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New approach for electric vehicles charging management in parking lots considering fairness rules

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ABSTRACT

Electric Vehicles are replacing conventional vehicles and imposing new challenges in the power systems management comprising all voltage levels. The methodologies proposed in the literature have as their main goal the minimization of operation costs neglecting fairness rules. Additionally, most of the methods were developed considering information regarding travel needs, which is far from reality. In the present paper, it is proposed an energy management system to be used in parking lots considering the optimization of a fairness index, low installed capacity, and low level of information exchanged between the Electric Vehicle (EV) and the parking energy management system as well as the use of charging stations with multiple outlets (charge more than one EV in the same charging station). The proposed approach is modelled as a mixed-integer linear programming problem with the main goal to improve fairness in the charging process considering different types of contracts (normal use, privileged contract and long-duration parking contracts). A case study is presented which considers 100 electric vehicles in a residential parking lot. Several options for charging stations are compared, and the proposed fairness methodology is compared with the First-In First-Served approach. The obtained results show the adequacy and fairness of the proposed methods. The fairness index increased from 0.289 to 0.748 on a scale of 0 to 1, where 1 is the perfect solution when all the EVs have 100% of State-of-Charge (SOC) at departure time. The proposed methodology can be adopted in real parking lots with different characteristics.

Nomenclature

Parameters

CS	Charge Station
EV	Electric Vehicle
$E_{max(EV)}$	Maximum Energy capacity of Electric Vehicle *EV* [kWh]
N_{CS}	Number of Charge Stations
N_{EV}	Number of Electric Vehicles
$P_{minCh(EV,t)}$	Minimum power charge of electric vehicle *EV* in period t [kW]
$P_{minMCP(EV,t)}$	Minimum power charge of electric vehicle *EV* in period t (used for minimum charge power – *MCP* penalization factor)-Defined by the user [kW]
$P_{maxCh(EV,t)}$	Maximum Power charge in Electric Vehicle *EV* in period t [kW]
$P_{maxCS(CS)}$	Maximum power in charge station *CS* (Technical limit) [kW]
$P_{maxCS(CS,t)}$	Maximum power in charge station *CS* in period t, including the technical limits and limits imposed by the upper management level
$P_{maxPark(t)}$	Maximum power consumption of Parking lot in period t [kW]
$P_{MCP(EV,t)}$	Minimum power charge of electric vehicle *EV* in period t (used for minimum charge power – *MCP* penalization factor) [kW]
$P_{ParkingSet(t)}$	Power Consumption setpoint in period t (used for *PParking* penalization factor) [kW]
$P_{SocL1max(EV,t)}$	Power charge of electric vehicle *EV* in period t (used for minimum SOC Level 1 defined by the user) [kW]
$P_{SocL2max(EV,t)}$	Power charge of electric vehicle *EV* in period t (used for minimum SOC Level 2 defined by the user) [kW]
$P_{SocL3max(EV,t)}$	Power charge of electric vehicle *EV* in period t

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(used for minimum SOC Level 3 defined by the user) [kW]
$PW_{minSOC(t)}$ Penalization factor of the minimum level of SOC
$PW_{PParking(t)}$ Penalization factor of power consumption setpoint of the parking lot– *PParking*
$PW_{SocL1(EV,t)}$ Penalization factor of SOC Level 1
$PW_{SocL2(EV,t)}$ Penalization factor of SOC Level 2
$PW_{SocL3(EV,t)}$ Penalization factor of SOC Level 3
$PW_{VarP(EV,t)}$ Penalization factor of power charge variation – *VarP*
$PW_{SocL1(EV,t)}$ Penalization factor of SOC Level 1
$PW_{SocL2(EV,t)}$ Penalization factor of SOC Level 2
$PW_{SocL3(EV,t)}$ Penalization factor of SOC Level 3
$SOC_{initial(EV,t)}$ Initial state of charge of Electric Vehicle *EV* in period *t* [kWh]
T Period
TF Time Factor
$X_{Place(EV,CS,t)}$ Binary parameter indicating the connection between Electric Vehicle *EV* and Charge Station *CS* in period *t*
$\Delta P_{ch(EV,t)}$ Maximum power charge variation for electric vehicle *EV* in period *t* [kW]
$\eta_{CSt(CS)}$ Charge Efficiency of charging station *CS* [%]
$\eta_{ChEV(EV)}$ Charge Efficiency of electric vehicle *EV* [%]

Decision Variables

$E_{(EV,t)}$ Energy stored at of Electric Vehicle *EV* in period *t* [kWh]
$F-\text{index}$ Fairness Index
$P_{ch(EV,t)}$ Power charged in Electric Vehicle *EV* in period *t* [kW]
$PF_{MCP(EV,t)}$ Penalization factor of minimum charge power – *MCP* [kW]
$PF_{minSOC(t)}$ Penalization factor of the minimum level of SOC [kWh]
$PF_{PParking(t)}$ Penalization factor of power setpoint of parking consumption – *PParking* [kW]
$PF_{SocL1(EV,t)}$ Penalization factor of SOC Level 1 [kWh]
$PF_{SocL2(EV,t)}$ Penalization factor of SOC Level 2 [kWh]
$PF_{SocL3(EV,t)}$ Penalization factor of SOC Level 3 [kWh]
$PF_{VarP(EV,t)}$ Penalization factor of power charge variation – *VarP* [kW]
$P_{SocL1(EV,t)}$ Power charge of electric vehicle *EV* in period *t* (used for minimum SOC Level 1 penalization factor) [kW]
$P_{SocL2(EV,t)}$ Power charge of electric vehicle *EV* in period *t* (used for minimum SOC Level 2 penalization factor) [kW]
$P_{SocL3(EV,t)}$ Power charge of electric vehicle *EV* in period *t* (used for minimum SOC Level 3 penalization factor) [kW]
$P_{VIPL1(EV,t)}$ Power charge of electric vehicle *EV* in period *t* (used for VIP users in *SOCL1* penalization factor) [kW]
$P_{VIPL2(EV,t)}$ Power charge of electric vehicle *EV* in period *t* (used for VIP users in *SOCL2* penalization factor) [kW]
$SOC_{(EV,t)}$ State of charge of Electric Vehicle *EV* in period *t* [kWh]
$SOC_{(EV,t_{last})}$ State of charge of Electric Vehicle *EV* in departure period t_{last} [kWh]
$X_{Ch(EV,t)}$ Binary variable indicating the charge state of electric vehicle *EV* in period *t*

1. Introduction

1.1. Context and motivation

The use of electric vehicles (EVs) is increasing significantly in recent years. This enhancement is motivated by environmental concerns and more recently by the energy crisis and consequent rise in the price of fuel-based sources. According to [1], in 2021, were sold 6.6 million EVs (including plug-in hybrid vehicles) in the World, and the EVs stock was more than 16 million. The increase of EVs, in coordination with the fast penetration of renewables, are two important pillars for the energy transition. The development of coordination algorithms will promote the faster development of these technologies [2]. Another important aspect that should be considered in the energy transition is the heating systems in buildings [3, 4] as well as district heating [5].

The EVs fast development introduced new challenges in power system operations due to the increase in power consumption [6]. At the same time, EVs can be seen as flexible load-creating opportunities when EV charging is managed [7, 8]. One of the solutions is the adoption of intelligent charging scheduling strategies [9]. EV charging scheduling functions can be integrated into different energy management systems. For example, the function can be integrated into a Smartbox used by individual users only for EV charging management, in-house/buildings or parking lot energy management systems, in the aggregator decision support system, and the system operator's supervisory control and data acquisition (SCADA).

Works already proposed in the literature consider that the user will provide information concerning travel needs. Nevertheless, in their quotidian, only a small amount of users will provide this information [10]. Another important point that is not already addressed is the inclusion of fairness indexes when the EVs are managed in parking lots. According to [11], fairness in recommendation, decisions and optimization is becoming more and more important for the user's adoption of a solution. The fairness index is important in situations where power capacity limits impose that some of the EVs cannot be charged at their maximum. The use of this index can avoid the need for capacity expansion of parking lots [12].

1.2. Contributions and objectives

The methodology proposed in the present paper intends to manage the electric vehicles charging in parking lots, considering a more realistic approach, only considering the available information obtained by the charging stations, and fairness indexes facilitating the adoption of the solution. The proposed methodology differs from the ones already proposed in the following aspects:

- The management system does not require information about the travel needs (or state of charge - SOC needs) of the EVs. In the methodology, is assumed that the only information known by the parking energy management system is the SOC when the EV is connected to the park and the maximum capacity of its battery. Management without information is challenging but closer to reality. At the same time, is more generic, when compared with the existing methodologies, and easily replicated in parking lots with different requirements and characteristics.
- Different types of contracts are considered. Most of the EVs can have normal contracts in which the EVs are charged with the same priority level as other EVs. However, the proposed methodology considers different types of contracts such as privileged contracts

and long-duration parking contracts. The consideration of these types of contracts is not considered in most of the studies already published.

- EVs with privileged contracts will have priority only under the same conditions (similar SOC level). Long-duration parking contracts are established by EVs that are connected in the parking lot during long periods. The EVs with this type of contract have less priority in the charging scheduling but will have lower parking rates, creating advantages for all the users.
- The proposed methodology profits from the possibility of charging stations with multiple outlets to charge more than one EV at the same time. Charging stations with two outlets are relatively common on the market [13, 14]. In [15], is proposed a fast charge system with 6 outlets and in [16] an extremely fast-charging infrastructure using a Direct Current (DC) bus, allowing the charge of multiple EVs, is presented.
- A fairness evaluation index for EV management is proposed. The main aim of this index is to measure the equity between the charging process of EVs when power capacity constraints exist and it is impossible to charge the EVs at the same level.
- The energy management algorithm, based on a mixed-integer linear programming optimization problem (MIP), follows a fairness strategy, trying to charge the EVs with lower SOC. Afterwards, the EVs are separated into 3 levels according to the SOC. Finally, a minimum power charge, defined in kW, is applied to guarantee that most EVs should be charged, at least, at this power.
- Beyond the considered fair rules in EVs charge, the methodology can deal with the limited power capacity available in the parking lot. This subject is extremely relevant because in most situations, mainly in big cities, the parking lot cannot increase the installed capacity due to the distribution system constraints. A fairness index is proposed to compare the EV charging approaches.

1.3. Paper structure

After the present introduction, Section 2 is a state-of-the-art concerning EVs management in parking lots. The proposed methodology considering fairness optimization is presented in Section 3. A case study considering a parking lot with 100 places is presented in Section 4. Finally, the main conclusions are presented in Section IV.

2. EVs management state-of-the-art

Several works have been published recently addressing the management of EVs. Recently, in [17], it was presented a review concerning the vehicle-to-everything mode of operation of EVs analysed the integration of vehicles in the electric grids, houses and between vehicles. However, the integration and management of parking lots are not referred to. In [18], is proposed a framework to manage the EVs in a parking lot considering the high level of information exchanged between the EVs and the parking lot management system. The main goal of the framework proposed in [18] is the optimization of energy supplied to EVs according to their requirements (energy for next travel). Parking lot management is also studied in [19] proposing three different methods, 1) first-come-first-served [20], 2) priority based on departure schedule [21], and 3) decision-making algorithm proposed by the authors. The decision-making is performed based on two decision levels namely the arrival time and an EV scoring system based on the difference between the required and the actual level of SOC. Compared with [18–21], the approach presented in the current study differs from the ones proposed in previous studies because the parking lot management system does not have information about the departure time and energy needs. This is a key point because in the real world this information is not available.

The parking lot management considers the participation of the parking lot operator (PLO) in electricity markets with the main aim of profit maximization [22]. In [22], the fuzzy modelling of EVs uncertainties and electricity market price uncertainties are modelled and integrated into the methodology using a fuzzy approach. The optimal trading of plug-in electric vehicles in a market environment is also addressed in [23]. However, the analysis is not limited to the EVs connected in the same parking lot. The participation of electric vehicle parking lots in the retail electricity market at the distribution level is also studied in [24]. The paper proposes a customer-centric design principle called eVoucher allowing the coordination between electric vehicle charging behaviour and economic incentives. This process should be managed by the distribution system operator and the incentives should be defined following the retailers. More centred in microgrids, optimal stochastic scheduling of EVs is proposed in [25]. In that case, EVs can be also used to supply energy to microgrids in case of lack of production acting as a mobile storage system.

The integration of renewables in parking lot management is analysed in [26]. In that case, the parking lot management is coordinated with the solar generation obtained by a rooftop photovoltaic (PV) system. The problem is analysed from a distribution system point of view, considering the parking lot as a flexible load. Scheduling of EV charging and discharging considering the impact on the distribution network is also analysed on [27] where a decentralized management algorithm is proposed. Optimal sizing of hybrid renewable energy systems considering EVs is presented in [28] using two algorithms, namely, multi-objective particle swarm optimization (MOPSO) and multi-objective crow search (MOCS). In [29], is proposed a cooperative game-theory approach to define the coordination between the utility (distribution system operator) and the parking lot manager. In that case, the utility tries to optimize the electricity price expecting different behaviours from the parking lot manager. This paper, [29], is mainly focused on parking lots dedicated to plug-in hybrid electric vehicles due to their higher charging flexibility. The optimal coalition of distributed energy resources using game theory is also proposed in [30]. In particular, a three-level gameplay-based intelligent structure to evaluate individual and collaborative strategies is proposed. All of the above papers are relevant but not considering the bahaviour of the end-users. Fairness indexes are not taken into acocunt and the proposed strategies only optimize the coordination with renewables.

A parking lot management system considering the existence of solar generation and energy storage systems is addressed in [31]. The main goal of the paper is the operation cost minimization of the parking lot considering the EVs needs (required SOC) and the PV generation. In [31] is also considered the ability of electric vehicles to provide vehicle-to-grid (V2G) services. An analysis of a parking lot with a PV system is also presented in [32] with the main aim of studying the solar energy potential in parking lots, maximizing the use of the energy provided by the PV system to charge the EVs batteries. The methodology proposed in [32], is assumed that the surplus generated energy by PV can be stored in a centralized energy storage system maximizing the use of PV-generated energy. A financial assessment is also provided showing the required payback time for the proposed solution. A real-time EV charging scheduling method in parking lots with PV units and energy storage system is also addressed in [33] using a grey wolf optimization method evolution called improved binary grey wolf optimizer (IBGWO). The model proposes the evaluation of the parking time and the charging demand needs to schedule the charge (0/1) of each electric vehicle considering an objective function that minimizes the cost of energy delivered by the main grid.

All the previously mentioned papers consider the existence of parking lot centralized management operated by an aggregator or parking lot operator. In [34], proposed a framework for local energy trading between electric vehicles and parking lots. In the same paper, is referred that electric vehicles can exchange energy (buy and sell) through buying and selling prices. The market platform is managed by a parking lot control centre (PLCC) providing offer/demand information. The market mechanism is based on Knapsack Algorithm (KPA) and the main goal is the maximization of the profit. Again, even in a distributed management of EVs, important aspects related to the fairness of the proposed methodology are not considered in the algorithm.

3. Proposed methodology

The parking lot management is modelled as a mixed-integer linear optimization problem and has been implemented in the MATLAB optimization toolbox. The uniqueness of the solution is assured by the solver. The problem is modelled as a discrete problem. The main architecture of the implemented methodology is presented in Fig. 1. In the following sub-sections, the constraints and objective functions are presented.

3.1. Parking lot constraints

The sum of the maximum power of all charging stations should be lower than the maximum capacity of the parking lot. This capacity can be the technical capacity imposed by the power transformer, by the cable's thermal limits or by the contractual capacity. Considering that the maximum power can also be imposed by the global building consumption algorithm [35], this limit can be different in each period *t*. The power limit is not applied directly to the EVs, but firstly to the charging stations *CS*.

$$\sum_{CS=1}^{N_{CS}} \frac{P_{maxCS(CS,t)}}{\eta_{CSt(CS)}} \le P_{maxPark(t)} \; \forall t \in \{1, \dots, T\} \tag{1}$$

3.2. Charge stations constraints

The power supplied by the charging station *CS* should be lower than its maximum capacity (technical constraint) and lower than the maximum power defined, if exists, by the upper-level energy management system (mainly in case of integration with buildings management). Parameter $X_{Place(EV,CS,t)}$ contains the information if the electric vehicle *EV* is connected to the charging station *CS* in period *t*. This parameter can be dynamic because is assumed that the same vehicle can be connected to a different charging station in different periods. When binary parameter $X_{Place(EV,CS,t)}$is zero, this means that the EV is not connected to charging station *CS* in period *t*, and consequently, the power charged in the EV ($P_{ch(EV,t)}$) is also zero. Charging stations can have more than one outlet. Is assumed that each outlet can provide the total power available in the charging station. This means that no additional restrictions are required to model the outlets. When the charging stations are not available due to technical issues, the binary variable $X_{Place(EV,CS,t)}$ is defined as 0 for all the periods.

$$\sum_{EV=1}^{N_{EV}} P_{ch(EV,t)} \le P_{maxCS(CS,t)} . X_{Place(EV,CS,t)} \quad \forall CS \in \{1, \dots, N_{CS}\} ; \; \forall t \in \{1, \dots, T\} \tag{2}$$

3.3. Electric vehicles constraints

For each EV, the power charge should be lower than the maximum power accepted by the EVs (Eq. (3)) [36]. It is also considered that the EV does not allow power charges below a limit (Eq. (4)) [36]. This value can be different for each EV and can also depend on the battery state-of-charge (SOC). If the available power in the parking lot or charging station is lower than the minimum required power ($P_{minCh(EV,t)}$) by the EV, the variable $X_{Ch(EV,t)}$ will be zero, avoiding infeasible solutions. The power charge is limited by the remaining energy needed by the electric vehicle batteries of (Eq. (5)) to achieve the *SOC = 100%*. The parameter *TF* (Time Factor) represents the relation between one hour and the duration of each period *t* (relation between the power and energy). As an example, if *t* represents 1 h (60 min), the value of *TF* is 60/60. If *t* represents 1 min, the value of *TF* is 1/60.

$$P_{ch(EV,t)} \le P_{maxCh(EV,t)} . X_{Ch(EV,t)} \; \forall EV \in \{1, \dots, N_{EV}\} ; \; \forall t \in \{1, \dots, T\} \tag{3}$$

$$P_{ch(EV,t)} \ge P_{minCh(EV,t)} . X_{Ch(EV,t)} \; \forall EV \in \{1, \dots, N_{EV}\} ; \; \forall t \in \{1, \dots, T\} \tag{4}$$

$$P_{ch(EV,t)} \le \left(1 - SOC_{(EV,t)}\right) . \frac{E_{max(EV)}}{TF} \; \forall EV \in \{1, \dots, N_{EV}\} ; \; \forall t \in \{1, \dots, T\} \tag{5}$$

In each period, the energy of each EV should be updated considering the previous state (*t-1*) and the power charged in period *t*. Additionally, the energy in the batteries should be lower than the maximum limit.

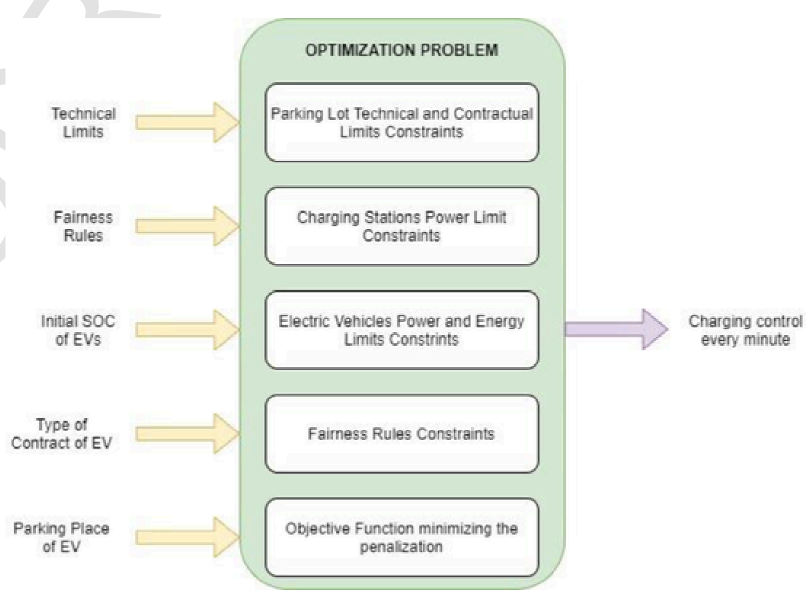

Fig. 1. Electric vehicles management system architecture.

When the EV arrives at the parking lot ($t = 0$) the information of the SOC is provided to the system. This matters because the parking lot management system doesn't have previous information relating to the EV (travels, etc.).

$$E_{(EV,t-1)} + P_{ch(EV,t)}.TF = E_{(EV,t)}\ \forall EV \in \{1,\dots,N_{EV}\};\forall t \in \{1,\dots,T\} \tag{6}$$

$$E_{(EV,t)} \le E_{max(EV)}\ \forall EV \in \{1,\dots,N_{EV}\}; \tag{7}$$

3.4. Parking rules constraints

Several rules can be implemented allowing the fair use of charging stations and parking lot infrastructures. The rules are defined based on penalizations with different weights. These penalizations will be used in the optimization function.

Minimum Power Charge penalization - $PF_{MCP(EV,t)}$

The main idea is to charge each EV at least with a minimum power ($P_{minMCP(EV,t)}$) in each instant t. This value can be defined by the users (parking lot manager) and can be different for each vehicle and different periods. For example, if the energy needed to completely charge the EV is lower than the minimum power, the value should be adjusted. If the system is not able to provide the minimum power charge ($P_{MCP(EV,t)}$), the penalization factor $PF_{MCP(EV,t)}$ will be higher than zero and the solution will be penalized in the objective function.

$$P_{MCP(EV,t)} - PF_{MCP(EV,t)} \le P_{ch(EV,t)}\ \forall EV \in \{1,\dots,N_{EV}\};\ \forall t \in \{1,\dots,T\} \tag{8}$$

$$P_{MCP(EV,t)} = \min\left(P_{minMCP(EV,t)};\left(1 - SOC_{(EV,t)}\right).\frac{E_{max(EV)}}{TF}\right)\ \forall EV \in \{1,\dots,N_{EV}\};\ \forall t \in \{1,\dots,T\} \tag{9}$$

State of Charge level penalization - $PF_{SOCL(EV,t)}$

The main goal of SOC-level penalization factors is to give more importance to EVs with lower SOC. Three levels are considered. The first level (between 0 and 50% of SOC) is the critical level. All the EVs that have a SOC lower than the level 1 limit, should have priority. Level 3 (between 80 and 90% of SOC) is the less priority level. Normally, the EVs with SOC higher than level 3 have enough energy for everyday use. Level 2 is a level between level 1 and level 3. The power needed for each EV in each level can be computed prior to optimization. If the SOC level is higher than the required SOC level, the value used in the optimization should be 0. Additionally, the parking lot manager can accept premium subscriptions. In that case, the users with privileged contracts (identified as VIP – a very important person in the equations) will have priority when compared with the other users with similar SOC levels. Because of this, an extra penalization factor can be included in the power factor limits and/or an additional penalization factor can be added to the objective function. Eq. (10) imposes the active power limits for the sum of the three levels. The SOC level boundaries are defined in Eqs. (11) – (13). In those equations, the charging power needed to achieve each level is defined considering the current SOC and the required SOC in each level. Eq. (13) limits the sum of the charging power in each level to the maximum allowed by the EV.

$$P_{SocL1(EV,t)} - PF_{SocL1(EV,t)} + P_{SocL2(EV,t)} - PF_{SocL2(EV,t)} + P_{SocL3(EV,t)} - PF_{SocL3(EV,t)} \le P_{ch(EV,t)}\ \forall EV \in \{1,\dots,N_{EV}\};\ \forall t \in \{1,\dots,T\} \tag{10}$$

$$P_{SocL1(EV,t)} = \max\left(0;\ \left(P_{SocL1\max(EV,t)} + P_{VIPL1(EV,t)} - SOC_{(EV,t)}\right).\frac{E_{max}}{t_{per}}\right)\ \forall EV \in \{1,\dots,N_{EV}\};\ \forall t \in \{1,\dots,T\}$$

$$P_{SocL2(EV,t)} = \max\left(0;\ \left(P_{SocL1\max(EV,t)} + P_{VIPL2(EV,t)} - SOC_{(EV,t)}\right).\frac{E_{max}}{t_{per}}\right)\ \forall EV \in \{1,\dots,N_{EV}\};\ \forall t \in \{1,\dots,T\}$$

$$P_{SocL3(EV,t)} = \max\left(0;\ \left(1 - SOC_{(EV,t)}\right).\frac{E_{max(EV)}}{t_{period}}\right)\ \forall EV \in \{1,\dots,N_{EV}\};\ \forall t \in \{1,\dots,T\} \tag{13}$$

Maximum variation in power charge - $PF_{VarP(EV,t)}$

This penalization intends to limit power charge variations in consecutive periods avoiding fluctuations in the charging level considering these periods. The limitation is only imposed in the charging power decrease.

$$P_{Ch(EV,t-1)} - P_{Ch(EV,t)} + PF_{VarP(EV,t)} \le \Delta P_{ch(EV,t)}\ \forall EV \in \{1,\dots,N_{EV}\};\ \forall t \in \{1,\dots,T\} \tag{14}$$

Minimum SOC - $PF_{minSOC(EV,t)}$

This penalization intends to give priority to the vehicles with lower SOC penalizing the minimum SOC of all EVs in the parking lot. This penalty factor is different from the previous one since is expressed in percentage and not in Power. However, it can be an important differentiator factor when two EVs arrive at the parking at the same moment and the system will give priority to the one that has lower SOC. This penalization is complementary to the SOC level penalization that will give higher priority to some EVs which are favoured over others despite having the same SOC level.

$$PF_{minSOC(t)} \le SOC_{(EV,t)}\ \forall EV \in \{1,\dots,N_{EV}\};\ \forall t \in \{1,\dots,T\} \tag{15}$$

Followa determinedpower consumption in the parking - $PF_{usePParking(t)}$

The main idea of this penalization factor is to have an upper level of management (in operational planning or real-time) defining a power operation setpoint to the parking lot. The upper level can be a complex management tool or a simple definition of different power operations levels according to the electricity prices. For example, if in some periods the price is higher than a pre-defined value, the maximum power setpoint ($P_{ParkingSet(t)}$) can be lower than the one imposed by technical limits.

$$\sum_{CS=1}^{N_{CS}} P_{maxCSt(CS,t)} - PF_{PParking(t)} \le P_{ParkingSet(t)}\ \forall CS \in \{1,\dots,N_{CS}\};\ \forall t \in \{1,\dots,T\} \tag{16}$$

3.5. Objective function

The objective function, for each period t, intends to minimize the penalization factors associated with the parking lot rules, thus assuring that the electric vehicles are charged in a fairway.

$$f_{(t)} = \min \sum_{EV=1}^{N_{EV}} \begin{pmatrix} PF_{MCP(EV,t)} \times PW_{MCP(EV,t)} + \\ PF_{SocL1(EV,t)}.\left(PW_{SocL1(EV,t)} + PW_{VL1(EV,t)}\right) + \\ PF_{SocL2(EV,t)}.\left(PW_{SocL2(EV,t)} + PW_{VL2(EV,t)}\right) + \\ PF_{SocL3(EV,t)}.\left(PW_{SocL3(EV,t)} + PW_{VL3(EV,t)}\right) + \\ PF_{VarP(EV,t)} \times PW_{VarP(EV,t)} \end{pmatrix} - PF_{minSOC(t)} \times PW_{minSOC(t)} + PF_{PParking(t)} \times PW_{PParking(t)} \tag{17}$$

The fairness index (F-Index), presented in Eq. (18), of the proposed model can be measured by the average of the SOC of EVs at departure time (t_{last}). Considering that the system doesn't have the information about the SOC required by the EVs, in an ideal situation, all the EVs will have the SOC at 100% and the F-Index will be equal to 1. To avoid the impact of the EVs with low energy requirements, only the EVs with a lower fairness level (50%) will be considered. To give more emphasis to the EVs with lower SOC, a second term considering only the 10% EVs with lower SOC was included. This means that the F-Index is a quadratic function of the SOC of the EVs that depart from the parking lot with lower SOC (in percentage).

$$F - \text{index} = \frac{\sum_{EV=1}^{0.5\times N_{EV}} SOC_{(EV,t_{last})}}{N_{EV}} \times \frac{\sum_{EV=1}^{0.1\times N_{EV}} SOC_{(EV,t_{last})}}{N_{EV}} \qquad (18)$$

4. Case study

In the present case study, the proposed methodology was tested considering a residential parking lot with 100 places to supply the needs of 100 EVs. The simulation was performed for one day and the optimization was executed every 1 min (a total of 1440 periods). In this case, it was considered a park in a residential area where most of the EVs are parked during the night. Because of that, the simulation started at 4:00 pm allowing the evaluation of the night period. The case study section has three sub-sections. In section A the main data are presented, section B presents the results without EVs with VIP contracts and in section C, the results consider EVs with privileged contracts.

4.1. Case study data

As already discussed, the use of electric vehicles has been studied by different authors. According to [37], several distributions for the everyday use of EVs were discussed without a consensual conclusion about the best type of distribution. Considering that no specific data is available, the following use profiles, proposed by the authors considering the use of residential buildings parking, were the following:

- Profile P1 – 3% of the EVs don't leave the parking lot during the simulation.
- Profile P2 – 70% of the EVs leave between 6:40 and 8:30 am and return between 5:30 and 8:30 pm.
- Profile P3 – 17% of the EVs have random behaviour.
- Profile P4 – 10% of the EVs leave between 6:30 and 8:00 am, return between 00:30 and 01:30 pm, leave between 01:30 and 2:00 pm and return between 6:30 and 9:00 pm.

The EV models and battery capacities considered in the use case are presented in Table 1.[1]

The behaviour of the EVs was randomly distributed in the mentioned time intervals and the SOC at arrival time varies from 5 to 50%. The arrival time and the level of SOC of each EV are presented in Fig. 2.

Regarding the parking lot rules and the penalization factor, the main assumptions are presented in Table 2. The penalization factors are defined only based on the SOC levels and not on the EVs characteristics. In the present case, the VIP penalization factor is added to the other penalizations and the long-duration penalization weight is multiplied by the other penalizations. As presented in Table 2, the VIP weight is enough to give priority to charge when the EVs are in the same step level of SOC (L1, L2 or L3) or, in an upper level. This means that:

- L2 VIP EVs have priority regarding L1 "normal" EV.
- L3 VIP EVs have priority regarding L2 "normal" EV.
- L3 VIP EV does not have priority regarding L1 "normal" EV.

[1] Data defined based on the models sold in Portugal in September of 2020.

Table 1
Electric vehicles information.

Model	Market share	Battery capacity	Profile 1	Profile 2	Profile 3	Profile 4
Nissan Leaf	16%	40 kWh	0	12	3	1
Tesla Model 3	13%	75 kWh	0	10	2	1
BMW i3	10%	42 kWh	0	7	2	1
Renault ZOE	10%	41 kWh	0	7	2	1
Jaguar i-Pace	9%	90 kWh	0	6	2	1
Mercedes E300	8%	13.5 kWh	0	6	1	1
BMW 530e	8%	12 kWh	0	6	1	1
Mini Countrymen	7%	7.6 kWh	0	6	1	0
Hyundai Kauai	6%	39 kWh	0	4	1	1
Mitsubishi Outlander	5%	12 kWh	0	3	1	1
Smart Fortwo	5%	17.6 kWh	0	3	1	1
Others	3%	20 kWh	3	0	0	0

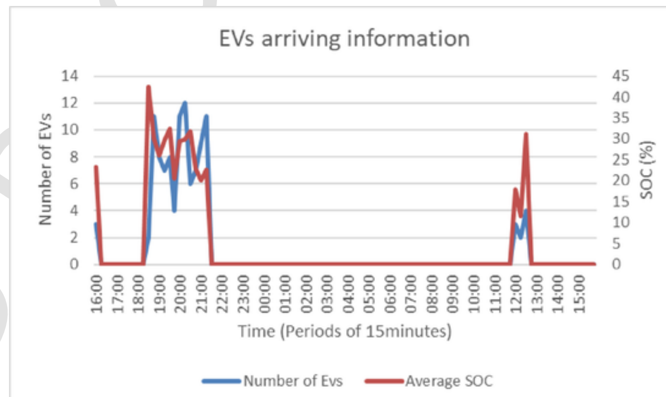

Fig. 2. Electric vehicles arriving information (Number of EVs and SOC needs).

Table 2
Parking lot rules and characteristics.

Description	Limit	Weight
Minimum charge [kW]	1	100
SOC Level 1 [%]	< 40%	50
SOC Level 2 [%]	< 85%	40
SOC Level 3 [%]	< 100%	30
VIP		+17
Long duration parking		*10%
ΔP [kW]	2	5
Min SOC		500

When the EVs have long-duration parking contracts (only 3 EVs in the present case study), the penalization weights are multiplied by 10%, significantly reducing their importance in the scheduling process.

For the parking lot constraints, is assumed that is a medium voltage (MV) consumer with an installed power of 250 kW (the reactive power is considered negligible). Due to the tariff scheme, MV consumers should pay for the energy consumed and for the available power. A tri-hourly tariff is considered where the off-peak period occurs between 00:00 and 7:00 am during weekdays.

Concerning the power, the medium voltage consumers should pay by the contracted power and by the use of the power (average power consumption during peak periods) in peak periods. According to [38], in Portugal, for the consumers that are not in the liberalized market, the price of contracted power is 1.418 €/kW (during a month) and the use of peak power is 9.859 €/kW. Taking into consideration the energy and power costs is assumed in this case study that in the peak periods the maximum consumption in the park is limited to 100 kW and in the off-peak period the limit is imposed by the technical limits (250 kW). As it is possible to see, considering a park for 100 EVs, and the average SOC of EVs at the arrival time, the limits imposed on the power are very challenging.

Several charging stations *CS* are available in the market. The most popular are the 7.2 kW (normal charge), 22 kW (fast charge) and (rapid charge) 50–60 kW. More recently, extra fast-charge stations with 120–180 kW and 350 kW have been proposed as presented in [13]. In the present paper, is considered that each charge station can supply energy to several EVs (multiple outlets charging stations). Table 3 presents the considered options. The total installed power in charging stations is considered "virtual" because the installed power of the parking lot, 250 kW, will impose on the global consumption of charging stations. In all the options, the efficiency of the charging station is considered as 98%.

4.2. *Parking lot energy management withoutVIP electric vehicles contracts and using the first-in-first-served approach*

In this section, the results of the proposed methodology are presented. To have a benchmark for comparison, a first-come-first-served (FCFS) approach was implemented. The obtained results are presented next figures. Fig. 3 presents the total power demand of EVs.

The values are lower than the limits due to the efficiency of the charging stations (98%). During a large amount of time, the power consumption is the same in all approaches and equal to the limit. Some differences can be seen in the first periods when only 3 EVs are parked and between the periods 1190 to 1300, corresponding to the lunchtime where few EVs are parked. Fig. 4 presents the minimum SOC of the EVs parked in the parking lot.

In that case, the minimum charge of the parked vehicles remains the same throughout most of the simulation (period 300 to 900). The last EVs arriving at the parking lot are not charged at all. In period 900, the EV should leave the park but the SOC remains at a very low level (around 5%). During the lunchtime period, except for the 7.2 kW solution, some EVs are also not charged. Fig. 5 shows a comparison between the SOC level at the EVs departure time.

In all situations, several EVs will have a very low level of SOC at departure. It is also interesting to notice that, when charging stations with 7.2 kW are considered, and compared with other solutions, a few EVs with low values of SOC are verified. This is of particular interest because the power charge limitation for each EV introduces a kind of fair rule in parking lot management. The fairness indexes (F-Index) in each charging station option are presented in Table 4, confirming that the higher fairness index (the best one) is Option 1 with chargers of 7.2 kW.

Table 3
Charging stations characteristics considering different options.

Option	Quantity of charging stations	Power [kW]	Number of ports	Total "virtual" power [kW]
1	100	7.2	1	720
2	20	22	5	440
3	5	50	20	250
4	3	120	33/34	360
5	1	250	100	250

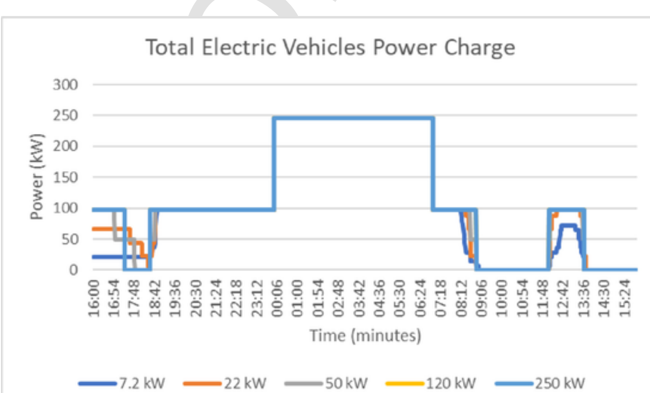

Fig. 3. Total electric vehicles active power charge – FCFS strategy.

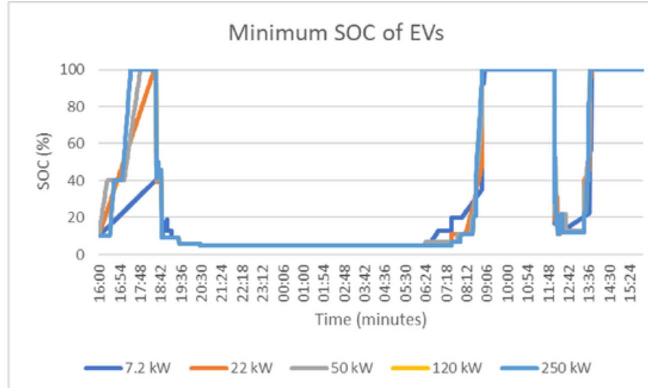

Fig. 4. Minimum SOC of the electric vehicles parked in the parking lot – FCFS strategy.

Fig. 5. SOC of electric vehicles at departure time – FCFS strategy.

4.3. *Parking lot energy management withoutVIP electric vehicles contracts and using the fair approach*

The results of the proposed methodology considering the fairness index are presented in Figs. 6, 7, and 8. Comparing Fig. 3 with Fig. 6, no significant differences were observed.

From the parking lot point of view, both approaches are similar, presenting similar consumptions. However, between periods 1030 to 1190, in the 7.2 kW solution, is possible to see that some EVs are charged. This occurs because the EVs with long-duration contracts are not charged when other EVs are parked. Comparing Fig. 4 with Fig. 7 significant differences can be seen.

After the EVs' arrival period (21:00 to 24:00), when the minimum SOC changes significantly every minute, is possible to observe that the SOC increases linearly. It is also noticeable that in the off-peak periods when the total power limit changes to 250 kW, the curve slope increases. Considering the 7.2 kW case, the increase is linear because of the existence of long-duration parking contracts vehicles. During

Table 4
Fairness index considering FIFS charging strategy.

Option 1	Option 2	Option 3	Option 4	Option 5
0.289	0.225	0.242	0.201	0.201

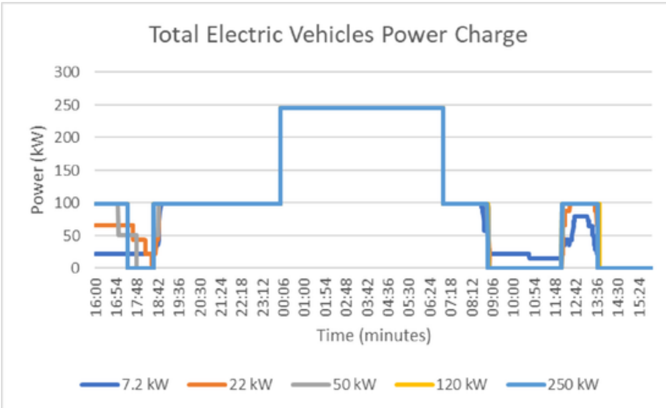

Fig. 6. Total electric vehicles active power charge – Proposed strategy without VIP contracts.

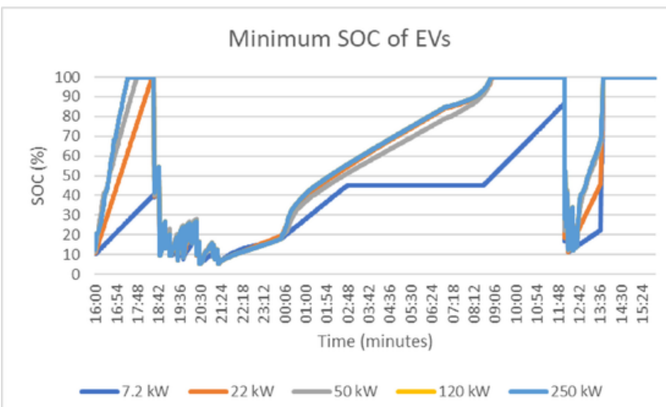

Fig. 7. Minimum SOC of the electric vehicles parked in the parking lot proposed strategy without VIP contracts.

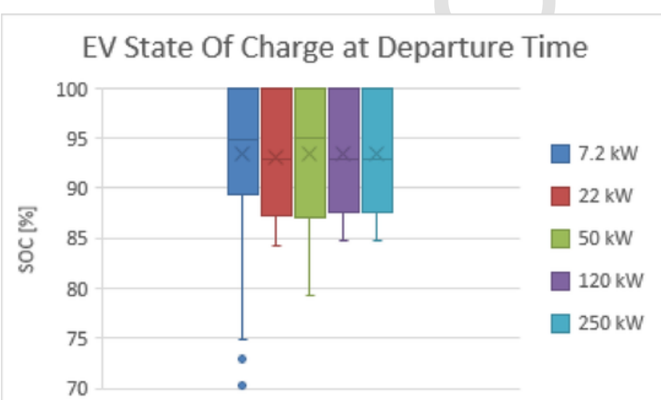

Fig. 8. SOC of electric vehicles at departure time – Proposed strategy without VIP contracts.

lunchtime, the increase is also linear. However, in that case, the differences between the charging solutions are more perceptible.

Comparing Fig. 5 with Fig. 8 is possible to see that all the EVs are now charged at a convenient level.

In the worst scenario, 7.2 kW, the EV with lower SOC at the departure time, achieves a SOC level of 70.3%. In the other solutions, the EV with lower SOC has its batteries at 79 to 85%. Is also important to analyse the differences between the 22 kW solution and the 50 kW solution.

In that case, the 22 kW case presents better results since the EV with lower SOC has 84% and the 50 kW case has 79%. This happens because the EV distribution in the charging stations is not optimized. Nevertheless, the average SOC at departure time is higher when considering 50 kW. The values of the fairness indexes are presented in Table 5. Comparing Table 5 with Table 4 is visible a significant increase in the fairness indexes in all the charging options. In that case, the highest value is obtained in options 4 and 5.

4.4. *Parking lot energy management withVIP electric vehicles contracts*

In the present simulation, the 22 EVs with the higher battery capacity (90 and 75 kW) are considered VIP EVs. These EVs will have priority compared with other EVs with similar SOC levels. The evolution of the minimum SOC level in all the EVs is presented in Fig. 9.

Comparing Fig. 9 with Fig. 7, it is possible to see that the minimum SOC continues increasing in all of the periods, showing the fairness of the proposed method. Nevertheless, the curve slope is lower. When the EVs with VIP contracts achieve SOC level 3 (SOC higher than 85%) the priority becomes lower than the priority of the EVs with normal contracts. In that case, these EVs are charged and the charge of EVs with VIP contracts remains at the minimum power (1 kW). The SOC of the EVs at departure time for the entire set of EVs and the EVs with VIP contracts is presented in Fig. 10. In all solutions, it is possible to see that the EVs with VIP contracts are charged at least 87% which is a very acceptable value considering the imposed limitations and the number of EVs with VIP contracts.

The EVs without privileged contracts are penalized and the minimum SOC at departure time decreases by 4 to 7%. Can be also observed that the solutions of 120 and 250 kW are more adapted to lead with VIP contracts mainly for the EVs without these contracts. However, is possible to conclude that the solution for charging stations with 22 kW and with five outlets can be a well-balanced solution for the present parking lot. Table 6 presents the fairness indexes for the different charging options considering VIP contracts. As expected, the fairness indexes decreased in all the charging options.

4.5. *Results analysis*

The proposed solution based on the optimization of the fairness index shows significant advantages when compared with the first-in-first-

Table 5
Fairness index considering fairness charging strategy.

Option 1	Option 2	Option 3	Option 4	Option 5
0.665	0.741	0.708	0.748	0.748

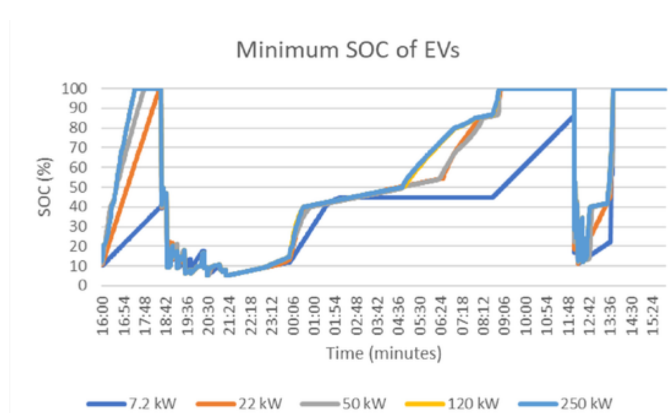

Fig. 9. Minimum SOC of the electric vehicles parked in the parking lot fairness strategy with VIP contracts.

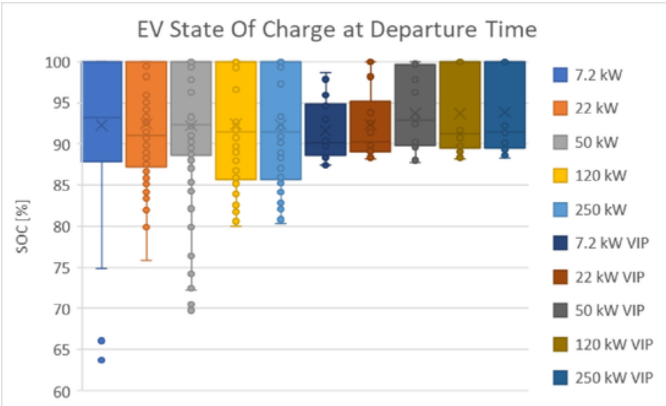

Fig. 10. SOC of electric vehicles at departure time – Fairness strategy with VIP contracts.

Table 6
Fairness index considering fairness charging strategy with VIP contracts.

Option 1	Option 2	Option 3	Option 4	Option 5
0.643	0.702	0.630	0.696	0.697

served approach. The proposed fairness index increases from around 0.2 to 0.7. In other words, the difference between the state-of-charge of the different EVs changes from 95% where some EVs are completely satisfied (100% of SOC) and other EVs have a very low SOC with, in the worst case, only 5% of its SOC. When the proposed methodology is used, the car with minimum SOC has around 70% of SOC. This quantity of energy is enough for the daily use of most regular users (around 40 km [39]). When privileged contracts are taken into account, as expected, the fairness index decreases by around 0.68. In any case, this value is much higher than the values obtained with the first-in-first-served strategy. Another important achievement is the better use of the installed power in the parking lot. With the proposed strategy, the total power is close to the maximum most of the time. This means a fast return on the investment. Finally, analysing the results, it is possible to conclude that the advantages to have charging stations with multiple outlets are not clear. An explanation for this can be the frequency of arrivals and departures of the EVs. It is also important to notice that the proposed methodology is transversal for any country, installed power, type of charging station and vehicles. The case study considered typical values but power capacity, fairness levels and type of contracts can be adjusted in the definition of initial parameters.

5. Conclusions

The present paper proposes an energy management algorithm be used in a parking lot considering a new fairness index, minimal use of information exchanges between the EVs and the management system and low installed or contracted power capacity. The main contribution of the proposed methodology is the introduction of a fairness index in EV charging management. Additionally, is introduced the possibility of using charging stations with multiple outlets allowing the charge of more than one EV at the same time. The methodology also considers different types of contracts, namely EVs with everyday use, EVs with privileged contracts and EVs with long-duration parking contracts. The proposed model is close to the real needs of parking lots and considers realistic assumptions. The problem is modelled as a mixed-integer linear program allowing the implementation in common hardware used in the industry. A case study considering a parking lot with 100 places for 100 EVs is presented comparing the proposed methodology with a first-come-first-served approach. The results show a significant improvement in the EVs charging distribution even when VIP contracts are considered. The state of charge at departure time is higher than 70% when individual charging stations of 7.2 kW are considered and higher than 85% for charging stations of 250 kW with multiple outlets. Comparing the fairness index (F-Index), the proposed scheduling solutions present a substantial increase from 0.289 in FIFS to 0.748 in the proposed approach. Additionally, the use of installed power is also higher meaning a faster return on investment in the charging infrastructure.

Future work will consider the use of the proposed method in a real parking lot to evaluate its performance in real situations. Additionally, integration with the building management system imposing variable consumption limits will be tested. Finally, the vehicle-to-grid capability will be considered.

Authorship statement

All persons who meet authorship criteria are listed as authors, and all authors certify that they have participated sufficiently in the work to take public responsibility for the content, including participation in the concept, design, analysis, writing, or revision of the manuscript. Furthermore, each author certifies that this material or similar material has not been and will not be submitted to or published in any other publication before its appearance in the Electric Power Systems Research Journal.

Authorship contributions

Category 1

Conception and design of study: H. Morais; acquisition of data: H. Morais; analysis and/or interpretation of data: H. Morais.

Category 2

Drafting the manuscript: H. Morais; revising the manuscript critically for important intellectual content: H. Morais.

Category 3

Approval of the version of the manuscript to be published (the names of all authors must be listed): H. Morais.

CRediT authorship contribution statement

Hugo Morais : Conceptualization, Methodology, Software, Data curation, Software, Visualization, Investigation, Validation, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

None

Data Availability

Data will be made available on request.

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