Energy Demand Estimation of Electric Vehicle Charging Stations in Modern Energy Systems Planning

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ABSTRACT

The increase in the Electric Vehicles (EVs) fleet will raise the energy demand due to the expansion of the infrastructure of public charging stations (PCS). Before this happens, the electrical system must be adequately prepared to maintain operational stability. On the other hand, planning is always tricky in times of new technology development. Given this, this work presents a methodology for estimating the energy demand of PCS where the dynamics of electromobility and the location of the PCS are considered. The proposal was tested in a large metropolis in northeastern Brazil to demonstrate application in energy and urban planning.

Keywords: Public Charging Stations, Electric Vehicle, Electromobility, Graph Theory, Power Distribution Systems Planning.

Introduction

Although there is progress in electromobility, the consolidation of a 100% electric scenario depends, among other factors, on cost reduction and the infrastructure of Public Charging Stations (PCS) [1]. However, with a rise in the fleet, the electricity demand is expected to increase [2]. This hypothesis emphasizes the need for appropriate planning, given the need to maintain operational stability and balance the supply-demand relationship [3]. On the other hand, planning is always complicated when developing new technologies. In this case, the fleet is still negligible, and the loading infrastructure and benchmarking studies are insufficient and inconclusive.

That said, this paper presents a methodology for estimating PCS energy demand. Real data from traffic simulations and the geographical location of the PCS are used together, making it possible to determine the consumption at each charging point. The proposal was tested in one of Brazil's largest capitals, considering two prospective EV penetration scenarios where its application in energy and urban planning stages was demonstrated.

Proposed Methodology

The proposal can be explained in two blocks, as shown in Fig. 1. In the first block, an algorithm based on the Shortest Path Problem (SPP) can identify where the EVs need to be recharged and calculate the path and the SOC. The information is mathematically modeled in the second to estimate each PCS's energy consumption.

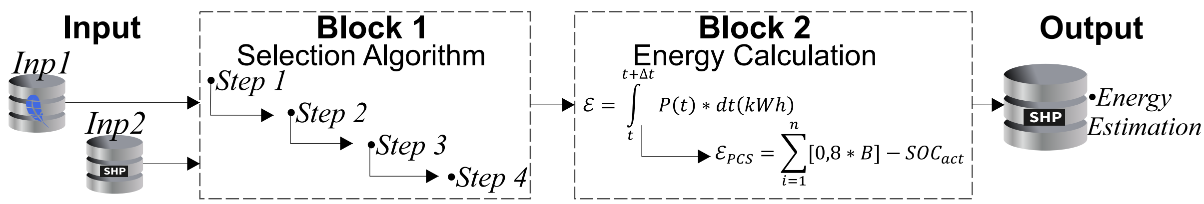

Figure 1: Proposed methodology architecture diagram.

A. Block 1: Selection Algorithm

Drivers of EVs and conventional vehicles behave very differently. This characteristic can be synthesized into two elementary factors: reach anxiety and the waiting time for loading (Which currently takes an average of 20 to 40 minutes). If the SOC is at low levels (Generally less than 30%), the path must be redirected for loading through an available PCS. Depending on how much energy you have left in your batteries, the nearest station is the best option [1]. In this way, the algorithm, illustrated in Fig. 2, emulates the situation above and provides data for calculating the energy demand of Block 2.

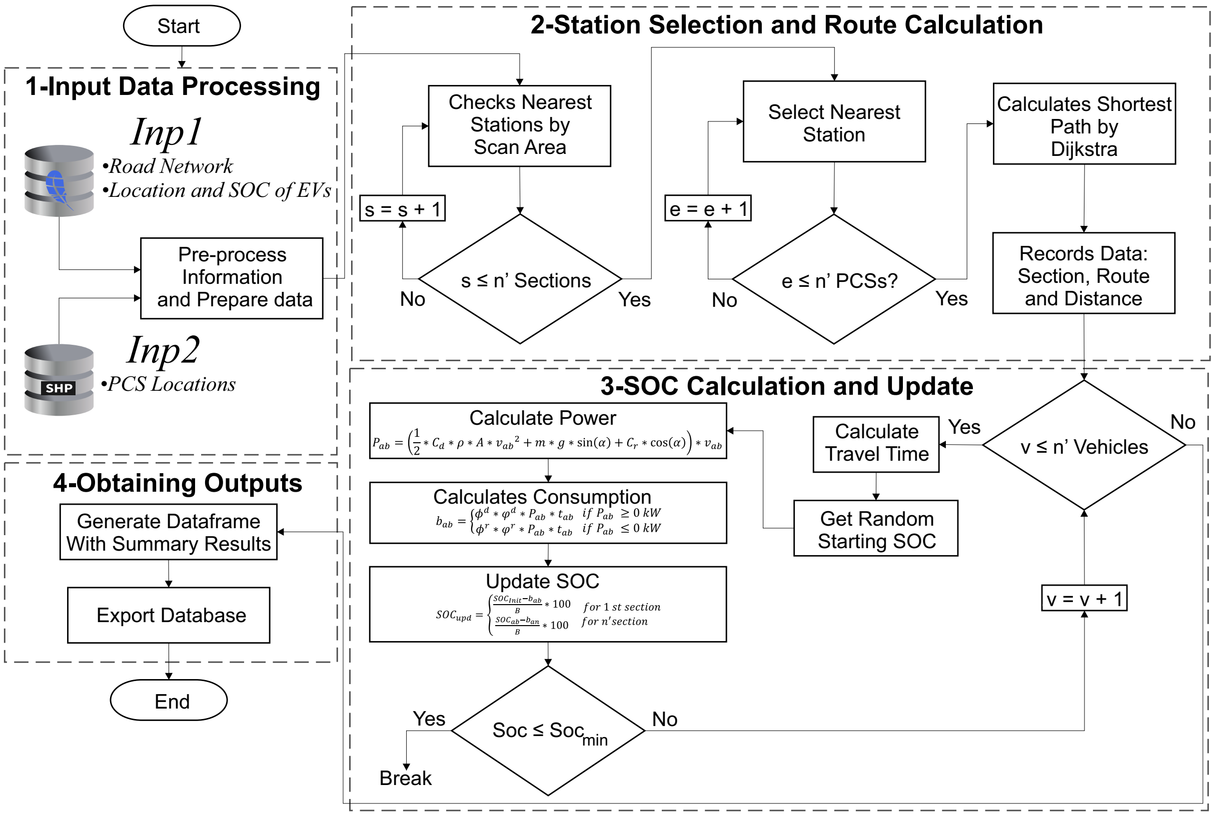

Figure 2: Flowchart algorithm: PCS selection, route choice, and SOC update.

a) Step 1: Input Data Processing

First, the input data is loaded and prepared to be modeled by graph theory [4]:

- ***Inp1*** **(Traffic Simulations)**: from this base, a road network was created yesterday where the vertices represent the EVs and the edges, the urban roads; the weight has been adjusted to match the length of each track. Additionally, the position and SOC of all EVs are processed to select those needing charging. The driver generally looks for charging when the SOC reaches between 20 and 30% [1].
- ***Inp2*** **(PCS Locations)**: concerns the geographical position of each PCS. This data can also be mapped according to the local charging infrastructure and georeferenced to compose the necessary spatial database. The base must be integrated into the previously modeled graph to form a new set of vertices.

b) Step 2: Station Selection and Route Calculation

In approaching the problem, the premise for choosing the route was based on the nearest station, emulating the actual behavior of the EV driver [1]. In the first loop, a scanning area is implemented to

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find the closest PCS around the EV, considering a predetermined radius. This alternative avoids the need to process the entire set of PCSs (Loaded in Step 1). If there is no PCS in this initial area, it is expanded until a location is found from which the choice can be made. In the second loop, calculating the vehicle's route between its stopping point and the chosen PCS is implemented, considering the entire road map imported in Step 1. This section was developed from the SPP approach and solved by Dijkstra's heuristic [5].

c) Step 3: SOC Calculation and Update

The EV energy consumption calculation was adapted from [6]. One of the reasons for the attractiveness of this model is the non-linear behavior; that is, it integrates factors closer to the actual consumption of the vehicle. In this model, the power required by the motor, the energy consumption, and the SOC are calculated, considering the path between your current location and the PCS selected in Step 2. The following assumptions were considered: 1) the speed and the angle terrain slope are fixed on the course, 2) the energy obtained by the regenerative braking system cannot be greater than the battery capacity, and 3) the state of charge of the batteries cannot be less than zero.

d) Step 4: Obtaining Outputs

In the last step, the data are compiled into tables and prepared to provide a file that summarizes the number of vehicles directed to each PCS and the updated SOC of each one. This file is used as input data for energy estimation in Block 2.

B. Block2: Energy Calculation

The energy consumed by the EV during charging can be modeled by integrating the power P during a time interval t that is, $P_t = V_t * i_t$ according to Eq. (1).

$$\xi = \int_{t}^{t+\Delta_t} P_t * dt(kWh) \tag{1}$$

The energy that the EV will demand is given by Eq. (2) being calculated by the term that determines the difference between 80% (Maximum limit commonly recommended by the manufacturer[6]) of the EV battery (B) and the updated SOC value when arriving at the PCS (SOC_{act}).

$$\xi_{PCS} = \sum_{i=1}^{b}(0.8 * B - SOC_{act}) \tag{2}$$

Application Case Study

Salvador (In Northeastern Brazil), with a fleet of over 1 million vehicles, was chosen to test the proposal's [7]. The input data were obtained from previously developed [3], and two scenarios of global penetration of EVs were considered: the first relative to 7% and the second 65%. In scenario 1, there are 46 PCSs, and in scenario 2,249.

A. Results and Analyzes

It is important to emphasize that the proposed analyses are carried out for a typical day, as provided by the input data used. Nevertheless, the methodology includes analysis for any period as long as the necessary data is in possession. First, in Step 1 (Fig. 2), the EVs needing charging are selected. The minimum SOC has been set to 25% of battery capacity for this selection. Thus, for scenario 1, 4,833 EVs were accounted for, and for scenario 6, 44,509. The analysis relative to the SOC update is performed using the histograms shown in Fig. 3. The superior figures show the SOC frequency distribution with which the EVs arrived at the PCSs and the inferiors, the percentage of charge required to supplement the

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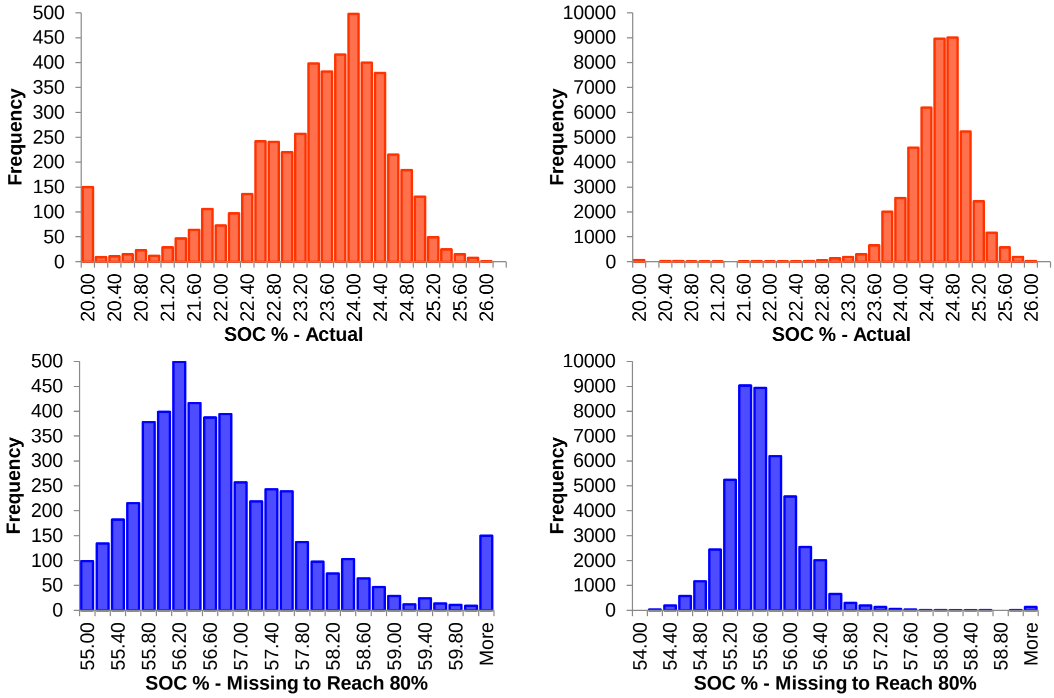
battery until it reaches 80% capacity. The results were reasonably grouped in both scenarios; most EVs sought the charging service with very close battery levels, with a variance of 2 percentage points.



(a) Scenario 1 (07%)

(b) Scenario 2 (65%)

Figure 3: Percentages of the current state of charge (Above) and to reach 80% battery (Below).

The analysis of energy consumption and number of EVs in each PCS is performed through Fig. 4. The horizontal axis lists the identifiers (ID) of the PCSs, while the two vertical axes show the number of EVs and the expected energy consumption (Calculated according to Eq. (2)). In scenario 1 (Fig. 4a), the low penetration resulted in less need for installed PCSs (46), reflected in the loading search. In this scenario, the three PCSs with the highest consumption recorded values very close to 400 MWh, and, in total, 142.32 MWh were consumed. In scenario 2 (Fig. 4b), there is evidence of greater energy demand, given the increase in the EV fleet and, consequently, the need for charging. In this case, the 249 PCSs reached a consumption of 1.34 GWh, an increase of 11 times the consumption registered in scenario 1. It is emphasized again that the results contemplate a typical day (24h).

Conclusions

The increase in the EV fleet will intensify energy consumption, changing several aspects of the electrical system. Considering this, the need emerges to propose models and create new tools that make it possible to integrate PCSs into the grid to estimate demand and its behavior.

This document presents a model for estimating the energy demand for future EV charging infrastructures. The results showed how the increase in the fleet tends to impact consumption and which facilities are more likely to receive vehicles. A premise of the proposal is that users, when they need to recharge, choose, as the only criterion, the nearest station. However, future work will address factors related to the user experience, such as waiting time, queue size, costs, and other variables that impact the decision.

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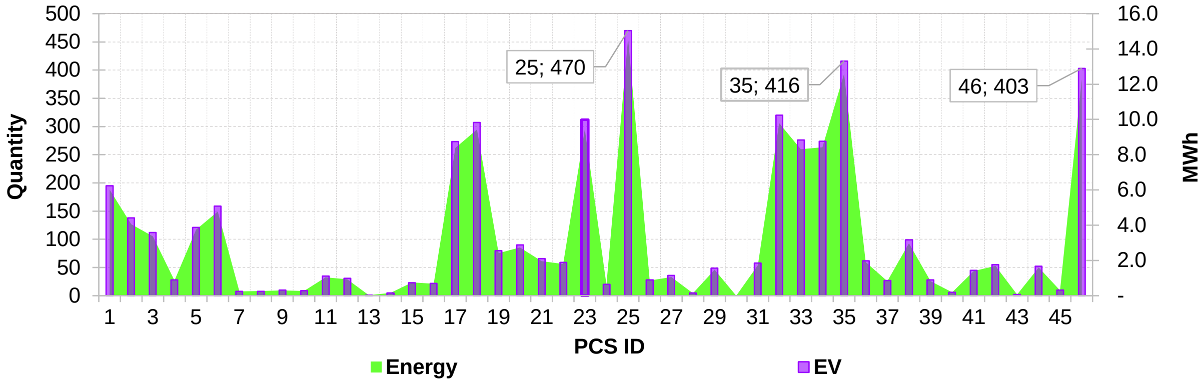
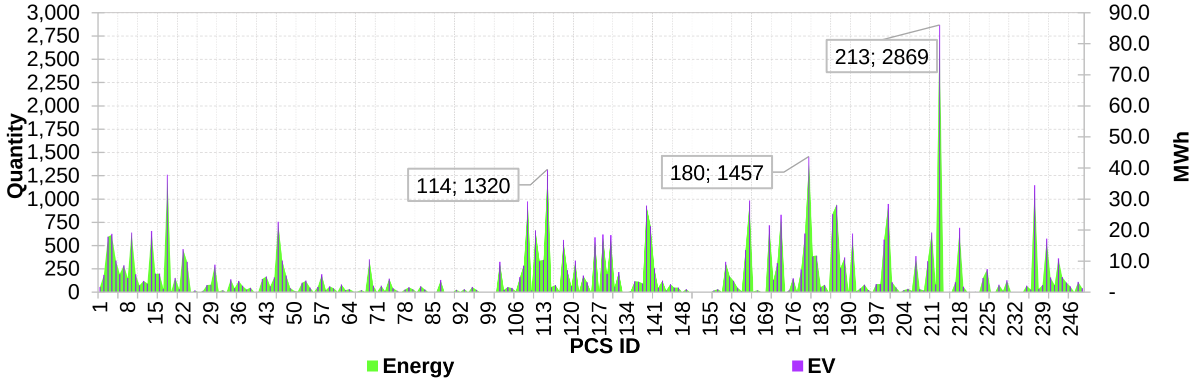


(a) Scenario 1 (07%)



(b) Scenario 2 (65%)

Figure 4: Energy consumption estimation and number of EVs in each PCS.

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