# A stochastic approach for EV charging stations in demand response programs

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**Abstract**

Demand response is expected to play a fundamental role in renewable energy communities to alleviate the electricity demand-supply mismatch, especially in the presence of stochastic load and generation. In this paper, we consider an electric vehicle charging station that participates in incentive-based demand response programs. A real-time charging scheme is devised to optimize the charging station operation by coordinating the charging process of the electric vehicles, and complying with the incoming demand response requests. In this context, vehicle demand is assumed uncertain, while demand response requests ask for a change in the charging profile over certain time

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intervals, in exchange for a monetary reward. By exploiting the probability distributions describing the vehicle charging process, a stochastic formulation is employed to devise a novel charging algorithm aimed at reducing the charging station operational cost. Such a procedure can (i) handle the uncertainty affecting the charging process in different settings and scenarios, and (ii) exploit the information collected in real-time to refine forecasts and hence ensure a higher demand flexibility. Numerical results show that the proposed approach ensures considerable cost reduction compared to the benchmarks, and features highly scalable runtimes.
*Keywords:* Electric Vehicles, Charging Stations, Demand Response, Receding Horizon

## 1. Introduction

Demand response (DR) programs play a key role in restoring the balance between electricity demand and supply in renewable energy communities (RECs). DR incentivizes users to change their electricity demand profiles with respect to their usual consumption patterns in response to time-based rates (price-based schemes) or financial incentives (incentive-based schemes) [1], hence providing several benefits for the grid stability [2, 3].

With the increasing penetration of electric vehicles (EVs), the question of whether they are suitable targets for DR programs comes naturally. The answer appears to be positive for two reasons. First, the EV power demand is expected to significantly contribute to the overall grid power consumption. In fact, differently from *low power appliances* like domestic ones, EVs can be considered *high power appliances*, being devices that require a significant amount of power during the charging process. Indeed, it is expected that public charger capacity will be around 600 GW by 2030 [4]. Second, differently from other kinds of high power appliances (like industrial loads), EVs feature higher potential flexibility since their charging process may be shifted or even interrupted over time. Consequently, the charging schedule can be managed to comply with EV owners charging requirements, while satisfying the incoming DR signals.

Despite the expected flexibility potential of EVs, the adoption of DR schemes in the mobility sector introduces some challenges. On one side, if the charging process of EVs is left uncoordinated, it can lead to energy shortage issues, and threaten the reliability and stability of the power system [5]. On the other side, EV charging loads are inherently stochastic, as they depend on users driving habits and traffic conditions. It is therefore clear that the development of strategies to handle and coordinate the stochastic EV demand is essential to achieve suitable levels of flexibility for participating in DR programs.

*Related works.* The importance of the investigated topic is testified by the growing body of literature proposing control methodologies for allowing the participation of EV charging stations (EVCSs) in DR programs (see surveys [6], [7] and [8]). Several problem settings and optimization approaches have been considered. In [9], a DR program requiring power reduction of an EVCS where vehicles are charged by exploiting an on-off policy is considered. In [10], an incentive-based DR scheme focused on the deviation from the nominal profile is analyzed, and control techniques based on deep reinforcement learning to minimize the daily EVCS cost in real-time are proposed. Further-more, [11] focuses on DR for load shaping and evaluates its impact on the distribution network, while [12] exploits dynamic programming for determining the optimal charging schedule for vehicle-to-grid regulation services. The use of particle swarm optimization routines to maximize the daily profit including DR incentives is considered in [13]: here the uncertainty on renewable generation is taken into account, while this is not the case as far as demand is concerned. Contributions concerning the development of receding-horizon algorithms to shave the peak power of an EVCS under EV uncertainty have been proposed in [14, 15, 16, 17, 18]; however, these approaches are not compatible with incentive-based DR structures. Similarly, [19] develops a dynamic programming approach for pricing schemes and relies on a "deduction" method to handle unknown information about the future behavior of vehicles. On a different direction, two-stage day-ahead settings are considered in [20], where the authors rely on stochastic programming to develop an EV pricing strategy for profit maximization, and in [21], where approximate dynamic programming is adopted to determine the optimal charging scheduling under total capacity constraints. In [22], a chance constrained approach is exploited to formulate a day-ahead planning for gathering EV charging flexibility where customers response to DR incentive prices is uncertain. A bilevel approach allowing the participation of energy communities with EVCSs in DR programs is described in [23]. Such a procedure relies on Montecarlo simulations to generate plausible scenarios for renewable sources and loads. In [24], a stochastic programming approach is proposed for optimal charging scheduling that can fit different types of DR programs (price-based and incentive-based) under renewable sources and market price uncertainties. However, both [23] and [24] are not suitable to operate in real-time. More recently, in [25] an end-to-end learning and optimization framework for price-responsive EV charging scheduling is proposed, while [26] develops an optimization-based approach to enable the participation of EVCSs into incentive-based DR programs. However, [26] does not consider the potential flexibility of incoming vehicles, hence offering less adaptation to DR programs.

*Novelty and contribution.* In this paper, we consider an EVCS that is part of a REC and participates in DR programs to help maintain the local demand-supply balance. According to the concept of "flexibility for energy" [27], we assume the existence of a contract between the REC manager and the charging station owner, where the EVCS gets compensated if it reduces/increases its energy consumption during certain time windows with respect to a nominal profile. In the considered setting, DR requests are disclosed to the EVCS with a limited lead time, hence leaving little time to react. To allow a flexible and resilient EVCS management, a novel stochastic receding-horizon methodology that coordinates the EV charging schedule of incoming vehicles is designed. Specifically, forecasting procedures that estimate the EVCS future load flexibility are embedded into the proposed algorithm to manage the charging schedule and comply with the incoming DR requests.

To the best of the authors' knowledge, there are no available receding horizon techniques that explicitly consider and model the EV uncertainty on plug-in and plug-out times under incentive-based DR programs. This paper aims to fill such a research gap through the following contributions:

1. a stochastic formulation to optimally schedule the charging process of EVs in a charging station participating in an incentive-based DR program is proposed. To deal with the randomness of vehicles aggregated demand, we introduce a formulation that allows one to consider different settings and scenarios with no specific assumption on the structure of the underlying probability distributions. Contrary to [26], the proposed approach takes explicitly into account the potential flexibility of future incoming vehicles, thus improving the EVCS performance and providing significant cost reduction, as witnessed by the reported numerical simulations.

2. a receding horizon algorithm that takes advantage of the information acquired online to derive load forecasts is designed to solve the above problem. The procedure requires the solution of an optimization program involving binary variables whose number scales with the number of daily DR requests. For fixed values of the binary variables the optimization problem is convex, making it affordable to branch and bound solution techniques. The scalability of the algorithm is demonstrated via numerical simulations.

*Paper structure.* In Section II, the problem formulation is described. In Section III, the receding horizon algorithm aimed at finding the optimal charging schedule to ensure daily cost minimization in the presence of DR requests is derived. In Section IV, numerical results to evaluate the effectiveness and the computational feasibility of the proposed approach are reported. Finally, conclusions and future research lines are reported in Section V.

*Notation and nomenclature.* $\mathbb{N}$ denotes the set of natural numbers, while $\mathbb{R}$ the set of real numbers. We define a probability space $\mathcal{W}$ as a unique tuple $\mathcal{W} = \{\Omega, \mathcal{F}, \mathcal{P}\}$, where $\Omega$ is its sample space, $\mathcal{F}$ its $\sigma$-algebra of events, i.e., the collection of all possible subsets of $\Omega$, and $\mathcal{P}$ its probability measure that assigns a probability $\mathcal{P}(A)$ to every event $A \in \mathcal{F}$. For an event $A \in \mathcal{F}$, the probability that $A$ occurs is written as $\mathcal{P}(A)$, whereas the probability of its complement is $\mathcal{P}(\overline{A}) = 1 - \mathcal{P}(A)$. Consider two events $A, A' \in \mathcal{F}$, then the joint probability that $A$ and $A'$ both occur is denoted by $\mathcal{P}(A, A') := \mathcal{P}(A \cap A')$, while the conditional probability that $A$ occurs given $A'$ is denoted by $\mathcal{P}(A|A') := \frac{\mathcal{P}(A \cap A')}{\mathcal{P}(A')}$. We define a random variable $X$ as a $\mathcal{F}$-measurable function defined on the probability space $\mathcal{W}$ mapping its sample space $\Omega$ to the real line $\mathbb{R}$, i.e., $X : \Omega \to \mathbb{R}$. For a random variable $X$, we denote by $\mathbb{E}[X]$ its expected value, whereas $\mathbb{E}[X|t]$ represents the expectation of $X$ conditioned to the available information at time $t$. Nomenclature is reported in the following table.

| Symbol | Description |
|---|---|
| $\Delta$ | Sampling time |
| $t_v^a$ | Arrival time of vehicle $v$ |
| $t_v^c$ | Time when charging ends for vehicle $v$ |
| $t_v^d$ | Departure time of vehicle $v$ |
| $\tau_v^f$ | Fulfillment duration of vehicle $v$ under nominal power charging schedule |
| $\tau_v^p$ | Parking duration of vehicle $v$ |
| $\tau_v^c$ | Charging duration of vehicle $v$ |
| $E_v^f$ | Declared energy requirement of vehicle $v$ |
| $S_v(t)$ | Energy charged into vehicle $v$ at time $t$ |
| $P_v(t)$ | Average charging rate of vehicle $v$ in the time interval $[t, t+1]$ |
| $r_v(t)$ | Nominal charging profile of vehicle $v$ at time $t$ |
| $N$ | Daily number of incoming vehicles |
| $Q(t)$ | Incoming vehicles after time $t$ |
| $H(t)$ | Number of vehicles charging at time $t$ |
| $W(k,t)$ | Number of vehicles charging at time $k$ incoming after $t$ |
| $\mathcal{V}(t)$ | Set of vehicles charging at time $t$ |
| $A(t)$ | Number of arrived vehicles up to time $t$ |
| $E^F(t)$ | Forecast of day-ahead aggregated energy consumption at time $t$ |
| $E^S(t)$ | Actual aggregated energy consumption at time $t$ |
| $E^U(t)$ | Aggregated energy consumption under uncoordinated nominal charging policy at time $t$ |

| | |
|---|---|
| $P_0$ | Nominal charging power |
| $\bar{P}$ | Maximum charging power |
| $\eta$ | Charging efficiency |
| $t_r^b$ | Begin time of DR request $r$ |
| $t_r^e$ | End time of DR request $r$ |
| $t_r^n$ | Notice time of DR request $r$ |
| $\overline{B}_r, \underline{B}_r$ | Upper and lower energy bound for DR request $r$ |
| $\delta_r$ | Energy violation associated to DR request $r$ |
| $\gamma_r$ | Monetary reward associated to DR request $r$ |
| $t_{v,r}^{in}$ | Last time instant when vehicle $v$ is charging during request $r$ |
| $\tau_{v,r}^{in}$ | Number of time slots when a vehicle is charging inside request $r$ |
| $\tau_{v,r}^{out}$ | Number of time slots when a vehicle is charging before request $r$ |
| $P_{v,r}^{in}$ | Reduced power of vehicle $v$ inside request $r$ |
| $P_{v,r}^{out}$ | Incremented power of vehicle $v$ before request $r$ |
| $\sigma_{v,r}^{in}(t)$ | Power reduction w.r.t. the nominal profile at time $t$ of vehicle $v$ inside request $r$ |
| $\sigma_{v,r}^{out}(t)$ | Power increase w.r.t. the nominal profile at time $t$ of vehicle $v$ before request $r$ |
| $\nu_r(t)$ | Expected value of the power reduction/increase at time $t$ for request $r$ |
| $c^g$ | Grid electricity price |
| $c^d$ | Unitary deviation cost |
| $k$ | Unitary reward |

## 2. Problem formulation

We adopt a discrete time setting where the sampling time is denoted by $\Delta$, and consider a reference day divided into $T$ time slots with running index $t = 0, \ldots, T-1$. The charging station is assumed to participate in a DR program to provide flexibility to the REC in exchange for a monetary incentive. The contract between the REC manager[2] and the charging station is structured as follows:

- the REC manager provides a discounted constant electricity price $c^g$ to the charging station;
- at the beginning of each day, the charging station communicates a forecast of its daily energy consumption, denoted by $E^F(t), t = 0, \ldots, T-1$, to the REC manager. This forecast can be the result of a day-ahead planning problem (see, for example, [28]);
- in addition to the energy price, the charging station is subject to a fee $c^d$ that is proportional to the deviation between $E^F(t)$ and the actual demand profile $E^S(t)$. Roughly speaking, this penalty encourages the charging station to provide a load profile that is as close as possible to $E^F(t)$, hence helping the balancing operations of the REC manager;
- when needed by the community, the REC manager sends a DR request to the EV charging station asking for a load reduction or increase over a given time window in exchange for a monetary reward.

[2]For ease of exposition, the REC manager and the electricity retailer are supposed to be the same entity.

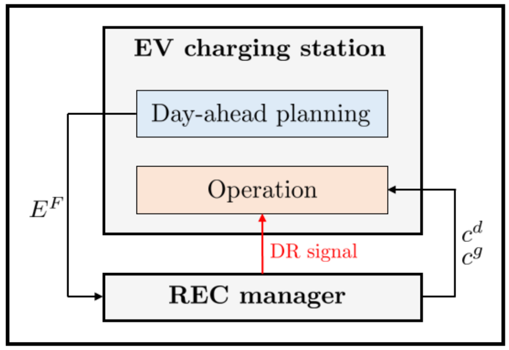


Figure 1: Graphical overview of the DR contract in place. Black arrows denote the information exchanged between the EVCS and the REC manager at the beginning of the day. The red arrow denotes a DR signal sent to the EVCS during the day.

An overview of the communication scheme between the charging station and the REC is reported in Fig. 1.

## *2.1. Charging station model*

We consider a parking lot equipped with charging units that serve the charging needs of plug-in electric vehicles. As a customer satisfaction criteria, it is assumed that the charging station guarantees an average (or nominal) charging power rate $P_0$ to every customer at any time. When vehicle $v$ arrives at the charging station at time $t_v^a$, it declares its requirement in terms of energy to be charged, denoted by $E_v^f$. Let $\eta$ be the vehicle charging efficiency, and let $\tau_v^f = \left\lceil \frac{E_v^f}{\eta \Delta P_0} \right\rceil$ be the number of time slots required to satisfy the request by charging the EV at nominal power rate, which we refer to as the *fulfillment duration*. Moreover, denote by $\tau_v^p$ the parking duration of the $v$-th vehicle, then the related *charging duration* $\tau_v^c$ equals to

$$\tau_v^c = \min\left\{\tau_v^p, \tau_v^f\right\}.$$

Let $S_v(t)$ denote the energy charged up to time $t$. To assure customer satisfaction, the following inequality must be enforced

$$r_v(t) \leq S_v(t) \leq E_v^f \quad t = t_v^a, \ldots, t_v^c, \tag{1}$$

where $r_v(t) = \min\{\eta \Delta P_0 (t - t_v^a), E_v^f\}$ is the nominal charging profile and $t_v^c = t_v^a + \tau_v^c$ is the time when charging ends. Constraint (1) requires the charging station to ensure a minimum average charging power rate $P_0$ to its customers, avoiding situations in which a vehicle is charged less than expected at departure. On the other hand, it prevents users to claim the full energy amount $E_v^f$ when they leave early (i.e., $\tau_v^f > \tau_v^p$). We assume that the charging station is equipped with enough charging units to satisfy all the incoming vehicles. As a consequence, a vehicle can be ignored after $t_v^c$. Indeed, an EV may in principle keep a charging unit busy for longer time than the actual charging duration. However, after $t_v^c$ such a vehicle will not be considered in the charging schedule since it either left the charging station, or its charging requirements have been fulfilled.

Let $P_v(t)$ denote the average charging rate of the vehicle in the time interval $[t, t+1]$. Then, the charged energy at time step $t+1$ evolves according to

$$S_v(t+1) = S_v(t) + \eta \Delta P_v(t) \quad t = t_v^a, \ldots, t_v^c - 1. \tag{2}$$

Finally, it is assumed that the charging power is bounded by

$$0 \leq P_v(t) \leq \bar{P} \qquad\qquad t = t_v^a, \ldots, t_v^c - 1, \tag{3}$$

where $\bar{P} \geq P_0$ denotes the maximum charging power of a single charging unit. In the considered framework, we assume no hard upper bound on the main grid power capacity to supply the charging station (constraints involving this aspect will be the object of future studies).

### *2.2. Demand response model*

The DR program consists of time windows during which the total energy demand of the charging station must lie within predefined bounds. These energy requirements may arise in situations where the REC manager needs to adjust the REC demand profile in response to forecasts concerning either renewable energy production or periods of high energy demand. Monetary incentives are provided to the charging station for complying with these requests. Let $R$ denote the number of requests in a day, $t_r^b$ and $t_r^e$ respectively the start time and end time of request $r = 1, \dots, R$, and $t_r^n \leq t_r^b$ the time when the REC manager sends the DR signal to the charging station, which we refer to as the *notice time*.

The $r$-th DR signal consists of an upper bound $\overline{B}_r$ and a lower bound $\underline{B}_r$ of the total EVCS energy demand in the associated time window. If we let $E^S(t)$ be the energy consumed by the charging station in the time interval $[t, t+1]$, we define the energy violation $\delta_r$ associated to the $r$-th DR window as

$$\delta_r = \max\left\{ \sum_{t=t_r^b}^{t_r^e-1} E^S(t) - \overline{B}_r,\ \underline{B}_r - \sum_{t=t_r^b}^{t_r^e-1} E^S(t), 0 \right\}. \tag{4}$$

The monetary DR reward $\gamma_r$ is modeled as a function of the violation $\delta_r$

$$\gamma_r = g_r(\delta_r) = \begin{cases} f_r(\delta_r) & \text{if } \delta_r \leq \overline{\delta}_r, \\ 0 & \text{otherwise.} \end{cases} \tag{5}$$

where $f_r(\cdot)$ is assumed to be a positive concave non-increasing function and $\overline{\delta}_r$ is a given parameter that denotes the maximum allowed violation. If

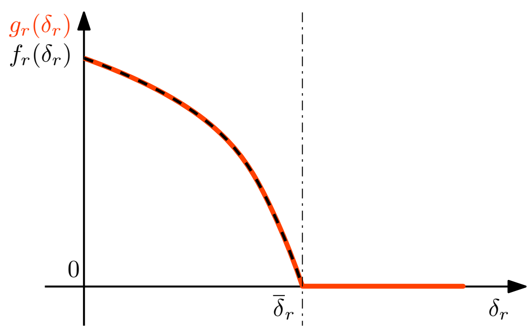


Figure 2: Example of monetary reward $\gamma_r$ (red) and of function $f_r(\delta_r)$ (black dashed).

the charging station wants to comply with the $r$-th request, then it seeks to coordinate the vehicle charging in such a way that the overall energy demand $\sum_{t=t_r^b}^{t_r^e-1} E^S(t)$ lies within the interval $[\underline{B}_r, \overline{B}_r]$ and the maximum reward $f_r(0)$ is provided. If the overall demand is outside $[\underline{B}_r, \overline{B}_r]$, then the incentive decreases as a function $f_r(\delta_r)$ of the violation incurred during the DR window, according to (5). Finally, if the violation is above $\overline{\delta}_r$, then no reward is provided to the charging station. A graphical representation of a reward function is depicted in Fig. 2

**Remark 1.** *Note that, in this setup, the participation into the DR program is provided by the charging station rather than each single vehicle. In fact, the charging station is committed to both ensure user satisfaction (guaranteeing a nominal power $P_0$) and support community tasks (by following the declared profile and participating to the DR program). From the EV perspective, this setup ensures the charging service without asking for the active participation of each customer. From the community perspective, the EVCS can optimize the charging schedule to provide a flexible and resilient operation to boost REC performance.*

*2.3. EV stochastic charging process description*

The number of daily incoming vehicles for different days is assumed to be independent, identically distributed according to some probability distribution. Similarly, the charging parameters $(t_v^a, \tau_v^p, \tau_v^f)$ are assumed to be independent and identically distributed for different vehicles according to day-invariant probability distributions. Moreover, assume that the related probability distributions (or an estimate of them) are available to the EVCS.

Let $E^U(t)$ be the load profile generated by considering an uncoordinated charging strategy at constant nominal power $P_0$. Clearly, such a profile cannot be known in advance due to the uncertainty affecting vehicles. However, since all the EVs are charged by using the same power rate $P_0$, the energy drawn at each time slot depends only on the number of connected vehicles at that time slot. The distribution of the number of vehicles, $H(t)$, charging at time $t$ is given by

$$\mathcal{P}(H(t)=n) = \sum_{m=n}^{\overline{N}} \mathcal{P}(H(t)=n|N=m)\,\mathcal{P}(N=m)\,,$$

where

$$\mathcal{P}\left(H(t)=n|N=m\right) = \binom{m}{n}\mathcal{P}(t^a \le t,\ t^c > t)^n \mathcal{P}(\overline{t^a \le t,\ t^c > t})^{m-n}\,, \qquad (6)$$

and $\overline{N}$ denotes the upper bound of the daily number of incoming vehicles, which is assumed to be known. The interested reader may refer to [15] for a detailed derivation of (6). Finally, let us define

$$E^F(t) = \mathbb{E}[E^U(t)] = \Delta P_0 \sum_{n=1}^{\overline{N}} n\mathcal{P}\left(H(t)=n\right).$$

Notice that the probability distribution of the charging time is not explicitly expressed, but depends on the realizations of the parking time and the fulfillment duration. Since the random variables related to each vehicle are assumed to be independent and identically distributed, we can derive the explicit form of the charging time probability distribution as

$$
\begin{aligned}
\mathcal{P}\left(\tau^c = k\right) &= \mathcal{P}\left(\min\{\tau^p, \tau^f\} = k\right) \\
&= \mathcal{P}\left(k-1 < \min\{\tau^p, \tau^f\} \leq k\right) \\
&= \mathcal{P}\left(\min\{\tau^p, \tau^f\} > k-1\right) - \mathcal{P}\left(\min\{\tau^p, \tau^f\} > k\right) \\
&= \mathcal{P}\left(\tau^p \geq k, \tau^f \geq k\right) - \mathcal{P}\left(\tau^p > k, \tau^f > k\right),
\end{aligned}
$$

where

$$
\mathcal{P}\left(\tau^p \geq k, \tau^f \geq k\right) = \sum_{\tau=k}^{\overline{\tau}^f} \mathcal{P}\left(\tau^p \geq k | \tau^f = \tau\right) \mathcal{P}\left(\tau^f = \tau\right), \tag{7}
$$

and $\overline{\tau}^f$ is a known upper bound on the fulfillment duration.

## 3. Receding horizon formulation

Let $\mathcal{V}(t)$ be the set of electric vehicles that are parked and charging at time $t$,

$$
\mathcal{V}(t) = \left\{v \in \mathbb{N} : t_v^a \leq t < t_v^d, \quad S_v(t) < E_v^f\right\}, \tag{8}
$$

where $t_v^d = t_v^a + \tau_v^p$ is the departure time of the $v$-th vehicle. The set of DR requests $\mathcal{R}(t)$ to be considered in the optimization horizon is defined as

$$
\mathcal{R}(t) = \left\{r \in \mathbb{N} : t_r^n \leq t \leq t_r^e - 1\right\}, \tag{9}
$$

and comprises requests announced by the REC manager ($t \geq t_r^n$) and not yet expired ($t \leq t_r^e - 1$).

### 3.1. Objective function

Optimization is performed over a shrinking horizon, starting from the current time step $t$ up to the end of the day. The objective function $J(t)$ represents the operating costs of the charging station from time $t$ up to time $T-1$ comprising

$$J(t) = \sum_{k=t}^{T-1} (\underbrace{\mathbb{E}[E^S(k)|t]c^g}_{\text{Electricity cost}} + \underbrace{\left|\mathbb{E}[E^S(k)|t] - E^F(k)\right| c^d}_{\text{Deviation cost}}) - \underbrace{\sum_{r\in\mathcal{R}(t)} \tilde{\gamma}_r}_{\text{DR reward}}, \qquad (10)$$

where $c^g$ is electricity price of the energy purchased from the grid, $c^d$ is the unitary cost for the deviation around the profile $E^F(k)$ and $\tilde{\gamma}_r$ is the decision variable concerning the reward of the $r$-th DR request. Note that in (10), all the quantities are computed according to the information available at time $t$.

### 3.2. Charging station energy demand

The expected value of the energy demand at time $k \geq t$ is given by

$$\mathbb{E}[E^S(k)|t] = \sum_{v\in\mathcal{V}(t)} \Delta P_v(k) \cdot \mathcal{P}(t_v^d > k | t_v^d > t) + \mathbb{E}[E^U(k)|t], \qquad (11)$$

where $\mathbb{E}[E^U(k)|t]$ is the expectation of the energy demand for future incoming vehicles assuming the uncoordinated charging at constant power rate $P_0$ conditioned on the current information up to time $t$. Note that for vehicles in $\mathcal{V}(t)$, since the related energy to be charged $E_v^f$ and consequently the fulfillment duration $\tau_v^f$ are provided at their arrival, the only source of uncertainty is related to the parking time $\tau_v^p$ and hence to $t_v^d$. This means that to compute the expected value of the energy demand of the connected vehicles, it one can only consider $t_v^d$ in the probability computations.

Concerning future charging events, let $A(t)$ be the number of vehicles that have arrived up to time $t$, and suppose that it equals to $n_a$. Moreover, denote by $W(k,t)$ the number of incoming after time $t$ and that are charging at time $k$, then

$$\mathbb{E}[E^U(k)|t] = \Delta P_0 \sum_{n=1}^{\overline{N}-n_a} n\mathcal{P}(W(k,t)=n|A(t)=n_a, t^a>t). \tag{12}$$

Let $Q(t)$ be a random variable denoting the number of incoming vehicles after time $t$. Then, its probability distribution conditioned to the information at time $t$ is equivalent to

$$\mathcal{P}\left(Q(t)=m|A(t)=n_a, t^a>t\right) = \mathcal{P}\left(N=m+n_a|A(t)=n_a\right). \tag{13}$$

By using (13), the probability in (12) can be computed as

$$\begin{aligned}
&\mathcal{P}(W(k,t)=n|A(t)=n_a, t_a>t) = \\
&\quad\sum_{m=n}^{\overline{N}-n_a} \mathcal{P}(W(k,t)=n|Q(t)=m, A(t)=n_a, t_a>t)\cdot\mathcal{P}(Q(t)=m|A(t)=n_a, t_a>t) \\
&\quad\sum_{m=n}^{\overline{N}-n_a} \mathcal{P}(W(k,t)=n|Q(t)=m, t_a>t)\cdot\mathcal{P}(N=m+n_a|A(t)=n_a).
\end{aligned}$$

Further details about these computations can be found in [15].

*3.3. DR constraints*

To each request $r \in \mathcal{R}(t)$ we associate a variable $l_r = \max\{t, t_r^b\}$. The decision variable concerning the reward $\tilde{\gamma}_r$ is constrained as follows

$$z_r^{DR} \in \{0,1\} \tag{14}$$

$$0 \leq \tilde{\gamma}_r \leq M z_r^{DR} \tag{15}$$

$$\tilde{\gamma}_r \leq f_r(\tilde{\delta}_r) \tag{16}$$

$$\tilde{\delta}_r \geq 0 \tag{17}$$

$$\tilde{\delta}_r \geq \left( \sum_{k=l_r}^{t_r^e - 1} \mathbb{E}[E^S(k)|t] \right) + E_{r,t}^P - \overline{B}_r - M(1 - z_r^{DR}) \tag{18}$$

$$\tilde{\delta}_r \geq \underline{B}_r - \left( \sum_{k=l_r}^{t_r^e - 1} \mathbb{E}[E^S(k)|t] \right) - E_{r,t}^P - M(1 - z_r^{DR}) \tag{19}$$

$$\tilde{\delta}_r \leq \overline{\delta}_r z_r^{DR} + M(1 - z_r^{DR}), \tag{20}$$

where $\tilde{\delta}_r$ is the forecast of the violation in the $r$-th DR window. Binary variables $z_r^{DR}$ represent the choice of the charging station to comply with the DR request ($z_r^{DR} = 1$) or not ($z_r^{DR} = 0$). In (15), the reward is constrained to be positive, while (16) provides the epigraph representation of the DR reward. In (17)-(19) the reformulation of the forecast of DR violation is derived. Finally, in (20), if the charging station wants to comply with the $r$-th request, the violation is enforced to be below $\overline{\delta}_r$. We make use of the so-called "big M" formulation for the binary variables, where $M$ denotes a "big enough" constant, while $E_{r,t}^P$ represents the past energy consumption of the system in the DR window up to time $t$ which is defined as

$$E_{r,t}^P = \begin{cases} \sum_{k=t_r^b}^{t-1} E^S(k) & \text{if } t > t_r^b, \\ 0 & \text{else.} \end{cases}$$

Finally, note that since $f(\cdot)$ is assumed to be concave, constraint (16) is convex.

### 3.4. EV forecast handling

Since $t_v^c$ is unknown for plugged-in vehicles, constraints (1)-(3) need to be adapted to be embedded into the optimization procedure. To this aim, let us define $t_v^f = t_v^a + \tau_v^f$ as the fulfillment time, then (1)-(3) become

$$r_v(t) \leq S_v(t) \leq E_v^f \qquad t = t_v^a, \dots, t_v^f, \tag{21}$$

$$S_v(t+1) = S_v(t) + \eta \Delta P_v(t) \qquad t = t_v^a, \dots, t_v^f - 1, \tag{22}$$

$$0 \leq P_v(t) \leq \bar{P} \qquad t = t_v^a, \dots, t_v^f - 1. \tag{23}$$

Note that, from the definition of $t_v^c$ one has $t_v^f \geq t_v^c$. Moreover, contrary to $t_v^c$ which is a random variable, the fulfillment time is fixed as soon as the vehicle arrives at the charging station.

Concerning vehicles that have not yet arrived at the charging station, it may happen that the simple uncoordinated charging forecast may be too restrictive during DR request windows. Therefore, a strategy providing more flexibility to these forecasts is presented in the following. Consider a vehicle $v$ and let $t_v^a$ and $t_v^c$ be given. For a given request $r$ satisfying $t_v^a < t_r^b < t_v^c$, define $t_{v,r}^{in} = \min\{t_v^c, t_r^e\}$ as the last time instant when the vehicle is inside the DR request. Next, let $\tau_{v,r}^{out} = t_r^b - t_v^a$ and $\tau_{v,r}^{in} = t_{v,r}^{in} - t_r^b$ be the number of time slots where a vehicle is charging before and inside the DR request, respectively. Hence, we may define as

$$\hat{E}_v = \Delta P_0(\tau_{v,r}^{out} + \tau_{v,r}^{in})$$

the amount of energy to be charged in the $v$-th vehicle from $t_v^a$ up to $t_{v,r}^{in}$, by charging at nominal power rate $P_0$. The maximum charging power rate that can be applied before the DR request begins is

$$P_{v,r}^{out} = \min\left\{\overline{P}, \frac{\hat{E}_v}{\Delta\tau_{v,r}^{out}}\right\} = \min\left\{\overline{P}, P_0\frac{\tau_{v,r}^{out}+\tau_{v,r}^{in}}{\tau_{v,r}^{out}}\right\}. \tag{24}$$

If a power reduction is requested, the reduced power rate inside the DR request is

$$P_{v,r}^{in} = \frac{\hat{E}_v - \Delta P_{v,r}^{out}\tau_{v,r}^{out}}{\Delta\tau_{v,r}^{in}} = \frac{P_0(\tau_{v,r}^{out}+\tau_{v,r}^{in}) - P_{v,r}^{out}\tau_{v,r}^{out}}{\tau_{v,r}^{in}},$$

where $P_{v,r}^{in} \geq 0$ due to (24). By using $P_{v,r}^{out}$ and $P_{v,r}^{in}$ one can compute the resulting average power increase occurring outside the DR request and the average power reduction during the request period. Let $\sigma_{v,r}^{out}(k)$ and $\sigma_{v,r}^{in}(k)$ be the average power increment and the average power reduction at time $k$, respectively. These quantities can be expressed as

$$\sigma_{v,r}^{out}(k) = \begin{cases} P_{v,r}^{out} - P_0 & \text{if } t_v^a \leq k < t_r^b \\ 0 & \text{else,} \end{cases}$$

and

$$\sigma_{v,r}^{in}(k) = \begin{cases} P_0 - P_{v,r}^{in} & \text{if } t_r^b \leq k < t_{v,r}^{in} \\ 0 & \text{else.} \end{cases}$$

Note that

$$\begin{aligned} &\sum_{k=t_v^a}^{t_{v,r}^{in}-1} \Delta\left(\sigma_{v,r}^{in}(k) - \sigma_{v,r}^{out}(k)\right) \\ &= (P_0 - P_{v,r}^{in})\tau_{v,r}^{in}\Delta - (P_{v,r}^{out} - P_0)\tau_{v,r}^{out}\Delta \\ &= P_0(\tau_{v,r}^{in} + \tau_{v,r}^{out})\Delta - P_{v,r}^{in}\tau_{v,r}^{in}\Delta - P_{v,r}^{out}\tau_{v,r}^{out}\Delta \\ &= P_{v,r}^{out}\tau_{v,r}^{out}\Delta - P_{v,r}^{out}\tau_{v,r}^{out}\Delta = 0, \end{aligned}$$

hence the increment of energy charged before the DR window equals the reduced amount inside the DR request. Notice that, since these quantities involve only vehicles that have not yet arrived (i.e., $t_v^a$ and $t_v^c$ are not known), $\sigma_{v,r}^{in}(k)$ and $\sigma_{v,r}^{out}(k)$ are actually random variables. Thus, these quantities will contribute to the demand forecasts by means of their expectation.

On aggregate level, the expected value of the energy reduction/increase at each time step is computed as follows

$$\nu_r(k) = \mathbb{E}\left[\sum_{v=1}^{N} \Delta\Big(\sigma_{v,r}^{in}(k) - \sigma_{v,r}^{out}(k)\Big)\right] = \Delta\mathbb{E}\left[\sum_{v=1}^{N} \sigma_{v,r}^{in}(k)\right] - \Delta\mathbb{E}\left[\sum_{v=1}^{N} \sigma_{v,r}^{out}(k)\right]. \tag{25}$$

Since $\sigma_{v,r}^{in}(k)$ are independent of the index $v$,

$$\mathbb{E}\left[\sum_{v=1}^{N} \sigma_{v,r}^{in}(k)\right] = \mathbb{E}[N] \cdot \mathbb{E}[\sigma_{v,r}^{in}(k)],$$

where

$$\mathbb{E}[\sigma_{v,r}^{in}(k)] = \sum_{l=0}^{t_r^b-1} \sum_{\tau=t_r^b}^{T-1} \mathcal{P}(t_v^a = l) \cdot \mathcal{P}(t_v^c = \tau | t_v^a = l) \cdot \sigma_{v,r}^{in}(k).$$

Note that we are considering all the charging time windows satisfying $t_v^a < t_r^b < t_v^c$. $\mathbb{E}\left[\sum_{v=1}^{N} \sigma_{v,r}^{out}(k)\right]$ can be obtained in a similar way, i.e.,

$$\mathbb{E}\left[\sum_{v=1}^{N} \sigma_{v,r}^{out}(k)\right] = \mathbb{E}[N] \cdot \mathbb{E}[\sigma_{v,r}^{out}(k)],$$

where

$$\mathbb{E}[\sigma_{v,r}^{out}(k)] = \sum_{l=0}^{t_r^b-1} \sum_{\tau=t_r^b}^{T-1} \mathcal{P}(t_v^a = l) \cdot \mathcal{P}(t_v^c = \tau | t_v^a = l) \cdot \sigma_{v,r}^{out}(k).$$

**Remark 2.** *The computation of the previous expected values can be adapted for a given time step $t$ by substituting to $N$ the random variable $Q(t)$, and by conditioning the probability distributions to the current available information (i.e., $A(t) = n_a$ and $t^a > t$).*

At this point, a set of auxiliary variables $\tilde{\nu}_r(k)$ can be added satisfying

$$\nu_r^-(k) \leq \tilde{\nu}_r(k) \leq \nu_r^+(k) \qquad k = t, \dots, T, \forall r \in \mathcal{R}(t) \tag{26}$$

$$\sum_{k=t}^{T} \tilde{\nu}_r(k) = 0 \qquad \forall r \in \mathcal{R}(t), \tag{27}$$

where $\nu_r^-(k) = \min\{0, \nu_r(k)\}$ and $\nu_r^+(k) = \max\{0, \nu_r(k)\}$.

On the other hand, in situations where a demand increase is requested, one can similarly compute the modified EV demand in the request window. In this case, EVs will be charged with the maximum power rate inside the DR window and then charged with a reduced power rate after the DR period. To this end, assume that the expected value of the demand increment is modeled via inside the variable $\omega_r(k)$. Then, one can add another set of auxiliary variables

$$\omega_r^-(k) \leq \tilde{\omega}_r(k) \leq \omega_r^+(k) \qquad k = t, \dots, T, \forall r \in \mathcal{R}(t) \tag{28}$$

$$\sum_{k=t}^{T} \tilde{\omega}_r(k) = 0 \qquad \forall r \in \mathcal{R}(t) \tag{29}$$

where $\omega_r^-(k) = \min\{0, \omega_r(k)\}$ and $\omega_r^-(k) = \max\{0, \omega_r(k)\}$. Finally, by combining (11) with $\tilde{\nu}_r(k)$ and $\tilde{\omega}_r(k)$, the shaped forecast $\mathbb{E}[\tilde{E}^S(k)|t]$ of the future energy demand becomes

$$\mathbb{E}[\tilde{E}^S(k)|t] = \mathbb{E}[E^S(k)|t] - \sum_{r \in \mathcal{R}(t)} (\tilde{\nu}_r(k) + \tilde{\omega}_r(k)) \quad \forall k = t, \dots, T, \tag{30}$$

Thus, $\mathbb{E}[\tilde{E}^S(k)|t]$ will be used as the forecast of the energy demand $\mathbb{E}[E^S(k)|t]$ in (10), (18) and (19), providing more flexibility to the optimization. In fact, thanks to (26)-(29), it is possible to add more elasticity to the EV demand forecasts by considering different charging strategies: the optimizer can choose any energy profile between the modified and the nominal one.

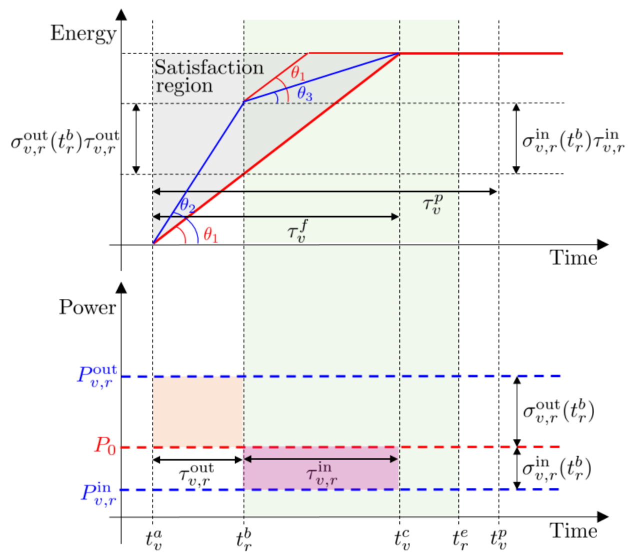


Figure 3: Graphical representation of the main quantities involved. The green area denotes the DR period, while the pink area denotes the energy increase (left area) and the energy reduction (right area). Finally, $\tan(\theta_1) = \Delta P_0$, $\tan(\theta_2) = \Delta P^{out}_{v,r}$ and $\tan(\theta_3) = \Delta P^{in}_{v,r}$.

Several other valuable strategies to shape the forecast of the EV charging process can be considered. The proposed procedure allows the charging station to anticipate the maximum amount of energy outside/inside the request windows for each vehicle, while guaranteeing the nominal charging profile as in (1). As a consequence, this is a good trade-off that provides a lower/upper bound on the energy demand inside DR requests. The scheme is summarized in Fig. 3.

### *3.5. Receding horizon procedure*

The proposed receding horizon strategy relies on the solution of an optimization problem at each time step $t$. The charging power commands for the EVs in $\mathcal{V}(t)$ are obtained as the solution of the following problem

**Problem 1.**

$$
\begin{aligned}
P_v^*(t) = \arg \min_{P_v(t):v\in\mathcal{V}(t)} & J(t) \\
\text{s.t.} \quad & (10) - (19) \\
& (21) - (23) \\
& (26) - (30).
\end{aligned}
$$

This optimization problem is a convex program except for the binary variables whose number is equal to the number of DR requests falling inside the optimization horizon. Since in real scenarios the number of DR requests per day is typically low, i.e., less or equal than two [29], Problem 1 can be effectively solved by standard optimization tools.

Algorithm 1 provides a sketch of the overall receding horizon procedure, whereas in Fig. 4 the visual representation of the procedure is shown.

At each time step $t$, the procedure is based on two main steps:

1. all the problem quantities are updated on the basis of the information available at time $t$;
2. Problem 1 is solved and the first command of the optimal solution is applied.

## 4. Numerical results

### *4.1. Simulation settings*

To test the performance of the presented approach, a 100 day simulation with a sampling time of $\Delta = 10$ minutes was performed. For each day, the realizations of the random variables concerning the EV charging process have

**Algorithm 1:** Receding horizon algorithm.

**Data:** $c^g$ and $c^d$, DR daily program, and distributions on the EV charging process.

Set $t = 1$;<br>
**while** $t \leq T$ **do**<br>
    $n_a = |\{v : t_v^a \leq t\}|$;<br>
    compute $\mathcal{V}(t)$ as in (8);<br>
    compute $\mathcal{R}(t)$ as in (9);<br>
    compute $\mathbb{E}[E^U(k)|t], k = t, \ldots, T-1$ as in (12);<br>
    compute $\nu_r(k), \forall r \in \mathcal{R}(t), k = t, \ldots, T-1$ as in (25);<br>
    compute $\omega_r(k), \forall r \in \mathcal{R}(t), k = t, \ldots, T-1$;<br>
    solve Problem 1 and get $P_v^*(t),\ \forall v \in \mathcal{V}(t)$;<br>
    $S_v(t+1) = S_v(t) + \eta \Delta P_v^*(t),\ \forall v \in \mathcal{V}(t)$;<br>
    $t = t + 1$;<br>
**end**

been drawn from probability distributions estimated from real data. Distributions concerning arrival time, energy to be charged and parking time have been estimated by using the historical data reported in [30], shown in Fig. 5. Specifically, the estimates provided in Fig. 5 represent the normalized histograms of the acquired data. The random variable concerning the daily number of incoming vehicles has been modeled through a Gaussian distribution with mean 175 and standard deviation 9 to obtain realizations in the interval $[150, 200]$ vehicles with high confidence. The nominal charging power $P_0$ has been set to 11 kW, the maximum charging power rate $\bar{P}$ to 22 kW and the charging efficiency to 0.9.

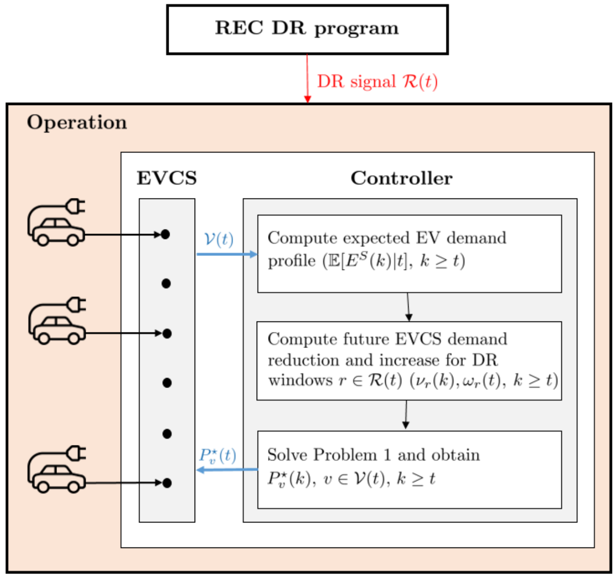


Figure 4: Graphical overview of the receding horizon algorithm proposed.

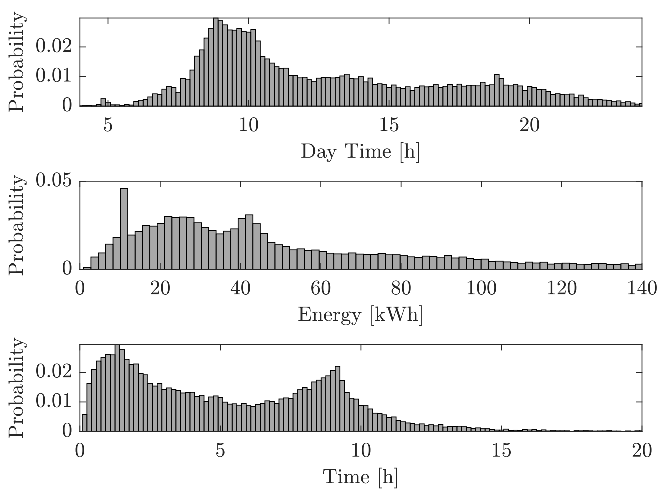


Figure 5: Charging process distributions. Top panel: Arrival time distribution. Middle panel: Energy to be charged distribution. Bottom panel: Parking time distribution.

For all days, the deviation cost $c^d$ is set to 0.20 €/kWh and the grid price $c^g$ to 0.05 €/kWh. The number of DR requests per day, $R$, is randomly chosen between 1 and 2 with equal probability. The starting time of each request has been generated according to a uniform distribution ranging from 9:00 AM to 3:00 PM, while the related time window is distributed in the interval $[60, 90]$ minutes. If two requests are considered for a given day, the minimum time between the end of the first request and the beginning of the second is set to 3 hours. The charging station gets the notification about the DR request according to a uniform distribution defined in a time window of $[6, 8]$ hours before the request begins. The DR bounds have been randomly generated by selecting one of the following two scenarios:

1. an upper bound $\overline{B}_r = 0.4 \sum_{t=t_r^b}^{t_r^e-1} E^F(t)$ and no lower bound, i.e., $\underline{B}_r = 0$;
2. a lower bound $\underline{B}_r = 1.6 \sum_{t=t_r^b}^{t_r^e-1} E^F(t)$ and no upper bound, i.e., $\overline{B}_r = \infty$.

Finally, the maximum reward has been chosen according to the formula

$$g_r(0) = \rho \cdot \max \left\{ \sum_{t=t_r^b}^{t_r^e-1} E^F(t) - \overline{B}_r, \underline{B}_r - \sum_{t=t_r^b}^{t_r^e-1} E^F(t) \right\},$$

where $\rho = 1$ €/kWh. The reward decreases according to the piecewise affine function

$$g_r(\delta_r) = f(0) \cdot \min_{d=1,2,3} \left( \alpha_{r,d}\delta_r + \beta_{r,d} \right).$$

whose coefficients $\alpha_{r,d}$ and $\beta_{r,d}$ are reported in Tab. 1 and $\overline{\delta}_r = -\beta_{r,3}/\alpha_{r,3}$. Simulations have been run using MATLAB, the formulation has been built using YALMIP [31] and solved by CPLEX [32] on an i7-11700K@3.6GHz with 32GB RAM.

Table 1: Values of $\alpha_{r,d}$ and $\beta_{r,d}$.

| $\boldsymbol{\alpha_{r,1}}$ | $\boldsymbol{\alpha_{r,2}}$ | $\boldsymbol{\alpha_{r,3}}$ | $\boldsymbol{\beta_{r,1}}$ | $\boldsymbol{\beta_{r,2}}$ | $\boldsymbol{\beta_{r,3}}$ |
|---|---|---|---|---|---|
| -4 | -6 | -6.67 | 1 | 1.10 | 1.17 |

### *4.2. Simulation results*

To validate the effectiveness of the proposed **receding horizon strategy (RH)**, we compare its performance with three benchmarks:

- **nominal charging policy (NCP)**: all the vehicles are charged at nominal charging power rate $P_0$;
- **RH with no forecast handling (NFH)**: a receding horizon procedure that considers $\nu_r(k) = \omega_r(k) = 0$ for all $k$. This amounts to solving Problem 1 without constraints (26)-(30). Upon appropriate modifications to fit the current setting, such an approach corresponds to that reported in [26];
- **omniscient oracle optimization (OR)**: a one-shot optimization problem with access to the realizations of all random variables. This amounts to an a-posteriori optimization performed at the end of the day, so the comparison is similar to evaluating the so-called "regret" of our strategy [33]. OR is clearly an optimistic, non-causal benchmark that cannot be implemented in practice.

The average daily cost of all the considered strategies is reported in Tab. 2, whereas the RH daily cost comparison w.r.t. NCP and NFH are reported in Fig. 6. The worst strategy is the NCP since it cannot coordinate the EV

Table 2: Average daily cost for all the strategies.

| | RH | NCP | NFH | OR |
|---|---|---|---|---|
| **Cost [€]** | 199.27 | 412.24 | 226.19 | 115.29 |
| **OR distance [%]** | 72.93 | 257.75 | 96.30 | 0 |

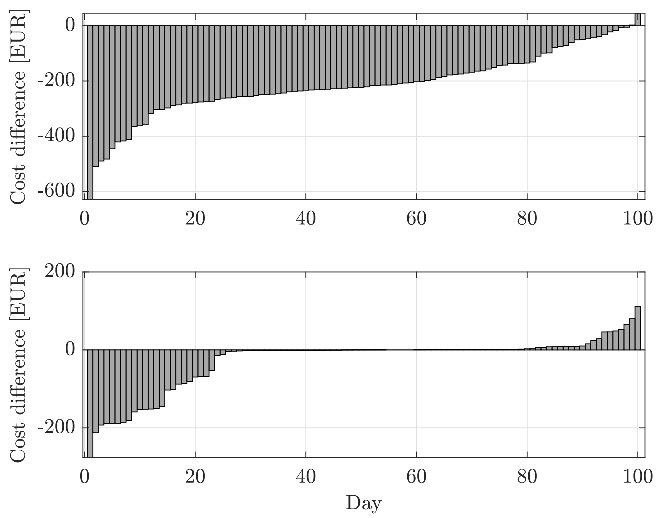


Figure 6: Top panel: Daily cost difference between NCP and RH sorted in ascending order. Bottom panel: Daily cost difference between NFH and RH sorted in ascending order.

charging to meet DR requests, nor track the declared profile $E^F(t)$. On the other hand, NFH improves cost performance. The main difference to RH is that the predictive capabilities of NFH are limited to the scenario where during DR windows all incoming vehicles are charged at the nominal charging power rate. By relaxing this constraint, the RH procedure further reduces the charging station cost by around 11.9%. Considering the algorithm behavior with respect to the OR, the RH daily cost is on average 83.98% larger. This comes as no surprise since the OR is based on the unrealistic assumption of perfect knowledge of the charging process. In the considered simulations, the number of fulfilled requests amounts to 101 for the RH procedure, to 2 for the NCP, to 81 for the NFH, and to 124 for the OR over 132 total requests.

In Fig. 7, the energy profiles declared to the REC manager and the actual energy consumption over three simulated days are reported. Fig. 7(a) considers a day with only one DR request, where both RH and OR can satisfy the request. In order to fulfill the incoming request and reduce vehicle demand during the DR period, both the RH and OR procedures are forced to anticipate vehicle charging. Fig. 7(b) considers a day with two DR requests, one requiring a demand reduction and the other a demand increase. Similar to the previous case, both RH and OR comply with the two requests. Differently from Fig. 7(a), RH is forced to anticipate vehicle charging in order to fulfill the first request since it does not have information about the exact realization of the incoming vehicles. Fig. 7(c) considers a day with two DR requests. Contrary to the previous cases, both requests have not been satisfied by the RH procedure. The first request has not been fulfilled since the actual EV demand is higher than the declared profile. In this case, the OR procedure is not able to fulfill the request either. On the other hand, the second request is satisfied by OR, but not by RH. RH fails to fulfill the request due to the presence of an EV demand peak during the DR window (see green profile) that has not been forecasted. The RH procedure first aims to comply with the request (see the spike in the energy before the beginning of the request). However, as the EV demand increases, the RH procedure recognizes that the request cannot be satisfied. Hence, the RH strategy is left with adapting the EV charging to match the declared profile.

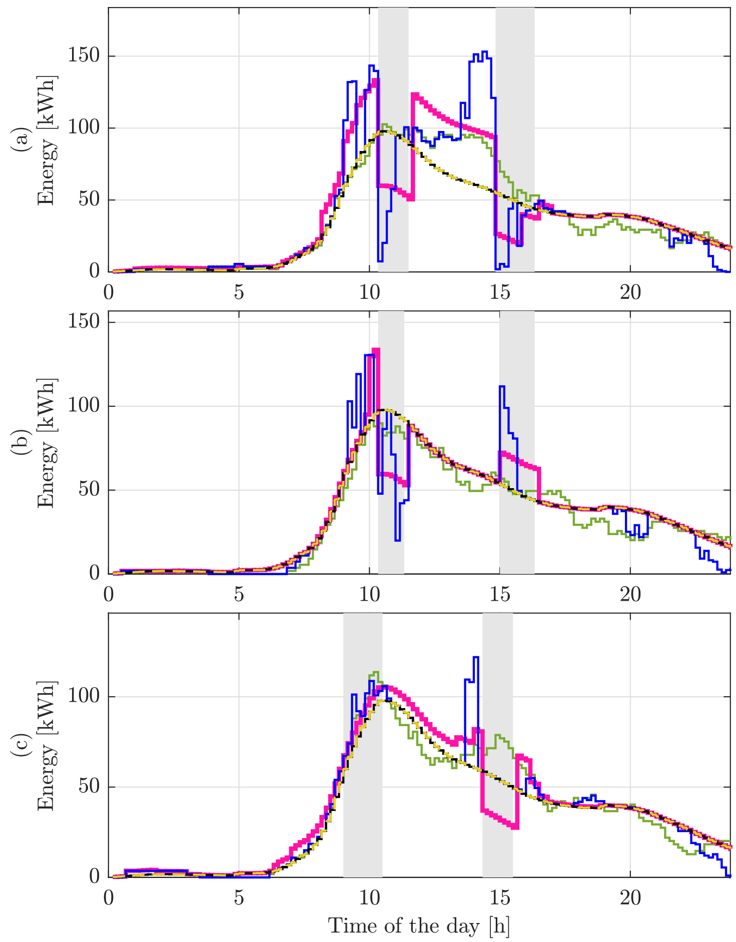


Figure 7: Energy profiles of the charging station of three days: energy forecast (yellow-black dashed), proposed RH strategy (blue), OR (purple) and NCP (green). The DR time interval is denoted by the grey area.

To show how the vehicle charging schedule changes according to different strategies, the energy charged in a vehicle during a given day is shown in Fig. 8. As a reference, the considered day is the same depicted in Fig. 7(a). During the charging period both the RH and OR anticipate EV charging in order to comply with the incoming DR request.

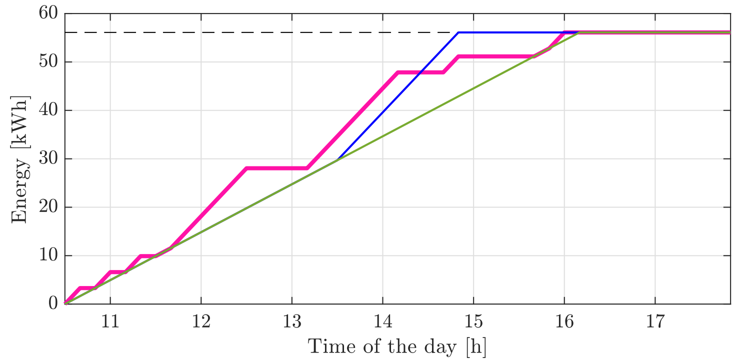


Figure 8: Energy charged in a vehicle for a given day: $E_v^f$ (black dashed), proposed RH strategy (blue), OR (purple) and NCP (green).

### *4.3. Sensitivity analysis*

In this section, some sensitivity analyses related to different parameters used by the proposed technique are reported. First, the performance of the considered algorithm has been evaluated with respect to changes of the deviation cost $c^d$ and the DR reward $\rho$. Specifically, we have considered problem instances where $c^d \in \{0.1, 0.2, 0.4\}$ €/kWh, while $\rho = 1$ €/kWh. Concerning the DR unitary reward, we consider $\rho \in \{0.5, 1.5\}$ €/kWh, while $c^d = 0.2$ €/kWh. To allow for a clear interpretation of the results, we assume the same realizations of the EV events and DR requests for all the considered setups. Daily operating costs of the EVCS according to price variations are reported in Tab. 3. For the sake of completeness, deviation cost, electricity cost and DR reward which compose the operation cost in (10) are reported in Tab. 4, 5 and 6, respectively. It is worthwhile to note that the costs reported in Tab. 3 are consistent with all the considered

Table 3: Average daily cost of the considered procedures according to different prices.

| | Overall cost [€] | | | |
|---|---|---|---|---|
| **Price [€/kWh]** | **RH** | **NCP** | **NFH** | **OR** |
| $\mathbf{c^d = 0.1}, \rho = \mathbf{1}$ | 125.52 | 331.46 | 164.26 | 53.07 |
| $\mathbf{c^d = 0.2}, \rho = \mathbf{1}$ | 201.83 | 412.23 | 227.74 | 115.23 |
| $\mathbf{c^d = 0.4}, \rho = \mathbf{1}$ | 343.45 | 573.77 | 356.09 | 237.33 |
| $\mathbf{c^d = 0.2}, \rho = \mathbf{0.5}$ | 304.96 | 412.98 | 312.69 | 252.04 |
| $\mathbf{c^d = 0.2}, \rho = \mathbf{1.5}$ | 95.89 | 411.49 | 145.01 | -22.66 |

Table 4: Average daily deviation cost of the considered procedures according to different prices.

| | Deviation cost [€] | | | |
|---|---|---|---|---|
| **Price [€/kWh]** | **RH** | **NCP** | **NFH** | **OR** |
| $\mathbf{c^d = 0.1}, \rho = \mathbf{1}$ | 77.38 | 80.77 | 66.84 | 62.16 |
| $\mathbf{c^d = 0.2}, \rho = \mathbf{1}$ | 149.03 | 161.54 | 130.51 | 124.32 |
| $\mathbf{c^d = 0.4}, \rho = \mathbf{1}$ | 288.03 | 323.08 | 248.41 | 239.50 |
| $\mathbf{c^d = 0.2}, \rho = \mathbf{0.5}$ | 142.87 | 161.54 | 117.43 | 119.75 |
| $\mathbf{c^d = 0.2}, \rho = \mathbf{1.5}$ | 152.19 | 161.54 | 130.55 | 124.32 |

scenarios. Clearly, RH and NFH exhibit lower cost difference in setups where the DR reward is less convenient than the deviation cost (i.e., when $c^d = 0.4$ €/kWh, or when $\rho = 0.5$ €/kWh). However, by focusing on Tab. 6, RH shows much better capabilities to comply with DR requests in all the investigated instances. Concerning electricity cost, as reported in Tab. 5, it is evident that the considered algorithms are less sensitive to price variations. On the contrary, the deviation cost reported in Tab. 4 results more sensitive, but

Table 5: Average daily electricity cost of the considered procedures according to different prices.

| | Electricity cost [€] | | | |
|---|---|---|---|---|
| **Price [€/kWh]** | **RH** | **NCP** | **NFH** | **OR** |
| $\mathbf{c^d = 0.1}, \rho = \mathbf{1}$ | 263.43 | 252.18 | 261.88 | 266.68 |
| $\mathbf{c^d = 0.2}, \rho = \mathbf{1}$ | 263.54 | 252.18 | 262.25 | 266.68 |
| $\mathbf{c^d = 0.4}, \rho = \mathbf{1}$ | 263.27 | 252.18 | 262.21 | 266.74 |
| $\mathbf{c^d = 0.2}, \rho = \mathbf{0.5}$ | 263.29 | 252.18 | 261.67 | 266.74 |
| $\mathbf{c^d = 0.2}, \rho = \mathbf{1.5}$ | 263.54 | 252.18 | 262.26 | 266.68 |

Table 6: Average daily DR reward of the considered procedures according to different prices.

| | DR reward [€] | | | |
|---|---|---|---|---|
| **Price [€/kWh]** | **RH** | **NCP** | **NFH** | **OR** |
| $\mathbf{c^d = 0.1}, \rho = \mathbf{1}$ | 215.30 | 1.49 | 164.46 | 275.78 |
| $\mathbf{c^d = 0.2}, \rho = \mathbf{1}$ | 210.74 | 1.49 | 165.02 | 275.78 |
| $\mathbf{c^d = 0.4}, \rho = \mathbf{1}$ | 207.85 | 1.49 | 154.53 | 268.90 |
| $\mathbf{c^d = 0.2}, \rho = \mathbf{0.5}$ | 101.20 | 0.75 | 66.41 | 134.45 |
| $\mathbf{c^d = 0.2}, \rho = \mathbf{1.5}$ | 319.84 | 2.24 | 247.80 | 413.67 |

it is linearly proportional to $c^d$. Therefore, even though the overall cost changes consistently with price variations, the presented algorithms show similar behaviors in all the problem instances.

Additional analyses have been performed (i) by increasing the duration of DR requests and (ii) by considering an inaccurate distribution for predicting the daily number of EVs. In the first case, the DR program has been modified to generate DR requests whose duration ranges in the interval $[1.5, 2.5]$ hours, while the remaining parameters are left unchanged. Note that this scenario provides more restrictive DR program, since the bound requirements are kept the same as in Section 4.1. In this setting, the behavior of RH compared with OR and NFH is similar to what obtained in the original setup. In fact, RH cost is 11.7% lower than NFH cost, and 84.3% higher than OR cost, which is in line with that reported in Table 2. Concerning DR fulfillment, the request satisfaction rate for OR is 82.90%, 54.7% for RH, and 36.8% for NFH, over 117 requests.

Similar conclusions can be drawn when considering an inaccurate probability distribution on the daily number of EVs. A 100-day simulation has been run by providing RH and NFH a distribution on the daily incoming vehicles modeled as a uniform distribution with support $[150, 250]$ vehicles. Despite the considered distribution is far from the actual one (both on expected value and shape), the cost performance turns out to be slightly reduced. Specifically, RH provides a cost that is 11.3% lower than NFH, and 78.2% higher than OR, while the request satisfaction rate remains almost unaffected, being 75%, 61.3%, and 93.9% for RH, NFH and OR, respectively. Simulations with more inaccurate distributions have been performed, too. As expected, in this case, both RH and NFH algorithms which rely on the knowledge of EV distributions fail, returning a total cost much higher than that provided by OR.

### *4.4. Scalability analysis*

In this subsection, the feasibility of proposed approach for real-world applications is assessed through simulations involving large-scale setups. To

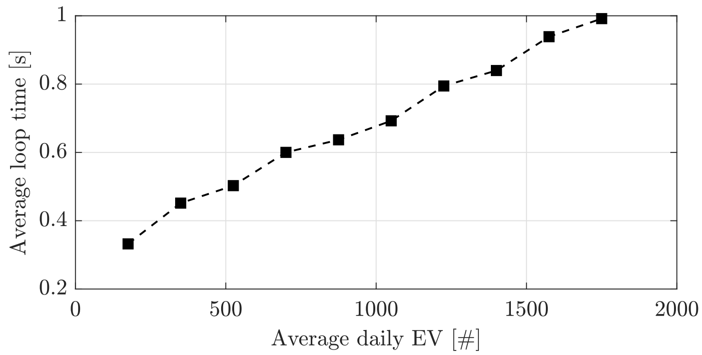


Figure 9: Average computation time to perform a loop iteration of Algorithm 1 according to different EV penetrations.

showcase the scalability of our method, we consider the following two cases.

First, a more demanding scenario involving 5 DR requests per day has been taken into account. The beginning time of the first request has been randomly chosen between 8:00 AM and 9:30 AM according to a uniform distribution, whereas the time duration between the end of one request and the beginning of the following one is uniformly drawn from $[30, 120]$ minutes. The duration of each request is generated using a uniform distribution whose support is $[30, 60]$ minutes. In this setting, the average computation time to run an iteration of Algorithm 1 amounts to 0.58 seconds, which amounts to a small fraction of the considered sampling time.

Second, the computational burden has been analyzed by considering increasing EV penetration. Specifically, a 100 days simulation has been run by setting different mean values of daily number of incoming vehicles. These values have been selected in a vehicle range starting from 175 up to 1750. Results concerning the average time to perform an iteration of Algorithm 1 are reported in Fig. 9. As it may be noticed, the algorithm computation time grows almost linearly with respect to the number of vehicles, showing feasible times even for 1750 vehicles per day. It is worthwhile to report that also the worst-case computation time is feasible for real applications. In fact, it amounts to 1.39 and 3.45 seconds when the mean value of incoming vehicles is 175 and 1750, respectively.

Notice that, for a fixed number of daily DR requests and vehicles, the additional computational effort due to reducing the discretization step is marginal, as it amounts to solving a larger linear program [34].

## 5. Conclusions

A stochastic receding horizon approach to manage an EV charging station participating in DR programs for RECs has been proposed. The developed procedure implements a stochastic approach that is (i) able to exploit online information to schedule the EV charging such that the aggregated power consumption lies within prescribed energy bounds during DR windows, and is (ii) computationally feasible to be deployed in real-world applications. Simulation results show that the proposed approach provides a substantial cost reduction with respect to the uncoordinated charging, as well as an increase of the performance of about 12% with respect to the optimization-based benchmark that does not exploit future forecast flexibility. Moreover, the computation time remains feasible even for scenarios involving a high EV penetration. Ultimately, results suggest that EVCSs, acting as aggregators of EVs, can be effective targets for DR programs: when *smart* charging policies are implemented, EVCSs can successfully contribute to the local demand-supply balance by suitably shifting their loads.

Future works may include the description of the customer satisfaction by probabilistic constraints, to allow for a greater degree of freedom, and robustification against distributional ambiguity in the case of estimated distributions from finite historical data. Additional developments may regard the adaptation of the procedure to dynamic traffic conditions, the integration of renewable resources, and the experimental validation of the approach in real-world RECs.

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