A chance constraint approach to peak mitigation in electric vehicle charging stations

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Abstract

The increased penetration of plug-in electric vehicles asks for efficient algorithms to be adopted in parking lots equipped with charging units. In this paper, the peak power minimization problem for a plug-in charging station is addressed. A chance constraint approach is adopted in order to minimize the daily peak power, allowing for a tolerance on the charging service customer satisfaction expressing the probability that a vehicle leaves the station violating the agreed level of charge. Numerical simulations are provided to evaluate the performance of the proposed approach as well as to make a comparison with other techniques.

Key words: Plug-in electric vehicles; EV parking lots; optimization; chance constraints; smart charging; peak reduction

1 Introduction

Electric vehicles (EVs) are a promising technology to overcome different kind of problems caused by carbon-fossil technologies. Indeed, the combined action of EVs with renewable generation makes it possible to reduce pollution and green house effect [31]. Moreover, as a byproduct, EV utilization moves gas emissions outside living centers. Conversely, several issues may arise in the presence of a huge EV penetration inside the power system. In fact, uncontrolled EV charging can bring to scenarios where neither safety nor technical constraints can be ensured, leading to low power quality service or instability issues. On the other hand, customer satisfaction related to waiting time, charging time, charging profile, etc., needs be taken into account, for obvious reasons.

Several solutions have been proposed in the literature to handle properly the EV integration into electricity systems. Using smart monitoring devices and designing suitable optimization algorithms allow for managing fleets of vehicles without changing the grid structure [14]. In [4], a receding horizon algorithm aimed at minimizing the electricity bill while guaranteeing proper working conditions of an industrial microgrid under high EV penetration has been developed. In [22], a strategy based on battery swapping has been devised to maximize the charging station profit while taking into account user waiting and charging time. On the other hand, in [12] battery swapping has been proposed to minimize the charging cost as well to lower power losses and voltage deviations in power networks. In [13], game theory has been exploited to maximize the profit of a charging station, while in [19] the minimization of travel time and charging cost has been studied. A decentralized EV charging strategy has been proposed in [16], where each vehicle aims at minimizing its charging cost while taking into account local grid and battery effects. An optimal power scheduling aimed at the maximization of the profit of an airport parking lot has been provided in [18], while in [26] the optimization strategy is focused on minimizing the electricity cost of a residential smart microgrid. To model and guarantee an appropriate charging service, works aimed on sizing and siting of charging stations have been proposed in [6] and [27].

Concerning peak load reduction, suitable strategies have been developed, too. A hierarchical approach to EV charging based on an offline coordination algorithm has been proposed in [5]. In [17], the coordinated operation of EVs with renewable sources and electrical storage made it possible to reduce the household power absorption. In [1] a peak shaving strategy has been

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developed at power network level, while in [7] a decentralized algorithm was devised to perform valley filling of a load profile.

A further important topic when dealing with EV charging is related to uncertainty. Indeed, EVs are typically stochastic loads due to the uncertainty associated to arrival times, energy to be charged and/or departure times. In this scenario, a deep study of uncertainty is needed to predict properly the behavior of future loads. An algorithm based on Markov decision processes aimed at minimizing the mean waiting time of EVs has been developed in [30], whereas in [28] uncertainty of the arrival time in a non-residential charging station is modeled in the real-time charging algorithm. Uncertainty affecting EVs is taken into account to properly manage a parking lot participating to a demand response program in [24]. A distributionally chance constrained approach has been developed to maximize the profit of a parking lot under unknown charging time in [2], while in [9] the parking lot profit was maximized under uncertainties on renewables.

In this paper, the problem of minimizing the daily peak power of an EV charging station is addressed. We suppose that the considered parking lot is equipped with several charging units able to perform EV charging. A constraint on customer satisfaction requirement is considered. Such constraint is related to a nominal charging power rate that is promised to the customer. Arrival time, departure time and desired level of charge (LOC) of vehicles are assumed uncertain variables. Vehicle-to-grid technology is not taken into account, that is plugged-in EVs cannot be used as storages.

The contribution of this paper consists in the development of a new algorithm for the solution of the problem introduced above. A distinguished feature of the proposed approach is to model the uncertainty affecting the departure time of a vehicle after its arrival at the station. In fact, several works available in the literature, like, e.g., [28,21,11,25,29,8,20], assume that the departure time is known once a vehicle arrives at the station. In this paper, to deal with the uncertainty on the departure time, a suitable customer satisfaction criterion has been devised. We assume the car park owner (CPO) aims at minimizing the daily peak power while guaranteeing a given level of customer satisfaction, i.e., allowing only an acceptable small fraction of vehicles to leave the parking with a LOC less than that negotiated. The proposed procedure is formulated in a receding horizon framework, where some knowledge on the stochastic processes is assumed to be available. As known, a possible way to handle uncertainty in a moving horizon approach is through the use of chance constraints [23]. Actually, in the proposed procedure, customer satisfaction constraints have been expressed as chance constraints. The resulting problem turns out to be a mixed integer linear program (MILP), where binary variables are employed to model the chance constraints. Numerical simulations and suitable comparisons with other methods show the effectiveness of the proposed approach in reducing the daily peak power and its feasibility from a computational viewpoint, even in the presence of a large number of electric vehicles.

The paper is structured as follows. In Section 2, the considered scenario is described and the problem formulation is introduced. Section 3 is devoted to the description of the proposed control algorithm and the related optimization program. Numerical simulations are reported in Section 4, while conclusions and future research are drawn in Section 5.

Nomenclature

$\mathbb{N}$	Set of natural numbers
Δ	Sampling time
t	Generic time step
v	Vehicle index
P_0	Nominal charging power
$\overline{P}$	Maximum charging power
η	Charging efficiency
t_v^a	Arrival time of vehicle v
t_v^d	Departure time of vehicle v
τ_v	Number of time slots needed to fulfill vehicle v
t_v^f	Fulfillment time of vehicle v
$\overline{t}^c$	Bound on the maximum charging time for all vehicles
$\overline{t}_v^d$	Bound on the maximum departure time for vehicle v
E_v^f	Desired level of charge for vehicle v
$V(t)$	Set of plugged-in vehicles at time t
$E_v(t)$	Level of charge at time t for vehicle v
$P_v(t)$	Mean charging power from t to $t+1$ for vehicle v
$r_v(t)$	Customer satisfaction profile for vehicle v at time t
$\widehat{\gamma}$	Daily peak power till the present time
$\widetilde{\gamma}$	Power for charging parked vehicles at maximum rate
ε	Dissatisfaction level
k	Time index used in the optimization problem
$P_v^*(t)$	Optimal charging power schedule at time t
γ_p	Predicted peak power
$T(t)$	Time horizon used in optimization at time t
$\alpha_v(t)$	Weights for cost function at time t
$\beta_v(k)$	Binary variables defining chance constraints at time t
N_m	Average number of incoming vehicles at each time step
E_m	Mean value of the charged energy for each vehicle
$P_a(k)$	Estimate of power consumption at time k of $v \notin V(t)$

2 Problem formulation

We consider a parking lot equipped with several charging units able to charge plug-in electric vehicles. We assume that the number of charging units is sufficient to satisfy all the incoming vehicles. When a vehicle arrives at the station, the customer declares the amount of energy to be charged; after that the charging unit computes the time needed to accomplish the request. This time is computed assuming to charge the vehicle at a nominal charging rate. Since the customer may decide to leave the parking before such time, we assume that he/she will be considered satisfied if at the departure time the vehicle has been charged at least at the promised rate, otherwise the customer will not be satisfied.

Before entering into technical details of the proposed solution, a brief sketch of the overall procedure is reported in Figure 1:

The problem is formulated in a discrete time setting, where Δ denotes the sampling time. Let v be the index denoting vehicle v, P_0 is the nominal charging power promised to the customer, and η is the charging efficiency. The level of charge (LOC) for vehicle v at time t is denoted by $E_v(t)$, while the required LOC is denoted by E_v^f. We refer to t_v^a and t_v^d as the arrival and departure time of vehicle v, respectively. So, the number of time slots needed to satisfy the request by applying the nominal charging rate is

$$\tau_v = \left\lceil \frac{E_v^f - E_v(t_v^a)}{\Delta P_0 \eta} \right\rceil .$$

We define as *fulfillment time* the time at which the vehicle will be fully charged assuming constant charging rate P_0, i.e.,

$$t_v^f = t_v^a + \tau_v . \tag{1}$$

Aim: minimize the daily peak power while guaranteeing customer satisfaction at a fixed level

Receding horizon procedure:
At each time step the charging command for each plugged-in vehicle is computed on the basis of:
- the peak occurred till the present time
- the overall charging power assuming to charge all the connected vehicles at maximum rate
- the solution of a stochastic optimization problem where:
  - probability distributions assumed known
  - time horizon large enough to allow charge of all connected vehicles
  - prediction of future peak is estimated
  - physical constraints enforced
  - chance constraints exploited to manage uncertainty
  - optimal charging power for each vehicle computed.

Fig. 1. Outline of the proposed technique.

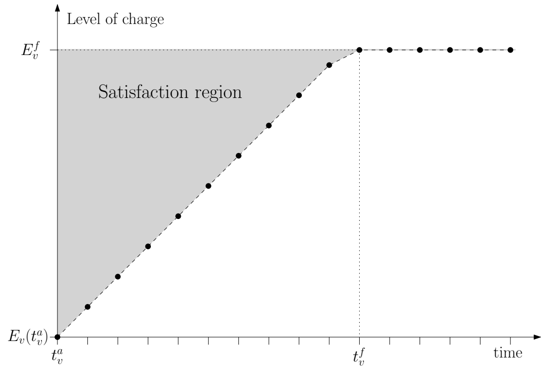

Fig. 2. Customer satisfaction region for a generic vehicle v (shaded area). t_v^a : arrival time, t_v^f : fulfillment time, $E_v(t_v^a)$: LOC at arrival, E_v^f : desired LOC at departure.

Let $\overline{t}^c$ be a bound on the maximum charging time for all vehicles. So, a bound on the maximum departure time for vehicle v is $\overline{t}_v^d = t_v^a + \overline{t}^c$, which implies

$$t_v^d \leq \overline{t}_v^d . \tag{2}$$

Let $P_v(t)$ denote the charging rate of vehicle v in the interval $[t-1, t]$. The battery LOC at a given time t can be modeled as

$$E_v(t) = E_v(t-1) + \Delta \eta P_v(t-1). \tag{3}$$

A customer is considered satisfied if, at the departure time t_v^d, the following inequalities hold

$$\min\{E_v(t_v^a) + \Delta \eta P_0 (t_v^d - t_v^a),\ E_v^f\} \leq E_v(t_v^d) \leq E_v^f . \tag{4}$$

In words, the LOC must be greater or equal to that obtained by applying the nominal charging rate P_0, while it must not exceed the maximum LOC defined by the customer, see Fig. 2. The lower boundary of the satisfaction region depicted in Fig. 2 is defined as

$$r_v(t) = \min\{E_v(t_v^a) + \Delta \eta P_0 (t - t_v^a), E_v^f\}. \tag{5}$$

Since the departure time is unknown, to guarantee customer satisfaction, at each step the LOC of a vehicle must be comprised between $r_v(t)$ and the required LOC E_v^f, i.e.,

$$r_v(t) \leq E_v(t) \leq E_v^f . \tag{6}$$

It is assumed that the charging rate is bounded as follows

$$0 \leq P_v(t) \leq \overline{P} \tag{7}$$

where $\overline{P} > P_0$ represents the maximum charging power of a single charging unit.

At a given time t, the set of all plugged-in vehicles is denoted by

$$V(t) = \{v\colon t_v^a \le t < t_v^d\}. \tag{8}$$

The scope of this work is to provide an algorithm able to dynamically define the charging rates in order to minimize the daily peak power consumed by the parking lot. To accomplish this task, we assume that the CPO be willing to accept that a given fraction of users may leave the parking lot unsatisfied, i.e., such that the energy charged at departure be below the satisfaction bound given in (4).

The reduction of the daily peak power can be related to smaller electricity cost for the CPO, as well as to the participation of the CPO to a demand response program.

3 Peak reduction charging algorithm

In this section, a procedure aimed to accomplish the peak reduction target is illustrated. Since the arrival time, the parking time and the amount of energy to be charged are uncertain variables, some information regarding the stochasticity of these variables need be considered. In particular, we assume that the probability distribution of such variables, or an estimate of them, are available to the CPO.

Since the aim of this work is to reduce the daily peak power, in the following we will choose a reference time interval of one day. At a given time t, let $\widehat{\gamma}$ denote the peak power occurred up to time t, while $\widetilde{\gamma}$ is the power consumed by charging all the connected vehicles at the maximum rate., that is,

$$\widetilde{\gamma} = \sum_{v\in V(t)} \min\left\{\overline{P}, \frac{E_v^f - E_v(t)}{\Delta\eta}\right\}. \tag{9}$$

Let ε be the maximum fraction of customers which may leave the parking unsatisfied, i.e., such that (4) does not hold. Let us call this quantity as *dissatisfaction level*. For instance, a dissatisfaction level $\varepsilon = 0.05$ means that at most 5% of vehicles may leave the parking lot unsatisfied. Since the departure time of vehicles is uncertain, a customer is unsatisfied whenever

$$E_v(t_v^d) < r_v(t_v^d)$$

that is, the charged energy at departure is less than promised. In other words, it occurs when the level of charge at departure lies outside the satisfaction region depicted in Fig. 2.

The rest of this section is divided in two parts. The first one is related to the optimization problem to be solved in order to compute the optimal charging rate at a given time, while in the second part the overall receding horizon algorithm is described.

3.1 Optimization program

The proposed method is formulated in a receding horizon framework, and, at each time step, it is based on the solution of the optimization program reported in Problem 1 (actually, there could exist time instants which do not need the computation of this program, as explained in Section 3.2). Let the superscript * denote the optimal solution of Problem 1 and let $\mathbf{P}(t)$ be the vector collecting all the elements $P_v(t)$.

Problem 1

$$\begin{cases}
[\mathbf{P}^*(t), \gamma_p^*] = \arg \inf\limits_{\mathbf{P}(t),\gamma_p} \left(\gamma_p - \sum\limits_{v\in V(t)} \alpha_v(t) P_v(t)\right) & \text{(10a)}\\
\text{subject to:} & \\
\beta_v(k) \in \{0,1\},\ v \in V(t),\ k = t+1,\dots,T(t) & \text{(10b)}\\
0 \le P_v(k) \le \overline{P},\ v \in V(t),\ k = t,\dots,T(t)-1 & \text{(10c)}\\
E_v(k+1) = E_v(k) + \Delta\eta P_v(k),\ \ v \in V(t),\ k = t,\dots,T(t)-1 & \text{(10d)}\\
r_v(k)\beta_v(k) \le E_v(k) \le E_v^f,\ \ v \in V(t), k = t+1,\dots,T(t) & \text{(10e)}\\
\widehat{\gamma} \le \sum\limits_{v\in V(t)} P_v(t) \le \gamma_p & \text{(10f)}\\
\sum\limits_{v\in V(t)} P_v(t) \ge \sum\limits_{v\in V(t)} P_v(k),\ k = t+1,\dots,T(t)-1 & \text{(10g)}\\
\sum\limits_{v\in V(t)} P_v(k)\mathcal{P}\left(t_v^d > k | t_v^d > t\right) + P_a(k) \le \gamma_p,\ \ k = t+1,\dots,T(t)-1 & \text{(10h)}\\
\widehat{\varepsilon}_v + \sum\limits_{k=t+1}^{T(t)} (1-\beta_v(k))\mathcal{P}(t_v^d = k) \le \varepsilon,\ \forall v \in V(t) & \text{(10i)}
\end{cases}$$

In Problem 1,

$$T(t) = \max\{\overline{t}_v^d \colon v \in V(t)\} \tag{11}$$

denotes the time horizon used for predictions. Notice that, according to (2), at time $T(t)$ none of the vehicles belonging to $V(t)$ will still be in charge.

Notation $\mathcal{P}(a|b)$ denotes the probability that event a occurs conditioned to the fact that event b is occurred. In (10h), $P_a(k)$ represents the mean value of the power needed to charge the incoming vehicles at the nominal rate; it is defined as

$$P_a(k) = N_m\, P_0\, \min\left\{k - t, \frac{E_m}{\Delta\eta P_0}\right\}\ , \tag{12}$$

where N_m, E_m denote the average number of incoming vehicles at each time step and the mean value of the charged energy, respectively.

It is worthwhile to notice that Problem 1 is a mixed-integer linear programming (MILP) problem, where all the optimization variables are real with the exception of $\beta_v(k)$ which are binary variables. Although in the formulation reported in Problem 1 the number of binary variables may be large, from an implementation point of view it can be greatly reduced by considering the maximum time a vehicle can stay in charge. Such an aspect will be discussed in Section 4, where it will be shown the computation feasibility of the optimization program.

In the following, a detailed description of Problem 1 is reported, dividing the treatment into two parts: the objective function and the constraints.

Objective function

The output of the optimization problem is the vector containing for each vehicle the charging rate to be applied during the t-th time slot, i.e., from t to $t+1$, and the predicted peak over the time horizon $T(t)$.

The cost function to be minimized is composed of two terms: the former is the predicted peak γ_p, while the latter is

$$-\sum_{v \in V(t)} \alpha_v(t) P_v(t) \tag{13}$$

whose aim is to distribute the total power consumed at time t among the connected vehicles. The weights $\alpha_v(t) > 0$ are chosen such that

$$\sum_{v \in V(t)} \alpha_v(t) = \alpha \ll 1\ , \tag{14}$$

where α is a fixed arbitrary constant much less than 1. This condition is enforced to disregard the contribution of (13) with respect to the predicted peak γ_p. In fact, by (10f) and (14), one has

$$\sum_{v \in V(t)} \alpha_v(t) P_v(t) \ll \sum_{v \in V(t)} P_v(t) \le \gamma_p\ ,$$

and then the contribution of (13) to the cost function is negligible. So, hereafter, we can state that the aim of Problem 1 is the minimization of the predicted peak γ_p.

How the term in (13) provides the assignment of the overall power at time t among vehicles is explained below.

Let γ_p^* be the optimal predicted peak. In absence of the term (13), all the possible feasible combinations such that

$$\sum_{v \in V(t)} P_v(t) = \gamma_p^* \tag{15}$$

are optimal solutions. Since different choices of $P_v(t)$ satisfying (15) lead to different performance of the whole algorithm, a smart choice of the weights $\alpha_v(t)$ is recommended. A heuristic which provides good results (see Section 4 for numerical simulations) consists in assigning a greater charging rate to vehicles which are expected to leave the parking lot later. A possible way to implement this procedure is as follows. Let us define

$$\widehat{\alpha}_v(t) = (\overline{t}_v^d - t).$$

So, by (11), $\widehat{\alpha}_v(t) > 0$ holds. Then, the weights to be used in (10a) can be chosen as

$$\alpha_v(t) = \alpha\, \frac{\widehat{\alpha}_v(t)}{\displaystyle\sum_{v \in V(t)} \widehat{\alpha}_v(t)}. \tag{16}$$

Constraints

Now, let us describe the constraints of Problem 1. In (10b), the binary variables $\beta_v(k)$ are defined. Such variables are related to the fact that the satisfaction constraint involving the vehicle v at time k be surely satisfied (if $\beta_v(k) = 1$), or it could be violated (if $\beta_v(k) = 0$). The bounds on the charging rate are enforced in (10c), while the LOC dynamics are given in (10d), according to (7) and (3), respectively. Constraints (10e) are similar to (6); if $\beta_v(k) = 1$, it is imposed that the LOC at time k belongs to the satisfaction region (see Fig. 2), while if $\beta = 0$, the left inequality is surely satisfied even if the LOC does not lie in the satisfaction region. In (10f), the power consumption at time t is bounded between the peak occurred till time t and the predicted peak over the optimization horizon. Constraints (10g) enforce the power consumed at time t to be greater or equal than that absorbed at future time. In (10h), the predicted power consumed at each step is bounded by the predicted peak γ_p. The left-hand side is composed of two terms: the former is related to the connected vehicles, and each power is weighted by the probability that the vehicle be in charge at a given time step; the latter concerns the power consumed by incoming vehicles. Finally, the chance constraints (10i) allow a vehicle to leave the parking lot unsatisfied with a probability no greater than ε. Specifically, $\widehat{\varepsilon}_v$ denotes the probability that the vehicle v had left the parking lot unsatisfied at past time steps, while the second term represents the probability that the vehicle departs unsatisfied at future time. The sum of these two terms is enforced to be no greater than ε, guaranteeing that the overall number of unsatisfied vehicles do not exceed the prescribed threshold.

Remark 1 *It is worthwhile to note that constraints* (10h) *and* (10i) *include some probability computations. Since the probability distribution of the parking time (or an estimate of it) is assumed to be known, when a vehicle arrives at the station also the distribution related to the departure time is known. So,* $\mathcal{P}(t_v^d = k)$ *is known for each* $v \in V(t)$ *and the corresponding value can be substituted in* (10i). *Regarding constraints* (10h), *the conditional probability* $\mathcal{P}\left(t_v^d > k | t_v^d > t\right)$ *has to be computed to solve Problem 1. However, it can be easily evaluated by discarding from the unconditional probability mass function of the departure time, the mass accounting for vehicles such that* $t_v^d \leq t$, *and normalizing the obtained distribution. At this step, numerical values can be directly substituted in* (10h) *and Problem 1 solved.*

3.2 Receding horizon algorithm

The pseudo-code of the proposed charging policy is reported in Algorithm 1. Such a procedure is based on a receding horizon framework and it is related to a generic day. The algorithm starts with the initialization to zero of some variables and the setting of the dissatisfaction level ε, after that the main loop begins. This loop goes on for the entire day. At each iteration, the set $V(t)$ and the maximum permissible charging power $\widetilde{\gamma}$ are computed according to (8) and (9), respectively. If the power required to charge all the connected vehicles at the maximum rate is no greater than the peak occurred up to the present time, the maximum rate is assigned to $P_v^*(t)$, $v \in V(t)$. Instead, if $\widetilde{\gamma} > \widehat{\gamma}$, then the optimization program described in Problem 1 is solved and $\widehat{\gamma}$ is updated accordingly. Afterwards, if the LOC of vehicle v at time $t+1$ is less than the corresponding customer satisfaction level, then $\widehat{\varepsilon}_v$ is increased by the probability that the considered vehicle will depart at time $t+1$. Finally, for both cases, the computed charging power is applied and the discrete time index is updated.

Algorithm 1 Overall control algorithm.

$\widehat{\gamma} = 0$; $t = 0$
$\widehat{\varepsilon}_v = 0$, for all possible v
set the dissatisfaction level ε
while day_not_over **do**
  compute $V(t)$
  $\widetilde{\gamma} = \sum_{v \in V(t)} \min\left\{\overline{P}, \frac{E_v^f - E_v(t)}{\Delta\eta}\right\}$
  if $\widetilde{\gamma} \leq \widehat{\gamma}$ **then**
    $P_v^*(t) = \min\left\{\overline{P}, \frac{E_v^f - E_v(t)}{\Delta\eta}\right\}, \forall v \in V(t)$
  else
    $[\mathbf{P}^*(t), \gamma_p^*] = solve\_Problem\_1(V(t), \widehat{\gamma}, \widehat{\varepsilon}, \varepsilon)$
    $\widehat{\gamma} = \sum_{v \in V(t)} P_v^*(t)$
    for $v \in V(t)$ **do**
      if $(E_v(t) + \Delta\eta P_v^*(t)) < r_v(t+1)$ **then**
        $\widehat{\varepsilon}_v = \widehat{\varepsilon}_v + \mathcal{P}(t_v^d = t+1 | t_v^d > t)$
      end if
    end for
  end if
  apply command $\mathbf{P}^*(t)$
  $t = t + 1$
end while

4 Numerical simulations

A simulation environment aimed at validating the effectiveness of the proposed algorithm has been developed. We refer to a parking lot provided with a number of charging units able to serve all incoming vehicles. The sampling time has been set to 10 minutes. The desired energy to be charged that each customer declares at arrival has been drawn from a symmetric triangular probability distribution defined on the interval [10, 50] kWh. The inter-arrival time of each vehicle has been supposed to follow an exponential distribution with expected value 20 minutes per vehicle, while the distribution of the parking time has been drawn from a symmetric triangular distribution centered in t_v^f with support ± 1.5 hours, i.e., on the interval $[t_v^f - 9,\ t_v^f + 9]$. The charging command ranges in the interval $[0,\ 22]$ kW, whereas the nominal power P_0 has been set to 11 kW. The weights used in the cost function of Problem 1 have been chosen according to (16) and the charging efficiency has been set to 0.9. Simulations have been performed on a 100 days scenario. In this setup, arrivals are allowed from 6:00 to 24:00, while departures can happen any time. For instance, in Fig. 3, the number of plugged-in vehicles during the 61-st day is depicted. It can be observed that from 6:00 onwards, the number of vehicles starts to increase, while it quickly decreases around 24:00.

According to Algorithm 1, the charging process differs from vehicle to vehicle. As an example, the level of charge of a given EV is reported in Fig. 4. During the first time instants, the charge is performed using the maximum

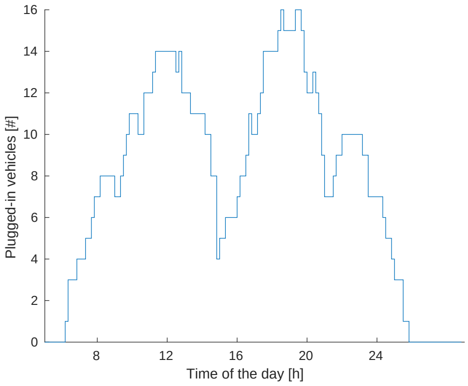

Fig. 3. Number of plugged-in vehicles during the 61-st day.

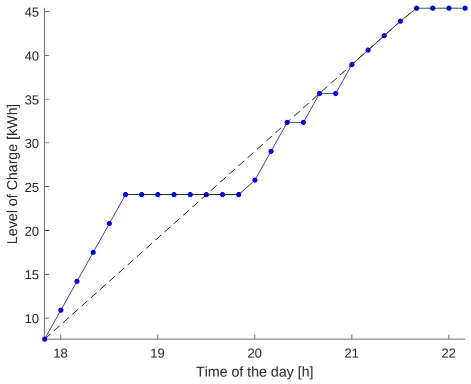

Fig. 4. Level of charge $E_v(t)$ of a single vehicle for $\varepsilon = 0.1$.

power probably because $\widetilde{\gamma} \leq \widehat{\gamma}$ in Line 7 of Algorithm 1, after that the charging power stops for 7 time steps; in this period, priority is given to charging other vehicles. Then, in order to lower the peak power, the level of charge $E_v(t)$ may remain under the satisfaction region for a certain time interval. Finally, the vehicle leaves the station after the LOC has reached its maximum value E_v^f.

The proposed receding horizon strategy with dissatisfaction level ε is denoted by *chance constrained policy with ε tolerance* (CCP-ε), while that which guarantees the customer satisfaction for sure is denoted by *receding horizon policy-prior* (RHPP), in accordance with [3]. Notice that RHPP coincides with the devised strategy when no chance constraint is present, i.e., $\beta_v(k) = 1$, $v \in V(t)$, $k = t+1, \ldots, T(t)$. Moreover, let the nominal uncoordinated charging strategy be denoted by *nominal charging policy* (NCP). Thus, NCP represents the trivial strategy which charges all the vehicles at nominal rate P_0 until the required energy is attained or departure occurs.

In Fig. 5, the power consumption related to the 61-st day is depicted. As it can be noticed, both RHPP and CCP-1% outperform the NCP, with an improvement of about 14% and 20%, respectively.

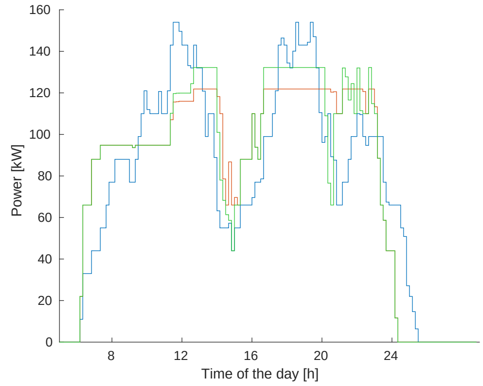

Fig. 5. Power consumption of NCP (blue), RHPP (green), and CCP-1% (red) in day 61.

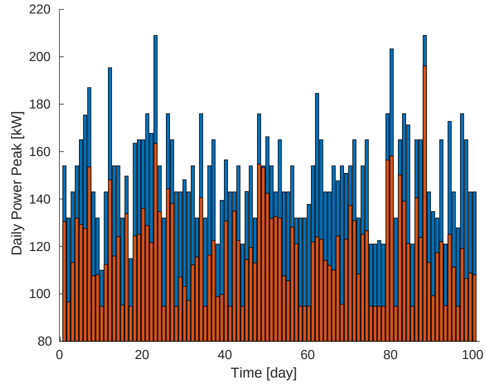

Fig. 6. Daily peak power of NCP (blue) and CCP-1% (red).

Concerning the overall simulation, the daily peak power obtained by NCP and CCP-1% over 100 days is depicted in Fig. 6. It can be noticed that the peaks provided by CCP-1% are always no greater than those of NCP, with an average peak power reduction of about 21.5%.

Performances of RHPP and CCP-1% are compared in Fig. 7, where their daily peak power differences are depicted. It can be observed that CCP-1% performs on average better than RHPP, with an average improvement of more than 4%.

Besides the peak reduction, a crucial aspect when dealing with the chance constraint policy regards the number of vehicles which leaves the parking lot unsatisfied. In Table 1, the fraction of unfulfilled vehicles and the mean peak power improvements with respect to NCP and RHPP are reported, for different values of ε. One may notice that the actual number of unsatisfied customer is in general much less than the fixed bound ε. Moreover, the performance of the CCP-ε is on average better than RHPP even for small values of ε. In fact, in the considered scenario, CCP-1% is able to provide

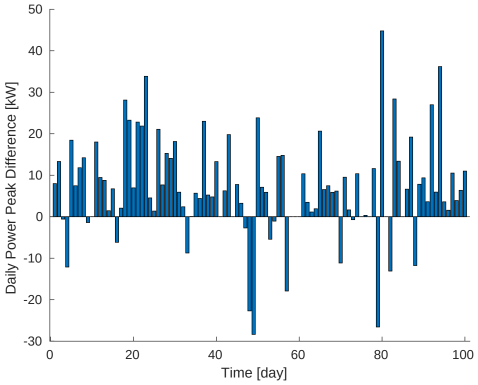

Fig. 7. Daily peak power difference between RHPP and CCP-1%.

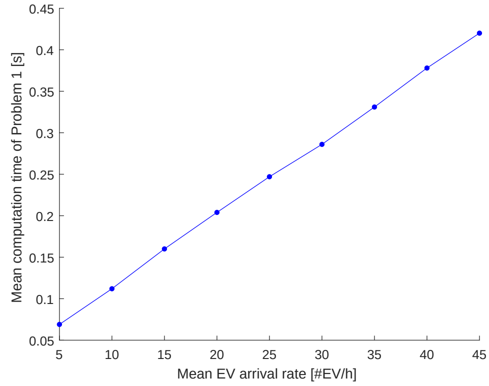

Fig. 8. Average computation time of the Problem 1 for different arrival rates of electric vehicles.

Table 1
CSS-ε performance for different values of ε

	$\varepsilon = 1\%$	$\varepsilon = 5\%$	$\varepsilon = 10\%$
Unsatisfied customers [%]	0.2	1.6	3.9
Peak reduction w.r.t. NCP [%]	21.4	22.3	24.0
Peak reduction w.r.t. RHPP [%]	4.3	5.1	6.9

a performance improvement of 4.3% in the face of 0.2% unsatisfied customers.

Regarding the computational burden, although Problem 1 requires the solution of a MILP, the number of binary variables which really affect the solution is quite limited. To support this statement, 100 days have been simulated for different arrival rates of EVs (the other parameters have been set as in the previous example). The dissatisfaction level has been fixed to $\varepsilon = 0.1$. The average time needed to compute a single iteration of Problem 1 is reported in Fig. 8. Notice that the computation time grows linearly with the vehicle arrival rates. Moreover, the reported time is that needed to solve Problem 1. If $\widetilde{\gamma} \leq \widehat{\gamma}$ in Line 7 of Algorithm 1, the proposed procedure does not require the solution of Problem 1, and hence the mean computation time of a single iteration is in general smaller than that reported in Fig. 8. Since a single iteration can be computed in a fraction of second, the procedure is feasible for real-time implementation, even for a large number of EVs. Numerical simulations have been performed by using Matlab, the Yalmip toolbox [15] and the Cplex solver [10], on an Intel Core i7-7700 CPU @3.60 GHz, 32 GB RAM.

5 Conclusions

A novel algorithm aimed at peak power minimization of EV charging stations has been reported. Such an algorithm is expressed in a receding horizon framework and its core consists in an optimization program which can be formulated as a MILP. Suitable chance constraints are introduced to allow the car park owner to set a bound on the fraction of vehicles which may leave the parking lot unsatisfied. Numerical simulations have been provided to compare the proposed approach with other techniques. It has been shown that even for low values of the dissatisfaction level, good improvements in terms of peak reduction may arise. Moreover, it has been shown that the computational burden of the proposed approach is acceptable, making the technique suitable for real-time implementation, even in the presence of a large number of electric vehicles.

Further studies will address the problem of peak power minimization for parking lots equipped with distributed generation facilities, where the presence of a PV plant (or a wind turbine) can help the CPO to lower the daily peak. A demand-response framework can also be considered, where a monetary reward can be granted to the CPO in the face of a power reduction at prescribed time. Moreover, future studies may involve alternative approaches for dealing with uncertainty, like, e.g., scenario-based approaches, in order to get more confidence in the level of quality, reliability and robustness of the results provided by the proposed technique.

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References

[1] M. J. E. Alam, K. M. Muttaqi, and D. Sutanto. A controllable local peak-shaving strategy for effective utilization of PEV battery capacity for distribution network support. *IEEE Transactions on Industry Applications*, 51(3):2030–2037, 2015.

[2] M. Casini, A. Vicino, and G. G. Zanvettor. A distributionally robust joint chance constraint approach to smart charging of plug-in electric vehicles. In *Proc. 58th IEEE Conf. on*

Decision and Control, pages 4222–4227, Nice, December 2019.

[3] M. Casini, A. Vicino, and G. G. Zanvettor. A receding horizon approach to peak power minimization for EV charging stations in the presence of uncertainty. *International Journal of Electrical Power & Energy Systems*, 126:106567, 2021.

[4] M. Casini, G. G. Zanvettor, M. Kovjanic, and A. Vicino. Optimal energy management and control of an industrial microgrid with plug-in electric vehicles. *IEEE Access*, 7:101729–101740, 2019.

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

[6] O. Erdinç, A. Taşcıkaraoğlu, N. G. Paterakis, İ. Dursun, M. C. Sinim, and J. Catalão. Comprehensive optimization model for sizing and siting of DG units, EV charging stations, and energy storage systems. *IEEE Transactions on Smart Grid*, 9(4):3871–3882, 2018.

[7] L. Gan, U. Topcu, and S. H. Low. Optimal decentralized protocol for electric vehicle charging. *IEEE Transactions on Power Systems*, 28(2):940–951, 2013.

[8] Rishabh Ghotge, Yitzhak Snow, Samira Farahani, Zofia Lukszo, and Ad van Wijk. Optimized scheduling of EV charging in solar parking lots for local peak reduction under EV demand uncertainty. *Energies*, 13(5):1275, 2020.

[9] Masoud Honarmand, Alireza Zakariazadeh, and Shahram Jadid. Self-scheduling of electric vehicles in an intelligent parking lot using stochastic optimization. *Journal of the Franklin Institute*, 352(2):449 – 467, 2015.

[10] IBM. IBM ILOG Cplex Optimizer. Online: https://www.ibm.com/products/ilog-cplex-optimization-studio.

[11] Linni Jian, Yanchong Zheng, Xinping Xiao, and CC Chan. Optimal scheduling for vehicle-to-grid operation with stochastic connection of plug-in electric vehicles to smart grid. *Applied Energy*, 146:150–161, 2015.

[12] Q. Kang, J. Wang, M. Zhou, and A. C. Ammari. Centralized charging strategy and scheduling algorithm for electric vehicles under a battery swapping scenario. *IEEE Transactions on Intelligent Transportation Systems*, 17(3):659–669, 2016.

[13] W. Lee, L. Xiang, R. Schober, and V. Wong. Electric vehicle charging stations with renewable power generators: A game theoretical analysis. *IEEE Transactions on Smart Grid*, 6(2):608–617, 2015.

[14] R. Leou, C. Su, and C. Lu. Stochastic analyses of electric vehicle charging impacts on distribution network. *IEEE Transactions on Power Systems*, 29(3):1055–1063, 2014.

[15] J. Löfberg. Yalmip : A toolbox for modeling and optimization in Matlab. In *In Proc. of the CACSD Conference*, Taipei, Taiwan, 2004.

[16] Zhongjing Ma, Suli Zou, Long Ran, Xingyu Shi, and Ian A Hiskens. Efficient decentralized coordination of large-scale plug-in electric vehicle charging. *Automatica*, 69:35 – 47, 2016.

[17] K. Mahmud, M. J. Hossain, and G. E. Town. Peak-load reduction by coordinated response of photovoltaics, battery storage, and electric vehicles. *IEEE Access*, 6:29353–29365, 2018.

[18] M. Maigha and M. L. Crow. A transactive operating model for smart airport parking lots. *IEEE Power and Energy Technology Systems Journal*, 5(4):157–166, 2018.

[19] Z. Moghaddam, I. Ahmad, D. Habibi, and Q. V. Phung. Smart charging strategy for electric vehicle charging stations. *IEEE Transactions on Transportation Electrification*, 4(1):76–88, 2018.

[20] Van-Linh Nguyen, Tuan Tran-Quoc, Seddik Bacha, and Be Nguyen. Charging strategies to minimize the peak load for an electric vehicle fleet. In *IECON 2014-40th Annual Conference of the IEEE Industrial Electronics Society*, pages 3522–3528, 2014.

[21] ZN Pan, T Yu, LP Chen, B Yang, B Wang, and WX Guo. Real-time stochastic optimal scheduling of large-scale electric vehicles: A multidimensional approximate dynamic programming approach. *International Journal of Electrical Power & Energy Systems*, 116:105542, 2020.

[22] M. R. Sarker, H. Pandžić, and M. A. Ortega-Vazquez. Optimal operation and services scheduling for an electric vehicle battery swapping station. *IEEE Transactions on Power Systems*, 30(2):901–910, 2015.

[23] A.T. Schwarm and M. Nikolaou. Chance-constrained model predictive control. *AIChE Journal*, 45(8):1743–1752, 1999.

[24] M. Shafie-khah, E. Heydarian-Forushani, G. J. Osório, F. A. S. Gil, J. Aghaei, M. Barani, and J. P. S. Catalão. Optimal behavior of electric vehicle parking lots as demand response aggregation agents. *IEEE Transactions on Smart Grid*, 7(6):2654–2665, Nov 2016.

[25] Wanrong Tang and Ying Jun Angela Zhang. A model predictive control approach for low-complexity electric vehicle charging scheduling: Optimality and scalability. *IEEE transactions on power systems*, 32(2):1050–1063, 2016.

[26] M. H. K. Tushar, C. Assi, M. Maier, and M. F. Uddin. Smart microgrids: Optimal joint scheduling for electric vehicles and home appliances. *IEEE Transactions on Smart Grid*, 5(1):239–250, 2014.

[27] Y. Xiong, J. Gan, B. An, C. Miao, and A. L. C. Bazzan. Optimal electric vehicle fast charging station placement based on game theoretical framework. *IEEE Transactions on Intelligent Transportation Systems*, 19(8):2493–2504, 2018.

[28] G. Zhang, S. T. Tan, and G. G. Wang. Real-time smart charging of electric vehicles for demand charge reduction at non-residential sites. *IEEE Transactions on Smart Grid*, 9(5):4027–4037, 2018.

[29] Lei Zhang and Yaoyu Li. Optimal management for parking-lot electric vehicle charging by two-stage approximate dynamic programming. *IEEE Transactions on Smart Grid*, 8(4):1722–1730, 2017.

[30] T. Zhang, W. Chen, Z. Han, and Z. Cao. Charging scheduling of electric vehicles with local renewable energy under uncertain electric vehicle arrival and grid power price. *IEEE Transactions on Vehicular Technology*, 63(6):2600–2612, 2014.

[31] Xiang Zhang and Xue Bai. Incentive policies from 2006 to 2016 and new energy vehicle adoption in 2010–2020 in China. *Renewable and Sustainable Energy Reviews*, 70:24–43, 2017.