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# An optimization model for the charging infrastructure of electric vehicles incorporating the topography: a case study for the island of Tenerife

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## Abstract

This study proposes a significant improvement in the optimization model of charging infrastructure for electric vehicles developed and applied to the island of Tenerife in previous work by incorporating the topographic variable through various approaches. An integrated approach has been developed that considers the slope from origin to destination, the average terrain elevation, and road curvature. This approach has identified optimal locations for charging points that minimize travel times and maximize energy efficiency. The innovative approach proposed herein represents a substantial contribution to the field of electric vehicle charging infrastructure: the methodology effectively addresses terrain topography challenges, leading to significant improvement in the coverage of the charging network and greater adaptability to the topographic conditions of the environment.

**Keywords:** Charging infrastructure, electric vehicles, optimization, topography, electromobility

## 1. Introduction

The transition towards electric mobility represents a pivotal milestone in the pursuit of more sustainable and environmentally friendly transportation systems. The deployment of charging infrastructure for electric vehicles (EVs) is therefore a strategic imperative. However, the optimal design for the charging network encounters notable hurdles, particularly in light of the terrain's variable topography.

The original optimization model of the charging network is based on traffic simulations and projections of EV user demand spanning a 20-year horizon, in addition to mobility studies conducted on the island of Tenerife (Rojano-Padrón et al., 2023). However, it does not account for the influence of topography in the planning and siting of charging points.

This aspect is especially relevant because the infrastructure planning models for electric vehicles (EVs) are based on cities or regions with minor variations in terrain relief (Ziemke et al., 2019). However, this is not the particular case in Tenerife, where topography plays a significant role and may represent an additional barrier to range anxiety, which already exists among potential EV users. Therefore, it is essential to consider the topography when planning the EV charging network in the selected case study. Moreover, the methodology can be extrapolated to other territories with similar characteristics.

This study proposes substantial enhancements to the optimization model by addressing this limitation, with a primary focusing on integrating the topographic variable through diverse methodologies. By accounting for factors such as slope gradients, average terrain elevations, and road curvatures, the aim is to refine the model's accuracy and efficiency, thus aligning it more closely with real geographical and topographical conditions.

Beyond the optimization of the spatial distribution of EV charging points, this research endeavors to contribute, comprehensively and precisely, to the broader advancement of charging infrastructure planning. Through the systematic integration of the topographic variable, the objective is to furnish a more resilient and efficacious tool for urban planning authorities and EV charging network operators, thereby facilitating the path toward enhanced accessibility and sustainability in electric mobility.

## 2. State of art

The unplanned deployment of EV charging stations undoubtedly presents a number of technical and economic challenges in the distribution network. Therefore, meticulous planning of the charging infrastructure is imperative. In response to this necessity, comprehensive evaluations have been conducted regarding EV charging (Khalid et al. 2019, Khan et al. 2018).

Recently, several methodologies have emerged for developing models to plan charging infrastructure. For instance, Quddus et al. (2019) suggest a two-level stochastic encoding model to address congestion at charging stations amidst uncertainty in energy demand. Conversely, Luo et al. (2018) devised a dynamic planning scheme for energy management at charging stations under uncertain conditions. Furthermore, Tao et al. (2018) proposed a game-theoretic approach to determine the pricing strategy at a PV-assisted charging station, considering factors such as minimizing battery wear, charging costs, and maximizing operating revenues. Within the realm of smart microgrids, Ahmad et al. (2017) proposed an energy management strategy for EVs, while Moghaddam et al. (2017) introduced a smart charging strategy utilizing metaheuristic algorithms.

In addition to ensuring stability in power distribution network parameters, it is crucial to consider the convenience of EV drivers and the road network topology when determining charging station locations. On the one hand, Xie et al. (2018) introduced a mixed integer linear programming (MILP) model that accounts for intercity traffic in charging infrastructure planning. Conversely, Rogge et al. (2018) addressed fleet sizing and charging optimization for electric buses. Moreover, Yang et al. (2020) proposed an optimization model based on real EV driving data.

Furthermore, Tao et al. (2018) emphasized demand prediction's significance in estimating necessary resources and rectifying potential voltage instabilities due to high energy demand in short time frames. This challenge constitutes the primary issue fast-charging stations face; hence, Campaña et al. (2021) developed a modular ultra-fast charging station (UFCS) architecture to overcome the inflexibility of existing fast-charging systems. Conversely, Leone et al. (2021) suggested the total installation cost of fast-charging stations and distribution losses as objective functions of an ant colony optimization model, aiming to minimize their impact on the distribution network and reduce the distance traveled by EV owners.

Other approaches to charging network planning leveraged Geographic Information Systems (GIS) and Multi-Criteria Analysis (MCDA) to select optimal sites for the city of Ankara (Phonrattanasak and Leeprechanon, 2014). Meanwhile, Erbas et al. (2018) applied graph theory to model and simulate the Stockholm Road network structure for optimal charging station placement. Besides, Jia et al. (2012) modeled a hybrid network system of EVs and internal combustion vehicles, considering two levels: maximum flow to deploy charging stations in links with higher demand at the first level, and a stochastic equilibrium model of users with elastic demands (SUE-ED) at the lower level. In contrast, models such as the one developed for the Indian city of Allahabad applied a hybrid algorithm based on genetic algorithms and an improved version of conventional particle swarm optimization, known as Genetic Algorithm Improved Particle Swarm Optimization (GAIPSO), to find optimal charging station locations (Gao et al., 2020).

Recent trends indicate that models employing a facility-to-site approach outperform those with a facility-to-location approach, as the former allows algorithms to freely assign facilities to the solution space, aiming to achieve the best result based on parameters and objective functions, albeit at a higher computational cost (Awasthi et al., 2027). This approach considers constraints such as EV demand, charging capacity of each station, access constraints, and spatial limitations.

Finally, it is worth noting the absence of planning approaches that incorporate terrain topography. This highlights the potential benefits of integrating this discipline alongside with agent mobility and electrical grid limitations. Such integration could lead to the development of an optimized charging network that effectively addresses the needs of EV users while considering geographical challenges.

## 3. Material and Methods

A series of specific methods and techniques were employed to improve the electric vehicle charging network optimization model. Initially, a multi-agent transport simulator was used to perform traffic simulations, called MATSim, implemented in Java. This simulator can model the individual behavior of multiple agents, such as vehicles and users, within a transportation network environment, in which they compete with each other for shared resources such as time and network capacity. It is an iterative model in which in each iteration, agents optimize their daily schedules of activities, select mobility plans, and replan based on demand and resource availability.

For the model preparation, a series of key input files called "Config" (software configuration), "Network" (transport network infrastructure) and "Population" (data from agents and their plans) were configured. Data preparation was based on previous mobility studies and the collection of geolocation, public transport and survey data to accurately model mobility patterns in the region under study.

Detailed topographic data of the study region, including terrain elevation and road gradients, were also collected. These data were integrated into a geospatial model to accurately represent the local topography.

Additionally, the transportation demand models were adjusted to reflect the expected adoption of EVs in the region over a specific time horizon. These adjusted demand models combined existing and projected charging point location data to generate an initial charging point network.

The methodology employed in this study aimed to improve the optimization model of the EV charging infrastructure by integrating the topographic variable through three distinct approaches: the average slope between origin and destination points, the accumulated vertical distance, and the road curvature. These three approaches, combined with the collection of geographical data, including elevation profiles, road network data, and projections of EV user demand for the island of Tenerife, have allowed for an enhancement of the model through different approaches.

### 3.1. Average Slope and Accumulated Vertical Distance

This approach entails calculating the average slope between each road segment's initial and final points. The average slope ($S_m$) is defined as the ratio between the difference in altitude ($\Delta h$) and the horizontal distance ($d_h$) between the initial and final points of the road. Mathematically, the average slope is expressed as

$$S_m = \frac{\Delta h}{d_h} \tag{1}$$

where:

- $S_m$ is the average slope between each road segment's initial and final point.
- $\Delta h$ represents the difference in altitude between the final and initial points.
- $d_h$ is the horizontal distance between the two points, which is calculated using the $x$ and $y$ coordinates of the initial and final points using the Euclidean distance formula:

$$d_h = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{2}$$

Therefore, the average slope ($S_m$) shall be calculated according to

$$S_m = \frac{h_2 - h_1}{\sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}} \tag{3}$$

Once the average slope ($S_m$) for each road segment was obtained, it was normalized to obtain a value (β) between -1 and +1. This normalized value was used to determine if adjustments were needed in the original charging point map. For this purpose, each charging point is associated with several routes, and the normalized factor between -1 and +1 was calculated for each point based on the average slope ($S_m$) of all the routes related to that point.

If the normalized value β is 0, no modifications are made to the charging point. If the value β is between -1 and 0, it is considered that the number of chargers associated with that point or their power should be reduced. On the other hand, if the value β is between 0 and 1, it is considered that the number of chargers or their power should be increased.

This approach provides a valuable tool for dynamically adjusting the EV charging infrastructure based on the terrain's topographic characteristics and their impact on efficiency and accessibility.

### 3.2. Road Curvature

This approach uses road curvature as an indirect indicator of the terrain's topography. Road curvature (κ) is calculated using the second derivative of the road function concerning the distance along the road. Mathematically, the formula to compute the curvature is expressed as

$$\kappa(x) = \frac{d^2y(x)}{dx^2} \tag{4}$$

where

- $\kappa(x)$ is the road curvature
- $y(x)$ is the road function, representing the terrain elevation as a function of the distance along the road.
- x is the distance along the road.

Road curvature provides information about the amount of curvature or directional change in the road. Regions with pronounced curvature may indicate uphill or downhill sections of roads, which can significantly affect the energy consumption of EVs. Vehicles traveling uphill on roads with pronounced curves will consume more energy than those traveling downhill.

By considering road curvature in the optimization model of charging infrastructure for EVs, we can identify areas where the terrain's topography presents specific challenges in terms of energy consumption. This enables us to adjust the location and capacity of charging points to optimize EVs efficiency and charging experience.

However, it is worth noting the significant challenge of gathering sufficient data to implement this second approach. This article proposes the approach and leaves open the possibility of developing this methodology to compare its results with the first approach.

## 4. Results and Discussion

We obtained results for two different scenarios from simulations conducted in MATSim (https://matsim.org/), an open-source framework designed to implement large-scale agent-based simulations for transport optimization. The simulation experiments were run on a 2.1 GHz Intel Xeon Core 6230 with 20 cores and 192 GB of RAM. Firstly, we examined the optimal distribution of the EV charging points without taking into account the topography (Figure 1). This approach focused solely on mobility-related aspects, disregarding terrain variations.

In contrast, the second scenario incorporated the average slope approach into the analysis (Figure 2). This methodology considered the topographic characteristics of the terrain when locating charging points. Each charging point was classified into three different categories based on its β value, which represents the relationship between the charging demand and the average slope of the surrounding area.

Charging points with β values between -1 and -0.5 were depicted in red on the figure, indicating low charging demand in those areas. Conversely, points with β values between -0.5 and 0.5 were shown in blue, suggesting charging demand within expected parameters. Finally, points with β values between +0.5 and +1 were represented in green, signaling high charging demand at those locations.

Table 1 shows the total number of charging points in each category (low demand, medium demand, and high demand), based on the β value obtained and the average altitude value at which each charging point is located.

**Table 1.** Number of points and average altitude of each category of recharging points

| Points category | β value | Number of points | Average altitude (m) |
|---|---|---|---|
| Low demand | $-1 < \beta < -0.5$ | 757 | 112 |
| Medium demand | $-0.5 < \beta < 0.5$ | 529 | 274 |
| High demand | $0.5 < \beta < 1$ | 227 | 439 |

Source: results obtained from the simulation. Provided upon request to the authors.

It can be observed that the average altitude of low-demand points is 112 m, the average altitude of medium-demand points is 274 m. Finally, the average altitude of high-demand points is 439 m. There is, therefore, a clear correlation between altitude and the type of point obtained in the simulation: the higher the altitude, the greater the tendency for demand. Consequently, it would be very important to consider this factor when reinforcing a specific area with more charging points, even at the expense of other areas where, due to topographic reasons, the demand may be lower than initially expected based solely on mobility criteria.

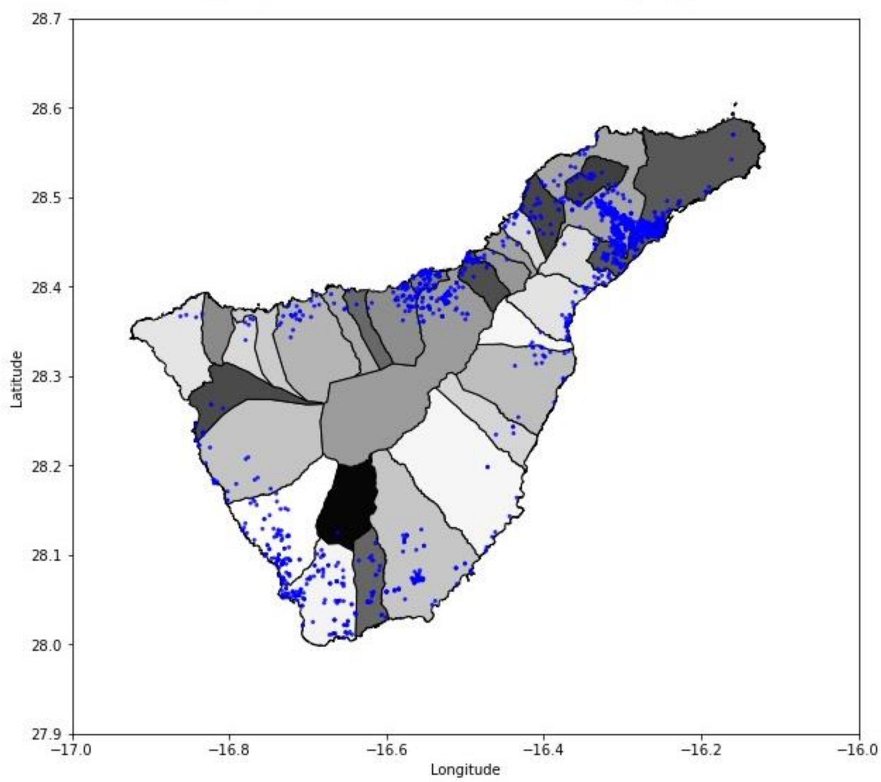


**Figure 1.** Distribution of charging points (blue dots) in Tenerife obtained after simulation in MATSim without considering the effects of topography.

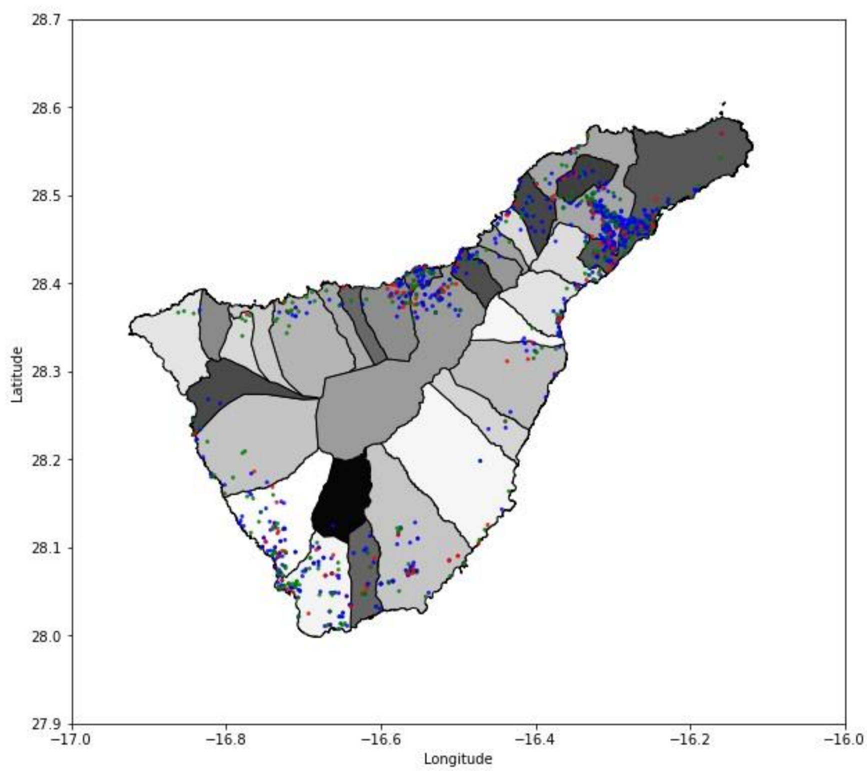


**Figure 2.** Distribution of charging points in Tenerife obtained after simulation in MATSim by considering the effects of topography. The simulation uses the average slope approach. Red dots represent charging points with lower demand than expected; green dots represent higher demand than expected; and blue dots represent charging points within the expected demand.

## 5. Conclusions

This study presents a significant advancement in the optimization model for EV charging infrastructure, particularly tailored to the unique topographic characteristics of the island of Tenerife. The optimization model has been substantially enhanced by integrating the topographic variable through various approaches, including slope gradients, average terrain elevations, and road curvatures.

The results demonstrate a clear correlation between altitude and charging point demand, with higher-altitude locations exhibiting greater demand for charging infrastructure. This underscores the importance of considering topography when planning the distribution of charging points, as it directly influences EV usage patterns and energy consumption.

Moreover, the proposed improvements to the optimization model provide valuable insights for urban planning authorities and EV charging network operators. By accounting for topographic factors, the model offers a more accurate and efficient tool for designing charging infrastructure that is responsive to mobility needs and adaptable to the geographical challenges posed by terrain variability.

Moving forward, the methodologies developed in this study can serve as a blueprint for enhancing EV charging infrastructure planning in other regions with similar topographic characteristics. By integrating the topography into optimization models, we can create more resilient and sustainable charging networks that meet the changing needs of electric mobility while also considering the terrain's topography.

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