A charging station planning model considering electric bus aggregators

Jean-Michel Clairand[a,*], Mario González-Rodríguez[a], Irvin Cedeño[b], Guillermo Escrivá-Escrivá[c]

[a]*Facultad de Ingeniería y Ciencias Aplicadas, Universidad de las Américas, José Queri, 170125 Quito, Ecuador*

[b]*Departamento Técnico, BYD E-Motors Ecuador, 170135 Quito, Ecuador*

[c]*Institute for Energy Engineering, Universitat Politècnica de València, Camino de Vera, s/ n, edificio 8E, escalera F, 5a planta, 46022 Valencia, Spain*

Abstract

Many governments are pushing for a cleaner transportation. In particular, the public transportation allows massive transportation of passengers, but it remains highly polluting, especially in high elevation cities. Thus, the progressive introduction of electric buses (EBS) will allow mitigating these environmental concerns. However, some technological problems must be addressed considering a massive penetration of EBs. The lack scarcity of flexibility and the time connection of scheduling for public transit makes the introduction of EBS harder than internal combustion ones. This work studies the impact of charging EBs at the bus station and suggests a new way to take EB aggregators into account to reduce energy costs while fulfilling grid restrictions. In addition, to find a different number of charging spots to be installed, a scheduling analysis is conducted.

Keywords: charging stations; electric bus; electric vehicle aggregators; long-term planning

Nomenclature

Indices

c	Index of charging spots
i	Index of EB

*Corresponding author.
Email address: jean.clairand@udla.edu.ec (Jean-Michel Clairand)

j,k	Indices of distribution node
t	Index of time intervals
y	Index of years
Parameters	
λ	Arrival Rate
μ	Charging rate of buses per hour
$\overline{P^h}$	Maximum charging power of an EB charger [kW]
$\overline{P_t^O}$	Maximum allowable load for EB charging at time interval t [kW]
π_t	Electricity cost at time interval t [$/kWh]
B_C	Nominal Battery Capacity [kWh]
C_p	Penalty cost for EB aggregator [$]
D	Daily time intervals
E_i^{req}	Daily energy required for each EB i [kWh]
N_c	Number of charging spots
N_n	Number of nodes
$P_{d,j}$	Active Power consumed at the node j [kW]
$P_{g,j}$	Active Power generated at the node j [kW]
$P_{t,i}$	Charging Power of an EB i at time interval t [kW]
$Q_{d,j}$	Reactive Power consumed at the node j [kVAr]
$Q_{g,j}$	Reactive Power generated at the node j [kVAr]
r	Discount rate [%]
R_D	Charging Ramp Down[kW]
R_U	Charging Ramp Up[kW]
$SOC_{t,i}$	State-of-charge of an EB i at time interval t [%]
T_P	Planning Horizon
UC_c	Unit Cost of EB charging spot [$]
YM_c	Yearly maintenance costs of EB charging spots [$]

Sets

A_h	Arrivals
H	Set of charging stations
T	Discrete Time Horizon

Variables

ΔE	Energy Variation between each time interval [kWh]
δ_j	Voltage angle at node j [p.u.]
$\theta_{j,k}$	Angle values between nodes j and k [p.u.]
C^{EB}	Total daily charging costs for all EBs [$]
E^B	NPC of Energy Cost of EBs [$]
I^B	NPC of Capital Cost of EBs [$]
L_q	Mean queue lenght
M^B	NPC of Total Maintenance Cost of EBs [$]
NPC	Net Present Cost [$]
P^{EB}	Total load of EBs [kW]
V_j	Voltage magnitude at node j [p.u.]
$Y_{j,k}$	Admittance magnitude between nodes j and k

1. Introduction

Electric Vehicles (EVs) are attracting interest due to their low environmental emissions. Various governments have proposed technical an economic incentives to increase the EV sales. A large deployment of EVs could, however, cause many power grid problems [1, 2, 3, 4]. Thus, several researchers have proposed strategies that allow mitigating those grid issues and proposing novel interactions between EVs and the grid.

So far, there has been fewer attention to the electrification of public transportation, like electric buses (EBs). The main characteristics of EBs are a battery capacity higher than 200 kWh, a charging power higher than 40 kW, and a more extended driving range of 200 km. In particular, EBs have better benefits than private EVs. They allow the mass transfer of passengers, avoiding road space and additional energy consumption. However, there are new challenges for EBs since they require high charging power and due to their time rigidity resulting in low flexibility for charging. There are three main options for charging EBs: fast-charging, battery swapping, and pantographs [5]. Fast-charging stations seem to be the most feasible economically and technically option in terms of costs to encourage the purchase of EBs. However, building and managing fast-charging stations brings new technical and logistic challenges.

Several researchers developed novel methodologies for the introduction of EBs in power systems, including various main objectives. Some authors have studied the Electric Bus Load Forecasting. For example, in [6], the Stochastic Modeling and Forecasting of Load Demand for EB Battery-Swap Stations is studied. The authors of [7] simulated the impact of EBs on a full transit network. In [8], the short-term forecasting of EB Load was performed using fuzzy clustering, and least squares support vector machine optimized by Wolf pack algorithm. The authors of [9] studied the impact of EB charging load on distribution substation and local grid in Warsaw, Poland.

Other studies have focused on the cost minimization of EB charging and swapping stations. For example, in [10], a strategy that reduces overall system costs is proposed considering energy storage at a fast charging EB plant was taken into account, indicating that energy storage reduces long-term costs. To solve this problem, mixed-integer non-linear programming was used, considering transformer capital costs, feeder transmission, and electricity storage constraints. The authors of [11] suggested a charge strategy for quick-charging stations based on a decision-making process, which took the position that the EBs pay only under the quick-charger load limit. In [12], the optimal deployment of fast-charging stations is studied. This work was complemented by [13], including energy storage system to optimise the economic benefits. The authors of [14] studied EB scheduling concerning multi-external factors. In [15, 16], scheduling strategies for wirelessly charged EB systems are proposed. The authors of [17] propose a charging strategy for plug-in EB charging station with PV and energy storage. In [18], the EB charging optimization is performed considering transit network constraints. The authors of [19] considered a demand response model for an EB public transportation system. In [20], the optimal charging scheduling and management for a fast-charging EB system is performed. The authors of [21] propose an intelligently charged electrified transit by considering V2G for EBs to support renewable energy in Austin power grid.

Some other authors have studied the planning of EB charging infrastruc-ture. For example, in [22], the planning of fast-charging stations for an EB system under energy consumption uncertainty is performed. The author of [23] proposes a charging station location and fleet sizing model for EBs considering demand uncertainty. In [24], the location of EB wireless charging stations is op-timized based on a genetic algorithm. The planning study of a PV-EB network is studied in [25]. In [26], the planning of am EB charging station including re-newable energy and flywheel is studied. The authors of [27] present an electrical infrastructure planning method for transit systems that operate with partially grid-connected vehicles incorporating on-board batteries in Medellin, Colombia.

Other works focused on other objectives such as minimizing both the number of charging spots and the average extra time stopped in the station to recharge [28], depicting the relationship between battery aging level and its influencing factors based on real-world operation datasets of electric city transit buses [29], improving the the economic benefits through the economic evaluation of EB battery charging and swapping stations, and to further promote the development of EVs, among others. In [30], a charging and discharging optimization model for electric buses is proposed to participate in the carbon trading market and the peak shaving auxiliary service market. The authors of [31] the impact of EBs on power distribution system reliability is evaluated by a dynamic charging model. In [32], the economic and technical feasibility of flywheel energy storage systems for supplying EBs is studied. The authors of [33] propose a cooperative decision making strategy for an EB parking lot considering PV generation and battery storage system.

Although all these works and others propose robust methodologies for the integration of EBs in the power grid, no work has proposed the participation of aggregators in the charging process of EBs, which is the main purpose of this work. Moreover, various studies considered the EB chargers' long-term investments; however, the impact of a different number of EB chargers in daily operation has not been studied. In a previous conference [34], the optimal charging operation of EBs in the power grid considering the participation of EB aggregators was proposed; however, the long-term planning problem was not considered.

Section 2 details the Charging and Planning Strategy. The case study is presented in Section 3. Section 4 discusses the main results. Finally, Section 5 is devoted to conclusions.

2. Charging and Planning Startegy

2.1. EB Aggregator for System Operation

In the future, due to uncoordinated charging by EBs, distribution system operators (DSO), and transmission system operators (TSO) could face technical challenges. Besides, there may be significant variations from day to day in residential load patterns. Both these issues have to be handled by DSO and TSO. Thus, an additional agent that works an intermediary between the EBs, and DSO and TSO is required [35]. This new agent is know as aggregator, which act as mediator/broker between users and the electricity operators [36, 37]. Various aggregators are defined, as the example of demand response aggregators whose role is to interact between residential and industrial customers and the electricity operators.

For the case of lights EVs, this entity is the EV aggregator, whose role is to group EVs considering their user's willingness to participate in electricity services [38]. This agent is decisive in managing geographically dispersed EVs, which have to be grouped since their load is relatively low for the power grid [39]. Various works considered the participation of EV aggregators in power systems [35, 38, 40, 41]. The objectives are related to mitigating grid issues while minimizing electricity costs, but EV aggregators can also participate in power markets such as spinning reserves or regulation services [42]. In many works, the Vehicle-To-Grid (V2G) mode is considered, which is defined as the EV's capacity to charge their batteries and supply electricity to the grid, resulting in a bidirectional flow between the grid and the EV [39].

On the other hand, it is still hard to evaluate EVs' real-life participation in electricity markets. The economic feasibility of V2G mode makes it hard to assume these actions for EBs. Besides, EBs have lower flexibility than light EVs due to driving schedules. Still, it is easier to aggregate EBs considering their high charging power rate, the lower number, and charging in public places.

The EB aggregator would become a required partner that will interact with DSO and TSO providing technical services. This paper assumes that EB aggregators will manage various EB charging stations that could be geographically dispersed. It is assumed that each charging station will charge a significant amount of EBs (more than 20) and owns various charging spots or only so-called chargers.

During the charging process, the EB aggregator will optimize the charging load, by minimizing the charging costs, while meeting various electrical constraints.

In the proposed approach, it is expected that system operators would offer this profile and related economic conditions to the EB aggregator.

The architecture of the proposed approach of the EB aggregators in power systems is illustrated in Figure 1.

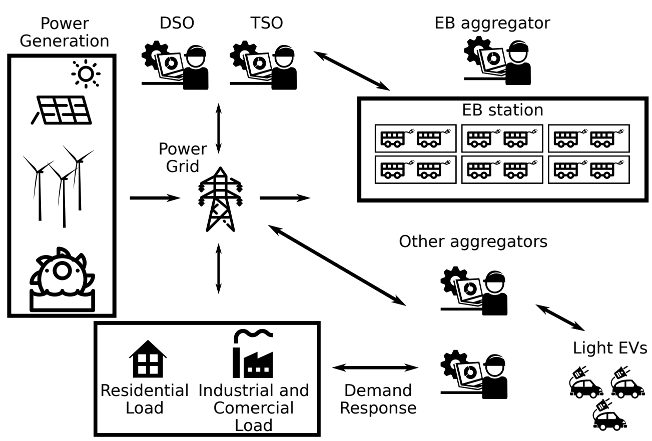

Figure 1: Architecture of the interaction of EB aggregators in power systems.

2.2. Model Definitions

Let's define a daily discrete-time horizon $T \triangleq \{1,2,..,D\}$ and a set of charging spots (chargers) $H \triangleq \{1,2,..,N_H\}$ in a EB station. It is assumed that for each $t \in T$, at least an EB is charged by a charging spot. Furthermore, for each charging spot h, a set of known sequence A_h of arrivals is defined for each EB i: $A_h \triangleq \{t_{c,i},\ i{=}1{,}2{,}..{,}N_{EB}\}$, where $t_{c,i} \in T$ is the arrival time of an EB i at a charging spot c. The model considers a bus line where all the buses drive the same route, and thus the driven distance for all the buses is almost similar. Therefore, the state-of-charge (SOC) for all the buses at the beginning of the charge is assumed to be the same. The framework of first come first served is used. If an EB arrives at the station and all the EB charging spots are in service, it must wait until an EB finishes its charging.

The charging load for all the EBs at each time interval t is defined:

$$P_t^{EB} = \sum_{i=1}^{N_{EB}} P_{t,i} \tag{1}$$

The SOC at a time interal t for an EB i is defined:

$$SOC_{t+1,i} = SOC_{t,i} + \frac{\Delta E}{Bc} \tag{2}$$

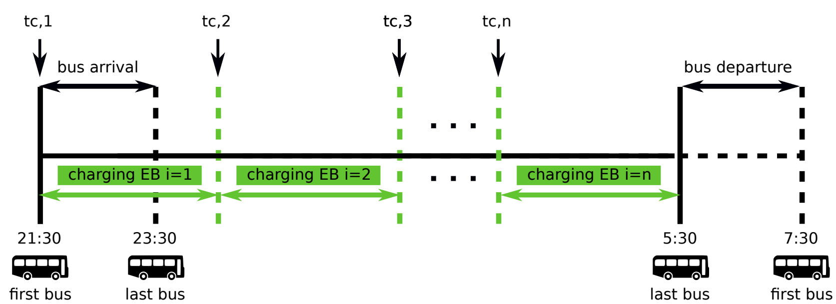

Figure 2: Charging system at the EB Station.

2.3. Problem Formulation

In this paper, it is assumed that the objective of the EB aggregator is to minimize the daily charging costs.

Let's assume $\mathbf{P}_t$, the vector of decision variables. It contains the power for each EB i for the time interval t.

$$\mathbf{P}_t^{EB} = \begin{bmatrix} P_{t,1} \\ P_{t,2} \\ ... \\ P_{t,N^{EB}} \end{bmatrix}$$

The optimization problem considers minimizing the charging costs are it is defined as follows:

$$min\ C^{EB} = min(C_p + \sum_{t=1}^{D} \pi_t.\mathbf{P}_t^{EB}) \tag{3}$$

This problem is subject to the following constraints:

$$0 < P_{t,i} < \overline{P^h} \ \forall t \in T \tag{4}$$

$$E_i^{req} = \sum_{t=1}^{D} P_{t,i}.\Delta T \ \forall t \in U_i \tag{5}$$

$$P_t^{EB} < \overline{P_t^O} \ \forall t \in T \tag{6}$$

$$P_{t-1,i} - P_{t,i} < R_D \ \forall t \in T \tag{7}$$

$$P_{t+1,i} - P_{t,i} < R_U \ \forall t \in T \tag{8}$$

$$P_{g,j} = \mid V_j \mid \sum_{k=1}^{N_n} \mid V_k \mid\mid Y_{j,k} \mid cos(\theta_{j,k} + \delta_j - \delta_k) + P_{d,j} \tag{9}$$

$$Q_{g,j} = \mid V_j \mid \sum_{k=1}^{N_n} \mid V_k \mid\mid Y_{j,k} \mid cos(\theta_{j,k} + \delta_j - \delta_k) + Q_{d,j} \tag{10}$$

$$\underline{V_j} \leq V_j \leq \overline{V_j} \forall g \in N_n \tag{11}$$

$$\underline{\delta_j} \leq \delta_j \leq \overline{\delta_j} \forall j \in N_n \tag{12}$$

Constraint (4) represents the EB charging power limits of the charger. Constraint (5) guarantees that all the energy needed for charging all the EBs is supplied. Constraint (6) imposes that the total charging load cannot overpass an allowable load established by the DSO and TSO. Constraints (7) and (8) are ramp-down and ramp-up limits that prevent extreme fluctuations of electric power supplied that could reduce the lifetime of the EB batteries. Constraints (9) and (10) ensure the power balance equations for active and reactive power that take into account the voltage magnitude, voltage angle and admittances of the distribution system. Constraint (11) is the Voltage magnitude limit, and finally constraint (12) is the voltage angle limit.

2.4. Planning Costs

The purpose of the long-term planning analysis is to identify the overall discounted costs of the EVs and the respective facilities, i.e., NPC, including electricity, operating costs, and purchasing costs [43].

The cost function of the planning model for the EB charging stations is defined as follows:

$$NPC = I^B + M^B + E^B \tag{13}$$

The NPC considers the costs that the government has to incur to discuss possible EV purchase incentives. The total NPC includes capital costs, maintenance costs, and energy costs, which are defined:

$$I^B = \sum_{y=1}^{T_P} \frac{\sum_{c=1}^{N_c} UC_c}{(1+r)^{y-1}} \tag{14}$$

$$M^B = \sum_{y=1}^{T_P} \frac{\sum_{c=1}^{N_c} YM_c}{(1+r)^{y-1}} \tag{15}$$

$$E^B = \sum_{y=1}^{T_P} \frac{365 \cdot \sum_{i=1}^{N_{EB}} \sum_{k=1}^{D} P_{k,i}.\Delta T}{(1+r)^{y-1}} \tag{16}$$

3. Case Study

3.1. Grid assumptions

To demonstrate the performance of this methodology for an EB aggregator, the case study of the electric grid of Quito, Ecuador, according to the to the commitment of the Quito City Hall to incorporate EBs into the bus network [44]. The electricity is supplied by Empresa Eléctrica Quito (EEQ), which is Quito public electric distribution company. Since the grid topology of the EEQ is not available, a modified test system of an IEEE 33-node distribution system was chosen to evaluate the methodology [45]. The EB charging station was assumed to be located in the third node, as depicted in Figure 3.1.

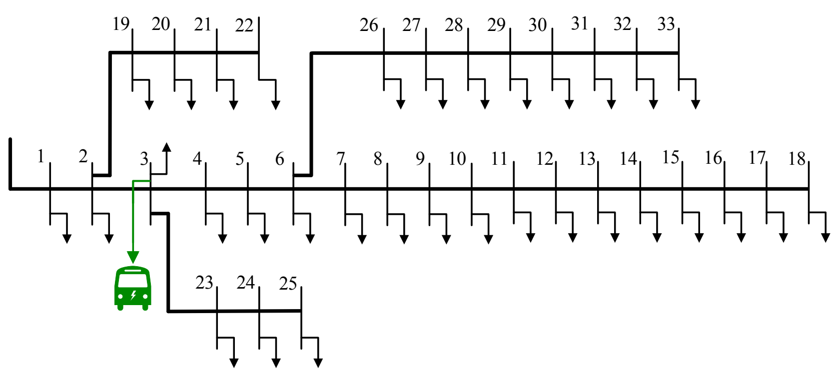

Figure 3: Modified IEEE 33-node distribution system with the EB charging station.

The residential electrical load was available during all the studied time horizon, and was thus distributed proportionally in all the corresponding nodes. Moreover, the load data from the studied feeder has overloading many times a day, and thus it is a suitable feeder to assess the impact of a new substantial load.

3.2. EB Assumptions

The bus line "Troncal Occidental" was chosen for the case study. It belongs to Metrobus-Q, which is a public transportation company. The Troncal Occidental is one of the main bus lines in Quito and operates from Ofelia terminal (north) to Quitumbe terminal (south). The Ofelia bus station hold 60 buses. It is assumed that all these buses will become electric, and have to be charged during the night at the end of service. From 5h30 AM and 07h30 AM, the buses begin their operations and end their operations between 9h30 PM and 11h30 PM. It is then expected that during the night stop, all the EBs must be charged.

The EB model K11A from the Chinese company BYD was selected for the study, since a few of these EBs were purchased for a pilot project in Troncal Occdidental bus line. The EB's fast charger can reach up to 200 kW battery capacity is 438 kWh. Furthermore, considering the bus routes, it is assumed that 85% of the SOC is consumed throughout the day operation.

3.3. Energy Price

In Ecuador, there is no electricity market and hence the electricity is vertically integrated. Each tariff has its own electricity tariff. However, the electricity rates are not related to the true electricity cost of generation, transmission, and distribution in real-time. Hence, in previous works [46, 47], a method of estimating electricity prices in Ecuador is proposed. Figure 4 depicts the electricity prices in Ecuador of a day. Note that this day was selected because the power market curve was relatively smooth, minimizing future economic savings and overlapping the strongest network operator constraints on the cheapest time.

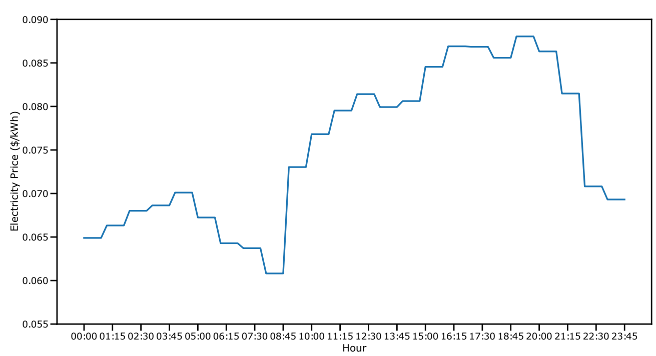

Figure 4: Electricity Prices.

3.4. DSO and TSO Constraint

The maximum allowable provided from DSO and TSO power is based on a previous work [35]. This daily pattern limits the power supplied for charging EBs and considers the operation of the electricity supplied for residential, industrial, and commercial loads to avoid grid issues such as voltage drops, voltage deviations, and power losses. This profile is depicted in Figure 5 for the study's

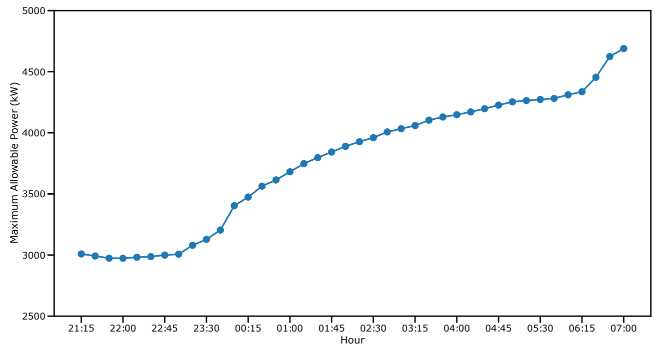

Figure 5: Operator Power Constraint

corresponding daily horizon. Observe that in the first hours of the EBs' arrival, there is less electricity available for charging EBs since a peak of the residential load limits the grid.

3.5. Model as an MMc queue system

The Ofelia bus charging system is assumed to be an MMc queue model, so that, approximate bounds for the number of chargers, can be defined. In Kendall's notation, MMc corresponds to exponential inter-arrival times, first letter, M, exponential serving time, second M, and multi-server system, with c, servers indicated by the final letter [48]. The MMc queue system, which is a generalization of the MM1 model with a single server queue. The MMc is a multi-server queueing model where bus arrivals form a single queue and are managed by a Poisson method, with c servers, with charging times that are exponentially distributed. Buses inter-arrival times are assumed to follow an exponential distribution, with an arrival rate:

$$\lambda = \frac{N_{EB}}{D} = 6EBs/hr \tag{17}$$

The charging times are also considered to follow an exponential distribution, with a charging rate:

$$\mu = \frac{1}{1.86} EBs/hr \tag{18}$$

The mean charging time for a single bus is 1.86 hours. A First-in-First-Out, FIFO, queue policy is used, and an infinite queue capacity is assumed. A lower bound for the number of chargers c must satisfy that the resource utilization should be lower than one, i.e.

$$\rho = \lambda/(\mu \times c) < 1. \tag{19}$$

The minimum value of the chargers c that satisfies Eq. 19, is $c = 12$ with $\rho = 0.93$, which is equivalent to 93% of the charging capacity usage. In the optimization model discussed in the following subsection, the values of c are analyzed around the limits determined by the queue analysis. An important measure for the system performance is the mean queue length L_q of buses in the system, and is defined according to [48] as follows:

$$L_q = \frac{P_0(\frac{\lambda}{\mu})^c \rho}{c!(1-\rho)^2}, \tag{20}$$

where

$$P_0 = \left[\sum_{m=0}^{c-1} \frac{(c\rho)^m}{m!} + \frac{(c\rho)^c}{c!(1-rho)} \right]^{-1}. \tag{21}$$

Using, both, the mean number of buses in the queue, L_q (see Eq. 20) and the resource usage ρ (Eq. 19) of the charging system, one can decide the limits for the number of chargers c in the Ofelia system.

Fig. 6-left depicts how the mean number of buses in the system queue L_q vary for to the number of chargers. Fig. 6-right shows the resource (EB chargers) usage versus the number of chargers. In the left panel an elbow behavior for L_q, can be appreciated, as the number of chargers increases. In the first part of the curve, from $c = 12$ to $c = 15$ number of chargers, the value of L_q declines rapidly and stabilize around $c = 15$ servers. At this point, the value for the mean number of buses in the system, slowly decreases, for $c > 15$, thus the elbow behavior around $c = 15$. At this elbow point, for $c = 15$ the EB chargers usage is $\rho = 0.744$, meaning a 74.4% system resoruce usage (as can be appreciated in Fig. 6-right). At the upper limit for the number of chargers, i.e. $c = 24$, a the EB charger is 46.5% which corresponds to a more adaptable charging system, in terms of service availability, as compared with a lower number of chargers with a higher usage of the EB station.

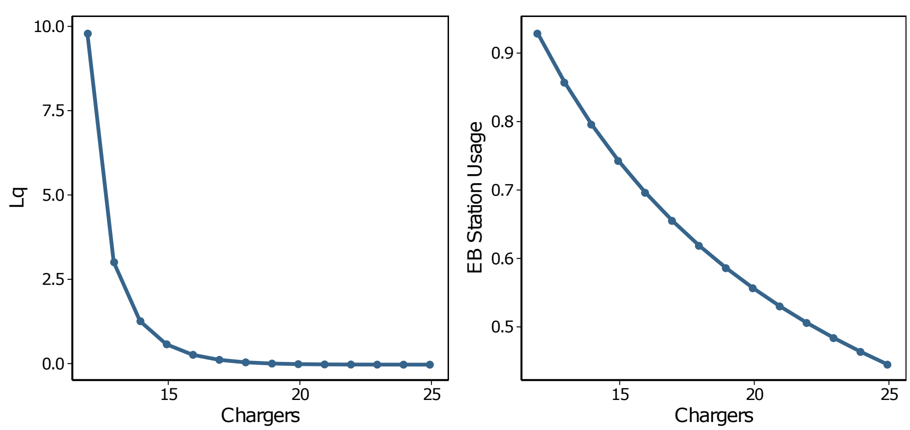

Figure 6: Resource (charger) utilization ρ (left) and mean number of buses in the queue L_q (right) as the number of server increases.

3.6. Model Simulation

The simulation of the proposed model was implemented using GAMS software, and the GAMS/CPLEX solver [49], with an Intel Core i7-8700 with 32 Gb of Ram. The IEEE 33-node distribution system was modeled and evaluated in MATPOWER [50].

4. Results and Discussion

4.1. Daily Charging Profile

Figure 7 illustrates the EB charging load considering 15 EB chargers. Observe that the curve remains in a maximum constant value between 23h00 to 05h30. The maximum value is 3,000 kW, which means that all the chargers work at the maximum power rate. Thus, there is not enough flexibility for the EB aggregator to benefit from lower daily charging costs by charging at the periods with lower electricity prices.

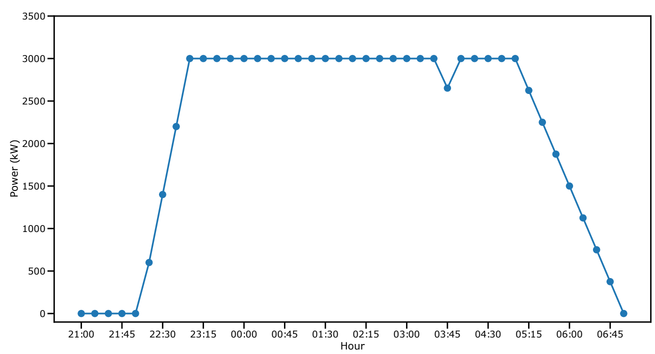

Figure 7: Daily Charging Profile of the EB charging station with 15 chargers.

In Figure 8, the charging load is depicted considering 24 EB chargers. In this case, there is more flexibility for the EB aggregator in all the time horizon and can better optimize the charging process while meeting electrical constraints, particularly when the electricity prices are low. Observe that the charging process begins an hour later, and a peak decrease is observed at 4h00, corresponding to a period when the electricity prices are relatively expensive.

Figure 9 illustrates the total EB load considering 24 chargers, the total residential load (without considering EBs), and the total electrical load during the studied time horizon. The residential load was proportionally distributed in all the nodes of the IEEE 33-node distribution system. Note that the EB load has a significant impact in the total electrical load.

In Figures 10 and 11, the voltage magnitude and angles profiles are depicted for the case of 24 chargers. Node 18 was selected since it is the node with lower voltage conditions. However, considering the real load data from the distribution feeder from Quito, and due to the EB load, the node 33 presents lower voltage profile. Observe that the EB load leads to voltage magnitude and angle drops. However, during all the studied time horizon, the voltage limits are respected.

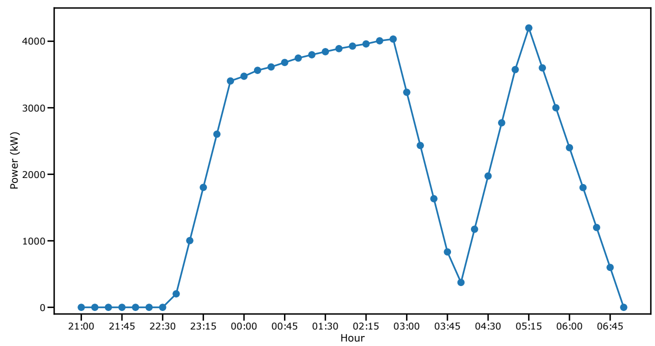

Figure 8: Daily Charging Profile of the EB charging station with 24 chargers.

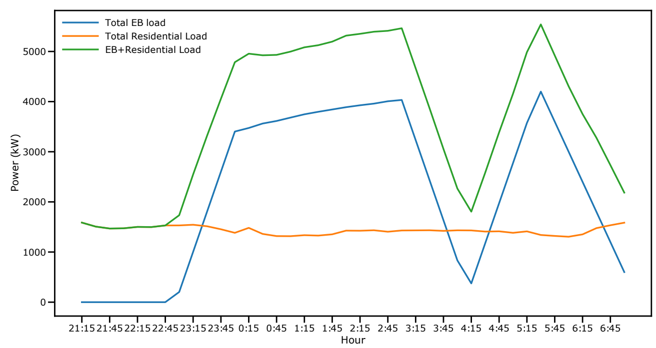

Figure 9: Electric Load Profiles

4.2. Assessment of the number of EB chargers in the charging costs

To assess the impact of the number of chargers in the EB daily charging costs, a sensitivity analysis is carried out. The lower and upper bounds are 15 and 24, respectively, with increases of a unit. Table 1 summarizes the total daily charging costs for considering a different number of EB chargers. The differences are found to be minimal. For 15 and 24 chargers, the cost difference is 1.22 %. Observe that EB charging costs are much superior than charging costs of typical light EV fleets since the required charging power is much higher.

In Figure 12, the daily charging load considering various number of chargers is illustrated. As depicted, an increase of the number of chargers leads to more significant decrease of the charging load at hour 4, at more significant increase in hour 2 and hour 5.

4.3. Long-Term Planning Results

The daily operation costs indicate that many EB chargers lead to the decrease of the daily charging costs since there is higher flexibility for charging in periods when electricity is cheaper. However, additional investment should be performed with an additional number of chargers. Thus, long-term planning

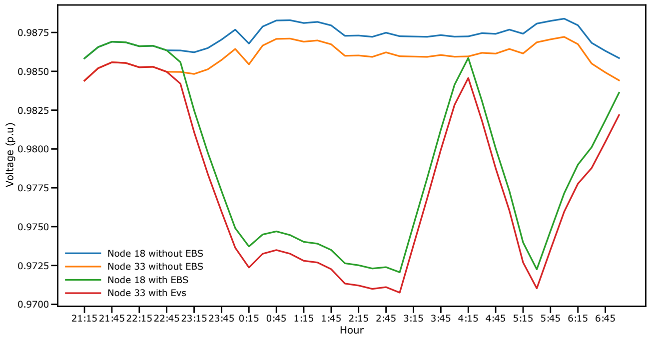

Figure 10: Voltage magnitude profiles at nodes 18 and 33 with and without EB load.

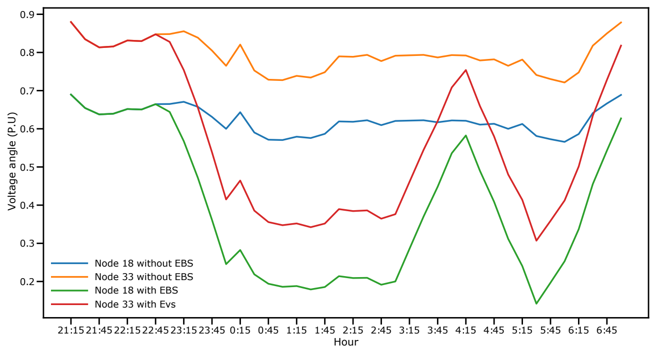

Figure 11: Voltage angle profiles at nodes 18 and 33 with and without EB load.

Table 1: Daily Charging Costs based on the number of EB charging spots

Number of EB chargers	Daily charging costs ($)
15	1510.5
16	1506.8
17	1503.7
18	1501.3
19	1499.8
20	1499.0
21	1498.4
22	1497.8
23	1497.2
24	1496.6

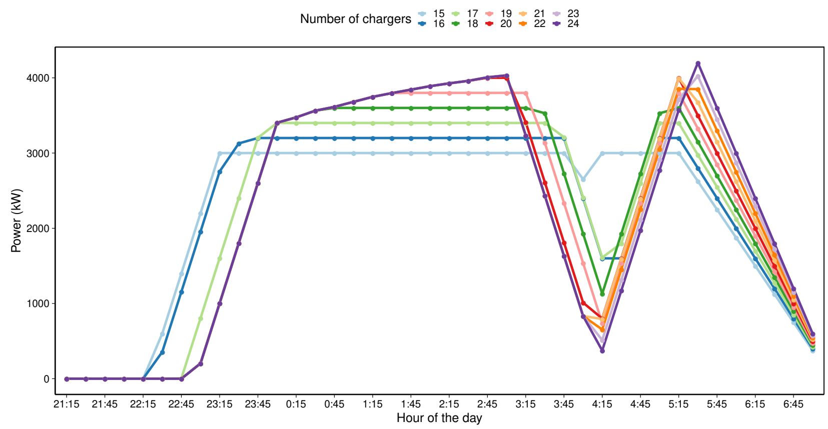

Figure 12: Daily charging profile of the EB charging station considering various number of chargers.

Table 2: Total Net Present Costs depending on number of EB chargers

Number of chargers	NPC (M$)
15	4.7598
16	4.7585
17	4.7586
18	4.7614
19	4.7666
20	4.7738
21	4.7819
22	4.7899
23	4.7980
24	4.8061

investments are also analyzed (see eq. 13). In the capital costs, only the price of an EB charger is considered, with a value of 9,000$ per additional charger, based on assumed information from BYD. The maintenance costs are assumed to be 100$/spot/year. The Total Net Present Costs considering a different number of EB chargers are summarized in Table 2. Note that the lowest NPC is observed with 16 chargers with a value of 4.7585 M$, as shown in Fig 13. When the number of chargers is bigger than 19, the decrease in daily charging costs is minimal, and the capital and maintenance costs increase, leading to a higher increase of the NPC.

In Figure 14, the summary of the different costs of the total NPC is depicted

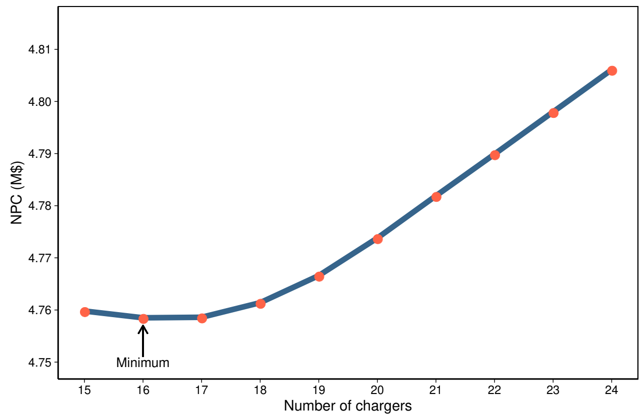

Figure 13: NPC depending on the number of chargers.

for 16 chargers, which is the number with the lower NPC. This results in annualized energy costs of 4.7487 M$, annualized operation costs of 12.549 k$, and annualized capital costs of 135 k$. Observe that the energy costs are by far the most higher. However, energy costs do not differ significantly in the number of charging spots.

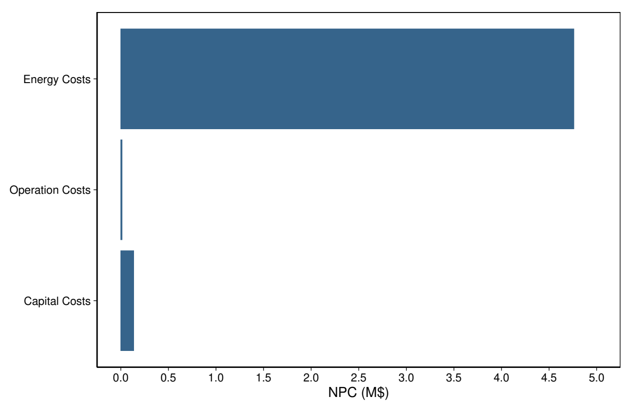

Figure 14: Summary of Costs considering 16 charging spots.

5. Conclusions

A planning methodology of EB charging stations is proposed in this paper considering EB aggregators' participation. The synergy of an EB aggregator with the DSO and TSO is proposed to handle this new important load properly. This work considers minimizing the daily charging costs considering power grid constraints. The long-term planning study is performed, considering capital and maintenance costs.

The real case study of Quito-Ecuador was considered to demonstrate the effectiveness of the methodology. Data from a bus station and from the local distribution company were used for the simulation. Various cases are studied, considering a different number of EB charging spots. The results show that with a bigger number of charging spots, the daily charging costs decrease little. However, the planning results indicate that the minimal NPC is obtained with 16 chargers.

Acknowledgements

This works belongs to the project SIS.JCG.19.03 from Universidad de las Américas - Ecuador. The authors would like to thank Paulo-Guerra Terán from Universidad de las Américas - Ecuador for the fruitful discussion.

References

[1] K. Clement-Nyns, E. Haesen, J. Driesen, The impact of Charging plug-in hybrid electric vehicles on a residential distribution grid, IEEE Trans. Power Syst. (2010). doi:10.1109/TPWRS.2009.2036481.

[2] Z. Darabi, S. Member, M. Ferdowsi, Aggregated Impact of Plug-in Hybrid Electric Vehicles on Electricity Demand Profile, IEEE Trans. Sustain. Energy 2 (4) (2011) 501–508.

[3] H. Morais, T. Sousa, Z. Vale, P. Faria, Evaluation of the electric vehicle impact in the power demand curve in a smart grid environment, Energy Convers. Manag. 82 (2014) 268–282. doi:10.1016/j.enconman.2014.03.032. URL `http://dx.doi.org/10.1016/j.enconman.2014.03.032`

[4] P. M. de Quevedo, G. Munoz-Delgado, J. Contreras, Impact of Electric Vehicles on the Expansion Planning of Distribution Systems considering Renewable Energy, Storage and Charging Stations, IEEE Trans. Smart Grid 10 (1) (2017) 794–804. doi:10.1109/TSG.2017.2752303.

[5] J.-M. M. Clairand, P. Guerra-Terán, X. Serrano-Guerrero, M. González-Rodríguez, G. Escrivá-Escrivá, Electric Vehicles for Public Transportation in Power Systems: A Review of Methodologies, Energies 12 (16) (2019) 3114. doi:10.3390/en12163114.

[6] Q. Dai, T. Cai, S. Duan, F. Zhao, Stochastic modeling and forecasting of load demand for electric bus battery-swap station, IEEE Trans. Power Deliv. 29 (4) (2014) 1909–1917. doi:10.1109/TPWRD.2014.2308990.

[7] M. Mohamed, H. Farag, N. El-Taweel, M. Ferguson, Simulation of electric buses on a full transit network: Operational feasibility and grid impact analysis, Electr. Power Syst. Res. 142 (2017) 163–175. doi:10.1016/j.epsr.2016.09.032.
URL `http://dx.doi.org/10.1016/j.epsr.2016.09.032`

[8] X. Zhang, Short-term load forecasting for electric bus charging stations based on fuzzy clustering and least squares support vector machine optimized by Wolf pack algorithm, Energies 11 (6) (2018). doi:10.3390/en11061449.

[9] K. Zagrajek, J. Paska, M. Kłos, K. Pawlak, P. Marchel, M. Bartecka, Ł. Michalski, P. Terlikowski, Impact of electric bus charging on distribution substation and local grid in Warsaw, Energies 13 (5) (2020). doi:10.3390/en13051210.

[10] H. Ding, Z. Hu, Y. Song, Value of the energy storage system in an electric bus fast charging station, Appl. Energy 157 (2015) 630–639. doi:10.1016/j.apenergy.2015.01.058.
URL `http://dx.doi.org/10.1016/j.apenergy.2015.01.058`

[11] N. Qin, A. Gusrialdi, R. Paul Brooker, A. T-Raissi, Numerical analysis of electric bus fast charging strategies for demand charge reduction, Transp. Res. Part A Policy Pract. 94 (2016) 386–396. doi:10.1016/j.tra.2016.09.014.
URL `http://dx.doi.org/10.1016/j.tra.2016.09.014`

[12] Z. Chen, Y. Yin, Z. Song, A cost-competitiveness analysis of charging infrastructure for electric bus operations, Transp. Res. Part C Emerg. Technol. 93 (December 2017) (2018) 351–366. doi:10.1016/j.trc.2018.06.006.
URL `https://doi.org/10.1016/j.trc.2018.06.006`

[13] H. Chen, Z. Hu, H. Zhang, H. Luo, Coordinated charging and discharging strategies for plug-in electric bus fast charging station with energy storage system, IET Gener. Transm. Distrib. 12 (9) (2018) 2019–2028. doi:10.1049/iet-gtd.2017.0636.

[14] Y. Gao, S. Guo, J. Ren, Z. Zao, A. Ehsan, Y. Zheng, An Electric Bus Power Consumption Model and Optimization of Charging Scheduling Concerning Multi-External Factors, Energies 11 (8) (2018) 1–17. doi:10.3390/en11082060.

[15] C. Yang, W. Lou, J. Yao, S. Xie, On Charging Scheduling Optimization for a Wirelessly Charged Electric Bus System, IEEE Trans. Intell. Transp. Syst. 19 (6) (2018) 1814–1826. doi:10.1109/TITS.2017.2740329.

[16] Y. Alwesabi, Y. Wang, R. Avalos, Z. Liu, Electric bus scheduling under single depot dynamic wireless charging infrastructure planning, Energy 213 (2020) 118855. doi:10.1016/j.energy.2020.118855.
URL `https://doi.org/10.1016/j.energy.2020.118855`

[17] S. M. Arif, T. T. Lie, B. C. Seet, S. M. Ahsan, H. A. Khan, Plug-in electric bus depot charging with PV and ESS and their impact on LV feeder, Energies 13 (9) (2020) 1–16. doi:10.3390/en13092139.

[18] A. Bagherinezhad, A. D. Palomino, B. Li, M. Parvania, Spatio-Temporal Electric Bus Charging Optimization with Transit Network Constraints, IEEE Trans. Ind. Appl. 56 (5) (2020) 5741–5749. doi:10.1109/TIA.2020.2979132.

[19] B. R. Ke, Y. H. Lin, H. Z. Chen, S. C. Fang, Battery charging and discharging scheduling with demand response for an electric bus public transportation system, Sustain. Energy Technol. Assessments 40 (February) (2020) 100741. doi:10.1016/j.seta.2020.100741.
URL `https://doi.org/10.1016/j.seta.2020.100741`

[20] Y. He, Z. Liu, Z. Song, Optimal charging scheduling and management for a fast-charging battery electric bus system, Transp. Res. Part E Logist. Transp. Rev. 142 (April) (2020) 1–24. doi:10.1016/j.tre.2020.102056.

[21] T. K. Wellik, J. R. Griffin, K. M. Kockelman, M. Mohamed, Utility-transit nexus: Leveraging intelligently charged electrified transit to support a renewable energy grid, Renew. Sustain. Energy Rev. 139 (November 2020) (2021) 110657. doi:10.1016/j.rser.2020.110657.
URL `https://doi.org/10.1016/j.rser.2020.110657`

[22] Z. Liu, Z. Song, Y. He, Planning of Fast-Charging Stations for a Battery Electric Bus System under Energy Consumption Uncertainty, Transp. Res. Rec. (2018). doi:10.1177/0361198118772953.

[23] K. An, Battery electric bus infrastructure planning under demand uncertainty, Transp. Res. Part C Emerg. Technol. 111 (January) (2020) 572–587. doi:10.1016/j.trc.2020.01.009.
URL `https://doi.org/10.1016/j.trc.2020.01.009`

[24] G. Chen, D. Hu, S. Chien, L. Guo, M. Liu, Optimizing wireless charging locations for battery electric bus transit with a genetic algorithm, Sustain. 12 (21) (2020) 1–20. doi:10.3390/su12218971.

[25] Z. Dalala, O. A. Banna, O. Saadeh, The feasibility and environmental impact of sustainable public transportation: A PV supplied electric bus network, Appl. Sci. 10 (11) (2020). doi:10.3390/app10113987.

[26] D. Erdemir, I. Dincer, Assessment of Renewable Energy-Driven and Flywheel Integrated Fast-Charging Station for Electric Buses: A Case Study, J. Energy Storage 30 (May) (2020) 101576. doi:10.1016/j.est.2020.101576.
URL `https://doi.org/10.1016/j.est.2020.101576`

[27] A. E. Díez, M. Restrepo, A Planning Method for Partially Grid-Connected Bus Rapid Transit Systems Operating with In-Motion Charging Batteries, Energies 14 (9) (2021) 2550. doi:10.3390/en14092550.

[28] M. T. Sebastiani, R. Luders, K. V. O. Fonseca, Evaluating Electric Bus Operation for a Real-World BRT Public Transportation Using Simulation Optimization, IEEE Trans. Intell. Transp. Syst. 17 (10) (2016) 2777–2786. doi:10.1109/TITS.2016.2525800.

[29] C. She, Z. Wang, F. Sun, P. Liu, L. Zhang, Battery Aging Assessment for Real-World Electric Buses Based on Incremental Capacity Analysis and Radial Basis Function Neural Network, IEEE Trans. Ind. Informatics 16 (5) (2020) 3345–3354. doi:10.1109/TII.2019.2951843.

[30] S. X. Yang, X. F. Wang, W. Q. Ning, X. feng Jia, An optimization model for charging and discharging battery-exchange buses: Consider carbon emission quota and peak-shaving auxiliary service market, Sustain. Cities Soc. 68 (October 2020) (2021) 102780. doi:10.1016/j.scs.2021.102780.
URL `https://doi.org/10.1016/j.scs.2021.102780`

[31] K. Qiu, W. Naim, E. Shayesteh, P. Hilber, Reliability evaluation of power distribution grids considering the dynamic charging mode of electric buses, Energy Reports 7 (2021) 134–140. doi:10.1016/j.egyr.2021.02.012.
URL `https://doi.org/10.1016/j.egyr.2021.02.012`

[32] B. Thormann, P. Puchbauer, T. Kienberger, Analyzing the suitability of flywheel energy storage systems for supplying high-power charging e-mobility use cases, J. Energy Storage 39 (April) (2021) 102615. doi:10.1016/j.est.2021.102615.
URL `https://doi.org/10.1016/j.est.2021.102615`

[33] A. Zahedmanesh, K. M. Muttaqi, D. Sutanto, A Cooperative Energy Management in a Virtual Energy Hub of an Electric Transportation System Powered by PV Generation and Energy Storage, IEEE Trans. Transp. Electrif. 7782 (c) (2021) 1–11. doi:10.1109/TTE.2021.3055218.

[34] J.-M. Clairand, M. González-Rodríguez, P. Guerra-Terán, I. Cedeño, G. Escrivá-Escrivá, The impact of charging electric buses on the power grid, in: 2020 IEEE Power Energy Soc. Gen. Meet., IEEE, 2020.

[35] J.-M. Clairand, J. Rodríguez-García, C. Álvarez-Bel, Smart Charging for Electric Vehicle Aggregators considering Users' Preferences, IEEE Access 6 (2018) 1–12. doi:10.1109/ACCESS.2018.2872725.

[36] L. Gkatzikis, I. Koutsopoulos, The Role of Aggregators in Smart Grid Demand, IEEE J. Sel. Areas Commun. 31 (7) (2013) 1247–1257.

[37] Ö. Okur, P. Heijnen, Z. Lukszo, Aggregator's business models in residential and service sectors: A review of operational and financial aspects, Renew. Sustain. Energy Rev. 139 (March 2020) (2021) 110702. doi:10.1016/j.rser.2020.110702.
URL `https://doi.org/10.1016/j.rser.2020.110702`

[38] J. P. Lopes, F. Joel Soares, P. M. Rocha Almeida, Integration of Electric Vehicles in the Electric Power System, Proc. IEEE 99 (1) (2011) 168 – 183. doi:10.1109/JPROC.2010.2066250.

[39] C. Guille, G. Gross, A conceptual framework for the vehicle-to-grid (V2G) implementation, Energy Policy 37 (11) (2009) 4379–4390. doi:10.1016/j.enpol.2009.05.053.

[40] C. Li, R. Zhao, D. Wang, W. Cai, C. Yu, Y. Gu, Q. Zhang, Optimal spatio-temporal scheduling for Electric Vehicles and Load Aggregators considering response reliability, Electr. Power Syst. Res. 162 (December 2017) (2018) 183–193. doi:10.1016/j.epsr.2018.05.007.
URL `https://doi.org/10.1016/j.epsr.2018.05.007`

[41] M. Rayati, M. Bozorg, R. Cherkaoui, Coordinating strategic aggregators in an active distribution network for providing operational flexibility, Electr. Power Syst. Res. 189 (August) (2020) 106737. doi:10.1016/j.epsr.2020.106737.
URL `https://doi.org/10.1016/j.epsr.2020.106737`

[42] W. Kempton, J. Tomić, Vehicle-to-grid power fundamentals: Calculating capacity and net revenue, J. Power Sources 144 (1) (2005) 268–279. doi:10.1016/j.jpowsour.2004.12.025.

[43] H. Seifi, M. S. Sepasian, Electric Power System Planning, Springer, 2011. arXiv:arXiv:1011.1669v3, doi:10.1007/978-3-642-17989-1.

[44] M. S. González-Rodríguez, J.-M. Clairand, K. Soto-Espinosa, J. Jaramillo-Fuelantala, G. Escrivá-Escrivá, Urban Traffic Flow Mapping of an Andean Capital : Quito , Ecuador, IEEE Access 8 (2020) 195459–195471. doi:10.1109/ACCESS.2020.3033518.

[45] M. E. Baran, F. F. Wu, Network reconfiguration in distribution systems for loss reduction and load balancing, IEEE Trans. Power Deliv. Deliv. 4 (2) (1989) 101–102.

[46] J.-M. Clairand, J. Rodriguez Garcia, C. Alvarez Bel, J. Rodríguez-García, C. Álvarez-Bel, Smart Charging for an Electric Vehicle Aggregator Considering User Tariff Preference, 2017 IEEE Power Energy Soc. Innov. Smart Grid Technol. Conf. (2017) 5doi:10.1109/ISGT.2017.8086068.
URL `http://ieeexplore.ieee.org/stamp/stamp.jsp?tp={\&}arnumber=8086068`

[47] C. Álvarez-Bel, P. Pesantez-Sarmiento, J. Rodriguez García, M. Alcázar-Ortega, J. Carbonell Carretero, P. Erazo-Almeida, D. X. Morales Jadan, G. Escrivá-Escrivá, A. Carrillo-Díaz, M. A. Piette, R. Llopis-Goig, E. Peñalvo-López, V. Martínez-Guardiola, M. I. Trenzano-García, A. Vicente-Pastor, V. Orbea-Andrade, J.-M. Clairand, Análisis para la implementación de redes inteligentes en Ecuador - Metodología de Previsión

de la demanda basada en redes inteligentes, Editorial Institucional UPV, 2016.

[48] R. M. Feldman, C. Valdez-Flores, Applied probability and stochastic processes, Springer Science & Business Media, 2009.

[49] GAMS, GAMS.
URL https://www.gams.com/

[50] R. D. Zimmerman, C. E. Murillo-Sánchez, R. J. Thomas, MATPOWER: Steady-state operations, planning, and analysis tools for power systems research and education, IEEE Trans. Power Syst. 26 (1) (2010) 12–19.