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Flexibility modeling for parking lots with multiple EV charging stations

Tohid Harighi *, Alberto Borghetti, Fabio Napolitano, Fabio Tossani

Department of Electrical, Electronic, and Information Engineering "Guglielmo Marconi", University of Bologna, Bologna, Italy

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ABSTRACT

The paper proposes an aggregated model that represents the flexibility potential of car parks equipped with multiple electric vehicle (EV) charging stations. The model is used in a stochastic optimization procedure to estimate in advance the maximum flexibility margins of the parking lot. The EV aggregator responsible for the charging stations offers intra-day ancillary services to the grid by specifying the possible margins within which the absorbed power can be varied, either up or down. These adjustments are made at the request of the distribution system operator, ensuring an appropriate level of EV charging. The effectiveness of the model is evaluated for parking lots with different numbers of charging stations and different daily profile forecasts of the number of EV arrivals and departures.

1. Introduction

Electric vehicle (EV) batteries are expected to play an expanded role in the provision of grid services, as described in [1] and references therein. This paper presents a multistage stochastic optimization procedure for calculating the flexibility capabilities of an electric vehicle (EV) parking lot equipped with many charging stations. The aggregator of the charging stations offers flexibility services in response to the distribution system operator's (DSO) requests. The paper does not address the possibility of concurrent participation in a wholesale flexibility market. The maximum deviations of the parking lot load consumption with respect to a reference profile need to be calculated in advance by the EV aggregator in order to support the DSO with the information needed to efficiently use the service.

Other than different model-based or data-driven approaches on EV charging power forecasting (e.g., [2] and references therein), the literature includes several studies that explore the impact of optimizing the operation of EV parking lots in addressing network congestions [3] and mitigating the variability of renewable energy sources [4]. Additionally, various models have been proposed to represent the participation of EV aggregators in energy and ancillary services markets, e.g. [5], and within the framework of demand response programs, as in [6].

The flexibility in the load profile of the EV parking lot can be harnessed by the DSO to address voltage or congestion issues, as shown in, for example, [7]. Procuring reserve flexibility should ensure the energy recovery needed for the provision of the expected charging services to the EVs [8]. Furthermore, the flexibility offered by EV charging stations can also play a significant role in optimizing the design and operation for energy communities and virtual power plants, as shown in, e.g., [9–11].

This paper focuses on the calculation of the maximum flexibility margins, i.e., the maximum up and down feasible variations with respect to the expected reference consumption profile. These margins are offered in advance by the EV parking lot aggregator to the DSO. To improve the dynamic adaptation of the margin calculation to current parking conditions (i.e., to the number and characteristics of the EVs actually connected to the charging stations), a multistage stochastic optimization approach is integrated with an intraday decision procedure. This approach allows the update of the calculated margins at the beginning of each stage in which the daily horizon is divided. In general, this approach produces results, specifically flexibility margins, that are close to those estimated assuming perfect information about the future (deterministic solution) and larger than those obtained by considering the worst-case scenarios (robust solution).

The paper presents a multistage optimization procedure based on an aggregated representation of the EV parking lot, which takes into account several factors, including power absorbed from the grid, the efficiency of EV battery charging and vehicle-to-vehicle (V2V) exchanges allowed by the use of bidirectional charging stations, self-discharge rates, and the energy levels of EVs upon arrival and departure from the car park.

The procedure begins by generating scenarios based on the forecasted number of EVs entering and leaving the parking lot. These scenarios account for the uncertainty associated with the daily forecast,

* Corresponding author.
E-mail addresses: tohid.harighi2@unibo.it (T. Harighi), alberto.borghetti@unibo.it (A. Borghetti), fabio.napolitano@unibo.it (F. Napolitano), fabio.tossani@unibo.it (F. Tossani).

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Nomenclature

Stochastic parameters

π^{ω}:	probability value of scenario ω
$N_{\mathrm{EV\ in}}^{\omega,t}$, $N_{\mathrm{EV\ out}}^{\omega,t}$:	number of electric vehicles (EVs) arriving and departing in period t, respectively
$E_{\mathrm{S+}}^{\omega,t}$, $E_{\mathrm{S-}}^{\omega,t}$:	cumulative stored energy of the EVs arriving and departing in period t, respectively
$E_{\mathrm{ini}\ j}^{\omega,t}$, $E_{\mathrm{g}\ j}^{\omega,t}$:	initial energy and energy gain of the EVs arriving in period j and leaving in period t
$N_{EV}^{\omega,t}$, $E_{\mathrm{Smax}}^{\omega,t}$, $P_{\mathrm{max}}^{\omega,t}$:	number of parked EVs at the end of period t, corresponding total battery size, and cumulative maximum charge power
$\mu^{\omega,t}$:	utilization fraction of EV energy entering at time t

Deterministic parameters

Δt:	single period duration
E_{EV}, P_{EV}:	EV battery size and its maximum charging power
η_{ch}, η_{V2V}:	efficiency of grid battery charging and of vehicle-to-vehicle (V2V) energy transfer
δ:	self-discharge rate of EV batteries
ρ_{TOU}^{t}, ρ_{flex}^{t}, ρ_{μ}:	time-of-use tariff of energy from the grid, of power flexibility services, and of initial EV energy use
t_{flex}, n_{flex}^{+}, n_{rec}:	first period of the flexibility interval, number of subsequent flexibility periods, and number of recovery periods
$N_{\mathrm{park\ max}}$:	maximum number of EV charging points

Sets

T_s:	periods in stage s
$S_{\mathrm{in}}^{\omega,t}$, $S_{\mathrm{out}}^{\omega,t}$:	sets of EVs entering and leaving the car park in period t

Variables

$\Delta P_{\mathrm{flex}}^{\omega,t}$, $R_{\mathrm{flex}}^{\omega,t}$:	maximum allowed increase or decrease in car park power consumption in period t and corresponding flexibility revenue
$C_{\mathrm{S}}^{\omega,t}$:	cost of using the initial EV stored energy
$E_{\mathrm{S\ net}}^{\omega,t}$, $E_{\mathrm{ch\ grid}}^{\omega,t}$:	net energy stored in the batteries and charging energy from the grid in period t
$E_{\mathrm{ch}\ j}^{\omega,t}$:	minimum energy profile to properly charge EVs arriving in period j
$P_{\mathrm{ref}}^{\omega,t}$:	reference consumption profile of the parking lot
$P^{\omega,t}$:	power absorbed by the parking lot from the grid
$l_{\mathrm{V2V}}^{\omega,t}$:	V2V energy transfer losses in period t

considering also the EV rated battery size and diffusion, as well as the maximum charging power. Subsequently, a clustering procedure is applied to construct a multistage scenario tree that represents various possibilities of EV charging. The optimization model, which is built upon the approach presented in [12], calculates the reference consumption profile for the representative scenario of each cluster. This is achieved by minimizing the procurement costs for the EV parking lot, which include both those associated with purchasing the energy from the grid and the consumption of the initial energy stored in the vehicles. Additionally, the model determines the maximum power reduction and increase margins to be offered as flexibility services.

The flexibility margins represent the maximum achievable power reduction and increase that ensure the maintenance of appropriate EV charging levels. Following a power change requested by the DSO, the considered regulatory framework allows the EV parking lot to recover its energy level within a predefined subsequent interval, through a constant variation in the absorbed power.

The structure of the paper follows. Section 2 describes the scenario management of the stochastic parameters, which represent the parked EVs, and the construction of the multistage scenario tree. Section 3 describes the optimization models of the EV parking lot that provide the demand flexibility services. Section 4 describes the case studies and the results for different sizes of parking lots. Section 5 concludes the paper.

2. Stochastic parameters and scenario management

The flexibility margins of the EV parking lot, which determine how much power consumption can be reduced or increased in response to a DSO request while ensuring appropriate EV charging level, are calculated using stochastic optimization, where some parameters and variables are subject to uncertainty or randomness. These uncertainties mainly relate to the characteristics and the number of EVs connected to the charging stations throughout the day.

The description of the procedure is divided into two parts. The first part, which is the subject of this Section, defines the stochastic parameters by using scenarios, each representing a different realization of the uncertain parameters, and performs scenario management. This process generates the multistage tree model, which aggregates similar scenarios at various stages of the day-long optimization horizon.

Section 3 deals with the second part of the procedure, which includes the definition of constraints and objectives of the stochastic models. A first optimization model calculates the daily reference consumption profile of the car park without any request for providing flexibility to the DSO. Two additional models allow the calculation of the maximum feasible reduction and increase in power consumption for each period. All of these models are formulated as linear programming mathematical problems, without the inclusion of binary variables, ensuring computational efficiency, even when dealing with a large number of EVs and charging stations. This is achieved by adopting an aggregate representation of the charging stations and EV batteries, which preserves the accuracy of the calculation of the power exchanges with the network and of the charge/discharge losses, including those associated with V2V exchanges.

2.1. Scenario generation

The procedure starts by generating a number of scenarios for the next day. The scenario generation procedure assumes the availability of the forecasts of the number of EVs entering and leaving the parking lot in each of the 96 periods of the following day. These forecasts can be obtained by the analysis of the EV entry and exit data from previous or similar days. All the entries and departures of a period are assumed to occur at the end of that period.

For each scenario ω, entering $N_{\mathrm{EV\ in}}^{\omega,t}$ and leaving $N_{\mathrm{EV\ out}}^{\omega,t}$ EV numbers are obtained by multiplying the corresponding forecast sequences by $1+k_t$, which accounts for the increasing forecast uncertainty throughout the day. Time series k_t is generated by using a normal distribution with the mean value set to zero, and the standard deviation calculated as $\sqrt{1-{\psi_t}^2}$, where ψ_t is a decreasing function of t. Each value obtained is rounded to the nearest positive integer. Moreover, for each scenario, the order of the numbers of leaving EVs is adjusted so that the number of parked EVs is never negative.

To construct an accurate aggregate model of the parking lot, the sequences of arriving and departing EV numbers are associated with specific populations of EVs. Each EV is defined by entry and exit time periods, ensuring that the entire population of EVs reproduces the sequences of arriving and departing EV numbers. To achieve this, a simple 'first in, first out' strategy is implemented. Only those EVs that can connect to an available charger are considered (i.e., they are limited by $N_{\text{park max}}$) and they are assumed to disconnect at their departure time.

Furthermore, each EV is characterized by its rated battery size E_{EV}, the maximum power P_{EV} allowed by the charging station, and the initial state of charge. To define the first two characteristics, the procedure uses a predefined categorization of currently available EV models and their market penetration. Specifically, the attributes of each EV are selected based on the prevalence of each category, which represents the probability that a vehicle entering the parking lot belongs to that category. The initial energy of the vehicles entering the car park follows a truncated normal distribution, with the mean and standard deviation values assumed to be 0.3 times the size of the battery.

It is assumed that the EVs leaving the parking lot are fully charged or charged to the maximum level allowed by the charging power and parking duration. While it is possible to account for scenarios where some EVs leave the parking lot with lower energy levels by introducing a penalty into the objective functions, this aspect is not addressed here for the sake of simplicity.

The results of this paper have been obtained assuming the same rated power for all charging stations, but the procedure can be adapted to the case where different types of charging stations are present.

2.2. Scenario clustering and tree construction

The procedure has been implemented as a day-ahead evaluation considering a 4-stage stochastic approach (one day-ahead stage and three intraday stages), where the day-ahead evaluation is updated every 6 h during the day to use information on the actual number and characteristics of the EVs in the parking lot. We assume that the EV parking lot aggregator provides the reference consumption profile and the down and up flexibility margins at the beginning of each intraday stage for each of the relevant 15-minute time periods.

For each stage s, similar scenarios are grouped into a scenario tree. For this purpose, the k-medoid clustering procedure is applied. Starting from a single cluster in the first (day-ahead) stage, each cluster can originate different clusters in the next stage. The clustering procedure provides both the medoid for each cluster and stage (i.e., one of the initial scenarios that minimizes the dissimilarity measure with respect to the other scenarios in the cluster) and probabilities π^{ω}. Compared to the k-means algorithm, which calculates centroids by averaging data points within clusters, the k-medoid approach avoids non-integer numbers of entering, leaving, and parked EVs. This ensures the preservation of scenario feasibility after clustering.

Here is a detailed description of the procedure. The clustering is based on the number of parked EVs (assuming that they are all connected to a charging station), $N_{EV}^{\omega,t}$. Alternatively, the clustering can use the sum of the battery sizes of the parked EVs. Even a combination of the two parameters can be considered, normalizing them based on their minimum and maximum values at each time period, as described in [13].

For each stage, the dissimilarity measure d, based on the Euclidean distance $\|\|_2$ between two scenarios $N_{EV}^{\omega_1,t}$ and $N_{EV}^{\omega_2,t}$ is

$$d\left(N_{EV}^{\omega_1,t}, N_{EV}^{\omega_2,t}\right) = \sum_{t\in T_s} \left\| N_{EV}^{\omega_1,t} - N_{EV}^{\omega_2,t} \right\| \tag{1}$$

where T_s is the subset of periods in stage s. Regarding the clustering procedure, different distance definitions can be used to assess the dissimilarities between scenarios, such as the Manhattan distance, as shown in [14].

At stage $s = 1$, a scenario ω_i is chosen as medoid $C_1^{s=1}$ such that the average dissimilarity between $N_{EV}^{\omega_i,t}$ and every other scenario $N_{EV}^{\omega_j,t}$ in the set of generated scenarios is minimized. At stage $s = 2$ and subsequent stages, the set of scenarios aggregated in the previous stage is divided into K clusters. The steps of the clustering routine applied in stage $s = 2$ and subsequent stages are the following.

(1) Selection of initial medoids: the first medoid is randomly chosen, and the remaining $K-1$ initial medoids are selected as the most distant $K-1$ scenarios by using (1). Various methods for selecting initial medoids are detailed in [15].
(2) Selection of the closest medoid: each scenario ω is grouped to the medoid for which the distance given by (1) is minimal. This results in the creation of K clusters denoted as C_1^s to C_K^s for stage s.
(3) Update of the medoids: within each cluster, the scenario that minimizes the average distance to every other scenario in the same cluster is chosen as the new medoid.
(4) Iteration and medoid update: after updating the medoids, the procedure is repeated starting from step 2. This iterative process continues until either the scenarios chosen as medoids do not change in consecutive iterations, or the maximum allowed number of iterations is reached.
(5) Cluster merging check: the distance between each pair of medoids and the average distance among the scenarios grouped in the relevant clusters is compared, and if the former is lower than the latter, the two clusters are merged.
(6) Scenario replacement: when stable medoids are obtained, all the scenarios of each cluster are replaced by the corresponding medoid, namely, the sequences of $N_{\text{EV in}}^{\omega,t}$ and $N_{\text{EV out}}^{\omega,t}$ for t in T_s. To ensure feasibility during the transition between stages, this replacement is performed at the level of each individual EV within the population, preserving all EV characteristics, including the rated battery size, maximum charging power, and initial charging level.
(7) Subsequent stages: the clustering routine is independently carried out for each cluster of the previous stage.
(8) Scenario tree construction: the described procedure results in the formation of a scenario tree composed of nodes (namely, the medoids) at each stage, connected by arcs. The probability associated with each node in the tree corresponds to the summation of the probabilities of each scenario assigned to the corresponding cluster.

The maximum number of clusters K is chosen to preserve the tractability of the problem by limiting the final number of scenarios in the tree while ensuring an adequate representation of the stochastic processes during the day. The scenario generation technique allows for the inclusion of specific metrics that assess the selection of the maximum value of K, such as the elbow method or the silhouette coefficient, using the obtained objective function values. Other metrics, like the value of stochastic solution and the expected value of perfect information, can also be considered. In this paper, the results are obtained for a maximum K equal to 3.

2.3. Characterization of each scenario in the tree

As a result of the scenario tree construction, sets $S_{\text{in}}^{\omega,t}$ and $S_{\text{out}}^{\omega,t}$ of entering and leaving EVs are defined, for each scenario ω and period t. The aggregated storage size $E_{\text{Smax}}^{\omega,t}$ of the parking lot and the maximum charging power $P_{\text{max}}^{\omega,t}$ are derived by summing the corresponding data of the individual arriving and departing vehicles, i.e. E_{EV}, P_{EV}. Moreover, the increase of stored energy due to the initial energy in the incoming EVs, $E_{\text{S+}}^{\omega,t}$, and the energy decrease due to the charged outgoing EVs, $E_{\text{S-}}^{\omega,t}$, are obtained as

$$E_{S+}^{\omega,t} = \sum_{i\in S_{\text{in}}^{\omega,t}} E_i^0 \tag{2}$$

$$E_{S-}^{\omega,t} = \sum_{i\in S_{\text{out}}^{\omega,t}} E_i^- \tag{3}$$

where E_i^0 and E_i^- are the energy of the ith EV when entering and leaving the parking lot, respectively. The difference between E_i^- and E_i^0 represents the final charge gain during the parking time, for the ith EV.

Each set of EVs that enter and leave in the same periods is grouped by means of two matrices, the rows of which indicate the entry periods and the columns the exit periods. Specifically, in order to retain the information on the period of entry and exit of the energy initially stored in the batteries, matrix $E_{\text{ini}\,j}^{\omega,t}$ is formed as the sum of E_i^0 for the EVs that enter in period j and exit in period t. Similarly, for the charge gain, matrix $E_{\text{g}\,j}^{\omega,t}$ is constructed as the summation of $E_i^- - E_i^0$ for the EVs entering at period j and leaving at period t.

2.4. Intraday decision procedure

The solution provided by the recourse model, which is based on the scenario tree constructed using the day-ahead forecasts of the number of arriving and departing EVs, generates multiple potential decisions at each stage beyond the first one (i.e., during the day). Consequently, a decision making procedure is implemented to determine the most suitable decision for each stage among those identified by the stochastic problem solution. This selection takes into account the current number of parked EVs. More precisely, at the beginning of each of the considered three stages after the first, the intraday procedure selects the scenario from the tree that offers the best match with the real number of parked EVs compared to those associated with the nodes/medoids of the scenario tree.

3. Optimization models to represent EV parking lot flexibility

Once the scenario tree is defined, the procedure uses the optimization models described in this Section. The models are formulated as linear programming problems and calculate, for each stage and node of the tree, non-negative variables $P_{\text{ref}}^{\omega,t}$ and $\Delta P_{\text{flex}}^{\omega,t}$ through repeated stochastic optimizations. Due to the aggregated structure of the EV parking lot model and its linearity, each optimization is computationally efficient, requiring only tens of milliseconds regardless of the number of EVs and charging stations.

The assumptions made include an agreement between the EV parking lot aggregator and the DSO that allows the parking lot to recover the power change during a predefined interval following the flexibility provision interval. Therefore, each flexibility margin is associated with a maximum recovery of opposite sign within the recovery interval. The actual recovery is assumed to be proportional to the effective reduction requested by the DSO. It is also assumed that the DSO does not request any further reductions or increases during the recovery period and that the power variation is constant over time.

The model calculates the flexibility margins assuming that the DSO request is limited to a single 15-min period, denoted as of t_{flex}. Furthermore, the calculation is repeated assuming that the DSO requires flexibility provision in additional consecutive 15-min periods after t_{flex}, denoted as n_{flex}^+. These calculations are performed with the constraint that the flexibility margin remains the same throughout the entire flexibility interval, i.e., from t_{flex} to $t_{\text{flex}}+n_{\text{flex}}^+$.

The values of $P_{\text{ref}}^{\omega,t}$ and $\Delta P_{\text{flex}}^{\omega,t}$, along with their associated recovery profiles, are provided to the DSO at the beginning of each stage.

3.1. Calculation of the reference consumption profiles

The objective function for the day-ahead calculation of the parking lot consumption profile $P^{\omega,t}$ is to minimize the procurement costs, considering probability π^ω of each scenario ω:

$$\min \sum_{\omega} \pi^\omega \sum_{t} \left(\rho_{TOU}^{t} P^{\omega,t} \Delta t + C_{\text{S}}^{\omega,t} \right) \tag{4}$$

The model considers the presence of bidirectional charging stations, used for V2V energy exchanges but not to inject power into the external grid. These exchanges help ensure that EVs depart with the maximum charge allowed by the parking duration, $E_{\text{S-}}^{\omega,t}$, using the energy stored in EVs expected to have prolonged parking times.

The energy balance equation for the parking lot is:

$$\begin{aligned} E_{\text{S net}}^{\omega,t} &= (1-\delta) E_{\text{S net}}^{\omega,(t-1)} + E_{\text{ch grid}}^{\omega,t} - E_{\text{S-}}^{\omega,t} + \\ &\mu^{\omega,t} E_{\text{S+}}^{\omega,t} - l_{\text{V2V}}^{\omega,t} + \sum_{j=1}^{t-1} (1-\mu^{\omega,j}) E_{\text{ini}\,j}^{\omega,t} \end{aligned} \tag{5}$$

that represents the aggregate energy stored in the parked EVs in scenario ω at the end of period $t > 0$. $E_{\text{S net}}^{\omega,t}$ takes into account not only the energy supplied by the grid $E_{\text{ch grid}}^{\omega,t} = \eta_{\text{ch}} P^{\omega,t} \Delta t$ but also the possibility to use for V2V a part of the initial energy $E_{\text{S+}}^{\omega,t}$ of the EVs that entered the parking lot in period t (namely, $\mu^{\omega,t} E_{\text{S+}}^{\omega,t}$). The fraction of the initial energy used is represented by non-negative variable $\mu^{\omega,t}$, which is subject to upper bound $\mu_{\max}^{\omega,t}$ that ensures a minimum energy margin $e_{\min}$ maintained in the EV batteries. The associated cost of using the initial energy of the EVs is represented by $C_{\text{S}}^{\omega,t} = \rho_\mu \mu^{\omega,t} E_{\text{S+}}^{\omega,t}$ in (4), which can be interpreted as the remuneration of the vehicles providing the service.

In the context of V2V energy exchanges, constraint (5) accounts for the associated energy losses through non-negative variable $l_{\text{V2V}}^{\omega,t}$ given by

$$l_{\text{V2V}}^{\omega,t} \ge \left(1-\eta_{\text{V2V}}\right) \left(E_{\text{ch grid}}^{\omega,t} - \sum_{j=1}^{t-1} E_{\text{ch}\,j}^{\omega,t} + \mu^{\omega,t} E_{\text{S+}}^{\omega,t} \right) \tag{6}$$

where η_{V2V} represents the efficiency of the V2V energy exchanges, taking into account the losses in the power electronic converters and in the batteries. The long-term reduction in efficiency due to aging and demanding operation is not considered.

$E_{\text{ch}\,j}^{\omega,t}$ for $t > j$ is the profile that ensures that the EVs parked in the interval $(j,\tau]$ receive $E_{\text{g}\,j}^{\omega,\tau}$, i.e., their final charge gain, before leaving the parking lot. $E_{\text{ch}\,j}^{\omega,t}$ is zero for $t \le j$. The sum of $E_{\text{ch}\,j}^{\omega,t}$ is equal to the total net charge increase at the departure period τ of the last EVs among those entered in period j, while it is larger before that period. The constraints representing $E_{\text{ch}\,j}^{\omega,t}$ are

$$\begin{aligned} &\sum_{t=j+1}^{i} E_{\text{ch}\,j}^{\omega,t} - \sum_{t=j+1}^{i} E_{\text{g}\,j}^{\omega,t} \ge 0 \quad \text{for all } i < \tau \\ &\sum_{t=1}^{j} E_{\text{ch}\,j}^{\omega,t} = 0 \\ &\sum_{t=j+1}^{\tau} E_{\text{ch}\,j}^{\omega,t} - \sum_{t=j+1}^{\tau} E_{\text{g}\,j}^{\omega,t} = 0 \end{aligned} \tag{7}$$

where τ is the departure period of the last EV among those entered in period j.

In the presence of V2V energy exchanges, some EVs receive more energy from the grid than they need to cover their final charge gain during their parking time. In (6), the term $E_{\text{ch grid}}^{\omega,t} - \sum_{j=1}^{t-1} E_{\text{ch}\,j}^{\omega,t} + \mu^{\omega,t} E_{\text{S+}}^{\omega,t}$ represents the energy from the grid that is used for V2V exchanges.

According to (6), $l_{\text{V2V}}^{\omega,t}$ losses are calculated when the excess energy is stored, not when the V2V exchange is performed. This does not affect the final result since η_{V2V} is assumed to be constant. If the chargers are not bidirectional, both μ and l_{V2V} are set to zero. The V2V energy can also be used to add a cost in the objective function (4) associated with the remuneration of vehicles providing the V2V service.

Non-negative variable $E_{\text{S net}}^{\omega,t}$ is constrained as

$$E_{\text{S net}}^{\omega,t} \le E_{\text{Smax}}^{\omega,t} - \sum_{j=1}^{t-1} (1-\mu^{\omega,j}) E_{\text{ini}\,j}^{\omega,t}, \tag{8}$$

Assuming that the connection of the parking lot with the external grid is limited by $P_{\text{max,grid}}$ then

$$P^{\omega,t} \le \min\left(P_{\text{max,grid}}, P_{\max}^{\omega,t}\right) \tag{9}$$

The solution of problem (4)–(8) provides reference profile $P_{\text{ref}}^{\omega,t} = P^{\omega,t}$ for all scenarios ω.

3.2. Calculation of the maximum power reduction and increase margins

The calculation of the flexibility margins is performed for each period, seprately for maximum power reduction and increase. It considers cases where flexibility is requested in a single period t_{flex} and cases where flexibility is also requested in additional consecutive periods n_{flex}^{+}, limited to $n_{\text{max,flex}}^{+}$.

The objective function is

$$\min \sum_{\omega} \pi^{\omega} \sum_{t} \left(\rho_{TOU}^{t} P^{\omega,t} \Delta t + C_{\text{S}}^{\omega,t} - R_{\text{flex}}^{\omega,t} \right) \tag{10}$$

where non-negative $R_{\text{flex}}^{\omega,t}$ is the revenue associated with the provision of the maximum flexibility in t_{flex}:

$$R_{\text{flex}}^{\omega,t} = \begin{cases} \rho_{\text{flex}}^{t} \, \Delta P_{\text{flex}}^{\omega,t} \, \Delta t & \text{if } t_{\text{flex}} \leq t \leq t_{\text{flex}} + n_{\text{flex}}^{+} \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

Predefined tariff ρ_{flex}^{t} is the compensation rate that the DSO pays to the flexibility provider for achieving a non-negative power change $\Delta P_{\text{flex}}^{\omega,t}$ in period t_{flex} compared to reference power level $P_{\text{ref}}^{\omega,t}$. $\Delta P_{\text{flex}}^{\omega,t}$ is defined as

$$\begin{aligned} &\Delta P_{\text{flex}}^{\omega,t} = P_{\text{ref}}^{\omega,t} - P^{\omega,t} \text{ for down margin} \\ &\Delta P_{\text{flex}}^{\omega,t} = P^{\omega,t} - P_{\text{ref}}^{\omega,t} \text{ for up margin} \\ &\text{for } t_{\text{flex}} \leq t \leq t_{\text{flex}} + n_{\text{flex}}^{+} \end{aligned} \tag{12}$$

The model includes the possibility for the EV parking lot to recover the power change with respect to $P_{\text{ref}}^{\omega,t}$ that occurred at $t \in [t_{\text{flex}}, t_{\text{flex}} + +n_{\text{flex}}^{+}]$ in a predefined number of periods n_{rec} after $t_{\text{flex}} + n_{\text{flex}}^{+}$. $\Delta P_{\text{flex}}^{\omega,t}$ is constrained to be uniform in the recovery interval by:

$$\begin{aligned} &\Delta P_{\text{flex}}^{\omega,t} \geq - \sum_{j=t_{\text{flex}}}^{t_{\text{flex}}+n_{\text{flex}}^{+}} \frac{\Delta P_{\text{flex}}^{\omega,j}}{n_{\text{rec}}} \\ &\text{for } t_{\text{flex}} + n_{\text{flex}}^{+} < t \leq t_{\text{flex}} + n_{\text{flex}}^{+} + n_{\text{rec}} \\ &\Delta P_{\text{flex}}^{\omega,t} = 0 \text{ for } t < t_{\text{flex}} \text{ and } t > t_{\text{flex}} + n_{\text{flex}}^{+} + n_{\text{rec}} \end{aligned} \tag{13}$$

The inequality of the previous constraint becomes an equality for the flex-up scenario to prevent the use of incremental losses (such as unnecessary V2V exchanges) to enhance the flexibility margin.

In the case of multiple consecutive periods of flexibility, the maximum margin is constrained to be the same in all the periods:

$$\Delta P_{\text{flex}}^{\omega,t} = \Delta P_{\text{flex}}^{\omega,t_{\text{flex}}} \quad \text{for } t_{\text{flex}} < t \leq t_{\text{flex}} + n_{\text{flex}}^{+}. \tag{14}$$

All the models are completed with nonanticipativity constraints, typical in stochastic optimization, which ensure that decisions made at different stages depend only on currently available information and not on future outcomes or information that will be revealed later.

4. Case studies and results

4.1. Test cases and scenarios

The case studies include three parking lots, denoted as PL A, B, and C, each with a maximum power import capacity of 3 MW. The number of available charging stations for these parking lots is 70 for PL A and PL B, and 45 for PL C. In all scenarios, the parking lots are empty at the beginning of the day, and all EVs leave before the end of the day.

Fig. 1 shows the different day-ahead forecasts for the number of EVs entering and leaving each parking lot in $\Delta t = 15$ min time periods. These forecasts are used to generate a total of 60 different daily scenarios. The ψ_t function is assumed to decrease linearly from 0.9999 in the first period to 0.99 in the last period. Similar scenarios are grouped together using the k-medoid method, resulting in a 4-stage tree composed of nodes representing the scenarios that are the medoids obtained. The profiles of scenarios with common nodes in the tree are bounded at each stage based on the tree structure. Fig. 2 illustrates the tree corresponding to parking lot PL A with 24 medoids in the last stage.

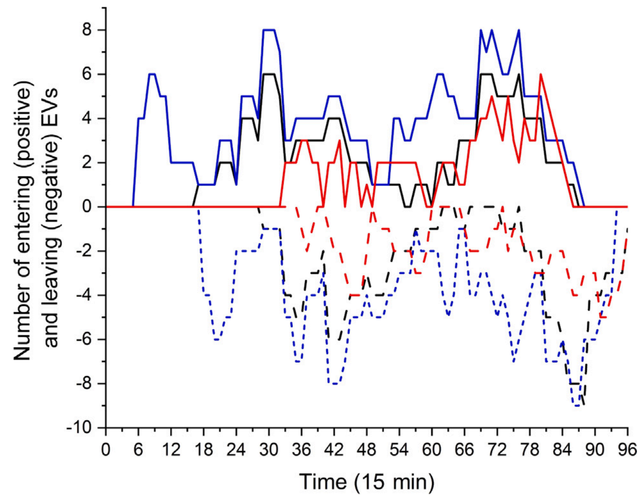

Fig. 1. Day-ahead forecast profiles of the number of EVs entering (solid lines) and exiting (dashed lines) in the three parking lots considered: PL A in black, PL B in blue, PL C in red.

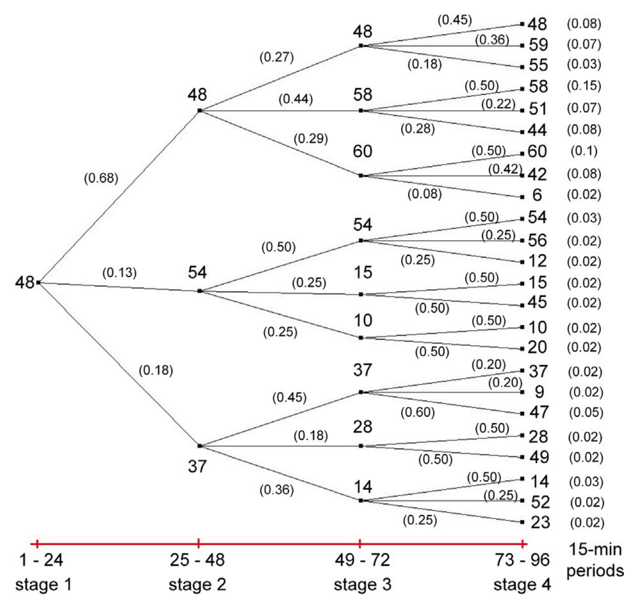

Fig. 2. Scenario tree for parking lot PL A. The identification numbers of the medoids are shown for each stage of 6 h, together with, between parenthesis, both the arc probabilities and scenario probabilities π^{ω}.

In the tests, the types of EVs are classified into 4 categories based on their battery capacities and market penetration rates: (1) $E_{\text{EV}} = 25$ kWh with 15% penetration, (2) $E_{\text{EV}} = 45$ kWh with 45% penetration, (3) $E_{\text{EV}} = 70$ kWh with 25% penetration, (4) $E_{\text{EV}} = 100$ kWh with 15% penetration. These values are derived from data available from various Internet sources. While they may be appropriate for the current situation in certain countries, it is essential to adapt them to the actual usage-specific conditions. A maximum charging power of 40 kW is assumed for each charging station, which is representative of typical ac charging stations installed in parking lots where EVs remain connected for extended periods of time.

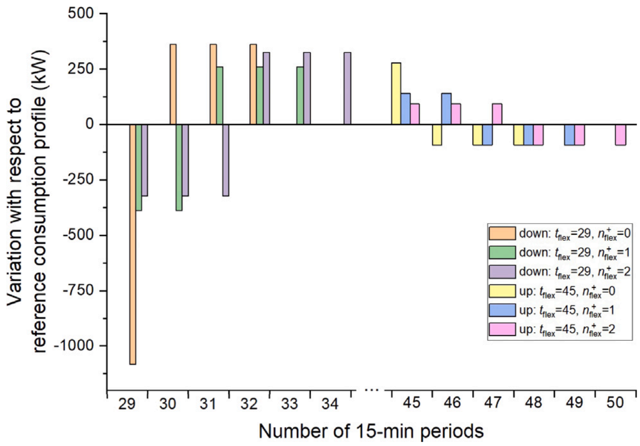

Fig. 3. Flexibility margins and corresponding recoveries of scenario 56 of PL A: down flexibility starting at t_{flex}=29 (7:15 am) and up flexibility starting at t_{flex}=45 (11:15 am).

For the EV batteries, δ is assumed to be zero. The charging and V2V energy transfer efficiencies, η_{ch} and η_{V2V}, are set to 0.96 and 0.92, respectively.

Time of use price ρ^{t}_{TOU} is equal to 72.39 €/MWh from 6 am to 10 pm and to 51.62 €/MWh at other times. If $\mu^{\omega,t}_{\mathrm{max}}$ is set greater than 0, the price for using the initial EV energy is ρ_{μ} = 50 €/MWh, which is lower than the grid price. In each period, minimum initial energy e_{min} is set to 20% of the sum of the rated capacity of the batteries of the entering EVs.

For both downward and upward power flexibility provided by the parking lot, predefined tariff ρ^{t}_{flex} is set to 100 €/MWh, significantly higher than the grid prices. For all the cases, the recovery interval is n_{rec}=3 periods after the end of the flexibility interval.

4.2. Results

AIMMS Developer was used to implement the optimization procedures. The adopted LP solver is Gurobi V10 on 4.7-GHz processors with 32 GB of RAM, running 64-bit Windows.

The objective function values of the stochastic optimizations for the three parking lots are: € 438 for PL A, € 568 for PL B, and € 242 for PL C. The average and maximum objective function reductions with single flexibility are: 1.32% and 8.63% for PL A, 1.08% and 12.11% for PL B, 1.37% and 18.71% for PL C, respectively. These reductions depend on the difference between ρ^{t}_{flex} and ρ^{t}_{TOU}.

As an illustrative example of the upward and downward flexibility margin evaluations and of the subsequent recovery periods, Fig. 3 shows the down and up margins in power variations at t_{flex}=29 and t_{flex}=45, respectively, relative to the reference profile for scenario 56 of PL A included in the stochastic tree of Fig. 2. The figure shows the results considering the flexibility interval given by a single period or 2 or 3 consecutive 15-min periods. While both up and down margins can generally be computed for the same interval, the figure separates the up and down flexibilities into distinct t_{flex} for clarity.

Fig. 4 shows the periods when the maximum up and down flexibility margins exceed 100 kW for scenario 56 in PL A. It considers the flexibility interval of a single 15-min period (n^{+}_{flex}=0), 2 periods (n^{+}_{flex}=1), and 3 consecutive periods (n^{+}_{flex}=2). Only the first period of the flexibility interval is shown in the figure. In time period 46, the parking lot can provide both up and down flexibility for n^{+}_{flex}=0. In several cases, when single period flexibility cannot be provided, a two- or three-period flexibility is allowed as the different recovery interval is more suitable.

Fig. 4 also shows the results obtained by tripling both the size (i.e., increasing the number of charging stations to 210) and the number

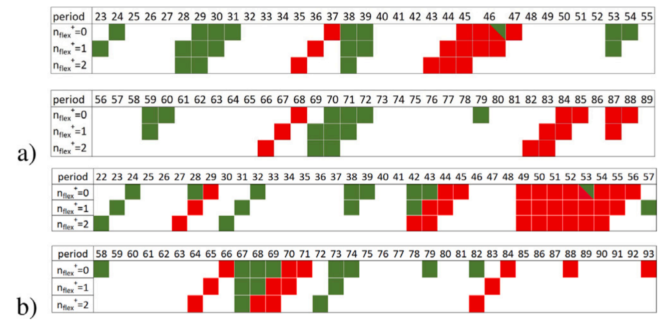

Fig. 4. Initial period of the flexibility intervals with a margin larger than 100 kW for scenario 56: (a) PL A, (b) PL D. Downward flexibility in green and upward flexibility in red.

of EVs entering and exiting with respect to PL A. This expanded scenario is referred to as PL D. As a result of the changes introduced, the operating conditions of the corresponding scenarios differ between the two parking lots. Nevertheless, the figure shows that the flexibility widens as the size of the parking lot increases, as expected. In scenario 56, for PL A, the maximum up flexibility is 54.0 kW with an average equal to 12.2 kW, and the maximum down flexibility is 70.8 kW with an average equal to 13.1 kW; for PL D, the maximum up flexibility is 101.0 kW with an average equal to 24.3 kW, and the maximum down flexibility is 129.2 kW with average equal to 38.6 kW. In time period 53, the PL D can provide both up and down flexibility for n^{+}_{flex}=0.

The computation time for the cases considered in the paper is always less than a few minutes.

5. Conclusion

The paper introduces a method to characterize the flexibility offered by parking lots equipped with EV charging stations, which can be used by the distribution system operator to address challenges such as voltage and congestion problems.

Key aspects of the method include computing the reference demand profile and flexibility margins for each period of the following day, considering predefined incentives for load changes. The approach uses a multistage stochastic procedure that adapts to real-time conditions and vehicle connections to the charging stations throughout the day.

Scenarios for stochastic optimization are created based on forecasts of EV arrivals and departures, accounting for factors like battery size, diffusion, and maximum charging power. Clustering of similar scenarios using the k-medoid method reduces computational complexity while maintaining scenario feasibility.

The optimization model aggregates EV battery behavior and formulates the problem as a linear one, making it computationally efficient even for large parking lots. It accounts for losses associated with grid charging and vehicle-to-vehicle energy exchanges enabled by bidirectional charging stations.

To enhance the flexibility of the EV parking lot, power reductions and increases in consecutive periods are considered while ensuring schedule feasibility, by including a recovery after the interval when the flexibility is requested.

This approach operates as a day-ahead evaluation with a 4-stage stochastic process, updating the decisions every 6 h to reflect real-time EV data. Numerical tests on parking lots of various sizes demonstrate the effectiveness of the method.

Overall, this procedure ensures that charging requirements are met and serves as a valuable tool for the EV aggregator offering flexibility services to improve the operation of the power distribution network and mitigate the impacts of electromobility. The typical main barriers to practical implementation are related to the lack of an appropriate regulatory framework for the local market and an efficient communication infrastructure.

CRediT authorship contribution statement

Tohid Harighi: Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing. **Alberto Borghetti:** Conceptualization, Methodology, Software, Supervision, Writing – original draft, Writing – review & editing. **Fabio Napolitano:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Fabio Tossani:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Alberto Borghetti and Fabio Tossani are on the editorial board of EPSR

Data availability

The results for selected scenarios are available at the web address: https://www.doi.org/10.17632/jntjgxr4ht.

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