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Smart Charging for Electric Vehicle Aggregators considering Users' Preferences

JEAN-MICHEL CLAIRAND[1,2], (Student Member, IEEE), JAVIER RODRÍGUEZ-GARCÍA[2], AND CARLOS ÁLVAREZ-BEL.[2], (Member, IEEE)

[1]Facultad de Ingeniería y Ciencias Agropecuarias, Universidad de las Américas, Quito, 170122 Ecuador

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

Corresponding author: Jean-Michel Clairand (e-mail: jean.clairand@udla.edu.ec).

ABSTRACT Most of the road transportation currently depends on fossil fuels, which result in significant environmental and health issues. This is being addressed with the deployment of electric vehicles. However, a massive penetration will lead to new technical and economic challenges for power systems. This paper proposes a novel way to account for the effect of this new load and to minimize the negative impacts by providing new tools for the agent responsible of managing the EV charge in some area (EV aggregator). The proposed method allows EV charging at the lowest cost while complying with technical constraints required by Distribution System Operator (DSO) and Transmission System Operator (TSO). Moreover, EV users are able to choose among different customer choice products (CCPs) that meets their needs in terms of charging time. A case study in the city of Quito (Ecuador) is analyzed in the paper where the advantages of the proposed coordinated charging method are quantified. The model presents cost benefits compared to uncoordinated charging while complying with technical constraints. Additionally, the savings using the presented model are at least 5% higher than uncoordinated charging, and can reach more than 50% at best.

INDEX TERMS Electric Vehicle, Smart Grid, Smart Charging, User Preference, Flexibility

Nomenclature

Indices

i	EV user index
k	Time step
x	CCP index: G for green, B for blue, R for red
y	Scenario

Parameters

$\underline{\eta}$	EV charging efficiency (%)
$\overline{P^{res}}$	Maximum residential load (kW)
$P_k^{EV,O}$	Operator load constraint at step k (kW)
π_k	Cost of electricity at the step k ($/kWh)
$\underline{E^{req}}$	Minimum required energy (kWh)
Bc_i	Nominal battery capacity of vehicle i (kWh)
D	Number of time intervals in a day
E_i^{req}	Energy required from EV i (kWh)
N^x	Number of EVs participating in x CCP
P^{cri}	Critical Power (kW)
$P^{x,av}$	Average charging power for x CCP (kW)
$P_{k,i}$	Load of an EV i at step k (kW)
st_i	Starting charging time of EV i

Sets

T	Set of time intervals in a day
U_i	Set of time intervals of a vehicle i that corresponds to charging period

Variables

ΔE_i	Energy variation between each step time of EV i (kWh)
ΔS_{y-3}^x	Daily cost difference percentage for x CCP from y scenario to third scenario ($)
$\overline{P^{ch}}$	Maximum charging power rate for an EV (kW)
$\overline{P_k^{EV,tot}}$	Maximum EV Power Constraint at step k (kW)
C^x	Daily Cost of all x CCP EV users ($)
C^{EV}	Daily costs for all EV users ($)
$C^{x,y}$	Daily Cost of x CCP in scenario y ($)
C_p	Penalty cost if the aggregator overpass operator charging pattern ($)
$E_{k,i}$	Energy stored in the EV battery at the step k (kWh)
$P^{x,av}$	Average power consumption for a x CCP (kW)
P_k^x	Total power consumed by cars participating in x CCP at step k (kW)

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P_k^{EV} Total EV load at step k (kW)
$P_k^{res,tot}$ Total residential load at step k (kW)
$SOC_{k,i}$ State of charge of vehicle i at step k (%)
T_i^x Duration of charge for vehicle i participating in x CCP (h)

I. INTRODUCTION

A. MOTIVATION AND BACKGROUND

CONCERNS about global warming, depletion of fossil fuel reserves, and health issues have pushed governments to think about new alternatives in the conventional transportation sector. Over the past years, electric vehicles (EVs) have been promoted to address some of these issues. EVs are less noisy, more efficient and generates lower CO_2 emissions than internal combustion engine propelled vehicles [1].

There are three EV power level types [2]. Levels 1 and 2, often called "slow charging", usually correspond to residential use and Level 3 for commercial use. Car manufacturers recommend Level 3 use only as "urgent charging" because this method of charging reduces the battery life [3]. In fact, Level 3 operates at high power, which results in higher stress and more mechanical damage to the active material inside the battery. As such, Level 3 charging leads to faster battery performance degradation [4], [5]. Hence, EV users mostly use slow charging levels.

The share of EVs in the car fleet is nowadays minimal, but it is expected that it will significantly increase due to the promotion of EVs, such as governments incentives. Nevertheless, a massive introduction of EVs into the electric grid could cause many problems, which include distribution system losses [6], [7], placement of charging infrastructures [8], important increment of distribution network investments [9], power transformers' loss of life [10], and peak load increase [11]. These problems result from uncoordinated charging.

Thus, some works have been proposed for the coordinated charging of EVs, which have different objectives that include minimization of distribution losses [6], [12], peak shaving and valley filling [13], [14], ancillary services [15], [16], smart charger applications [17], [18], EV integration in Smart Homes [19], and EV charging stations allocation [20]. So far, fewer works have studied charging costs minimization.

To manage geographically dispersed EVs and to alleviate distribution and transmission operator functions, a new electricity entity is proposed: the EV Aggregator. In [21], it is presented the contribution of a vehicle aggregation that consists of a consolidation of the batteries of the EVs as an appropriate size load and provides an interface with the independent system operator or regional transmission organization. Several authors have considered this new player as the focus of their works [22]–[26].

All these methodologies for the EV integration into the grid could result efficient in the grid performance. Nevertheless, the EV charging management is mostly based on schedules or EV load shifting, which can discourage the car users to buy EVs instead of internal combustion vehicles. As indicated in [27], users can have strong reactions to technologies and inhibit their implementation. It is crucial to offer EV users different alternatives for the EV charging, considering their preferences. Hence, this is one goal of this work.

B. RELATED WORK

Related work of this paper is divided into two parts. In the first part, an overview of the main works related to charging cost minimization is described. Then, some of the works that have considered user preferences are described.

1) Charging cost Minimization

The following works have addressed the problem of defining methodologies for minimizing the EV charging costs.

In [29], it was proposed that an EV aggregator minimizes a time-varying electricity price, based on the case of the Netherlands. The authors of [30] presented optimal-cost scheduling of EV charging stations, considering the uncertainties of renewable energy generation; however, they consider the problem of a charging station and not a main grid. In [31], a hierarchical model for coordinated charging is presented, which consists of three levels, and it was applied to case studies in China. The authors of [32] proposed four charging methods to maximize battery charging speed while minimizing electricity cost. In [33], a decentralized charging control is studied, where a load aggregator optimizes the charging of a plug-in EV fleet, considering price-based signals. The authors of [34] have modeled the charging problem as a Markov decision process to reduce the charging costs; however, the approach does not consider the participation of an EV aggregator, which can interact with the DSO and TSO taking into account their technical constraints.

These methodologies are useful to minimize charging costs, but users' preferences are not significantly considered, which can create a barrier for users to adopt EVs.

2) EV users' Preferences

Only a few works have considered the EV users' preferences in their methodologies, which are shown below.

In [35], a charging methodology is presented that jointly optimizes pricing, scheduling, and admission control of an EV charging station, based on a multi-sub-process admission control scheme. This work considers to reduce the excessive waiting time (time between the arrival and that the EV receives service) for EV users; however, even if this waiting time is minimal, it can negatively impact on EV user experience, and this work only considers the case of a charging station.

The authors of [36] proposed an EV charging tariff to incentivize EV users' provision of load flexibilities; but, these tariffs only considered the flexibilities for load-shifting techniques.

In [37], a decentralized PEV charging selection algorithm was studied to maximize user convenience, while respecting predefined circuit-level load limits. The authors of [38] have proposed a distributed algorithm to coordinate charging of PEVs, maximizing user convenience subject to the constraints imposed by the power utility. In [39] an interactive charging management system for EV charging is investigated, guarantying EV users' preferences. Although user convenience was maximized, these works did not consider the EV charging costs. To overcome this drawback, reference [40] presented a bi-objective optimization based on charging costs minimization and maximizing user convenience; however, the problem was only addressed in a microgrid scale and considered that all the EV users have the same waiting behavior.

C. MAIN CONTRIBUTIONS AND OUTLINE

The aim of this paper is to present a novel methodology for an EV aggregator, which will adjust slow charging power to fulfill technical constraints imposed by network operators while EVs are charged at the lowest cost. In this vein, EV users could select among different customer choice products (CCPs) depending on their time flexibility. This paper is an extension of an earlier conference [28], which has been significantly refined. The innovative contributions of the proposed method are highlighted as follows:

- EV users would have the possibility of selecting a CCP (before starting the charging process) depending on their time flexibility, and this will avoid some typical management problems such as unexpected interruptions of the charging process or waiting for a long time before driving. The charging method consists of modulating the charging power rate, which will be remotely controlled by an EV aggregator taking into account the electricity prices and technical constraints.
- An interaction is proposed between the EV aggregator and the Distribution System Operator (DSO) and the Transmission System Operator (TSO), which will avoid technical problems in the electricity network while the charging costs are optimized.
- Different user behaviors will be considered to simulate their charging patterns provided by EV chargers when an EV is plugged such as State of Charge (SOC), starting charging time and waiting time. This model can be adjusted to any electricity network, independently of the country in which it may be located, and even if the demand conditions, electricity prices, and users behavior are different from the case study presented in this paper.

The rest of the paper is organized as follows: Section II discusses the smart charging methodology considering EV users' preferences. Then, the case study is presented in Section III. Section IV validates the methodology, based on the results and discussion. Finally, Section V highlights the main conclusions and contributions of the paper.

II. SMART CHARGING METHODOLOGY CONSIDERING EV USERS' PREFERENCES

A. EV AGGREGATOR FOR SYSTEM OPERATION

DSO and TSO may have troubles in the future due to the presence of EVs uncoordinated charging. In addition, residential load patterns could have significant changes from day to day. DSO and TSO have to manage all these problems using all the available resources. The EV aggregator becomes a mandatory partner that provides technical services to the DSO and TSO. The EV aggregator will act as an intermediate agent among operators, who will probably use market mechanisms to get the necessary resources and EVs consumers.

This agent will provide flexible demand packages that can be offered to grid managers and other interested agents. This flexible potential will be provided by the EV users by charging power modulation facilities. The EV aggregator will offer its services to TSO and DSO for grid operations and possibly to other electricity partners to optimize their buying energy portfolio.

In a future scenario, TSO and DSO will probably have, in their operation area besides the EV aggregators, Demand Response aggregators that will manage flexible load from residential, commercial and industrial customers. In this paper, this load will be considered as a non-flexible load, and TSO and DSO will interact with this new EV aggregator and with other aggregators to solve daily technical problems as peak or valley loads. This EV aggregator will compensate this non-flexible load with the EV charging load when flexible. Consequently, the aggregator will modulate the EV charging curve in order not to exceed the maximum available power for EV charging at any moment of the day determined by network operating requirements (Distribution and Transmission). The EV aggregator will be economically benefited in case it complies (not overpass) this "Maximum EV Load Profile".

It is assumed in the proposed methodology that system operators will provide the EV aggregator with this profile as well as the associated economic conditions.

B. EV USERS OPTIONS

As stated before, people may hesitate to adopt the previous EV charging strategies because charging conditions are not in accordance with their time flexibility. It is clear from EV aggregator's point of view that it is better to charge the EVs when the price is cheapest, but it is not in accordance with user preferences. It is assumed that the EV aggregator will use charging power modulation, between 0 kW and the maximum charging power from EV charger in slow charging mode. Moreover, some users could wait for a long time before having their EV completely charged and others would need their EV quickly charged if they pay an extra fee. Some of the works presented before considered that all users have the same charging behavior. In that way, it is crucial to consider all these different EV charging preferences. Hence, in this methodology, customer choice products (CCPs) are proposed for charging EVs. They are defined as different electricity pricing for charging EVs, which will be coordinated by the EV aggregator. They differ from a tariff because it is the EV aggregator which fix the pricing and not the electricity regulator. For the methodology, three CCPs are proposed, but this number could be modified depending on users and grid conditions. The CCPs are associated with an average charging power rate related to the total duration of charging. In this case, the EV user must select one CCP before starting the charging process. The number of CCPs and their characteristics (e.g., average charging power rate) could be modified according to user's preferences from different countries where they are applied. For this methodology, it is considered that there will be installed smart chargers that allow EV users to know the end time of a specific charging. The Smart Chargers are currently in research development, but it is expected that they will have a screen for showing various pieces of information to users such as energy delivered, remaining time, charging power rate. They will be able to communicate this information to the utilities and the EV aggregator. The EV aggregator will be able to make decisions concerning the charging of all the EVs in an area, so remote controlling is also needed. When a user plugs its EV, the duration for each CCP will be calculated and showed in the display as well as the associated average electricity price. After that, the EV user will be able to select one of them according to his needs, but he must consider that if he stops the charging process before ending the selected charging period, there is no guarantee to achieve the selected charge level. The CCPs proposed are defined as green, blue and red.

The CCPs proposed by the authors are defined as:

- Green CCP: it is the cheapest CCP. The user is committed to let the EV aggregator modulate its charging power rate, depending on electricity markets conditions. It means that when the electricity is more expensive, charging power could be adjusted to zero, but when the electricity is cheaper, it could be adjusted to the maximum power rate that is 7.2 kW. Its charging duration will be the longest because the average charging power will be the lowest. For an EV user i who selects this CCP, his charging duration T_G^i will depend on his energy required E_{req}^i and the average charging power rate $P_{G,av}$ from the green CCP.
- Blue CCP: it is a more expensive CCP than the green. In the same way, the user is committed to let the EV aggregator modulate its charging power rate. Its duration time T_B^i will be shorter than the green because its average charging power $P_{B,av}$ will be higher.
- Red CCP: it is the most expensive CCP. The user will have to pay the highest price for the energy required, but he can constantly charge at the maximum charging power that is established in 7.2 kW. This CCP is designed for users that need their cars ready as soon as possible and are willing to pay a high price for that. These users will prefer to charge at work or home in order not to charge in a fast charging station.

The charging duration of an EV i from each x CCP is defined:

$$T_i^x = \frac{E_i^{req}}{P^{x,av}} \tag{1}$$

Figure 1 represents the architecture scheme associated with the proposed methodology.

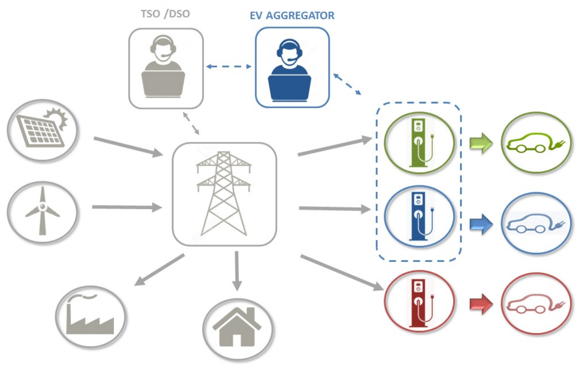

FIGURE 1: Methodology System Architecture.

C. EV USERS REQUIREMENTS

EV users have different behaviors, so it is hard to forecast the daily EV load curve. These behaviors depends on different parameters such as starting charging time, end charging time, charging power rate, vehicle's battery type, and SOC, among others. To address these uncertainties, the EV aggregator needs to know the different data related to the charging process of all EVs. For this purpose, it is crucial that the EV users, or parking lots, that participate in the proposed energy management program install smart meters to communicate this data with the EV aggregator, such as the one presented in [41]. In this paper, the data is assumed to be gathered in real time. Moreover, the EV aggregator has to predict the overall EV load curve each day, based on techniques such as presented in [42], [43].

On a day, it is considered D discrete time intervals (15 minutes). The set of time intervals are defined:

$$T = \{1, 2, \ldots\ldots, D\} \tag{2}$$

For each EV i, it is considered a plug time $U_i \in T$, which is the set of sample times between starting charging time and the time at which the charging process is completed.

The power consumed by all EVs and managed by the EV aggregator at each step time k P_k^{EV} is, the sum of the overall power consumed by EV users of green CCP P_k^G, blue CCP P_k^B and red CCP P_k^R:

$$P_k^{EV} = P_k^G + P_k^B + P_k^R, \forall k \in T \tag{3}$$

Moreover, the total load corresponding to the charging of EVs from each x CCP are defined:

$$P_k^x = \sum_{i=1}^{N_x} P_{k,i}^x \tag{4}$$

Thus:

$$P_k^{EV} = \sum_{i=1}^{N_G} P_{k,i}^G + \sum_{i=1}^{N_B} P_{k,i}^B + \sum_{i=1}^{N_R} P_{k,i}^R, \forall k \in T \quad (5)$$

The energy stored in a EV battery i will depend on the last value and on the power delivered $P_{k,i}$ on each step time ΔT. It is calculated as:

$$E_{k+1,i} = E_{k,i} + \eta.P_{k,i}.\Delta T = E_{k,i} + \Delta E_i \quad (6)$$

The total energy dispatched in a day to all EVs participating in an x CCP is defined as:

$$E^{x,tot} = \sum_{k=1}^{D} P_k^x.\Delta T \quad (7)$$

The total energy dispatched in a day to all EVs is defined as:

$$E^{EV,tot} = \sum_{k=1}^{k=D} (P_k^G + P_k^B + P_k^R).\Delta T \quad (8)$$

The SOC (%) also depends on the last value and on the difference between the energy ΔE_i and the capacity of the battery Bc_i. It is calculated as:

$$SOC_{k+1,i} = SOC_{k,i} + \frac{\Delta E_i}{Bc_i} \quad (9)$$

D. EV AGGREGATOR COSTS

The EV aggregator has to pay the electricity that it supplies to their customers (EV users). Additionally, the EV aggregator has a compromise to respect DSO and TSO conditions. In case it is not possible, for example for the excess demand of EV users, the EV aggregator has to pay a penalty cost that is assumed as five times the price, as per [44].

In that way, the EV aggregator costs can be defined as:

$$C^{EV} = C_p + \sum_{k=1}^{k=D} \pi_k.(P_k^G + P_k^B + P_k^R) \quad (10)$$

The first term corresponds to the possible penalty cost and the second to the electricity price.

E. PROBLEM FORMULATION

The interest for the EV aggregator is to minimize the charging costs.

Let's suppose $\mathbf{P}_k^G$, $\mathbf{P}_k^B$, and $\mathbf{P}_k^R$ the vectors of decision variables for green, blue and red CCPs, at a step k they are defined based on the number of EV users they have.

$$P_k^G = \begin{bmatrix} P_{k,1}^G \\ P_{k,2}^G \\ \dots \\ P_{k,N^G}^G \end{bmatrix}$$

$$P_k^B = \begin{bmatrix} P_{k,1}^B \\ P_{k,2}^B \\ \dots \\ P_{k,N^B}^B \end{bmatrix}$$

$$P_k^R = \begin{bmatrix} P_{k,1}^R \\ P_{k,2}^R \\ \dots \\ P_{k,N^R}^R \end{bmatrix}$$

In this way, the problem is formulated as:

$$min\ C^{EV} = min(C_p + \sum_{k=1}^{D} \pi[k].(P_k^G + P_k^B + P_k^R) \quad (11)$$

The problem depends on the next constraints:

- Minimum and Maximum Power: The charging power rate from each user will vary from zero to a maximum value in slow charging, which is 7.2 kW, depending on grid conditions. This constraint is defined as:

$$0 < P_{k,i} < \overline{P^{ch}}\ \forall k \in T \quad (12)$$

- When a user plugs its EV i to the charger, he selects the energy required for its EV E_i^{req} (depending if he wants to fully charge or partly charge his battery). It is assumed that the charger will indicate the SOC. The EV aggregator has to dispatch all this energy needed. Prior to this, the EV user has to select a CCP, and he will receive the information about the charging duration as specified in equation (1). It is necessary that the user leaves its EV plugged the time U_i. More than one charging a day could be considered for a user, for example at work and home, but in every case, EV users have to specify the energy they need. This constraint is defined as:

$$E_i^{req} = \sum_{k=1}^{D} P_{k,i}.\Delta T\ \forall k \in U_i \quad (13)$$

- Operator charging pattern: total charging power from all EV users will not have to exceed limits imposed by the DSO and TSO. This constraint is defined by generation, transmission and distribution conditions. In case that the problem has no solution, the EV aggregator will have to pay a penalty to the DSO and TSO and not disconnect EV. This is in order to respect EV users' preferences. This condition is defined as:

$$0 < P_k^G + P_k^B + P_k^R < \overline{P_k^{EV,O}}\ \forall k \in T \quad (14)$$

This problem can be solved by a linear optimization.

The problem formulation assumed a simplified battery charging model since the SOC cannot be measured directly. In real life, the battery charge will have some estimation deviations. Nevertheless, for massive electric vehicle simulations

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in a grid level, the model is able to grant accurate and credible results. Furthermore, in the future, the EV Aggregator has to consider advanced SOC estimators to avoid these sensitivity errors in individual cars, such as presented in [45].

F. IMPLEMENTATION

- One day prior to the scheduled charging, the EV aggregator receives from the electricity market the predictions related to the electricity prices of that day.
- At the beginning of the day, it has to take into account all charging processes that are still in progress. This is a result available from the optimization performed for this day.
- At the beginning of every time interval, the EV aggregator has to receive real-time information about new cars plugged in. This will be done through smart meters installed in the customer facilities, where the EV users will have the information of the costs from the different CCPs in real-time. If new cars are plugged, each smart meter has to send the associated information to the EV aggregator: SOC and CCP selected. The EV aggregator will combine this received data with the actual and short-term EV status, resulting from the last optimization periods to calculate the maximum constraint for this period that can be defined by either the maximum EV total power required or the operator.
- After the maximum constraints are computed, an optimization process is performed to obtain a charging profile for each EV taking into account the calculated charging period U_i and the total power needed. As a result, it will also be known the moment when an EV will be charged entirely. The optimization process will determine the new charging according to both the network constraints and the committed charging in previous steps.
- This process will be repeated every time interval until the end of the day. The optimization will consider that the EV charging will continue in the next day if charging starts late in the day, but this charging pattern has to be considered as mentioned at the beginning of the new day.

III. CASE STUDY

To illustrate this novel methodology for an EV aggregator, the case study of the Distribution System of Quito, Ecuador was selected, according to the Ecuadorean government willingness to introduce EVs in the automobile market [46]. Furthermore, Quito was selected by the government as a pilot city for the introduction of the EVs. The goal of the case study is to demonstrate the technical and economic improvements in the EV charging process for different scenarios. The variables that are used in this optimization problem are described in this section. The area of Quito selected for the study is called Cristianía. Electricity is distributed by Empresa Eléctrica Quito (EEQ) in Quito, which belongs to the Ecuadorian public company CELEC EP. A distribution feeder of the EEQ has been selected to evaluate the proposed methodology. This feeder was chosen because it presents overloading several times a day, so it is suitable to evaluate the management of a new significant load.

A. CHARGING SCENARIOS

Three scenarios will be considered, considering the type of charging:

1. Uncoordinated charging at maximum power: this scenario assumes that EV users start charging their EV immediately when plugged in at maximum charging power rate, for having their EVs charged in the shortest possible time. It reflects the worst case in term of power demand.

2. Uncoordinated charging at average power: this scenario assumes that EV users also start charging their EV immediately when plugged in, but fairly limiting the power demand. This technique is often used by distribution companies to mitigate the effects of high power demand from EVs. EV users will charge their EV at a constant power corresponding to the value of the average charging power rate from each CCP. In this case, the EV users are grouped into different CCPs. Hence, the power $P_{k,i}$ is constant for each step time and the energy of an EV i becomes:

$$E_i^{req} = \sum_{k=1}^{D} P_{k,i}.\Delta T = P_{x,av}.\sum_{k=1}^{D} \Delta T = P_{x,av}.\Delta T.D \tag{15}$$

3. Proposed Smart Charging with charging power rate modulation: the number of users from each CCP is the same that previous case, but charging power rate from each user will vary between zero to 7.2 kW, to optimize power delivered depending on prices and grid conditions. Nevertheless, the energy required will be delivered to EV users and at the same time established that previous scenario. This means that in these two last scenarios, it will be the same average charging power, depending on CCP selected.

To address the uncertainties of possible EV penetration levels, simulations will be performed for each scenario considering EV penetration levels of 50%, 75%, and 100%.

B. EV INPUT VARIABLES

1) Number of EVs of each CCP

In a previous work [47], it was concluded that the number of vehicles of this zone was nearly 1000. This value is assumed as the total number of vehicles.

For the evaluation of the case study, the portions of the green, blue and red CCPs are assumed respectively as 60%, 30% and 10% in this study. Table 1 describes the number of vehicles for each penetration level of EV.

2) Starting charging time

From studies about road traffic in Quito, and working conditions starting charging time is considered by the following way [48], [49]:

TABLE 1: Number of vehicles from each CCP depending on penetration level.

Penetration Level	N^G	N^B	N^R
50%	300	150	50
75%	450	225	75
100%	600	300	100

- 20% of EV users who participate in the program plug their EV at work between 07h00 and 10h30.
- 40 % of EV users who participate in the program plug their EV at home, after returning from work between 16h00 and 21h00.
- The rest of EV users who participate in the program plug their EV in different periods of the day (shops, home, work, etc).

In order to create starting charging time profiles, uniform random numbers were generated according to these schedules. For each vehicle, a starting hour st^i is assigned. The histogram corresponding to the starting charging time of EV users in a day is represented in Figure 2.

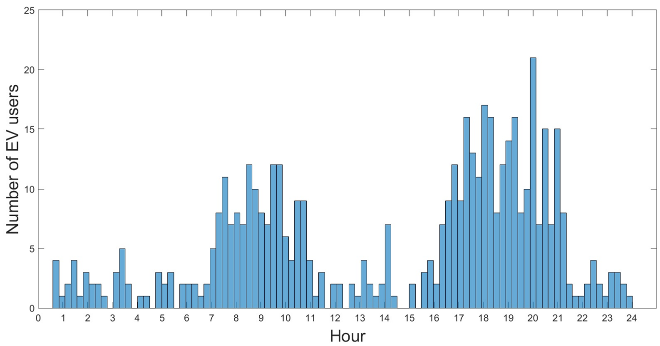

FIGURE 2: Histogram of the starting charging time of EV users in a day in the selected zone in Quito.

3) Daily energy needed from each EV

It is expected that different types of EVs (brands and models) will soon be seen on roads all over Ecuador. Some of them are Nissan Leaf, BYD e5, BYD e6 and Kia Soul EV. These EVs have different battery capacities from 24 kWh to 75 kWh. Thus, it is more valuable to consider in the calculation the daily energy consumed by each EV user than the battery capacities of each EV. According to several studies, it is considered that near half of the people drive less than 50 km a day [50], [51]. In [52], it is verified that in ideal circumstances of traffic EV drivers do 8,19 km/kWh in Quito, which means 0.122 kWh/km. Considering a system energy efficiency of η=0.85%, it is concluded that 0.144 kWh of grid electricity will be consumed per kilometer driven. A frequency curve about electricity consumption for 100 km is shown in [53]. For this study, it is assumed that different levels of energy are going to follow the pattern of this probability curve, but considering last average value. Moreover, it is established that EV users must charge at least 4 kWh to participate in this EV aggregator program. It is considered that the more suitable curve is Weibull density probability, from where random values will be selected. This curve is defined as:

TABLE 2: Average power for each CCP.

CCP	Green	Blue	Red
$P_{x,av}$ (kW)	1.5	2.5	7.2

$$f(\theta; a, b, c) = \frac{b}{a}.(\frac{\theta + c}{a})^{b-1}.e^{-(\frac{\theta+c}{a})^b} \tag{16}$$

The charging needs may vary from 4 kWh to 28 kWh, but with more values between 6 and 10 kWh, these are the most common quantity of energy required [51]. This curve allows having different values of energy required by the user, which differs significantly. It has to be noted that models such as BYD e6 have a battery capacity of 60 kWh, but EV users that require more than 28 kWh are ignored in the simulation. Note that these parameters are also selected with the conditions of the case of the behavior of people from Quito, but this curve could differ importantly in other places. So, the values for the parameters selected are: a=7,5;b=1,5;c=4. The density probability curve is depicted in Figure 3.

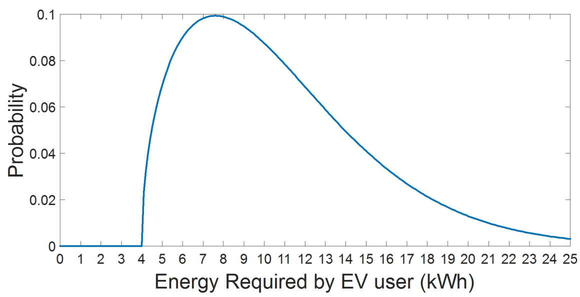

FIGURE 3: Probability Density Curve of Energy required by EV user.

The Energy required from EV users E_i^{req} is a random number from this distribution.

From this way, each set of time intervals U_i that correspond to charging period of an EV i is defined by:

$$U_i = \left[st_i; st_i + \frac{E_i^{req}}{P^{av}} \right] \tag{17}$$

C. CCPS AVERAGE CHARGING POWER

Each EV user has to select a CCP depending on the average charging power defined as in Table 2. As mentioned before, slow charging can vary from zero to 7.2 kW. Red CCP is selected as the maximum value, and for the other two CCPs, small values are selected in order to have a good time to optimize the charging process.

Observe that EV users who select red CCP will have their charging power rate constant and established at its maximum value. There will not be an optimization for this case. Red CCP users are committed to paying a high price to this end.

D. MAXIMUM OPERATOR POWER PATTERN

The function of this constraint can be defined as:

$$\overline{P_k^{EV,O}} = P^{cri} - P_k^{res,tot} \tag{18}$$

It is assumed P^{cri}=$\overline{P^{res}}$*1.05.

A critical power P^{cri} is considered that is 5% higher than the maximum value of the residential load. This consideration was done because the feeder has reactive energy compensation, and the limit of the transformer can be determined by this active power. The maximum operator power pattern is represented in Figure 4.

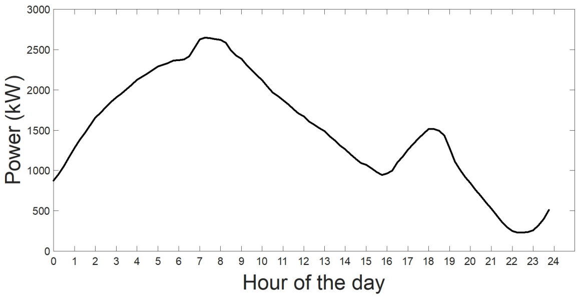

FIGURE 4: Maximum operator power pattern.

Note that in the first hours of the day, the available power is significant, but is limited in the last hours, when several EV users plug their EVs.

E. ELECTRICITY PRICE CURVE

In Ecuador, the electricity sector is vertically integrated, so there is no electricity wholesale market. There is a tariff for each type of customer. These tariff rates are not linked to the real costs of electricity generation, transmission, and distribution in real time. In this way, in previous work [47], the authors proposed a method to calculate the electricity prices based on above-mentioned costs of generation, transmission, and distribution. The electricity price curve of the selected workday in Ecuador is represented in Figure 5. As it can be observed in Figure 5, this curve has been selected because it is a critical case where the electricity price curve is relatively flat, reducing the potential economic savings, and the cheapest period overlaps the strongest network operator's constraints. Observe that that during the first hours of the morning (e.g., hours 8 to 9) the electricity price is at its lowest. This is because most of the Ecuadorean are going to work, so the electricity consumption in homes and offices is very small. Since the electricity demand is low, the electricity price is also low.

F. MODEL SIMULATION

The simulations were performed in Matlab R2016a, using the "Optimization toolbox" for the linear optimizations. In this way, based on the electricity prices that the EV aggregator receives and the different EV users parameters, any day could be simulated.

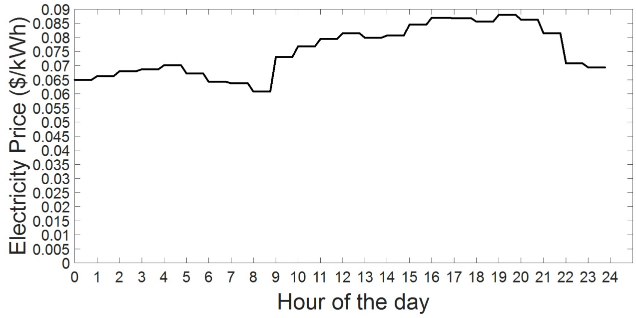

FIGURE 5: Proposed Electricity Price of June 9^{th} 2014.

IV. RESULTS AND DISCUSSION

In order to demonstrate the performance of the proposed methodology, the results of the EV load in the daily operation are shown by comparing with the scenarios of uncoordinated charging. Then, the EV load trends of each CCP are evaluated. The daily costs of the EV aggregator for each scenario are also studied.

A. DAILY OPERATION

Figure 6 illustrates the daily load from the different charging scenarios, with 50 % EV penetration. EV smart charging is compared to the first two scenarios, which are uncoordinated. It is observed that scenarios 1 and 2 present a significant EV load during the hours of the evening, which could create overloading problems because the operator has not enough power available for satisfying this load, especially if the EV penetration level is higher. Furthermore, the EV load is significant in time periods when the electricity is expensive. Besides, scenario 2 curve has lower peak loads than scenario 1, which is normal because of the difference of charging power rate used. Nevertheless, as mentioned before, it is not a good solution to make the users charge their EV at minimum charging power rate.

It should be noted that the EV load curve in scenario 3 (smart charging) presents high variations in comparison to the curves of the two other scenarios, but it allows to flatten the total load, which may decrease total load variance and so the distribution losses according to [6]. Moreover, the EV load significantly decreases when the available operator power is small.

In Figure 7, the curves for EV charging in scenario 3 for different EV penetration levels are represented. Charging load presents a high peak between hours 8 and 9, which corresponds to the time when people charge their EV at work and when the electricity is less expensive during these hours. This peak may not create problems for the grid because the operator constraint shows that the energy availability is high enough, which means that the residential load is minimal and so the EV load could flatten the total load curve. Moreover, between 19h and 21h, the smart EV charging load is under the minimum of operator constraint. This was not observed in the previous scenarios with uncoordinated charging. Thus,

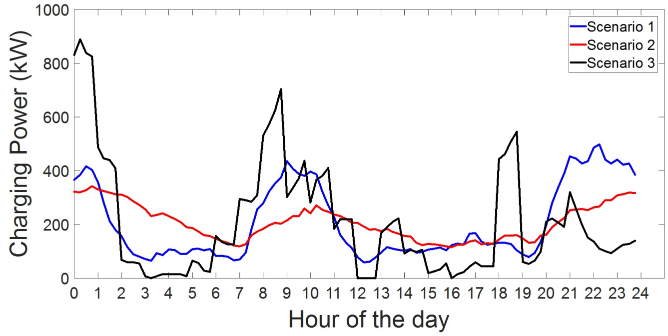

FIGURE 6: EV Load comparison of the three scenarios with 50 % EV penetration.

the smart charging methodology satisfies the technical constraints.

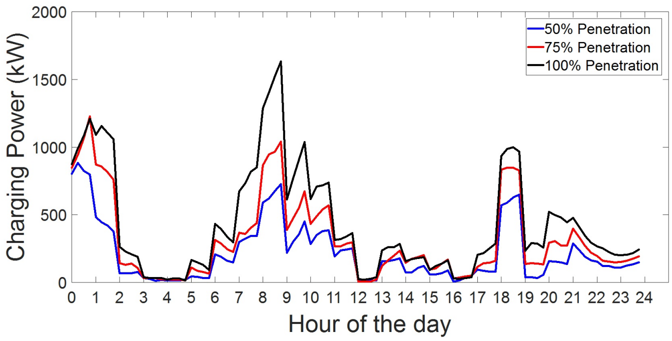

FIGURE 7: Scenario 3: EV Load with different EV penetration levels.

B. CCP LOAD COMPARISON

The EV load corresponding to each CCP for the assumptions considered is represented in Figure 8. Green CCP is the one that presents the most critical variations in a day. Note that a high peak is observed at midnight, which corresponds to a time when the electricity is cheap. The red CCP presents a similar pattern than the total EV load of the uncoordinated scenarios, which could result detrimental for the grid if the number of users who select this CCP is high.

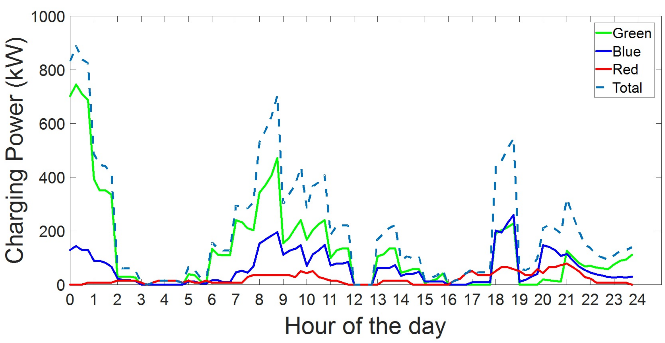

FIGURE 8: EV load by CCP with 50% EV penetration.

TABLE 3: EV aggregator Costs by CCP and by scenario.

Scenario	EV P. (%)	C^G($)	C^B($)	C^R ($)	C^{EV}($)
1	50	241.2	117.79	39.33	398.32
1	75	483.19	282.53	59.93	825.65
1	100	894.16	472.17	76.60	1442.93
2	50	326.12	154.62	39.33	520.08
2	75	578.54	299.69	59.93	938.16
2	100	894.54	479.81	76.60	1450.95
3	50	213.51	111.75	39.33	364.67
3	75	321.03	184.55	59.93	565.51
3	100	427.23	254.78	76.60	758.61

C. EV AGGREGATOR COSTS BY SCENARIO

Daily costs of the aggregator from each scenario are resumed for the day selected in Table 3. Is it observed that the largest the EV penetration is, the more significant are the costs of uncoordinated charging. Besides, two kinds of uncoordinated charging have similar daily costs, which shows the importance of having a smart charging. Note that the penalty cost impacts the costs of uncoordinated charging, so the grid could not be able to satisfy such uncoordinated EV load.

D. WEEK SAVING

To evaluate the methodology in a longer horizon and with different input parameters (e.g., electricity price), simulations were implemented for a week. The data of the EEQ from the Monday, June 9th 2014, to the Friday, June 13th 2014 was used. For this analysis, penalties imposed by network operators were considered. The weekend was not considered in this analysis since the DSO and TSO do not present technical difficulties in their operation because EV users generally do not work. Note that the electricity price curve differs from one day to another, as shown in Figure 9.

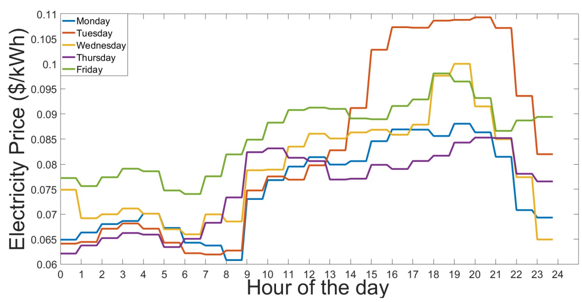

FIGURE 9: Electricity Price Curve of the days of the studied week [47].

To evaluate the cost-effectiveness of the methodology, a daily cost difference percentage was defined for green and blue CCP, between first and third scenario, and between second and third scenario. This parameter is evaluated based on the cost $C^{x,y}$ of x tariff and y scenario (y=1,2, and 3):

$$\Delta S_{y-3}^{x} = \frac{C^{x,y} - C^{x,3}}{C^{x,y}} \tag{19}$$

Figure 10 illustrates the cost difference percentage between scenario 1 and 3 in a week for different EV penetration

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levels, both for green and blue CCP. Observe that with 100% EV penetration, the maximum value for green CCP is on Tuesday because on this day the electricity is the most expensive during an extended period when the users plug their EVs, as shown in Figure 9. Furthermore, with 100 % EV penetration, the maximum value for blue CCP is on Wednesday, because there is a short peak on the electricity price in a period when several users plug their EV.

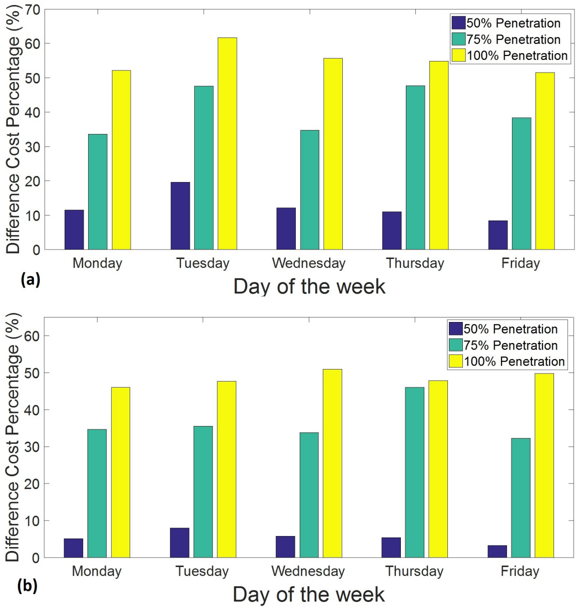

FIGURE 10: Cost difference percentage between scenario 1 and 3 (a) for green CCP; (b) for blue CCP

Figure 11 depicts the cost difference percentage between scenarios 2 and 3 in a week of the for different EV penetration levels, both for green and blue CCP. Note that with 100 % EV penetration, the maximum value for green CCP is on Wednesday, because the electricity price varies significantly during this day. The maximum value for blue CCP is on Wednesday because the electricity price also varies significantly but in shorter periods.

Comparing to the two first scenarios, the smart charging always presents more economic savings, even with 50% EV penetration where there is no penalty cost because uncoordinated charging EV load does not overpass the operator constraint.

On the other hand, green CCP presents more savings than the blue CCP, especially with low EV penetration levels. Hence, it is crucial to consider strategies to incentive EV users to adopt especially the green CCP.

The savings from scenario 1 and 2 to 3 are quite similar, which shows that EV aggregator savings does not depend on a constant power rate, but on its EV load modulation throughout the day.

Finally, with the increase in EV penetration, savings of smart charging also increase. This is because uncoordinated charging overpass during long periods the operator constraint

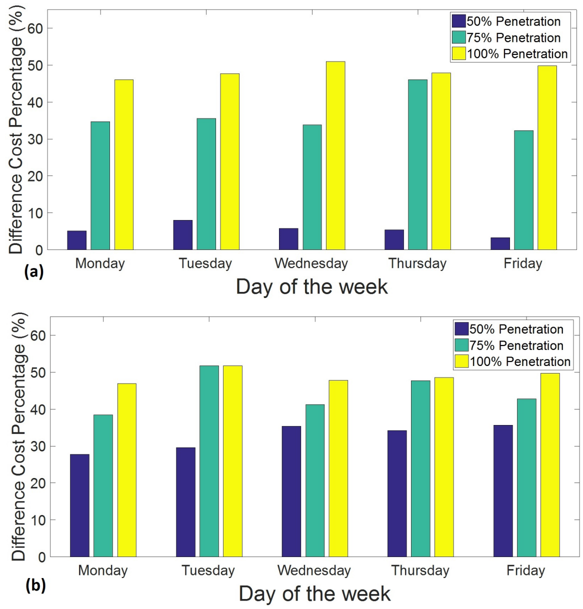

FIGURE 11: Cost difference percentage between scenario 2 and 3 (a) for green CCP; (b) for blue CCP.

and the penalty costs make most of the price. Thus, the smart charging methodology presents also economic benefits.

E. DISCUSSION

Particular technical challenges need to be considered to implement the proposed methodology Several smart chargers have to be installed at user's homes, offices, and public places; which creates challenges for research, logistics, and economics.

Another technical challenge is the communication of all the corresponding data from the EVs and the grid constraints, which has to be fast, secure, and reliable. Without this, the EV aggregator cannot correctly optimize the EVs charging.

Even though, the model presents several advantages regarding charging costs and grid technical constraints. Furthermore, since the CCPs meet users' needs in terms of charging time, the methodology could be massively adopted.

V. CONCLUSION

A novel methodology of smart charging for EV aggregator has been presented in this paper. The EV aggregator will have to optimize power delivered to the EV battery through charging power rate modulation in slow charging. The novelty lies in consideration of three different CCPs that will be suitable depending on EV user preferences. EV aggregator will also consider technical specifications as a maximum charging pattern given by the DSO and TSO.

Simulations of the proposed smart charging and two cases of uncoordinated charging were performed under different EV penetration levels considering data analysis from the city of Quito, Ecuador. In the cases of uncoordinated charging, it was considered a constant charging power rate, which was fixed at 7.2 kW in the first one (maximum slow charging power) and the average power of the proposed EV CCPs in the second one. The input data was taken from working times and traffic conditions of studies from Quito to obtain proper results. Moreover, the technical constraints were based on real and actual data sets from previous studies.

The results show that with the smart charging, the EV aggregator can have benefits comparing to two cases of uncoordinated charging while respecting technical conditions. The savings are at least 5 % and become significant when EV penetration levels increase because of total EV uncoordinated charging overpass technical operator constraint.

To address the variations of electricity prices from day to day, a full week was simulated, comparing the two cases of uncoordinated charging and smart charging. Results indicate that an increase of the number of vehicles leads to a significant increase of the benefits of the green smart charging (reaching up to more than 50 % with 100% EV penetration), which demonstrates the benefit of the methodology when the penetration of EVs is important compared to the capacity of the grid. The main drawbacks of this method are the technical and economic challenges for implementing this methodology in a real infrastructure.

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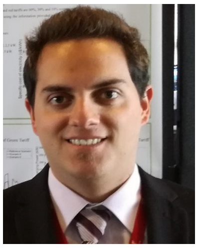

JEAN-MICHEL CLAIRAND (S'16) was born in Quito, Ecuador, in 1990. He received the M.Sc. degree from the Ecole Nationale Supérieure de l'Electronique et Ses Applications (ENSEA), Cergy-Pontoise, France, in 2014. He is currently working toward the Ph.D. degree in Industrial Production Engineering at the Universitat Politècnica de València. He did an international visit in the department of electrical engineering at the University of Waterloo, Canada, between October 2017 to March 2018.

He has been lecturer in Universidad de las Américas, Quito, Ecuador, since 2014. He worked between 2014 to 2015 in Empresa Eléctrica Quito, which is a local electricity distribution company. He has been involved in the Project "Smart Grids in Ecuador" that was funded by Inter-American Development Bank (IADB) in 2015 where 5 distribution networks in the most relevant areas in the country were designed according to smart grid definitions. His research interests include electric vehicles, smart grid optimization and microgrids.

JAVIER RODRÍGUEZ GARCÍA was born in Valencia, Spain, in 1977. He received his M.Sc. in Electrical Engineering from the Universitat Politècnica de València (UPV) in 2004. He is currently working toward the Ph.D. degree in Industrial Production Engineering at the same university.

After working in the private sector a couple of years, he has been working in the Institute for Energy Engineering ever since. In this period, he has been involved in the Project "Smart Grids in Ecuador" that was funded by Inter-American Development Bank (IADB) in 2015 where 5 distribution networks in the most relevant areas in the country were designed according to smart grid definitions, and also in many international (United States, Europe, South America) and national research projects and consulting works with public and private funding in the fields of Demand Response, Smart grids and Energy efficiency and management, which are basically his interest areas.

CARLOS ÁLVAREZ BEL (M'80) was born in Cuenca, Spain, in 1954. He received his M.Sc. and Ph.D. in Electrical Engineering in 1976 and 1979 from the Universidad Politécnica de Valencia, Spain, where he is Professor since 1989.

His professional activity has been performed in the electric energy systems field in the framework of utilities, research centers and Universities. He has been involved in many projects and consulting work with utilities both in Spain and abroad (USA, EU), in the fields of load modelling, standard markets, micro-grids, etc. He has been involved in the Project "Smart Grids in Ecuador" that was funded by Inter-American Development Bank (IADB) in 2015 where 5 distribution networks in the most relevant areas in the in the country were designed according to smart grid definitions.

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