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Research Article

Determining the Number of Stops and Recharging Time for Electric Vehicle Trips Using GIS and k-Means Clustering

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ABSTRACT

The increasing adoption of electric vehicles (EVs) worldwide is driven by environmental concerns and the depletion of fossil fuels. Yet, the limited battery range remains a significant barrier to their widespread use, particularly for long-distance travel. This study addresses this challenge by developing a methodology to determine the number of recharging stops, their durations, and strategic locations for electric vehicle charging stations (EVCSs) using *k*-means clustering analysis, with proposed station locations visualized within a GIS framework. The method integrates quantitative data from questionnaires administered to transportation experts and professionals (N=24) and applies it to case studies across three major highway routes in Ceará, Brazil. The *k*-means clustering proposed a solution of three stops with a 28-minute recharge time; however, subsequent analysis revealed this time was an overestimate compared to a more precise, distance-based linear model. A key implication is that while clustering can group user preferences, its direct output for operational parameters like charging time can be imprecise. Therefore, we demonstrate the necessity of calibrating such models with physically-grounded equations to achieve practical and efficient trip planning. This approach highlights the importance of integrating user preference data with distance-based models to create more realistic EV infrastructure plans for long-distance corridors.

Keywords: electric vehicles, charging stations, *k*-means clustering, Geographic Information Systems, recharge time

INTRODUCTION

The global energy sector faces unprecedented pressure from escalating fossil fuel consumption and climate change imperatives, with transportation contributing to 24% of global CO_2 emissions [1], [2], [3]. The rapid global transition towards electric vehicles (EVs) represents a significant paradigm shift in transportation, driven by increasing environmental concerns, rising fuel costs, and advancements in battery technology [4], [3]. Electric vehicles have emerged as a critical decarbonization pathway, supported by international policies like the EU's AFIR and U.S. NEVI programs [3]. As EV adoption accelerates, the development of robust, accessible, and efficiently located charging infrastructure becomes paramount to support long-distance travel and alleviate one of the primary barriers to widespread EV acceptance: range anxiety [4], [5], [6]. The psychological aspect of "range anxiety" further underscores the need for methodologies that not only calculate optimal routes but also instill driver confidence by providing reliable and predictable charging experiences [5]. A universally recognized solution to range anxiety is the widespread expansion of charging networks, making them more ubiquitous, reliable, and accessible across all geographies. Globally, the stock of public charging points increased by over 30% in 2024 alone, with particularly strong growth observed in the deployment of fast and ultra-fast chargers [3].

The main problem of long-distance trips is related to the limited range of the battery of electric vehicles and the long recharging time [7]. The recharge time can be influenced by various factors, including the type of charging station (e.g., fast chargers vs. standard chargers), the battery capacity of the EVs, and the state of charge (SoC) upon arrival at the station [8]. The solution is to create a dense network of Fast-Charging Stations (FCS), while simultaneously increasing battery capacity. However, determining the optimal placement of these stations introduces a new challenge: the Electric Vehicle Charging Station Location Problem (EVCSLP). This is a multifaceted optimization challenge characterized by numerous variables, constraints, and often non-linear objective functions, which poses significant computational challenges for finding exact solutions [12]. To address this, researchers have explored a range of methodological approaches, each with distinct strengths and limitations.

Traditional approaches to EVCS placement often rely on geographical partitioning, demand patterns, and vehicular capacity distribution to minimize travel distances to the nearest station [13]. GIS-integrated *k*-means clustering emerged as fundamental tools for the initial grouping of geographical areas to identify potential EV charging station locations, by efficiently grouping high-demand zones like shopping centers [14]–[15]. For instance, Tambunan et al. [13] successfully integrated *k*-means with GIS to identify high-demand areas for EVCS in urban environments. They applied *k*-means in Jakarta, reducing 95 sites to 19 optimal clusters. Hybrid approaches like *k*-means with genetic algorithms (GA) refine locations under capacity constraints [15], [17]. Bendiabdellah et al. [15] utilized a hybrid algorithm with improved *k*-means clustering and genetic algorithm to find optimal number and place of charging stations. The *k*-means clustering algorithm considers the capacity of the charging stations and is used to minimize the distance between the charging stations and restrict the research space where the genetic algorithm is employed to determine the optimal locations for the charging stations. Furthermore, Richard et al. [16] used a hierarchical clustering algorithm and spatial-temporal data in order to assess if low-demand EVCS groups could be identified, since there are overestimations of charging stations in Canada, the USA and Europe.

Al-Khafaji et al. [17] presented a novel approach that combines *k*-means clustering and GA to create dynamic and practical routing solutions for electric vehicles (EVs). It optimizes EV routes by considering charging constraints, energy consumption, and other critical factors like travel distance, time, and charging station logistics, addressing real-world challenges such as charging station queue lengths. Shukla et al. [18] utilized *k*-means and fuzzy C-means clustering to analyze locations for FCS by estimating the service radius of EVs and their energy consumption patterns. Kalakanti and Rao [14] discussed the significance of clustering in the context of charging station planning, noting that service providers often prefer clustering charging stations rather than distributing them widely. This clustering approach minimizes the total distance traveled by EV owners to reach the nearest charging station, thus enhancing user convenience and promoting the adoption of electric vehicles. While these studies display the potential of clustering algorithms for urban settings, the complexities of ensuring seamless intercity and interstate EV travel necessitate a specialized approach to charging station placement and operation.

Recent research has significantly advanced the understanding and modeling of EV charging infrastructure. Multiobjective optimization models are increasingly prominent, aiming to concurrently optimize conflicting objectives such as minimizing construction costs, reducing EV user waiting times, optimizing station capacity utilization, and ensuring grid stability [19]. Liu et al. [20] formulated a finite-horizon Markov decision process (FH-MDP) problem to select the optimal charging time and charging station along a long-distance trip, considering the battery level and the driven distance. Their algorithm showed a reduction of 12.6% in the total travel time compared to alternative methods. Hassler et al. [21] presented an approach to coordinate EV charging station choices in the case of long-distance trips, with results showing a 10% reduction in charging time at the stations.

Sun et al. [9] evaluated both the use of FCS and Slow-Charging Stations (SCS) for short and long-distance trips in China and concluded that the distance traveled, the location of the stations and the budget available determined the

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degree of coverage of the EV demands in the analyzed paths. Jochem et al. [10] determined the minimum number of FCS for the highway network of several European countries using the flow-refueling location model (FRLM). They concluded that 314 FCS would be enough to attend to the demand of the region, whereas in 2018 the number of FCS was overestimated, but their location should be carefully planned to attend the EV users needs.

Beyond static placement, the integration of advanced Artificial Intelligence (AI) and Machine Learning (ML) techniques, including Reinforcement Learning (RL) and Multi-Agent Reinforcement Learning (MARL), is enabling real-time control and dynamic management of EV charging networks, adapting to fluctuating demand, grid conditions, and user behavior [22], [23] [24]. AI algorithms analyze real-time data to optimize EV charging networks, balance grid demand, and improve the driver experience [25]. Predictive AI analyzes customer insights, grid conditions, weather, and traffic to create optimal charging schedules, reducing costs and charging times. For example, Mosalli et al. [22] developed a reinforcement learning model for dynamic load balancing and pricing in EV charging networks, which adapts to localized demand and global network dynamics, ensuring improved network stability and user satisfaction. These dynamic systems are crucial for optimizing load balancing, resource allocation, and even dynamic pricing.

Recent technological breakthroughs enhance EV viability: solid-state batteries improve energy density and safety, while lithium iron phosphate (LFP) batteries reduce costs [4]. Ultra-fast chargers (350 kW) replenish 80% battery capacity in 15 minutes, mitigating range limitations for long trips [4], [11]. These innovations underscore EVs' feasibility but demand sophisticated infrastructure planning to maximize socioeconomic benefits.

Although recent studies have incorporated clustering with genetic algorithms for routing [17] or used Markov processes to select charging stations [20], a foundational, integrated framework that systematically determines the number of stops, charging durations, and station locations in a single, geospatially-grounded methodology is still lacking. This is particularly vital for strategic, long-term infrastructure planning where complex, real-time AI models may be premature. While predictive tools and advanced navigation systems exist to incorporate optimal charging stops [11], a foundational framework that systematically determines these parameters through a combined geospatial and clustering approach remains essential, particularly for initial infrastructure planning and in regions with developing EV ecosystems [3].

As such, the primary objective of this study is to propose and validate a new methodology for determining the optimal number of stops, the necessary charging time, and the strategic location of electric vehicle charging stations (EVCSs) specifically for long-distance trips. The study's methodology represents a significant strength through its effective integration of GIS and *k*-means clustering for EVCS location planning. A notable aspect is its distinctive integration of both quantitative data and key qualitative factors — such as time reduction, comfort, convenience, infrastructure, and meal availability — derived from expert opinions, offering a more comprehensive view of the problem. The application of this approach to a specific case study in Ceará, Brazil, offers valuable practical validation within a regional context. To enhance practicality, we also develop a linear equation to calibrate the recharge time estimates obtained from the initial model, addressing discrepancies caused by factors such as battery degradation and temperature effects that the primary algorithm does not capture. By integrating these robust analytical tools, this research aims to provide a systematic and data-driven framework that can effectively support infrastructure planners and policymakers in optimizing EV charging networks for extended journeys.

METHODS

The methodological approach of this study involved several key steps. First, criteria were selected to guide the determination of both the number and locations of Electric Vehicle Charging Stations (EVCSs). Next, a

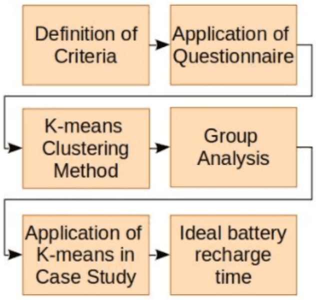

Figure 1. Flowchart Showing the Main Methodological Steps

questionnaire was administered to transportation professionals, allowing them to identify the most suitable alternative for each criterion. Following this, the *k*-means clustering method was applied to classify the alternatives into distinct groups based on quantitative attributes. The characteristics of each group were then analyzed to better understand their relevance and suitability. The clustering results were subsequently applied to three specific case study routes, and finally, the ideal charging time was determined for each route (Figure 1). From these steps, it was possible to determine the ideal number of EVCS, and based on the average autonomy of electric vehicles (EV) in Brazil, their location for three routes leaving from the municipality of Fortaleza to Juazeiro do Norte.

Determination of Criteria

To train the *k*-means clustering algorithm, responses obtained from a questionnaire administered to transportation professionals were utilized. The questionnaire was prepared considering factors impacting the implementation of new EVCSs, which are: 1) Time reduction, 2) Comfort, 3) Convenience, 4) Financial Impact, 5) Infrastructure, and 6) Passenger food.

To move from these conceptual factors to a practical, measurable model, we developed five operational criteria that served as the inputs for the *k*-means clustering algorithm. These five criteria were selected because they provide the most appropriate and measurable operationalization of the broader conceptual factors for determining the optimal number and location of EVCSs. The relationship between the initial factors and the final operational criteria is explicitly detailed in Table 1. The factors of Comfort and Convenience are operationalized through the C1 and C3 criteria, respectively, by focusing on reducing Stops for recharging and ensuring strategic Installation in urban

Table 1. Correspondence between Six Conceptual EVCS Factors and Five Operational Assessment Criteria

Initial Conceptual Factor	Operational Assessment Criterion	Initial Conceptual Factor
Time reduction	C2: Time for recharging	Directly measures the time-saving component of the EVCS location/technology.
Comfort	C1: Stops for recharging	Measures the need to reduce the frequency and number of required stops to improve user experience.
Convenience	C3: Installation in urban centers	Measures the accessibility and ease of reaching the EVCS location (i.e., proximity to population/demand centers).
Financial Impact	C3: Installation in urban centers	Indirectly relates, as urban installations often have higher initial costs but higher return on investments due to greater usage density.
Infrastructure	C4: Site Infrastructure	Directly measures the required physical and technical readiness of the site.
Passenger Food	C5: Proximity to restaurants and gas stations	Measures the availability of crucial complementary services, which directly addresses the "Comfort" and "Passenger Food" factors.

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Table 2. Mean Vehicle Range Autonomy for Brazil, Used As Reference in The Questionnaire

Factors	Values	Units
EV autonomy (Brazillian Average)	272	Km
Battery storage capacity	60	kWh
Electrical grid power	75	kW
% battery charge in 30 mins	80	%

centers. The Passenger Food factor is combined with broader location considerations in C5 Proximity to restaurants and gas stations, acknowledging that the need for user amenities is a key determinant of site quality. Time reduction is directly and solely measured by C2 Time for recharging, making it a clear, direct input into the model's efficiency calculations. This mapping ensures that all six conceptual factors are adequately represented by a parsimonious and measurable set of five operational criteria that directly feed into the clustering algorithm.

Criterion C1, designated as Stops for Recharging, is based on the number of stops drivers would be willing to make during their trip to recharge their battery, with this number depending on the distance of the journey. The establishment of this criterion aims to bring comfort to EV users, as trip planning is inherently tied to the time spent on the route. Adding or reducing a recharging stop will alter the travel time. In this sense, respondents to the questionnaire were provided with Table 2 to assist in their responses and to choose between 1 to 10 stops. The following question was posed: "How many recharging stops would you consider necessary to establish a certain level of comfort during the journey?"

Recharge Time (C2) is the criterion designed to capture the amount of time electric vehicle (EV) users are willing to wait during stops to achieve a sufficient charge, allowing them to continue their journey safely and comfortably. The formulation of this criterion is directly linked to C1 (Stops for recharging). Specifically, once a stop has been made, the question becomes: how much time should the stop consume before the pre-established route can be safely continued? Therefore, C2 is a quantitative criterion that measures the time, in minutes, that drivers deem necessary to obtain a certain level of battery charge to proceed with their trip securely and comfortably.

The third criterion (C3) titled "Installation in Urban Centers" was developed to measure the importance that EV users attribute to the installation of charging stations in urban centers. The aforementioned point was considered to bring more convenience and comfort to users, as it is known that installation in urban centers brings certain attributes such as better access to the Internet. It is also worth noting that the implementation of charging stations in urban centers facilitates access to certain establishments that can address some challenges that may arise during the journey, such as tire repair shops, pharmacies, supermarkets, among other options. Based on issues such as those mentioned above, C3 is classified as a qualitative criterion, which aims to assess the importance for EV users that a charging station be installed in urban centers.

Since criteria C3 to C5 are qualitative criteria, it was decided to insert another support table in the questionnaire based on the Likert scale [27] (Table 3). Thus, respondents rated the level of importance of the criterion on a scale of 1 to 5, considering the following question for C3: "On the Likert Scale, rate the importance of the criterion Installation in Urban Centers compared to the installation of charging stations."

Criterion C4, "Site Infrastructure," establishes the level of relevance that EV drivers place on infrastructure when choosing the location for constructing a charging station. The infrastructures mentioned in C4 include easy and stable accessibility to the electrical grid, the physical infrastructure of the environment, and the number of chargers per station. In the questionnaire, the importance level of site infrastructure when implementing new EVCSs was listed, using the five ratings of the Likert scale, with the following question posed: "On the Likert Scale, rate the criterion Site Infrastructure compared to the Installation of charging stations."

Table 3. Likert Scale, Value Based on Qualitative Information

Value	Term
1	It's not important
2	Sometimes is important
3	Average importance
4	Important
5	Very important

The last criterion, C5 "Proximity to gas stations and restaurants," measures the importance of installing charging stations near fueling stations and restaurants. It is worth noting that the commercial establishments mentioned above are strategically implemented, and travelers can enjoy the services or even the infrastructure of these places, thereby adding more comfort and quality to the journey. Therefore, the last criterion also falls under the qualitative category, as it indicates the quality of the journey from the perspective of the EV user. In the questionnaire, the importance level of installing charging stations near gas stations and restaurants was listed, using the five ratings of the Likert scale, with the following question posed: "On the Likert Scale, rate the criterion Proximity to Gas Stations/Restaurants compared to the Installation of charging stations."

Application of Questionnaire

The five criteria were included in a questionnaire created on Google Forms, where respondents provided their personal information and answered five multiple-choice questions related to each criterion. After the form was it was sent to the target audience and received 24 responses within a 23-day window. The small sample size of 24 responses is a limitation of this study, primarily due to the time constraints required for its completion. The communication channels used to reach the audience were email, messaging apps, and face-to-face conversations. The participants provided informed consent, and their responses were anonymized. The study was conducted in full compliance with relevant ethical guidelines.

To assist respondents in answering the questionnaire, Table 2 was prepared, and the context of the trip was described, namely a journey from Fortaleza to Juazeiro do Norte, with an average distance of 533 km and a duration of around 7 hours and 30 minutes. The questionnaire was distributed among professionals in the transportation or logistics field, professors from higher education institutions, master's students, and doctoral students. Each professional's complete set of answers defined a unique alternative that the *k*-means algorithm subsequently classified.

Total Distance

While the five criteria were the direct survey inputs, the model training was significantly enhanced by a crucial derived metric: Total Distance. This metric was not included in the questionnaire but was calculated for each alternative based on two specific criteria—C1 (Number of stops) and C2 (Recharging time)—and fixed Electric Vehicle (EV) parameters. For this calculation, we adopted an average EV autonomy in Brazil of 272 km (Table 2), based on a survey of available EV models. The key assumption for fast-charging stations was that 80% of the battery is recharged in 30 minutes, which is equivalent to recovering approximately 217.6 km of range. The Total Distance for an alternative was then determined by multiplying the distance recovered in a single stop (C2) by the number of stops (C1), providing a vital measure of intercity travel capability.

The final dataset, consisting of the five original criteria and the newly calculated Total Distance metric, was then used to train the *k*-means clustering algorithm. After the clustering process, the alternatives were allocated into groups. We analyzed the central tendencies of these groups by determining the average values for C1, C2, and the

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Table 4. Within-Cluster Sum of Squares for *k*

k	**WCSS**	***k***	**WCSS**
1	1,575,385.45	5	64,052.43
2	721,349.39	6	27,906.23
3	251,529.45	7	12,495.34
4	110,014.14	8	7,232.94

Total Distance. Furthermore, the minimum and maximum distances within each group were calculated to help determine the ideal operational criteria required to safely and comfortably cover various intercity routes.

The *k*-means Clustering Method

Clustering algorithms establish rules for grouping data into clusters with similar characteristics, where the partitioning of a given dataset into clusters occurs without any prior knowledge about the dataset [25]. In an ideal clustering, each cluster contains similar data that are significantly different from the data in other clusters.

The *k*-means clustering algorithm was proposed by MacQueen in 1967, and it is a partition-based clustering analysis method [29]. It is considered one of the top ten clustering algorithms for data analysis due to its efficiency in processing large volumes of data quickly. However, it also has several limitations: the number of clusters (k) needs to be predetermined, the initial cluster centers are arbitrarily selected, and the algorithm is influenced by noisy data.

For determining the number of clusters, the Elbow method was applied. The Elbow Method is an approach used in data analysis and machine learning to identify the optimal number of clusters in a dataset. It involves analyzing the variance explained by different numbers of clusters and determining the inflection point, called the "elbow," where the reduction in variance stabilizes, indicating an appropriate number of clusters for analysis or modeling.

The Elbow Method consists in choosing the value of k where there is the largest drop in the total within-cluster sum of squares (WCSS), before the gain starts to decrease significantly with increasing k. Table 4 and Figure 2 show the WCSS values for different clusters, where it can be observed that the ideal number of clusters is 4, as indicated by the stabilization of variance. The *k*-means was generated with the following variables: C1 (number of stops), C2 (charging time) and Total Distance. To evaluate performance, the *k*-means algorithm calculated the ratio between the between-cluster sum of squares and the total sum of squares for all data points. The resulting value (93%) indicates that the clustering explains 93% of the data variance, demonstrating that the clusters are well-defined and clearly distinct from one another.

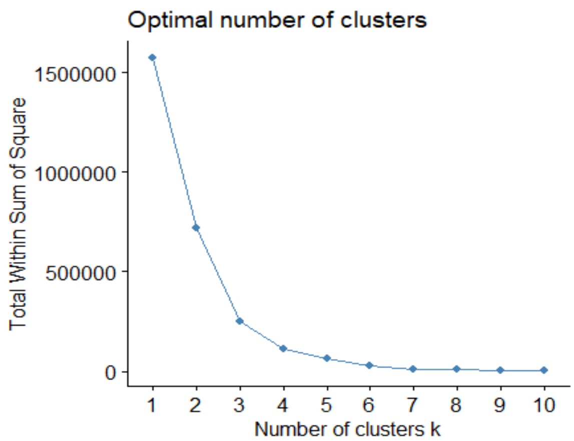

Figure 2. Elbow graph generated from the 24 alternatives

Case Study

In order to assess the effectiveness of the *k*-means method, five potential routes with touristic or economic significance in the state of Ceará were evaluated, and routes with origin in Fortaleza and destination in Juazeiro do Norte were selected for the case study. The three possible routes departing from Fortaleza to Juazeiro do Norte show variation in total distance traveled, ranging from 481 km to 564 km, depending on the route chosen by the driver. Considering that the average autonomy of EVs sold in Brazil is 272 km and the distance from Fortaleza to Juazeiro do Norte averages 528 km in length, it will be necessary to implement charging stations along the route.

As there are several possible routes from Fortaleza to Juazeiro do Norte, three routes were evaluated, each covering different highways: the route through BR-020, through BR-122, and through BR-116, with the total distance of each route obtained from Google Maps (Figure 3). The first route departs from Fortaleza using BR-020 and passes through the municipalities of Canindé, Boa Viagem, Tauá, and Arneiroz, with a total distance of 564 km. The second route uses BR-122 and passes through the municipalities of Horizonte, Quixadá, Banabuiú, and Cedro, with a total distance of 481 km. The third route uses BR-116 and crosses the municipalities of Morada Nova, Limoeiro do Norte, Jaguaribe, and Icó, with a total distance of 539 km.

To assess the potential existence of charging stations along the routes, the Plugshare app was used in October 2023, which shows the presence of charging stations on the routes indicated in the app. No charging stations were detected along the BR-020, BR-122, and BR-116 highways on the route from Fortaleza to Juazeiro do Norte.

The methodology for locating the Electric Vehicle Charging Stations (EVCs) began by selecting the ideal group parameters and the average values for criteria C1 and C2, which accounted for the variation in distance across the three routes. This selection directly determined the necessary number of stops and the required charging time. To spatially determine the EVC locations, QGIS v3.18 software was utilized, incorporating spatial datasets of the municipal headquarters and the highway network, both sourced from IPECE (Ceará Institute of Economic Research and Strategy). The calculated charging time then informed the distance between each stop. For placement, each charging station location was referenced to the nearest municipal headquarters along the highways. This specific referencing was achieved by executing a distance analysis in GIS, which analyzed the proximity between the municipal headquarters point features and the highway spatial dataset to pinpoint the optimal station site.

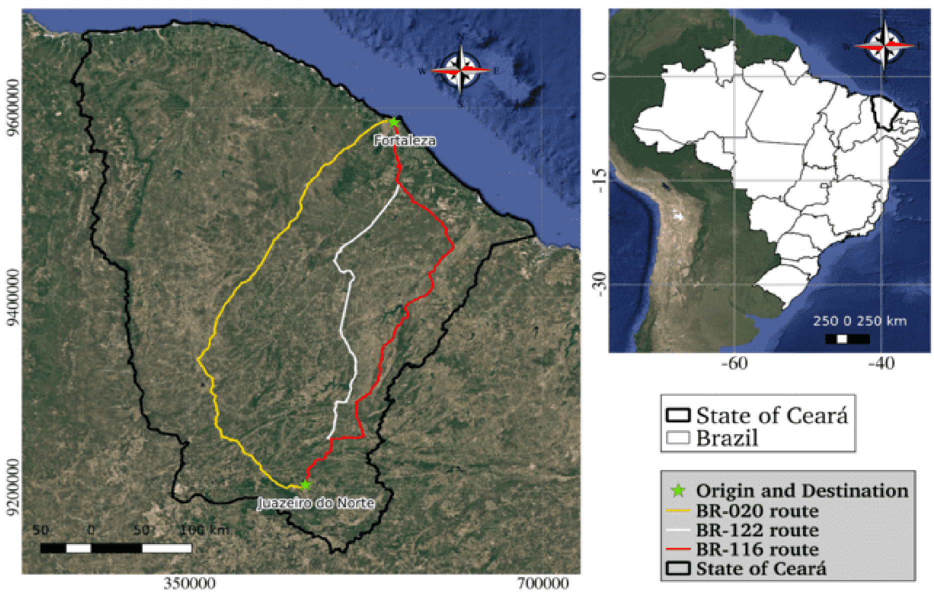

Figure 3. Routes selected for the study case in the state of Ceará, Brazil

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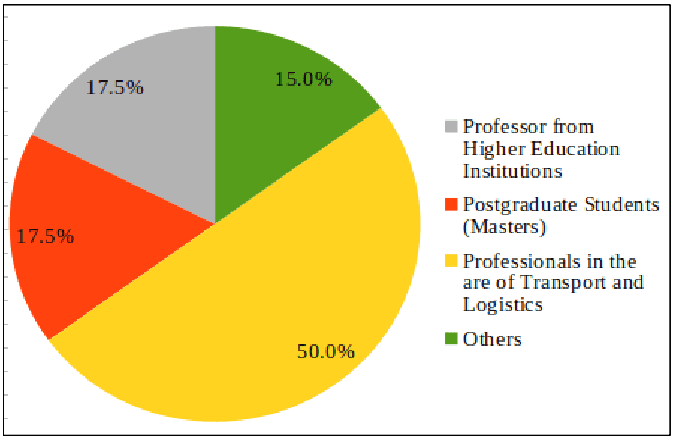

Figure 4. Answer to The Questionnaire Regarding the Criteria for Determining the Number and Location of EVCS

RESULTS AND DISCUSSION

The alternatives derived from the questionnaire and implemented into the *k*-means clustering algorithm are discussed, as well as information regarding the percentage of professionals of different areas that answered the questionnaire. Then the grouping of the alternatives is represented by the number of responses, the average, minimum and maximum values for each criterion and for each group. This is followed by application of the ideal group for the study case of each route, and the analysis of both the number of stops and optimal battery recharging time.

Alternatives obtained from the questionnaire

In Figure 4, it is possible to observe the percentage of the target audience that responded to the questionnaire, with the distribution being made as follows: 50% of Professionals in the area of Transport and Logistics, in which directors, coordinators and analysts in the area are present within this universe. that operate in the market; 17.5% represent Professors from Higher Education Institutions who are mostly professors at UFC (Federal University of Ceará); 17.5% represent the percentage of Postgraduate Students (Masters) and around 15% of the responses come from the other category, in which we can mention professionals who work with PCPM, Quality Inspection and Administrative Assistance. Another point that can be highlighted is that it was not possible to obtain responses from Postgraduate (Doctorate) Students.

The questionnaire responses corresponded to the alternatives evaluated by the *k*-means method, as shown in Table 5. For C1, concerning the number of stops, the average of the responses was 2.75 or 3 stops. As for C2, the overall average was approximately 24 minutes, meaning respondents would be willing to wait an average of 24 minutes to recharge their EVs. For C3, C4, and C5, referring to local infrastructure, location in urban centers, and proximity to gas stations and restaurants, the average responses were 4.45, 4.54, and 4.29, respectively. Considering the Likert scale, all respondents considered these criteria Important.

After applying *k*-means analysis, 5 responses were classified in group 1, 7 in group 2, 1 in group 3, and 11 in group 4 (Table 6). Group 2 had the lowest total distance traveled, ranging from 123 km to 246 km, with 1 to 2 stops with a recharge time of 17 minutes. In this context, it would be necessary to recharge every 123 km, totaling 246 km for two stops. Group 4 had the highest number of responses, suitable for routes with distances ranging from 181 to 544

Table 5. Alternatives Evaluation through *k*-means clustering of responses

Alternatives	C1	C2	C3	C4	C5	Alternatives	C1	C2	C3	C4	C5
1	2	35	3	5	4	13	3	30	5	5	4
2	3	10	4	4	2	14	2	5	5	5	5
3	1	20	5	5	5	15	1	30	5	4	4
4	4	20	4	3	5	16	2	30	4	3	5
5	4	30	4	4	3	17	2	20	5	5	5
6	3	20	4	5	3	18	2	30	5	5	4
7	1	15	5	5	5	19	2	35	4	4	4
8	3	20	4	4	5	20	5	15	5	5	5
9	4	15	4	4	5	21	2	30	4	4	5
10	3	30	5	5	4	22	6	30	5	5	4
11	3	30	4	5	4	23	4	15	5	5	3
12	2	20	4	5	5	24	2	30	5	5	5

Table 6. K-means clustering of alternatives

Group	N° of Answers	C1	C2	Distance (km)
2	7	1	17	123
		2	17	246
4	11	1	25	181
		2	25	362
		3	25	544
1	5	1	28	203
		2	28	406
		3	28	609
3	1	1	30	217
		2	30	434
		3	30	651
		4	30	868
		5	30	1085
		6	30	1302

km, and stops ranging from 1 to 3 with a recharge time of 25 minutes. The criteria of group 1 would be suitable for routes with a total distance ranging from 203 to 609 km, with up to 3 stops with 28 minutes of recharge at each stop, covering a maximum of 203 km between each stop (Table 6).

The selection of Group 1 for the three routes from Fortaleza to Juazeiro do Norte is based on its suitability for the route distances, which range from 493 km to 564 km—distances that exceed the maximum range allowed for Groups 2 and 4. Although Group 4 has 11 responses, it was excluded because its maximum distance does not support these routes. Between Groups 1 and 3, both accommodate the routes with three charging stops; however, Group 1 was chosen due to a slightly shorter charging time of 28 minutes per stop compared to 30 minutes in Group 3. While this two-minute difference is minor, Group 1 also offers a higher number of overall responses, suggesting stronger user preference or acceptance. Additionally, Group 1 allows for recharging up to 75% of the battery with a maximum travel distance of 203 km between stops, which aligns well with the route requirements. Therefore, the selection reflects both practical distance coverage and user feedback rather than relying solely on the small difference in

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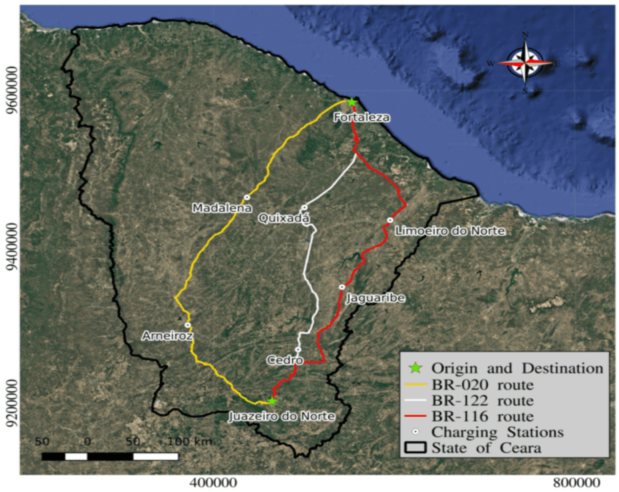

Figure 5. Location of EVCS for each route.

charging time. The location of the charging stations were defined considering the municipal seat closest to the highway on a maximum route of 203 km and considering the installation of two charging stations for each route/scenario, as one of the stops would occur in Fortaleza before the start of the trip. The premise was adopted that the electric vehicle would depart from Fortaleza with a range of 272 km and 100% battery charge. The municipality of Fortaleza has 14 chargers in operation, according to data from Plug Share from May 2024 (https://www.plugshare.com/br). The destination in Juazeiro do Norte also has a charging station available, meaning it is not necessary to install charging stations. In this sense, considering the three routes, it would be necessary to install 6 EVCSs.

Figure 5 illustrates the installation of two Charging Stations on each route. For the BR-020 route, it will be necessary to install an EVCS in the city of Madalena, 185 km from Fortaleza and another in Arneiroz, 200 km from Madalena and 179 km from Juazeiro do Norte. For the route via BR-122, the EVCSs were located in Quixadá, 162 km from Fortaleza and 222 km from Cedro, and another in Cedro, 97 km from Juazeiro do Norte. Regarding the BR-116 route, it will be necessary to implement 2 EVCSs, one in Limoeiro do Norte, 203 km from Fortaleza and 120 km from Jaguaribe, and another in Jaguaribe, 216 km from Juazeiro do Norte. It is important to highlight that it is possible to select other points for installing EVCS on the routes, considering the distance limitation from one section to another of 203 km.

Table 7 shows the result of applying the criteria of Group 1 to each route (BR-020, BR-122, and BR-116) from Fortaleza to Juazeiro do Norte. Starting from Fortaleza with a full vehicle charge of 272 km, via the BR-020 route,

Table 7. Group 1 application results: three 28-minute stops, 75% charge, and 203 km range increase

Routes	Segments	Distance (km)	Res. Autonomy	% Battery
BR-020	Fortaleza-Madalena	185	87	32%
BR-020	Madalena-Arneiroz	200	72	26%
BR-020	Arneiroz-Juazeiro do Norte	179	93	34%
BR-122	Fortaleza-Quixadá	162	110	40%
BR-122	Quixadá-Cedro	222	50	18%
BR-122	Cedro-Juazeiro do Norte	97	156	57%
BR-116	Fortaleza-Limoeiro do Norte	203	69	25%
BR-116	Limoeiro do Norte-Jaguaribe	120	152	56%
BR-116	Jaguaribe-Juazeiro do Norte	216	56	21%

which has a total distance of 564 km, it would be necessary to recharge the vehicle at least 2 times during the journey. It is worth noting that the percentage of charge at the start of the journey in Fortaleza influences the remaining charge and the total distance traveled between each charging station along a route.

By adopting the criterion of a 28-minute recharge at DC, or an additional 75% battery charge, equivalent to 203 km, the first recharge could be in Madalena, 185 km from Fortaleza. These 203 km would be added to the remaining 87 km, totaling 290 km. Since the electric vehicle has a full charge of 272 km, it would not be necessary to recharge the vehicle for 28 minutes as proposed by the *k*-means method. This example repeats for most sections of the three routes, where the recharge time proposed by the *k*-means method exceeds the time needed to reach the maximum autonomy of the electric vehicle of 272 km. Only for the BR-122 route from Quixadá to Cedro, BR-116 from Fortaleza to Limoeiro do Norte, and from Jaguaribe to Juazeiro do Norte, does the 28-minute recharge time and an additional 203 km coincide with the distance between the EVCSs (Table 7). The last recharge in Juazeiro do Norte would not be necessary to complete the journey, as the driver would already have reached the destination.

Clustering based on survey data can diverge from the physical constraints of infrastructure planning for several reasons. Survey responses reflect subjective judgments, habits, and expectations that may not always align with the objective technical realities of battery chemistry, vehicle range limits, and charger specifications. For example, respondents may report a willingness to make more frequent stops for reasons of comfort or convenience, but those stops may not correspond to the energy needs dictated by battery state-of-charge, leading to either unnecessary downtime or, conversely, insufficient charging opportunities for longer segments. As a result, the clustering algorithm may segment user groups in a way that prescribes charging infrastructure placements and durations that are misaligned with practical travel requirements, as evidenced in the study's own finding that *k*-means recommended longer or more frequent charging sessions than were actually needed according to battery specifications and route distances.

As a suggestion to avoid this problem, one solution can be the development of hybrid approaches—combining machine learning outputs with linear or optimization models that ensure all recommendations remain technically feasible. Another option is the recalibration of the results from survey data through post hoc adjustment, ensuring real-world relevance and preventing the overestimation of the charging time. To adjust the charging time to practical results, we assumed a constant charging power of 120 kW, a battery capacity of 60 kWh and a range of 217.6 km (80% of 272 km). Considering that it takes 30 minutes to charge 217.6 km (Table 2), the added range per minute is 7.25 km, as such the following equations were developed: $D = 7.25 \times T$ or $T = D/7.25$, where D = Distance Travelled (km) and T = Charging Time (minutes). As such, the distance to each charging station was calculated and the actual charging time was determined for each segment and route. Considering the distances between segments, regardless of the remaining charge from the previous segment, the average recharge time for the three routes would be 24 minutes, not 28 minutes as proposed by the *k*-means method.

In Table 8, the distances between segments and the recharge time for each distance are presented. It is observed that in some segments, such as for the BR-122 route and the segment from Cedro to Juazeiro do Norte, where the distance is 97 km, the recharge time would be approximately 13 minutes, while for the BR-122 route from Quixadá to Cedro, the recharge time should be over 30 minutes. Thus, in some segments, the recharge time is much higher or lower than proposed by the *k*-means method. Based on the *k*-means method, the driver would spend additional time recharging the vehicle unnecessarily. It would be 6 minutes more for the BR-020 route, 17 minutes more for the BR-122 route, and 9 minutes more for the BR-116 route. In practice, when reaching 100% charge, the driver would proceed with the recharge, so the time proposed by the *k*-means method is unrealistic, and the ideal time proposed in Table 8 should be adopted. The *k*-means results reflect the responses from the survey, where charging times were chosen according to users' perceptions of how long they would be willing to wait to recharge their vehicles, rather than being determined by the actual charging capacities or battery specifications of electric vehicles.

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Table 8. Calibration of recharge time based on battery capacity–distance relationship

Routes	Segments	Distance (km)	Recharge time	Difference with *k*-means
BR-020	Fortaleza-Madalena	185	25.5	2.5
BR-020	Madalena-Arneiroz	200	27.6	0.4
BR-020	Arneiroz-Juazeiro do Norte	179	24.7	3.3
BR-122	Fortaleza-Quixadá	162	22.3	5.7
BR-122	Quixadá-Cedro	222	30.6	-2.6
BR-122	Cedro-Juazeiro do Norte	97	13.4	14.6
BR-116	Fortaleza-Limoeiro do Norte	203	28.0	0.0
BR-116	Limoeiro do Norte-Jaguaribe	120	16.5	11.5
BR-116	Jaguaribe-Juazeiro do Norte	216	29.8	-1.8

To ensure that the recharge time is consistent at each EVCS regardless of whether there will be 2 or 3 stops along the journey, it is necessary to adopt a constant distance. This distance should not take into account the municipalities' headquarters, as not all of them are close to the highway, and the distances between the municipalities' headquarters are not the same. To facilitate the placement of EVCS, it is important to assess the availability of gas stations along the route and other ideal points for the installation of EVCS. Also, while GIS and *k*-means are powerful for initial siting, this study revealed that for long-distance travel, they must be tightly coupled with physical energy models to avoid prescribing inefficient charging schedules. This underscores the limitation of preference-based surveys for this application and suggests that future hybrid models should prioritize energy constraints over perceived comfort for the stop-time calculation.

CONCLUSION

This study used *k*-means clustering to optimise the location of EVCS (Electric Vehicle Charging Stations) for long distance journeys. A survey was carried out among 24 transport experts, professors and students on six criteria (time, comfort, convenience, financial impact, infrastructure, food for passengers). Data was trained with the *k*-means algorithm to determine the optimal location of the EVCS. The case study looked at three routes (average length: 528 km) between Fortaleza and Juazeiro do Norte. Given the average EV range in Brazil (272 km), the research highlighted the need for strategically placed recharging points. The methodology used multivariate analysis and the elbow method for the determination of the number of clusters. An equation for calculating the charging time based on the battery capacity and the distance travelled has been proposed, which will allow for route planning by distance and charging interval. Key findings show that user preferences help to guide the location of charging stations, but charging times need to be based on vehicle energy requirements, not user preferences. The limitations include small sample size, mismatch between subjective preferences and physical requirements, and *k*-means limitations (sensitivity to initial centroid, spherical cluster hypothesis, predefined number of clusters). The results are specific to the State of Ceara and cannot be generalised without further validation. Future work will include integration of spatial analysis and multi-criteria decision making to increase accuracy and realism, taking into account distance, availability, user preferences and operational factors. The extension of the urban EV networks is also being explored.

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CONFLICT OF INTEREST

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DATA AVAILABITY STATEMENT

Due to privacy restrictions, the data are not publicly available. De-identified data may be available from the corresponding author upon reasonable request.

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