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An Improved Methodology for the Hierarchical Coordination of PEV Charging

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ABSTRACT This paper proposes an improved methodology for the hierarchical coordination of daily Plug-in Electric Vehicle (PEV) charging. The aim is to limit the power supplied by the primary distribution transformer (PDT) while minimizing the energy costs of the aggregators. This methodology consists of an iterative optimization of the total aggregated power at the PDT level, considering the local power constraints of the aggregators and the PEVs with a reduced number of decision variables and constraints which only depend on the number of time intervals. Moreover, it defines the energy boundaries of the optimization problem in each iteration through a proposed method for simulating early charging and delayed charging, considering the power constraints of the aggregators. Otherwise, it evenly distributes the total power among the aggregators, and the local power of each aggregator among the PEVs, maximizing the feasible region of the optimization problem. The proposed methodology is applied to two case studies. The uncertainties related to the charging scenarios are considered by means of Monte-Carlo simulations. The results obtained show that the total power profile is effectively limited, while the profits of the aggregators are not significantly affected by the coordinated approach that is expected to be performed by the Distribution System Operator (DSO). Additionally, to demonstrate the reduction of the impact of PEV charging on the distribution system, the voltage profile, the transformer loss of life and the power and energy losses are reported.

INDEX TERMS Asset management, electric vehicles, load management, power distribution, power transformers, smart grid.

LIST OF ABBREVIATIONS

i	PEV index.
a	Aggregator index.
N	Number of intervals in the total period.
A	Number of aggregators.
d	Distribution line index.
A_d	Subset of aggregators supplied by the distribution line d.
V_a	Number of PEVs of aggregator a.
Δt	Time interval length (in hours).
j	Index of the iteration of the main algorithm. This varies from 1 to N.
k	Auxiliary index used in the calculation of the SOC limits. This varies from j to N.
r	Auxiliary index used for the cumulative energy constraints. This varies from j to k.
b	Index of the order of the $E_{i,a}$ of the PEVs.
np	Number of active PEVs in the calculation of flexible power of charging.
u	Auxiliary variable used in the calculation of the deferrable charging power of PEVs.
w	Auxiliary index used to adjust the total optimum power according to the voltage limits.
S_R	Rated power of the primary distribution transformer.
$h_{i,a}^{arr}$	Arrival time of the PEV i of aggregator a.
$h_{i.a}^{dep}$	Departure time of the PEV i of aggregator a.
$\eta_{i,a}$	Efficiency of charging of the PEV i of aggregator a.
$B_{i,a}$	Battery capacity of the PEV i of aggregator a.

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$C(t_k)$	Energy cost of interval t_k.
C_H	Penalty cost of exceeding the rated power of the PDT.
$L(t_k)$	Total base load power at time interval k.
$E_{i,a}(t_k)$	Maximum feasible remaining energy to charge the PEV i of aggregator a at time interval k.
$H(t_k)$	Surplus of power above the nominal power of the PDT at time interval k.
$P_a^{av}(t_k)$	Available power of aggregator a at time interval k.
$P^{opt}(t_k)$	Optimum total power of the system at time interval k, under DSO coordination.
$P_a^{optAG}(t_k)$	Optimum power of aggregator a at time interval k, without DSO coordination.
$P_a^{coorAG}(t_k)$	Optimum power of aggregator a at time interval k under DSO coordination.
$P_a^{lim}(t_k)$	Limit of power of aggregator a at time interval k.
$P_{i,a}^{maxEV}(t_k)$	Maximum feasible charging power of the PEV i supplied by aggregator a.
$P_{i,a}^{maxEV'}(t_k)$	Maximum feasible charging power of the PEV i supplied by aggregator a after the assignation of the non-deferrable power.
$P_a^{maxAG}(t_k)$	Maximum feasible power of total charging of aggregator a at time interval k.
$P_a^{maxAG'}(t_k)$	Maximum feasible power of total charging of aggregator a after the assignation of the non-deferrable power at time interval k.
$P_{i,a}^{ch}(t_k)$	Maximum power of the charger of the PEV i supplied by aggregator a at time interval k.
$P_{i,a}^{EV}(t_k)$	Assigned power to the PEV i supplied by aggregator a in the algorithm of early charging.
$P_{i,a}^{optEV}(t_k)$	Optimum power of the PEV i of aggregator a at time interval k, under coordination.
$P_{i,a}^{non}(t_k)$	Non-deferrable charging power of the PEV i of aggregator a at time interval k.
$P_{i,a}^{non'}(t_k)$	Adjusted value of the non-deferrable charging power of the PEV i of aggregator a at time interval k depending on $P_a^{maxAG}(t_k)$.
$P_{i,a}^{def}(t_k)$	Deferrable charging power of the PEV i of aggregator a at time interval k.
P^{aux}	Power added to the PEVs in the calculation of the deferrable charging power.
$P_d^{max}(t_j)$	Maximum power of the distribution line d at time interval j.
$R(t_k)$	Energy retail price at time interval k.
$SOC_{i,a}(t_k)$	SOC of the PEV i of aggregator a at time interval k.
$SOC_{i,a}^{up}(t_k)$	Upper limit of the SOC of the PEV i of aggregator a at time interval k.
$SOC_{i,a}^{up'}(t_k)$	Upper limit of the SOC of the PEV i of aggregator a at time interval k before the assignation of the deferrable power at time interval k.
$SOC_{i,a}^{low}(t_k)$	Lower limit of the SOC of the PEV i of aggregator a at time interval k.
$SOC_{i,a}^{F}(t_k)$	Final feasible SOC of the PEV i of aggregator a, estimated at time interval k.
$\mathbf{U}(t_j)$	Vector of length A with the bus voltage magnitudes of the aggregators in time interval j.
U^{min}	Minimum limit of bus voltage magnitude.
U^{max}	Maximum limit of bus voltage magnitude.

I. INTRODUCTION

Nowadays, society, in general, seeks a technological revolution to reduce the environmental pollution produced by the conventional transportation system, which is based on internal-combustion engines [1]. Today, the technology available for such a revolution is based on plug-in electric vehicles (PEVs). Recent surveys report increasing numbers of PEVs both manufactured and sold, and this trend is growing at an exponential rate in different deployment scenarios [2].

The massive connection of PEVs to the distribution networks will have a significant impact, which may be negative if the recharging of the PEV batteries is not properly coordinated. Some of the expected impacts include accelerated aging of primary and secondary distribution transformers (SDT), increase of power losses, deterioration of power quality, and increase in peak demand, among others [3], [4].

In this paper, a methodology to coordinate the recharging of multiple PEVs, in a distribution grid, is proposed. The methodology considers a power constraint imposed by the primary distribution transformer (PDT) that supplies the medium voltage grid. The fulfillment constraint is achieved through the coordination of aggregators that manage the PEV charging systems plugged into low voltage networks. At the aggregator level, power constraints due to the SDTs are also considered.

The main objective of the proposal is to minimize charging cost (under a time of use tariff scheme) while respecting the limits imposed by the above-mentioned constraints and maximizing the energy stored in the PEV batteries at their time of departure. The proposed methodology is tested in two case studies. The first corresponds to the same case study used in [5], which consists of a distribution system with four aggregators coordinated by a Distribution System Operator (DSO). In this case, results obtained by applying the methodology formulated in [5] are compared with those obtained through the approach proposed in this paper. In the second case study, the proposed methodology has been applied to a larger grid, which has been designed by using the IEEE 33-bus test distribution system. This case allows for testing the proposed methodology in a grid which approaches a real distribution system. Moreover, a diversity of PEV models available in the e-mobility market are considered. Regarding the analysis of results, in both cases, the impact of the coordinated charging strategy on the energy costs of the aggregators has been analyzed. However, only in the second case study, the voltage profile and the power and energy losses were computed to analyze the impact of the PEV charging on the distribution system.

This paper has been organized as follows: a brief review of the state of the art regarding PEV charging strategies is presented in section II. The proposed methodology is presented in detail in section III. The case studies in which the proposal is tested are reported in section IV. The results obtained are summarized and discussed in section V. Finally, the conclusions of this work are given in section VI.

II. PEV CHARGING STRATEGIES

There are several studies which deal with the problem of PEV charging management. Usually, these studies are aimed at reducing the peak load in the demand daily profile in order to mitigate the impacts mentioned above. Most of the studies can be classified into two general groups, those which perform charging management at an aggregator level, and those which in addition consider coordination among multiple aggregators.

In [6]–[16], the charging of PEVs is managed only at the aggregator level. Analyses performed in these references include power flow calculation, transformer loss of life estimation, and network congestion assessment, among others. Nevertheless, it is necessary to consider the coordination among multiple aggregators supplied by the same network to adequately avoid undesired overloads and stress of network components.

Regarding the coordination among aggregators, there are several approaches that consider different control frameworks and objectives. It is noted that the daily scheduling of the PEV charging is usually performed at two levels. At the first level, the coordinator applies an algorithm to obtain the optimum daily power profile demanded by all the aggregators. At the second level, the total power profile obtained is distributed among the participants.

In [17], the participation of large fleets of PEVs in electricity day-ahead markets is studied. The PEV charging is scheduled considering an inter-aggregator cooperation mechanism based on coordinated bids. The aggregators inform a third-party coordinator of the individual requirements and the coordinator then optimizes the global bids. In [18], an inter-aggregator collaboration model is proposed. It formulates a charging scheduling model which consists of a bi-level optimization problem to maximize the aggregator profit. However, the above studies only model the features of the power market, and they do not consider constraints imposed by the distribution network to perform the aggregators' coordination. In [19], a hierarchical dispatch model based on traditional unit commitment is proposed. It formulates an optimization problem of charging/discharging coordination of PEVs, since it is assumed that PEVs can also inject power into the network in a vehicle to grid mode (V2G), in this way modifying the generator dispatch problem. A control strategy for scheduling the charging/discharging of the PEVs controlled by an aggregator, through the use of a priority evaluation index, is then presented. In [20], an online coordination method for the charging/discharging of PEVs is proposed. It aims at maximizing the satisfaction of PEV owners and minimizing system operating costs without violating power system constraints. The whole system is served by one central vehicle controller. It is considered that the aggregators' role is to send the operator's charging/discharging decisions to the charger controllers. In [21] a mixed-integer linear programming model for PEV charging coordination is proposed. The load unbalance of distribution systems is considered and a methodology to linearize a mixed-integer nonlinear programming problem is presented. The control variables of the formulated optimization problem are the charging power of each PEV. The work considers both the V2G charging mode and vehicle-to-vehicle energy exchanges. In this regard, it has been observed in several reports that bi-directional V2G technology could offer some benefits for the grid, but still presents some drawbacks, e.g. battery degradation acceleration, complex requirements in hardware infrastructure, high investment costs and social barriers [4]. In particular, V2G implementation depends on advances in research on PEV batteries, information which will allow us to consider the economic suitability of V2G as an option for improving network operation.

Taking into account the above considerations, references [5], [22]–[24] have focused their research only on the PEV charging issue, without considering the V2G mode. In [22], charging coordination aims at matching uncertain wind supply with PEV charging demand. The problem is then formulated as a Markov decision process and solved using a bilevel simulation-based policy improvement method. In [23], a scheduling approach is proposed to coordinate PEV charging with the network base load and electricity price. The upper level model is formulated as a multi-objective optimization problem. An improved particle swarm optimization algorithm is used to solve both levels. In [5] a methodology to coordinate the charging of PEVs among multiple aggregators is proposed. The power and energy constraints of the aggregators are computed as a simple summation of the individual PEV power and energy constraints. The optimum power profiles of the aggregators under a time of use (TOU) tariff are then solved using a linear optimization model. This includes a constraint that limits the total power of the distribution grid. It solves the problem iteratively, sending the scheduled power of the first interval to the aggregators and repeating and solving the optimization formulation starting from the next interval. This last methodology is improved in [24] where it is adapted to a three-level framework. The main conclusion after reviewing [5], [22]–[24] is that the state of charge (SOC) constraints of the individual PEVs are aggregated as a simple summation, which may be not adequate, as is revealed in section III.*A*.

Therefore, compared to the studies mentioned, the major contributions of this paper are as follows:

1. The calculation of the constraints of the total SOC of the PEVs is achieved through an iterative methodology which allows for obtaining a feasible region in the optimization problem. It improves the simple summation of individual constraints used in other works, which would not be suitable in cases where the available power of the aggregator is not enough to charge all of the connected PEVs at a certain time interval.

2. The distribution of the assigned power of each aggregator among the PEVs, after the calculation of optimum power under DSO coordination, is performed through a methodology which maximizes the feasible region of the optimization problem and the final energy charged. In this sense, this methodology includes in the feasible region the most severe power profile that could cause a PEV charging scenario, from the perspective of the DSO. Moreover, the methodology distributes the total power among the aggregators, considering their energy requirements and the influence on their energy costs.

3. Finally, the proposed methodology formulates the optimization problem of the power of charging of PEVs with a reduced number of variables independent of the number of aggregators and PEVs, decreasing the computational burden in applications of large distribution.

III. METHODOLOGY

The proposed methodology calculates the optimum charging power profiles of groups of PEVs that are directly controlled by aggregators which are coordinated by the DSO. The aim of the DSO is to constrain the total power supplied by the PDT, i.e. the baseload power (BL) and the power demanded by PEV chargers, to its rated value, while the profit of the aggregators is maximized. A scheme of the components involved in the charging coordination is presented in Fig. 1.

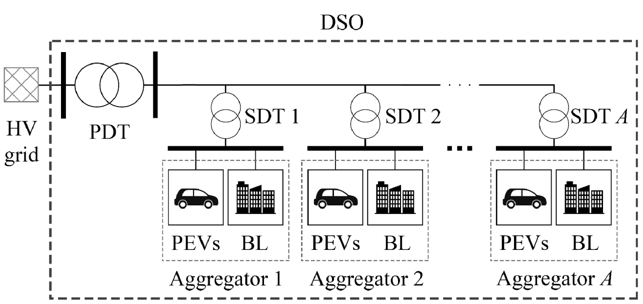

FIGURE 1. Components involved in the charging coordination.

The proposed methodological scheme is shown in Fig. 2. In the first block, input data defines the PEV charging scenario to be optimized by the methodology. However, it is necessary to note that some of the inputs related to the problem are only known with uncertainty, e.g. PEV energy requirements associated with $SOC_{i,a}(t_0)$, $B_{i,a}$, $h_{i,a}^{arr}$, $h_{i,a}^{dep}$, and the BL which affect $P_a^{av}(t_j)$. To deal with this issue,

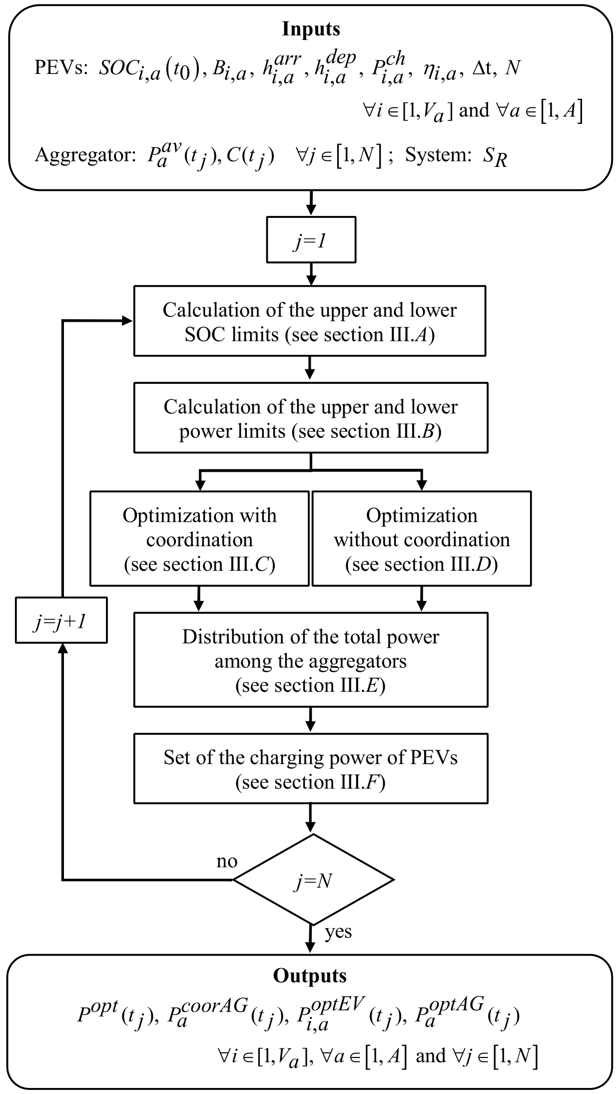

FIGURE 2. Block diagram of the proposed methodology for the coordination of PEV aggregators.

Monte Carlo simulations (MCSs) are performed. Each MCS requires the use of the complete methodology illustrated in Fig. 2, by using as inputs a set of random numbers generated from the probability density functions of the stochastic variables in order to create a deterministic charging scenario.

Once the set of random input parameters is generated, it is used to calculate the coupling constraints among all PEVs in the optimization stage, i.e., SOC and power limits, which are presented in Sections III.*A* and III.*B*, respectively. Then, the optimization problem formulated in Section III.*C* is solved to obtain the optimum total power of the system under coordination, in the *j*th time interval. In parallel, the optimum power of each aggregator without coordination, in the *j*th time interval, is obtained individually, as is highlighted in Section III.*D*. The results obtained from both optimization blocks are used to evenly distribute the total optimum power among the aggregators, as is shown in Section III.*E*.

Finally, the power assigned to each aggregator is distributed among the PEV chargers, using the method presented in Section III.F, and the new SOC reached by the PEVs is computed. The iteration ends and the total problem decreases in a time interval.

The entire methodology is repeated for the next time interval, i.e. $j + 1$, and so on until the calculation of the output variables of the entire time frame, i.e., the N time intervals, is completed. The block corresponding to outputs contains the control variables of the methodology, which are the optimum total power profile, the optimum power profile of the aggregators and the optimum power profile of the PEV chargers under DSO coordination. These control variables are stored after each MCS in order to finally be able to analyze the results statically.

A. CALCULATION OF THE UPPER AND LOWER SOC LIMITS

This step consists of the calculation of the upper and lower SOC constraints required to optimize PEV charging. These constraints are obtained through simulation of both early and late charging, respectively. Since the available power of each aggregator is limited, the calculation of the early and late charging power profiles requires distributing the available power among the PEVs in each time interval. In addition, such distribution must suitably consider which PEVs are selected to be charged in each time interval.

Considering the above information, the proposed algorithm first calculates the non-deferrable charging power, i.e., the energy that cannot be supplied to the PEV batteries in future time intervals and assigns the available power to this demand. Then, the rest of the available power is assigned to charge a part of the flexible demand, which is referred to as deferrable charging power. Through the proposed algorithm, such assignation is performed in a way that allows for increasing the maximum feasible charging power of the aggregator in future time intervals, thus maximizing the feasible zone of the stored energy in the PEV batteries. These energy limits are expressed in terms of SOC variables. Those variables are expressed in per unit terms instead of in percent terms in order to abbreviate the equations.

1) UPPER SOC LIMITS

In [5], early charging is computed assuming that energy is supplied to each PEV immediately at its time of arrival and the process is continued until all PEV batteries complete their full charge (or desired final SOC). However, this way of computing early charging fails if the power limit at each aggregator (the difference between the rated power of the SDT and the base load supplied by it) is not considered. In this paper, in order to simulate early charging in a suitable manner, a three-step methodology, shown in Fig. 3, is proposed. The calculation processes involved in each block, noted as (1.1), (1.2), and (1.3) in Fig. 3, are described in detail in the numerals *1.1, 1.2*, and *1.3*, respectively.

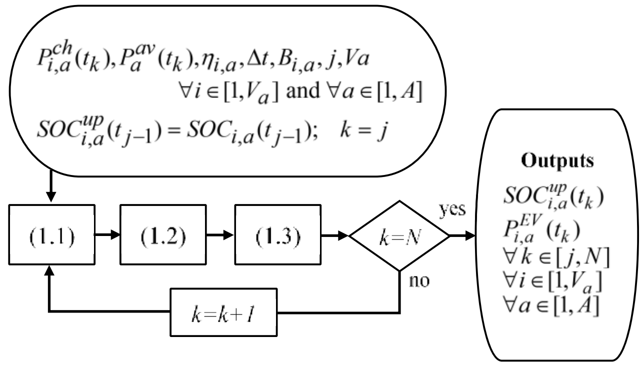

FIGURE 3. Block diagram of the proposed methodology for the distribution of aggregator power among PEVs.

a: CALCULATION OF THE MAXIMUM CHARGING POWER OF THE PEVS

The maximum charging power of the PEVs at the kth time interval is calculated according to (1). It is considered that the maximum power of charging of a PEV is the minimum value among the charger power, the available power of the aggregator and the power needed to reach the final feasible SOC in one interval. The power of the PEV charger can be considered to be constant during charging time. However, in this work it is expressed as a time function so as to consider the real charging curves.

$$P^{maxEV}_{i,a}(t_k) = \min\left(P^{ch}_{i,a}(t_k), P^{av}_a(t_k), \frac{SOC^F_{i,a}(t_k) - SOC^{up}_{i,a}(t_{k-1})}{\eta_{i,a}\ \Delta t} B_{i,a}\right) \tag{1}$$

where

$$P^{ch}_{i,a}(t_k) = \begin{cases} 0 & if\ t_k < h^{arr}_{i,a} \\ f(t_k) & if\ h^{arr}_{i,a} \le t_k < h^{dep}_{i,a} \\ 0 & if\ h^{dep}_{i,a} \le t_k \end{cases} \tag{2}$$

$$SOC^F_{i,a}(t_k) = \min\left[1, SOC^{up}_{i,a}(t_{k-1}) + \frac{\eta_{i,a}\ \Delta t}{B_{i,a}} \sum_{t=t_k}^{t_N} \min\left(P^{ch}_{i,a}(t), P^{av}_a(t)\right)\right] \tag{3}$$

b: CALCULATION OF THE TOTAL CHARGING POWER OF THE AGGREGATOR

The next step is to define the total charging power of PEVs for each aggregator in the kth time interval, according to (4). It aims at charging the maximum feasible power in the time interval.

$$P^{maxAG}_a(t_k) = \min\left(P^{av}_a(t_k), \sum_{i=1}^{V_a} P^{maxEV}_{i,a}(t_k)\right) \tag{4}$$

c: CALCULATION OF THE CHARGING POWER OF THE PEVS

In this step, the total charging power of the aggregator in the kth time interval is distributed among the PEV chargers, in such a way as to reach the maximum feasible upper SOC limit in the total period of charging. The proposed methodology consists of two sub-stages: a) assignation of non-deferrable charging and b) assignation of deferrable charging. The first consists of defining the energy that cannot be charged in later time intervals, i.e., the difference between the energy required to complete battery capacity and the energy that could be charged during the rest of the optimization time window, considering the power limits of the PEV charger and the aggregator. The power required to charge the total of that energy, or the maximum feasible charging, of each PEV in a time interval is calculated as shown in (5).

$$P_{i,a}^{non}(t_k) = \min\left[P_{i,a}^{maxEV}(t_k), \max\left(0, \frac{SOC_{i,a}^{F}(t_k) - SOC_{i,a}^{up}(t_{k-1})}{\eta_{i,a}\,\Delta t} B_{i,a} - \sum_{t=t_k}^{t_N} P_{i,a}^{maxEV}(t)\right)\right] \tag{5}$$

Then, those values are adjusted evenly according to the total charging power, as is shown in (6).

$$P_{i,a}^{non'}(t_k) = \left(\min\left[1, \frac{P_a^{maxAG}(t_k)}{\sum_{i=1}^{V_a} P_{i,a}^{non}(t_k)}\right]\right) P_{i,a}^{non}(t_k) \tag{6}$$

After that, the SOC and the power of each PEV are recalculated using (7) and (8), respectively, as is the total charging power of the aggregator by using (9). These variables, together with those calculated in (10), are needed for the assignation of deferrable charging. The algorithm shown in Fig. 4 is then performed to calculate the deferred charging power of each PEV.

$$SOC_{i,a}^{up'}(t_k) = SOC_{i,a}^{up}(t_{k-1}) + \frac{P_{i,a}^{non'}(t_k)\,\eta_{i,a}\,\Delta t}{B_{i,a}} \tag{7}$$

$$P_{i,a}^{maxEV'}(t_k) = P_{i,a}^{maxEV}(t_k) - P_{i,a}^{non'}(t_k) \tag{8}$$

$$P_a^{maxAG'}(t_k) = P_a^{maxAG}(t_k) - \sum_{i=1}^{V_a} P_{i,a}^{non'}(t_k) \tag{9}$$

$$E_{i,a}(t_k) = (SOC_{i,a}^{F}(t_k) - SOC_{i,a}^{up}(t_k))B_{i,a} \tag{10}$$

Finally, the final values of the SOC and the charging power of early charging in the kth interval are obtained according to (11) and (12).

$$SOC_{i,a}^{up}(t_k) = SOC_{i,a}^{up'}(t_k) + \frac{P_{i,a}^{def}(t_k)\,\eta_{i,a}\,\Delta t}{B_{i,a}} \tag{11}$$

$$P_{i,a}^{EV}(t_k) = P_{i,a}^{non'}(t_k) + P_{i,a}^{def}(t_k) \tag{12}$$

2) LOWER SOC LIMITS

To obtain the lower limit of the SOCs, delayed charging must be simulated. For that purpose, the methodology presented for early charging can be simply adapted to calculate the charging power of the PEVs starting from the Nth time interval.

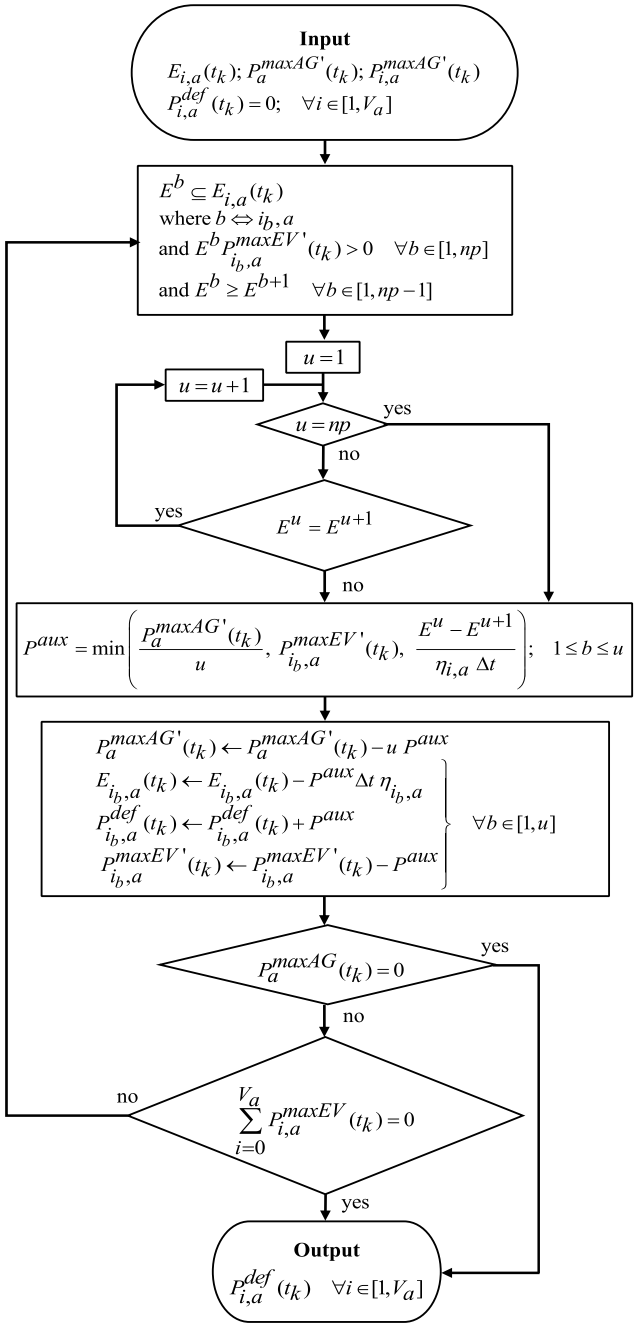

FIGURE 4. Block diagram of the proposed methodology for the calculation of deferrable PEV charging.

B. CALCULATION OF THE UPPER AND LOWER POWER LIMITS

In this step, the power constraints, which are used in the optimization stage, are calculated. For that purpose, the individual maximum charging power and the feasible final SOC of the PEVs are recalculated according to (1) and (3) respectively, but using $SOC_{i,a}(t_{j-1})$ instead of $SOC_{i,a}^{up}(t_{k-1})$.

Then, the maximum power constraints $P_a^{maxAG}(t_k)$ are recalculated according to (4). The minimum power constraints of the aggregators are considered null for any time interval, as V2G is not considered in the proposed methodology.

C. OPTIMIZATION WITH COORDINATION

In this step, the optimization problem corresponding to coordinated charging is formulated as a linear programming model, as shown in (13). It minimizes the total charging costs of the aggregators, limiting the total power through a penalization for exceeding the rated power of the PDT. It can be noted that as the proposed model in this section is formulated as the optimization of the total charging power profile, the number of control variables depends only on the length of the time span of each iteration, i.e., it is independent of the number of aggregators and PEVs. Thus, the size of the optimization problem is reduced significantly, and it can be easily solved with a basic algorithm, e.g. simplex, which enables the optimization of PEV charging of large distribution systems.

$$\begin{aligned}
&\min \sum_{k=j}^{N} C(t_k)\, P^{opt}(t_k)\, \Delta t + C_H \sum_{k=j}^{N} H(t_k) \\
&s.t. \sum_{r=j}^{k} P^{opt}(t_r)\Delta t \le \sum_{a=1}^{A}\sum_{i=1}^{V_a} \Big[\Big(SOC_{i,a}^{up}(t_k) \\
&\quad -SOC_{i,a}(t_{j-1})\Big) B_{i,a}/\eta_{i,a}\Big]; \\
&\quad \sum_{r=j}^{k} P^{opt}(t_r)\Delta t \ge \sum_{a=1}^{A}\sum_{i=1}^{V_a} \Big[\Big(SOC_{i,a}^{low}(t_k) \\
&\quad -SOC_{i,a}(t_{j-1})\Big) B_{i,a}/\eta_{i,a}\Big]; \\
&\quad P^{opt}(t_k) \le \sum_{a=1}^{A} P_a^{maxAG}(t_k); \\
&\quad P^{opt}(t_k) \ge 0; \\
&\quad P^{opt}(t_k) + L(t_k) - H(t_k) \le S_R; \\
&\quad k \in [j, N] \quad and \quad r \in [j, k]
\end{aligned} \tag{13}$$

The first and second constraints define the upper and lower limits of the SOC, respectively, calculated in Section III.*A*. The third and fourth constraints define the upper and lower limits of the total power, respectively, calculated in Section III.*B*. The last defines the excess of charging power, $H(t_k)$, above the rated power of the PDT.

Since the controllable variables of the optimization problem are the total power of all PEVs supplied by the primary distribution system in each time interval, i.e., $P^{opt}(t_k)$, it is not possible to consider the finalization of the charging of an individual PEV battery in the calculation of the upper limit of the total power. As such, the feasibility of the solution cannot be ensured for all time intervals $j + 1$ to N. Because of this, the methodology considers the solution of an optimization problem for the entire assessed remaining period, to then store only the optimum power obtained at the jth time interval, which is in addition distributed among the PEVs. After this first optimization, a second reformulated optimization problem, reduced in time interval, i.e., from, the $j + 1$ th to the N time intervals, is calculated, and the optimum power at the $j + 1$ th time interval is again stored. This procedure is repeated until it completes the solution to the N reformulated optimization problems and obtains the N optimum powers to be supplied to the PEVs.

D. OPTIMIZATION WITHOUT COORDINATION

In this step, the optimum power of charging of each aggregator, i.e. $P_a^{optAG}(t_k)$, is calculated, minimizing their charging costs without considering coordination among them. The corresponding optimization problem is presented in (14), which is formulated and solved individually for each aggregator.

$$\begin{aligned}
&\min \sum_{t=t_k}^{t_n} P_a^{optAG}\, C(t_k)\, \Delta t \\
&s.t. \sum_{r=j}^{k} P_a^{optAG}(t_r)\Delta t \le \sum_{i=1}^{V_a} \Big[\Big(SOC_{i,a}^{up}(t_k) \\
&\quad -SOC_{i,a}(t_{j-1})\Big) B_{i,a}/\eta_{i,a}\Big]; \\
&\quad \sum_{r=j}^{k} P_a^{optAG}(t_r)\Delta t \ge \sum_{i=1}^{V_a} \Big[\Big(SOC_{i,a}^{low}(t_k) \\
&\quad -SOC_{i,a}(t_{j-1})\Big) B_{i,a}/\eta_{i,a}\Big]; \\
&\quad P_a^{optAG}(t_k) \le P_a^{maxAG}(t_k); \\
&\quad P_a^{optAG}(t_k) \ge 0; \\
&\quad k \in [j, N] \quad and \quad r \in [j, k]
\end{aligned} \tag{14}$$

The first and second constraints define the upper and lower limits of the SOC, respectively. The third and fourth constraints define the upper and lower limits of the total power. Once (15) is solved for each aggregator, the obtained optimum powers of the jth time interval are used to distribute the optimum total power obtained under DSO coordination, as is shown in section III.*E*. It can be noted that the optimum power profiles of the aggregators obtained in this section could be defined externally from the methodology, e.g. being calculated daily or hourly for the aggregators and reported to the DSO.

E. DISTRIBUTION OF THE TOTAL POWER AMONG THE AGGREGATORS

After the optimization stages have been performed, the next step is to distribute the total optimum power, obtained by using the coordination strategy, evenly among the aggregators by considering their optimum power profiles. This even distribution of the total optimum power is computed by using a direct proportion between the deviation of power assigned to the aggregator from its optimum value and its maximum feasible deviation, as it is expressed in (15) and (16). The maximum feasible deviation is defined as the difference between the optimum power of the aggregator and its power limit $P_a^{lim}(t_j)$, which would be the upper or the lower limit depending on the need to increase or decrease the total power $P^{opt}(t_j)$, respectively, from the sum of the optimum individual powers of the aggregators $P_a^{optAG}(t_j)$. Additionally, a power flow calculation is performed to verify the system stability. In this stage, the values of $P^{opt}(t_j)$ and $P_a^{coorAG}(t_j)$ are modified to satisfy the power flow constraints by using the methodology shown in Fig. 5. As a first step, if the current constraints are violated in one or more lines, the values of $P_a^{coorAG}(t_j)$ of the aggregators supplied by each saturated line d are adjusted according to the criteria defined in (15) and (16), but by using $P_d^{max}(t_j)$ instead of $P^{opt}(t_j)$ and considering the subset A_d of aggregators supplied by the saturated distribution line d, instead of A. Secondly, if the voltage constraints are not satisfied, $P^{opt}(t_j)$ is adjusted using the variable w defined in (17). Then, the values of $P_a^{coorAG}(t_j)$ are recalculated and the power flow is verified again.

$$P_a^{lim}(t_j) = \begin{cases} \dfrac{\sum_{i=1}^{V_a} \left[SOC_{i,a}^{low}(t_j) - SOC_{i,a}(t_{j-1})\right]}{\eta_{i,a}\ \Delta t} B_{i,a}; \\ \text{if } P^{opt}(t_j) \le \sum_{a=1}^{A} P_a^{optAG}(t_j) \\ \dfrac{\sum_{i=1}^{V_a} \left[SOC_{i,a}^{up}(t_j) - SOC_{i,a}(t_{j-1})\right]}{\eta_{i,a}\ \Delta t} B_{i,a}; \\ \text{if } P^{opt}(t_j) > \sum_{a=1}^{A} P_a^{optAG}(t_j) \end{cases} \tag{15}$$

$$\frac{P_a^{coorAG}(t_j) - P_a^{optAG}(t_j)}{P_a^{lim}(t_j) - P_a^{optAG}(t_j)} = \frac{P^{opt}(t_j) - \sum_{a=1}^{A} P_a^{optAG}(t_j)}{\sum_{a=1}^{A} P_a^{lim}(t_j) - \sum_{a=1}^{A} P_a^{optAG}(t_j)} \tag{16}$$

$$w = \begin{cases} \dfrac{\max\left[\mathbf{U}(t_j)\right] - U^{min}}{\max\left[\mathbf{U}(t_j)\right] - \min\left[\mathbf{U}(t_j)\right]} \\ \qquad \textit{if } \min\left[\mathbf{U}(t_j)\right] < U^{min} \\ \dfrac{\max\left[\mathbf{U}(t_j)\right] - \min\left[\mathbf{U}(t_j)\right]}{U^{max} - \min\left[\mathbf{U}(t_j)\right]} \\ \qquad \textit{if } \max\left[\mathbf{U}(t_j)\right] > U^{max} \end{cases} \tag{17}$$

F. DISTRIBUTION OF AGGREGATOR POWER AMONG THE PEVS

Finally, to complete the jth iteration, the charging power and the new SOC of each PEV are calculated using the methodology presented in step *1.3* of Section III.*A*. For each aggregator, the value of k and the power to distribute among the PEVs are defined as shown in Fig. 6.

IV. CASE STUDIES

A. CASE STUDY I

We have tested the same case study presented in [5], composed of four aggregators which manage PEV charging in four low voltage distribution systems powered by a medium voltage grid. The same stochastic variables and the same system have been used, with the aim of comparing the cited work and the methodology proposed in this paper. The TOU tariff defined in the cited work is shown in Table 1.

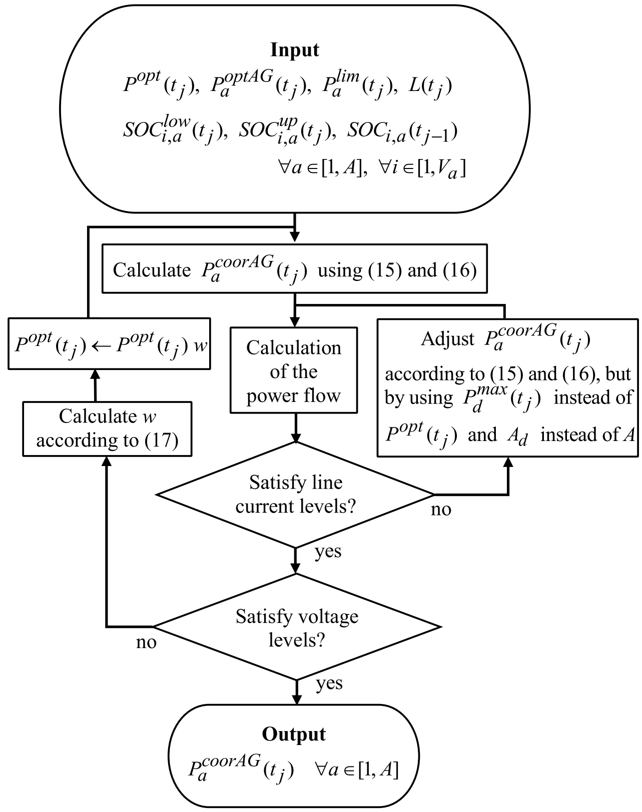

FIGURE 5. Block diagram of the proposed methodology for the distribution of total power among the aggregators.

TABLE 1. TOU tariff.

	TOU price ($/kWh)	Time
Peak	0.138	(8:00-12:00] and (17:00-21:00]
Shoulder	0.109	(12:00-17:00] and (21:00-24:00]
Off-peak	0.058	(0:00-8:00]

B. CASE STUDY II

1) POWER SYSTEM

The IEEE 33-bus test distribution system [25] has been adapted to this case study. A total of 32 SDTs of 12.66/0.38 kV have been added, connecting the base load and the PEV chargers to the medium voltage grid. Additionally, the main grid is supplied through a PDT of 5 MVA. It is considered that in each of the SDTs a unique aggregator manages the PEV chargers connected to it. A standard base load profile of 24 hours from San Juan, Argentina was used. The same TOU tariff from case study I has been used. A permissible voltage deviation of ±5% from the rated value has been considered.

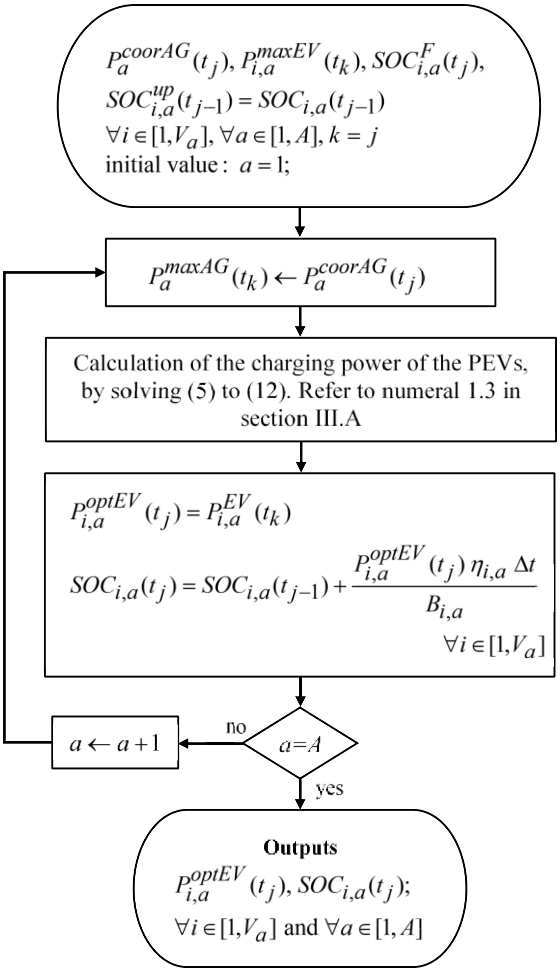

FIGURE 6. Block diagram of the proposed methodology for the set of PEV charging power.

2) VEHICLE FLEET

A total of 450 hybrid PEVs were considered, which are connected to the SDTs by chargers of 7 kW. The battery capacity of the PEVs varies between 40 and 60 kWh, taken from real models available on the market, e.g., Tesla Model S, Nissan Leaf and BMW i3. To calculate the initial charging capacities, travelling distance was estimated using a Gaussian distribution N $(50,15^2)$ (km). It was assumed that the arrival time and departure time of the PEVs to the charging stations follow Gaussian distributions N (20:00, $(1\text{ h})^2$) and N (7:00, $(1\text{ h})^2$), respectively.

V. RESULTS

A. CASE STUDY I

Monte Carlo simulations were performed for this case, with a total of 500 randomly generated charging scenarios (which satisfies the convergence diagnosis method of Gelman and Rubin [26]). The total power profiles obtained with and without coordination are shown in Fig. 7. The obtained mean power profiles of the four aggregators are shown in Fig. 8. The charging strategies with and without coordination are referred to respectively as WC and WOC for abbreviation. The baseload power is referred to as BL.

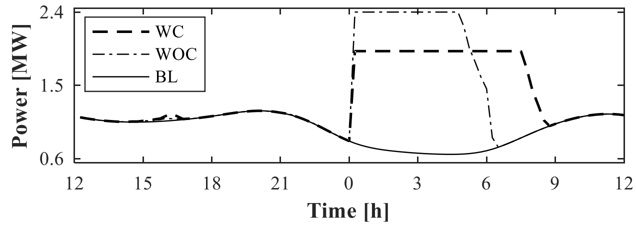

FIGURE 7. Total power profiles of the aggregators.

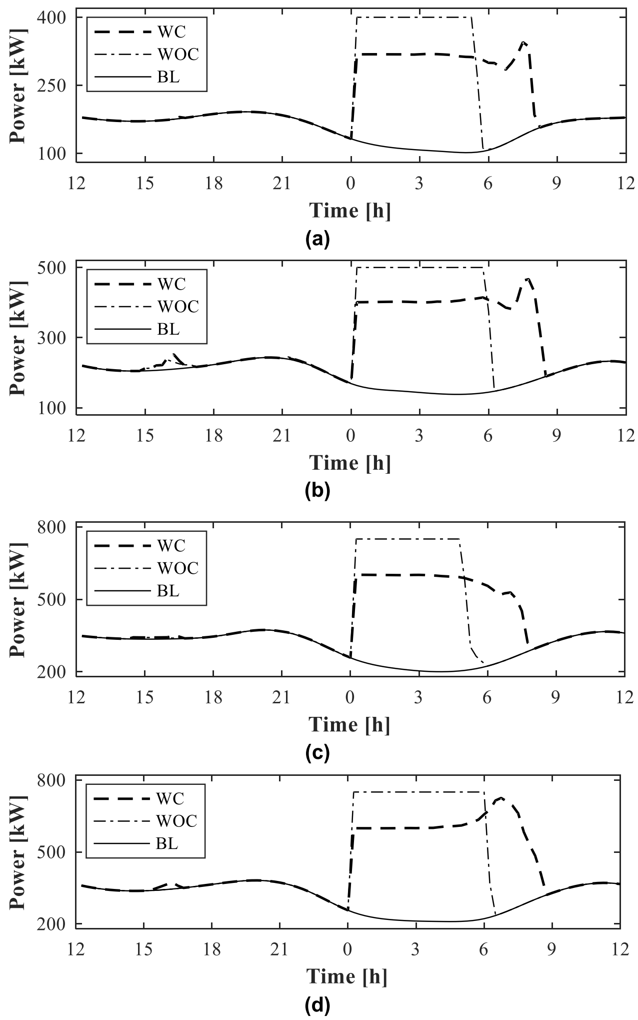

FIGURE 8. Power profiles of the (a) aggregator 1, (b) aggregator 2, (c) aggregator 3, (d) aggregator 4.

No significant differences in the graphs of the total power profiles can be observed as compared to the cited work. On the contrary, significant differences can be noted in the individual power profiles of the aggregators. This is mainly because the third aggregator benefits under the proposed methodology since it demands a lower fraction of its total available energy for PEV charging. This makes sense because the aggregator costs are less affected by increases in energy demanded by the other aggregators.

In [5] the total profits of the aggregators are 900 \$/day and 901 \$/day, with and without coordination respectively. The total and individual profits obtained with the proposed methodology are shown in Table 2.

TABLE 2. Profits in [\$/day].

Charging strategy		Agg. 1	Agg. 2	Agg. 3	Agg. 4	Total
WOC	$\bar{x}_1$	154.01	205.51	256.23	307.85	923,62
	σ_1	4.953	5.482	6.180	6.778	11.753
WC	$\bar{x}_2$	153.55	202.82	255.62	303.73	915.74
	σ_2	4.666	4.064	5.884	4.637	7.281
$(\bar{x}_1 - \bar{x}_2)/\bar{x}_1$ [%]		0.2984	1.3046	0.2369	1.3397	0.8524

Regarding the computational complexity of the problem, it must be noted that, in the case of the proposed methodology, the maximum number of controllable variables and constraints in the DSO optimization problem are independent of the number of aggregators, which are $2N$ and $5N$ respectively, i.e. 192 and 480 for the case study. In the case of the methodology presented in [5], the maximum number of controllable variables and constraints are $2\ NV_a$ and $N(4V_a + 1)$ respectively, i.e. 768 and 1632 for the case study.

In this regard, the computational complexity theory states that the expected number of iterations in the solution of a linear programming problem is at least polynomial, i.e. $O(n^{\alpha})$, with $\alpha > 3.5$, depending on the algorithm, e.g. interior point method, dual-simplex method, etc., [27], and, in the worst case, the complexity has behaves exponentially, i.e. $O(2^n - 1)$, as is the case for the simplex method, [28], where n is directly related to the number of control variables and the number of constraints. Thus, the number of constraints and variables of the LPs are those that determine the increase or decrease in computational complexity. Therefore, with the proposed approach, the total profit increased by 15.74 \$/day, while the computational complexity decreased at least $V_a^{3.5}$ times, i.e., 128 times in the case of only four aggregators.

B. CASE STUDY II

Monte Carlo simulations of 1000 randomly generated charging scenarios have been performed for this case (which satisfies [26]). The mean power profiles obtained with and without coordination are shown in Fig. 9. In all cases, the total power profile has been limited to the rated power of the PDT, which is 5 MW. A boxplot of the SOC evolution of the complete fleet of PEVs of the 32 aggregators during the 24-hour period is shown in Fig. 10. It can be noted that, all the PEV batteries are fully charged at the end of the period. In addition, a boxplot of the voltage magnitudes of the IEEE 33-bus test distribution system with and without coordination during the 24-hour period is shown in Fig. 11. It has been verified that in all time intervals the voltage magnitudes are within the permissible range. In both boxplots, the box represents the interquartile

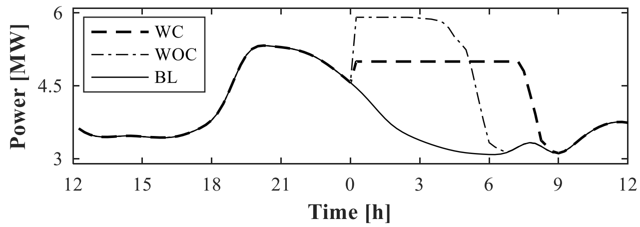

FIGURE 9. Total power profiles of the case with 32 aggregators.

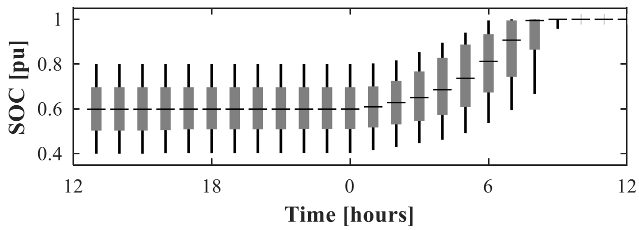

FIGURE 10. Boxplot of the SOC evolution of the complete fleet of PEVs.

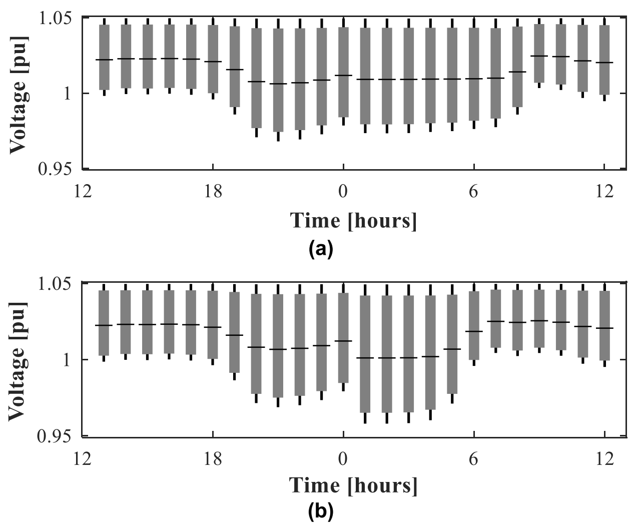

FIGURE 11. Boxplot of the voltage magnitudes of the IEEE 33-bus test distribution system (a) with coordination, (b) without coordination.

range of 68%, while the whiskers are given by 95% of each data distribution.

In Fig. 12 the power loss profiles with and without coordination during the 24-hour period are shown. In the coordinated scenario, the maximum power losses during the hours

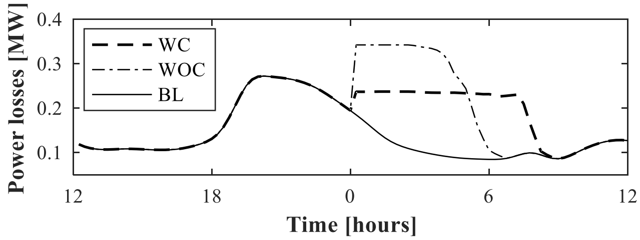

FIGURE 12. Power losses of the IEEE 33-bus test distribution system.

of PEV charging are 30% lower than in the uncoordinated case. The daily energy losses are 4.33 and 4.47 MWh (4.16% and 4.3% of the total supplied energy, respectively) for the coordinated and the uncoordinated charging, respectively.

The loss of life has been calculated for the case with and without coordination, using the Susa thermal model [29] and the IEEE aging model [30]. Results are shown in Table 3. The parameters used as the inputs of the transformer thermal model, which correspond to a 5 MVA ONAN-cooled transformer, are shown in Table 4.

TABLE 3. PDT loss of life.

	With coordination	Without coordination
Mean value	9.2682 h	16.5243 h
Standard deviation	0.0923 h	0.2358 h

TABLE 4. Susa thermal model parameters.

R	τ_w [min]	τ_{TO} [min]	$\Delta\theta_{TO,R}$ [ºK]	$\Delta\theta_{H,R}$ [ºK]	$\theta_{A,R}$ [ºC]
10	7	125	55	20	35

The average cost of energy supplied to the PEVs without coordination is 0.058045 $/kWh, increasing to 0.058325 $/kWh for the case with coordination. The percentage of variation is 0.48%, which indicates that the profits of the aggregators are not significantly affected. The average cost of energy and the ratio of the energy used to charge PEVs and the available energy for each of the 32 aggregators are shown in Fig. 13. It can be noted that both curves are shaped similarly. This means that the aggregators which demand a greater percentage of the local available energy have higher energy costs. Once again, this makes sense because they are contributing in a higher degree to the PDT overloading that is being avoided through the charging coordination.

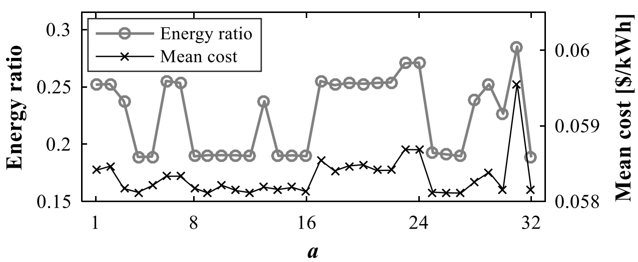

FIGURE 13. Comparison between the use of available energy and the mean cost per unit of energy. *Energy ratio* is, for each aggregator, the ratio of the energy used to charge PEVs and the available energy.

Results demonstrate that the proposed methodology allows for the mitigation of the impact of the PEV charging on the distribution grids. Such impact can be reflected in the system operation savings, i.e. savings related to the transformer loss of life, the energy losses, and the violation of the voltage constraints, among others. The DSO can then compensate for the decrease in the aggregators' benefit by using the aforementioned savings. In addition, the obtained charging strategy ensures the reliability of the system operation.

VI. CONCLUSION

In this paper, an improved methodology for optimizing PEV charging through the coordination of aggregators is proposed. This methodology minimizes energy costs of the aggregators while constraining the power supplied by the PDT to the medium voltage grid and the power supplied by the SDTs to the aggregators.

The optimization problem of the power of charging of PEVs has been formulated as a linear model, which is easily solvable with the most widespread and simple optimization algorithm, i. e. simplex algorithm. Additionally, the number of variables of such an optimization problem is independent of the number of aggregators and PEVs, decreasing the computational burden in applications of large distribution systems, as was concluded through the results of case study I.

Moreover, the calculation of the constraints of the total SOC of the PEVs has been achieved through an iterative methodology that applies a proposed algorithm of assignment of the aggregator power among the PEVs, improving upon the simple summation of individual constraints used in other works (e. g. [5], [22]–[24]). Such improvement can be observed in the results obtained in case study I since an increase of the total daily profits of the aggregators can be noted in comparison with those obtained in [5]. This achievement is mainly related to the improvement of the mentioned constraints of the optimization problem, thus allowing us to obtain a more accurate solution in each iteration.

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REFERENCES

[1] J. Buekers, M. Van Holderbeke, J. Bierkens, and L. I. Panis, "Health and environmental benefits related to electric vehicle introduction in EU countries," *Transp. Res. D, Transp. Environ.*, vol. 33, pp. 26–38, Dec. 2014.

[2] K. B. Naceur and J. F. Gagné, "Global EV outlook 2017," Int. Energy Agency, Paris, France, Tech. Rep., 2016, pp. 27–30. [Online]. Available: https://www.iea.org/publications/freepublications/publication/GlobalEVOutlook2017.pdf

[3] S. Deb, K. Tammi, K. Kalita, and P. Mahanta, "Impact of electric vehicle charging station load on distribution network," *Energies*, vol. 11, no. 1, p. 178, 2018.

[4] J. Y. Yong, V. K. Ramachandaramurthy, K. M. Tan, and N. Mithulananthan, "A review on the state-of-the-art technologies of electric vehicle, its impacts and prospects," *Renew. Sustain. Energy Rev.*, vol. 49, pp. 365–385, Sep. 2015.

[5] Z. Xu, Z. Hu, Y. Song, W. Zhao, and Y. Zhang, "Coordination of PEVs charging across multiple aggregators," *Appl. Energy*, vol. 136, pp. 582–589, Dec. 2014.

[6] H. Suyono, T. M. Rahman, H. Mokhlis, M. Othman, A. H. Illias, and H. Mohamad, "Optimal scheduling of plug-in electric vehicle charging including time-of-use tariff to minimize cost and system stress," *Energies*, vol. 12, no. 8, p. 1500, 2019.

[7] C. Z. El-Bayeh, I. Mougharbel, M. Saad, A. Chandra, D. Asber, L. Lenoir, and S. Lefebvre, "Novel soft-constrained distributed strategy to meet high penetration trend of PEVs at homes," *Energy Buildings*, vol. 178, pp. 331–346, Nov. 2018.

[8] C. Z. El-Bayeh, I. Mougharbel, D. Asber, M. Saad, A. Chandra, and S. Lefebvre, "Novel approach for optimizing the transformer's critical power limit," *IEEE Access*, vol. 6, pp. 55870–55882, 2018.

[9] L. Yao, W. H. Lim, and T. S. Tsai, "A real-time charging scheme for demand response in electric vehicle parking station," *IEEE Trans. Smart Grid*, vol. 8, no. 1, pp. 52–62, Jan. 2017.

[10] E. L. Karfopoulos, K. A. Panourgias, and N. D. Hatziargyriou, "Distributed coordination of electric vehicles providing V2G regulation services," *IEEE Trans. Power Syst.*, vol. 31, no. 4, pp. 2834–2846, Jul. 2016.

[11] P. You, Z. Yang, M.-Y. Chow, and Y. Sun, "Optimal cooperative charging strategy for a smart charging station of electric vehicles," *IEEE Trans. Power Syst.*, vol. 31, no. 4, pp. 2946–2956, Jul. 2016.

[12] A. Cortés and S. Martínez, "A hierarchical algorithm for optimal plug-in electric vehicle charging with usage constraints," *Automatica*, vol. 68, pp. 119–131, Jun. 2016.

[13] J. de Hoog, T. Alpcan, M. Brazil, D. A. Thomas, and I. Mareels, "A market mechanism for electric vehicle charging under network constraints," *IEEE Trans. Smart Grid*, vol. 7, no. 2, pp. 827–836, Mar. 2016.

[14] Q. Gong, S. Midlam-Mohler, E. Serra, V. Marano, and G. Rizzoni, "PEV charging control considering transformer life and experimental validation of a 25 kVA distribution transformer," *IEEE Trans. Smart Grid*, vol. 6, no. 2, pp. 648–656, Mar. 2015.

[15] L. Hua, J. Wang, and C. Zhou, "Adaptive electric vehicle charging coordination on distribution network," *IEEE Trans. Smart Grid*, vol. 5, no. 6, pp. 2666–2675, Nov. 2014.

[16] E. Karfopoulos and N. Hatziargyriou, "Distributed coordination of electric vehicles for conforming to an energy schedule," *Elect. Power Syst. Res.*, vol. 151, pp. 86–95, Oct. 2017.

[17] A. Perez-Diaz, E. Gerding, and F. McGroarty, "Coordination and payment mechanisms for electric vehicle aggregators," *Appl. Energy*, vol. 212, pp. 185–195, Feb. 2018.

[18] J. C. Mukherjee and A. Gupta, "Distributed charge scheduling of plug-in electric vehicles using inter-aggregator collaboration," *IEEE Trans. Smart Grid*, vol. 8, no. 1, pp. 331–341, Jan. 2017.

[19] Q. Zhang, H. Liu, and C. Li, "A hierarchical dispatch model for optimizing real-time charging and discharging strategy of electric vehicles," *IEEJ Trans. Electr. Electron. Eng.*, vol. 13, no. 4, pp. 537–548, 2018.

[20] M. F. Shaaban, M. Ismail, E. F. El-Saadany, and W. Zhuang, "Real-time PEV charging/discharging coordination in smart distribution systems," *IEEE Trans. Smart Grid*, vol. 5, no. 4, pp. 1797–1807, Jun. 2014.

[21] J. F. Franco, M. J. Rider, and R. Romero, "A mixed-integer linear programming model for the electric vehicle charging coordination problem in unbalanced electrical distribution systems," *IEEE Trans. Smart Grid*, vol. 6, no. 5, pp. 2200–2210, Sep. 2015.

[22] Q. Huang, Q.-S. Jia, and X. Guan, "A multi-timescale and bilevel coordination approach for matching uncertain wind supply with EV charging demand," *IEEE Trans. Autom. Sci. Eng.*, vol. 14, no. 2, pp. 694–704, Apr. 2016.

[23] C. Deng, N. Liang, J. Tan, and G. Wang, "Multi-objective scheduling of electric vehicles in smart distribution network," *Sustainability*, vol. 8, no. 12, p. 1234, 2016.

[24] Z. Xu, W. Su, Z. Hu, Y. Song, and H. Zhang, "A hierarchical framework for coordinated charging of plug-in electric vehicles in China," *IEEE Trans. Smart Grid*, vol. 7, no. 1, pp. 428–438, Jan. 2016.

[25] M. E. Baran and F. F. Wu, "Network reconfiguration in distribution systems for loss reduction and load balancing," *IEEE Trans. Power Del.*, vol. 4, no. 2, pp. 1401–1407, Apr. 1989.

[26] A. Gelman and D. B. Rubin, "Inference from iterative simulation using multiple sequences," *Statist. Sci.*, vol. 7, pp. 457–472, Nov. 1992.

[27] N. Ploskas and N. Samaras, *Linear Programming Using MATLAB*. Piscataway, NJ, USA: Institute of Electrical and Electronics Engineers, 2017. doi: 10.1109/TSG.2015.2394489.

[28] R. Cottle and M. N. Thapa, *Linear and Nonlinear Optimization*, vol. 253. Piscataway, NJ, USA: Institute of Electrical and Electronics Engineers, 2017. doi: 10.1109/TASE.2016.2585180.

[29] D. Susa, M. Lehtonen, and H. Nordman, "Dynamic thermal modelling of power transformers," *IEEE Trans. Power Del.*, vol. 20, no. 1, pp. 197–204, Jan. 2005.

[30] *Guide for Loading Mineral-Oil-Immersed Transformers and Step-Voltage Regulators*, IEEE Standards C57.91-2011, IEEE Standards Association, 2012.

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