Figure 3.30 and in Table 3.24.

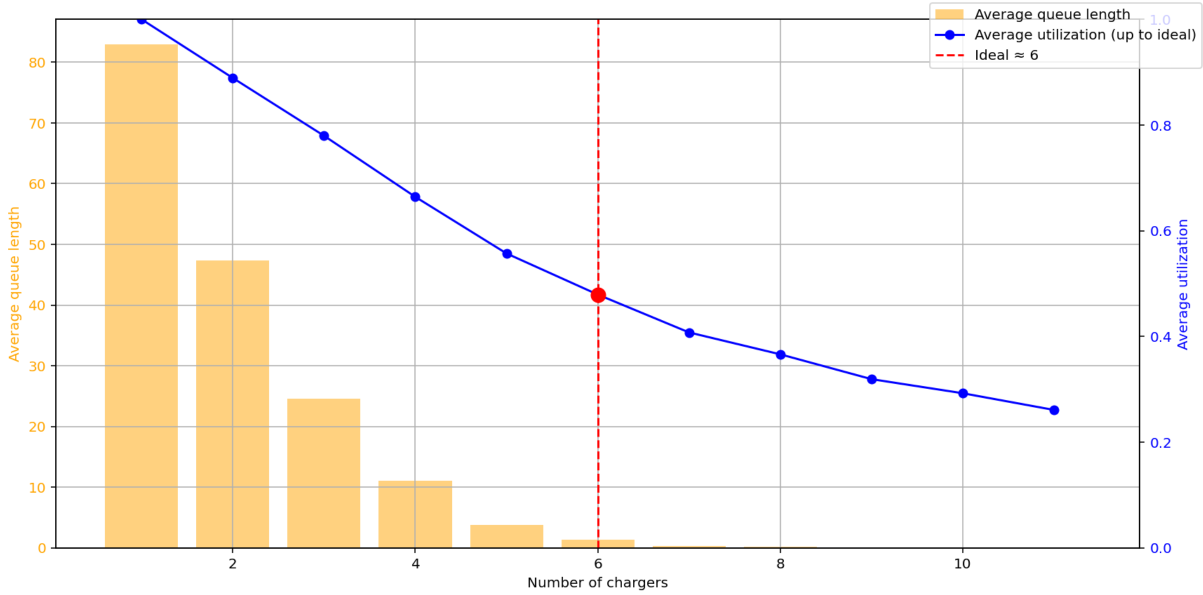

Figure 3.29 Low-Growth Ideal Chargers, Utilization, and EV Queuing, 2030
Source: PNCT, 2025.

Table 3.23 Low-Growth EVC Utilization and Average Queue, 2030

NUMBER OF CHARGERS	UTILIZATION	AVERAGE QUEUE (VEHICLES)
1	100%	82.92
2	88.90%	47.31
3	77.97%	24.60
4	66.41%	11.09
5	55.70%	3.81
6	47.92%	1.34

Source: PNCT, 2025.

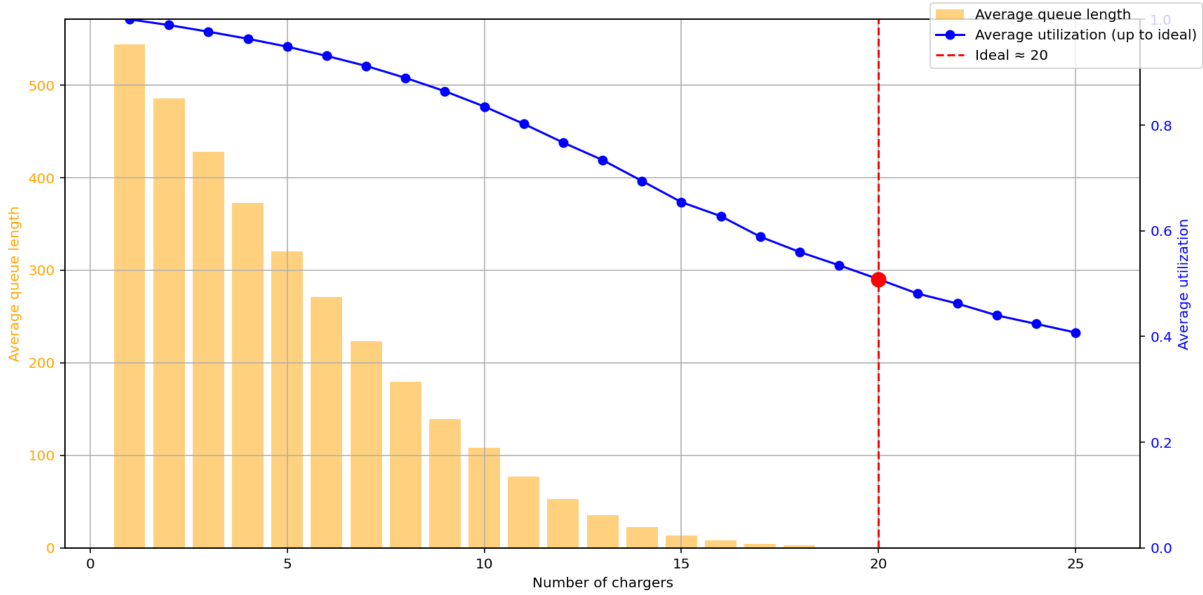

Figure 3.30 High-Growth Ideal Chargers, Utilization, and EV Queuing, 2030
Source: PNCT, 2025.

Table 3.24 High-Growth EVC Utilization and Average Queue, 2030

NUMBER OF CHARGERS	UTILIZATION	VEHICLES QUEUE
1	100.00%	543.77
2	98.92%	485.72
3	97.67%	428.03
4	96.33%	372.70
5	94.84%	320.28
6	93.08%	271.40
7	91.19%	223.62
8	88.93%	178.96
9	86.41%	139.44
10	83.51%	108.12
11	80.23%	77.33
12	76.69%	52.89
13	73.38%	35.40
14	69.42%	22.23
15	65.42%	13.54
16	62.76%	08.01
17	58.87%	4.59
18	55.99%	2.46
19	53.47%	0.83
20	50.84%	0.47

Source: PNCT, 2025.

Finally, to facilitate the understanding, a comparative analysis of all the ideal number of chargers was created, as shown in Table 3.25.

Table 3.25 Comparative Analysis of Ideal Number of Chargers

YEARS	SCENARIOS	IDEAL NUMBER OF CHARGERS
2025	Baseline	3
	Arriving at Once	21
2030	Low-Growth	6
	Baseline	13
	High-Growth	20
	Arriving at Once	368

3.6.2 Economic Viability of Chargers

The economic viability is based on the cost to implement the number of chargers in the charging stations and the expected financial return. There are different scenarios, each one of them have a different number of ideal number of chargers and costs involved.

The first step is to determine how much does it cost to implement a single 150 kW Ultra-fast charger in a station. This was done by calculating an average of the most commonly used Ultra-fast charger and their current prices. The data was gathered from several sources (BRASIL CHARGER, 2025). The price range was between R$ 160.000 and R$ 250.000. For this study, the price used for an Ultra-fast charger is around R$ 200.000. Additionally, a 5% maintenance annually cost was implemented for the study (PACHECO, 2025). Resulting in R$ 10.000 for maintenance yearly per charger.

The second step is to understand how much revenue a single Ultra-fast charger can generate. This was done by analyzing the purchase and sale prices of energy and the amount of energy consumed yearly. In Brazil, the average purchase price (kW) is around R$ 0.60 and the price of sales for recharging the EVs is around R$ 1.75 (DME-PC, 2025). The weighted average of the energy to be added between 25% and 100% was also calculated taking into consideration Table 3.18. The weighted average of the energy resulted in 36.09 kW.

For all feasibility evaluations, it was necessary to include the Net Present Value (NPV) using a 6% discount rate. This rate accounts for the time value of money, recognizing that funds available today are worth more than the same amount in the future due to potential returns if invested elsewhere. The choice of 6% reflects the typical opportunity cost of capital in similar infrastructure and energy-related projects, providing a realistic benchmark for comparison. By discounting future cash flows to their present value, the analysis can more accurately assess whether each scenario represents a financially sound investment over time.

Finally, the third step is to create the economic projection for all the different scenarios. The first projection, shown in Table 3.26 and Figure 3.31, is the Annual Energy Profit for all the years and scenarios. The second projection, shown in Table 3.27 and Figure 3.32, is the NPV not taking into account the Chargers installed in previous years. Thus, each year's result represents an independent projection. For instance, if three chargers are installed in 2025 baseline and four are needed in 2026 low-growth, the projection assumes four new installations in 2026 low-growth. The Arriving at Once was eliminated because of the notable high cost of installation and the long period of time exceeding the time forecast.

Table 3.26 Annual Energy Profit for EV Charging Scenarios

YEARS	SCENARIOS	EVS PER YEAR	ENERGY (KW)	ENERGY PURCHASE PRICE (R$)	ENERGY SALE PRICE (R$)	ENERGY PROFIT (R$)
2025	Baseline	7300	263,457	158,074.20	461,049.75	302,975.55
2026	Low-Growth	19345	698,161.05	418,896.63	1,221,781.84	757,438.88
	Baseline	36865	1,330,457.85	798,274.71	2,328,301.24	1,443,421.25
	High-Growth	54385	1,962,754.65	1,177,652.79	3,434,820.64	2,129,403.63
2027	Low-Growth	25550	922,099.50	553,259.70	1,613,674.13	943,765.07
	Baseline	55480	2,002,273.20	1,201,363.92	3,503,978.10	2,049,318.42
	High-Growth	85045	3,069,274.05	1,841,564.43	5,371,229.59	3,141,389.43
2028	Low-Growth	32120	1,159,210.80	695,526.48	2,028,618.90	1,119,290.10
	Baseline	77745	2,805,817.05	1,683,490.23	4,910,179.84	2,709,190.82
	High-Growth	123370	4,452,423.30	2,671,453.98	7,791,740.78	4,299,091.53
2029	Low-Growth	38690	1,396,322.10	837,793.26	2,443,563.68	1,271,920.57
	Baseline	103660	3,741,089.40	2,244,653.64	6,546,906.45	3,407,787.19
	High-Growth	168265	6,072,683.85	3,643,610.31	10,627,196.74	5,531,654.56
2030	Low-Growth	45990	1,659,779.1	995,867.46	2,904,613.43	1,426,326.03
	Baseline	133955	4,834,435.95	2,900.661.57	8,460,262.91	4,154,457.54
	High-Growth	220095	7,943,228.55	4,765,937.13	13,900,649.96	6,825,988.82

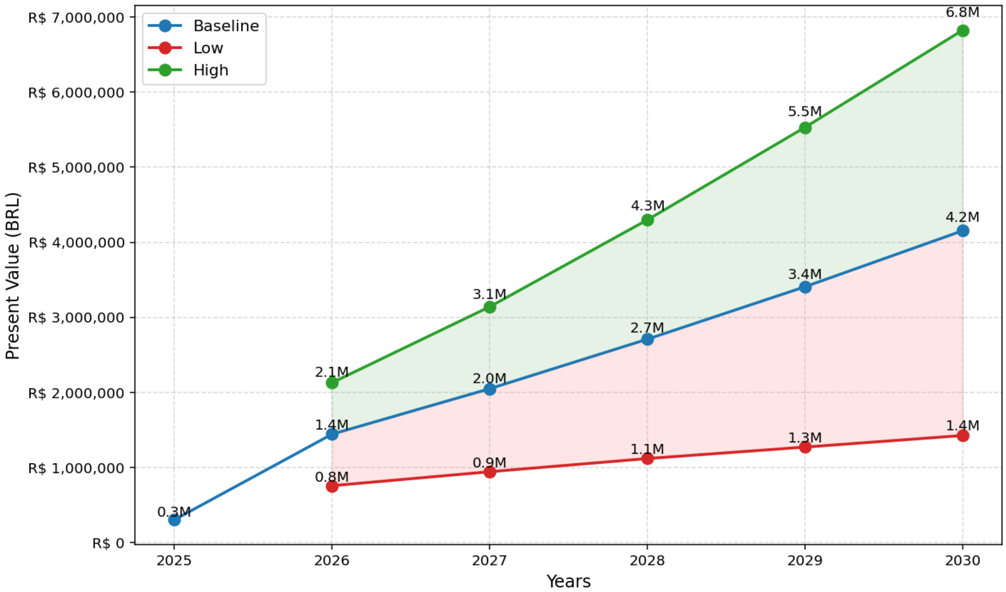

Figure 3.31 Annual Energy Profit

Table 3.27 Independent NPV

YEARS	SCENARIOS	NUMBER OF CHARGERS	CHARGERS + MAINTENANCE (R$)	ENERGY PROFIT (R$)	NPV (R$)
2025	Baseline	3	630,000	302,975.55	-327,024.45
2026	Low-Growth	4	840,000	802,885.21	-35,013.95
	Baseline	5	1,050,000	1,530,026.53	452,855.22
	High-Growth	6	1,260,000	2,257,167.85	940,724.39
2027	Low-Growth	4	840,000	1,060,414.43	196,168.06
	Baseline	7	1,470,000	2,302,614.18	741,023.66
	High-Growth	9	1,890,000	3,529,665.16	1,459,296.16
2028	Low-Growth	5	1,050,000	1,333,092.42	237,689.85
	Baseline	8	1,680,000	3,226,689.61	1,298,630.42
	High-Growth	12	2,520,000	5,120,286.80	2,183,250.94
2029	Low-Growth	5	1,050,000	1,605,770.42	440,222.23
	Baseline	11	2,310,000	4,302,252.81	1,578,050.83
	High-Growth	16	3,360,000	6,983,586.43	2,870,219.85
2030	Low-Growth	6	1,260,000	1,908,745.97	484,780.73
	Baseline	13	2,730,000	5,559,601.34	2,114,442.73
	High-Growth	20	4,200,000	9,134,712.83	3,687,504.49

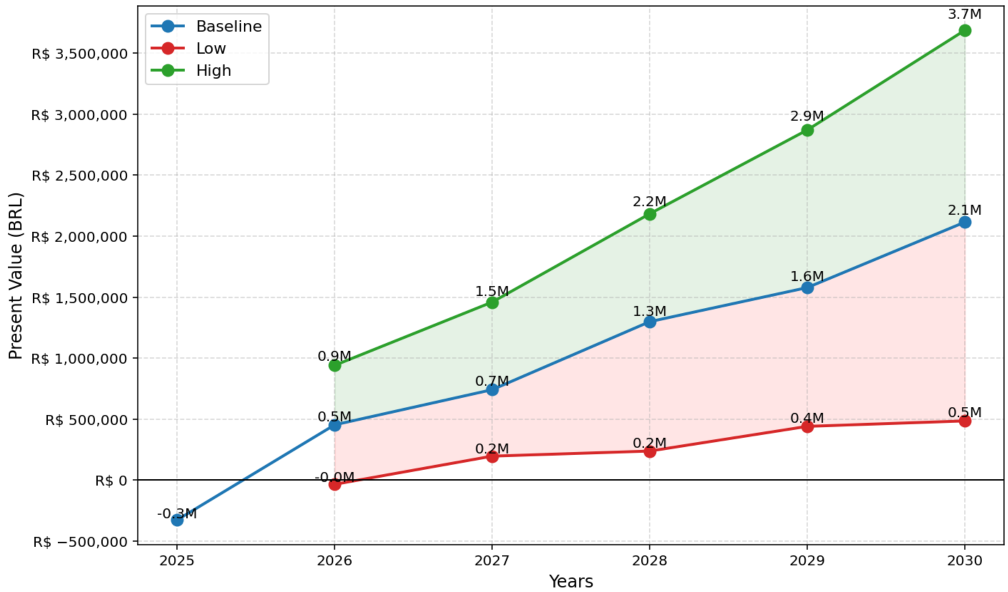

Figure 3.32 Independent NPV

Other economic projections were made taking into account Chargers installed in previous years. Accordingly, the investment payback was also calculated and will be presented for each projection. For this projection, some cases were also created.

First Case: Installing three Chargers in 2025 to understand how the NPV would change, following the ideal number of chargers of 2025 and for all other years and scenarios. Table 3.28 and Figure 3.33 show the results.

Table 3.28 3 Chargers in 2025 NPV

YEARS	SCENARIOS	CHARGERS INSTALLED	CHARGERS + MAINTENANCE (R$)	ANNUAL ENERGY PROFIT (R$)	NPV (R$)
2025	Baseline	3	630,000	302,975.55	-327,024.45
2026	Low-Growth	4	240,000	802,885.21	203,999.33
	Baseline	5	450,000	1,530,026.53	691,868.50
	High-Growth	6	660,000	2,257,167.85	1,179,737.67
2027	Low-Growth	4	40,000	1,060,414.43	1,600,033.71
	Baseline	7	470,000	2,302,614.18	2,322,888.60
	High-Growth	9	690,000	3,529,665.16	3,219,160.39
2028	Low-Growth	5	250,000	1,333,092.42	3,232,273.88
	Baseline	8	280,000	3,226,689.61	4,796,986.02
	High-Growth	12	720,000	5,120,286.80	6,017,454.25

Continuation of Table 3.28 3 Chargers in 2025 NPV

YEARS	SCENARIOS	CHARGERS INSTALLED	CHARGERS + MAINTENANCE (R$)	ANNUAL ENERGY PROFIT (R$)	NPV (R$)
2029	Low-Growth	5	50,000	1,605,770.42	6,029,301.91
	Baseline	11	710,000	4,302,252.81	7,642,386.70
	High-Growth	16	960,000	6,983,586.43	9,568,230.66
2030	Low-Growth	6	260,000	1,908,745.97	8,874,425.61
	Baseline	13	530,000	5,559,601.34	11,400,797.41
	High-Growth	20	1,000,000	9,134,712.83	13,721,117.35

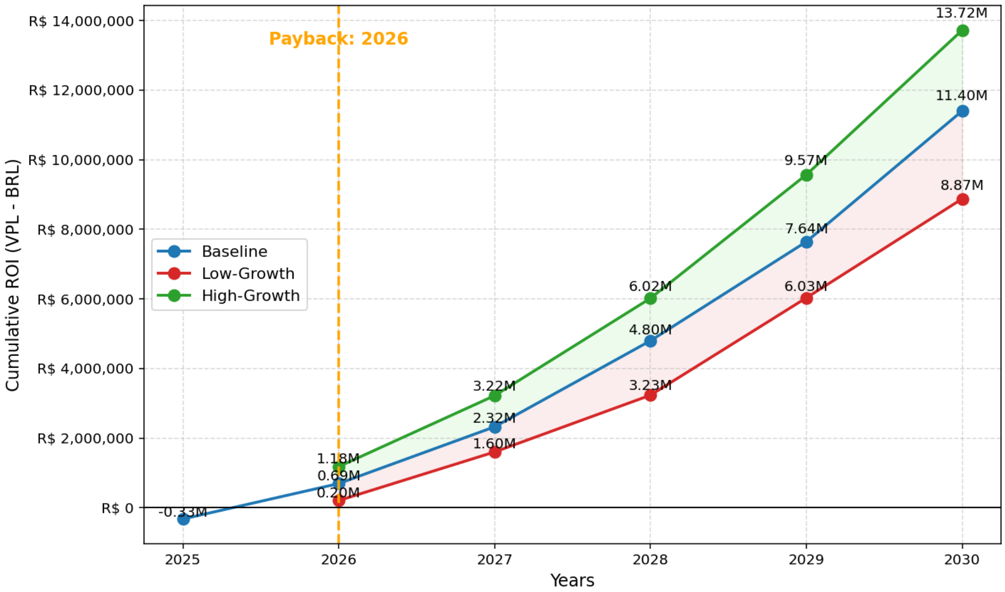

Figure 3.33 3 Chargers in 2025 NPV

Second Case: Installing 10 Chargers in 2025 to have a better understanding of the NPV after the installation of half of all the chargers needed in the scenario with the higher ideal number of chargers, 2030 high-growth. Table 3.29 and Figure 3.34 show the results.

Table 3.29 10 Chargers in 2025 NPV

YEARS	SCENARIOS	CHARGERS INSTALLED	CHARGERS + MAINTENANCE (R$)	ANNUAL ENERGY PROFIT (R$)	NPV (R$)
2025	Baseline	10	2,100,000	302,975.55	-1,797,024.45
2026	Low-Growth	10	100,000	802,885.21	-1,133,925.20
	Baseline	10	100,000	1,530,026.53	-447,942.82
	High-Growth	10	100,000	2,257,167.85	238,039.56
2027	Low-Growth	10	100,000	1,060,414.43	406,822.61
	Baseline	10	100,000	2,302,614.18	1,512,375.96
	High-Growth	10	100,000	3,529,665.16	2,604,446.96
2028	Low-Growth	10	100,000	1,333,092.42	2,547,704.13
	Baseline	10	100,000	3,226,689.61	4,137,604.85
	High-Growth	12	520,000	5,120,286.80	5,374,865.47
2029	Low-Growth	10	100,000	1,605,770.42	5,330,316.06
	Baseline	11	310,000	4,302,252.81	7,299,843.00
	High-Growth	16	960,000	6,983,586.43	8,908,849.49
2030	Low-Growth	10	100,000	1,908,745.97	8,651,443.21
	Baseline	13	530,000	5,559,601.34	11,058,253.71
	High-Growth	20	1,000,000	9,134,712.83	13,378,573.65

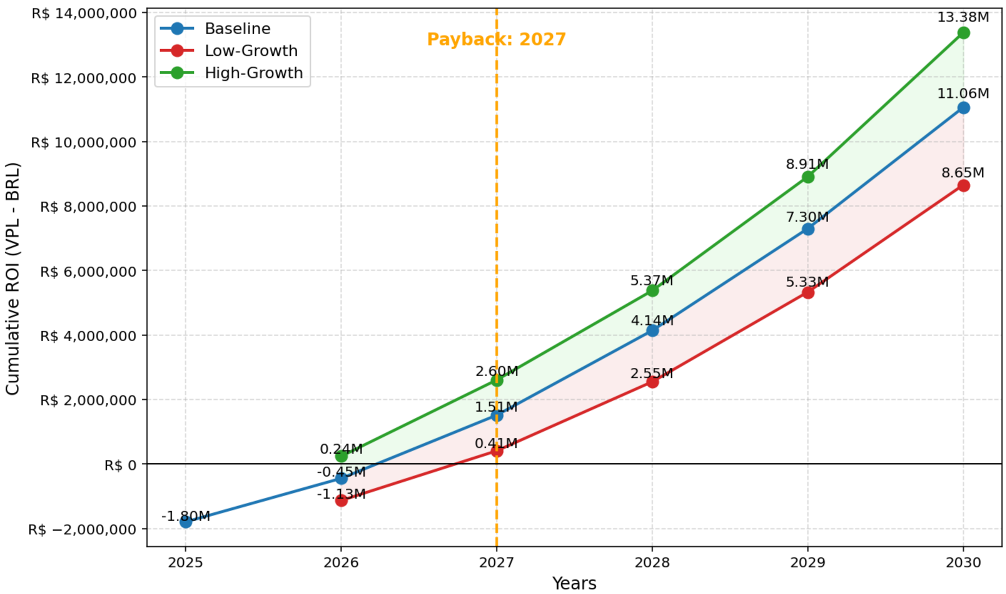

Figure 3.34 10 Chargers in 2025 NPV

Third Case: Installing 20 Chargers in 2025 to have a better understanding of the NPV after the installation of all the chargers needed in the scenario with the higher ideal number of chargers, 2030 high-growth. Table 3.30 and Figure 3.35 show the results.

Table 3.30 20 Chargers in 2025 NPV

YEARS	SCENARIOS	CHARGERS INSTALLED	COST OF CHARGERS (R$)	ANNUAL ENERGY PROFIT (R$)	NPV (R$)
2025	Baseline	20	4,200,000	302,975.55	-3,897,024.45
2026	Low-Growth	20	200,000	802,885.21	-3,328,264.82
	Baseline	20	200,000	1,530,026.53	-2,642,282.44
	High-Growth	20	200,000	2,257,167.85	-1,956,300.06
2027	Low-Growth	20	200,000	1,060,414.43	-1,876,516.66
	Baseline	20	200,000	2,302,614.18	-770,963.31
	High-Growth	20	200,000	3,529,665.16	321,107.70
2028	Low-Growth	20	200,000	1,333,092.42	180,402.94
	Baseline	20	200,000	3,226,689.61	1,770,303.65
	High-Growth	20	200,000	5,120,286.80	3,360,204.37
2029	Low-Growth	20	200,000	1,605,770.42	2,883,805.50
	Baseline	20	200,000	4,302,252.81	5,019,672.11
	High-Growth	20	200,000	6,983,586.43	7,143,539.48
2030	Low-Growth	20	200,000	1,908,745.97	6,296,546.50
	Baseline	20	200,000	5,559,601.34	9,024,678.02
	High-Growth	20	200,000	9,134,712.83	11,696,209.29

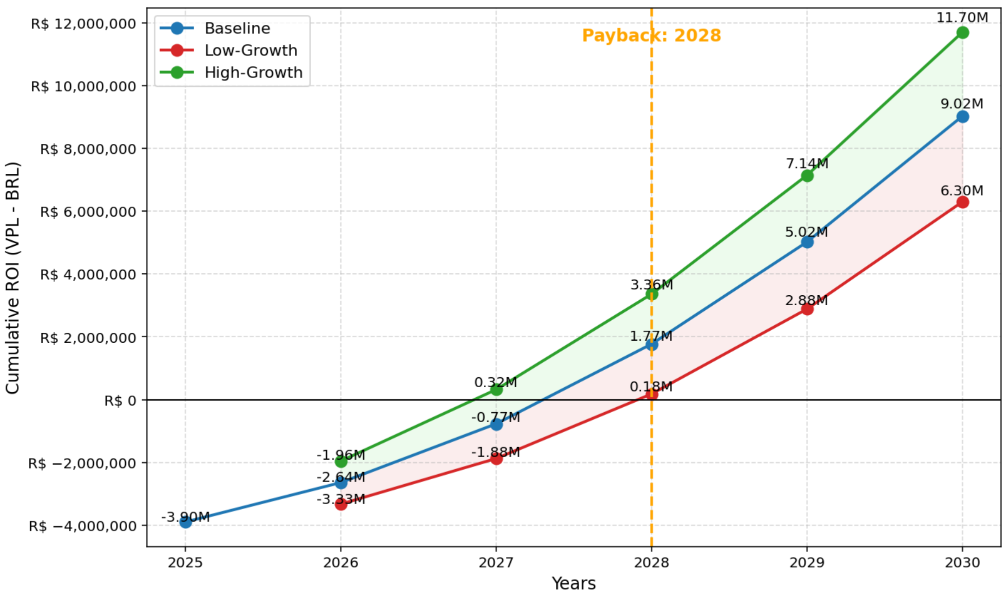

Figure 3.35 20 Chargers in 2025 NPV

4 PROBLEM MODELING

This section describes how the developed model was implemented in the GA model.

4.1 POPULATION SIZE AND THE NUMBER OF GENERATIONS

The objective to consider the population size is to determine how many individuals will go through the study. A population of 50 individuals was chosen for this study, since other metaheuristics applied the same number of individuals (GHORBANI *et al.*, 2018).

The number of generations refers to the number of interactions generated by the individuals. Therefore, the number of 40 generations was chosen because it is an intermediate value, without messing the data quality or implying a higher processing time (IBRAHIM *et al.*, 2019).

4.2 FIXED SEED AND CROSSOVER

The fixed seed 42 was chosen to ensure reproducibility of the results, not having any real impact on the GA itself.

The crossover is done in the GA by selecting a random point on the chromosome where the parents' parts exchange will take place. Therefore, the crossover brings up a new set of offsprings based on the exact exchange spot chosen with particular parts of the parents (HASSANAT *et al.*, 2019). Within this study, a Blend Crossover was used with an alpha of 0.5.

4.3 MUTATION AND SELECTION

Mutation, inside the GA study, normally is done after the crossover applies the changes randomly to one or more genes to produce a new offspring, creating new adaptive solution. It then avoids local optimization, providing the best global optimization solution (HASSANAT *et al.*, 2019). For this study, the mutation type was defined as being a Gaussian mutation, with mean (mu) 0 and standard deviation (sigma) of 20 km and the individual probability of mutation is 0.3. Therefore, about 30% of mutations for all genes in 20 km is considered.

The selection of individuals for the next generation is the most important to determine the pattern of the results of any GA model (Hussain *et al.*, 2022). For this study, a Tournament Selection was chosen with Tournament Size of three individuals. This means that there is a good balance between selecting good individuals and still maintaining diversity, because of the small Tournament Size.

4.4 POSSIBLE OPTIMAL POINTS AND PENALTIES ALGORITHM

Based on the length of the BR-386 studied, it was imposed that the GA could suggest up to five optimal points along the highway, depending on the individual that has proven the most efficient throughout the model.

There was a high penalty for the one-sided optimization in the BR-386 concession. Therefore, it limits the possibility of an optimal solution to be on either extremes of the section. Another penalty applied was that the total distance among chargers had to be smaller than the autonomy of 230 km. This restriction allows the EV to recharge at one optimal charging point and being able to reach the next charging station with its autonomy. The distance among the chargers has another penalty, being the minimum distance between them of 50 km. Table 4.1 was created to summarize the parameters used.

Table 4.1 Genetic Algorithm Model Parameters

PARAMETER	VALUE	DESCRIPTION
Population Size	50	Number of individuals per generation
Number of Generations	40	Number of generations the GA evolves
Fixed Seed	42	Fixed seed to ensure reproducibility
Mutation Type	Gaussian	Type of mutation applied to genes
Mutation Mean (mu)	0	Mean of the Gaussian mutation
Mutation Std (sigma)	20 km	Standard deviation of the mutation
Individual Probability	0.3	Probability that each gene in the individual is mutated
Crossover Type	Blend Crossover	Type of crossover between parents
Alpha	0.5	Controls how far offspring can go beyond the parents' interval
Selection Method	Tournament Selection	Method used to select individuals
Tournament Size	3	Number of individuals per tournament
Possible Optimal Points	1 to 5 points per individual	Each point represents a position along BR-386 (0–266 km)

4.5 FINAL PLOT

Once the model was calibrated, the optimal points within BR-386 restrictions were found. The two optimal charging points are shown in Table 4.2. The distance between the two points was calculated for both Canoas and Caraizinho

Table 4.2 Optimal Points of the Genetic Algorithm Model

DIRECTION	POINT	KM ALONG BR-386	LATITUDE	LONGITUDE
Carazinho → Canoas	Point 1	74.12	-28.951891	-52.373210
Carazinho → Canoas	Point 2	196.56	-29.558211	-51.888378

After finding the optimal points, three figures were plotted for visual understanding where the two optimal charging points are located. The first figure, Figure 4.1, shows the entire BR-386, and the other two figures, Figure 4.2 and Figure 4.3, are a more intense zoom in areas of the optimal points.

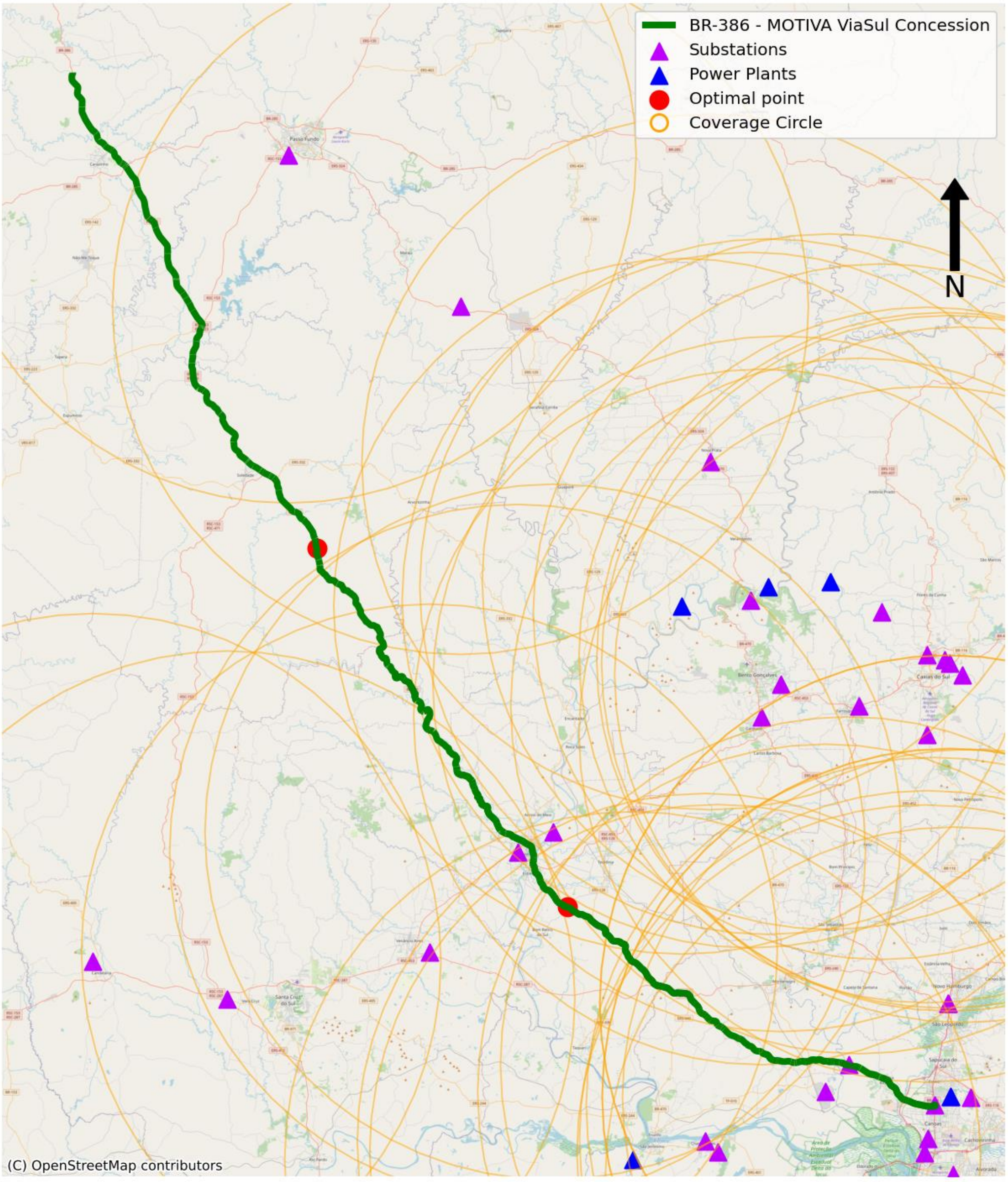

Figure 4.1 Optimal Points

Figure 4.2 Zoom on Optimal Point 1

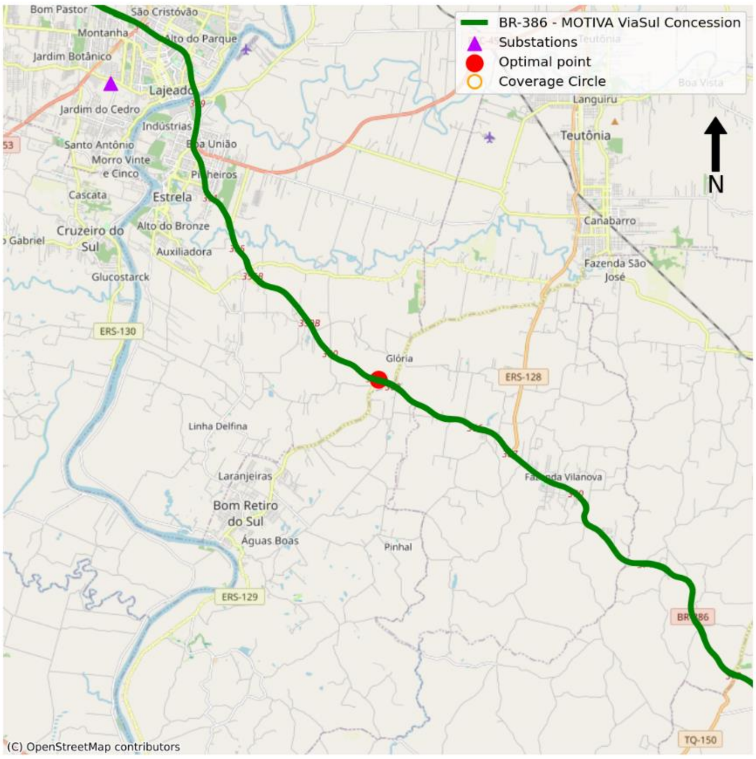

Figure 4.3 Zoom on Optimal Point 2

5 CONCLUSIONS

The main objective of this study was to determine the optimal points for the EVCs. This objective was achieved taking into account the maximum number of vehicles, traffic flow, queueing time and utilization. The applied model found two optimal location points for these EVCs and several choices for the ideal number of chargers, depending on the analyzed scenario. It is now the MOTIVA's responsibility to implement these chargers in the way that makes the most economic sense for them, always thinking about the 2030 projection.

The results could be further analyzed by critically examining economic barriers, public policy considerations, and the applicability of the findings to other Brazilian highways. Factors such as implementation costs, governmental incentives, and environmental regulations can significantly influence the location and the number of the EVCs in highways.

Additionally, the methodology is not limited to BR-386. All the data required for the analysis, such as traffic volumes, growth rates, and infrastructure characteristics, are also available for other highways. The differences among the roads are only the magnitude and the specific values of these parameters, but the structure of the model and the approach remain fully applicable. Another study including a socioeconomic analysis would provide a more understanding of the opportunities and challenges associated with expanding the EVC network in Brazil. The parameters considered in the socioeconomic analysis can include, for instance, value of time for rich and poor commuters.

For future studies, one proposal to overcome the limitations regarding the data uncertainty would be to measure the vehicle flow more specifically for the EV models and brands, with some tracking aligned with the toll booths and points spread across the highway. Another proposal would be to carry out the study with the concessionaire daily data, making the approximation unnecessary and the results even more robust to the studied case. Thus, making the study more precise in the analysis, not having to estimate the parameters. Different algorithms can also be applied to compare the obtained among them. Nevertheless, it is true that the applied algorithm in this study is the one that it has been more applied in other studies. Finally, this study has applied a GA algorithm to determine the best location for the charging stations taking into account also the revenues and costs accrued by these electric charging stations. This same study can be applied to other highways being important to understand the impact of the EVCs in a connected non-urban environment. The robustness and the results obtained by the applied GA algorithm can definitely aid the concessionaire to achieve better results improving its efficiency not only for the company but also for the society.

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