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OPTIMIZING ELECTRIC VEHICLE CHARGER INSTALLATION ON A NON-URBAN HIGHWAY: A CASE STUDY OF BR-386, MOTIVA VIASUL, BRAZIL

Otimização da instalação de carregadores para veículos elétricos em rodovias não urbanas: um estudo de caso da BR-386, Motiva Viasul, Brasil

Optimización de la instalación de cargadores para vehículos eléctricos en carreteras no urbanas: un estudio de caso de BR-386, Motiva Viasul, Brasil

Tiago de Oliveira Mafra Teixeira [1] **& Reinaldo Crispiniano Garcia** [2]

[1] The University of Texas at Arlington [1 2] Universidade de Brasília (UnB)
[1] tiago.mafrateixeira@gmail.com [2] rcgarcia@unb.br

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*** Corresponding Author**: **Teixeira, T. de O. M.**

ABSTRACT

This study aims 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 applies 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 is the acquisition and cleaning of the database because the data is obtained from several different sources. The second stage is the implementation of the GA model. This phase uses the applied data, including traffic flow (both in 2025 and an estimate for 2030), electrical energy infrastructure and EV specifications. The third stage is 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 size, and utilization percentage of the chargers depending on the scenario, either the 2025 one or the 2030 scenario.

RESUMO

Este estudo visa encontrar os pontos ótimos para a instalação de carregadores para veículos elétricos (EVs) na rodovia não urbana BR-386, parte da concessão da MOTIVA ViaSul. Este trabalho aplica um modelo de Algoritmo Genético (GA) combinado com o Sistema de Informação Geográfica (GIS) para determinar as localizações ótimas das estações de carregamento. O trabalho foi implementado em três etapas. A primeira etapa consiste na aquisição e limpeza do banco de dados, uma vez que os dados são obtidos de diversas fontes. A segunda etapa consiste na implementação do modelo de GA. Esta fase utiliza os dados aplicados, incluindo o fluxo de tráfego (tanto em 2025 quanto uma estimativa para 2030), a infraestrutura de energia elétrica e as especificações dos EVs. A terceira etapa consiste na aplicação de diferentes cenários para obter a solução ótima para o modelo. O modelo encontrou duas localizações ótimas para a alocação de carregadores de EVs, além do número ideal de carregadores, do tamanho médio da fila e da porcentagem de utilização dos carregadores, dependendo do cenário, seja o de 2025 ou o de 2030.

RESUMEN

Este estudio tiene como objetivo encontrar los puntos óptimos para la instalación de cargadores para vehículos eléctricos (EVs) en la carretera no urbana BR-386, perteneciente a la concesión MOTIVA ViaSul. Para ello, se aplica un modelo de algoritmo genético (GA) combinado con un sistema de información geográfica (GIS). El trabajo se implementó en tres etapas. La primera consistió en la adquisición y limpieza de la base de datos, ya que los datos se obtuvieron de diversas fuentes. La segunda etapa fue la implementación del modelo de GA. Esta fase utilizó los datos aplicados, incluyendo el flujo de tráfico (tanto en 2025 como en una estimación para 2030), la infraestructura de energía eléctrica y las especificaciones de los EVs. La tercera etapa fue la aplicación de diferentes escenarios para obtener la solución óptima del modelo. El modelo identificó dos ubicaciones óptimas para la asignación de cargadores de EVs, además del número ideal de cargadores, el tamaño promedio de la cola y el porcentaje de utilización de los cargadores, según el escenario: el de 2025 o el de 2030.

INTRODUCTION

The utilization of fossil fuels is the main source of vehicle transportation worldwide (Huang et al., 2018). However, this utilization has turned into a questionable and negative issue because of the harmful effects on Earth (Karnauskas et al., 2020). Even though Brazil's energetic sources mainly come from renewable sources, this urge for replacing fossil fuels has become a government proposition (Lima et al., 2020; Oliveira et al., 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 Canoas to Caraizinho having an extension of 266 km.

With the large number of non-urban highways in Brazil, it is possible to say that there exists the possibility to transition, even in a non-urban area, the fuel-based cars to an EV. However, Brazil needs to have the required infrastructure to make the transition from fuel-based cars to EVs. The main problem is the lack of charging stations through these highways and their optimal localization allowing longer trips and more security for those driving an EV (Noel et al., 2019). Therefore, this study aims to determine where the possible locations are, considering the maximum number of vehicles, the traffic flow, the queuing time and the utilization, to optimize the installation of EVCs in the non-urban highway BR-386, concession MOTIVA ViaSul.

LITERATURE REVIEW

Evolution of EV in the World

The Electric Vehicles (EVs) are those cars being propelled partially or fully by electric motors (Ruan & Song, 2019). Its popularization and commercialization initiated only almost 170 years ago once the first prototype was done by A´nyos Jedlik, around the year 2000 (Barbosa et al., 2022).

One of the many problems is the phenomenon known as range anxiety, considered one of the most influential factors to decide to purchase an EV or not (Noel et al., 2019). Range anxiety is the fear of running out of electricity before reaching other EVC (Neubauer & Wood, 2014). The mentioned anxiety issue is amplified by the lack of EVC near highways, as seen in Rio Grande do Sul.

In order to solve the range anxiety problem, there are, mainly, two possibilities. The first is to increase the EV autonomy, making the vehicle range increase from 200 km to 600 km per charge. The second possibility is to provide more charging stations, EVC (Pevec et al., 2019). The first one is more technology dependent, and the second one is more economic dependent. Moreover, nowadays, there are different types of cars that are considered as EV (Table 1).

Table 1. The main difference of EVs types and characteristics

Vehicle Type	Energy Source	Electric Range (km)	Additional Fuel	Plug-in Charging	CO2 Emissions
Battery Electric Vehicles (BEVs)	Only electric battery	High (100-600)	None	Yes	Zero
Plug-in Hybrid Electric Vehicles (PHEVs)	Battery + combustion engine	Medium (30-100)	Gasoline or diesel	Yes	Low
Hybrid Electric Vehicles (HEVs)	Battery + combustion engine	Low (5-10)	Gasoline or diesel	No	Moderate
Fuel Cell Electric Vehicles (FCEVs)	Hydrogen fuel cell	High (300-700)	Hydrogen	No	Zero

Source: Research data (2025).

This study mainly considers Battery Electric Vehicles (BEVs) once they are the only ones needing strict Plug-in Charging to operate.

Evolution of EVC in the World

Electric Vehicle Charging (EVC) stations are needed to recharge the battery of the BEVs and the PHEVs. Their localization is responsible to increase or decrease the range anxiety (Xu et al., 2020). Therefore, the most important aspect is to match the waiting time to charge the car and the waiting time to fill up the car in the gas stations besides considering how many kilometers will be required to charge or fill up the car (Gnann et al., 2018; Singh et al., 2020).

It is also important to consider the high consumption of electricity for an installed unit (Muratori et al., 2019). The EVC can normally charge 5 kWh up to 50 kWh, resulting in a waiting time of 11 hours to 30 minutes (Hemavathi & Shinisha, 2022). The mentioned time can vary between 132 to 6 times slower than a regular fossil fuel-based car on a gas station. Furthermore, four types of EVC are basically being used worldwide: Slow or normal charger, Semi-fast charger, Fast charger and Ultra-fast charger. In particular, the Ultra-fast charger has a minimum of 150 kilowatts (kW) of power, charging a vehicle in under 30 minutes. The Ultra-fast charger is the one to be applied in this research.

OPTIMIZATION METHOD

Different models can be applied to analyze and obtain the optimal localization for the same problem. The applied model depends on the problem itself, data analysis, theory behind and, mainly, about the criteria and what are the expected outputs of the model (Zhou et al., 2022).

This work implements the metaheuristic method to solve the studied problem applying in particular the Genetic Algorithm (GA). The GA solves both constrained and unconstrained optimization problems being inspired in the biological evolution process (Katoch et al., 2020). It is a population-based search algorithm, using the concept of the survival of the fittest or the strongest producing the new populations by iterative use of genetic operators on individuals 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).

For this study, a GA location optimization method is developed due to the large number of variables to optimize the installation of the EVC on a specific kilometer of the BR-386, concession ViaSul.

GEOGRAPHIC INFORMATION SYSTEM (GIS)

A Geographic Information System (GIS) is a system of computer software, hardware and data, making it possible to analyze the data set, and the information tied to a location on the earth's surface. There are different definitions for the Geographic Information System, each developed from a different perspective or disciplinary basis. Some focus on the map connection, some stress the database, or the software tool kit emphasizing applications such as decision support systems.

One of its main applications is that the model can be a combination of the GIS tools with Multi-Criteria Decision Analysis (MCDA) or GA methods, delivering a better spatial decision by integrating multiple criteria from various spatial data sources (Kazemi & Akinci, 2018). Therefore, the main benefit to implement the GIS is that the developed model will be trained to achieve a better solution, tied to a location on the earth's surface. Thus, the GIS allows to show the locations where the EVC will be installed.

METHODOLOGY

This study consists of three different phases. The first phase is the acquisition and cleaning of the applied data set. The data is obtained by multiple locations and sources. The applied data includes traffic flow, traffic by period of the day, car model, average time spent in the highway by the cars, the length of the highway and the electrical energy infrastructure. The second phase is the construction of the GA model besides evaluating the data set, applying the Python software language, the GIS and the ARENA simulation software. Thus, the third phase is the implementation of different scenarios to make the applied model a more robust one. The goal is to implement scenarios enabling the decision makers to optimally locate the EVC.

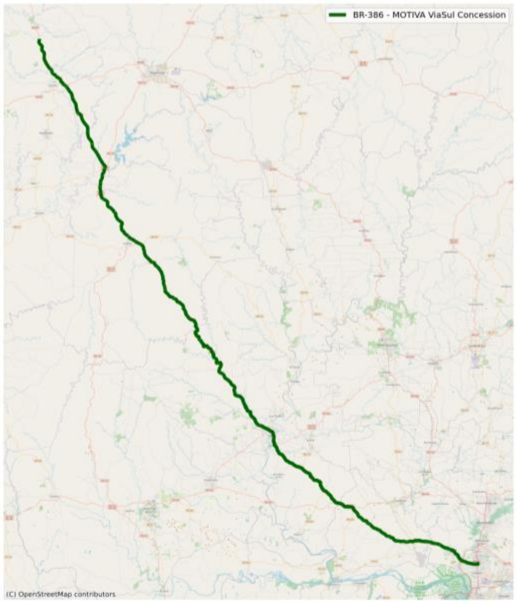
The Applied Data Set

Length BR-386 in Concession (km)

At first, it is plotted the studied BR-386 highway. The BR-386 has a length of 266 km having its starting point in the city of Caraizinho and finishing point in the city of Canoas. Therefore, a map using the Python script and the OpenStreeMap is obtained. Figure (1) has a detailed plot of the BR-386 and Figure 2 shows the BR-386 in concession by the MOTIVA Via Sul.

Figure 1. BR-386 Full Size

Figure 2. BR-386 Concession MOTIVA ViaSul



Source: Research data (2025).

Traffic Flow (2025)

The traffic flow was calculated from the data collected in two different locations in the BR-386 highway, the kilometer 422,6 and the kilometer 362,8. This data was obtained through PNCT (National Traffic Control Plan) and the data was compiled from 2024 onwards. The percentages of EVs calculated from the data of the DETRANRS (RS State Department of Transit) public on its website. The EVs in Rio Grande do Sul represent approximately 0.13% of the fleet in circulation in RS (Table 2). Thus, the traffic flow of EVs in the highway BR-386, annually, also was calculated (Table 3).

Table 2. Percentage Distribution of Traffic Flow in 2025

Category	Quantity in RS	Percentage of Fleet
EVs	5,918	0.13%
All vehicles	4,627,979	100%

Source: Research data (2025).

Table 3. Traffic Flow Analysis 2025

Section	Cars Observed	Days observed	Total Number of Cars	Total Number of Cars/Day	Total 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**

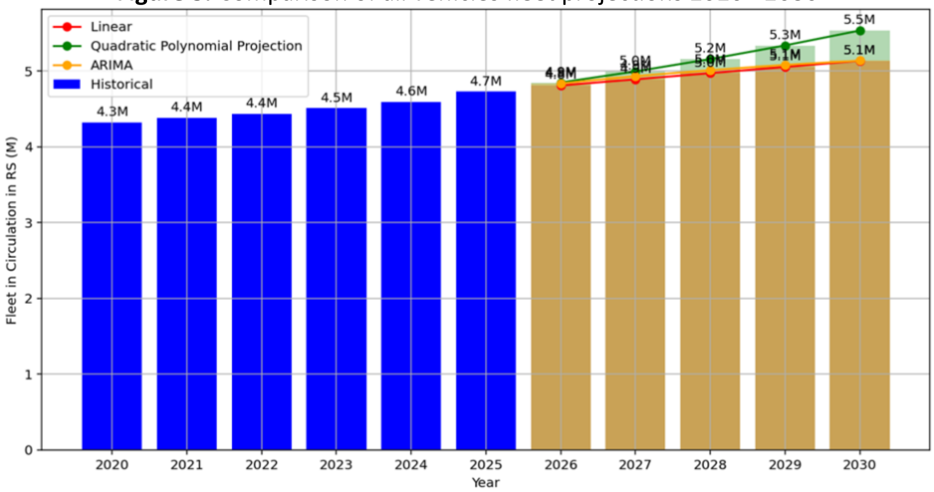
Source: Research data (2025).

Both numbers of the EVs/Year were used being constraints to the studied problem. Sensitivity analyses were also implemented to evaluate any location for charges in the EVCs. 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.

Traffic Flow (2030)

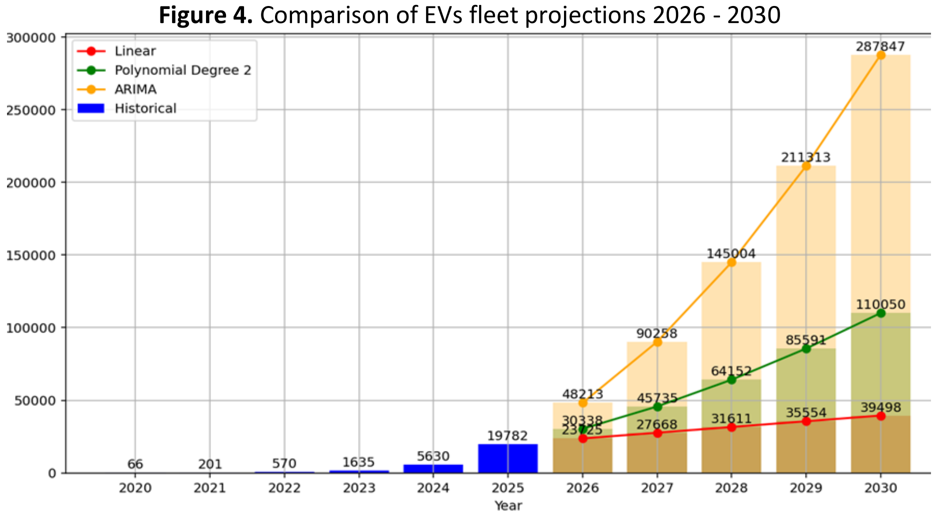
Traffic flows for the year 2030 were then evaluated to determine if the optimal location of EVC station would really depend on the magnitude of the traffic flows. The forecasts were made applying the Quadratic Polynomial Projection technique. Nevertheless, the Linear Method, the ARIMA and the Quadratic Polynomial approaches are shown in Figures 3 and 4.

Figure 3. Comparison of all vehicles fleet projections 2026 - 2030



Source: Research data (2025).

Figure 4. Comparison of EVs fleet projections 2026 - 2030



Source: Research data (2025).

The Quadratic Polynomial Projection was the chosen one due to its ability to fit the acceleration of the growth in recent years, once from 2024 to 2025 the growth was 251.5%. This sharp increase indicates a non-linear trend that cannot be adequately represented by simple linear models or ARIMA. The Quadratic Polynomial Projection, however, is capable of expressing both the level and the acceleration of traffic demand, making it suitable for short term projections where sudden increases may occur. Thus, the projection used to predict, in 2030, the total number of vehicles and the total number of EVs will be the Quadratic Polynomial Projection.

The total number of all vehicles expected for 2030 will be considered as 5,536,186 and the number of EVs is 110,050 in the baseline proposition. The EVs will then represent about 2% of the Rio Grande do Sul (Table 4). Thus, the traffic flow of EV, expected in the highway BR-386 in 2030, annually, is calculated and displayed in Table 5.

Table 4. Baseline Distribution of Traffic Flow in 2030

Category	Quantity in RS	Percentage of Fleet
EV	110,050	2%
All vehicles	5,536,186	100%

Source: Research data (2025).

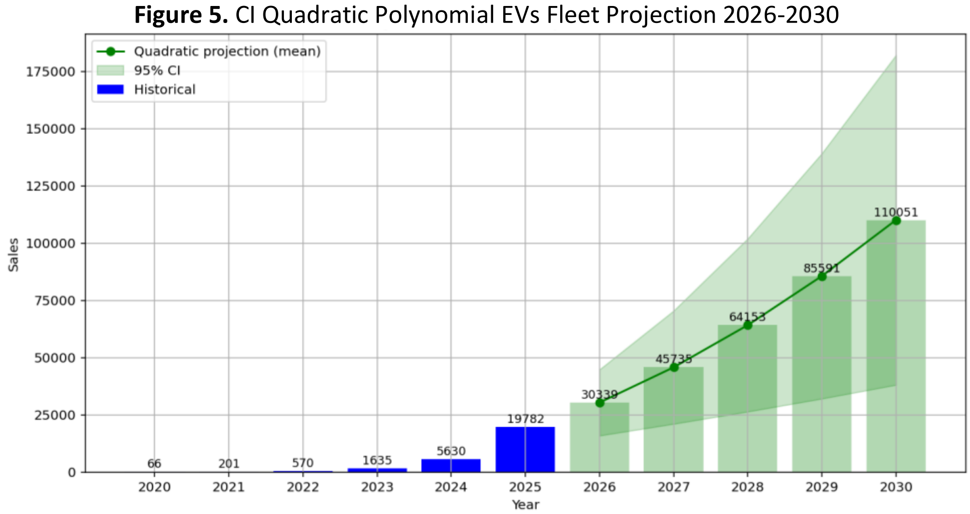
Table 5. Baseline Annual Traffic Flow in 2030

Section	Cars Observed	Days observed	Total Number of Cars	Total Number of Cars/Day	Total 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: Research data (2025).

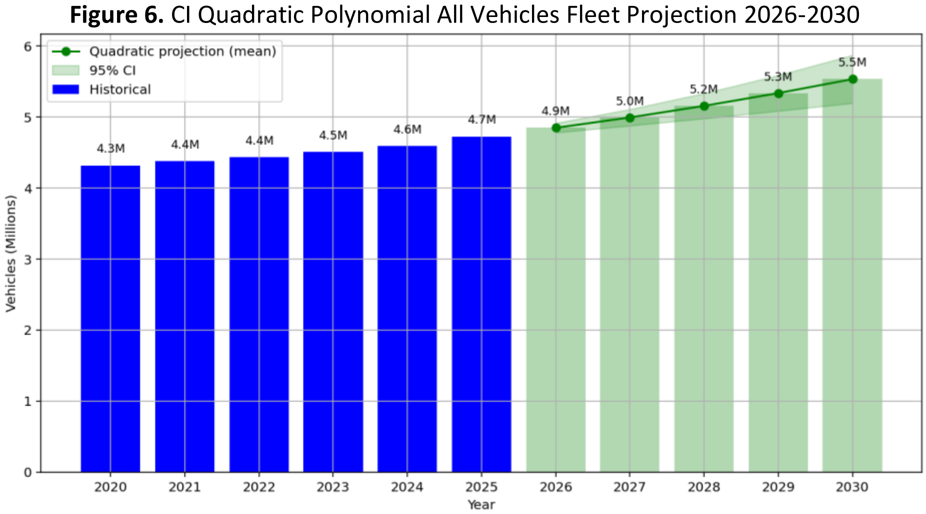
The daily number of EVs of 367 was obtained and a Confidence Interval (CI) of 95% for the year 2030 was calculated for the Quadratic Polynomial Projections (Figure 5 and 6) to create a more accurate analysis. By incorporating confidence intervals into the projection, the analysis also ensures transparency regarding the uncertainty of forecasting. This allows decisionmakers to assess both the expected trajectory and the plausible range of demand outcomes.

Figure 5. CI Quadratic Polynomial EVs Fleet Projection 2026-2030



Source: Research data (2025).

Figure 6. CI Quadratic Polynomial All Vehicles Fleet Projection 2026-2030



Source: Research data (2025).

To determine what would happen to the ideal number of chargers in 2030, a two-scenario analysis was created as well as the baseline scenario. The low-growth scenario and the high-growth scenario makes 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. Both scenarios were calculated using the same procedure as the baseline one. The daily number of EVs for the low-growth scenario is expected to be about 126 EVs per day and high-growth scenario is expected to be about 603 EVs per day.

The Electrical Energy Infrastructure

Afterwards, it is important to evaluate the electricity demand of an EVC. All the Substations and Power Plants available in the region were gathered via data extracted by the SIN Maps and the ONS (National Electrical System Operator). Figure 7 was obtained incorporating this data into the Python Script and Figure 8 considers a 75 km required radius around them to observe if all the optimal points will have the supply.

Figure 7. BR-386 Substations and Power Plants

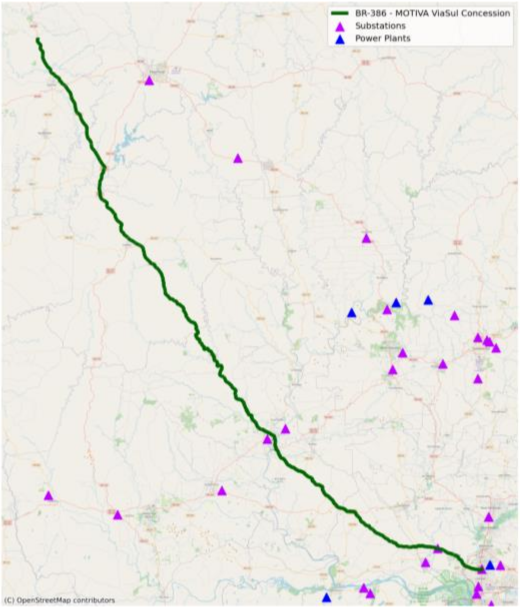
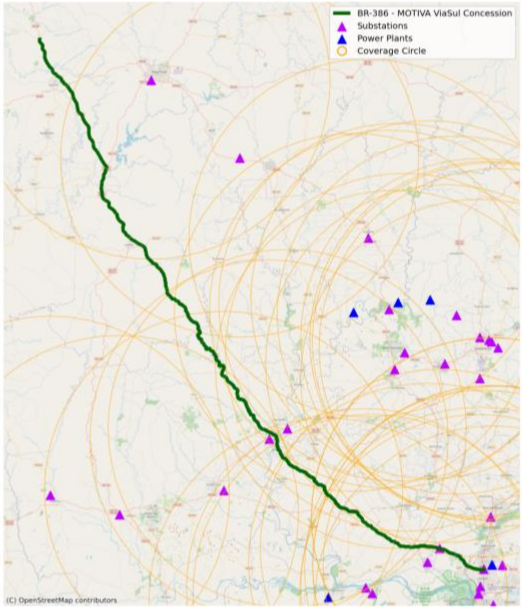


Figure 8. BR-386 Substations and Power Plants radius



Source: Research data (2025).

It is also important to measure the energy needed for an EVC to work with its battery fully loaded. This is determined by what EVC is taken into consideration, because each one of them has a different average power (kW). The best EVC for highways is the Ultra-fast charger, because it is the fastest to charge an EV, taking about 20 minutes to load the battery as already mentioned. This study assumes then 150 kW of average power for the EVC.

EVs Specification

The model of the EVs to be considered in the study looked at the number of the EVs being used in Brazil, their autonomy in the road and their recharge waiting time. The EVs data since 2015 was obtained from the SENATRAN because it showed the most used model, showing the possibility to calculate the autonomy and the capacity of the battery.

Since most of the EVs are manufactured by the BYD, a second analysis was made to determine which BYD model was the most used one. Furthermore, a weighted average for these models was made showing an Autonomy of 309 km and a Battery Capacity of 48 kWh being used to represent the characteristics of the EVs in this study.

Another important point is to measure the average time to charge for these models, considering an Ultra-fast charger with 150 kW. The time was calculated for charge between 25% and 100%. Furthermore, by doing a weighted average for these models, in this study, a time to charge of 18,4 minutes will be used representing the characteristics of the EVs.

Construction of the Ga Model

The ViaSul Highway and the EVs Autonomy

The BR-386 highway is plotted by the OpenStreetMap via Overpass API. Once all the elements are obtained connecting to the "BR-386", the points of interest result in one line by LineString. Afterwards, there are the boundaries of the studied area, specifying the geographic coordinates of Canoas (-51.1839, -29.9122) and Caraizinho (-52.7360, -28.2896) being the two cities limiting the studied area. Thus, the average autonomy of the EVs for this study is about 309 km. However, to prevent the possible range anxiety of not having enough electricity and taking into account that not every EV will have their battery fully loaded before arriving in the highway, a 25% reduction in their autonomy was imposed, resulting in an autonomy of 230 km.

Substations, Power Plants and Battery Capacity

The EVC to charge the EVs will need a lot of energy, coming from the Substations and Power Plants, assuming a radius of 75 km around them, (Figure 6). The optimal point is necessarily within the coverage circle since it requests the necessary energies support for the EVCs to work properly. Also, the average battery capacity is about 50 kWh being the one used in the model to determine the number of ideal chargers in the EVC.

Traffic Flows in 2025 and 2030

As shown, in Tables 3 and 5, the average total number of EVs per year in 2025 is 3464 in direction C and 3471 in direction D. For 2030, however, this number goes to 64.418 in direction C and 64.545 in direction D. This is one of the most important constraints, not only to limit the amount of EVs needed to charge, but also to test and see the utilization, waiting time and queuing time, for instance.

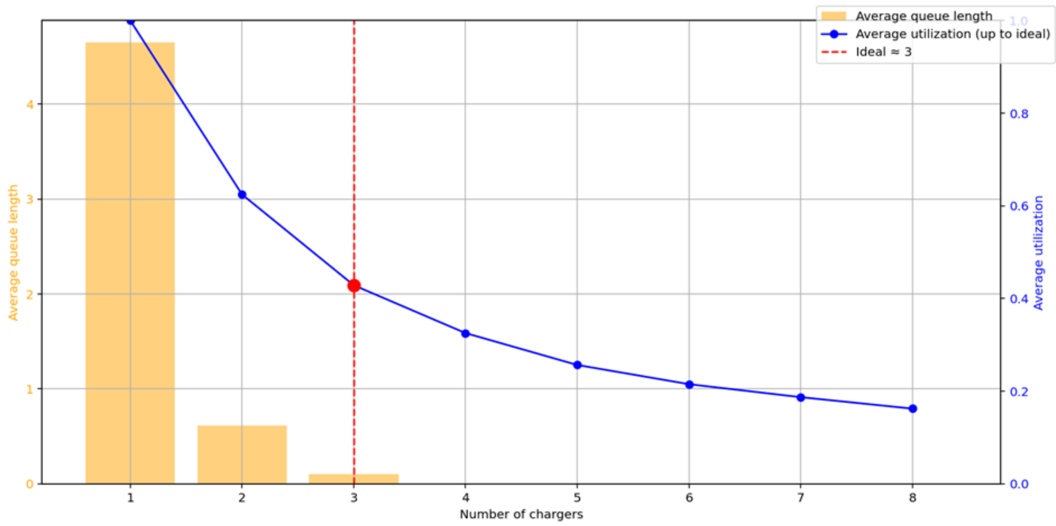
Time to Charge and Number of Chargers

The average time to charge, from 25% up to 100%, is about 18,4 minutes, assuming a constant of 150 kW ultra-fast charger. This charging time is increased by 20% capacity because the charging will go slower when the battery is already charged at 70% or 80% (Kostopoulos et al., 2020). Consequently, the time increases to about 22 minutes.

One then needs to determine the arrival pattern of the data generated by the PNCT. The Input Analyzer, of the ARENA software, was applied. 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. The evaluated arrival distribution of EVs was determined as being a Poisson, having a rate (lambda) of 20 in 2025 and 367 for baseline 2030.

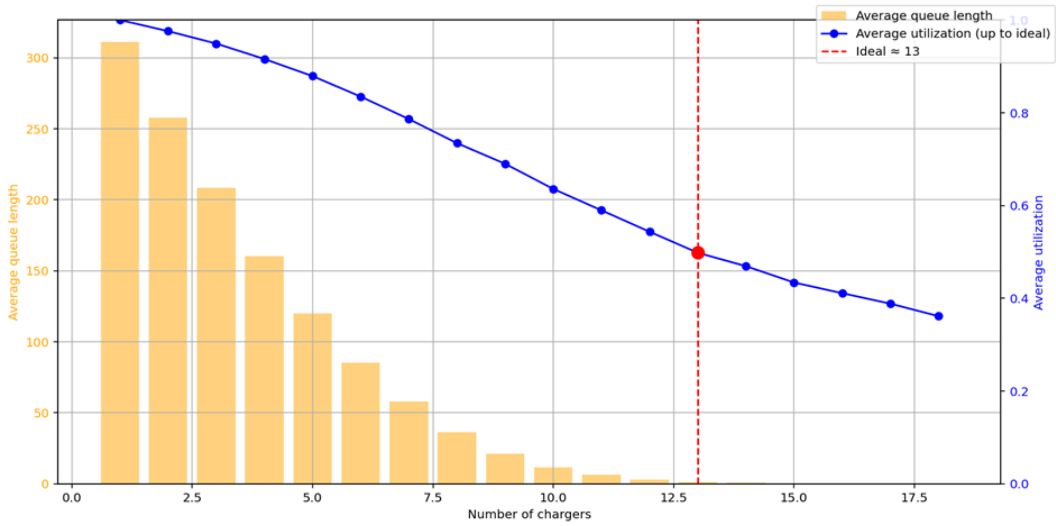
These factors of the time to charge, daily traffic flow, the time that the EVC would be available, the average arrival and arrival deviation were then considered. The next step was to find the ideal number of chargers. It was then fixed the utilization percentage at 50%, and the average queue time was calculated by the number of cars arriving in the system (Figures 9 and 10).

Figure 9. Ideal Chargers, Utilization, and EV Queuing, Baseline 2025



Source: Research data (2025).

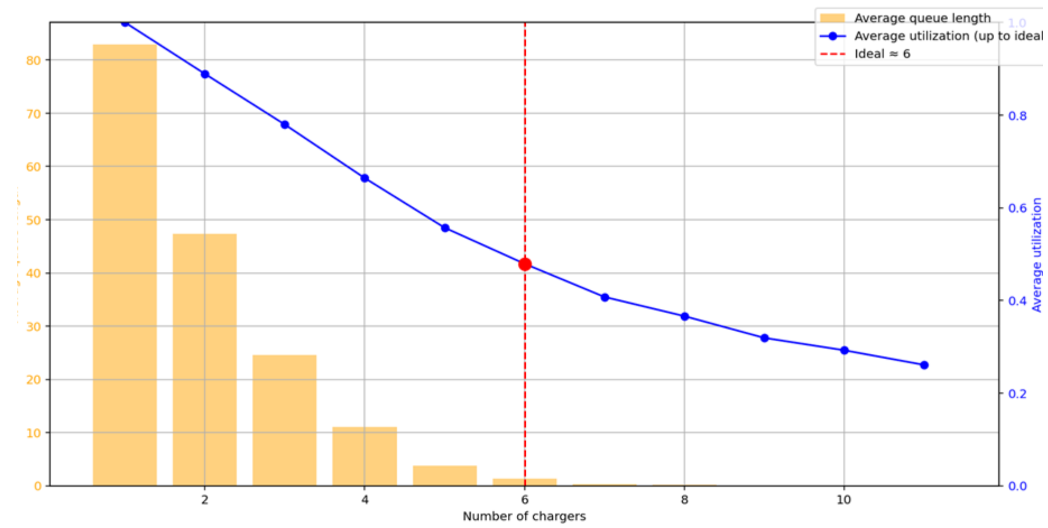
Figure 10. Ideal Chargers, Utilization, and EV Queuing, Baseline 2030



Source: Research data (2025).

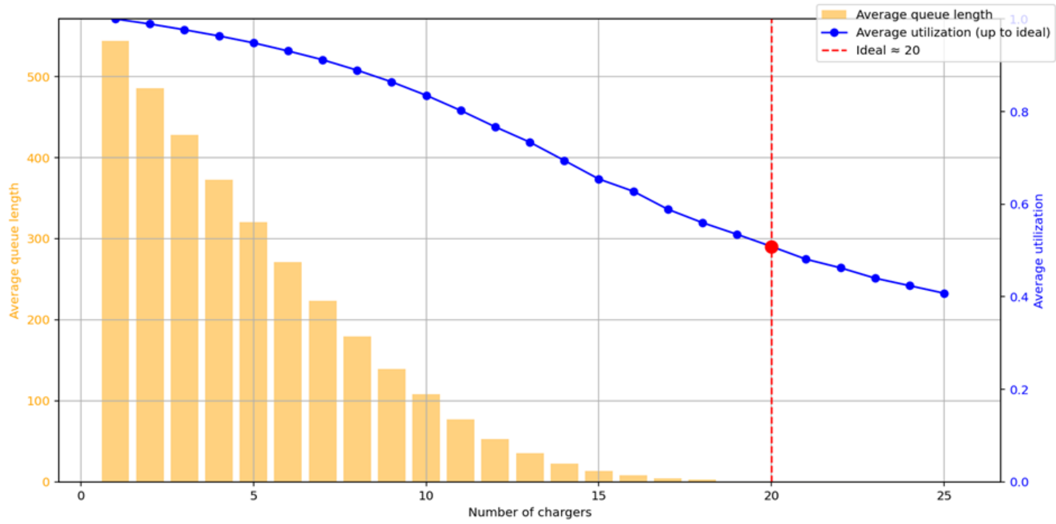
It was done the same study for the low-growth with 126 EVs per day (Figure 11) and for the high-growth scenario, with 603 EVs (Figure 12).

Figure 11. Ideal Chargers, Utilization, and EV Queuing, Low-Growth 2030



Source: Research data (2025).

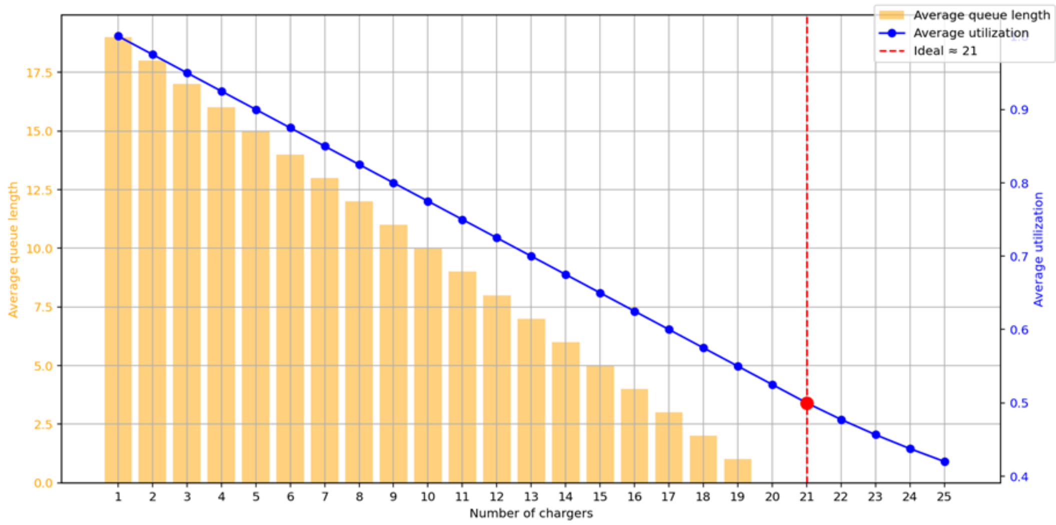
Figure 12. Ideal Chargers, Utilization, and EV Queuing, High-Growth 2030



Source: Research data (2025).

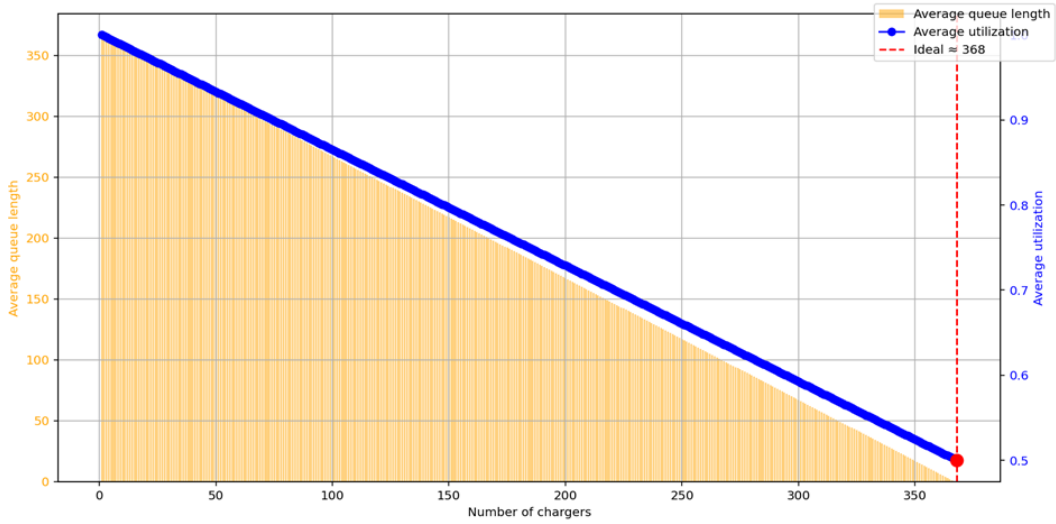
Finally, it was simulated if the entire flow of vehicles, in this case 20 EVs for 2025 baseline and 367 for 2030 baseline, arrived at the EVCs at once (Figures 13 and 14).

Figure 13. Ideal Chargers, Utilization, and EV Queuing – Arriving at Once, Baseline 2025



Source: Research data (2025).

Figure 14. Ideal Chargers, Utilization, and EV Queuing – Arriving at Once, Baseline 2030



Source: Research data (2025).

Finally, a comparative analysis of all the ideal number of chargers was created (Table 6).

Table 6. Comparative Analysis of Ideal Number of Chargers

Year	Scenarios	Ideal Number of Chargers
2025	Baseline	3
2025	Arriving at Once	21
2030	Low-Growth	6
2030	Baseline	13
2030	High-Growth	20
2030	Arriving at Once	368

Source: Research data (2025).

RESULTS

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).

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.

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.

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.

ROBUSTNESS AND SENSITIVITY ANALYSIS

The GA was evaluated by running it 35 independent times. The result shows a mean fitness of 295.92 ± 310.37, with the best and worst fitness values being 0.00 and 1076.74, respectively. The high standard deviation indicates that the GA explores a wide range of solutions, reflecting the variability in the initial population and stochastic effects of the evolutionary operators. The fact that the best fitness is 0.00 shows that the algorithm is capable of finding an optimal solution that fully satisfies the constraints, while the wide gap between best and worst fitness highlights the diversity of the population.

A sensitivity analysis was also performed by varying crossover probability and mutation probability to evaluate their effect on solution quality. The results indicated that, despite variability in the population fitness, the GA reliably identifies optimal solutions.

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 7. The distance between the two points was calculated for both Canoas and Caraizinho

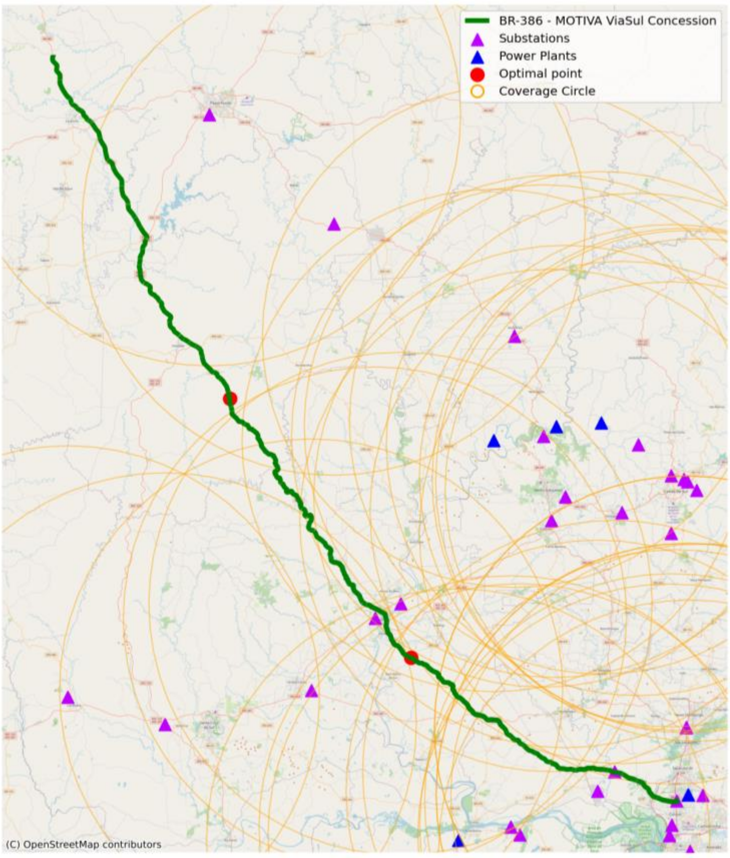
Table 7. Optimal Points

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

Source: Research data (2025).

After finding the optimal points, three figures were plotted for visual understanding where the two optimal charging points are located. The first figure, (Figure 15), shows the entire BR-386, and the other two figures, (Figures 16 and 17), are a more intense zoom in areas of the optimal points.

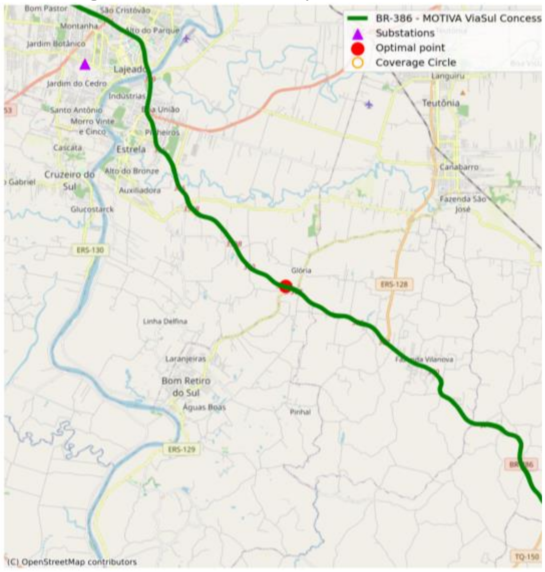
Figure 15. Optimal Points



Source: Research data (2025).

Figure 16. Zoom on Optimal Point 1

Figure 17. Zoom on Optimal Point 2



Source: Research data (2025).

DISCUSSION

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. It is now the concessionaire responsibility to implement these chargers making 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.

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. Finally, this same study can be done in other highways once it is important to fully understand the impact of the EVCs in a connected non-urban environment.

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