

Multiobjective EV Charging Station Planning for Large-Scale Transportation Systems

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RESUMO

Este artigo propõe uma estratégia escalável para alocar e dimensionar estações de carregamento (EC) de veículos elétricos (VE) com sistemas fotovoltaicos (PV), a partir de um modelo de programação não-linear inteira mista (PNLIM). Considerando o sistema de compensação de créditos de energia para um investidor privado, o modelo PNLIM proposto minimiza os custos de investimento e operação para indicar as localizações e capacidades adequadas para as instalações de EC e PV. Os locais são avaliados como candidatos a partir de dados públicos sobre o tráfego e o sistema de transporte. A estratégia multiobjetivo utilizada para encontrar boas soluções reduz o esforço computacional e permite que estudos em escala real sejam explorados pelo método. O estudo de caso utiliza um cenário real do estado de São Paulo considerando duas tarifas de energia e 5% de penetração de VE em relação a frota total. Os resultados mostram que a infraestrutura proposta permite que um VE trafegue por no máximo 140 km sem passar por uma EC, e os sistemas fotovoltaicos são estrategicamente planejados com net-metering para maximizar a utilização da energia produzida.

KEYWORDS. Estações de carregamento, veículos elétricos, otimização multiobjetivo.

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ABSTRACT

This paper proposes a scalable strategy to allocate and size charging stations (CS) for electric vehicles (EV) combined with carport photovoltaic (PV) systems using a mixed-integer non-linear programming (MINLP) model. Considering the net-metering scheme and a private investor perspective, the proposed MINLP model minimizes the investment and operation costs to indicate the proper locations and sizes of CS and PV carport systems. Locations are evaluated using only public data on the traffic and the transportation system. The multiobjective strategy addressed here to obtain optimal solutions leads to a reduced computational effort, which allows large-scale studies. A real-world Brazilian case considering two time-of-use energy tariffs and 5% EV penetration is used to test the strategy. The results show that the entire CS infrastructure does not cover up to 140 km of EV trips on state highways, and photovoltaic systems are strategically designed with the net-metering scheme to maximize the use of the energy produced.

KEYWORDS. Charging stations, electric vehicle, multiobjective optimization.

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1. Introduction

Modern power systems increasingly rely on distributed energy resources (DER). In recent years, the electric vehicle (EV) fleet overcame 16 million units (11.2 million having pure-electric powertrain), and 1.77 million publicly charging stations (CS) have been available since 2021 [IEA, 2022]. Also, the photovoltaic (PV) systems expanded 167.8 GWp in 2021, representing a 21% development compared to the previous year [Walburga et al., 2022]. The increase of DER requires the study of new planning practices to address the system expansion problems, the operation of electric grids, and power generation.

There are many challenges to be faced in planning the CS infrastructure: (i) where the CS should be installed; (ii) how many charging points each location should have; and (iii) how large the carport and, consequently, the PV system should be. To select CS locations the methods usually use the perspective of the electric system, minimizing the grid violations (voltage and current) [Scheiper et al., 2019] and [Ahmad et al., 2022]. Other contributions consider the transportation system perspective to maximize the EV owners served by searching for high traffic flow areas and checking if the roads can cope with the additional traffic flow [Alp et al., 2022]. When a broader perspective is applied, the deployment of the CS infrastructure can be planned to cover a geographic area and consider the coupling between transport and electric systems [Andrade et al., 2020]. These strategies screen the places for CS in small regions, such as a set of cities, a city, and districts; therefore, the problem for large-scale transportation systems (for instance, state and country) is not addressed. As an usual objective function, the mentioned proposals usually adopt technical and economic aspects; however, many of these methods are complex and not scalable, entailing an extra computational burden to solve the CS allocation problem in large-scale regions.

The sustainability power system outlook considers the clean energy generation to reduce greenhouse gas emissions. A possible planning approach is building the CS infrastructure of carports covered with PV panels. This combined system may also reduce the total operation costs; however, it worth remarking that PV source is non-dispatchable and the energy produced needs to be temporally displaced to meet the EV recharge demand. In [Kumar et al., 2021], the CS allocation, sizing, and operation problem with PV carports are addressed simultaneously. However, the proposed strategies do not guarantee the optimality of the solution and do not provide applications for large-scale regions. A solution less explored to support the energy generation control from a PV system is the net-metering scheme. In countries where the net-metering scheme is adopted, the bulk power system takes the role of a storage system; the customer receives billing credits when energy is exported to the system and can use these credits later to support their demand [ANEEL, 2015].

This paper proposes a model that considers all major information of the transportation system to solve the CS location problem and sizing the CS capacities for large-scale regions, providing the electromobility facilities from a private investor perspective. The optimal solution defines the location and characteristics of the set of new CS, and the capacities of PV carport systems; it also considers the net-metering scheme as a operation planning alternative to minimize the operation costs. The tests are performed on a real case study using public data of the transportation system. A Monte Carlo simulation with a representation of stochastic charging demand scenarios is use for further evaluation of the solutions obtained with the proposed MINLP model. The main contributions of this paper are as follows: a) a mixed-integer nonlinear programming (MINLP) model for the CS allocation and sizing problem; b) an optimization method to address the CS operation scenarios considers renewable alternatives to reduce fixed costs.

2. Preprocessing Data from Transportation System

The solution space of the CS allocation problem is represented by a non-oriented graph $G(\mathcal{L}, \mathcal{N})$, where all links (say, highways and expressways) of the transportation system ($\mathcal{L}$) provide a benefit to allocate a CS and additional facilities; the end points ($\mathcal{N}$) are obtained with public data provided by the Brazilian government agencies of the transportation system [DNIT, 2021]. The traffic flow of each candidate of $\mathcal{L}$ helps to qualify the benefits of the CS allocation considering the fleet of EV and combustion vehicles. The rationale behind this approach considers that a link highly used by combustion vehicles has a great potential of being used by EV owners.

A preprocessing data allows providing the most detailed information about the traffic flow, the behavior of the EV owners, and the frequency of charge and discharge. This solution space study is achieved with three complementary procedures: (i) first procedure defines the approximate EV fleet for each links l of $\mathcal{L}$, and provides the average daily volume of EV owners (adv_l) and the total fleet (tf) parameters; (ii) second procedure defines the number of charging points (cp_l) based on the approximate EV fleet parameters (adv_l and tf) and time-of-use profile of real gas stations; (iii) third procedure computes the CS load shapes based on data provided in the previous step and the EV owners behaviors.

2.1. Forecasting the EV Fleet

The first procedure searches to estimate the EV fleet of each link l of $\mathcal{L}$ (adv_l) and the total fleet (tf) over the years of the planning. This estimation method considers the historical growth rate of light cars (only combustion vehicles) and the expected percentage of EV owners concerning the fleet of light cars. These data provide the EV fleet that will use the transportation systems in the final year of the planning horizon — the worst-case scenario.

2.2. Computing the Capacity of Charging Stations

The second procedure considers the time-of-use profile of real gas stations and the adv_l to compute the number of charging points (cp_l) of each link l of $\mathcal{L}$; this hypothetical scenario considers that gas stations and CS may have the same pattern of time-of-use profile. The procedure considers the probability of EV owners arriving at the CS to recharge at a given instant t of $\mathcal{T}$ and the average weekly frequency of customers using gas stations (say, time-of-use profile). The time-of-use profile are used as a probability density function to select the arrival time of the EV at the CS. Therefore, cp_l is defined as the most significant number of users at a single time. A deeper discussion of these issues can be accessed in [Barbosa et al., 2020].

2.3. Unveiling the CS Load Shapes

The third procedure unveils the CS load shapes ($E_{l,t}^d$) of each link l of $\mathcal{L}$. All scenarios evaluated by the method are random, and consider the probability density function that can describes the daily behavior of the driver arriving at the station in a given instant $t \in \mathcal{T}$. This strategy focuses on the CS event variables: the waiting queue; the charging start time; the charging duration. The wait queue includes EV owners who arrived at the station to charge at a given instant t ; the available slots in the wait queue are the same as the number of cp_l for each l of $\mathcal{L}$. Therefore, any EV owner who arrives at the station with all waiting queue slots occupied must give up the recharge. The charging start time is modeled by a uniform distribution function that provides a randomly chosen from $\mathcal{T}$. A deeper discussion of these issues can be accessed in [Barbosa et al., 2020].

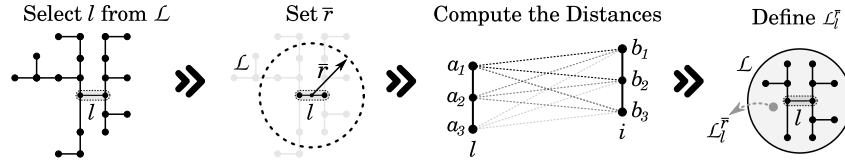


Figure 1: Preprocessing data to address the cover edge on to the optimization model.

3. A Graph Theory Approach

The proposed optimization approach considers the edge cover problem of a graph to address the CS allocation problem [Gross et al., 2018]. The strategy searches for optimal places to accommodate the CS and additional facilities, exploring topological aspects that allow providing a charging point to the EV owners across the entire transportation system. In the original proposal, the edge cover method searches for edges in $\mathcal{L}$ that ensures each node of $\mathcal{N}$ (here, consider $\mathcal{N}$ as the set of nodes of a given graph) is incident to at least one edge of the set $\mathcal{L}$; the method can also address cases in which a radius of a given $\bar{r}$ length limits the coverage area of a given node $n \in \mathcal{N}$ by an edge l if $d(l, n) \leq \bar{r}$, where $d(\cdot)$ is the Euclidean distance. In the CS allocation method, the coverage of the transportation systems is provided by the coverage between links, as illustrated in Fig.1 and expressed as $\mathcal{L}_l^{\bar{r}} = \{i \in \mathcal{L} \mid d(l, i) \leq \bar{r}\}, \forall l \in \mathcal{L}$.

The preprocessing data provides a set for each link l in $\mathcal{L}$ that represents all coverage links i according to the length specified to $\bar{r}$; the distance between links ($d(l, i)$) is approximated as the minimum value of the set $\{d(a_1, b_1), d(a_1, b_2), \dots, d(a_3, b_2), d(a_3, b_3)\}$, as indicated in Fig. 1. Note that the solution space is defined as $\mathcal{L} = \mathcal{L}_1^{\bar{r}} \cup \mathcal{L}_2^{\bar{r}} \dots \mathcal{L}_{l-1}^{\bar{r}} \cup \mathcal{L}_l^{\bar{r}}$ for any $\bar{r}$. The proposal addresses the benefits of allocating a CS through the β_l parameter that indicates the EV traffic rate in a given link l ; note that the sets $\mathcal{L}_l^{\bar{r}}$ are obtained in the preprocessing method mentioned above. The computation of β_l is expressed in (1).

$$\beta_l = \left(1 - \frac{\text{adv}_l}{\text{tf}}\right)^{\text{cp}_l} \quad \forall l \in \mathcal{L} \quad (1)$$

Equation (1) evaluates the transport benefits of a link l ; the parameters adv_l indicate the estimated EV fleet of a given link l . Note from (1) that parameter β_l also considers the expected number of charging points; this approach elevates the avoidance of selecting links with little ($\text{cp}_l = 1$, for instance) or no ($\text{cp}_l = 0$) foreseen demand, as $(1 - \text{adv}_l/\text{tf}) < 1.0$. The choice of a given link l as a candidate to allocate a CS and facilities also considers the connectivity between links that belong to the same set $\mathcal{L}_l^{\bar{r}}$. The rationale behind the ρ_l parameter is that a user can move from any link ($i \in \mathcal{L}_l^{\bar{r}}$) to the link l where the CS is allocated. Equation (2) expresses this idea.

$$\rho_l = \frac{|\mathcal{L}_l^{\bar{r}}|}{\sum_{i \in \mathcal{L}_l^{\bar{r}}} \text{path}(l, i)} \quad \forall l \in \mathcal{L} \quad (2)$$

In (2), the connections between links that belong to the same set $\mathcal{L}_l^{\bar{r}}$ are evaluated. The set with higher value of ρ_l indicates a less connectivity between links; otherwise, ρ_l takes on a small value. The $\text{path}(l, i)$ binary parameter indicates whether ($\text{path}(l, i) = 1$) or not ($\text{path}(l, i) = 0$) there is a path between l and i . Note that in the optimal scenario (fully connected set $\mathcal{L}_l^{\bar{r}}$), the parameter $\rho_l = 1$; for any other planning scenario, its value will always be $\rho_l > 1$.

4. CS Infrastructure Planning

The proposed optimization model assumes the perspective in the planning of CS and supposes that no additions are necessary to the electric power system (to support the CS demand and additional facilities). As input data, the EV fleet and the demand for links in $\mathcal{L}$ are already defined, and consequently, the active output power for these places has forecasted values ($E_{l,t}^d$), as discussed in the previous section (Section 2). Another assumption is that all CS facilities belong to the same private investor; it allows surplus energy to be exported to the electric system as energy credits through the energy compensation system (net-metering). It is also worth remarking that the model aims to provide optimal locations (links) for CS on a given transportation system (graph), considering the PV carport systems as planning alternatives.

4.1. Mathematical Notation

The mathematical notations are defined as follows. The sub-indexes indicate the set of parameters and variables, while the super-indexes are used as a reference object.

Sets and Indices	$\mathcal{L}/l, i$	set/indexes of links.
	$\mathcal{T}/t$	set/index of intervals.
	$\mathcal{K}/k$	set/index of PV types.
Binary Variables	x_l	charging station allocation with the link l .
	$w_{l,k}$	building a carport in a link l and PV of type k .
Variables	$E_{l,t}$	energy supply to the link l at the interval t .
	$E_{l,t}^{-nm}$	imported energy by the link l at the interval t .
	$E_{l,t}^{+nm}$	exported energy by the link l at the interval t .
	E_t^{nm}	total energy of the net-metering scheme at interval t .
	$\hat{E}_{l,t}^{-nm}$	imported energy by the link l at the peak intervals.
	$\hat{E}_{l,t}^{+nm}$	exported energy by the link l at the peak intervals.
	$\tilde{E}_{l,t}^{-nm}$	imported energy by the link l at the off-peak intervals.
	$\tilde{E}_{l,t}^{+nm}$	exported energy by the link l at the off-peak intervals.
Parameters	c_l^{cs}	CS allocation cost with the link l .
	c_k^{pv}	PV carport allocation cost of capacity k .
	c_t^e	energy cost at the interval t .
	P_k	nominal power of a PV of type k .
	$sh_{l,t}$	generation percentage of PV at link l in the interval t .

4.2. The MINLP Model for the CS Allocation Problem

The proposed MINLP model for the CS allocation problem with the PV carport system considering the net-metering scheme is described in (3)-(12).

$$\min \left\{ \sum_{l \in \mathcal{L}} x_l c_l^{cs} + \sum_{l \in \mathcal{L}} \sum_{k \in \mathcal{K}} c_k^{pv} y_{l,k}, \frac{1}{(1 + \alpha)^h} \left[\frac{(1 + \alpha)^{\Delta h} - 1}{\alpha (1 + \alpha)^{\Delta h}} \right] \sum_{l \in \mathcal{L}} \sum_{t \in \mathcal{T}} c_t^e E_{l,t}, \sum_{l \in \mathcal{L}} x_l \rho_l \beta_l \right\} \quad (3)$$

$$\text{s.t.: } E_{l,t} + E_{l,t}^{pv} + E_{l,t}^{-nm} = x_l E_{l,t}^d + E_{l,t}^{+nm} \quad \forall l \in \mathcal{L}, \forall t \in \mathcal{T} \quad (4)$$

$$E_{l,t}^{pv} = \sum_{k \in \mathcal{K}} w_{l,k} sh_{l,t} P_k \quad \forall l \in \mathcal{L}, \forall t \in \mathcal{T} \mid sh_{l,t} \in [0, 1] \quad (5)$$

$$E_{l,t}^{+nm} = \begin{cases} 0, & \text{if } E_{l,t}^{pv} \leq E_{l,t}^d \\ E_{l,t}^{pv} - E_{l,t}^d, & \text{otherwise} \end{cases} \quad \forall l \in \mathcal{L}, \forall t \in \mathcal{T} \quad (6)$$

$$\sum_{l \in \mathcal{L}} E_{l,t}^{-nm} \leq E_{t-1}^{nm} \quad \forall t \in \mathcal{T} \mid t > 0 \quad (7)$$

$$E_t^{nm} = \sum_{l \in \mathcal{L}} E_{l,t}^{+nm} \quad \forall t \in \mathcal{T} \mid t = 0 \quad (8)$$

$$E_t^{nm} = E_{t-1}^{nm} + \sum_{l \in \mathcal{L}} (E_{l,t}^{+nm} - E_{l,t}^{-nm}) \quad \forall t \in \mathcal{T} \mid t > 0 \quad (9)$$

$$\sum_{i \in \mathcal{L}_l^{\bar{r}}} x_i \geq 1 \quad \forall l \in \mathcal{L} \quad (10)$$

$$\sum_{k \in \mathcal{K}} a_k w_{l,k} \leq x_l cp_l \bar{a} \quad \forall l \in \mathcal{L} \quad (11)$$

$$\sum_{k \in \mathcal{K}} w_{l,k} \leq x_l \quad \forall l \in \mathcal{L} \quad (12)$$

$$E_{l,t}, E_t^{nm}, E_{l,t}^{+nm}, E_{l,t}^{-nm} \geq 0 \quad \forall l \in \mathcal{L}, \forall t \in \mathcal{T} \quad (13)$$

4.3. Objective Function

The objective function (3) minimizes the costs of the CS allocation and the system operation, considering the PV carports and energy credits compensation system as planning alternatives. In addition, the graph aspects are also evaluated in (3) considering the CS allocation strategies described in Sec. 3. The first part of (3) describes the investment costs, which is composed of the costs of the CS, c_l^{cs} , and the costs of PV systems over carports, $c_{l,k}^{pv}$; the nominal capacities are based on the active power demands estimated from the transportation system data. The operation cost over the planning horizon are stated in the second part of (3) and considers the topology of the CS facilities planned in the initial year of the payback period. An annual interest rate of α is introduced to provide its present value for the time interval Δ ; the investment and operation timeline with a payback period of (Δ) years. The third part of (3) evaluates the transportation benefits of allocating a CS in a given set of links in $\mathcal{L}$. For brevity, herein, the three-part of (3) are stated as follows: C^{in} represents the investment costs; C^{op} is the operation costs; and f describes the graph aspects to evaluate the transportation benefits.

4.4. Energy Balance Constraints

The energy balance constraints (4)–(7) are used to model the operation of the carport with conventional (fixed) tariff and consider the energy compensation system with the energy support from PV sources; these balance ideas are illustrated in Fig. 2. Constraint (4) represents the energy balance at each link l of the set $\mathcal{L}$ in a given instant t . In (4), the energy magnitude variables are adopted from the active power balance in [Santos et al., 2020]. Equation (5) addresses the energy produced by a PV source $E_{l,t}^{pv}$ of type s at the instant t is defined. The parameter $sh_{l,t}$ imposes the daily rate of solar radiation of each link l considering any value within the closed interval $[0, 1]$ – where 0 is no power generation, and 1 is the nominal active power of the PV generator of a given type k , P_k . Equation (6) provides the surplus energy management, which identifies the amount of energy exported to the net-metering scheme ($E_{l,t}^{+nm}$).

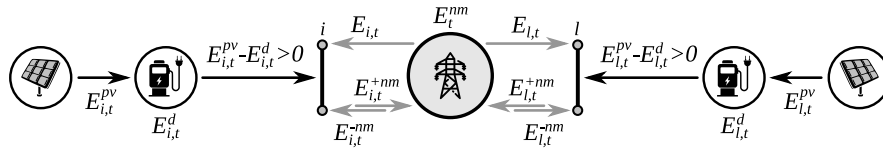


Figure 2: Energy balance scheme for the planned EV charging facilities.

4.5. Energy Credits Management Constraints

Constraints (6)–(9) provide the optimal control of the energy compensation system for conventional tariff. Equation (6) defines the amount of energy that can be exported to the energy compensation system ($E_{l,t}^{+nm}$). In (7), the maximum amount of imported energy ($E_{l,t}^{-nm}$) is defined; note that $E_{l,t}^{-nm}$ must be less than or equal to the total available energy of the system at the last instant (E_{t-1}^{nm}). Equations (8)–(9) calculate the total available energy in the compensation system at the instant $t = 0$ and $t > 0$, respectively. Note that E_t^{nm} has no link index, which means that all CSs belong to the same private investor.

4.6. Considering the Variable Cost Tariff

The variable cost (say, time-of-use) tariff means that the price of energy changes throughout the day; usually, the highest price matches with the period of the highest consumption of the electric system (peak), while the lowest price is applied the rest of time (off-peak). The inclusion of the variable cost tariff in the optimization strategy introduces two new sets to the problem: the set of off-peak intervals, $\tilde{t}$, and the set of peak intervals, $\hat{t}$ ($\mathcal{T} = \hat{t} \cup \tilde{t}$). The variable rate also changes the energy balance. For instance, the import and export of energy to the net-metering system can not be carried out freely over time; energy exported to the system at the instant t must be imported as energy credits into the same set of instants. Therefore, $E_{l,t}^{+nm}$ and $E_{l,t}^{-nm}$ in (4) and (6)–(9) should be replaced by (14)–(15).

$$E_{l,t}^{+nm} = \hat{E}_{l,t|\hat{t}}^{+nm} + \tilde{E}_{l,t|\tilde{t}}^{+nm}, \quad \forall l \in \mathcal{L}, \forall t \in \mathcal{T} \quad (14)$$

$$E_{l,t}^{-nm} = \hat{E}_{l,t|\hat{t}}^{-nm} + \tilde{E}_{l,t|\tilde{t}}^{-nm}, \quad \forall l \in \mathcal{L}, \forall t \in \mathcal{T} \quad (15)$$

Note from (14) and (15) that four new variables are introduced into the CS allocation optimization problem. Their descriptions are as follows: $\hat{E}_{l,t|\hat{t}}^{+nm}$ e $\hat{E}_{l,t|\hat{t}}^{-nm}$ describes the exported and imported energy to the net-metering scheme on a given peak instant t , respectively; $\tilde{E}_{l,t|\tilde{t}}^{+nm}$ e $\tilde{E}_{l,t|\tilde{t}}^{-nm}$ describes the exported and imported energy to the net-metering scheme on a given off-peak instant t , respectively.

4.6.1. Building the CS with PV Carport Systems

Equations (10) and (12) evaluate the CS allocation optimization problem and the PV carport systems as planning alternatives; its facilities must to satisfy all technical constraints at the lowest possible cost. Parameters used for selection evaluations are based on the nominal power of the PV system as follows. Equation (10) ensures that a link l is covered by at least one CS. In (11), the maximum area of the PV system with capacity k (a_k) is imposed to allocate it over a carport at link l ; the available area ($\bar{a}$) corresponds to the perimeter of all the charging points (cp_l). Equation (12) limits the number of PV system that can be allocated at the link l .

4.7. Multiobjective Solution Strategy for the MINLP Model

The proposed MINLP model searches for the optimal locations to accommodate the CS and additional facilities. As expressed in (3), the objective function minimizes operation and investment costs (C^{in} and C^{op}) and evaluates the location benefits in f . Note that the terms of the objective function do not deal with the same unit of measurement; consequently, the optimization process might lead to imprecise calculation results. Furthermore, it should be remarked that there is a conflict between the costs and f because an optimal result of f means a high cost for investment and operation — the more EV owners served (minimizing f), the greater are the investments and operating costs.

The multiobjective approach addressed here is an alternative to assess this problem; the main building blocks are the terms preferences in the objective function. The purpose is to adopt the ideas from the Lexicographic method to deliver optimal solutions (locations, sizing, and operation policy) for the CS allocation optimization problem. The Lexicographic method allows for solving a multiobjective optimization problem by ordering the objective functions according to their importance or significance, rather than by assigning weights. For the proposed MINLP model, the Lexicographic method can deliver a solution with two complementary steps, as defined as follows: [i] the first procedure solves the proposed MINLP model with f as the whole objective function (in Alg. 1, lines 5 and 6). The rationale behind this approach is that the demand for CS is a higher priority than saving on investment and operating costs. [ii] The second procedure minimizes the costs of investment and annual operations ($\omega C^{\text{in}} + \omega C^{\text{op}}$) considering the building of PV over carports as planning alternatives; a single weight ω is applied to both cost functions (for instance, $\omega = 1$). The value of f is evaluated in a new equality constraint (16), where the model must reach solutions that are equal to the previous solution z^* (in Alg. 1, lines 8, 9, and 10).

Algorithm 1 presents the entire computation process to solve the MINLP model considering the lexicographic method. Note from Alg. 1 that the preprocessing steps are included into the computation description through the lines 2 and 3.

Algorithm 1: Lexicographic Method to Solve the MINLP Model.

input : $\mathcal{L}$, $\mathcal{T}$, adv_l , tf , and $\bar{r}$
output: CS Locations $\leftarrow \{l \in \mathcal{L} \mid x_l = 1\}$

- 1 // Analysis of Input Data
- 2 **Computation Step (Sec.2 and Sec.3):** $E_{l,t}^d$, β_l , ρ_l
- 3 // First Step of the Lexicographic Method
- 4 **Set:** $z \leftarrow f$
- 5 **Solve:** $z^* \leftarrow \min\{z\} \text{ s.t.: (4)–(15)}$
- 6 // Second Step of the Lexicographic Method
- 7 **Set:** $\hat{z} \leftarrow (\omega C^{\text{in}} + \omega C^{\text{op}})$
- 8 **Set:** New Constraint (16) $\leftarrow \sum_{l \in \mathcal{L}} x_l \rho_l \beta_l = z^*$
- 9 **Solve:** CS Locations $\leftarrow \min\{\hat{z}\} \text{ s.t.: (4)–(15) and (16)}$

4.8. Final Remark

To sum up, the CS allocation optimization problem that reveals the best location for CS is given by (3)–(15). Commercial solvers for integer nonlinear programming problems (for instance, Gurobi [Gurobi Optimization, LLC, 2021]) can deliver optimal solutions for the two steps of the Lexicographic method described in Alg. 1.

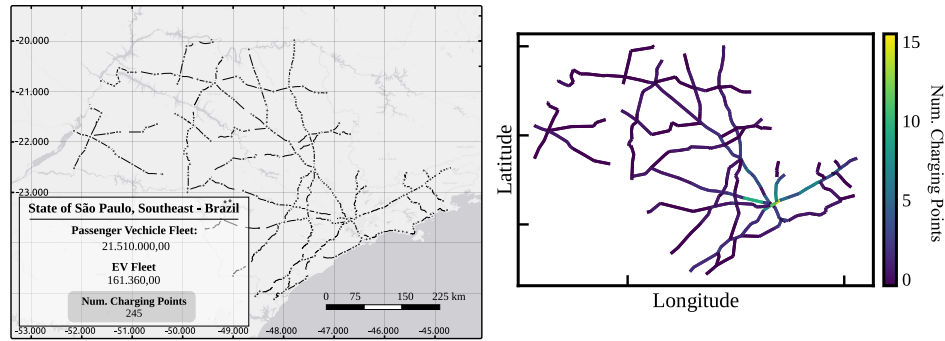


Figure 3: Recharge points forecast for the state of São Paulo.

5. Tests and Results

The proposed optimization model were coded in the mathematical programming package Gurobipy from Python language and solved with the optimization solver Gurobi [Gurobi Optimization, LLC, 2021]. The real-world planning problem considers the allocation of CS across the entire state of São Paulo (only for federal highways) in the southeast of Brazil. All data for the region and the passenger vehicle fleet are provided by the National Department of Transportation [DNIT, 2021]. In all studies, an annual interest rate is $\alpha = 10\%$ and a payback period of 5 years are considered; here, each year has 52 weeks. The IP model addresses the CS week-hourly operation problem for a set $\mathcal{T}$ with 168 points (total hours of the week). The length of the radius coverage is $\bar{r} = 25$ [km]. The energy tariff prices are based on a local Brazilian utility defined in [ANEEL, 2010], and all data for the investment values and the PV system parameters are available from [Solar, 2021]; it is considered that each carport has enough area ($\bar{a} = 25 \text{ m}^2$) to add up to 4 kW at each charging point for a PV panel with 280 Wp and 1.6 m^2 in area.

The application of the preprocessing approach is described in Sec. 5.1. Following, two studies are performed using a Monte Carlo study to provide 60 possible demand scenarios of EV charging. The first study (Sec. 5.2) applies the MINLP model to evaluate the locations and sizing for each candidate from the transportation system. The second study (Sec. 5.3) evaluates the benefits of planning alternatives on the CS operation planning stage. The same data of PV power generation are applied for both studies; a real solar radiation database is used to compute different weekly average generation for each candidate $l \in \mathcal{L}$.

5.1. Preprocessing of Transportation System Data

The original solution space ($\mathcal{L}$) is represented with an entire region with 366 links (Fig. 3); the traffic data of the state of São Paulo are also shown at the box in Fig. 3. The forecast for the EV fleet is provided to the reference year (5 year ahead) using the prediction of the Brazilian Energy Research Office [EPE, 2021], which foresees a 50% EV penetration in 25 years ahead from 2021. Therefore, based on the strategies described in Sec.2, the EV fleet provides the estimated scenario of charging points illustrated in the colormap in Fig. 3.

From the data unveiled in Fig. 3 and considering the 60 scenarios evaluated by the Monte Carlo Study, the MINLP model provides the most selected locations illustrated in Fig. 4. The following studies address the CS allocation optimization problem from an economic and technical perspective considering the locations and number of charging points indicated in Fig.3 and Fig.4, respectively. Planning alternatives (PV and PV + Net-metering) were evaluated individually by the MINLP model and compared with the base case, which assesses decisions to the CS locations without considering alternatives to support the operation.

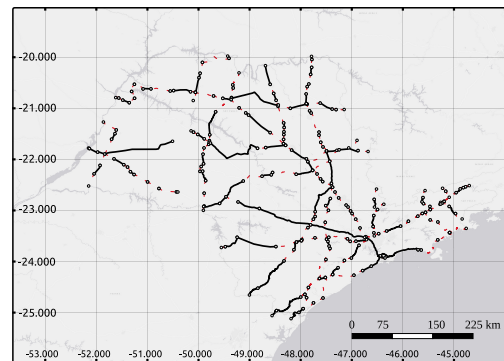


Figure 4: Selected locations for the CS infrastructure (black lines represent selected links and red dashed links represent unused locations)

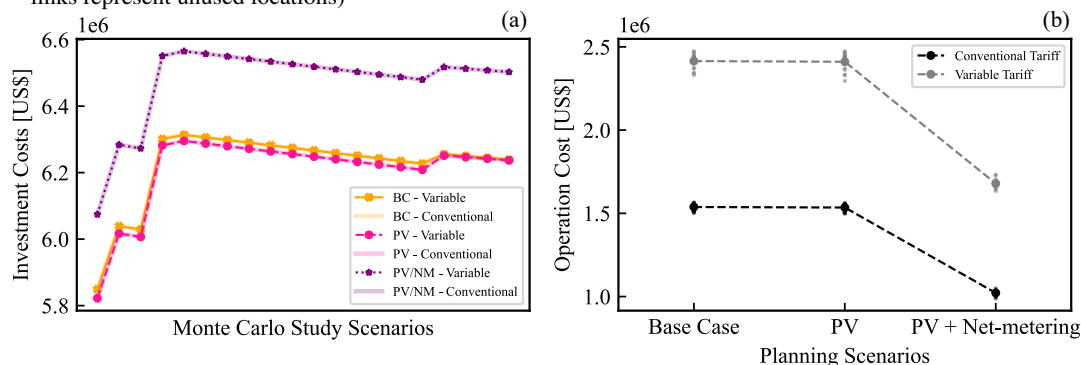


Figure 5: Economic aspects of results: (a) 95th percentile of the investment costs; and (b) average operation costs. Consider: base case (BC); PV system (PV); PV system and net-metering scheme (PV/NM).

5.2. Addressing the CS Location Planning

The first study evaluated 60 scenarios of recharge the EV fleet considering the topology illustrated in Fig.4. The planning alternatives and the two energy tariffs were assessed in these scenarios to compute the total investment costs, as illustrated in Fig.5-a. Note from Fig.5-a that there is no change in the investment costs of the CS and additional facilities to the two tariffs evaluated in this study. In addition, the similarity between the results of the base case (BC) and PV as a planning alternative indicates that the model chooses not to invest in building PV since there is no proper management of energy surpluses produced by these renewable sources; these results indicate the importance of meeting recharge demands at exact times. Including the net-metering scheme as a planning alternative, the model chose to build the PV over carports; therefore, an average increase of 6% in cost is observed when compared to the base case scenarios.

5.3. Addressing the CS Operation Planning

The second study verifies the benefits of planning alternatives to the CS weekly operation over the planning horizon. Using the alternatives (PV and net-metering), the MINLP model achieves an average reduction of 35% in operation costs, as illustrated in Fig.5-b. These results are obtained with 50% (conventional) and 70% (variable) of the PV carport systems using the entire available area at the CS; therefore, the optimization allows for saving investments to build the PV systems over carports. Figure 6 demonstrates these results.

As a support for the analysis of operation costs, the energy balance constraints allowed for defining the optimal demand management policy, as shown in the results in Fig. 7. The multi-objective approach proposed here supposes that all surplus energy (in Fig.7, exported energy) must

be used over the week ($\forall t \in \mathcal{T}$); the policy for the use of energy credits changes according to the tariff applied. As illustrated in Fig. 7, the management of credits (imported energy) in the variable tariff assesses the operation from a cycle policy (Fig. 7-a), while the conventional tariff considers the accumulation for later use (Fig. 7-b).

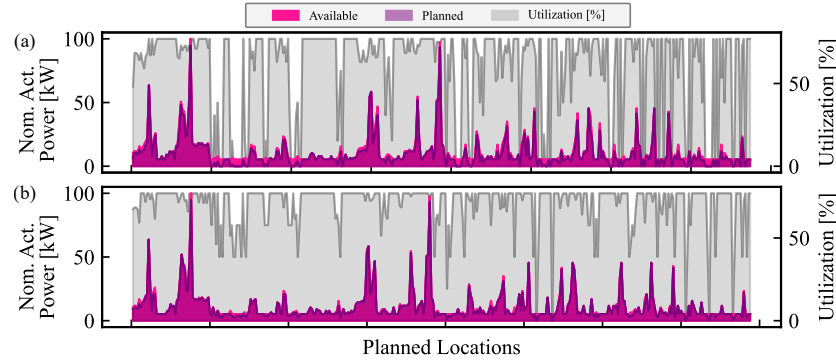


Figure 6: Designed PV capacities: (a) conventional energy tariff; and (b) variable energy tariff.

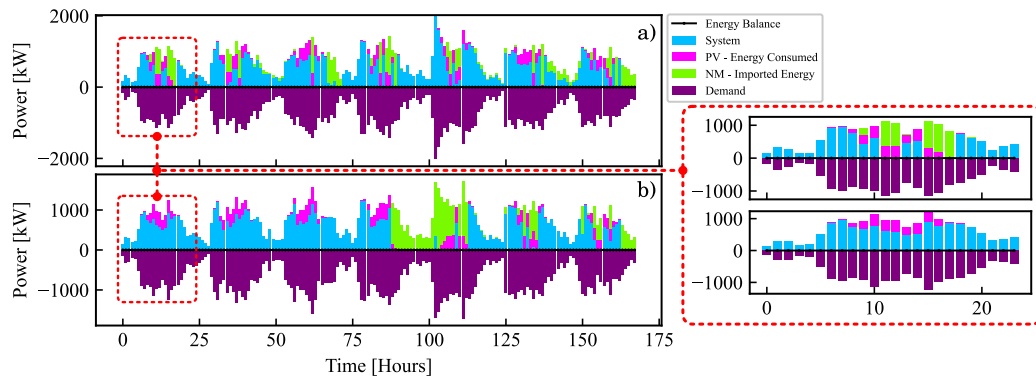


Figure 7: Optimal operation policy considering the planning of PV and net-metering: (a) variable energy tariff; and (b) conventional energy tariff.

6. Conclusions

An MINLP model for solving the CS allocation and sizing problem considering the PV systems and the net-metering scheme has been developed. The optimization strategy addresses the public data on the traffic and the transportation system, while the objective functions minimizes the investment and operation costs. The energy balance of the system is represented by a nonlinear constraints that takes into account the power generation from PV systems. Optimal solutions for the proposed model are obtained with an MINLP solver. EV travels are uncovered by the CS infrastructure up to 140 km, approximately 40% of an EV autonomy nowadays. The case studies put the approach into perspective with two tariff scenarios for the allocation of PV systems over carports. Even if the investment costs grow by up to 6% with the PV systems, the savings in operation can be 30% less than the base case value.

7. Acknowledgments

The authors kindly acknowledge the support of CNPq, Grants No. 422765/2021-0 and 309925/2021-5, and the São Paulo Research Foundation (FAPESP), Grants No. 2020/13578-4, 2016/08645-9, and 2020/09838-0.

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