A receding horizon approach to peak power minimization for EV charging stations in the presence of uncertainty

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Abstract

The increasing penetration of plug-in electric vehicles in recent years asks for specific solutions concerning the charging policies to be used in parking lots equipped with charging stations. In fact, simple policies based on uncoordinated charge of vehicles lead, in general, to high peak power demand, which may cause high costs to the car park owner. In this paper, the problem of minimizing the daily peak power of a charging station is addressed. Three sources of uncertainty affect the incoming vehicles: the arrival time, the departure time and the demanded energy to be charged. To assess the quality of the charging service under such uncertainties, a suitable customer satisfaction policy is employed. Depending on the information available on the uncertain variables, two algorithms based on a receding horizon approach are designed. Such algorithms require the solution of linear programs and provide the charging power for each plugged-in vehicle. Numerical simulations are provided to assess performance and computational burden of the algorithms, showing the effectiveness and feasibility of the proposed techniques.

Keywords — Plug-in electric vehicles; optimization; smart charging; peak reduction; uncertainty.

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1 Introduction

The development of renewable generation technologies and electric vehicles (EVs) makes it possible to tackle several issues causing green house effect and pollution. On the energy production side, renewable generation has been adopted to produce green energy without impact on the environment. Concerning EVs, their utilization allows to move gas emissions outside living centers and to reduce the overall fossil fuel consumption by exploiting renewable sources [1, 2]. On the other hand, existing power systems might not be capable to manage the electricity demand needed for a high number of electric vehicles. In fact, safety and technical constraints may be violated in the presence of high penetration of EVs. Several studies available in the literature propose EV charging solutions to face different problems. In [3, 4], battery swapping strategies have been developed to reduce the user waiting time, charging time and to maximize the station profit, while in [5], a centralized charging strategy based on battery swapping has been adopted to minimize the total charging cost, as well as to reduce power loss and voltage deviations in power networks. In [6], a study focused on the minimization of travel time and charging cost has been performed, whereas in [7], a price competition game aimed at maximizing charging station revenues has been developed. In [8], it has been shown that by exploiting smart metering tools and optimization techniques it is possible to handle a high penetration of EVs without changing the power system structure. Energy management of an industrial microgrid including the charging policy for EVs has been studied in [9], with the scope of minimizing the overall electricity bill and satisfying network stability constraints. To guarantee satisfactory EV charging service, sizing and siting of charging stations in the network have been investigated, see [10, 11, 12, 13]. In [14], vehicle arrivals are modeled through an ergodic Markov chain, and an algorithm to minimize the mean waiting time has been proposed, while in [15], a charging strategy to maximize the profit based on a distributionally robust joint chance constraint approach has been presented. Regarding location of charging station for EVs, parking lots represent an opportunity which has been often exploited in several cities. To this purpose, a number of works are focused on the management of charging units located in parking lots, like, e.g., [16, 17, 18, 19, 20].

Various charging strategies have been proposed to reduce the peak load consumption. A decentralized EV charging schedule aimed at filling the valleys in electric load profiles has been developed in [21], while in [22] a similar approach has been proposed taking into account future incoming vehicles, too. In [23], a coordinated strategy between renewables, EVs and electrical storage devices has been implemented to reduce domestic peak load, while in [24], the peak shaving problem has been addressed at network distribution level. The problem of reducing the peak load under demand response programs in a parking lot has been recently considered in [25].

A crucial aspect to consider when dealing with EVs is related to the uncertainty which inevitably affects their behavior, like the arrival time, the parking time and the demanded energy. If not properly handled, these uncertainties may generate drawbacks, degrading performance or causing problems to the grid. Different solutions have been devised to handle such issues. In [26], dynamic programming has been exploited to provide a real-time algorithm for a cost saving/load flattening problem by clustering EVs on the basis of their departure time. A smart charging algorithm providing peak shaving is described in [27] for non-residential sites. Vehicle arrivals are uncertain, while times of departure are assumed to be known whenever a vehicle plugs-in. In a vehicle-to-grid framework, an event driven optimization has been proposed in [28], where rescheduling is performed when a new vehicle arrives or when an EV leaves the station before the declared time. In [29], a power schedule aimed at reducing the overall charging cost is considered. Incoming vehicles are supposed to be affected by uncertainty and the departure time is fixed when a vehicle arrives at the station. A similar setting is considered in [30], where vehicle arrivals are generated following a Poisson distribution. If the EV is not fully charged at departure, a monetary penalty is applied. Photovoltaic generation in an EV charging station has been considered in [31]. Here, charging strategies based on Model Predictive Control have been devised to achieve peak reduction. In [32], peak reduction is achieved by two algorithms, based on interruption (on-off) and modulation strategies, respectively. In both cases, the energy to be charged and the departure time of vehicles are known once they reach the station. The above mentioned works require the knowledge of the departure time of plugged-in vehicles. Such information can be hard to be notified in several practical situations, like for instance, in charging stations located in commercial centers, where the parking time can be affected by several unpredictable events. To fill this gap, charging techniques which do not assume such information have been proposed.

Paper contribution

In this paper, we consider a charging station equipped with a number of charging units for plug-in electric vehicles. The aim of this work is to design a charging power schedule for each unit able to minimize the overall daily peak power while satisfying the customer requirements in terms of charged energy. Assuming that the energy price the car park owner (CPO) has to pay to the energy provider depends on the daily peak power, the minimization of such peak will lead to an increase of the CPO profit. Moreover, the station may participate in a demand response program [33], where a peak reduction is rewarded by a monetary remuneration. The arrival and departure times of EVs as well as the amount of energy to be charged are assumed to be uncertain. In the present setting, vehicle-to-grid power exchange is not considered.

The contribution of the paper consists in the development of two novel algorithms aimed at solving the above mentioned problem. Differently from other approaches available in the literature (like, e.g., [26, 27, 28, 29, 30, 31, 32]), the considered setting does not require the knowledge of the departure time of plugged-in vehicles. To deal with this setting, a suitable policy has been devised to assess the customer satisfaction, where a nominal charging power is guaranteed to the customer, which may decide to leave the station even before the demanded energy be effectively charged. The proposed algorithms are formulated in a receding horizon framework. In particular, the first one refers to the case where the CPO has no prior knowledge about the uncertain variables affecting the system, while the second one is suitable for the case when some information about them is available, e.g., in terms of probability distributions. Both algorithms turn out to be computationally feasible even for a large number of charging units, thus resulting appropriate to be implemented in real applications. In fact, they are based on the solution of a linear program efficiently solved by standard mathematical tools. To evaluate the performance and the computational feasibility of the proposed techniques, numerical simulations have been performed and comparisons are provided versus the uncoordinated charging policy and an ideal (omniscient) algorithm able to provide a lower bound on the daily peak power.

Paper organization

The paper is structured as follows. In Section 2, a sketch of the considered problem is described, while in Section 3, a rigorous formulation is reported. The proposed charging algorithm assuming no information available on the uncertain variables is provided in Section 4. In Section 5, an improved version of the charging procedure is presented, assuming that some information on the uncertain variables are available. In Section 6, numerical simulations are reported to evaluate the performance and the computational feasibility of the devised methods and to provide comparisons with other charging strategies. Finally, in Section 7, some conclusions are drawn together with perspectives on future work.

Acronyms

CPO	Car park owner
DEC	Desired energy to be charged
EV	Electric vehicle
NCP	Nominal charging policy
RHP	Receding horizon policy
RHPP	Receding horizon policy with prior information
ICP	Ideal charging policy

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^f	Number of time slots needed to fulfill vehicle v
t_v^f	Fulfillment time of vehicle v
E_v^f	Desired energy to be charged for vehicle v
$V(t)$	Set of plugged-in vehicles to be charged at time t
$E_v(t)$	Energy charged till 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
k	Time index used in optimization problems
$P_v^*(t)$	Optimal charging power schedule at time t
γ_p	Predicted peak power
$T(t)$	Time horizon used in optimization at time t
$\varepsilon_v(t)$	Weights for cost function at time t
$\mathcal{E}(t)$	Vector collecting $\varepsilon_v(t)$
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 description

In this work, we focus on a plug-in EV charging station, which can be supposed to belong to a parking lot.

We assume that the car park owner contracts with customers according to the following policy:

- The CPO promises a given nominal charging rate to customers.
- Once a vehicle arrives, the customer selects the desired amount of energy to be charged (DEC), or equivalently, the desired level of charge at departure.
- Based on the promised charging rate, the charging unit estimates the time at which the request will be fulfilled (*fulfillment time*), and communicates it to the customer.
- When the customer leaves the parking lot, he/she will be marked as satisfied if the EV has been charged with an average charging power which is greater or equal to the promised one. Otherwise he/she will be not satisfied. For instance, if the customer leaves the parking lot at the fulfillment time (or later), he/she will be marked as satisfied if the vehicle has been charged with the DEC.

The charging profile promised by the CPO is depicted in Fig. 1. The slope of the quantized ramp represents the nominal charging power rate. The customer is marked as satisfied if the energy charged at departure lies in the satisfaction region (gray area in Fig. 1). In a realistic scenario, several uncertainties are related to the incoming vehicles. To deal with such issues, in this paper, three sources of uncertainty are considered for each vehicle: the arrival time, the parking time and the desired energy to be charged.

The aim of this work is to devise a charging policy for the station such to minimize the peak power on a daily basis while guaranteeing customer satisfaction. Reducing the peak power is convenient whenever the energy price the CPO has to pay to the energy provider is related to the daily peak power consumption. One more reason may concern the participation of the charging station in a demand response program, where a monetary reward is granted to the CPO in the face of a power reduction request [33]. To accomplish this goal, the problem is formulated in a receding horizon framework, where a suitable optimization problem is solved in order to compute the charging power of all active units

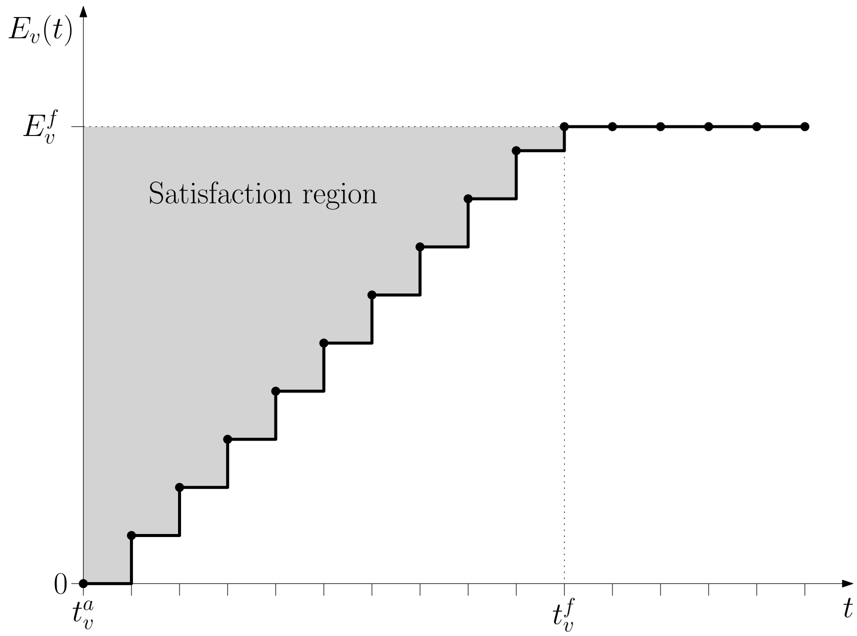

Figure 1: Customer satisfaction region for a generic vehicle v. $E_v(t)$ denotes the energy charged till time t, t_v^a denotes the arrival time, t_v^f the fulfillment time and E_v^f the desired energy to be charged.

at each time step. Two different control algorithms are proposed depending on the prior knowledge the CPO has about the uncertain variables.

It is worthwhile to remark that the choice of a satisfaction region as in Fig. 1 allows to evaluate the customer satisfaction under uncertain departure time. In fact, differently from other works where a customer notifies its departure time when the vehicle arrives at the station, in this framework EVs leave the station at uncertain time. By assuring a minimum charging power, the CPO can modulate the actual charging power to reduce the daily peak, while guaranteeing customer satisfaction.

3 Problem formulation

The problem is formulated in a discrete time setting, where Δ denotes the sampling time.

Let $v \in \mathbb{N}$ denote a vehicle involved in the charging process. For a given vehicle v, we denote by $t_v^a \in \mathbb{N}$ and $t_v^d \in \mathbb{N}$ the arrival and departure time steps, respectively. We denote by $E_v(t)$ the energy charged till time t and by $P_v(t)$ the mean charging power between the time step t and $t+1$.

Once a vehicle plugs-in to the charging unit, the customer declares a desired energy to be charged E_v^f. Assuming to charge the vehicle at a constant nominal power P_0, and denoting by η the charging efficiency, the number of time slots needed to fulfill the request is

$$\tau_v^f = \left\lceil \frac{E_v^f}{\Delta P_0 \eta} \right\rceil . \tag{1}$$

Thus, the DEC will be reached at time

$$t_v^f = t_v^a + \tau_v^f . \tag{2}$$

Let us call t_v^f as the *fulfillment time* of vehicle v. Moreover, let t_v^d denote the departure time of vehicle v. Notice that in a realistic scenario t_v^d may be greater, less or equal than t_v^f.

The set of plugged-in vehicles in charge at the present time t is denoted by

$$V(t) = \left\{ v \colon t_v^a \leq t < t_v^d \text{ and } E_v(t) < E_v^f \right\} \ . \tag{3}$$

In this framework, we suppose that there is a sufficient number of charging units to ensure the connection of new arriving vehicles.

The dynamics of the charged energy of vehicle v can be expressed as

$$E_v(t+1) = E_v(t) + \Delta P_v(t)\eta. \tag{4}$$

It is assumed that the charging power is bounded, i.e.,

$$0 \leq P_v(t) \leq \overline{P} \ , \tag{5}$$

where $\overline{P} > P_0$ denotes the maximum power of the charging units.

According to (4), the customer satisfaction lower bound $r_v(t)$ can be expressed as follows (see Fig. 1)

$$r_v(t) = \min \left\{ \Delta\, P_0\, \eta\, (t - t_v^a),\ E_v^f \right\} \ . \tag{6}$$

Thus, the satisfaction region in Fig. 1 is defined by the constraint

$$r_v(t) \leq E_v(t) \leq E_v^f . \tag{7}$$

It is worthwhile to remark that, for any possible departure time, customer satisfaction is guaranteed whenever (7) holds.

In the next sections, two procedures aimed at minimizing the daily peak power consumed by the charging station while maintaining customer satisfaction are described. These procedures rely on different hypothesis on the information available to the CPO about the uncertain variables.

4 EV charging policy without a-priori information

In this section, it is assumed that no information about vehicle arrival/departure time and DEC is available to the car park owner. The goal of the CPO is to minimize the daily electricity peak power while guaranteeing customer satisfaction.

Let us denote by $\widehat{\gamma}$ the peak power consumption occurred in the considered day till the present time t. At time t, we denote by $\widetilde{\gamma}$ the power needed to charge all the parked vehicles at the maximum rate without exceeding the DEC, i.e.,

$$\widetilde{\gamma} = \sum_{v \in V(t)} \min \left\{ \overline{P}, \frac{E_v^f - E_v(t)}{\Delta\eta} \right\} . \tag{8}$$

It is apparent that charging the vehicles with an overall power less than or equal to $\widehat{\gamma}$ does not increase the daily peak, i.e., $\widehat{\gamma}$ remains the same. So, a preliminary check can be done in order to evaluate if the power needed to charge all the parked vehicles at the maximum rate is less than or equal to $\widehat{\gamma}$, that is:

$$\widetilde{\gamma} \leq \widehat{\gamma} . \tag{9}$$

If (9) holds, then each vehicle is charged with power

$$P_v(t) = \min \left\{ \overline{P}, \frac{E_v^f - E_v(t)}{\Delta\eta} \right\} \ , \ \forall v \in V(t) \tag{10}$$

without affecting $\widehat{\gamma}$. Notice that, as previously stated, $P_v(t)$ represents the mean charging power from time t to $t+1$ for vehicle v.

If (9) does not hold, an optimization algorithm has to be devised in order to find a charging schedule aimed at minimizing the daily peak power. To accomplish this task, a receding horizon approach is adopted. Since we are interested in minimizing the daily peak power, we will consider an operation time horizon of one day.

In Algorithm 1, the pseudo-code of the proposed receding horizon optimization algorithm is reported. After the variable initialization at the beginning of the day, a loop is

Algorithm 1: Receding horizon control algorithm.

$\widehat{\gamma} = 0;$
$t = 0;$
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
    $[P_v^*(t), \gamma_p^*] = charge\_no\_prior\_info(V(t), \widehat{\gamma});$
    $\widehat{\gamma} = \sum_{v \in V(t)} P_v^*(t);$
  end
  apply command $P_v^*(t)$;
  $t = t + 1;$
end

performed until the day is over. Each loop iteration corresponds to a time step. At a generic time step t, the set $V(t)$ containing the indices of charging vehicles is obtained and the maximum overall power at time t is computed as in (8). If $\widetilde{\gamma} \leq \widehat{\gamma}$, the power schedule at time t is set according to (10), otherwise it is computed by the *charge_no_prior_info* routine. Such a function returns the solution of a suitable optimization problem (described below) in terms of charging power schedule ($P_v^*(t)$) for the next time slot; after that $\widehat{\gamma}$ is updated accordingly. Then, the computed charging power schedule is applied to vehicles and the loop iterates.

It is apparent that the crucial step of Algorithm 1 resides in the optimization problem the function *charge_no_prior_info* has to solve at each time instant. The rest of this section is devoted to describe and comment such an optimization program, whose solution will define the charging power for all plugged-in vehicles at the present time t.

In view of the constraints introduced in Section 3 related to physical and customer satisfaction constraints, the following optimization problem is formulated.

Problem 1 (charge_no_prior_info)

$$\begin{cases} [P_v^*(t),\gamma_p^*] = \arg \inf\limits_{P_v(t),\gamma_p} \left(\gamma_p - \sum\limits_{v\in V(t)} \varepsilon_v(t)P_v(t)\right) & \text{(11a)} \\ \text{subject to:} & \\ 0 \le P_v(k) \le \overline{P},\ v\in V(t),\ k=t,\dots,T(t)-1 & \text{(11b)} \\ E_v(k+1) = E_v(k) + \Delta P_v(k)\eta,\ v\in V(t),\ k=t,\dots,T(t)-1 & \text{(11c)} \\ r_v(k) \le E_v(k) \le E_v^f,\ v\in V(t),\ k=t+1,\dots,T(t) & \text{(11d)} \\ \widehat{\gamma} \le \sum\limits_{v\in V(t)} P_v(t) \le \gamma_p & \text{(11e)} \\ \sum\limits_{v\in V(t)} P_v(t) \ge \sum\limits_{v\in V(t)} P_v(k),\ k=t+1,\dots,T(t)-1 & \text{(11f)} \end{cases}$$

where $T(t)$ denotes the optimization time horizon defined as

$$T(t) = \max\{t_v^f : v \in V(t)\}\ . \tag{12}$$

Notice that, according to (2), all the vehicles belonging to $V(t)$ will be fully charged or will have left the parking at time $T(t)$.

The optimization variables in Problem 1 are the power schedule for all vehicles $P_v(k)$, $\forall v \in V(t), k = t, ..., T(t)-1$, and the predicted peak power γ_p, while the optimal variables of interest for Algorithm 1 are only the charging powers at the present time step t, i.e., $P_v(t), v \in V(t)$. Let us denote by the superscript * the optimal value of the optimization variables.

In Problem 1, we aim at minimizing the difference of two quantities: γ_p and $\sum_{v\in V(t)} \varepsilon_v(t)P_v(t)$. For the sake of simplicity, for the moment, let us neglect the latter one in (11a) and let us focus on the minimization of γ_p, i.e., the predicted peak power till the time horizon $T(t)$. Constraints (11b) are related to the charging power bounds in (5), while (11c)-(11d) concern the dynamics of the charged energy and the customer satisfaction constraints as defined in (4) and (6), respectively. Constraint (11e) bounds the total power consumed at time t to belong to the interval $[\widehat{\gamma}, \gamma_p]$, while (11f) enforces the overall power consumed at time t to be greater or equal to the power absorbed at next time steps. So, constraints (11e)-(11f) impose that the maximum peak power until time $T(t)$ be less than or equal to γ_p. Then, the optimal value of γ_p represents the minimum predicted peak power within the time horizon.

Remark 1 *Constraints* (11f) *may appear somehow obscure. Along with* (11e)*, these constraints impose that the optimal predicted peak* γ_p^* *be attained at the first time step* t*, that is,*

$$\sum_{v \in V(t)} P_v^*(t) = \gamma_p^* \ . \tag{13}$$

Notice that, since $E_v(k) \geq E_v(t)$*,* $k = t+1, \ldots, T(t)-1$*, according to* (8)*, the maximum charging power (of vehicles belonging to* $V(t)$*) which can be consumed at time* t *is greater than or equal to those occurring at next time instants, i.e.,*

$$\begin{aligned} \widetilde{\gamma} &= \sum_{v \in V(t)} \min \left\{ \overline{P}, \frac{E_v^f - E_v(t)}{\Delta\eta} \right\} \\ &\geq \sum_{v \in V(t)} \min \left\{ \overline{P}, \frac{E_v^f - E_v(k)}{\Delta\eta} \right\}, \ k = t+1, \ldots, T(t)-1. \end{aligned}$$

So, constraints (11f) *are surely feasible. Moreover, the introduction of* (11f) *does not change the optimal predicted peak* γ_p^**, but it forces such a peak to occur at the current time step* t*. In fact, assuming that* γ_p^* *be a reliable estimate of the future peak, it is convenient to force the present power consumption to equal this estimate.*

Remark 2 *Notice that Problem 1 is an LP problem, whose solution can be efficiently found through standard optimization solvers. Moreover, one may easily prove that such a problem is always feasible. In fact, by charging all the vehicles at the maximum power until the DEC is attained, one gets*

$$\sum_{v \in V(t)} P_v(t) = \widetilde{\gamma} \ .$$

Since Problem 1 is evaluated only if $\widetilde{\gamma} > \widehat{\gamma}$ *(due to line 6 in Algorithm 1), constraint* (11e) *is surely satisfied, as well as* (11b)*-*(11d)*. Finally, by Remark 1,* (11f) *holds, too.*

It is worthwhile to stress that since the problem is formulated in a receding horizon framework, only the charging powers related to the present time step will be actually applied. However, since the CPO has no information about the uncertainty affecting vehicles, each computation of Problem 1 involves only the vehicles which are plugged-in at time t.

In the above reasoning, we neglected the second part of the cost function, i.e.,

$$-\sum_{v \in V(t)} \varepsilon_v(t) P_v(t) \ . \tag{14}$$

In (14), $\varepsilon_v(t) > 0$ denote weights which satisfy $\sum_{v \in V(t)} \varepsilon_v(t) = \epsilon$, for a fixed $\epsilon \ll 1$. In (13), it is stated that the optimal cost (neglecting (14) from (11a)) is

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

So, it is straightforward to note that, since $\epsilon \ll 1$, the introduction of (14) in the cost function does not significantly change the optimal cost. However, it allows to allocate the optimal overall charging power at time t among vehicles on the basis of the weights $\varepsilon_v(t)$.

Such weights can be chosen in several ways. A heuristics which provides good results (see Section 6) is to assign greater charging power to vehicles which have longer fulfillment time. A possible way to do that is described below.

Let us define

$$\tilde{\varepsilon}_v(t) = t_v^f - t \quad , \quad v \in V(t) \tag{15}$$

and let $\widetilde{\mathcal{E}}(t)$ be the vector collecting $\tilde{\varepsilon}_v(t)$. By the definition of $V(t)$ in (3), one has $E_v(t) < E_v^f$. Moreover, by (1)-(2) one gets $t < t_v^f$ and hence $\tilde{\varepsilon}_v(t) > 0$, for all $v \in V(t)$. So, by defining the weighting vector $\mathcal{E}(t)$ as

$$\mathcal{E}(t) = \epsilon \frac{\widetilde{\mathcal{E}}(t)}{\|\widetilde{\mathcal{E}}(t)\|_1} \ , \tag{16}$$

it is easy to show that $\|\mathcal{E}(t)\|_1 = \sum_{v \in V(t)} \varepsilon_v(t) = \epsilon$.

Thus, the amount of power given by γ_p^* will be split among vehicles to favor those with greater fulfillment time.

Let us call the procedure reported in Algorithm 1 as *receding horizon policy* (RHP). Moreover, let us denote by *nominal charging policy* (NCP) the uncoordinated charging schedule where each vehicle is charged with constant nominal power P_0 till departure or the DEC is attained.

In the following, we want to show that RHP always returns a peak power which is less or equal to that obtained by NCP. To this purpose, some notation needs be introduced. Let us call by $\widehat{\gamma}^r(t)$ and $\widehat{\gamma}^n(t)$ the peak power occurred up to time t by adopting the RHP and NCP strategy, respectively. Hereafter, we denote by the superscript r and n all the variables related to RHP and NCP, respectively. To simplify the exposure, let us define $\widehat{V}(t) = \{v \colon t_v^a \leq t < t_v^d\}$. By (3), one has $\widehat{V}(t) \supseteq V(t)$ since $\widehat{V}(t)$ contains also the vehicles which are charged with the DEC but have not left the parking lot. Since the charging power is null for such vehicles, they do not contribute to the charging schedule.

The charging power applied by NCP at time step t is

$$P_v^n(t) = \min\left\{P_0, \frac{E_v^f - E_v^n(t)}{\eta\Delta}\right\} \quad , \quad v \in \widehat{V}(t). \tag{17}$$

By definition, the peak power function up to time t satisfies

$$\widehat{\gamma}^n(t) = \max\left\{\widehat{\gamma}^n(t-1), \sum_{v\in\widehat{V}(t)} P_v^n(t)\right\}. \tag{18}$$

The fact that the peak power obtained by RHP cannot be greater than that of NCP is stated by the following theorem.

Theorem 1 *At a given time t, the following inequality holds*

$$\widehat{\gamma}^r(t) \leq \widehat{\gamma}^n(t) \quad , \quad \forall t \geq 0.$$

Proof: See Appendix. □

This theorem states that, for any possible distribution involving the uncertain variables, the proposed algorithm outperforms the uncoordinated charging policy, that is RHP is able to reduce the daily peak power while guaranteeing customer satisfaction.

5 EV charging policy with a-priori information

In this section, it is assumed that the CPO has some knowledge about the uncertain variables involved in the charging process, i.e., the arrival and charging time of vehicles and the DEC. We suppose that the probability distributions (or an estimate of them) of the previously mentioned variables are available, obtained for instance by using historical data. Under such an assumption, the technique described in Section 4 can be refined, in order to obtain better performance, i.e., reduced daily peak power.

The main procedure is like to that reported in Algorithm 1, with the only difference that the function *charge_no_prior_info* used to solve Problem 1 in Line 9 is replaced by *charge_prior_info*, aimed at solving Problem 2.

Problem 2 (charge_prior_info)

$$
\begin{cases}
[P_v^*(t), \gamma_p^*] = \arg \inf\limits_{P_v(t), \gamma_p} \left(\gamma_p - \sum\limits_{v \in V(t)} \varepsilon_v(t) P_v(t) \right) & \text{(19a)} \\
\text{subject to:} & \\
0 \leq P_v(k) \leq \overline{P},\ v \in V(t),\ k = t, \dots, T(t)-1 & \text{(19b)} \\
E_v(k+1) = E_v(k) + \Delta P_v(k)\eta,\ v \in V(t),\ k = t, \dots, T(t)-1 & \text{(19c)} \\
r_v(k) \leq E_v(k) \leq E_v^f,\ v \in V(t),\ k = t+1, \dots, T(t) & \text{(19d)} \\
\widehat{\gamma} \leq \sum\limits_{v \in V(t)} P_v(t) \leq \gamma_p & \text{(19e)} \\
\sum\limits_{v \in V(t)} P_v(t) \geq \sum\limits_{v \in V(t)} P_v(k),\ k = t+1, \dots, T(t)-1 & \text{(19f)} \\
\sum\limits_{v \in V(t)} P_v(k) \mathcal{P}\left(t_v^d > k | t_v^d > t\right) + P_a(k) \leq \gamma_p,\ k = t+1, \dots, T(t)-1 & \text{(19g)}
\end{cases}
$$

where

$$
P_a(k) = N_m \, P_0 \, \min \left\{ k - t, \frac{E_m}{\Delta \eta P_0} \right\} \ , \tag{20}
$$

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

Problem 2 differs from Problem 1 since constraints (19g) have been added in the former with the aim of obtaining a better estimate of the future peak power γ_p. Notation $\mathcal{P}\left(t_v^d > k | t_v^d > t\right)$ in (19g) denotes the probability that the departure time of vehicle v be greater than k, conditioned to the fact that it is greater than t. The left hand side of (19g) can be decomposed in this way

$$
\underbrace{\sum_{v \in V(t)} P_v(k) \mathcal{P}\left(t_v^d > k | t_v^d > t\right)}_{current\ vehicles} + \underbrace{P_a(k)}_{future\ vehicles}
$$

where, at time k, the left part denotes the expected value of the overall power consumption given by the vehicles which are charging at time t, while $P_a(k)$ provides an estimate of the overall power consumption given by vehicles which will arrive at future time, assuming nominal charging power. In the expression of $P_a(k)$ in (20), it is assumed that each vehicle asks for an amount of energy to be charged equal to E_m. In (20), the expression $\frac{E_m}{\Delta \eta P_0}$

denotes the mean number of time slots needed to complete the charge. So, while plugged-in vehicles are considered individually in (19g), future EVs are managed in an aggregated way, by exploiting average values of uncertain variables.

The introduction of constraints (19g) in the optimization problem leads to a better estimate of the predicted peak power γ_p^*, improving the performance of the overall algorithm, as reported in the following section.

6 Numerical results

To assess the performance of the proposed algorithms, numerical simulations and comparisons have been performed. A parking lot equipped with charging units is considered. The simulated scenario covers 100 days with a sampling time $\Delta = 10$ minutes. EV arrivals have been modeled through an exponential distribution with rate of 4 vehicles per hour, while the desired energy to be charged has been taken from a uniform distribution in the interval [10, 50] kWh. The parking time has been chosen according to a triangular distribution with support $[t_v^f - 12,\, t_v^f + 12]$ with mean value t_v^f. We suppose that the parking lot is open to arrivals from 6:00 till 22:00, while departure may occur at any time. The nominal power P_0 has been set to 11 kW, while the maximum power $\overline{P}$ is 22 kW. Charging efficiency has been set to 0.9, while the optimization weights $\varepsilon_v(t)$ are chosen according to (15)-(16).

The number of plugged-in vehicles changes during a day. For instance, the evolution of plugged-in vehicles in the 29-th day of simulation is depicted in Fig. 2. One may notice that vehicles starts to arrive in the parking lot from 6:00, while after 22:00 no more vehicle arrives and the number of charging EVs quickly decreases.

In addition to RHP and NCP introduced in Section 4, let us define the following acronyms. Let us call the procedure described in Section 5 as *receding horizon policy-prior* (RHPP), and let the *ideal charging policy* (ICP) be the procedure aimed at minimizing the daily peak power assuming all the future realizations of the uncertain variables are available. It is clear that this charging strategy is unrealistic, since it relies on future outcomes of stochastic variables. However, ICP will be useful for assessing algorithm performance since it provides a lower bound for the daily peak power.

To evaluate the effectiveness of RHP, the power schedules of NCP and RHP for the simulation day 29 are depicted in Fig. 3. As it can be observed, RHP tries to coordinate the vehicle charging to maintain the power consumption equal to the current peak power

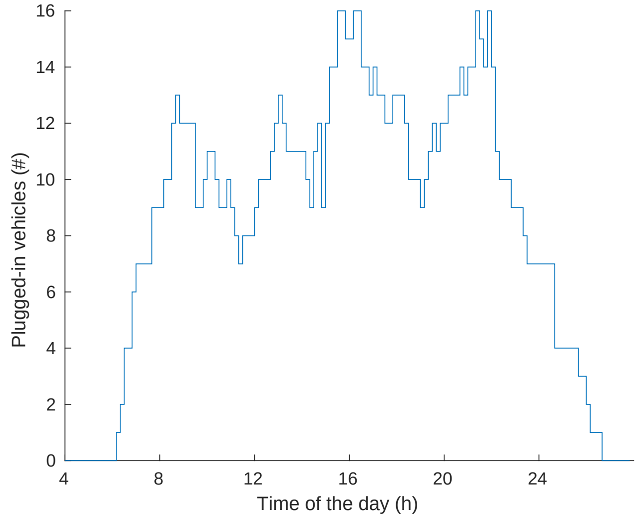

Figure 2: Number of plugged-in vehicles during the 29-th day of simulation.

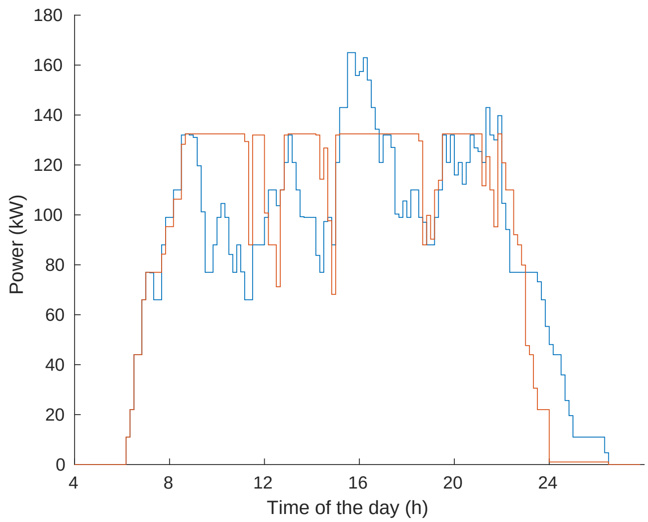

Figure 3: Power consumption of NCP (blue) and RHP (red) in simulation day 29.

$\widehat{\gamma}$. In Fig. 3, this corresponds to the intervals where a flat behavior occurs. According to the condition in Line 6 of Algorithm 1, power values below $\widehat{\gamma}$ are related to situations in which all the vehicles are charging at the maximum power rate. In the considered day, RHP is able to lower the NCP peak by 32.6 kW, corresponding to a relative peak power reduction of about 19%.

In Fig. 4, daily peak powers of NCP and RHP are depicted. As stated in Theorem 1, RHP cannot perform worse than NCP. Indeed, the daily peak differences between the proposed procedure and NCP are represented by the blue bars above the red ones. The peak power reduction provided by RHP w.r.t. NCP in the simulated 100 days amounts to 20.6 kW, on average.

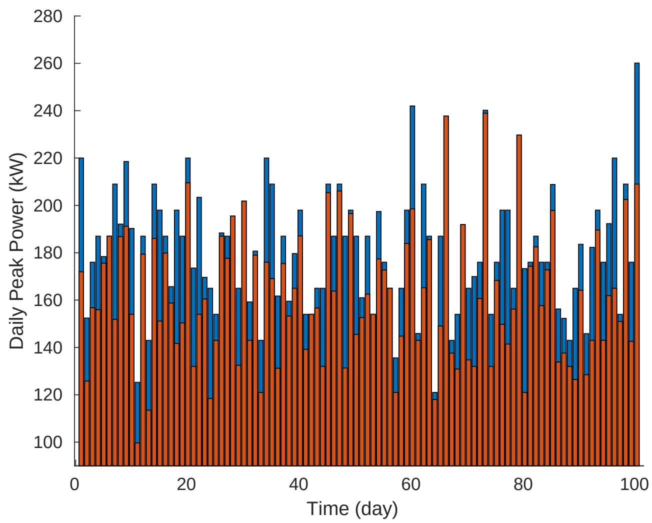

Figure 4: Daily peak power of NCP (blue) and RHP (red).

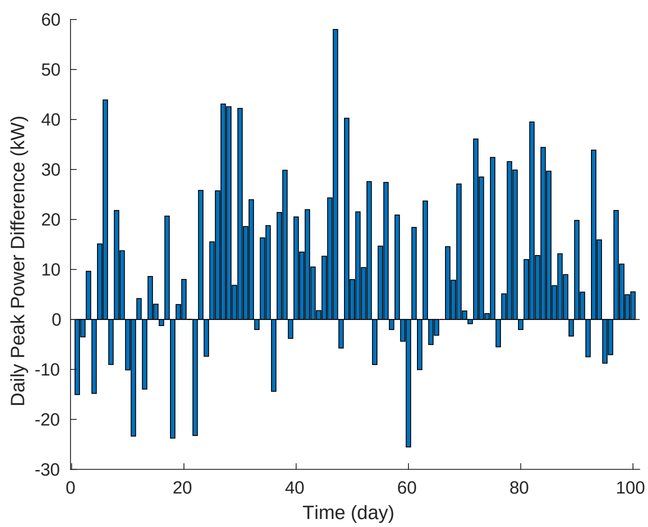

Figure 5: Daily peak power difference between RHP and RHPP.

Focusing on RHPP, its performance has been compared with that of RHP. In particular, daily peak power differences between the two procedures are reported in Fig. 5. It can be

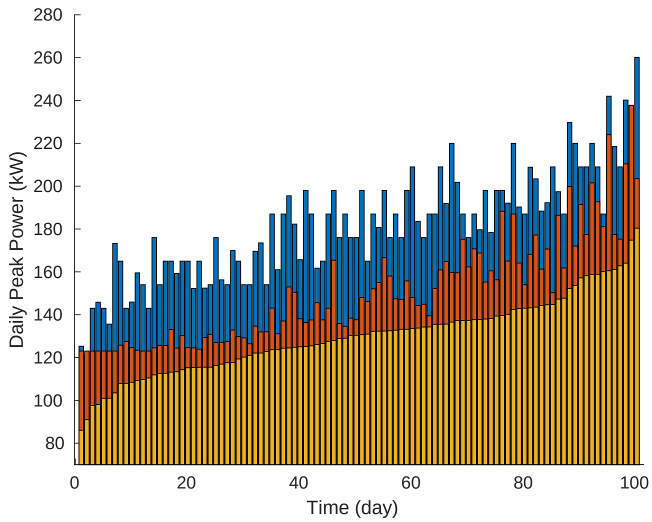

Figure 6: Daily peak power of NCP (blue), RHPP (red) and ICP (yellow), sorted in ascending order of ICP.

noticed that RHPP performs better than RHP in most of the days. In fact, the peak power obtained by RHPP is on average 10.8 kW lower than of RHP (31.4 kW lower than NCP).

The effectiveness of the RHPP can be noticed also comparing it with ICP. In Fig. 6, daily peaks of NCP, RHPP and ICP are reported. For ease of reading, the peaks provided by ICP are sorted in ascending order, and those obtained by NCP and RHPP are reported accordingly. It can be noticed that RHPP performs well also when compared with the best admissible solution. Indeed, knowledge of reliable statistical information about arrivals, charging time and DEC, makes RHPP capable to provide peak powers close to the those given by the benchmark charging policy. However, it is worthwhile to remind that the ICP provides a lower bound on the peak power and it is not feasible from a practical viewpoint since it depends on the knowledge of actual realizations of stochastic variables.

Finally, to evaluate the improvement given by the introduction of the weights (14) in the cost function, we will refer to the RHPP procedure. Specifically, in Fig. 7, daily peak power differences between RHPP without weights and RHPP with weights chosen as in (15)-(16) is depicted. As it can be noticed, the use of weights leads to a reduction of the daily peak power, which, in the considered simulation, amounts to 5.2 kW, on average.

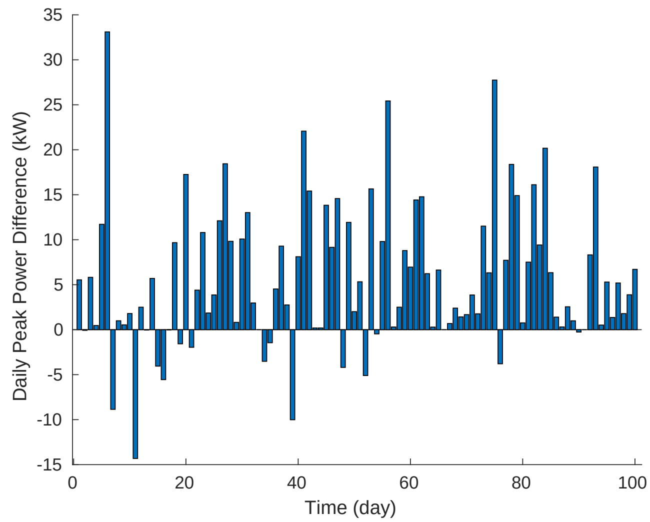

Figure 7: Daily peak power difference between RHPP without weights and RHPP with weights.

Computational time and scalability issues

To validate the computational feasibility of the proposed algorithms, several simulations with different EV arrival rates have been performed. Since the time needed to perform a single iteration differs significantly whether condition in Line 6 of Algorithm 1 holds or not, we only considered the worst case setting when $\widetilde{\gamma} > \widehat{\gamma}$. In fact, in this case, the computation of the solution of a linear program is required. In Fig. 8, the mean time of each iteration is depicted for different EV arrival rates. It can be observed that the computational burden scales almost linearly with the EV penetration. It is worthwhile to note that even for an arrival rate of 50 vehicles per hour both algorithms require computation times much lower than the sampling time (10 minutes), which shows their actual potential for real applications. Simulations have been performed using Matlab, the Yalmip toolbox [34] and the Cplex solver [35], on an Intel Core i7-9700 CPU @3.00 GHz, 16 GB RAM.

7 Conclusions

In this paper, two algorithms aimed at the daily peak power minimization of an EV charging station have been proposed. The two procedures differ in that the first one does not assume any info on uncertain variables, while the second one exploits some statistical knowledge

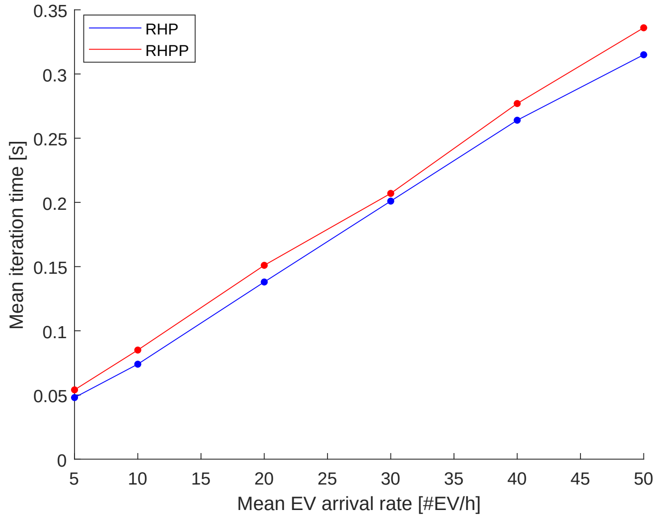

Figure 8: Mean computation time for an optimization loop.

on vehicles arrivals, departures and desired energy to be charged. Both algorithms have been formulated in a receding horizon framework and rely on the solution of a linear programming problem, which provides the optimal charging power for each connected vehicle at each time step. Numerical simulations and comparisons show the effectiveness of the devised techniques, as well as the computational feasibility for implementation in real applications.

Further studies will address the problem of peak power reduction in EV charging stations coupled with distributed generation or in the presence of demand response, and the possibility of reducing the peak power at the cost that a fraction of vehicles would not be fully charged at departure.

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Appendix

Proof of Theorem 1.

The theorem will be proven by induction.

At time $t = 0$, one has $\widehat{\gamma}^r(0) = \widehat{\gamma}^n(0) = 0$.

Let us suppose that at time $t-1$ it holds

$$\widehat{\gamma}^r(t-1) \leq \widehat{\gamma}^n(t-1). \tag{21}$$

We want to prove that $\widehat{\gamma}^r(t) \leq \widehat{\gamma}^n(t)$. If $\widetilde{\gamma} \leq \widehat{\gamma}^r(t-1)$, then by the condition in Line 6 of Algorithm 1, the peak power is not updated and so, by (21) and (18)

$$\widehat{\gamma}^r(t) = \widehat{\gamma}^r(t-1) \leq \widehat{\gamma}^n(t-1) \leq \widehat{\gamma}^n(t).$$

If $\widetilde{\gamma} > \widehat{\gamma}^r(t-1)$, the charging schedule provided by RHP is given by the solution of Problem 1, and according to Line 10 of Algorithm 1, it holds

$$\widehat{\gamma}^r(t) = \sum_{v \in \widehat{V}(t)} P_v^r(t) \ . \tag{22}$$

Let us define the charging command

$$\widehat{P}_v(t) = \min\left\{P_0, \frac{E_v^f - E_v^r(t)}{\eta\Delta}\right\} \ , \ v \in \widehat{V}(t). \tag{23}$$

Since RHP provides a charging schedule which guarantees the customer satisfaction, surely $E_v^r(t) \geq E_v^n(t)$, and hence by comparing (17) and (23), one has

$$\widehat{P}_v(t) \leq P_v^n(t) \ , \ \forall v \in \widehat{V}(t) \ . \tag{24}$$

We have to study two different cases. First, let us consider the case $\sum_{v \in \widehat{V}(t)} \widehat{P}_v(t) < \widehat{\gamma}^r(t-1)$. Since $\widetilde{\gamma} > \widehat{\gamma}^r(t-1)$, then there surely exist $P_v^r(t) \geq \widehat{P}_v(t), \ v \in \widehat{V}(t)$ such that

$$\sum_{v \in \widehat{V}(t)} P_v^r(t) = \widehat{\gamma}^r(t-1),$$

and hence

$$\widehat{\gamma}^r(t) = \widehat{\gamma}^r(t-1) \leq \widehat{\gamma}^n(t-1) \leq \widehat{\gamma}^n(t) \ .$$

It remains to study the case $\sum_{v \in \widehat{V}(t)} \widehat{P}_v(t) \geq \widehat{\gamma}^r(t-1)$. It is easy to note that $\widehat{P}_v(t)$ satisfies constraints (11b)-(11e). Moreover, also constraints (11f) are satisfied. In fact, by choosing in (11f) the sequence $\widehat{P}_v(k),\ k = t+1,\dots,T(t)-1$ like in (23), one has $\widehat{P}_v(t) \geq \widehat{P}_v(k),\ \forall v \in \widehat{V}(t),\ k = t+1,\dots,T(t)-1$. Hence, constraints (11f) are satisfied, and the charging sequence $\widehat{P}_v(t)$ is a feasible solution of Problem 1, in the sense that it satisfies all its constraints.

Since the schedule $P_v^r(t)$ is the optimal solution of Problem 1, one has $\sum_{v\in\widehat{V}(t)} P_v^r(t) \leq \sum_{v\in\widehat{V}(t)} \widehat{P}_v(t)$, and then, by (22), (24) and (18), it holds

$$\widehat{\gamma}^r(t) = \sum_{v\in\widehat{V}(t)} P_v^r(t) \leq \sum_{v\in\widehat{V}(t)} \widehat{P}_v(t) \leq \sum_{v\in\widehat{V}(t)} P_v^n(t) \leq \widehat{\gamma}^n(t).$$

□

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