

Article

A Multi-Criteria Approach for Optimizing the Placement of Electric Vehicle Charging Stations in Highways

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Abstract: The electric vehicle (EV) industry has made significant progress but, in many markets, there are still barriers holding back its advancement. A key issue is the anxiety caused to the drivers by the limited range of current EV models and the inadequate access to charging stations in long-distance trips, as is the case on highways. We propose an intuitive multi-criteria approach that optimally places EV charging stations on highways that (partially) lack such points. The approach, which is applied in an iterative fashion to dynamically evaluate the alternatives, considers a set of practical criteria related to the traffic intensity and the relative location of the charging stations with interchanges, major cities, and existing stations, thus supporting decisions in a pragmatic way. The optimal locations are determined by taking into consideration constraints about the EV driving range and installation preferences to improve the operation of the highway while ensuring reasonable cost of investment. The proposed approach is showcased in the Egnatia Motorway, the longest highway in Greece that runs a total of 670 km but currently involves a single EV charging point. Our findings illustrate the utility of the proposed approach and highlight its merits as a decision-support tool.

Keywords: multi-criteria analysis; electric vehicles; charging stations; highways



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1. Introduction and Background

The wide adoption of electric vehicles (Electric Vehicles (EVs) involve fuel cell vehicles (FCVs), Plug-in Hybrid Electric Vehicles (PHEVs), and Battery Electric Vehicles (BEVs), the latter of which we will consider in this study) is a key factor for advancing sustainable mobility and reducing greenhouse gas emissions [1]. Yet, the high purchase cost, long charging time, limited range, and inadequate availability of public EV charging stations (EVCSs) are major barriers to the promotion of EVs [2,3]. As a result, EVs are mostly used for short-distance trips in urban areas, such as for commuting, shopping, and entertainment, being less frequently used for long-distance travels [4] that may be constrained by insufficient infrastructure [5]. It becomes evident that improving the placement of EVCSs on highways is a critical step towards reducing the anxiety of the EV drivers [6] and expanding the adoption of EVs [7], especially in early-stage markets such as Greece [8].

Deciding on the location of EVCSs is a challenging task as the “optimal” solution is subject to multiple, conflicting factors, such as driver convenience versus cost of investment. Moreover, the alternative locations are usually substantial in numbers and mutually influence each other, thus significantly increasing the overall complexity of the problem and rendering the use of traditional numerical optimization methods inefficient. To that end, various approaches have been proposed in the literature to optimize the placement of

EVCSs, mostly using fuzzy, greedy, heuristic, or genetic algorithms [9,10]. Guo et al. [6] formulated the EVCSs allocation problem as a bi-level integer programming model based on a range anxiety function. The upper-level problem was to determine a strategy for the location of EVCSs that minimizes the sum of the location cost and the lower-level problem was EV users' path-choice behavior. The problem was solved using an iterative greedy heuristic algorithm. Then, a parameter analysis was performed in the highway network of Hubei province in China by taking into account EV users' range anxiety and their deviation behavior. A bi-level mathematical model to optimize the location of EVCSs with the consideration of driving range was also developed by He et al. [11]. The upper-level problem was to maximize the flows served by EVCSs, while the lower-level problem was to depict the route choice behavior depending on the location of the EVCS. However, these heuristic algorithms did not take into consideration additional important factors that simulate the demand (e.g., traffic intensity, currently installed charging infrastructure), convenience of use (e.g., proximity with major cities and interchanges), and the availability of the power transmission network, among others.

For these reasons, multi-criteria decision analysis (MCDA) methods have also gained attention in the field due to their natural ability to simultaneously take into account several factors, even those that are challenging to quantify in practice [12,13]. In addition, MCDA methods can take into consideration potential uncertainties and imprecisions, are easy to interpret and to communicate with the stakeholders, and allow interaction with the decision makers [14].

Recent studies have exploited several MCDA methods for facing the problem of optimal EVCS placement, including the TOPSIS (technique for order of preference by similarity to ideal solution), AHP (analytical hierarchy process), and PROMETHEE (preference ranking optimization method for enrichment evaluation) methods, among others. Erbaş et al. [15] used the fuzzy AHP technique to determine the optimal EVCS locations in Ankara, Turkey. They considered a four-stage methodology to define and weight the evaluation criteria, using a panel of experts, and to score and rank the alternative EVCS sites, using the TOPSIS method. Similarly, Guo and Zhao [16] used the fuzzy TOPSIS method to select the optimal EVCS locations in Beijing districts, China, by exploiting an innovative index system. The criteria used, defined based on published studies and reports, were of environmental, societal, and economic nature, while their weights were estimated by five groups of experts. Csiszár et al. [17] used an arc-based location optimization method that used a geographic information system (GIS) and a greedy algorithm. The method considered several demographic, neighborhood, and transport-related attributes and applied MCDA to deploy EVCSs in motorways. Mahdy et al. [18] linked the AHP method with a GIS to optimize the siting of EVCSs in Winchester District, UK. The assessment considered key criteria such as road type, road access, current/planned charging points, and population distributions.

Wu et al. [19] selected EVCS locations using a cloud-model-based PROMETHEE method, which can make up for many flaws and inadequacies of traditional MCDA approaches Xidonas et al. [20]. They then used the analytical network process (ANP) method to perform a sensitivity analysis and measure the correlation of the criteria. PROMETHEE has also been used by Raposo et al. [21] for optimizing the EV charging network in Angra do Heroísmo city center. The authors presented a variant of the original MCDA method, called dynamic-PROMETHEE, in an attempt to reinforce its attributes and add decision memory over time, versatility, and adaptability. A relevant study has also been conducted for Greece, where Anthopoulos and Kolovou [22] exploited the AHP method to optimally deploy EVCSs from the point of view of e-mobility investors. Even though this study differs from the others, focusing more on defining the most appropriate business model among the existing alternatives, it paves the way for future research in the field in Greece.

Although MCDA has been proved to be suitable for optimizing the placement of EVCSs, its use has focused on urban areas and limited work has been conducted to exploit its full potential for the case of the highways. Moreover, most of the studies apply MCDA

in a static fashion, thus ignoring the effect that the placement of an EVCS has over the points to be subsequently selected. In this paper, we investigate the utility of MCDA for the optimal placement of EVCSs on highways that partially or completely lack charging points. We focus on fast EVCSs (e.g., DC stations) that can effectively support long journeys and consider criteria that are more relevant to long-distance trips. The proposed approach evaluates the alternative locations dynamically, taking also into consideration constraints about the EV driving range and installation preferences to decrease the anxiety of the drivers, reduce the cost of investment, and provide pragmatic suggestions. We assess the robustness of our results using a sensitivity analysis and demonstrate the merits of our approach as a decision-support tool for the case of the Egnatia Motorway, the longest highway in Greece. Based on the above, the main contributions of our work are three-fold:

- In contrast to previous studies that have used MCDA methods to properly place EVCSs in urban areas and broader regions, our paper focuses specifically on the optimal placement of EVCSs on highways. This geospatial difference has a major impact on the methodological approach to be used for solving the problem in terms of defined criteria, objectives, and constraints, among others. Effectively, this difference has a major effect, both on the charging behavior assumed for the EV drivers and the way their range anxiety is formed.
- Our approach puts particular emphasis on the anxiety of the EV drivers, suggesting EVCS locations that mitigate its negative effect and promote sustainable mobility. This is opposed to the relevant literature, where potential EVCS locations have been mostly evaluated from a financial point of view.
- We employ the proposed MCDA method in a dynamic fashion, re-ranking the alternative locations each time a new EVCS is placed. Therefore, our approach extends the relatively more static methods proposed in the literature, ignoring the effect that previous EVCS placements have on the selection of future EVCS locations.

In terms of key findings, these can be summarized as follows:

- A minimum number of seven EVCS locations is required to sufficiently serve the EV drivers across the Egnatia Motorway.
- By introducing two additional EVCS locations (9 in total), the range anxiety of the EV drivers is expected to be diminished.
- According to the sensitivity analysis performed, the identified EVCS locations remain the same regardless of the weights used for employing the MCDA, meaning that the proposed locations remain either the same or very close to the original proposals.
- The EVCS locations should be carefully selected after taking into consideration their relative position, distance from major interchanges, cities, and existing EVCSs, as well as road traffic.

The rest of the paper is structured as follows: Section 2 describes the problem of optimal EVCS placement, specifies its objectives and constraints for the examined case study, and provides an overview of the proposed approach. Section 3 presents the methodological approach in more detail, including the criteria and MCDA method used, while Section 4 illustrates and discusses our results. Finally, Section 5 concludes the paper and provides directions for future research.

2. Problem Description and Approach Overview

Motorway A2, officially named Egnatia Motorway (or Egnatia Odos), is the longest highway in Greece that runs a total of 670 km and crosses the regions of Epirus, Macedonia, and Thrace, starting from the port of Igoumenitsa, which provides links to Italy, and ending to Kipi of Evros (Greek-Turkish borders). The motorway consists of 59 road segments (RSs), each connecting two consecutive junctions.

At the moment of the study, Egnatia Motorway has a single DC fast EVCS, located 282km east of the port of Igoumenitsa. Moreover, most of the Greek highways connecting with Egnatia Motorway currently involve a limited number of fast chargers that, in most

of the cases, are located far from the respective interchanges. This forces EV drivers to make long detours to charge their vehicles, increasing their travel time and anxiety [23]. As a result, establishing a robust EV charging infrastructure along the Egnatia Motorway is urgent for serving the predicted influx of EVs in the near future.

In view of the above, the objective of the examined problem is to determine the number and location of the EVCSs required so that (a) the anxiety of the EV drivers is reduced while (b) the cost for deploying the EVCSs is kept at a reasonable level. To achieve such an objective, the locations of the EVCSs are selected progressively, each time considering (i) the expected range of the drivers present at a particular RS and (ii) the overall utility of the RS in terms of some pre-defined criteria. Since the range of the EVs will eventually be subject to the existing (or previously placed) EVCS locations, new stations are being placed based both on their relative distance to the existing (or previously placed) stations and the utility they are expected to add to the overall network of stations. As a result, the network is formed dynamically in several consecutive steps and the overall cost of deployment depends on the level of the anxiety of the drivers that can be reduced (the lower the anxiety, the shorter the distance between the EVCSs, and the higher the cost of investment).

Given that the utility of the RSs may be measured using both quantitative and qualitative criteria (e.g., traffic intensity and relative location with interchanges, major cities, and existing charging stations), a MCDA method is used to evaluate the overall utility of the alternatives. Note, however, that since at each step of the evaluation process the possible alternatives are subject to the selected range of the EVs, the MCDA method will consider only the RSs that secure power availability. For instance, given an existing EVCS at RS_i , the set of alternatives $\{RS_{i+1}, RS_{i+2} \dots RS_{i+n}\}$ to be considered by the MCDA method for selecting the next station, where RS_{i+n} is the most distant RS from RS_i , will be reduced to include just the RSs with a distance lower than D_{max} and larger than D_{min} from RS_i , where D_{max} denotes the maximum distance that an EV may cover from an EVCS to the next, while D_{min} the minimum assumed distance between two EVCSs.

To specify the eligible alternatives at each step of the evaluation process, we assume that there is a lower limit in an EV's battery state of charge (SoC), denoted as SoC_{low} , that forces the driver to seek for an EVCS. Similarly, we assume that there is an upper limit up to which the driver will decide to charge the EV before continuing traveling, denoted as SoC_{up} . Consequently, to sufficiently reduce the anxiety of the EV drivers, a minimum battery SoC is required at each EVCS to reach the next one, denoted as SoC_{min} , and the minimum/maximum distance between two consecutive EVCSs along the highway (D_{min}/D_{max}) is computed as follows

$$D_{min} = (SoC_{low} - SoC_{min}) \times EVr, \quad (1)$$

$$D_{max} = (SoC_{up} - SoC_{min}) \times EVr, \quad (2)$$

where EVr is the average driving range assumed for the EVs.

Currently, there are various EV models of different battery characteristics that affect their autonomy. In search of finding a representative value for EVr , the electric range of the 15 most popular EV models in Europe in 2021 were identified (Figures retrieved from Jato Dynamics' reports (<https://www.jato.com/>, accessed on 30 August 2022)), as shown in Table 1. Consequently, EVr was defined as the weighted average of the individual ranges, calculated as follows

$$EVr = \frac{\sum_{i=1}^{15} Reg_i \times EVr_i}{\sum_{i=1}^{15} Reg_i}, \quad (3)$$

where Reg_i and EVr_i are the number of registrations and the range of EV model i .

Table 1. Popular EV models in Europe (2021) along with their corresponding number of registrations and range.

EV Model	Registrations (2021)	Electric Autonomy (km)
Tesla Model 3	141,221	412
Renault Zoe	71,579	284
VW ID.3	69,090	214
VW ID.4	54,476	349
Kia Niro	46,790	213
Fiat 500	44,334	221
Skoda Enyaq	44,039	279
Hyundai Kona	42,920	248
Peugeot 208	42,450	230
VW Up	40,973	160
Nissan Leaf	34,643	230
Mini Cooper	29,712	176
Smart Fortwo	27,990	90
Dacia Spring	27,569	182
Peugeot 2008	26,453	262

The proposed approach is summarized in Figure 1.

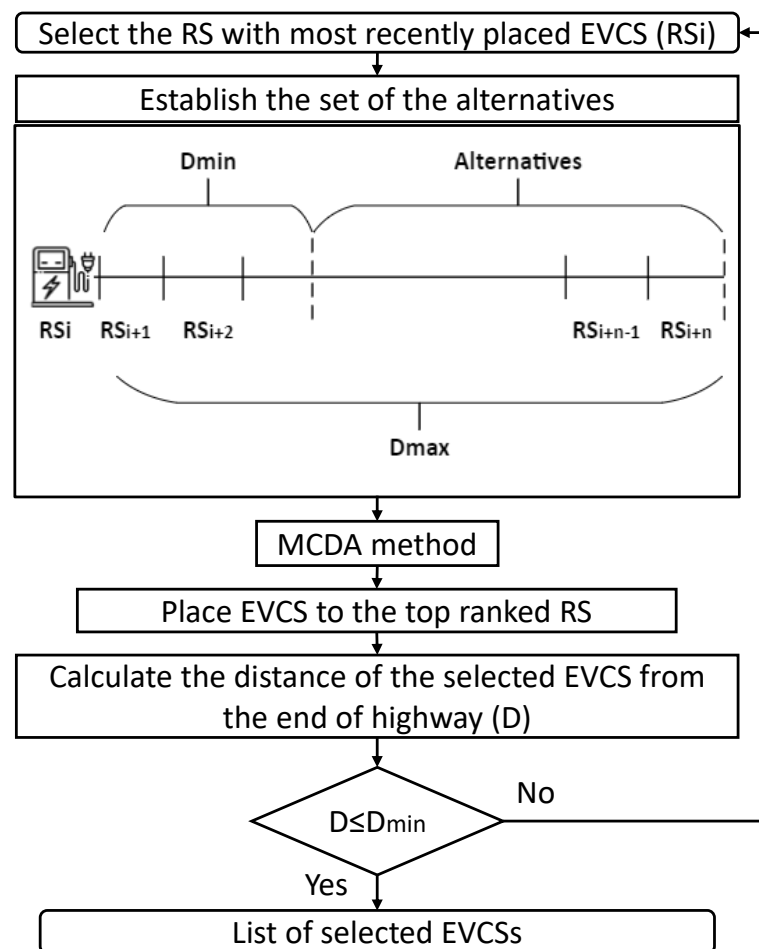


Figure 1. Overview of the proposed EVCS placement optimization approach. At each step of the process, the examined alternatives are the RSs with a distance lower than D_{max} and larger than D_{min} from RS_i (existing station).

3. Multi-Criteria Decision Analysis

In this section, we present the criteria defined for evaluating the utility of the RSs, the MCDA method considered for ranking the alternatives, and the methodology used for estimating the weights of the criteria.

3.1. Criteria Description

The MCDA method ranks the alternatives considering five criteria $\{C_1, C_2, C_3, C_4, C_5\}$ that cover major features of the RSs, namely the traffic intensity and their relative location with interchanges, major cities, and existing EVCSs. Below, we provide a brief description for each criterion and explain how its value was measured.

C₁: Average daily traffic. Since EV traffic data are not available for the Egnatia Motorway, it is assumed that the traffic distribution of the EVs across the RSs simulates that of the total vehicle population. The average daily traffic of each RS, as provided by the Egnatia Motorway S.A., is illustrated in Figure 2 using a heatmap. Higher traffic suggests higher utility.

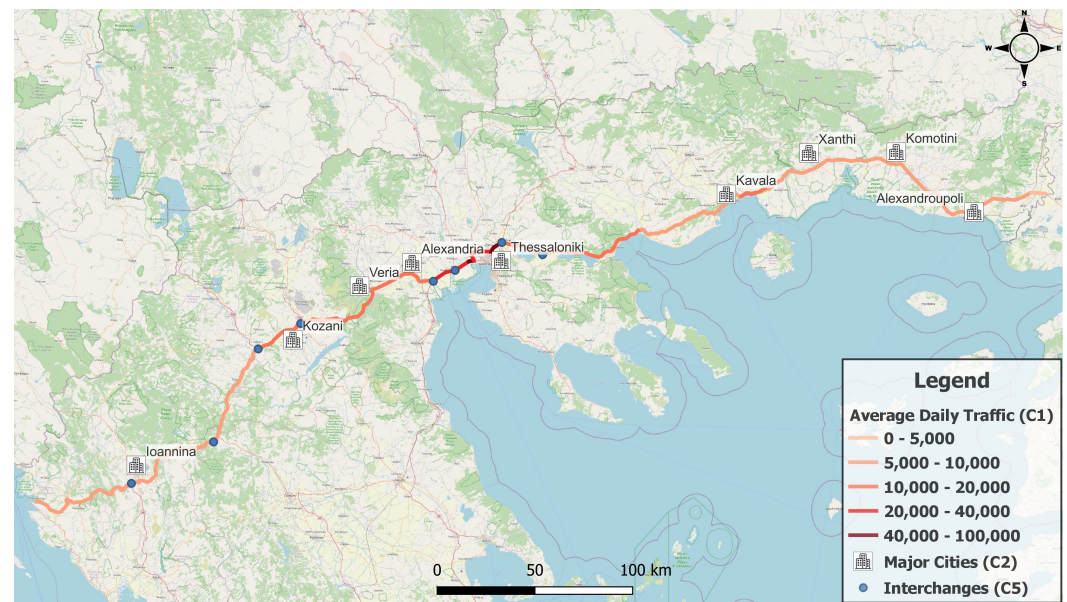


Figure 2. Average daily traffic, major cities, and interchanges considered for calculating the C_1 , C_2 , and C_5 criteria of the proposed MCDA.

C₂: Population adjusted distance from major cities. EVCSs placed in RSs that are close to major cities are expected to add more value to the overall utility of the network, serving more drivers that are also more likely to enter or exit the highway from said segments. The cities that have been included in the MCDA are presented in Figure 2. As a result, the closer a RS is to a major city and the larger the population of that city is, the higher the utility of the alternative should be, measured as follows

$$\frac{\text{PopId}_i}{D_{i,j}} \times 1000, \quad (4)$$

where PopId_i is the population index (The reason of transforming the original, continuous scale of the population into an interval, 3-point scale is two-fold. First, to mitigate the negative effect that significantly larger cities would have on the normalized scores of the smaller cities. Second, to make sure that cities of similar populations are equally likely to promote a RS.) (see Table 2) of city i , being the closest city of more than 10,000 inhabitants to RS_j , and $D_{i,j}$ is the distance between the city and the middle of the RS. Higher values suggest higher utility.

Table 2. Index value of C_2 based on the population of the closest city to the RSs.

Population	Index Value
10,000–50,000	1
50,000–100,000	2
>100,000	3

Please note that although RSs located close to major cities are likely to display high average daily traffic, C_1 differs significantly from C_2 in the sense that (i) high traffic may be realized in several RSs before and after major cities, (ii) high traffic may be caused by other factors than just the existence of a major city, (iii) C_2 takes into account the convenience of the EV drivers, i.e., their ability to charge their vehicles at the very beginning or end of their trip, and (iv) C_2 considers the potential use of the installed EVCSs by the intra-city travelers and local population.

C_3 : Number of EVCSs in close proximity. If a RS is close to an area with sufficient charging infrastructure, consisting of a high number of fast EVCSs, then there is less utility in being assigned an EVCS. In this regard, for each RS, the number of EVCSs in close proximity (distance smaller than D_{min}) is determined (Number and location of stations determined using the PlugShare’s EVCS map (<https://www.plugshare.com/>, accessed on 30 August 2022).) and the utility added is scored according to Table 3. As seen, lack of EVCSs suggest a score of 1, sufficient EVCSs a score of 0, and intermediate infrastructure a score of 0.5. The number and location of the existing EVCSs in close proximity to Egnatia Motorway are shown in Figure 3.

Table 3. Value of C_2 based on the number of fast EVCSs available in proximity to the RSs.

Fast EVCSs	Evaluation Value
0	1
1–3	0.5
>3	0

**Figure 3.** Number of EVCSs (highway EVCSs excluded) in close proximity to Egnatia Motorway and their approximate location considered for calculating the C_3 and C_4 criteria of the proposed MCDA.

C_4 : Distance from the closest EVCS (highway EVCSs excluded). It is preferable that the EVCSs are placed in RSs that are not in close proximity with other EVCSs. Such a design will provide more coverage to the EV drivers and there will be little overlap between the

radius service of the individual stations. Therefore, the distance (in km) between the middle of each RS and the closest EVCS is calculated, and the alternatives are scored accordingly (the farther away the station from the RS, the greater the score of the alternative). The approximate location of said EVCSs is shown in Figure 3.

C₅: Distance from interchanges. EVCSs are expected to add more value when placed near interchanges, especially in close proximity with other highways and major national roads that may not involve enough EVCSs. In this regard, the distance (in km) between the middle of each RS and the closest interchange (Seven motorways (A1, A3, A5, A24, A25, A27, and A29) are connected to Egnatia Motorway through different interchanges.) is calculated and the alternatives are scored accordingly (the farther away the interchange from the RS, the lower the score of the alternative). The interchanges are illustrated in Figure 2.

3.2. MCDA Method

The MCDA method used to determine the most suitable locations for EVCSs along highways was the TOPSIS method, one of the most used approaches that was originally proposed by Hwang and Yoon [24]. The method builds on two essential points, the positive ideal solution (PIS) and the negative ideal solution (NIS), evaluates the alternatives in accordance with specific criteria, and then compares the alternatives according to the ideal solutions, i.e., an alternative which is the closest distance to the PIS and at the same time at the outermost distance to the NIS. TOPSIS belongs to the family of compensatory methods, thus, relatively poor performance of an alternative in certain criteria can be compensated for by relatively high performance in some other criteria [25]. The process implementing the TOPSIS method is summarized in the following steps:

Step 1: Construction of evaluation matrix consisting of m alternatives and n criteria, with the intersection of each alternative and criteria given as x_{ij} , we therefore have a matrix $(x_{ij})_{(m \times n)}$.

Step 2: The matrix $(x_{ij})_{(m \times n)}$ is normalized to form the matrix $R = (r_{ij})_{(m \times n)}$, using the normalized method $r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{k=1}^m x_{kj}^2}}$.

Step 3: Calculated the weighted normalized decision matrix $c_{ij} = r_{ij} \times w_j$, where $i = 1, 2, \dots, m$ and $j = 1, 2, \dots, n$, so that $\sum_{i=1}^n w_i = 1$.

Step 4: Determine positive and negative ideal solutions.

$$C^+ = \{c_{ij}^+\} = \{(\max c_{ij}, i = 1, 2, \dots, m | j \in J_+), (\min c_{ij}, i = 1, 2, \dots, m | j \in J_-)\},$$

$$C^- = \{c_{ij}^-\} = \{(\min c_{ij}, i = 1, 2, \dots, m | j \in J_+), (\max c_{ij}, i = 1, 2, \dots, m | j \in J_-)\},$$

where $J_+ = \{j = 1, 2, \dots, n | j\}$ and $J_- = \{j = 1, 2, \dots, n | j\}$ are associated with the criteria having a positive and negative impact, respectively.

Step 5: Calculate the distance from each scheme to the positive and negative ideal solution. The distance from each scheme to the positive and negative ideal solution are as follows:

$$d_i^+ = \sqrt{\sum_{j=1}^n (c_{ij} - c_{ij}^+)^2}, i = 1, 2, \dots, m,$$

$$d_i^- = \sqrt{\sum_{j=1}^n (c_{ij} - c_{ij}^-)^2}, i = 1, 2, \dots, m.$$

Step 6: Calculate the closeness of ideal solution as

$$C_i = \frac{d_i^-}{d_i^- + d_i^+}, i = 1, 2, \dots, m.$$

The closeness degree of each scheme to the ideal solution is sorted in descending order, and the scheme with the largest closeness degree is the best scheme selected.

3.3. Criteria Weights

Determining the weights of the criteria defined is probably one of the most critical and complicated processes for implementing a MCDA method as different weights can result in significantly different decisions. In general, weight determination methods are either subjective or objective. Subjective methods are based on expert opinion and typically require the analyst to present to the decision makers a set of questions that can extract the relative importance of the criteria. However, in practice, it is difficult for the decision makers to supply numerical relative weights, especially when they consist of large groups of people. In contrast, the objective methods derive the weights from information gathered through mathematical models and do not require any intervention with the decision makers.

Due to the absence of experts to evaluate subjectively the importance of the criteria, we considered a computational method that exploited the information available for the already existing EVCS. Specifically, using the TOPSIS method, a MCDA problem was solved, with the weights being the unknown variables, the best ranking alternative (existing RS) being the known solution, and the set of alternatives being the set of RSs that satisfy Equation (1). When solving the MCDA problem, various sets of weights that satisfy the objective were identified. Therefore, the set of the lowest weight variation was selected to mitigate possible biases. The estimated weights are presented in Table 4.

Table 4. Calculated criteria weights.

Criteria	Weight
C ₁	0.075
C ₂	0.175
C ₃	0.175
C ₄	0.275
C ₅	0.300

4. Results and Discussion

By using the proposed EVCS placement approach, we identify the optimal locations of the fast-charging points, as determined by the TOPSIS method, the defined criteria, and the estimated criteria weights. To do so, we consider two implementation scenarios, each assuming a different driving behavior or, equivalently, a different level of range anxiety, as shown in Table 5.

Table 5. Setup of the two implementation scenarios considered for showcasing the proposed EVCS placement optimization approach. The selected SoC_{low}, SoC_{up}, and SoC_{min} values suggest different driving behaviors and, therefore, require different solutions.

Scenario	SoC _{low}	SoC _{up}	SoC _{min}
1	40%	80%	20%
2	30%	70%	20%

In the first scenario, SoC_{low} is set to 40% and SoC_{up} to 80%. In other words, it is assumed that the EV driver will try to stop at an EVCS when the battery SoC drops at 40% and charge the EV up to 80%. This is because, in a typical DC charging system, the battery is usually fast-charged to only 80% capacity, as the charging rate significantly slows down for the remaining 20% due to the battery's increase in internal resistance [26]. As a result, charging an EV at its full capacity is inapplicable to long-distance traveling, also precluding other drivers from using the EVCS [27]. The second scenario simulates a relatively less anxious EV driver that will try to identify an EVCS when the battery's SoC drops at 30% and charge the EV up to just 70%. Consequently, the second scenario is expected to

require more EVCSs to meet the constraints of the examined problem, also providing a reasonable comparison to the first, less flexible scenario. Please note that in both scenarios the minimum battery SoC required for reaching an EVCS is 20%. Additionally, please note that RS₂₅ is where the existing EVCS is located (see Figure 2), serving as the starting point for applying the proposed optimization approach (the approach runs two times, the first for the west part of the highway, while the second for the east part of the highway).

The optimal location of the EVCSs along the Egnatia Motorway are presented in Figure 4. As seen, the first scenario requires six EVCSs (in addition to the existing one), while the second scenario includes two more stations. We observe that four of the RSs were selected in both the scenarios, while two of the RSs that were selected in the first scenario (RS₁, RS₄₀) were in very close distance to those selected in the second scenario (RS₃, RS₃₉). Therefore, we conclude that some parts of the highway are of particular utility and that even when different driving behaviors and constrains are assumed, the optimal set of RSs remains practically the same.

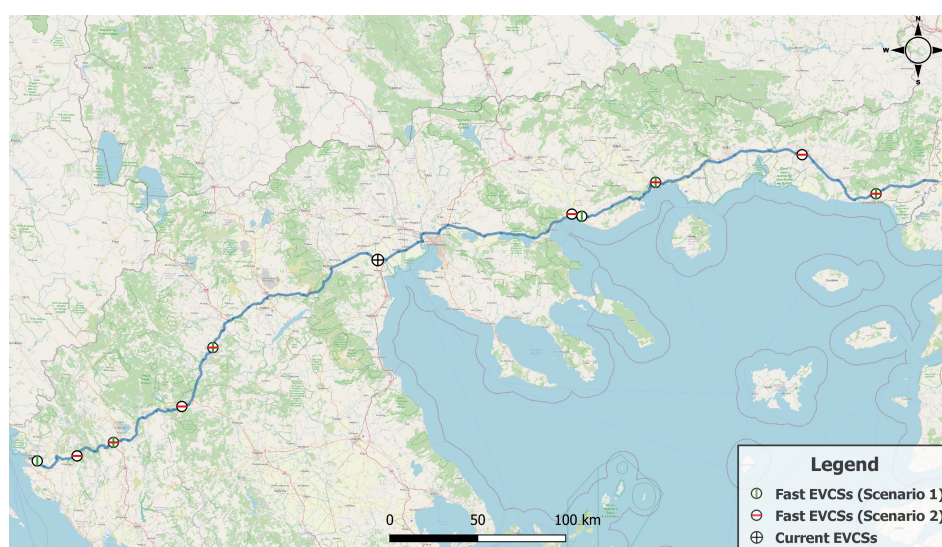


Figure 4. Optimal location of the EVCSs based on the two implementation scenarios examined. By indexing the RSs from the West to the East, the first scenario involves {RS₁, RS₅, RS₁₅, RS₄₀, RS₄₆, RS₅₈}, while the second {RS₃, RS₅, RS₁₂, RS₁₅, RS₃₉, RS₄₆, RS₅₃, RS₅₈}.

As a next step in our analysis, we test the sensitivity of our results when different sets of criteria weights are used for implementing the MCDA method under the first scenario. This analysis can provide useful insights about the uncertainty of the decisions to be made based on the proposed optimization approach. Specifically, a maximum random change of 15% is applied to the weights originally calculated (as per Table 4) and the results from a total of 307 different weight combinations is examined. Figure 5 summarizes the results of the sensitivity analysis. As seen, the RSs that have been originally selected using the initial set of weights (first scenario) {RS₁, RS₅, RS₁₅, RS₄₀, RS₄₆, RS₅₈} are also those that report the highest number of appearances in the simulations performed. This result confirms that changing the relative importance of the criteria does not significantly affect the optimal set of solutions, suggesting that the original proposals are both robust and trustworthy. In other words, the EVCS locations identified as optimal are expected to remain the same (or very close to those originally proposed) regardless of the weights used for employing the MCDA method.

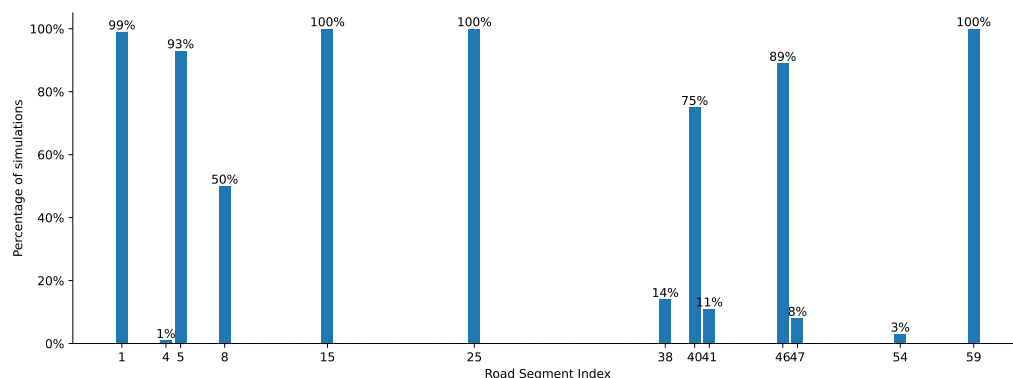


Figure 5. Top ranked RSs under the first implementation scenario, as determined when conducting the sensitivity analysis (307 different weight combinations). The horizontal axis corresponds to the RSs (indexed from the West to the East), while the vertical axis indicates the percentage of simulations that the respective RS was included among the set of solutions. For instance, in the first iteration, conducted for the highway part that is on the east side of the starting point (RS₂₅), the alternatives used as inputs in the MCDA method were {RS₃₅, RS₃₆, RS₃₇, RS₃₈, RS₃₉, RS₄₀, RS₄₁}. In the initial scenario, RS₄₀ was the top ranked alternative. Using different weight combinations, we find that RS₄₀ still remains the best option (75% of the simulations performed suggest its adoption), followed by RSs that are in close proximity with RS₄₀, i.e., RS₃₈ (14% of simulations suggest its adoption) and RS₄₁ (11% of simulations suggest its adoption).

5. Conclusions

We have proposed a dynamic, MCDA-based approach for optimally placing fast-charging points on highways that partially or completely lack EVCSs. The TOPSIS method was used to identify the optimal set of locations for the case of the Egnatia Motorway considering critical infrastructure- and operation-related criteria as well as pragmatic constraints about the minimum and maximum driving distance between the EVCSs. Our results were showcased under two different scenarios of driving behavior that realistically simulate different levels of range anxiety and were stress-tested for various combinations of criteria weights.

We find that seven EVCS locations are currently required to sufficiently serve the EV drivers across the Egnatia Motorway. Moreover, we conclude that the introduction of two more EVCSs could practically diminish the range anxiety of the drivers, encouraging further the use of EV in long-distance trips. More importantly, our analysis suggests that the optimal set of solutions experiences minor variations when different criteria weights and constraints are assumed. Thus, although less flexible charging scenarios may result in networks that consist of more EVCSs, the identified locations are expected to be in close proximity. As a result, we conclude that the proposed approach can effectively be exploited to support decisions about the location and number of EVCSs required on highways for securing EV traveling under low levels of anxiety. In any case, future EVCS locations should be carefully selected by investigating their relative distance from major interchanges, cities, and existing EVCSs, as well as road traffic.

Future work could focus on improving some limitations of the present work. First, the criteria and the constraints used could be expanded to reflect the financial aspects of the EVCS deployment, such as the return of investment or the cost of installation and maintenance. Second, the approach could be extended to provide information about the number of chargers required per station. Given that different EVCS locations may experience different traffic intensity, a different number of chargers may be required per case so that the EV drivers are served within a reasonable time. Accordingly, the future influx of EVs and possible reserves that ensure availability could be considered to further improve the experience of the EV drivers, motivate the use of EVs in long-distance trips, and promote sustainable mobility. Finally, another aspect that could be taken into consideration

is the availability of the appropriate power transmission network for the EVCS connection, as well as the underlying costs of installation. Although these specific criteria have been widely used in the literature, in the present study they were omitted due to the absence of related information at the time the work was conducted.

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Abbreviations

The following abbreviations are used in this manuscript:

EV	Electric vehicle
FCV	Fuel cell vehicle
PHEV	Plug-in hybrid electric vehicles
BEV	Battery electric vehicle
EVCS	Electric vehicle charging station
MCDA	Multi-criteria decision analysis
TOPSIS	Technique for order of preference by similarity to ideal solution
RS	Road segment
SoC	State of charge
D_{\max}	Maximum distance between two consecutive EVCSs
D_{\min}	Minimum distance between two consecutive EVCSs
SoC_{low}	Lower limit of an EV's battery SoC
SoC_{up}	Upper limit of an EV's battery SoC
SoC_{min}	Minimum EV's battery SoC to counter range anxiety

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