

Article

Operation Model Based on Artificial Neural Network and Economic Feasibility Assessment of an EV Fast Charging Hub

José F. C. Castro ^{1,2,*} , Augusto C. Venerando ^{3,4}, Pedro A. C. Rosas ^{1,2} , Rafael C. Neto ^{1,2} ,
Leonardo R. Limongi ^{1,2} , Fernando L. Xavier ^{1,2}, Wesley M. Rhoden ⁴, Newmar Spader ⁴,
Adriano P. Simões ⁴, Nicolau K. L. Dantas ⁵, Antônio V. M. L. Filho ⁵ , Luiz C. P. Silva ³ and Pérolla Rodrigues ²

¹ Department of Electrical Engineering and Power Systems, Federal University of Pernambuco—UFPE, Recife 50670-901, PE, Brazil

² Electrical Engineering Department, IATI—Advanced Institute of Technology and Innovation, Recife 50751-310, PE, Brazil

³ School of Electrical and Computer Engineering, State University of Campinas—UNICAMP, Campinas 13083-852, SP, Brazil

⁴ EDP Energias do Brasil, São Paulo 05069-900, SP, Brazil

⁵ Institute of Technology Edson Mororó Moura—ITEMM, Belo Jardim 55150-550, PE, Brazil

* Correspondence: filho.castro@ufpe.br

Abstract: The energy transition towards a low-emission matrix has motivated efforts to reduce the use of fossil fuels in the transportation sector. The growth of the electric mobility market has been consistent in recent years. In Brazil, there has been an accelerated growth in the sales rate of new electric (and hybrid) vehicles (EVs). Fiscal incentives provided by governments, along with the reduction in vehicle costs, are factors contributing to the exponential growth of the EV fleet—creating a favorable environment for the dissemination of new technologies and enabling the participation of players from sectors such as battery manufacturing and charging stations. Considering the international context, the E-Lounge R&D joint initiative aims to evaluate different strategies to economically enable the electric mobility market, exploring EV charging service sales by energy distribution utility companies in Brazil. This work describes the step-by-step development of an ideal model of a charging hub and discusses its operation based on a real deployment, as well as its associated technical and economic feasibility. Using EV charging data based on the E-Lounge’s operational behavior, an artificial neural network (ANN) is applied to forecast future energy consumption to each EV charging station. This paper also presents an economic analysis of the E-Lounge case study, which can contribute to proposals for electric vehicle charging ecosystems in the context of smart energy systems. Based on the operational results collected, as well as considering equipment usage projections, it is possible to make EV charging enterprises feasible, even when high investments in infrastructure and equipment (charging stations and battery storage systems) are necessary, since the net present value is positive and the payback period is 4 years. This work contributes by presenting real operational data from a charging hub, a projection model aimed at evaluating future operations, and a realistic economic evaluation model based on a case study implemented in São Paulo, Brazil.

Keywords: electric mobility; EV charging hub; forecasting energy consumption; artificial neural network



Citation: Castro, J.F.C.; Venerando, A.C.; Rosas, P.A.C.; Neto, R.C.; Limongi, L.R.; Xavier, F.L.; Rhoden, W.M.; Spader, N.; Simões, A.P.; Dantas, N.K.L.; et al. Operation Model Based on Artificial Neural Network and Economic Feasibility Assessment of an EV Fast Charging Hub. *Energies* **2024**, *17*, 3354. <https://doi.org/10.3390/en17133354>

Academic Editor: Riccardo Berta

Received: 26 May 2024

Revised: 28 June 2024

Accepted: 4 July 2024

Published: 8 July 2024



Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

The transportation sector has been a major contributor to greenhouse gas emissions worldwide, making this sector strategic when considering the internationally agreed upon commitments to combat climate change [1]. The decarbonization of transportation is a critical component of governments’ efforts to reduce greenhouse gas emissions in support of climate mitigation goals. The electrification of vehicle fleets, particularly in countries with increasing shares of renewable electricity supply, represents a key pathway toward low-carbon mobility [2]. According to the International Energy Agency (IEA), to achieve

the goal of net-zero carbon dioxide emissions by 2050, it would be necessary for 60% of global car sales to be electric vehicles by 2030, which is within 7 years [3]. For comparison, electrified vehicles (EVs) [4] comprised 2.5% of the total registrations in Brazil in 2022. The growth of the electric mobility market has been constant in recent years. In some European countries, such as Norway, the number of electric vehicle (EV) sales already surpasses that of traditional combustion vehicles.

In the specific context of the Brazilian market, it is observed that the cost of electrifying the vehicle fleet is still a sensitive point. In Brazil, EV prices have been decreasing over the years, but the cheapest fully electric vehicle (BEV—battery electric vehicle) may still cost more than twice that of the cheapest available conventional model (ICE—internal combustion engine).

Although the costs associated with the acquisition of BEVs are still significantly higher than those of conventional ICE vehicles, the operating and maintenance costs of an electric vehicle, compared to a gasoline-powered vehicle, can be four to six times lower. Thus, considering the total cost of ownership (TCO), integrating the components of acquisition cost and O&M in the long term, from the consumer's point of view, depending on the intensity of EV use and the costs associated with recharging, the TCO of BEVs may be equivalent to or even lower than that of ICE vehicles.

Considering a scenario in which the sale of EVs is intensified and increasingly encouraged by automakers, it is necessary to study in greater detail the experience of using this type of vehicle and the strategies for supplying the recharging service, since refueling a conventional combustion vehicle is profoundly distinct from recharging an electric one. In this context, within the scope of the ANEEL's (the Brazilian national electric energy regulatory agency) Strategic Call 22, the creation and practical testing of a new EV charging infrastructure model prioritizing the electric vehicle user's experience were proposed within the E-Lounge initiative, i.e., the implementation of a hub with multiple charging stations and the possibility of offering convenience services, providing an ideal experience for the EV user.

One of the challenges for the wide proliferation of charging infrastructure, particularly in developing countries, is the high costs associated with the deployment, acquisition, and operation of charging stations and auxiliary equipment. To evaluate economic feasibility, historical operation data of the E-Lounge are used as a case study. For long-term analyses, projections are made using an artificial neural network (ANN), a robust tool capable of capturing the inherent non-linearities in the variables of interest in the modeling of charging station energy consumption and peak power demand [5].

Paper Structure

This paper is divided into eight sections. A brief introduction to the context of the electrification of the transportation sector in Brazil was presented in this section. Section 2 presents a review of EV charging infrastructure models in terms of business models and billing strategies in different regions. Considering international experiences, Section 3 describes the challenges of developing charging enterprises worldwide, as the regional characteristics of each country necessitate adaptations to or reformulations of installations and services offered to users. After identifying the general interests of the target audience, a facility model for EV charging developed in the context of the Brazilian market is presented in Section 4, which describes the case of the E-Lounge project and presents historic operational data obtained through measurement. Using data from the initial months of operation (the energy consumption of each charging station), Section 5 presents projections for a ten-year future horizon using an artificial neural network (ANN). Aggregating the operational data and consumption projections of the charging stations, as well as considering the implementation costs and charging sales revenues, Section 6 presents an economic model for evaluating economic viability. The numerical results of the feasibility analysis are detailed in Section 7. Finally, the main conclusions and a summary of the results and experiences are described in Section 8.

2. Electric Vehicle Charging Infrastructure—An Overview

The growing demand for electric vehicles (EVs) and the need for charging infrastructure have driven the development of business models for the provision of charging services for electric vehicles through charging stations. Since the economic environment can drastically change between locations, there is still a lack of business and financing models for electric vehicle charging infrastructure.

Pricing and Business Models

A review on business models for electric vehicle charging infrastructure was presented in [6], identifying the main existing models, such as pay-per-use, monthly subscriptions, loyalty-based discounts, and integration with complementary services, such as parking and convenience stores. The authors also propose a new model based on a credit system, in which users purchase credits in advance and use them to charge their vehicles.

Considering the structure of utility service providers, business models for electric vehicle charging infrastructure can be segmented into six categories of commercial transaction models for charging services: pay-per-use, monthly subscriptions, energy sales, infrastructure leasing, public–private partnerships, and infrastructure investment. It was observed that the most effective models are those that allow users to pay flexibly based on their energy consumption.

Reference [7] analyzes the planning and operation of public charging infrastructure for electric vehicles based on a proposed value chain considering the different actors. This value chain is divided into the main actors intervening in the energy supply flow. It starts with the electric vehicle, followed by the infrastructure and service of charging stations, and finally ends with the power system infrastructure wherein the distribution system and the transmission system are responsible for providing electrical supply to the local electrical substation and to the regional or national electrical substations, respectively.

A case study analysis of models for managing electric vehicle charging infrastructure in different countries is presented in [2]. Based on international experiences and the aspects observed in different platforms/structures of various countries, due to the specific market characteristics of each region, it is still not possible to define a predefined ideal business model that is suitable in all contexts, as the choice of the model should consider local characteristics, such as the demand profile and the tariff structure by which energy costs are regulated.

In this context, this paper presents a general description of the technical and economic aspects associated with the implementation and operation of a test enterprise, with reference to a charging infrastructure solution developed under the Research and Development Program coded PD-07267-0021/2019, entitled “E-Lounge—A solution for recharging electric vehicles in fleets in Brazil”. In addition to the charging points, the proposed hub features power support through a battery energy storage system (BESS) using lithium-ion batteries, aimed at mitigating impacts on the power grid and ensuring the use of clean and renewable energy on-site (recharging EVs with clean renewable energy). This work describes preliminary technical studies estimating the energy demand. Finally, an economic analysis considering implementation, operation, and maintenance costs, as well as different possibilities of energy costs, is presented. One of the research objectives is to test a model that allows for the replication of the type of hub to encourage scalability to other locations (in different application contexts) and contribute to accelerating the expansion of recharging infrastructure for electric vehicles in the context of smart energy systems.

3. Assessing the Deployment Challenges for EV Charging

For the development of the evaluation model for the operation of the charging station, initially, we constructed a conceptual structure of the space type and how, qualitatively, the location would be used, impacting essential strategic issues such as the following: the type of vehicle charging equipment; local infrastructure; additional services; and the utilization scheme. These items directly impact the cost of implementation, operation, and

maintenance, as well as the generation of revenue necessary for the economic viability and long-term sustainability of the proposed charging infrastructure model.

The following topics describe the challenges and strategies to converge on essential strategic points for the development of the model infrastructure for the electric vehicle charging ecosystem.

3.1. EV Users' Charging Behavior

In terms of the stage of development of equipment and solutions for vehicle charging, it is observed that it is already widely available in the market, essentially requiring the acquisition and installation of charging stations and related connection elements. Considering conventional slow or semi-fast charging stations, their installation usually does not require drastic adaptations to power grids, making it technically feasible to install charging points in commercial and residential condominiums.

Studies indicate that up to 90% of charges will be carried out at home or at work [8], which allows us to infer that, considering the use of the vehicle in urban environments and the availability of charging locations for long periods (home/work), charges in public or semi-public locations (such as supermarkets and shopping malls) are for convenience; i.e., they will not be carried out due to urgent need.

In this way, there is an opportunity to offer a new type of space, an aspect already recognized by companies in other countries, such as Gridserve [9] and Fastned [10], which are both in England, and Sortimo [11] in Germany, where the experience becomes the center of operation, not just the vehicle charging operation.

In this context, the hypothesis mapped includes three fundamental conceptual pillars for the location: innovation, sustainability, and user experience. In this context, it was determined that the location should have renewable energy technologies with the least possible impact on the local distribution network, already projecting the model to mitigate restrictions related to the local energy infrastructure power grid.

Furthermore, the space should have a social area to attract not only those waiting for their vehicle to charge but also individuals interested in technology, as well as to enable actions that promote discussions around the future of energy.

For testing purposes, the chosen location should be easily accessible, in an area with high potential for the circulation of electric vehicle users and visited by people interested in the project's conceptual pillars.

3.2. Charging Hubs as Smart Energy Microgrid System

In line with the concept of sustainability and the integration of technologies in a smart microgrid system, EV charging hubs ideally should be equipped with a clean and renewable energy generation system, as well as an energy storage system, in order to reduce the impact (of connecting high-power charging stations) on the local distribution grid, as proposed in [12].

In the conceptual models in an analysis under the R&D project PD-07267-0021, both on-grid and off-grid solutions for EV charging are evaluated, considering aspects such as the planning and expansion of the distribution system, ensuring support to the grid without significant modifications to the existing infrastructure. The goal is to combine EV chargers, energy storage systems, and, where applicable, distributed generation from efficient and renewable sources, promoting an integrated solution that meets the charging requirements of vehicles and, through the secondary use of energy storage, provides support to the local electrical grid. In Figure 1, the main components/subsystems to be integrated into the EV charging facility model (called E-Lounge) are presented.

The deployment of battery energy storage systems (BESSs) in an EV charging hub offers advantages, such as improved grid stability through peak shaving and demand response, resulting in a reduced load and enhanced reliability. With the growth of the EV fleet, storage systems and demand control strategies for charging stations can be a tool to enable the connection of chargers. When operating electrically and logically integrated,

charging hubs can even function as microgrids with optimized dispatch. In microgrids, energy storage systems enhance operational flexibility in energy management, performing the function of enabling the power supply even in areas with low grid availability, thereby reducing the electrical and energy impact of connecting charging stations [12]. However, for the greater dissemination of these types of elements in distribution networks, decentralized microgrids/nanogrids must be formed, and challenges associated with technical connection rules [13] and, primarily, aspects of economic feasibility [14] must be overcome.

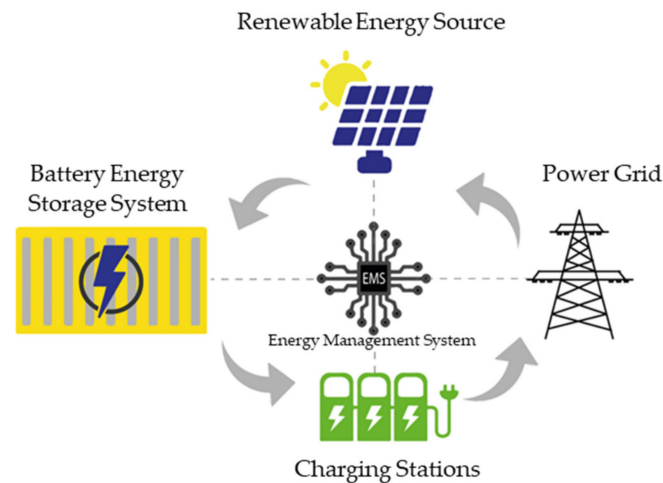


Figure 1. Components of smart energy system in an EV charging hub.

3.3. Conceptual Model for an Ideal Charging Hub

Figure 2 illustrates a generic conceptual model of a structure for electric vehicle charging, equipped with fast and semi-fast chargers, with an energy storage system and photovoltaic solar generation. Figure 2b presents a derivation of the model, considering only the presence of semi-fast chargers. It is possible to observe through the side view with the detailed allocation of chargers that there are different possibilities/strategies for positioning at different points of an establishment/enterprise.



Figure 2. Conceptual model for an ideal EV charging hub: (a) With fast and semi-fast charging stations; (b) Model with allocation of semi-fast chargers (side view).

3.4. Infrastructure and Complementary Amenities

Although electric mobility has been growing significantly lately, electric vehicle charging in Brazil is still not a large-scale movement, especially when compared to the number of gas stations and combustion engine cars observed. In this context, considering the

need to evaluate the economic operation of EV charging enterprises equipped with not only fast chargers but also photovoltaic generation systems and BESSs (battery energy storage systems), an electronic questionnaire was used. The aim was to understand, from the perspective of drivers/owners, the desirable characteristics for a charging hub to be implemented and define the services to be offered to users in general in the common areas of the E-Lounge in line with consumer expectations in the Brazilian market.

The preliminary results of the opinion survey are presented in Figure 3. As can be observed through the opinion survey, the options most desired by users for services/amenities are the following: (1) bathrooms, (2) food services, (3) internet (Wi-Fi), (4) convenience stores, (5) ATMs, and (6) car services, respectively.

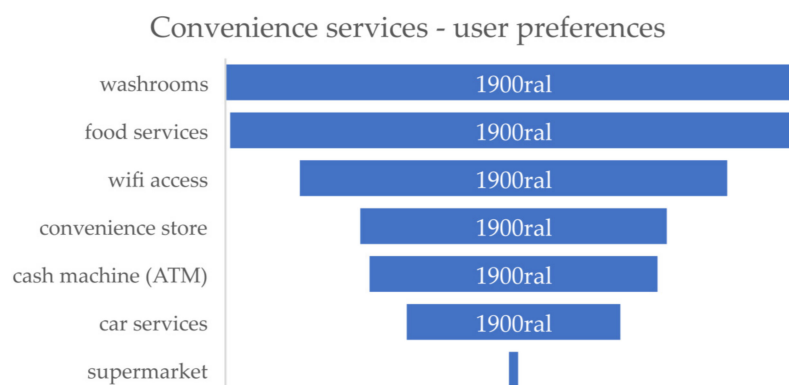


Figure 3. Opinion poll—EV users' preferences.

The questionnaire was answered by a group of EV owners. Seventy (70) responses were obtained. Most of the respondents were male (94%), with few responses from females (3%), and a small proportion preferred not to declare their gender (3%). Regarding the age group of respondents, 34% were between 45 and 64 years old, 30% were between 35 and 44 years old, 20% were between 25 and 34 years old, 12% were up to 24 years old, and 4% consisted of respondents over 65 years old.

3.5. Recharge and Billing Profile

As previously described, opinion surveys with electric vehicle users provided important data to design the utilization of the E-Lounge. For example, 29% of the respondents recharge their vehicles whenever there is an opportunity, not necessarily when the battery charge is low, which reinforces the convenience charging issue; and 41% consider the battery to be on "low charge" only when there is less than 20% energy remaining, meaning this scenario is unlikely to occur at a charging station that is outside of a safe and known location for the user (their residence and/or workplace). Restrooms, shops, food, Wi-Fi, and convenience stores were cited as the most important services to have at a public charging location.

Another surveyed point concerns the charging fee; 50% of the respondents find it fair to pay up to BRL 1.50/kWh for charging, and "Pay-per-use, without a plan", "Monthly plan, with a discount on the charging fee", and "Prepaid plan, similar to cellphone plans" were the most cited charging models as choices for payment. In the R&D project, the values and charging models are evaluated within the constructed model and then tested on-site at the E-Lounge hub. The following topic presents an economic analysis, considering the charging data described previously.

4. E-Lounge Charging Hub

After conducting the studies described above and considering design constraints, the E-Lounge was located in the city of São Paulo/SP in the Pinheiros neighborhood. In its common area, the location features social spaces (with outlets for electronic devices such as

cell phones and computers), a café, washrooms, and four areas for partner installations. Figure 4 illustrates a drawing of the allocation of stations and the associated charging infrastructure adapted to the conditions of the selected installation site.

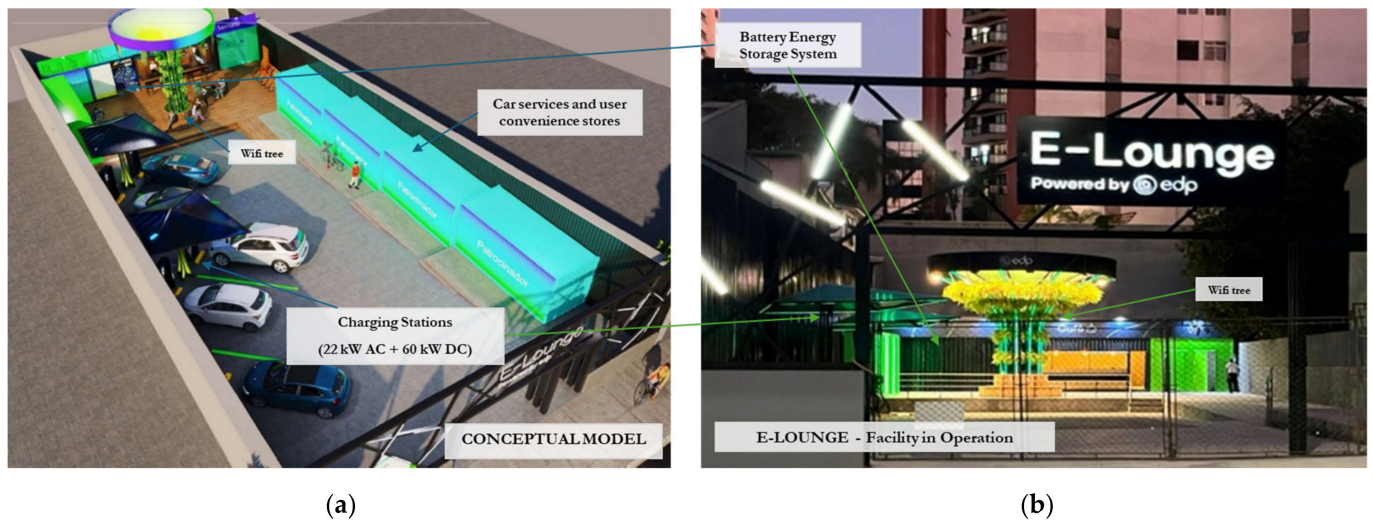


Figure 4. Charging hub final model: (a) Conceptual design; (b) E-Lounge—EV charging hub (infrastructure deployed) located in the city of São Paulo/SP.

For EV charging services, the E-Lounge has four charging stations with 22 kW each, totaling 88 kW of AC installed charging capacity, as well as a fast-charging station of 60 kW with two CCS (combined charging system) type 2 plugs. Figure 5 illustrates the single-line conceptual electrical connection of the equipment. In essence, the main difference between AC charging and DC charging from the user's perspective is the charging speed. AC charging uses onboard converters within the vehicle, limiting the power delivered to the batteries. In contrast, DC chargers use external converters (offboard), enabling the use of higher-power AC/DC converters and increasing the charging current to the batteries (DC chargers are commonly known as fast charging stations [15]). A review of electric vehicle charging technologies, standards, architectures, and converter configurations can be found in Ref. [16].

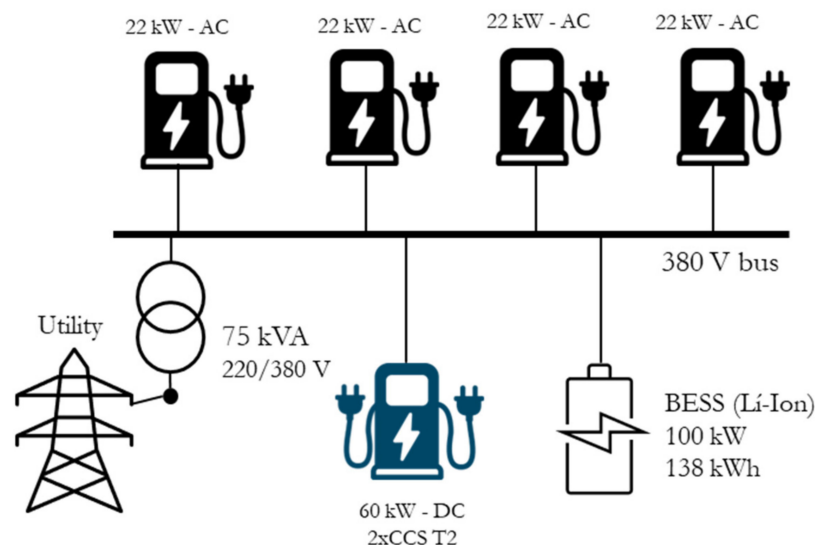


Figure 5. E-Lounge single-line conceptual electrical connection of equipment.

There is a 100 kW battery energy storage system, with an energy capacity of 138 kWh, based on lithium iron phosphate (LFP) battery cell technology. The E-Lounge model is a sustainable ecosystem of electric vehicle charging, structured in a microgrid format to reduce the impact generated by the EV charging stations' peak power operation on the distribution network. Figure 6 illustrates the power supply dynamics for a day of operation. The BESS/EMS (energy management system) power control algorithm is configured to limit the power supplied by the network to 70 kW. BESS recharging preferably occurs during the nighttime period, from 10:00 p.m. to 04:00 a.m. During peak network hours (4:30 p.m. to 6:30 p.m.), power management also seeks to reduce the power requested from the distribution grid (the peak shaving mode is illustrated in Figure 5), in an application associated with reducing energy consumption during peak hours.

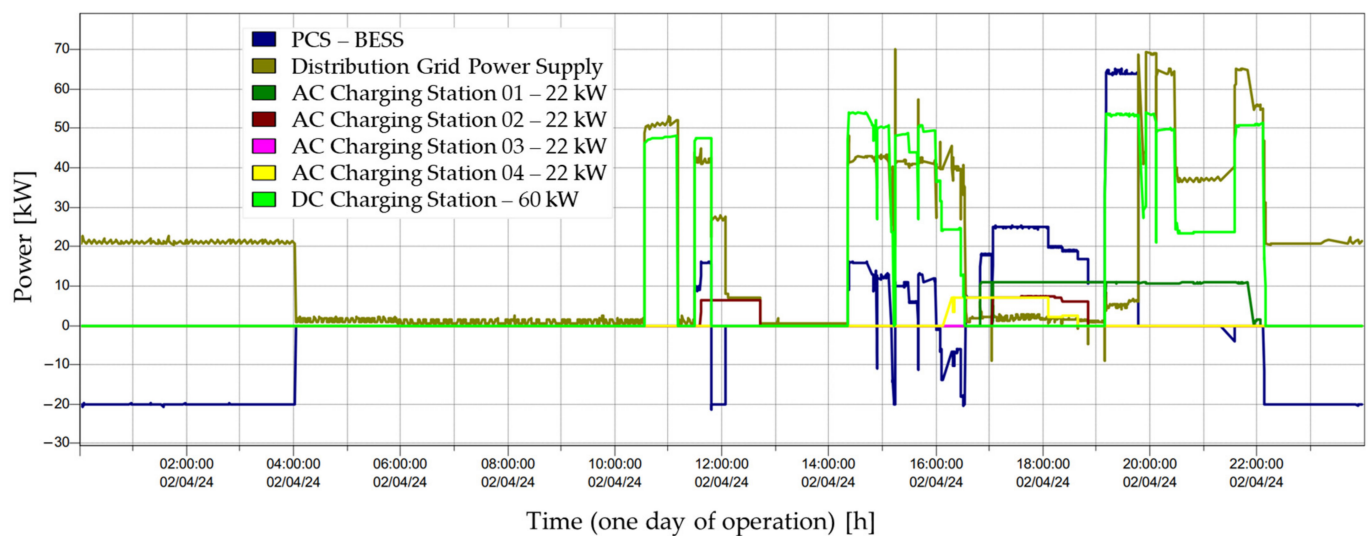


Figure 6. E-Lounge—EV charging hub: BESS/EMS power control operation.

4.1. EV Charging Frequency and Energy Consumption

One of the critical aspects for making charging ventures viable is the charging frequency or the number of vehicles using the charging stations. To couple the sizing and specifications of the components with the reality of the market, keeping in mind the expected lifetime of the equipment, power demand and energy consumption estimations are needed. This information is essential but difficult to measure since public charging points can be accessed by different types of users with different profiles.

To estimate the energy consumption of EV stations, the first step is to model the electric vehicle fleet. Mathematical models can be applied to make projections for and scenarios of the adoption of electric vehicles and charging energy consumption for a charging station, as presented in [15]. However, the utilization rate of charging stations can vary significantly depending on the context (the nearby residents, traffic flow, proximity to intercity transport routes, location, and regional fleet, among other aspects). Due to the early stage of development of the electric mobility market in Brazil, there is a lack of operational data to support the proposition of charging station models adequately tailored to the socio-economic reality of users. In this context, one of the main aims of the R&D project is to test a model of supply infrastructure and support service chain for the charging infrastructure in the country, considering the E-Lounge as a case study. The following section describes the consolidated real data associated with its operation, regarding the quantity of charging events and energy consumed in the first ten months of its operation.

4.2. Historical Operational Data for the E-Lounge Charging Stations—Period from June/23 to March/24

At the start of the E-Lounge's operation, some initial data were recorded. Table 1 illustrates the quantity of recharges and the energy delivered to EVs each month from June/23. It is possible to observe that the number of charging events (and associated energy) shows a growing trend, as also illustrated in Figure 7 and through the trend related to the moving average. In the first six months of operation, as an incentive, the use of the charging stations was free (there was no fee/charge for EV recharges). Charges for EV recharges began from the seventh month of operation onwards. Additionally, there were initially four AC charging stations in the first 6 months. The 60 kW DC fast charging station was installed in the seventh month (and operated for one month with free charging). After the initial testing period, a payment system based on the energy provided was implemented, with a tariff of BRL 1.50/kWh for semi-fast charging at AC chargers and BRL 1.85/kWh for fast charging at DC chargers.

Table 1. Number of recharges and energy delivered each month of operation based on installed capacity and recharge cost.

Operation Month	Month/Year	Total Energy (kWh/Month)	Number of EV Charging Events/Month	Charging Stations' Capacity Installed	Cost of AC Recharging (BRL ¹ /kWh)	Cost of DC Recharging (BRL ¹ /kWh)
1	June/23	41.53	19	88 kW: 4 × 22 kW	0.00	-
2	July/23	210.15	19	88 kW: 4 × 22 kW	0.00	-
3	August/23	1036.07	123	88 kW: 4 × 22 kW	0.00	-
4	September/23	2393.74	180	88 kW: 4 × 22 kW	0.00	-
5	October/23	2766.48	161	88 kW: 4 × 22 kW	0.00	-
6	November/23	5948.96	350	88 kW: 4 × 22 kW	0.00	-
7	December/23	5203.02	286	148 kW: 4 × 22 + 1 × 60 kW	1.50	0.00
8	January/24	4720.77	226	148 kW: 4 × 22 + 1 × 60 kW	1.50	1.85
9	February/24	7001.74	301	148 kW: 4 × 22 + 1 × 60 kW	1.50	1.85
10	March/24	8715.42	387	148 kW: 4 × 22 + 1 × 60 kW	1.50	1.85

¹ BRL: Brazilian real.



Figure 7. Charging events—operational data: (a) Monthly energy delivered (associated with EV charging); (b) Number of charging events.

Since the beginning of the E-Lounge's operation, considering the period from June to March (1 June 2023 to 31 March 2024), 2052 recharges were performed. The total energy delivered during this period (the energy measured at the charging terminals of the plugs at the connection point of electric vehicles) was 38.037 MWh. Figure 8 illustrates the accumulated values of recharges and electrical energy supplied during the period.

Figure 9 illustrates the historical data associated with the operation of the 60 kW DC charging station for the 10th month of its use (March 2024). Figure 10 illustrates the daily quantity of recharges, and Figure 11 illustrates the charger usage time. Over the 31 days, 219 recharges were performed, delivering a total of 6.343 MWh to the electric vehicles. On average, there were seven recharging events per day, each with an estimated consumption of 28.95 kWh per recharge and 204.62 kWh per day. The recharges have an average duration of approximately 59 min and 30 s. The DC charger was responsible for 72.78% of the energy delivered and 56.59% of the recharges for the month.

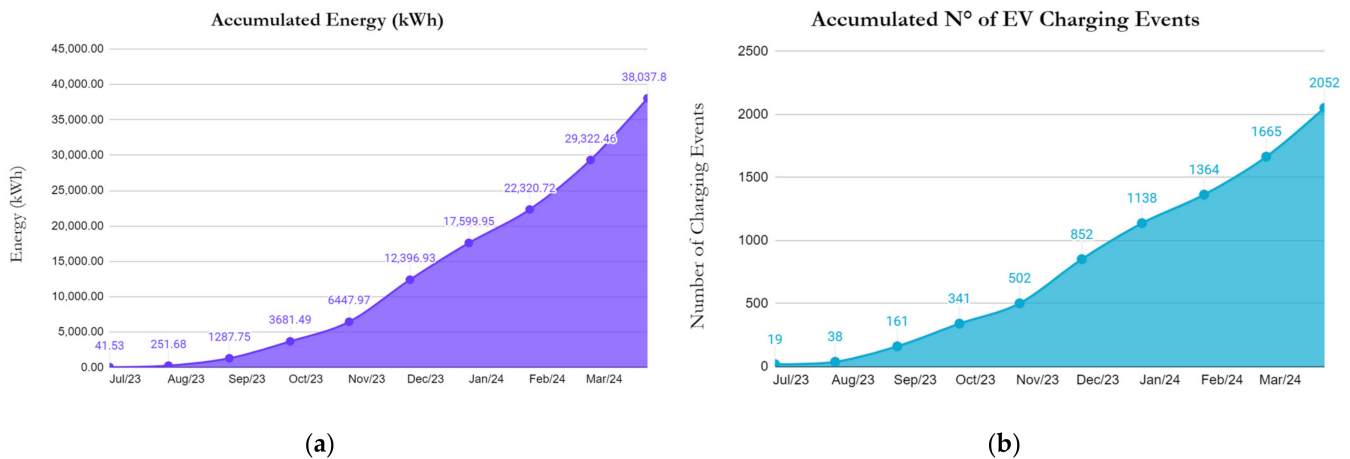


Figure 8. Charging events—operational data: (a) Energy (accumulated values over the months); (b) Number of EV charging events.

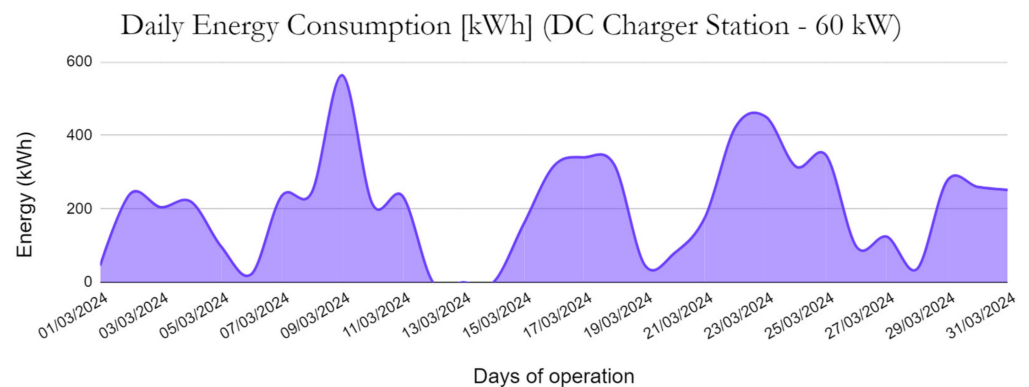


Figure 9. DC charger (60 kW) operational historic data—Daily energy consumption associated with EV charging.

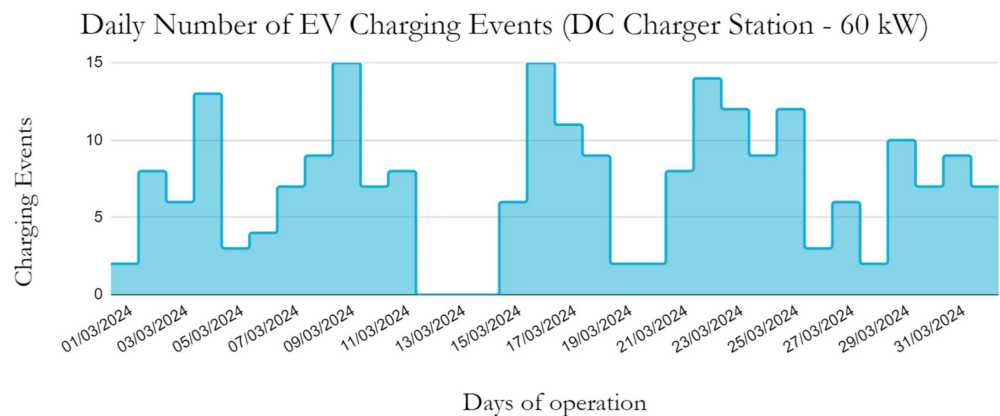


Figure 10. DC charger (60 kW) operational historic data—Daily number of EV charging events.

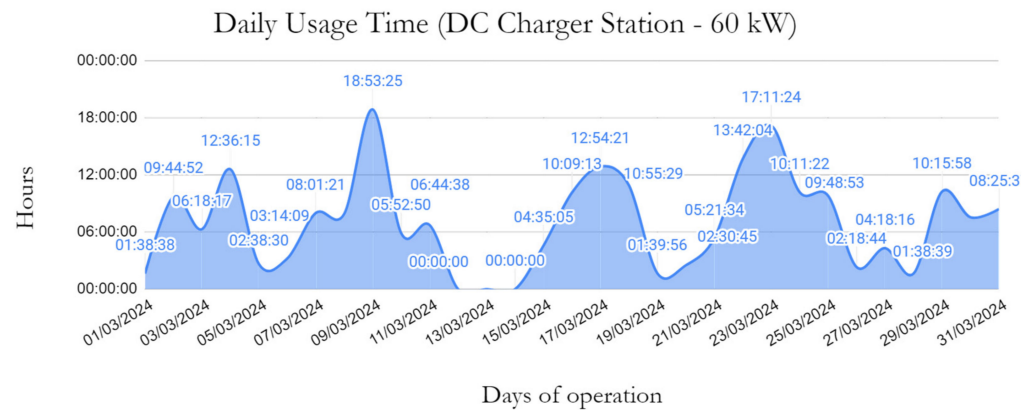


Figure 11. DC charger (60 kW) operational historic data—Daily usage time (hours per day).

5. Artificial Neural Network to Estimate EV Energy Consumption Projection for the E-Lounge

Considering the historical data associated with recharges at each charging station of the E-Lounge, projections of usage for each charger can be employed to evaluate the feasibility of its future operation.

Forecasting methods can be based on curve fitting, time series techniques [17], and artificial intelligence (AI) techniques, among others. Methods based on AI, specifically utilizing artificial neural networks (ANNs), have the advantage of capturing learning obtained through data processing. ANNs offer significant improvements over conventional forecasting methods by leveraging the ability to model non-linear relationships, automatically learn relevant features, handle high-dimensional and varied data types, and effectively manage sequential data. These strengths enable ANNs to make accurate forecasts and adapt to a wide range of applications [18].

In this regard, an ANN trained using the Levenberg–Marquardt method [19,20] with its performance measured through the MSE (the mean squared error) [21] was used to project the energy associated with each charger for a horizon of ten years. The ANN was trained with the historical data from each charger. For each charger, a dataset of 190 days was used for training and validation.

While artificial neural networks have been applied to forecasting aggregated load profiles [22] and EV charging power peak demand [5], in this paper, the E-Lounge's data are used to project the energy consumption associated with each charger from a group of five stations located in the same space at an EV charging hub. Then, these projections feed into an economic model to verify its long-term feasibility.

Figure 12 illustrates the general topology of the ANN for each EV charging station based on a two-layer (i.e., one hidden layer) feed-forward neural network. To predict future consumption values ($y = E_c$), the network is trained using as input the historical data recorded at each interval t , including the number of available plugs at the location (N_c), the energy consumption recorded at each plug (E_c), and the cost (EV charging fee—BRL/kWh) associated with each plug (T_{C-EV}). The input samples are automatically divided into training, validation, and test sets. The training set is used to teach the network. Training continues as long as the network continues improving on the validation set. The test set provides an independent measure of network accuracy. The input dataset is composed of 189 days of operational history. The target dataset for training the ANN consists of energy consumption measurements for each charger over a period of 189 days of operation, corresponding to six months of operation (from October/23 to March/24).

The following section describes the results of the daily consumption forecast. Initially, the forecast for one of the AC chargers (for plug 02) is presented, followed by the forecast for the 60 kW DC charger, and finally, for the E-Lounge.

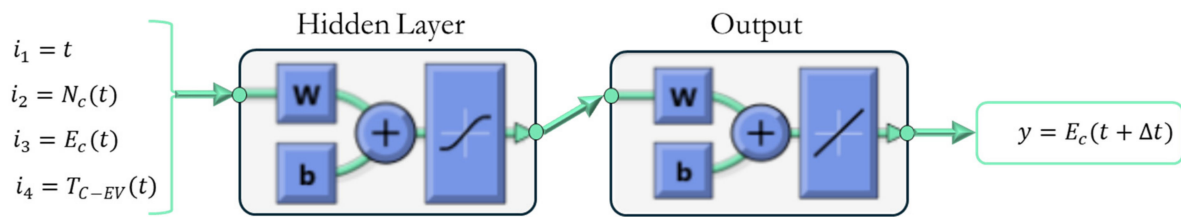


Figure 12. Two-layer artificial neural network (ANN) for EV charging station energy consumption forecasting.

5.1. Recharge Projection for the 22 kW AC Charger

For the AC charger (plug 02), an ANN with 80 neurons in the hidden layer was used with the structure/topology illustrated previously in Figure 12. After training, the mean squared error was minimized (at epoch 5), as shown in Figure 13a. The ANN's performance can be measured in terms of the mean squared error (MSE), calculated according to Equation (1) and shown in log scale in Figure 13a.

$$MSE = \frac{1}{n} \sum_i^n (y_i - \hat{y}_i). \quad (1)$$

where y_i is the desired neural network output, $\hat{y}_i$ is the neural network output, and n is the number of output nodes. The MSE rapidly decreased as the network was trained (over the epochs). The selected training function for the network was the Levenberg–Marquardt function due to its fast convergence. The performance of each of the training, validation, and test sets is shown. The final network (selected for the energy projections) is the network that performed best on the validation set (at epoch 5).

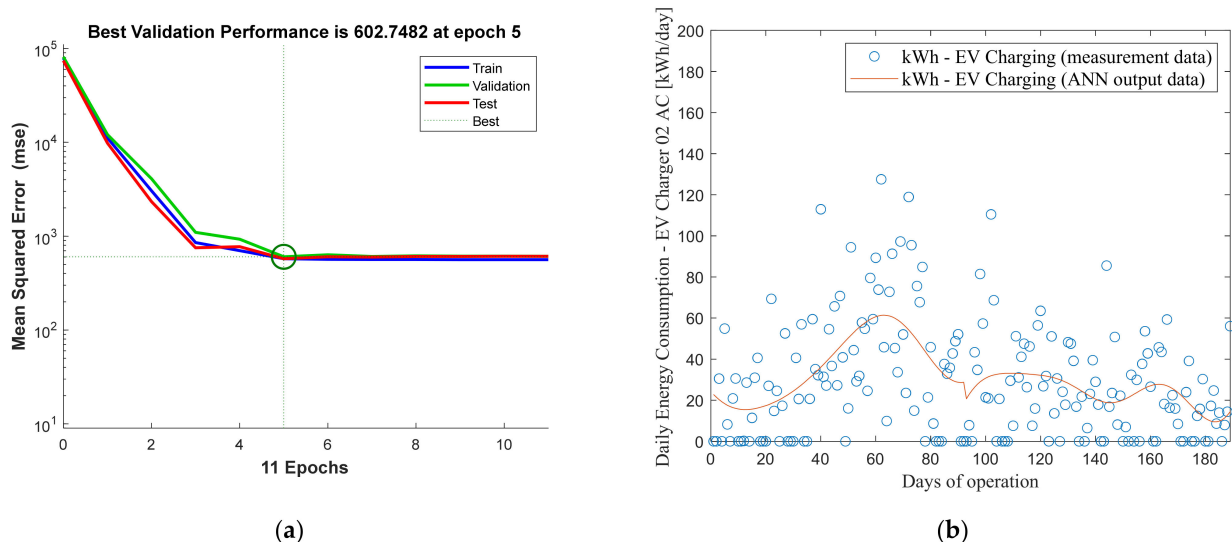


Figure 13. ANN training using E-Lounge AC charger historic operational data: (a) Error variation during the training process; (b) Result of the ANN fitting for AC charger 02.

Figure 13b illustrates the comparative result of the prediction using the ANN and historical data, in which it can be observed that the ANN captures the variation trends of the variable associated with the daily consumption of charger 02 (AC 22 kW).

Figure 14a illustrates the projections of daily consumption with recharges, considering a period of 10 years. Figure 14b shows the expected average value of daily consumption, considering the annual average predicted by the ANN for charger 02 of the E-Lounge.

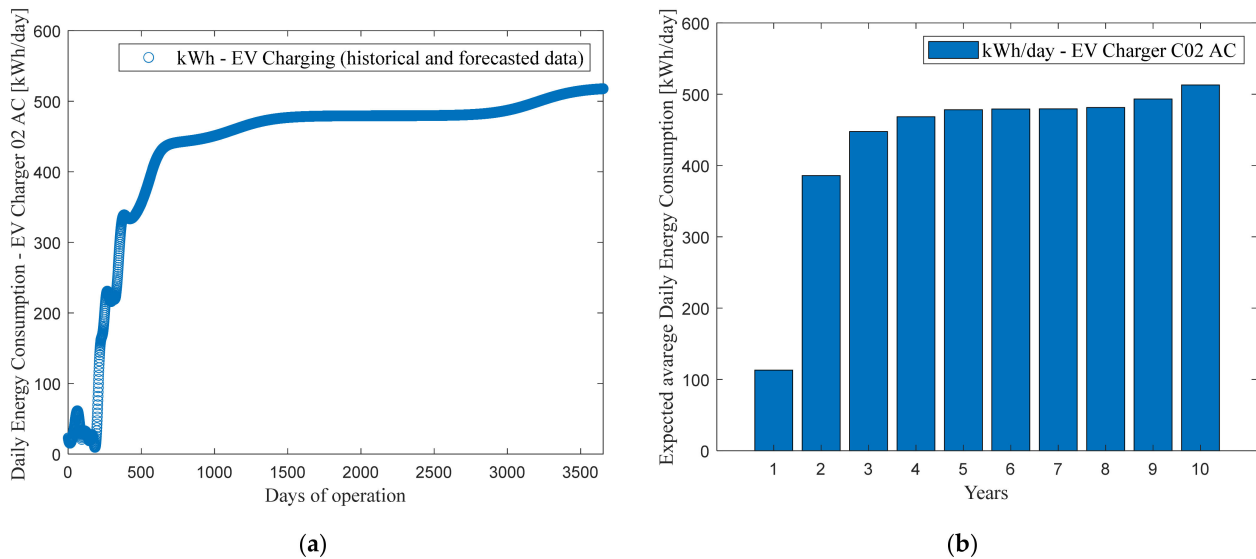


Figure 14. ANN projection results—E-Lounge AC charger forecasted data: (a) Projection results of recharge in kWh/day for charger 02; (b) Projection of average annual recharge in kWh/day for AC charger 02.

5.2. Recharge Projection for the 60 kW DC EV Charging Station

For the DC EV charger (station 05), an ANN with one hidden layer and 15 neurons was used. After training, the mean squared error was minimized at epoch 5, as illustrated in Figure 15a. Figure 15b illustrates the comparative result of the prediction using the ANN and historical data. It can be observed that, despite the dataset dispersion, the ANN captures the variation trends of the variable associated with the daily consumption of charging station 05 (DC—60 kW CCS).

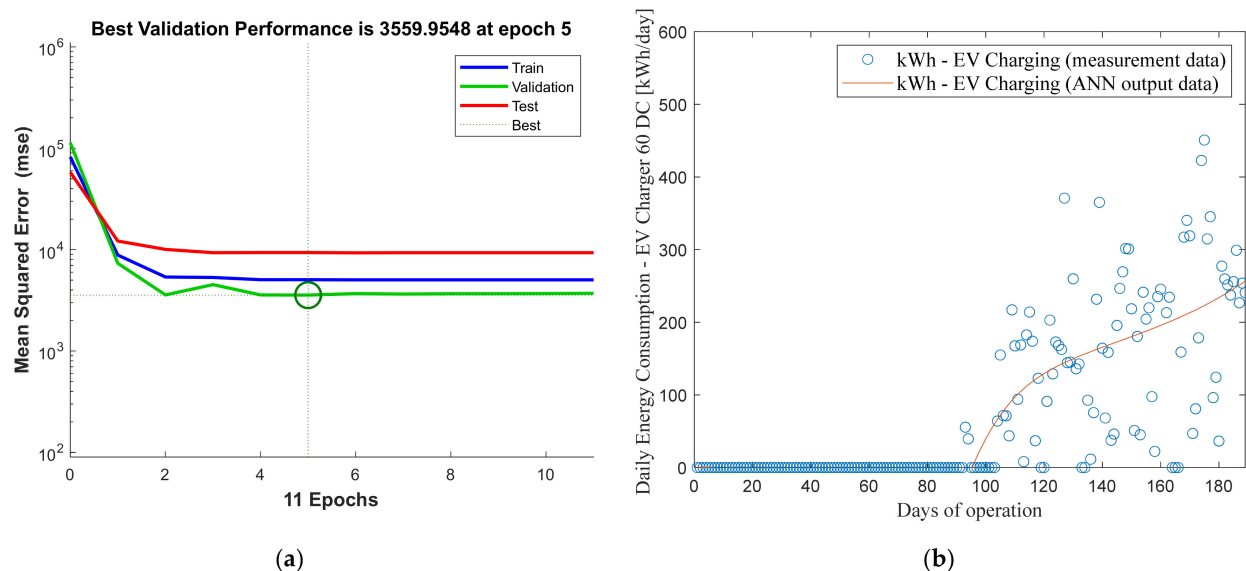


Figure 15. ANN training using E-Lounge AC charger historic operational data: (a) Error variation during the training process; (b) Result of the ANN adjustment for charger 05 (DC 60 kW).

Figure 16a illustrates the projections of daily consumption (EV recharges), considering a period of 10 years (3650 days). Figure 16b shows the expected average value of daily consumption, considering the annual average predicted by the ANN for the 60 kW DC charger.

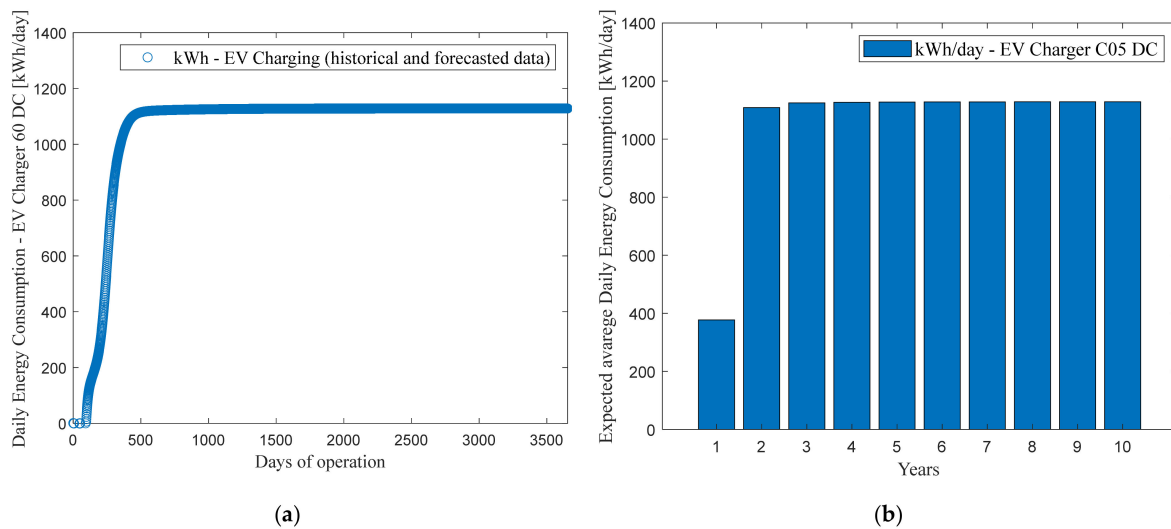


Figure 16. ANN projection results—E-Lounge AC charger forecast data: (a) Projection results of recharge in kWh/day for charger 05 (DC-60 kW); (b) Projection of average annual recharge in kWh/day for charger 05.

5.3. Recharge Projection for the E-Lounge

Considering the individual projections of each charger/plug, the projection of consumption/energy delivered by the E-Lounge, integrating the energy from the five chargers, is illustrated in Figure 17, as per Equation (2) as shown below:

$$E_{total} = \sum_{k=1}^{N_c} E_c(k), \quad (2)$$

where E_{total} is the forecasted energy of the E-Lounge, estimated as the sum of the energy from the N_c chargers, with each k -th one having a forecasted daily energy consumption equal to E_c . It can be observed from Figure 17 that the projections indicate accelerated growth until the third year, followed by relative stabilization. The stabilization occurs without reaching the maximum utilization limit, equivalent to the continuous, uninterrupted use of all plugs for 24 h. This is due to the pattern, captured by the ANNs, of lower usage of the DC charger during the nighttime period. The energy consumption recharge projections are variables/inputs to support the model of economic viability (as described in the following sections, Sections 6 and 7).

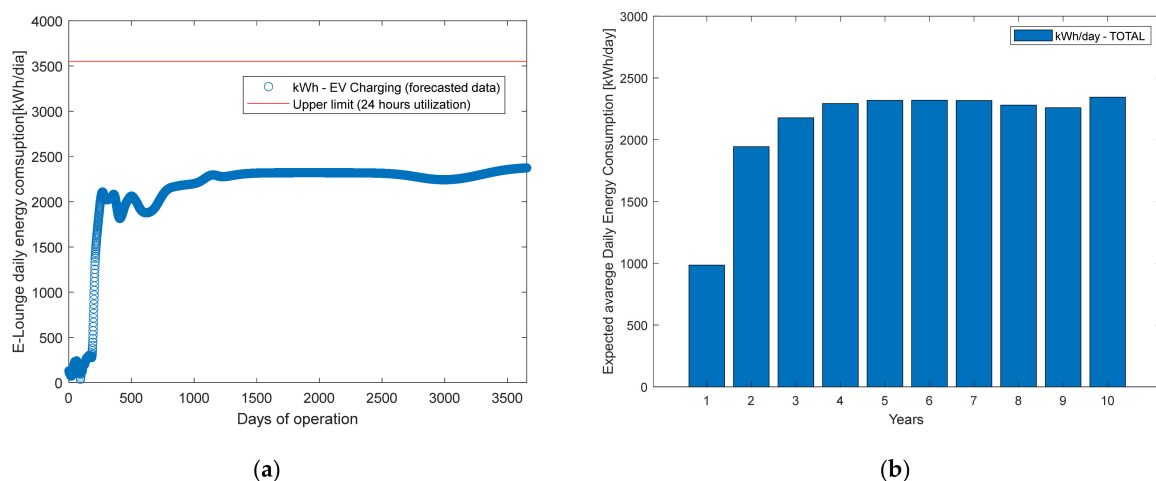


Figure 17. ANN projection results—E-Lounge AC charger forecast data: (a) Recharge projection in kWh/day at the E-Lounge; (b) Projection of average annual recharge in kWh/day at the E-Lounge.

6. Economic Feasibility Assessment

One of the challenges in disseminating charging infrastructure is the viability of enterprises. In some countries, research indicates that due to high initial investment costs and low, uncertain future demand, the EV charging business may not be feasible [23,24]. To make it viable, charging operators must explore additional revenue sources, such as advertising, commodity sales, parking fees, and food services, alongside the charging fee [25]. Moreover, government subsidies play a crucial role in sustaining public charging stations. Therefore, a robust economic model, based on consistent data, is needed to allow charging station operators to recover their expenditures while offering EV consumers a charging price competitive with that of internal combustion engine vehicles [23,26].

In models based on the commercialization of charging energy, the energy required at each charger depends on the number of vehicles served, the users' charging profile, and the storage capacity of EV batteries, among other parameters. One of the basic premises for evaluating the economic feasibility of a charging station is to estimate the utilization of the equipment (the number of recharges per day, daily energy consumption, and hours of use, among others). Considering the E-Lounge model, this section describes the mathematical representation of the cost structure associated with the charging station. The objective is to evaluate the feasibility of the implementation alternative, aiming to contribute by providing information to enhance the dissemination of a similar charging infrastructure.

Economic Modelling for EV Charging Station Hubs

The main costs associated with charging stations can be divided into three categories: investment costs, fixed costs, and variable costs [27]. These costs will use the information provided by the project as premises. In a given year of operation, the main investment components in the charging station hubs can be segmented into the following modular costs of the subsystems:

$$C_{i-CSH} = C_i(ESS) + C_i(PV) + C_i(CS) + C_i(Con) + C_i(gi), \quad (3)$$

where $C_i(ESS)$ is the investment cost in the energy storage system; $C_i(PV)$ is the investment cost in the energy generation system (e.g., a photovoltaic plant); $C_i(CS)$ is the investment cost for acquiring the charging stations; $C_i(Con)$ is the investment cost for acquiring and installing the equipment necessary for connecting the charging stations to the utility grid (associated with panels, transformers, and general electrical equipment); and $C_i(gi)$ is the cost associated with general civil infrastructure adjustments (such as foundations, earthworks, concrete bases, flooring, and general infrastructure adaptations).

To economically evaluate different sizing alternatives in charging station hubs, one of the economic objectives can be the maximization of revenues $Rev(h,y)$ associated with the investments over the hours of operation, considering the long-term operation period (this period can be, for example, the useful life of the assets), as described in Equations (4)–(7) as follows:

$$\max \sum_{h=1, y=1}^{H,T} Rev(h,y) \quad (4)$$

$$Rev(h,y) = benPV(h) + benCS(h) + benESS(h) - C_{varop}(h) - C_{i-CSH}(y) \quad (5)$$

$$benSFV = \sum_{h=1}^H \gamma(h) \times P_{PV} \times T_{PV}(h) \times \eta_{loss}(h) \quad (6)$$

$$benCS = \sum_{h=1}^H [E_c(h) \times T_{C-EV}(h)]. \quad (7)$$

where $benPV$ is the remuneration associated with the photovoltaic solar generation system; $benCS$ is the remuneration associated with the charging stations; $benESS$ is the remuneration associated with the energy storage system; $C_{varop}(t)$ is the hourly variable cost associated mainly with energy import transactions from the grid, the cost of wire usage (contracted demand), and the O&M cost (operation and maintenance); $\gamma(h)$ is the normalized produc-

tion factor of the photovoltaic system, which converts, on an hourly basis, the peak power dimensioned into energy production in the considered interval; η_{loss} is a factor representing the efficiency loss due to panel degradation; $T_{PV}(h)$ is the tariff for remuneration for the use of energy from the photovoltaic system (when there is a commercialization of credits or surplus); $T_{C-EV}(h)$ is the EV consumption energy sale tariff (BRL/kWh) associated with the commercialization of energy consumption E_c ; h is the time interval for simulating the operation of the charging station, in hours; H is the total operation time; and y is the year of operation from one to T (the number of years of the planning horizon).

7. Numerical and Economic Results

7.1. Investment Costs

The CAPEX associated with the deployment of the E-Lounge model includes the components of equipment acquisition (chargers, accessories, and freight), as well as infrastructure (for charger installation) and installation services. The associated cost components in the building phase are costs of foundations/earthwork, metal structures, labor, finishing, civil works/construction, and licensing, activities which are the responsibility of a type of agent, an EPC contractor. Finally, there is also a cost component associated with the acquisition and installation of the energy storage system (and the photovoltaic solar generation system—local or remote). Considering real market costs associated with equipment in Brazil, Figure 18 illustrates the share of investment components for a charging station hub, considering as a reference the ideal E-Lounge model.

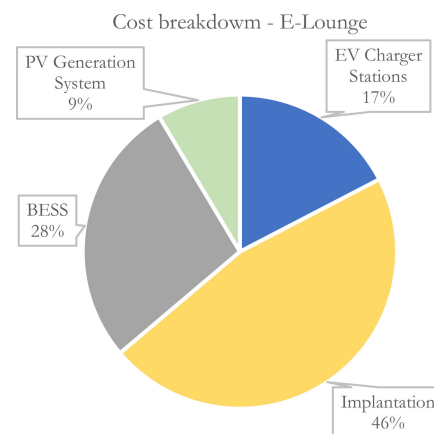


Figure 18. CAPEX for a charging hub—based on the ideal E-Lounge model.

7.2. Variable Costs

The main variable costs associated with charging stations are related to the purchase of electricity (C_{grid}), equipment maintenance, personnel expenses (night security), and other monthly recurring expenses (internet and water supply, among others):

$$C_{varop}(h) = C_{grid}(h) + C_{O\&M}(h) \quad (8)$$

$$C_{grid}(h) = T_{cp} \times C_{e_{peak}}(h) + T_{c_{fp}} \times C_{e_{f_{peak}}}(h) + T_{dp} \times D_{peak}(h) + T_{dfp} \times D_{f_{peak}}(h) + T_{udp} \times \Delta Du_{peak}(h) + T_{udfp} \times \Delta Du_{fponta}(h) \quad (9)$$

$$C_{O\&M}(h) = C_{water}(h) + C_{aluguel}(h) + C_{servicos}(h) + C_{marketing}(h) \quad (10)$$

where T_{cp} is the on-peak consumption tariff, $C_{e_{peak}}$ is the energy consumption that occurs during peak hours, $T_{c_{fp}}$ is the off-peak consumption tariff, $C_{e_{f_{peak}}}$ is the energy consumption that occurs during off-peak hours, T_{dp} is the demand tariff for peak hours, T_{dfp} is the demand tariff for off-peak hours, D_{peak} is the contracted demand for peak hours, and $D_{f_{peak}}$ is the contracted demand for off-peak hours. Depending on the type of connec-

tion, the tariff structure is altered according to current regulations. For charging stations connected at low voltage, the cost components associated with demand are incorporated into the consumption tariff, and there is no time-of-use segmentation. In Brazil, for deployment/implementation alternatives with a maximum power demand of 75 kW, the tariff structure for consumer group B may be considered, while for alternatives with a peak demand exceeding 75 kW, the tariff structure for consumer group A should be considered.

7.3. Analysis of Economic Results

One of the main costs for the operation of charging enterprises is the acquisition of electrical energy. Considering the energy consumption projections (related to EV charging stations) described in the previous sections, Figure 19 provides an estimate of the annual energy cost of supplying energy to recharge EVs and the average energy cost (levelized cost of energy). On the other hand, one of the main sources of revenue is the sale of recharges. Financial gain is obtained by transacting energy at an average acquisition cost lower than the recharge selling price. Figure 20 illustrates the annual gross revenue before deducting operational costs and the EV charging energy price (BRL/kWh).

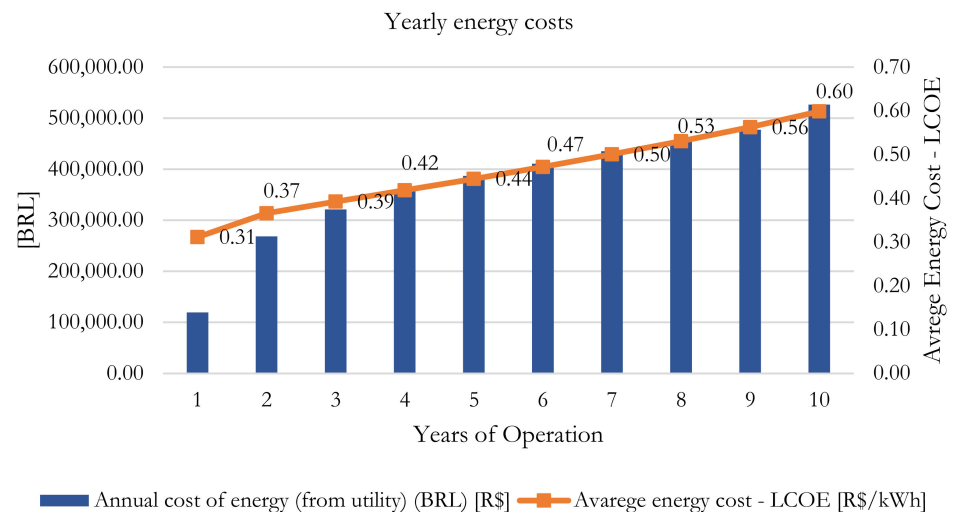


Figure 19. Annual energy costs based on the ANN forecasted data: Estimated annual total costs of supplying energy to recharge EVs at the E-Lounge and the LCOE.

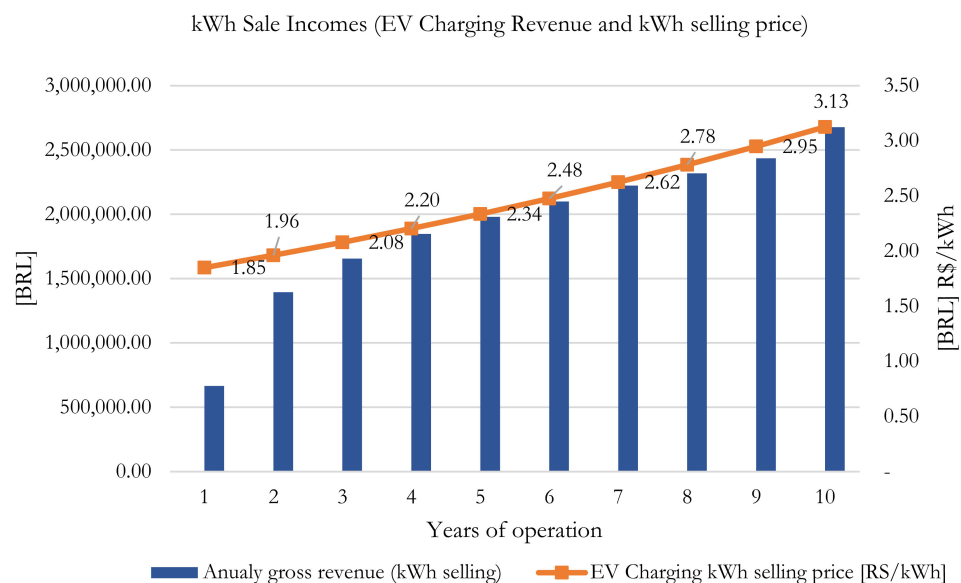


Figure 20. Annual energy costs and revenues based on the ANN forecasted data: Annual gross revenue from recharge sales.

Despite the potential for gross revenue from selling recharges to EVs, general operating expenses degrade the economic performance of charging enterprise operations. Figure 21 illustrates the cash flow, showing percentages of expected values for economic losses associated with operations in a given year. These losses (O&M costs) are linked to deductions (profit taxes), energy acquisition costs, general operating costs (maintenance, security, surveillance, and the operation of support applications), and federal taxes. Ultimately, the net profit is the amount used to offset the initial investment in deployment and equipment.

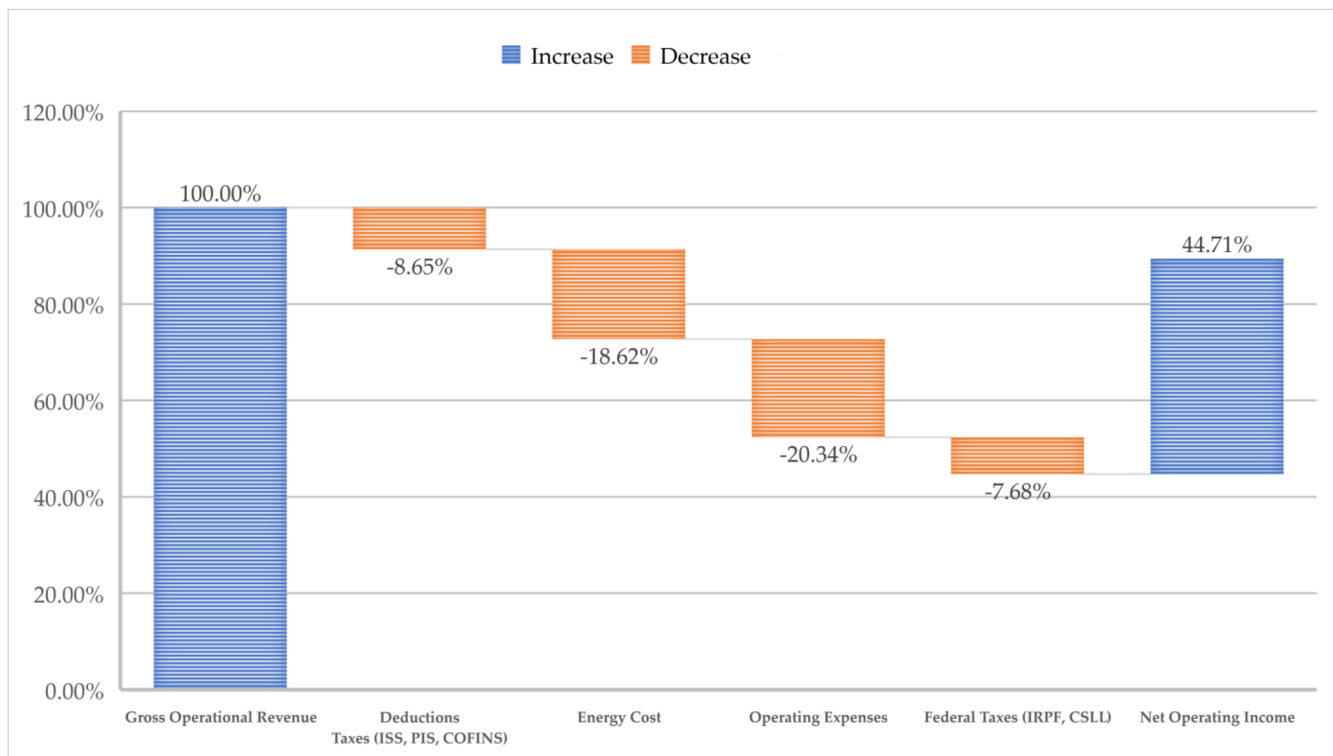


Figure 21. Expected cash flow (% of cash losses/deductions associated with energy costs and operation and maintenance for a year of operation).

Considering the operational cost deduction, Figure 22 illustrates the yearly operational cash flow (the net result of subtracting the operational expenses from the annual revenue), in which it is possible to observe that positive net values associated with energy EV recharge sales can be obtained.

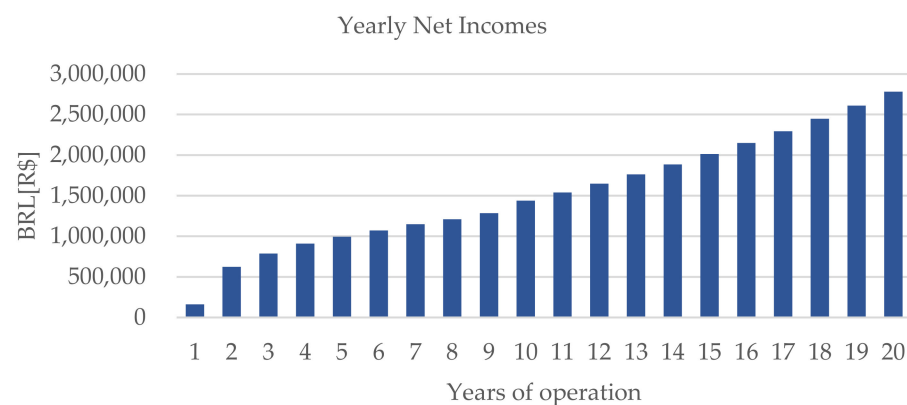


Figure 22. Net operational profit over the years of operation.

The yearly net cash flow is presented in Figure 23, while Figure 24 illustrates the simple accumulated cash flow value over the years (OPEX and CAPEX). The period required to amortize the initial investments is five years. Despite the various environmental advantages of electrifying the transportation sector, these preliminary economic results indicate that there are still challenges to making charging infrastructure viable in Brazil, such as high initial investment costs and the need to keep assets operating for long periods to economically enable the implementation of dedicated electric vehicle charging locations.

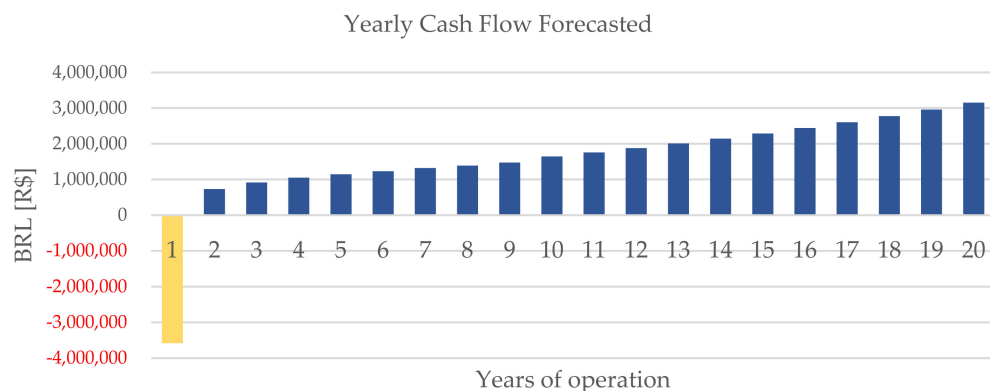


Figure 23. Annual cash flow over the years of operation.

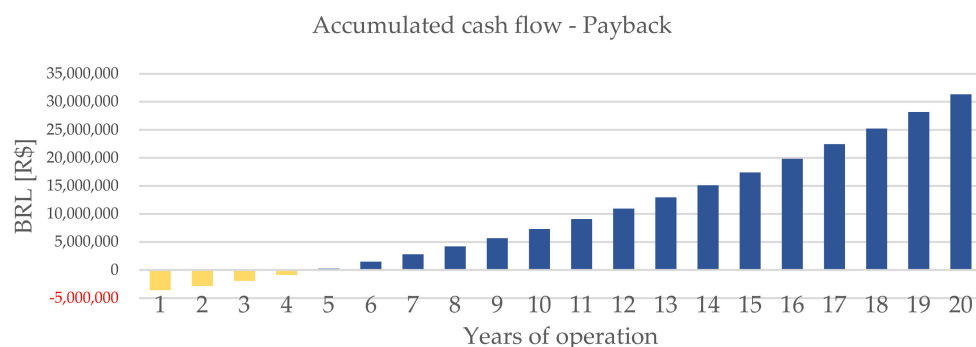


Figure 24. Net cash flow accumulated over the years.

As can be observed in Figure 24, the payback/return period for the investments is approximately 4 years. Considering the charging projections over the evaluated period within a 20-year operation horizon, for a minimum attractiveness rate of 8% per year, the net present value (NPV) of the project is estimated at 11,389,394 BRL (R\$), with an internal rate of return (IRR) of approximately 31.19%. However, this may represent an optimistic scenario highly susceptible to risk due to market dynamics, since these values are estimates, which have associated risks such as the possibility of equipment failure (requiring a replacement), fluctuating energy prices, changes in consumer behavior, the redirection of subsidies and incentives for the acquisition of new electric plug-in vehicles. Geopolitical or macroeconomic policies, among other factors, also may impact the adoption of EVs in the country and lead to different economic feasibility results.

8. Conclusions

Electric vehicles are considered a disruptive technology with the potential to contribute to the global environmental sustainability of the transportation sector. In Brazil, there has been observed rapid growth in its fleet of electric vehicles. However, there is still a scarcity of charging infrastructure. In this sense, within the scope of the Research and Development Program of the National Electric Energy Agency (ANEEL), through the research and development project PD-07267-0021/2019 E-Lounge—“A solution for electric vehicle fleet

charging in Brazil”, an ideal charging infrastructure model was developed that is aligned with the reality of the user profile in Brazil.

To evaluate its technical and economic feasibility, one of the main associated metrics is the expected energy consumption for each EV charging station. In this context, based on the recorded historical data, this work proposes a new application using artificial neural networks to project future consumption.

Based on the E-Lounge case study, preliminary results indicate that the implementation and operation costs for charging stations can be high. In certain contexts, these costs can even economically hinder the deployment of charging ventures with fast stations equipped with storage system support. On the other hand, projections indicate that with the growth in demand for charging, as well as the establishment of rational charging fees, it is possible to deploy charging station enterprises that are economically feasible in Brazil.

Finally, the presented results are related to a specific application context, focusing on the case of the E-Lounge and the Brazilian EV market. Aspects of the projection method and feasibility analysis can be applied to other contexts/countries but should be adapted considering local constraints, as well as the economic, regulatory, and market assumptions of each region.

Author Contributions: Conceptualization, J.F.C.C., P.A.C.R. and A.C.V.; methodology, J.F.C.C. and A.C.V.; software, J.F.C.C., F.L.X. and A.C.V.; validation, J.F.C.C., P.A.C.R. and A.C.V.; formal analysis, J.F.C.C. and A.C.V.; investigation, A.C.V. and L.C.P.S.; resources, J.F.C.C., P.A.C.R. and A.C.V.; data curation, J.F.C.C. and F.L.X.; writing—original draft preparation, J.F.C.C., P.R. and A.C.V.; writing—review and editing, J.F.C.C., P.R., A.C.V., R.C.N., L.R.L., L.C.P.S., W.M.R., N.S., A.P.S., N.K.L.D. and A.V.M.L.F.; visualization, J.F.C.C., P.R., A.C.V., R.C.N., L.R.L., L.C.P.S., W.M.R., N.S., A.P.S., N.K.L.D. and A.V.M.L.F.; supervision, J.F.C.C., P.A.C.R., A.C.V., L.C.P.S., N.S. and P.R.; project administration, P.A.C.R., N.S. and P.R.; funding acquisition, A.C.V., N.S., W.M.R. and A.P.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Program of R&D of the National Brazilian Electricity Regulatory Agency (ANEEL) and EDP Energias do Brasil, under the strategic call n° 22. This research is associated with the E-Lounge project, grant number PD-07267-0021/2019, and the APC was funded by the R&D project PD-07267-0021/2019.

Data Availability Statement: The data are contained within the article.

Acknowledgments: The authors would like to thank the EDP group for its technical and financial support through the research and development project “E-Lounge—A Solution for electric vehicle fleet recharging in Brazil”, with resources from the ANEEL’s R&D program under Strategic Call 22 for electric mobility. Furthermore, the authors would like to thank the anonymous reviewers and editor for their valuable comments and suggestions.

Conflicts of Interest: The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

References

1. Climate Watch, Historical GHG Emissions (World Greenhouse Gas Emissions by Sector, End Use and Gases). Available online: <https://www.climatewatchdata.org/ghg-emissions> (accessed on 11 February 2024).
2. LaMonaca, S.; Ryan, L. The state of play in electric vehicle charging services—A review of infrastructure provision, players, and policies. *Renew. Sustain. Energy Rev.* **2022**, *154*, 111733. [CrossRef]
3. International Energy Agency—IEA. Key Milestones on the Pathway to Net Zero Emissions by 2050. Available online: https://iea.blob.core.windows.net/assets/17960fd8-0625-4f05-a2b7-1aacc656624b/WE02022infographic_AnupdatedroadmaptoNetZeroEmissionsby2050.pdf (accessed on 11 March 2023).
4. ABVE (Brazilian Association of Electric Vehicles). In a Year of Records, Plug-in Vehicles Advance (In Portuguese: Em ano de Recordes, Veículos Plug-in Avançam). Published 11/01/2023. Available online: <https://abve.org.br/em-ano-de-recordes-veiculos-plug-in-ganham-mercado/> (accessed on 11 February 2024).
5. Bharat, M.; Dash, R.; Reddy, K.J.; Murty, A.S.R.; Dhanamjayulu, C.; Muyeen, S.M. Secure and efficient prediction of electric vehicle charging demand using α 2-LSTM and AES-128 cryptography. *Energy AI* **2024**, *16*, 100307. [CrossRef]

6. Martin, S. Developing a Business Model for Commercial Electric Vehicle Charging Infrastructure. Master's Thesis, IIIIEE Lund University, Lund, Sweden, 2015. Available online: <https://lup.lub.lu.se/luur/download?func=downloadFile&recordId=8893278&fileId=8893279> (accessed on 10 February 2024).
7. Anadón Martínez, V.; Sumper, A. Planning and Operation Objectives of Public Electric Vehicle Charging Infrastructures: A Review. *Energies* **2023**, *16*, 5431. [\[CrossRef\]](#)
8. General Motors Authority. Says 90 Percent Of EV Users Charge at Home or Work. Available online: <https://gmauthority.com/blog/2022/09/gm-says-90-percent-of-ev-users-charge-at-home-or-work/> (accessed on 22 March 2023).
9. Errity, S. Gridserve Opens Electric Forecourt Charging Hub in Norwich. Available online: <https://www.drivingelectric.com/charging/982/gridserve-opens-electric-forecourt-charging-hub-in-norwich> (accessed on 22 March 2023).
10. Perry, S. Europe's Biggest Electric Vehicle Charging Hub Opens in Oxford. Available online: <https://www.oxfordmail.co.uk/news/20258048.europes-biggest-electric-vehicle-charging-hub-opens-oxford/> (accessed on 22 March 2023).
11. Zusmarshausen (Germany). The Sortimo Innovation Park Zusmarshausen. Available online: <https://lightaz.com/led-project-details/the-sortimo-innovation-park-zusmarshausen?p=3247> (accessed on 22 March 2023).
12. Filho, A.V.M.L.; Vasconcelos, A.S.M.; Junior, W.d.A.S.; Dantas, N.K.L.; Arcanjo, A.M.C.; Souza, A.C.M.; Fernandes, A.L.; Zhang, K.; Wu, K.; Castro, J.F.C.; et al. Impact Analysis and Energy Quality of Photovoltaic, Electric Vehicle and BESS Lead-Carbon Recharge Station in Brazil. *Energies* **2023**, *16*, 2397. [\[CrossRef\]](#)
13. Castro, J.F.C.; Roncolato, R.A.; Donadon, A.R.; Andrade, V.E.M.S.; Rosas, P.; Bento, R.G.; Matos, J.G.; Assis, F.A.; Coelho, F.C.R.; Quadros, R.; et al. Microgrid Applications and Technical Challenges—The Brazilian Status of Connection Standards and Operational Procedures. *Energies* **2023**, *16*, 2893. [\[CrossRef\]](#)
14. Assis, F.A.; Coelho, F.C.R.; Castro, J.F.C.; Donadon, A.R.; Roncolato, R.A.; Rosas, P.A.C.; Andrade, V.E.M.S.; Bento, R.G.; Silva, L.C.P.; Cypriano, J.G.I.; et al. Assessment of Regulatory and Market Challenges in the Economic Feasibility of a Nanogrid: A Brazilian Case. *Energies* **2024**, *17*, 341. [\[CrossRef\]](#)
15. Castro, J.F.; Marques, D.C.; Tavares, L.; Dantas, N.K.; Fernandes, A.L.; Tuo, J.; de Medeiros, L.H.; Rosas, P. Energy and Demand Forecasting Based on Logistic Growth Method for Electric Vehicle Fast Charging Station Planning with PV Solar System. *Energies* **2022**, *15*, 6106. [\[CrossRef\]](#)
16. Acharige, S.S.; Haque, M.E.; Arif, M.T.; Hosseinzadeh, N.; Hasan, K.N.; Oo, A.M.T. Review of Electric Vehicle Charging Technologies, Standards, Architectures, and Converter Configurations. *IEEE Access* **2023**, *11*, 41218–41255. [\[CrossRef\]](#)
17. Box, G.E.; Jenkins, G.M.; Reinsel, G.C.; Ljung, G.M. *Time Series Analysis: Forecasting and Control*, 5th ed.; John Wiley & Sons: Hoboken, NJ, USA, 2015; pp. 129–174.
18. Goodfellow, I.; Bengio, Y.; Courville, A. *Deep Learning*; MIT Press: Cambridge, MA, USA, 2016; pp. 164–223.
19. Moré, J.J. The Levenberg-Marquardt algorithm: Implementation and theory. In *Numerical Analysis*; Watson, G.A., Ed.; Lecture Notes in Mathematics; Springer: Berlin/Heidelberg, Germany, 1978; Volume 630, pp. 105–116. [\[CrossRef\]](#)
20. Hagan, M.T.; Menhaj, M.B. Training feedforward networks with the Marquardt algorithm. *IEEE Trans. Neural Netw.* **1994**, *5*, 989–993. [\[CrossRef\]](#) [\[PubMed\]](#)
21. Willmott, C.; Matsuura, K. Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance. *Clim. Res.* **2005**, *30*, 79–82. [\[CrossRef\]](#)
22. Panahi, D.; Deilami, S.; Masoum, M.A.S.; Islam, S.M. Forecasting plug-in electric vehicles load profile using artificial neural networks. In Proceedings of the 2015 Australasian Universities Power Engineering Conference (AUPEC), Wollongong, NSW, Australia, 27–30 September 2015; pp. 1–6. [\[CrossRef\]](#)
23. Sapkota, D.P.; Pokharel, G.R.; Bhattarai, N.; Rai, P.J. Business model for financially sustainable electric vehicle charging station using EV charging financial analysis tool. *J. Innov. Eng. Educ.* **2021**, *4*, 109–116. [\[CrossRef\]](#)
24. Pillai, R.K.; Suri, R.; Kundu, S.; Singh, H.; Roy, S.S.; Dhuri, S. *Electric Vehicle Charging Stations Business Model for India*; India Smart Grid Forum: New Delhi, India, 2018.
25. Zhang, Q.; Li, H.; Zhu, L.; Campana, P.E.; Lu, H.; Wallin, F.; Sun, Q. Factors influencing the economics of public charging infrastructures for EV—A review. *Renew. Sustain. Energy Rev.* **2018**, *94*, 500–509. [\[CrossRef\]](#)
26. Madina, C.; Zamora, I.; Zabala, E. Methodology for assessing electric vehicle charging infrastructure business models. *Energy Policy* **2016**, *89*, 284–293. [\[CrossRef\]](#)
27. Markkula, J.; Rautiainen, A.; Järventausta, P. The business case of electric vehicle quick charging—No more chicken or egg problem. *World Electr. Veh. J.* **2013**, *6*, 921–927. [\[CrossRef\]](#)

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.