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Influence of Optimal Charging Station Integration on Electric Power Distribution Grid: Case of Electric Bus-Based Transport System †

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Abstract: Electric mobility is one of the main pillars of the global energy transition towards a more sustainable and environmentally responsible model. Greenhouse gas emissions could be drastically reduced with electric mobility massification. Public transport systems represent the first step of this massification due to government policies, but these electromobility projects should optimize their resources to be cost-effective. Furthermore, the implementation of charging stations could cause negative impacts on electrical distribution networks, which should be evaluated beforehand for the adequate planning of power grids. A methodology was developed and implemented herein for the technical and economic evaluation of electric bus-based transport systems.

Keywords: electric mobility; electric power distribution; electric public transportation; optimization

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1. Introduction

The incorporation of electric buses (EBs) into the public transportation system is a valuable asset in the energy transition process, as they reduce environmental pollution with low noise levels and zero CO_2 emissions [1]. Due to the advantages of electric mobility, the incorporation of EBs is growing worldwide. According to Bloomberg New Energy Finance's Electric Vehicle Outlook, it is projected that by 2025, the number of EBs worldwide will reach 1.2 million, which would imply that 47% of buses will be electric [2]. In 2024, Ecuador approved the "Energy Competitiveness Law", which established that by 2030, all vehicles incorporated into the country's public transportation system must be zero-emission or electric [3].

EB-based transport systems have some limitations, for example their limited driving range and extended charging time, much longer than a fuel-powered bus. Therefore, it is essential to implement charging strategies for EBs to maintain their daily operations properly in accordance with planning schedules. The choice of these strategies will influence not only the number of buses available to be deployed on a transit route but also the energy consumption level and battery life expectancy. As studied in [1], to implement charging strategies for EBs, it is necessary to accurately know the energy consumption of each transport unit along the operational route. This depends not only on the mechanical and electrical characteristics of each unit but also on the topographical features of the route and traffic conditions [2]. The conventional charging strategy consists of recharging the battery when it is almost depleted until it is fully charged. However, based on [2], it has been shown that bringing the vehicle battery to its minimum charge level significantly reduces its lifespan. Therefore, to mitigate this depreciation, it is advisable to maintain battery operation at an adequate charge level (ACL). However, this condition would require increasing the size of the bus fleet. Considering battery characteristics, an intelligent option

is to maximize downtime during off-peak hours to recharge EBs. This will increase their driving range, reduce energy consumption, and avoid the early need to expand the fleet size due to charging demands, maintaining the ACL at a reasonable level and prolonging battery life. The duration and number of downtimes for each bus during daily operations directly depend on the trips it must make, which are organized by schedules [2].

So far, several investigations emphasize planning the charging strategy from a battery, vehicle, and route perspective. Besides the charger deployment, how to schedule the bus fleet in an efficient way is also a critical issue for the BEB system. It is demonstrated that the reasonable scheduling of the bus fleet has great potential to reduce the fleet size and corresponding investment costs [4]. Simulation optimization approaches have been used to evaluate energy consumption and determine optimal charging station placement [5]. Bi-level optimization models have been developed to design efficient transit routes and locate charging infrastructure simultaneously [6]. Operational challenges, such as limited range and long charging times, can be addressed through optimization models that assign buses to routes, allocate parking spaces, and optimize charging schedules [7]. Several techniques such as genetic algorithms have been employed to solve this combinatorial optimization problem, considering factors like battery autonomy, charging opportunities, user demand, and vehicle capacity to determine optimal timetables and fleet composition [8]. These previous studies demonstrate the potential of optimization techniques to overcome the limitations of electric buses and support the design of sustainable public transportation systems.

Likewise, it is necessary to analyze the impact of incorporating charging stations for EBs into the electric power distribution grid (EPDG) [9]. Charging stations connect to the EPDG, and due to their consumption characteristics, they can generate negative impacts on the grid, such as transformer overloading, distribution line overloading, increased power and energy losses, voltage disturbances, and power quality issues [10]. Therefore, a key challenge in station planning is to find an optimal sizing for new charging stations that meets transportation demand and is cost-effective from an electrical grid perspective. Considering both perspectives will not only reduce total costs from a systems perspective, thus increasing social welfare, but will also accelerate the incorporation of EBs into transportation companies [11]. Over the years, efforts toward the construction and management of electrified transit systems have been made by both the industrial and academic communities [12].

This article focuses primarily on analyzing the impact of incorporating charging stations for electric buses into the EPDG. The analysis will be conducted for the route studied in [3], starting with a description of the case study, and then studying EB energy consumption and incorporating battery charging restrictions. The optimization problem will be described, as it is necessary to find an optimal sizing for the charging stations. The second part of this work is focused on vehicle charging stations' impact on the EPDG. It begins with a demand analysis, incorporating energy consumption characteristics of BEBs into a database modeled in specialized software for electrical studies in distribution power systems such as CYME 9.3. Once the charging station demand is incorporated into the feeder that provides electricity in the operational area of the case study route, quasi-steady-state simulations will be performed to evaluate distribution grid performance. Finally, the results obtained will be presented and analyzed, followed by the conclusions drawn from this work.

2. Study Case Description

2.1. Public Transportation Route Model

For this study, the "Marín–Ciudadela Tarqui" route was used, which is currently a public transportation route in Quito–Ecuador. This route covers a total distance of 10.67 km. The selection of this route was due to the significant elevation changes along its path and the traffic levels it experiences. It is considered that the altitude difference is a determining parameter for electric vehicle consumption in Quito. Topographic information was obtained

from the United States Geological Survey (USGS), which provides the necessary SRTM files to determine the elevation of any point on Earth with 30 m resolution [3].

2.2. Electric Bus Parameters

Technical specifications of electric buses used in this study were obtained from manufacturer catalogs and are summarized in Table 1. The selected bus manufacturer has units operating in several cities across Latin America, including Ecuador, and according to the e-bus radar platform [13], their vehicles account for 45% of the buses operating in the region.

Table 1. Technical specifications of electric urban transport buses.

Parameter	Value
Brand	BYD
Model	C9
Engine Power	360 kW
Battery Capacity	438 kWh
Autonomy	300 km
Height	3.55 m
Length	12.9
Width	2.55
Weight	18,000 kg
Capacity	53 p

Hence, an optimization model was developed to determine the optimal strategy for the electric bus charging system, aiming to minimize annual operational costs while ensuring the proper operation of the BEB transportation system. The most critical considerations for the optimization problem are detailed in Section 4, including the objective function and problem constraints.

3. Energy Consumption for Electric Buses

Electric bus battery (EBB) performance depends on environmental variables such as temperature and humidity, construction factors like manufacturing tolerances, and other variables that are more difficult to determine precisely, such as the battery's age and previous usage patterns. The route model presented in Section 2.1 was implemented using SUMO 1.21.0 (Simulation of Urban Mobility) software. It is one of the most efficient and frequently adopted microscopic traffic simulation tools. An energy estimation model was implemented based on vehicle and road characteristics [14]. BEBs were also modeled based on the parameters shown in Table 1, considering traffic demand.

For this study, five operational scenarios were analyzed to evaluate battery consumption. Two scenarios assessed the battery state of charge (SOC) for the "Marín–Ciudadela Tarqui" route, considering the topographic profile presented in Figure 1. The remaining three scenarios incorporated levels of service (LOSs) related to vehicular traffic, considering three levels of service: light, moderate, and heavy. Each scenarios was also associated with an occupancy level ranging from 20% to 100% of the total passenger capacity [3]. Based on the conclusions reached in [3], battery charge has a moderate dependency on traffic levels, but its consumption behavior significantly changes when considering the elevation profile. This is evident in Figure 1a, which shows the evolution of the SOC along the route at 100% occupancy, considering both flat and hilly routes. In the present study, the battery consumption model considered a hilly route with elevation changes, medium traffic levels, and 100% occupancy, to provide an energy performance very close to the real operating conditions performance. With these considerations, the battery consumption is shown in Figure 1b.

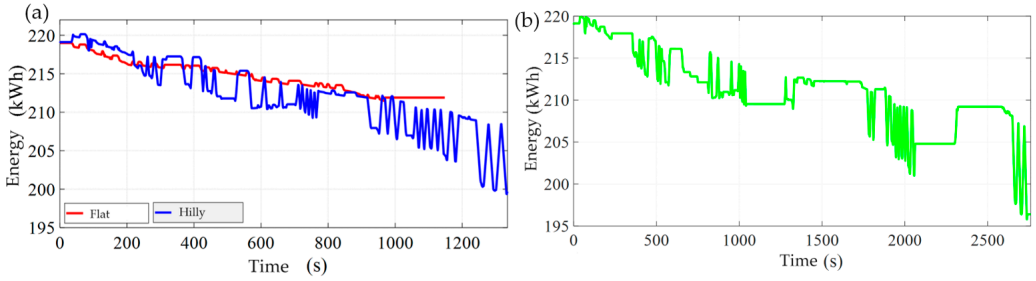


Figure 1. BEB SOC considering (**a**) elevation and (**b**) elevation and traffic level [3].

4. Optimization Problem

The case case entails a transport system, which is composed of a departure terminal (the starting point) and a main terminal (the terminal point). The departure station has a plug-in charging infrastructure and a bus depot. A service loop is considered to be the path from where the BEB departs from the starting point and operates along the route until it returns to the starting point. The BEB one-line transport system considered in this study is illustrated in Figure 2. This section aims to determine the optimal scheduling of the BEB charging system, minimizing the total costs while ensuring the normal operation of the system [15]. Therefore, some assumptions were considered to achieve the optimization problem formulation:

- Each bus has a predetermined schedule that specifies the arrival and departure frequencies to terminals.
- In every loop, the charging times are the same for all buses in the route.
- All loops have the same length, duration, and energy consumption, and all buses were produced by the same manufacturer and have the same driving range.
- There is only one charging station in the transportation system located at the starting point.
- All chargers are identical, and each charger is equipped with only one outlet.

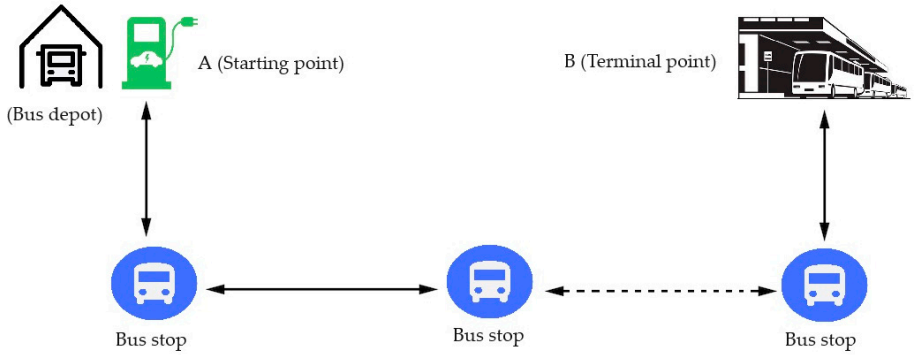


Figure 2. BEB transportation system architecture.

4.1. Problem Formulation

Considering the assumptions declared above, the objective function is structured as follows:

$$min\ C = \sum_{b\in B}\sum_{i\in S} c_m d_{ib} D + \sum_{i\in S}\sum_{n\in N}(c_e p_c u_n) D X_i^n + \sum_{n\in N} 12\ p_c c_d + \sum_{n\in N} \alpha c_{f1} + \sum_{n\in N}\left(\alpha c_{f2} + D c_{m2}\right) \quad (1)$$

where c_m is unit cost of maintenance (\$/km), d_{ib} is each loop driving distance (km), c_e is the electric energy cost (\$/kWh), c_d is the electric demand cost (\$/kW), p_c is the charger power (kW), u_n is the charging duration (h), D is the number of operating days in a year, x_i^n is a binary variable which represents whether each bus recharges its battery in trip i at charging station n, α is the annualized factor, c_{f1} is the fixed cost per BEB (purchase investment, \$), c_{f2} is the charging station fixed cost (construction investment, \$), and c_{m2} is the charging

station maintenance costs. N indexed n is the set of chargers in charging station, and S is the set of scheduled loops [16]. B indexed b is the set of BEBs operating on the route.

The constraints associated with the study problem are shown below [16]:

$$\sum_{n \in N} x_i^n \leq 1 \qquad \forall\, i \in S \tag{2}$$

$$E_i + \sum_{n \in N} (T_c u_n)\, x_i^n \leq E_{max} \quad \forall\, i \in S \tag{3}$$

$$E_j = E_i + \sum_{n \in N} (T_c u_n)\, x_i^n \quad \forall\, i \in S \tag{4}$$

$$E_i \geq E_{min} \qquad \forall\, i \in S \tag{5}$$

$$E_{min} = 0.2\ E_{cap},\ \ E_{max} = 0.8\, E_{cap} \qquad \forall\, i \in S \tag{6}$$

$$x_i^n = \{0,1\}, \qquad \forall\, i \in S, \forall\, n \in N \tag{7}$$

where E_i is the remaining energy at the end of trip i (kW), T_c is the recharging rate, E_{max} is the electric bus battery maximum useful charging capacity (kW), E_{min} is the electric bus battery minimum useful charging capacity (kW), E_j is the remaining energy at the beginning of the trip j (kW), and E_{cap} is the electric bus maximum battery capacity declared by the manufacturer. The constraint in Equation (2) prevents two buses from charging on the same charger at the same time. The constraint in Equation (3) does not allow the maximum percentage of battery charge to be exceeded during charge cycles. The constraint in Equation (4) refers to energy conservation. The constraint in Equation (5) ensures that energy is not consumed beyond the minimum battery capacity. Constraint (6) establishes the minimum and maximum recommended SOC values. Constraint (7) is a binary requirement.

4.2. Route Optimization Results

The problem formulated above corresponds to a combinatorial optimization problem, where the decision variables are discrete (p_c and N). In the optimization method choice process, rhw objective function evaluation computational cost was analyzed. Since the assumptions considered simplify the problem substantially, it is possible to perform multiple evaluations of objective function in a relatively short time with low computational cost, which makes the optimization problem quite tractable. The problem was solved using a combinatorial search algorithm under different scenarios of BEB prevalence. For example, a 20% prevalence rate will mean that 20% of the route units are electric. Considering incentives and regulations issued by the Ecuadorian government, an exponential growth of electric bus prevalence in public transportation is expected. Under a "Maximum effort towards energy transition" (MEET) scenario, 85% of the bus fleet being electric would be reached by the year 2050 by considering the aggressive growth in the number of electric buses, while under a "Conservative effort towards energy transition" (CEET) scenario, the electric bus number would reach 34% in 2040. Conversely, in a "Business as Usual" (BAU) scenario, electric bus prevalence is negligible [17].

Route frequencies are adapted to different levels of BEB prevalence. Figure 3a,b show the distance covered as a function of time in each loop completed by BEBs under 10% and 50% prevalence scenarios, respectively.

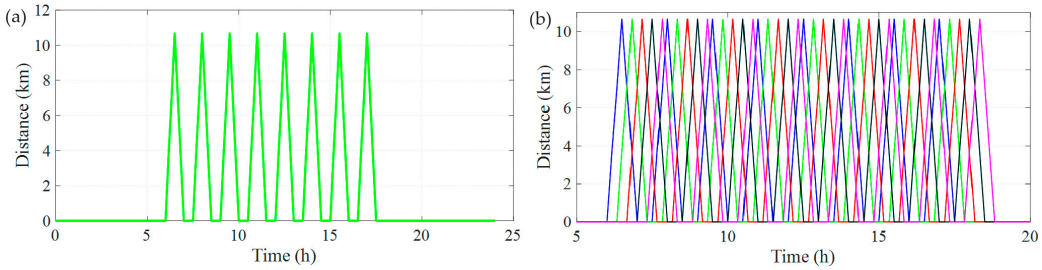


Figure 3. BEB daily position; (**a**) prevalence of 10%, (**b**) prevalence of 50%.

One of the most important results of the optimization problem is the operational programming of charging time intervals in accordance with technical and logistical constraints. The BEB public transport system operation time per day is divided into Y periods, and travel and charging periods are interleaved equally between all transport units. The charging models used in this work to calculate the battery SOC were obtained experimentally by the Ecuadorian National Energy Regulatory Agency ARCERNNR, based on measurements at various charging station models. Figure 4 shows the charging models obtained.

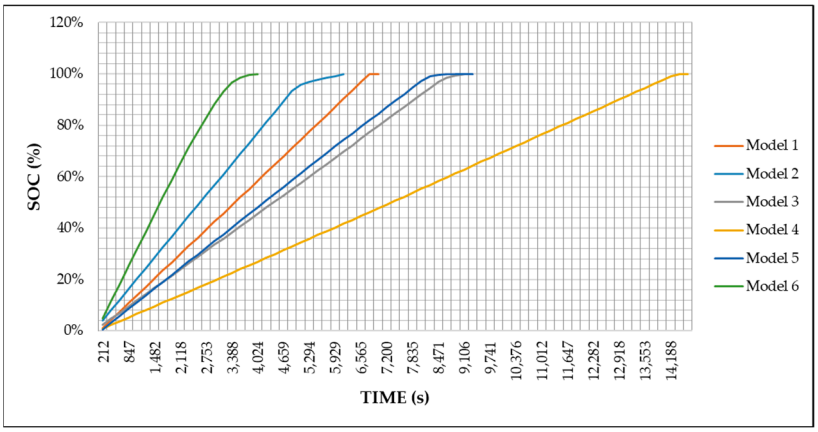


Figure 4. Electric vehicle charging models.

Optimal results were obtained for the scenarios shown in Table 2, considering 80 kW chargers.

Table 2. Optimal solutions summary.

Scenario (Prevalence)	Projected Year	Charging Stations	Minimum Total Costs (USD)
20%	2030 [1]	1	85,464.55
50%	2037 [1]	1	204,626.64
100%	2055 [1]	2	413,614.68

[1] Foresight scenarios based on [17].

Figure 5 shows the battery SOC of each electric bus on the route in the highest prevalence scenario. It denotes the constraints fulfillment considering that batteries can only safely operate without a detrimental impact on their health and longevity at between a 20 and 80% SOC level [18].

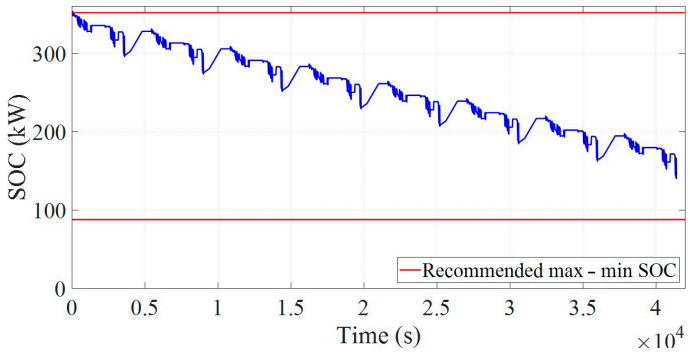


Figure 5. BEBs daily SOC—prevalence of 100%.

5. Demand Analysis

A feeder labeled as 5D in "Chilibulo´s" substation is where the charging station would be connected, and it belongs to the "Empresa Eléctrica Quito" electric utility company. This feeder is located in southern Quito–Ecuador, and it is characterized by predominantly residential customers. It supplies power to 268 distribution transformers at a 22.8 kV voltage level. To further analyze the impact of implementing the charging stations on the case study feeder, it is necessary to estimate the customer and charging station demand curves. The customer demand curves correspond to typical curves obtained from stratified customer cluster analyses [19]. This methodology allows for the obtaining of typical customer power demand curves, which adapt to the monthly consumption of any feeder customer. Using estimated daily power load profiles, quasi-dynamic load flows can be carried out on the feeder.

Electric Chargers Demand Profile

Based on optimal charging scenarios obtained in the previous section, the charger demand curves corresponding to each prevalence level are established and included in the 5D feeder power flow analysis. Figure 6a shows the daily power demand curve of the charging station corresponding to the 20% prevalence level. The charging time and intervals allow the electric bus fleet to adequately maintain its charge level and minimize transport system operating costs. Figure 6b shows the daily power demand curve for the 50% prevalence level, which represents the maximum level at which a single charging station can supply all the system. Note that hourly tariffs have not been considered in the energy cost calculation, which means that low-demand nighttime hours are not prioritized for charging.

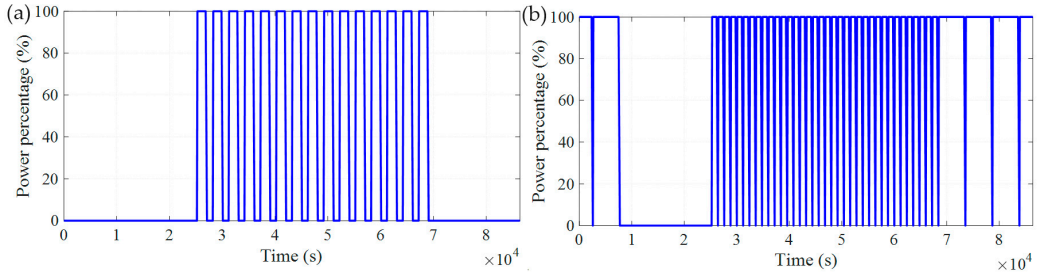


Figure 6. Charging station demand curve; (**a**) prevalence of 20%, (**b**) prevalence of 50%.

Figure 7 displays the daily power demand curve in a 60% prevalence scenario where one single charging station does not meet the BEB system's charging needs, even if it operates 24 h a day. This prevalence scenario requires the installation of a second charging station. Finally, the daily power demand profile for two charging stations required in a 100% prevalence scenario is shown in Figure 8.

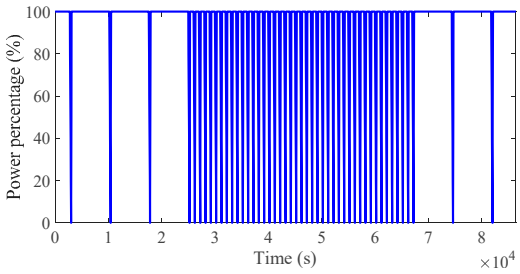


Figure 7. Charging station demand curve—prevalence of 60%.

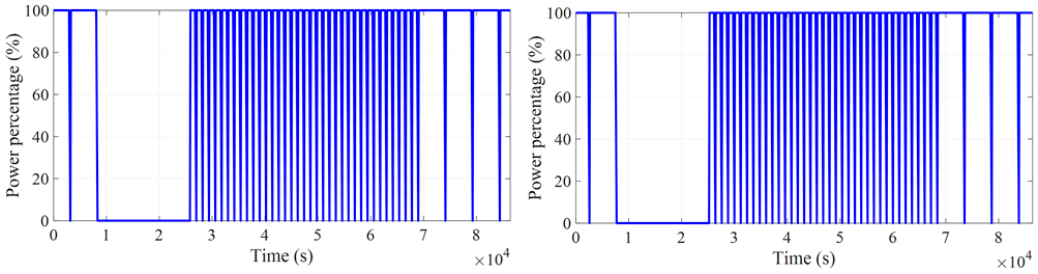


Figure 8. Charging stations demand curves—prevalence of 100%.

6. Impact Evaluation

The CYME software was used to analyze the impact of installing charging stations on the studied feeder during this work. In Ecuador, the CYME software is widely used among electric utility companies to perform several studies in primary distribution networks, as in the present work. Figure 9 shows the current power demand daily profiles of the feeder under study. The three curves displayed represent the power demand for the respective phases of the feeder. Demand data at 15 min intervals are considered for the power flow analysis.

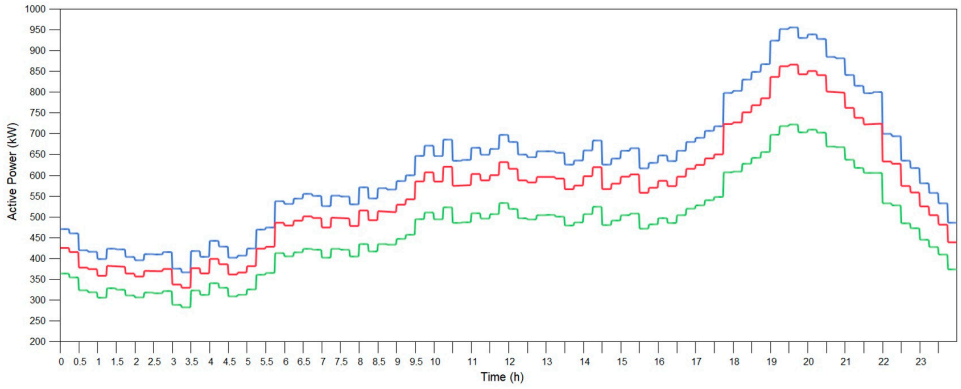


Figure 9. Current 5D Chilibulo's feeder daily power demand curves.

Electric utilities are now facing the challenge of managing new energy uses, such as electromobility and distributed renewable sources of energy interconnected with the EPDG. Both cases should be analyzed using power demand and energy production curves, allowing for the conducting of quasi-dynamic power flows. The CYME software can perform time-series simulations to study the impact of load variations and intermittency of renewable sources, preparing the EPDG for future higher prevalence levels. Figure 10 shows the feeder power demand daily curves for a 100% electric bus prevalence level. A 6% increase in the maximum demand can be noted, considering that the charging times coincide with the system's peak hours. This results in a significant increase in power losses of 8% during peak hours. The increase in demand is consistent across all phases, attributable to the installation of three-phase charging stations.

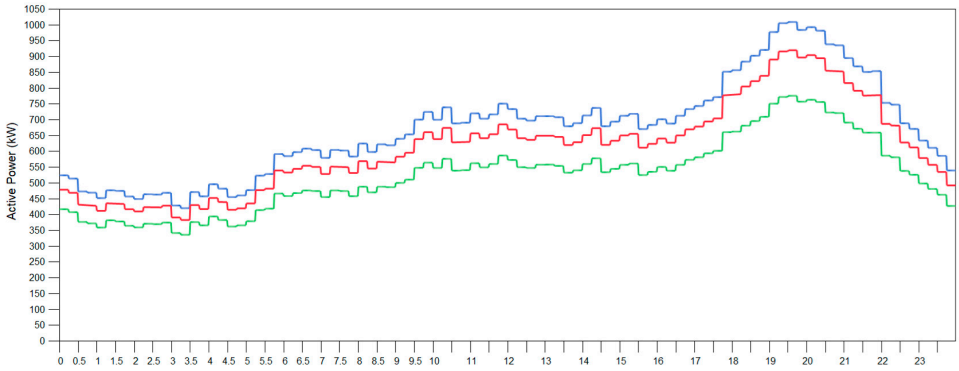


Figure 10. The 5D Chilibulo's feeder daily power demand curves—prevalence of 100%.

7. Conclusions

The operation of a BEB transport system requires the optimal management of financial and energy resources, considering technical and operational constraints. In the present work, a methodology for solving the optimization problem was successfully proposed and implemented, with a focus on a small case study. However, modern transportation systems include multiple routes, with variable frequencies adapted to passenger demand. Although these issues increase the complexity of the optimization problem (increased extension with multiple solutions), the problem formulation does not change significantly.

The results indicate that BEB purchase costs, energy consumption, and demand charges have the most significant impacts on total system annualized costs (approx. 65%).

Although the investment and maintenance costs of charging stations are not significant in contrast to total system annualized costs, in more demanding routes, system efficiency and BEB autonomy could be improved through opportunity charging implementation, where pantograph or induction are typically used.

The impact degree of charging stations on the power distribution grid is highly dependent on the BEB prevalence level; high prevalence levels will cause high occupancy rates in charging stations; therefore, the coincident peak demand of the system may be significantly increased, producing possible negative effects on grid such as feeder overloading, voltage drops, and an increase in power losses.

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