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Optimal siting and sizing of electric taxi charging stations considering transportation and power system requirements

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ABSTRACT

Electric vehicles (EVs) have become more popular to address transportation-related environmental concerns. However, to integrate a massive fleet of EVs, it is crucial to properly build charging stations by considering the optimal geographical placement and number of charging spots. This task is particularly challenging for users with rigid schedules such as taxi drivers. Hence, an optimal siting and sizing approach for an electric taxi (ET) charging station is proposed in this study, considering both transportation and power system needs. In addition, particular attention to taxi drivers' needs is considered. Fixed installation costs, land costs, and trip costs are the factors evaluated in this proposed approach. A network modeling approach based on a winner-takes-all edge trimming was used to identify interest points of the city in terms of traffic flows. Ecuador's capital, Quito, was considered a case study. A sensitivity analysis was also carried out to address traffic flow uncertainties such as trip expenses and restrictions.

1. Introduction

Electric vehicles (EVs) have emerged as a viable option for addressing transportation-related environmental concerns, particularly emission of greenhouse gases (GHGs) from burning fossil fuels. EVs are considerably more efficient than cars with internal combustion engines (ICEs). They do not pollute locally, and their average worldwide pollution level is lower, especially with greener charging sources that use renewable energy [1,2].

EVs entail a number of potential difficulties that must be overcome. It has been shown that large-scale use of EVs may result in power grid difficulties including power losses, voltage sags, and voltage variations [3–5]. Thus, power system restrictions must be considered in charging solutions [6]. Compared with ICE cars, EVs have a restricted driving range, which can cause “range anxiety,” the concern of not having sufficient electrical energy in the battery. Range anxiety may be exacerbated for taxi drivers, whose charging behavior is likely to be considerably less flexible.

Studies examining the planning and functioning of EV charging stations have been documented. Several studies have investigated the operation and scheduling of EV charging stations [7], charging navigation systems for EV charging stations [8], and transportation and electric power networks [9].

Several studies have investigated the siting and sizing of EV charging stations. These studies can be mainly divided into four categories: the ones that consider power system constraints, that consider only road congestion, that considers budget and geographical constraints, and that consider coupled power and traffic constraints.

Various works have studied the siting and sizing of EV charging stations considering power systems constraints. An optimal planning of plug-in EV fast charging stations using an auction-based method was proposed [10]. An unsupervised learning methodology for deploying charging public infrastructure for EVs in sprawling cities was proposed [11]. Fast-charging station siting and sizing based on a mixed-integer nonlinear programming approach was proposed [12]. A station in the EV charging station planning problem was assumed, in which an investor intended to maximize profit in a competitive environment [13]. A robust model of EV

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Nomenclature

Indices

i, j	Index for nodes in transportation network
k	Index for charging station
s	Index for electric substation
v	Index for electric taxi

Parameters

β	Weighted resource leveling
$\Delta D_{k,k+1}$	Resource leveling term between consecutive charging stations
η	Charging efficiency of charging spot [%]
ω	Monetary value of travel time
$\overline{I_k}$	Current limits at station k [A]
$\overline{N_{ch}}$	Upper limit for number of charging spots in each charging station
$\overline{P_{ch}}$	Maximum charging power for ET charging station [kW]
$\underline{N_{ch}}$	Lower limit for number of charging spots in each charging station
$\underline{Q_k}, \overline{Q_k}$	Reactive power limits at station k [kVar]
$\underline{V_k}, \overline{V_k}$	Voltage limits at station k [V]
d_{ij}	Distance matrix element
DT_k	Mean travel distance of station k
E_{av}	Average daily electricity energy required by each ET v [kWh]
E_{req}	Total electricity energy required to charge all ETs [kWh]
f_{ij}	Time (flow) matrix element
$N_{\mathcal{V}}$	Number of taxis in Quito
N_K	Number of interest locations for ET charging stations
P_s^F	Feeder capacity at substation s [kW]
T	Time horizon for charging ETs in the charging stations in a day [h]
V_D	Voltage drop [V]
V_{SS}	Substation voltage[V]
x_k^{in}	(Time) Flow indegree
x_k^{tot}	Total flow degree
xk_k^{out}	(Time) Flow outdegree

Sets

$\mathcal{E}$	Set of edges of transportation
$\mathcal{G}$	Graph
$\mathcal{K}$	Set of charging stations
$\mathcal{N}$	Set of transportation nodes
$\mathcal{S}$	Set of electric substations
$\mathcal{V}$	Set of ETs

Variables

C^m	Material costs [$]
C^w	Workforce costs [$]
C_k	Total investment cost for a charging station k [$]
C_k^{it}	Installation costs [$]
C_k^l	Land cost for each charging station k [$]
C_k^{tr}	Travel cost for each charging station k [$]
n_k	Number of charging spots at charging station k
$n_{k,s}$	Number of charging spots at charging station k in the area of substation s

charging station location considering renewable energy and storage equipment was studied [14]. The authors of [15] determine the optimal charging station placement considering V2G technology, by considering the minimization of line loading, voltage deviation, and circuit power loss. The optimization is performed through quantum binary lightning search algorithm, which is a heuristic optimization technique. In Ref. [16], a queuing-theory-based charging station sizing algorithm that benefits EV users and improves spots capacity utilization is proposed. The case study of Al Ain City, UAE, is studied. These studies have reported essential findings for EV charging station sizing and siting. However, they have mainly considered power system requirements; traffic constraints were not considered simultaneously.

Other studies have focused only on road congestion, with minimal or no power grid limitations. The optimal location of an EV charging station was obtained based on actual vehicle travel patterns [17]. Pile assignment was used in the charging station placement problem [18]. A sizing and siting model was proposed considering EV characteristics such as EV flow and charging station technical specifications [19]. A data-driven intelligent location of public charging stations for EVs was performed considering massive GPS-enabled trajectory data [20]. The growth of electric vehicles in urban traffic networks is linked to the development of charging infrastructure. Currently, siting and sizing of EV charging stations is an open problem. The paper [21], describes the process of sizing and placing electric vehicle charging stations, establishing variables to represent charging demand, modeling the structure of the road network using graph theory, and solving an optimization problem. The model's goal is to reduce the combined cost of charging stations and users. The calculations show that the strategy can effectively cut construction and operation expenses, as well as facilitate user pricing, from Stockholm, Sweden.

Increasing the usage of electric energy for transportation and promoting EVs to reduce harmful emissions and noise is a worldwide trend. Common difficulties when it comes to the location of charging stations are related to budget and geographical constraints. The authors of [22] proposed a method that enables for the selection of a subset of existing parking lots for selecting the siting of the charging stations. In this work, a set of optimal solutions for multiple predefined restrictive and partially contradictory criteria was established using a genetic algorithm combined with fuzzy logic and Pareto front analysis. In Ref. [23], the location optimization of EV charging stations is performed by covering economic and environmental costs and using geographical information from Ireland. The authors of [24] propose a techno-economic optimization of renewable-based charging stations in Qatar, where the configuration with the least net present cost is selected.

To date, a limited number of studies have investigated coupled power and traffic constraints for siting and sizing of EV charging stations. The siting and sizing problem includes power and traffic system constraints; however, the land cost was not considered in the placement conditions [25]. An optimal planning method was studied for the location of fast charging station for EVs considering operators, drivers, vehicles, traffic flow, and power grid [26]. The optimal location and sizing of fast-charging stations was studied [27]. A methodology that find the optimal location and size of public charging stations, which can maximize the benefit of the investment, was considered [28]. A multi-objective synergistic planning approach for EV fast-charging stations was proposed for integration into the distribution system [29]. A network equilibrium model that captured the spatial and temporal variations of power and traffic flows was studied [30]; these variations are helpful in the siting and sizing of charging stations. In Ref. [31], a zonal approach is proposed for the siting and sizing of fast-charging stations. The authors of [32] propose a sizing of plug-in EV fast-charging stations with Markovian demand characterization; nonetheless, the siting problem is not considered. In Ref. [33], a graph automorphic approach is considered for the placement and sizing of charging stations.

Although these and other studies have recommended the optimal location and size of EV charging stations, they have focused on passenger automobiles. The location and size of charging stations for public transportation with variable schedules, such as electric taxis (ETs), have received less attention. The allocation of fast-charging ET stations was proposed, with particular attention to taxi services [34–36]; however, power system conditions were not strongly considered. Several studies have considered construction of fast-charging stations, which has been linked to battery degradation. Their time and location requirements differ from those of private passenger EVs. Installing only fast-charging stations for ETs is not technically advisable, as it may cause battery damage leading to unusability.

The majority of studies discuss theoretical instances rather than realistic case studies, using restricted data and assumptions rather than actual data that considers transportation circumstances. Coordinated ET charging station siting and sizing based on real-world traffic and power-system circumstances are proposed in this study. This paper is an extension of a previous conference [37], which has significantly been improved. The key contributions of this study are presented as follows.

- A comprehensive siting and sizing methodology for ET charging stations is developed based on actual data. Particular attention is devoted to the needs of taxi drivers regarding operating schedules by considering trip costs.
- The optimal investment for charging stations is determined by considering power grid and transportation constraints to ensure sustainable purchase of ETs.
- A sensitivity analysis is performed to resolve uncertainties, considering probable trip expenses and restrictions to present more realistically acceptable results.

The remainder of this paper is organized as follows: The approach for location and sizing of ET charging stations is described in Section 2. The case study and assumptions are presented in Section 3. Section 4 discusses the results of the case study. Section 5 summarizes the key conclusions.

2. Methodology for sizing and locating charging stations

The recommended strategy for locating and sizing ET charging stations is presented in this section. The first step consists of identifying potential locations for ET charging stations based on actual traffic conditions. After identifying the interest points, the optimal number of charging spots to be installed is calculated.

For the siting and sizing of EV charging stations specifically for taxis, a technical criterion that can help determine the location and number is the type of road. For example, on urban roads, charging stations include fewer charging spots because they use the existing low-voltage power distribution infrastructure of such roads. From the transformers that already feed different loads (homes and businesses), the distribution company installs individual charging points distributed along the street or at taxi stops. Thus, both low-voltage cabling and transformers are available for charging at night when the consumer load (homes and businesses) decreases. Capacity is available for charging point loads. A flowchart of the proposed methodology is presented in Fig. 1.

2.1. Transportation modeling

For the transportation modeling, points of interest around the city are identified. The city street network was modeled as a graph, built using the Python OSMnx API [38], where nodes are interest points connected by streets in a driving path, where the driving distance and time were acquired using the Google Directions API. The interest points are determined using an edge trimming heuristic for simplifying the city street graph, based on a winner takes all approach, where the best edge was selected during the trimming process. The resulting graph gives us the interest points with the best connections. The process is mostly automated, which is useful to model city street networks and traffic flow. In this particular case, we are not building all possible origin and destinations for taxis but based our analysis on the resulting network of interest points around the city [21,22].

Other usual approach for trimming a graph is based on node removal instead of edge removal, as is our case. The trimming is done from the structural properties of the network, i.e., the edge length. A structural measure for the nodes usually employed is the network degree, for the city network, given that is a regular grid (approximately), node based measured are pretty uniform. Thus, we carry out the trimming based on edges, as built from identifying interest points and their full connected paths as driving distances, and times. We could think of edge-based algorithms such as building a spanning tree, but the restriction of the algorithm, of nodes connected without cycles, did not give a proper structure to build the intended network. Thus, we opted for a heuristic based on winner-takes-all approach.

Two requirements must be met to prototype a transportation system:

1. a foundational structure, such as a city street network, generally represented as a grid
2. a traffic flow model.

OSMnx produces a graph $\mathcal{G} = (\mathcal{N}, \mathcal{E})$, where the nodes $\mathcal{N}$ corresponds to the interest points and the edges $\mathcal{E}$ to the paths (streets) connecting the interest points around the city. Quito street network was built using the package Open Street Maps in Python [39]. The edge length was used as a criterion for trimming the extracted network. The graph $\mathcal{G}$ can be represented as the adjacency matrix D, where elements smaller than the 75th percent, $d_{ij} < p_{75th}$, become zero. The **OD** matrix is summarized at the node level, where the node degree is expressed as:

$$x_a^{tot} = x_k^{in} + x_k^{out} \tag{1}$$

with:

$$x_k^{in} = \sum_j f_{ij} \tag{2}$$

and:

$$x_k^{out} = \sum_j f_{ji} \tag{3}$$

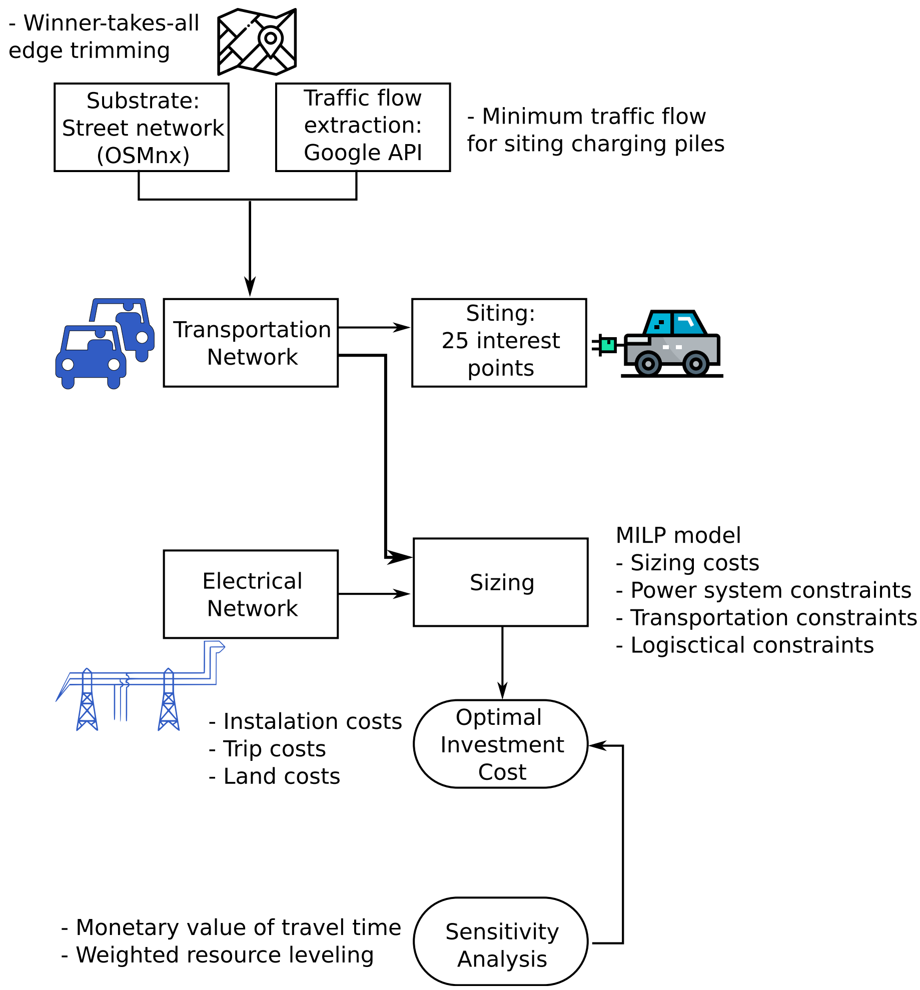

Fig. 1. Flowchart of proposed ET charging station siting and sizing methodology.

where x_k^{in} is the time flow indegree, xk_k^{out} the time flow outdegree, and x_k^{tot} measures the traffic flow of each point that is a candidate for the placement of charging station k.

2.2. Problem formulation

It is possible to obtain a large number of N_K candidate charging stations. The number of charging spots n_k is defined as a decision variable for each ET charging station k. For each charging station, the search space for the number of charging locations was examined, and optimization was performed. The goal is to minimize the cost of establishing public charging stations for electric vehicles. The cost of ET travel is included in the overall price as it is a significant incentive for taxi drivers to use EVs. For each charging station, a typical fixed installation cost, land cost, and trip cost are defined, representing the overall cost to be modeled for the charging station size.

$$C_k = C_k^{it} + C_k^{l} + C_k^{tr} \tag{4}$$

As each interest point is located in a different zone with different land prices, the land cost is a variable.

The installation cost is assumed to be:

$$C_k^{it} = C^m + C^w \tag{5}$$

The fixed costs are represented by the two terms. The first term refers to material costs, including the price of the electric equipment and charging stations. The second term refers to workers responsible for constructing parking lots with charging stations.

The work includes a trip cost because the transportation needs of taxi drivers must be considered to incentivize the purchase of ETs. For each charging station k, the travel cost is a variable term defined as:

$$C_k^{tr} = \omega \cdot DT_k \tag{6}$$

The objective is to minimize the sizing costs of the ET charging stations formulated as Eq. (7):

$$min \quad C = min \sum_{k \in \mathcal{K}} C_k \tag{7}$$

Subject to:

$$\underline{Q_k} \le Q_k \le \overline{Q_k} \tag{8}$$

$$\underline{V_k} \le V_k \le \overline{V_k} \tag{9}$$

$$|I_k| \le \overline{I_k} \tag{10}$$

$$\sum_{k \in \mathcal{K}} n_{k,s} \cdot P_{ch} \cdot \eta < P_s^F \quad \forall s \in \mathcal{S} \tag{11}$$

$$\underline{N_{ch}} \leq n_k \leq \overline{N_{ch}} \tag{12}$$

$$\sum_{k \in \mathcal{K}} n_k \cdot P_{ch} \cdot \eta \cdot T \geq E_{req} \tag{13}$$

$$n_{k+1} - n_k \leq \beta \cdot \Delta D_{k,k+1} \tag{14}$$

Constraint (8) represents the lower and upper limits of reactive power necessary for compensation at charging station k. Constraint (9) imposes the lower and upper voltage limits at each bus i. Constraint (10) imposes the lower and upper voltage limits at each bus k, guaranteeing the maximal current limits in each feeder. The electrical substation capacity limit of each charging station k belonging to substation $s \in \mathcal{S}$ is imposed by constraint (11). The minimum and maximum number of charging spots in each charging station are defined by constraint (12). During the time range in which taxi drivers are free to stop and charge their EVs, constraint (13) ensures that all charging stations can supply the total required energy for all taxi drivers. Constraint (14) is a ramp-up limit between each charging station, suggesting that there should be a maximum difference between charging stations for the shortest driving distance to discourage taxi drivers from going long distances if all charging station spots are used.

Mixed-integer linear optimization can be used to address this problem. Active and reactive power limits for each charging station represent the power flows that can occur at a bus or node in a network. As the time-series loading data for substations and the conductor parameters were not available, an alternative approach to the T&D network load flow was used. A power flow only provides the minimum and maximum voltage values for one year at the substation end and not at the node. The voltage at a node can be obtained by accounting for the voltage drop (along its length) from the substation voltage:

$$V_k = V_{SS} - V_D \tag{15}$$

However, the total load at each node was not available for evaluating the current for ET charging.

Accordingly, a substation loading analysis was performed to calculate the minimum and maximum power at each node. It was assumed that each substation could be loaded to 80% of its rated capacity. Further, based on land price, the substations were considered loaded to 50% or 70% of their capacity. In prime locations, with prices exceeding 600 $\$/m^2$, substations are more heavily loaded; it is safe to assume a practical maximum loading limit of 70%. For all other substations with locations in less economically active zones, their operating limit was assumed to be 50% of their capacity. As each substation is sized to serve either one, two, or three types of consumers, industrial, residential, and commercial, EV charging must increase loading beyond the safe limits.

Accordingly, the minimum and maximum space for EV loading were considered to be an additional load of 5–15%. Thus, for 66 MVA substations, which are primarily residential, a minimum of 5% of the rated capacity can be accommodated as the EV charging load. A maximum EV charging load corresponding to 15% of the rated capacity was allowed. For other large substations, 75–80% of the rated capacity was used as the operating limit considering EV charging in addition to other loads. A practical assessment of substation loading and distribution of EV charging load was conducted to model the power flow constraints.

The methodology can be summarized by the following pseudocode:

Algorithm 1
Siting and sizing process.

Data: Network, Traffic flow, Power grid parameters Set cost variables;

Result: Optimal siting based on interest points

Process
City network and traffic flow based on winner takes all edge trimming and minimum traffic flow;
Define cost function Set power grid conditions based on interest points in the city;
Minimize cost function subject to constraints;
Obtain optimal sizing for each charging station at minimum investment cost;
Perform sensitivity analysis considering monetary value time and resource weighted leveraging;

2.3. Sensitivity analysis

In a mathematical model, a function f can determine one or various possible output variables from given input variables. This function might be quite complex in many instances (e.g., not linear), and as a result, determining the influence of the inputs on the output might be difficult [40].

Sensitivity analysis is therefore a tool for determining how model input uncertainties impact model response. It illustrates how the relative input influences output variability. The presented model is based on an objective function that is subject to various constraints, where some parameters are assumed (e.g.: monetary value of trip time, and weighted resource leveling), and it is implemented by a mathematical code. Hence, performing sensitivity analysis is crucial for addressing output uncertainties (i.e.: number of charging spots).

For this model, a sensitivity analysis for the monetary value of trip time ω and weighted resource leveling β is performed. These parameters were selected in order to address uncertainties concerning probable travel expenses and restrictions.

3. Case study and assumptions

A case study of Quito, Ecuador was chosen based on the mayor's commitment to gradually replace internal combustion taxis with EVs. Quito is located 2800 m above sea level; automobile combustion is inefficient as a result of the high altitude, resulting in considerable pollution issues. As taxis are a large source of traffic and noise, the mayor must provide other modes of transportation.

3.1. Potential locations of ET charging stations

The urban traffic flow mapping in Quito was completed in a previous study [41]; numerous prospective ET charging stations were chosen.

The city can be modeled as a street network [42], as a weighted multi-graph $\mathcal{G} = (\mathcal{N}, \mathcal{E}, \mathcal{W})$. A graph is a set of nodes $\mathcal{N}$ interconnected by a set of edges $\mathcal{E}$ which are weighted connections with weights $\mathcal{W}$. Each vertex $n_i \in \mathcal{N}$, corresponds to an interest point in the city, and is embedded with its geographical position. Each edge $e_i \in \mathcal{E}$, corresponds to the streets, avenues, and highways, with an embedded a geometry, indicated by a vector representing its geographic spatial component. An edge can be defined as the ordered tuple $e_i = (n_i, n_j)$ connecting nodes n_i and n_j. The Python OSMnx library was used for extraction and modeling of the street network of Quito. OSMnx is a Python package that allows geospatial data to be downloaded from OpenStreetMap to model, project, visualize, and analyze real-world street networks and other geospatial geometries [38].

Once the city street network substrate has been defined, traffic flow information must be obtained. The Google Distance Matrix API was used to extract real-time traffic data from one vertex v_i to its connected neighbors in the street network [41]. The Google Distance Matrix API provides the travel distance and time based on the recommended driving route e_k between two vertices $e_k = (n_i, n_j)$. The extracted driving distance and driving time define the weight of the street edge e_k, and can be represented as the unordered tuple $w_k = (d_{ij}, f_{ij}) = (driving\_distance, driving\_time)$. Requests are made to the Google Distance Matrix API, providing the start and end points corresponding to the origin n_i and destination n_j nodes for each connection in the city street network. Registers for traffic and flows record data with the following structure: Each register, for the traffic, flows, records the data with the following structure:

```
from(latitude, longitude),
to(latitude, longitude),
mean_time,
mean_distance.
```

The extracted data for the edge weightsedges of the' edges-weights, can be summarized as described in Eq. (1); the weight times f_{ij} are used to model the incoming and outgoing flows for each node.

In this study, 25 candidate locations were selected based on their minimum average time, according to the explanation at the beginning of Section II. The number of locations must be considered for geographically dispersed charging stations in the city; installing too many charging spots in the same station could lead to grid issues. Fig. 2-left shows the 25 candidates for EV charging stations in blue, and the electrical substations in red, located in the north center of Quito. A fully connected graph for the 25 selected locations was built using the driving traffic distances extracted from the Google API.

Fig. 2-right shows the Hamiltonian cycle connecting the ten selected charging stations. A Hamiltonian cycle visits each node only once, and reduces the overall driving distance. Each site has a distinct land cost. Table 1 summarizes the sites of interest with the shortest flow time, the associated land costs, and the nearest substation capacity. The land costs were obtained from local property sales company [43]. The power grid data was obtained based on the local electricity distribution company, which is Empresa Eléctrica Quito [44], and from the Ecuadorian Regulatory company, which is Arconel [45].

3.2. ET charging parameters

After identifying the potential locations of ET charging stations, the number of charging spots at each charging station was calculated. To this end, the daily peak load and daily required energy for the ETs were estimated. A practical estimation approach for the arrival of ETs at charging stations is presented, based on accurate data from taxi driver travel behavior, which differs significantly from that of typical drivers. In general, users of privately-owned EVs charge their vehicles at home during the night. On the contrary, taxi drivers would have to charge the EVs during the night, but also during the day. This is due since taxi drivers drive much longer distances than a typical driver and the energy supplied during the night is not enough. Moreover, since taxi drivers work all day, they do not have time flexibility as other drivers, and they just have a lunch pause that could be used as a time to charge the ETs. The arrival time in the day depends on the state of charge (*SOC*) of

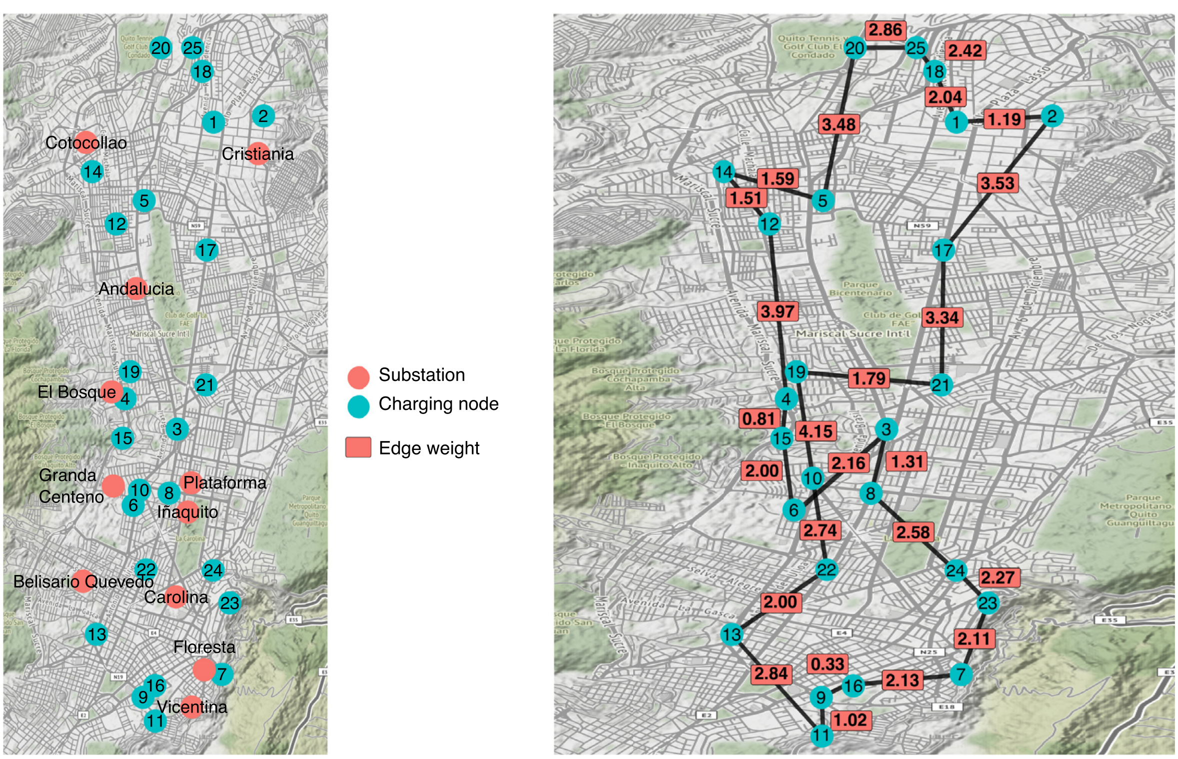

Fig. 2. Left panel: potential locations of electrical substations and charging stations in the city of Quito. Right panel: potential locations of charging stations and Hamiltonian cycle connecting them.

Table 1
Interest points with minimum flow time selected as pre-feasibility stations.

node	mean time (min)	land cost ($/m^2)	substation capacity (MW)
1	6.44	600	66
2	7.03	600	66
3	11.07	780	20
4	11.72	780	20
5	11.67	780	20
6	10.42	950	20
7	11.76	2000	40
8	10.76	780	20
9	10.62	1200	200
10	10.01	1300	200
11	10.80	1300	200
12	9.07	1200	20
13	11.99	2000	20
14	12.11	2000	40
15	9.75	2000	10
16	7.94	1400	10
17	8.48	1130	20
18	10.78	1400	20
19	8.41	780	20
20	10.75	780	20
21	10.77	780	166
22	8.43	780	166
23	11.67	600	166
24	12.29	600	66
25	11.58	600	66

the ET, determined based on the travel distance as per reference [46]. The arrival process at the charging stations is described as a Markovian queuing system. The system is defined as MMCK per the Kendall notation. The inter-arrival (M) and service times (M) are exponential; arrival is governed by a Poisson process, with C servers and queue capacity K, the maximum number of EVs that can be accommodated in the servers.

There are 8633 taxis in Quito. With so few ETs in Quito, charging behavior must be analyzed to provide a charging load curve for optimal charging station sizing. To that end, GPS data from driving behavior were gathered from taxi drivers in Quito [47]. A gasoline-to-electricity conversion rate is used to divide the required electricity energy by the number of taxis, resulting in an average required energy of 30.35 kWh per taxi. For simplicity the value is rounded to nearest integer of an average of 30 kWh per taxi. The

Table 2
System parameters for case study.

Parameter	Value
Number of taxis $N_{\mathcal{V}}$	8633
Time horizon T for charging ETs [h]	5
Spot charging power P_{ch} [kW]	22
Charging efficiency of charging spot η [%]	0.9
Maximum number of charging spots $\overline{N_{ch}}$	40
Minimum number of charging spots $\underline{N_{ch}}$	5
Daily electricity required by ET E_{av} [kWh]	15
Assumed land used for an individual parking lot [m^2]	20
Monetary value of travel time ω	3500
Weighted resource leveling β	10

histogram of the daily required energy for ETs is illustrated in Fig. 3. The average required energy was calculated from Fig. 3.

Most taxi drivers take a break from 3 to 8 p.m., after lunch, and when there are few clients. This will result the time horizon. Based on the previously traveled distance, 50% of the required energy should be delivered during these periods, which is when the assumed peak load is observed, and corresponds to an E_{av} of 15 kWh. The other 50% will be delivered at night in taxi drivers homes, which is not considered in this study. Thus, the energy required in Eq. (13) results in:

$$E_{req} = \sum_{v \in \mathcal{V}} v \cdot E_{av} \tag{16}$$

A few ETs have been purchased in Quito and other Ecuadorian cities; the BYD e5 model was chosen to represent the taxi driver demographic [48]. This EV has a charging power of $P_{ch} = 22$ kW; the charging efficiency η was assumed to be 90% [49].

Based on quotes, the fixed investment cost of each charging location, including materials and labor, is estimated to be $ 3000 [43]. The surface area of the land used for each parking lot was assumed to be 20 m^2.

The minimum number of spots n_k in each charging station k is considered to be five, and the maximum is 40 The monetary value of travel time ω is considered to be 3,500, and the weighted resource leveling β is considered to be 10. In Table 2, the system parameters for case study are summarized.

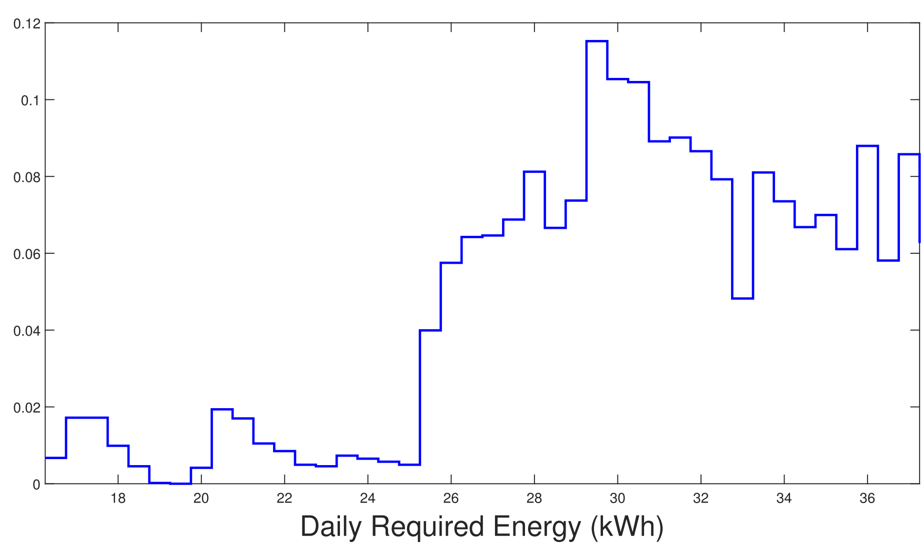

Fig. 3. Histogram of the daily required energy for ETs [47].

Table 3
EV characteristics.

Station	Number	Cost
1	40	1244.5
2	40	1302.8
3	17	786.6
4	17	814.3
5	21	1003.4
6	21	1008.9
7	40	2895.5
8	17	773.6
9	40	2142.4
10	34	1836.5
11	40	2239.6
12	21	1043.1
13	21	1532.6
14	8	586.2
15	10	673.8
16	10	508.5
17	21	983.0
18	21	1216.7
19	17	673.5
20	21	954.9
21	17	774.1
22	40	1587.4
23	40	1767.5
24	40	1829.4
25	40	1758.1
Total	654	31936.8

3.3. Stakeholders involved

The proposed methodology for the siting and sizing of ET charging stations is relevant to the different nature of stakeholders involved. For public nature stakeholders, such as the city hall and state government, because this study facilitates the introduction of ETs in the community stimulating green and climate change policies in the area in which they are interested and are currently investing. For private nature, there are different stakeholders to consider. For zone distributors, the optimization of the charging station facilitates the use of the distribution network, avoiding pressures to enlarge the electrical local network to face the increment in the electrical load due to the introduction of ETs. For traders, it enables the consumption and the increment of business because of the new energy consumption, especially in hours with an actual lower consumption (nights and weekends) for ETs stimulated by new tariffs that may be proposed. Finally, taxi companies, because can move to electrical technology with lower exploitation costs and lower CO2 penalties that public entities are introducing, especially in the center of the cities. Some of the new stations may be installed with private funds directly by the taxi companies.

3.4. Model simulation

Eqs. (7)–(14) represent the sizing model corresponding to a mixed-integer nonlinear programming (MINLP) problem. To avoid a complex formulation, the problem can be decomposed into two subproblems. The decoupled problem starts with constraints (8)–(10), obtaining a maximum power constraint that can be delivered to each charging station, and then to constraints (11)–(14), which are mainly logistic and transportation constraints.

In this study, GAMS 33.1.0 with CPLEX performed the simulations of the proposed MILP model using an Intel Core i7-8700 with 32 GB of RAM [50].

When solving mixed integer programming (MIP) models, CPLEX employs branch-and-cut search. The branch-and-cut process handles a node-based search tree. Every node represents a linear programming (LP) or quadratic programming (QP) subproblem to be processed, that is, solved, tested for integrality, and maybe further studied. CPLEX continues to process active nodes in the tree until there are no more active nodes available or a limit is reached. The formation of two new nodes from a parent node is referred to as a branch. A branch happens when the boundaries on a single variable are changed, and the new bounds apply to that new node as well as any of its descendants. A cut is an additional constraint to the model. The goal of adding any cut is to reduce the size of the solution domain for continuous LP or QP problems represented at the nodes while leaving legal integer solutions in place. As a result, the number of branches necessary to solve the MIP is reduced [51]. Solving MILP problems necessitates significantly more numerical calculation than solving comparably sized pure linear problems.

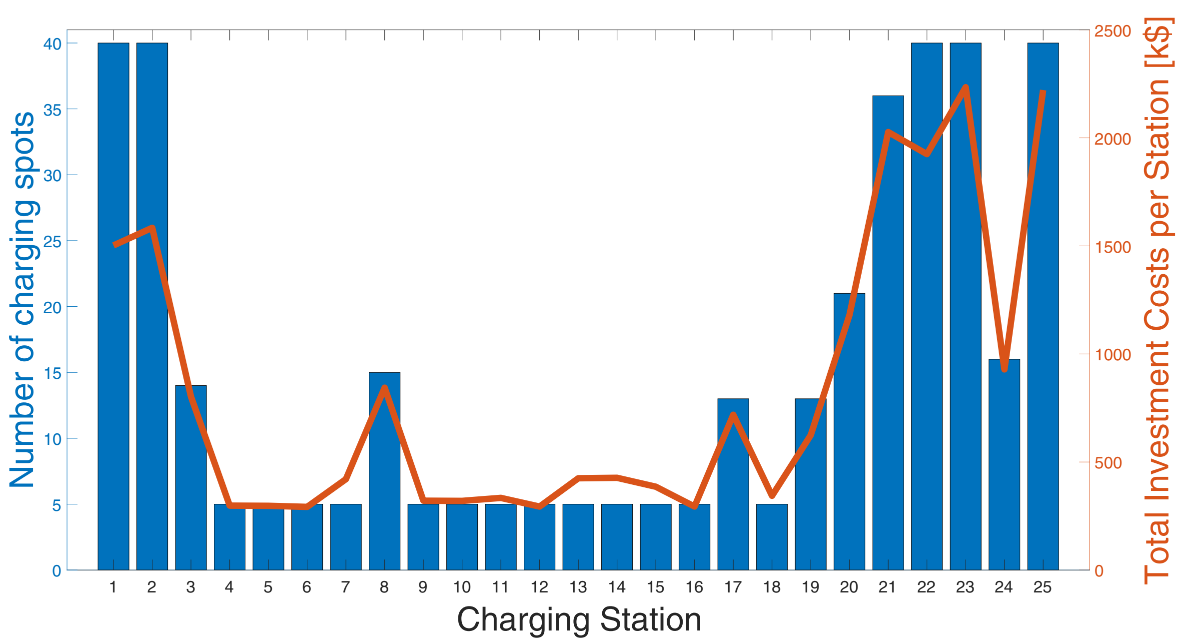

Fig. 4. Number of charging spots and costs for an ET penetration level of 30%.

The solution of simple integer problems takes an inordinate amount of time [50].

4. Results and discussion

Three scenarios were investigated, with different amounts of EV penetration (30%, 40%, and 50%).

4.1. Number of charging spots and costs

For an ET penetration of 50%, the total number of charging spots and the associated expenses are presented in Table 3.

As the land cost is high, the station with the fewest charging spots is Station 14, with eight charging spots. The maximum number of charging spots is reached at stations with the lowest land cost.

The number of charging spots to be installed and the total investment costs for each charging station for ET penetration of 30%, 40%, and 50% are illustrated in Figs. 4–6, respectively. With 30% ET penetration, several charging stations reach their charging spot number or power limit. A total of 393, 524, and 654 charging spots must be constructed for ET penetration levels of 30%, 40%, and 50%, respectively.

Table 4 summarizes the investment costs for ET penetration of 30%, 40%, and 50%. Between ET penetration of 30% and 50%, fixed costs increase by 40%, land costs by 93%, and trip costs by 72%.

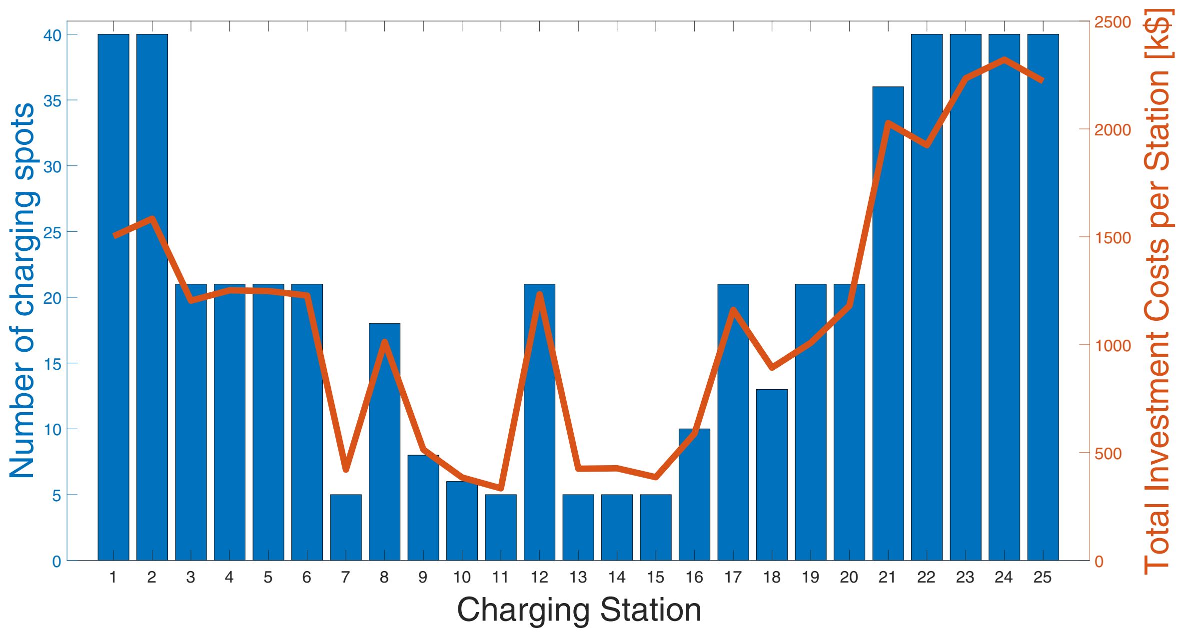

Fig. 5. Number of charging spots and costs for an ET penetration level of 40%.

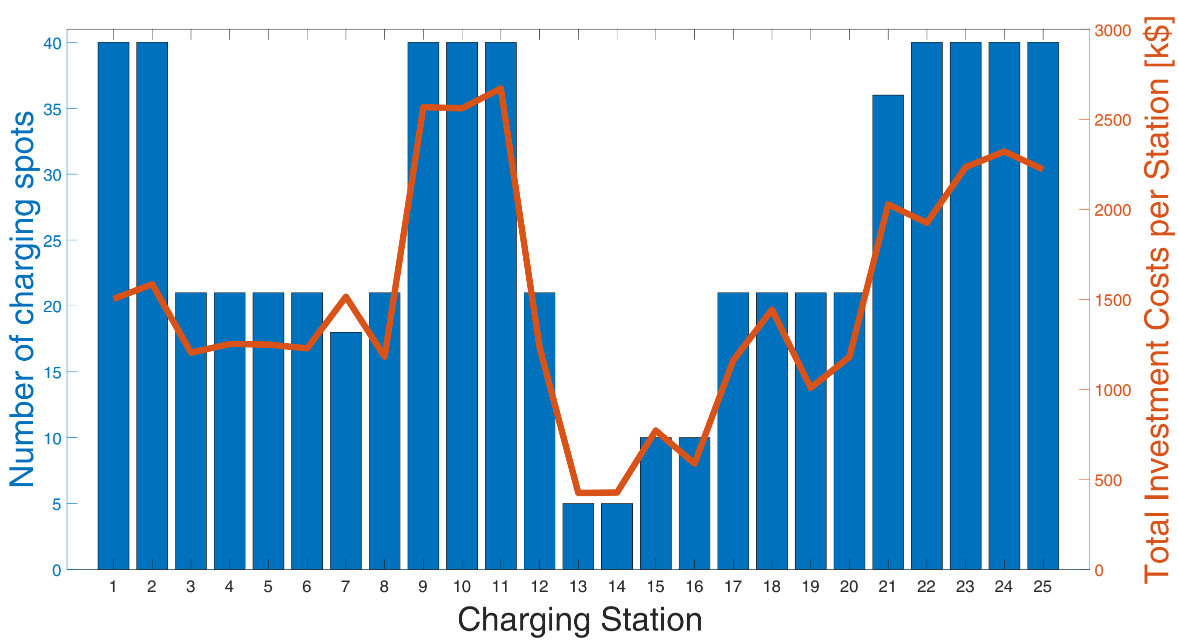

Fig. 6. Number of charging spots and costs for an ET penetration level of 50%.

Table 4
Summary of the various investment costs for different ET penetration levels.

ET penetration (%)	30	40	50
Fixed costs (k$)	1179	1572	1962
Land costs (k$)	6405	8804	12,357
Trip costs (k$)	13,460	18,339	23,162
Total costs (k$)	21,045	28,715	37,481

Figs. 7–9 show the investment costs per station for ET penetration of 30%, 40%, and 50%, respectively. The most significant costs are land and trip costs.

4.2. Sensitivity analysis results

As previously indicated, a sensitivity analysis was performed for the monetary value of trip time ω and weighted resource leveling β to address uncertainties concerning probable travel expenses and restrictions. Parameter β was varied from 5 to 15 in increments of 0.2. Parameter ω was varied from 2000 to 5000 in 60 increments.

The surface plots of land costs and total investment costs for an ET penetration of 30% are shown in Figs. 10 and 11, respectively.

It is observed that land costs vary substantially, especially with variations in the weighted resource leveling β. The surface plot of

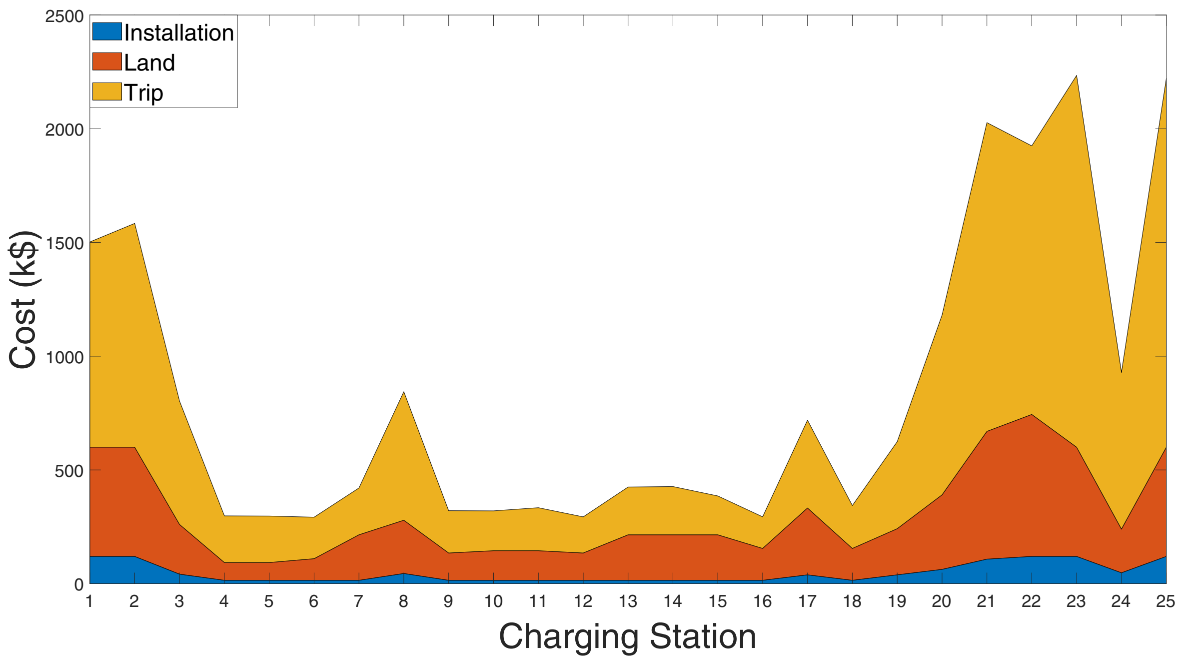

Fig. 7. Investment costs for an ET penetration level of 30%.

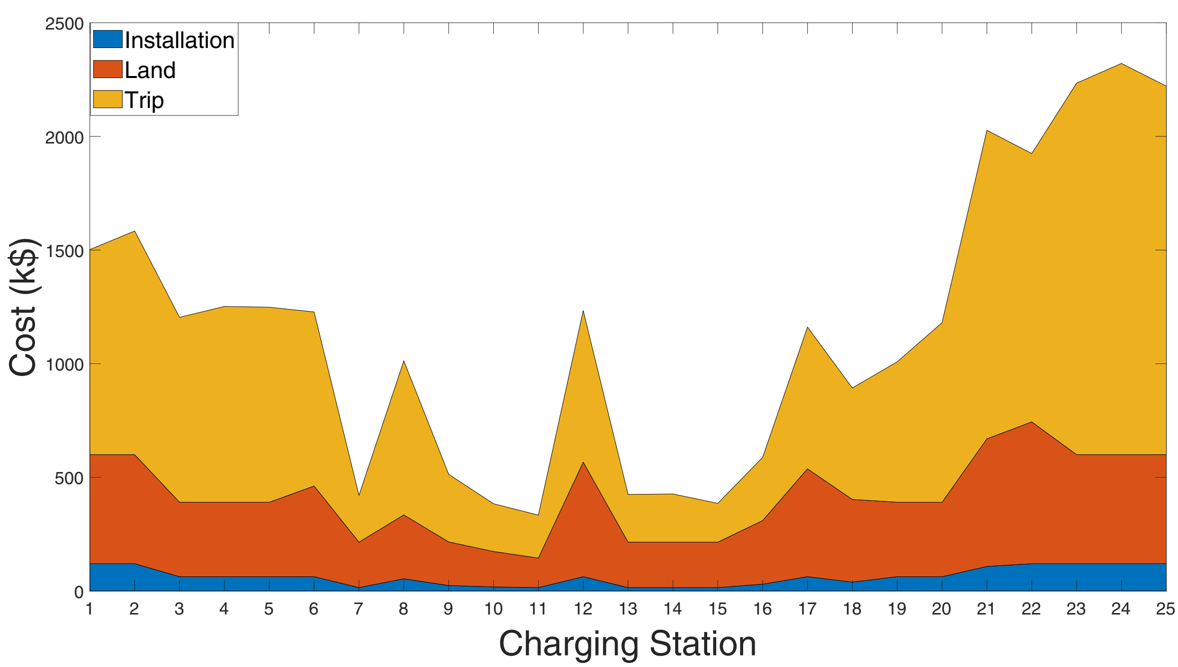

Fig. 8. Investment costs for an ET penetration level of 40%.

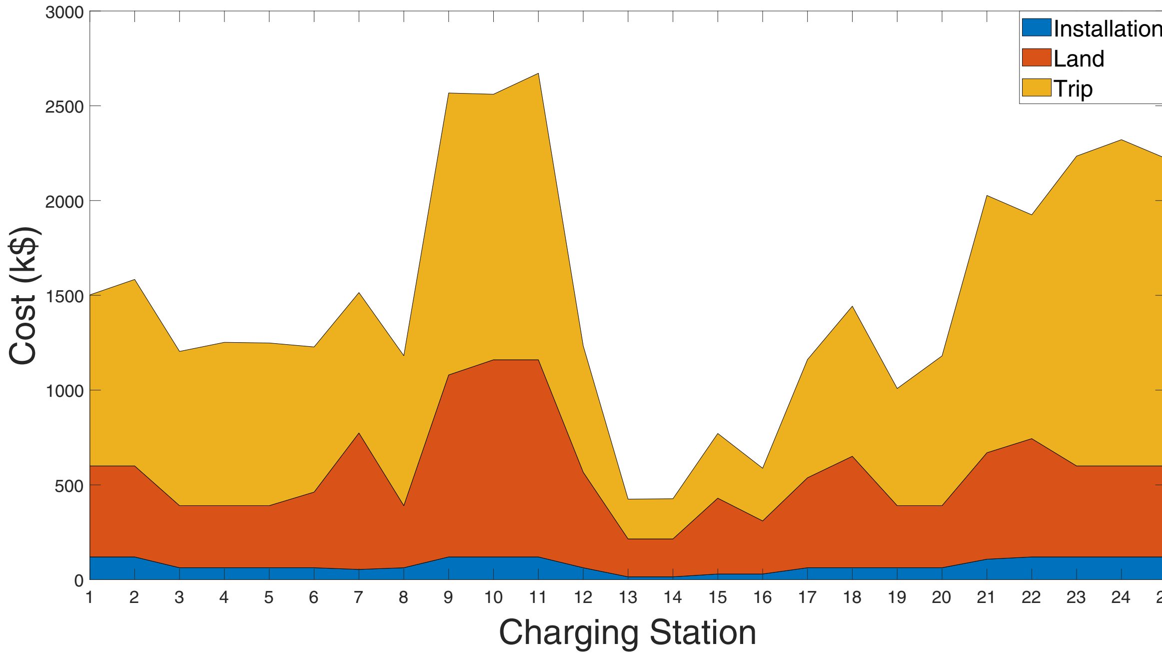

Fig. 9. Investment costs for an ET penetration level of 50%.

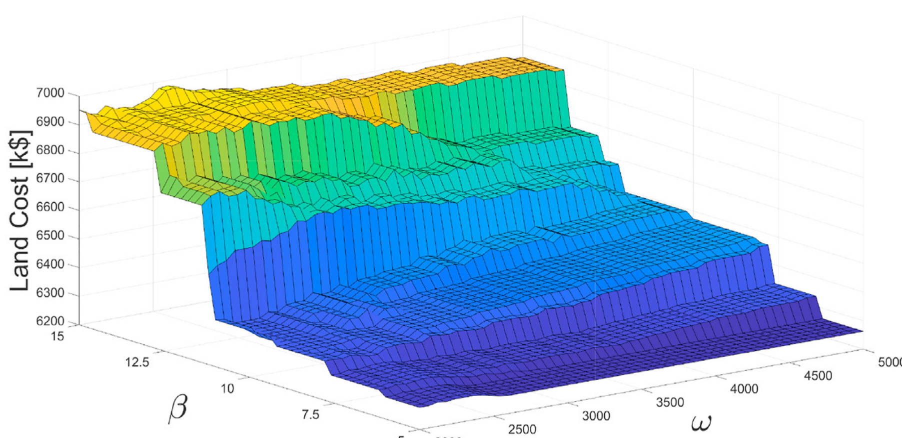

Fig. 10. Investment costs depending on β and ω.

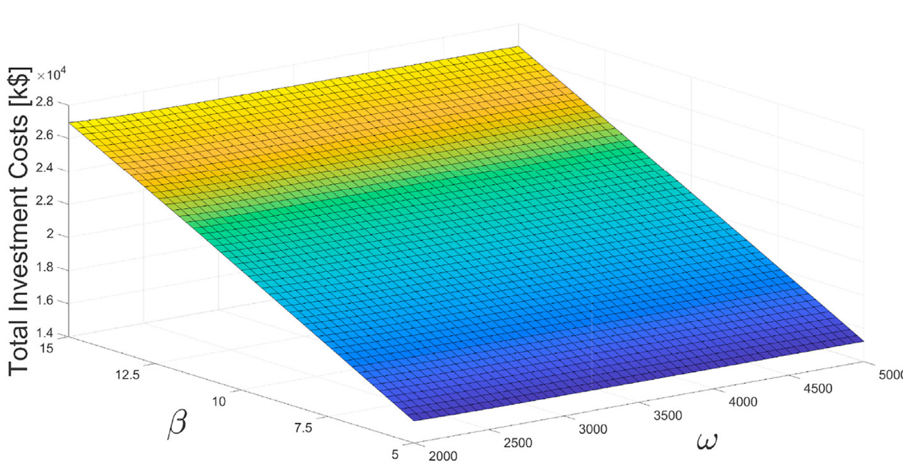

Fig. 11. Total investment costs depending on β and ω.

the total costs is relatively flat; variation in the monetary value of travel time ω does not lead to a change in costs. However, an increase in the weighted resource leveling β leads to an increase in costs.

4.3. Discussion

The optimal siting and sizing of various kinds of EVs is a topic that need to been significantly investigated for the proper integration of EVs in power systems and the diffusion of market sales. Some works such as [25–31] have already considering both the power and traffic constraints and present robust methodologies. However, this paper presents a new way of reducing traffic jams by considering winner takes all methodology. In addition, the particular time schedules and time rigidity of taxi drivers have been considered. With this proper planning of ET charging stations, this will result in a higher adoption and sales of EVs for public transportation.

To achieve reduction in emissions in transportation, it not sufficient to electrify various fleets, but the electricity should originate from renewable generation. In Ecuador there was a large investment in renewable generation based on hydroelectricity in the 2007–2017 decade. In 2018, 72.58% of the total produced electricity was from renewable energy, from which 97.47% is from hydroelectricity, 1.8% from Biomass, 0.18% from solar PV, 0.38% from wind, and 0.21% from bio-gas [52]. Thus, Ecuador is a country that has a strong potential to reduce its global emissions in transportation by shifting to electric mobility, and it is crucial to have policies for investing in public charging stations such as for ETS.

5. Conclusions

Optimal siting and sizing of ET charging stations are determined in this study to minimize total charging costs, considering transportation and power system restrictions. The city of Quito, Ecuador was investigated as a case study. The total costs include installation costs, land costs, and trip costs. A network modeling approach based on a winner-takes-all edge trimming was used to identify interest points of the city in terms of traffic flows, and 25 prospective ET charging stations were identified. The driving behavior of taxi drivers in Quito was also considered.

The findings indicate the number of charging spots that should be installed in each station. A higher number of charging spots to be installed was observed in the charging stations with lower land costs. A sensitivity study was also performed to address parameter variability in the proposed model.

Credit author statement

Jean-Michel Clairand: Conceptualization, Data Curation, Formal Analysis, Investigation, Methodology, Software, Writing-original draft. **Mario González- Rodríguez**: Data Curation, Formal Analysis, Validation, Methodology, Software Writing-original draft. **Rajesh Kumar**: Conceptualization, Supervision, Validation. **Shashank Vyas:** Conceptualization, Validation, Writing – review& editing. **Guillermo Escrivá-Escrivá**: Conceptualization, Supervision, Validation, Writing – review& editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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