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A Receding Horizon Scheme for EV Charging Stations in Demand Response Programs

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***Abstract*— Demand response is expected to play a fundamental role in providing flexibility for balancing operations to the grid. On the other hand, the fast electrification of the transportation sector calls for new solutions to enforce safe and reliable grid operation. Here we consider an electric vehicle charging station that participates in demand response programs. The demand response program asks for a change of the charging station load profile in exchange for a monetary reward. A stochastic receding horizon scheme that exploits the charging flexibility is then designed to optimally coordinate vehicle charging. Numerical simulations show that the proposed approach ensures substantial cost reduction compared to simpler benchmarks while maintaining the computation time feasible for real-world applications.**

I. Introduction

Demand Response (DR) involves shifting or shedding electricity demand to provide services in wholesale and ancillary power markets. The changes in end-users electrical profiles are induced by either changes of electricity price over time (price-based schemes) or monetary incentives (incentive-based schemes) designed to generate an electricity reduction with respect to a normal consumption pattern. Such request can occur in consequence of high wholesale market prices or grid congestion [1]. The fundamental role of DR programs in reaching the Net Zero Emission 2030 scenario is highlighted in [2]: "*a quarter of the forecasted tenfold increase in energy system flexibility, defined as the hour to hour change in output required from dispatchable resources, is projected to be globally covered via DR by 2030*".

In this context, the transporation sector is expected to contribute for a worldwide share of 3.5% in total flexibility provision by 2030, with a forecasted capacity of 50 GW coming from electric vehicles (EVs) [2]. Countries such as France, Italy, the Netherlands and US are experimenting with vehicle-to-grid approaches to allow vehicles to input electricity into the grid. Another possibility to unlock the flexibility provision potential of EVs is through coordinated charging policies in EV charging stations, as outlined in [3] and empirically demonstrated in pilot projects [4], [5].

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To increase the DR capacity in accomplish the Net Zero targets, governments and regulators should accelerate the use of demand-side flexibility to support energy security and system resilience via the establishment of novel market designs that reward DR resources and allow them to compete fairly with supply-side sources of flexibility [2]. Here we consider an EV charging station participating in a DR program under an aggregator that wishes to maintain the balance between supply and demand. Specifically, we will assume the existence of a DR contract between the two entities, where the EV charging station owner gets compensated if it reduces its power consumption during certain time windows.

Literature review. While DR programs have been extensively investigated in industrial, commercial and residential sectors [6], the flexibility provision potential of the transportation sector has been less explored. The main challenge addressed is the stochasticity of the charging process. In [7], the profit maximization of an EV parking lot under uncertain EV arrival and departure times is investigated, while [8] proposes a chance constrained strategy to ensure users satisfaction during operations under uncertain EV loads. The approach is extended in [9] to provide a probabilistic guarantee on the daily profit. Furthermore, [10] and [11] develop real-time smart-charging algorithms considering expected electric vehicle fleet connections, while [12] proposes a two-stage formulation for the management of EV parking lots, utilizing predicted short-term future information and long-term estimation from historical data to model the uncertainties in the charging process.

Main contributions. We consider an EV charging station participating in a DR program and we design a novel online methodology to coordinate the charging of a fleet of EVs to provide the requested flexibility. The contribution of the paper is twofold:

1) a stochastic formulation to optimally schedule the charging process of EVs at a parking lot equipped with charging stations to ensure participation in DR programs. To deal with the randomness of the charging process, we propose a formulation that allows one to deal with different configurations and scenarios, with no specific assumptions on probability distributions;
2) a receding horizon algorithm of the above problem that takes advantage of the knowledge acquired online. The resulting procedure is based on the solution of a Mixed Integer Linear Program (MILP), that is

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shown to be feasible for real-world applications.

Paper structure. In Section II, the problem formulation is introduced. In Section III, a receding horizon algorithm for participation in DR programs is derived. In Section IV, numerical results evaluating the effectiveness of the proposed approach are reported. Finally, conclusions and future research lines are provided in Section V.

Notation. The set of natural and real numbers is represented by $\mathbb{N}$ and $\mathbb{R}$, respectively. Given a random event e, the probability that e occurs is written as $\mathcal{P}(e)$, the probability of its complement is $\mathcal{P}(\bar{e})$. Consider two events e and e', then the joint probability that e and e' occur is denoted by $\mathcal{P}(e, e')$, while the conditional probability that e occurs given e' is denoted by $\mathcal{P}(e|e')$. Finally, for a given random variable ξ, its expected value is denoted as $\mathbb{E}[\xi]$.

II. Problem formulation

An EV charging station that aims at minimizing the daily operating cost of charging incoming vehicles is considered. We adopt a discrete time setting where the sampling time is denoted by Δ and suppose that a reference day is divided into T time steps with the running index $t = 0, \ldots, T-1$. In this context, the charging station is assumed to participate into a DR program to provide flexibility to the aggregator in exchange for a monetary incentive. The contract between the aggregator[1] and the charging station is structured as follows:

- the aggregator provides a discounted constant price for charging stations subscribing to the contract;
- at the beginning of each day, the charging station communicate a forecast of its daily energy consumption, denoted by by $E^F(t), t = 0, \ldots, T-1$, to the aggregator. This forecast can result from a day-ahead planning problem (see, for example, [13]);
- in addition to the energy price, the charging station is subject to a fee that is proportional to the deviation between $E^F(t)$ and the actual demand profile $E^S(t)$. Roughly speaking, this penalty encourages the EV charging station to provide a load profile that is as close as possible to $E^F(t)$, hence helping the balancing operations of the aggregator;
- when needed by grid balancing requirements, the aggregator sends a DR request to the EV charging station asking for a load reduction or increase over a given time window. If the charging station provides the requested flexibility, a monetary reward is granted.

A. Charging station model

We envision the following setup: when a 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. The charging station then computes the time needed to satisfy such request based on a nominal charging power P_0 that is guaranteed throughout. Let $\tau_v^f = \left\lceil \frac{E_v^f}{\Delta P_0} \right\rceil$ 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.* Thus, if we let $S_v(t)$ denote the energy charged into the vehicle v at time t, the following constraints must be enforced

$$S_v(t) \le E_v^f \qquad t = t_v^a, \ldots, T \tag{1}$$

$$S_v(t_v^d) = E_v^f. \tag{2}$$

where $t_v^d = t_v^a + \tau_v^f$ denotes the *departure time* of vehicle v. Note that in principle a vehicle may keep a charging unit busy for longer time than the actual charging duration. However, we can neglect this vehicle once its battery level has reached E_v^f since it will not be charging anymore. To avoid considering the queuing problem, we assume that the charging station is equipped with a number of charging units able to satisfy the incoming vehicles.

Let $P_v(t)$ denote the average charging rate of vehicle v in the time interval $[t, t+1]$. The state of charge evolves according to

$$S_v(t+1) = S_v(t) + \Delta P_v(t) \quad t = t_v^a, \ldots, T-1. \tag{3}$$

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

$$0 \le P_v(t) \le \bar{P} \qquad t = t_v^a, \ldots, T-1, \tag{4}$$

where $\bar{P} \ge P_0$ denotes the maximum charging power of a single charging unit.

B. Demand response model

The DR program consists in time windows during which the power consumption per time step must lie within predefined bounds. Let R denote the number of requests in a day, Suppose that the number of requests in a day is R, t_r^b and t_r^e respectively the *start time* and the *end time* of the request $r = 1, \ldots, R$, and $t_r^n \le t_r^b$ the *notice time*, i.e., the time when the aggregator sends the DR request to the charging station. This is in contrast with similar works (see for example [14] and [15]) where the set of DR requests is assumed to be known at the beginning of the day.

The r-th DR request consists of an upper bound $\overline{B}_r$ and a lower bound $\underline{B}_r$ delimiting the interval where the power demand of the charging station must lie during the DR period, and a reward γ_r. Let $E^S(t)$ be the energy consumed by the charging station in the time interval $[t, t+1]$. We define the violation δ_r associated to the r-th DR period as

$$\delta_r = \max_{t = t_r^b, \ldots, t_r^e} \{E^S(t) - \Delta \overline{B}_r, \Delta \underline{B}_r - E^S(t), 0\}, \tag{5}$$

that denotes the maximum deviation around the bounds. Then, the monetary DR reward γ_r is modeled as a piecewise affine function (PWA) of the violation δ_r

$$\gamma_r = \max \left\{ \min_{d=1,\ldots,D} \left(\alpha_{r,d} \delta_r + \beta_{r,d} \right), 0 \right\}, \tag{6}$$

[1]For ease of exposition, the aggregator and the electricity retailer are supposed to be the same entity.

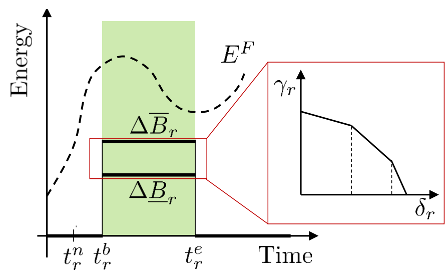

Fig. 1. Main axis: DR signal over time. Secondary axis: DR reward.

where $\alpha_{r,d}$, $\beta_{r,d}$ are given parameters. In (6), D denotes the number of functions in the PWA, $\alpha_{r,D} \leq \alpha_{r,D-1} \leq \ldots \leq \alpha_{r,1} < 0$ and $\beta_{r,d} > 0$, $d = 1, \ldots, D$. If the charging station energy demand $E^S(t)$ stays within the interval $[\Delta\underline{B}_r, \Delta\overline{B}_r]$ for $t = t_r^b, \ldots, t_r^e$ then the maximum reward is provided. If the overall demand is outside $[\Delta\underline{B}_r, \Delta\overline{B}_r]$ then the incentive decreases as a function of the violation incurred during the DR period, according to (6). This modeling choice allows one to encourage the charging station to adapt its consumption profile without giving rise to power peaks during the DR period.

A schematic representation of the DR scheme in place is reported in Fig. 1.

C. EV stochastic charging process description

It is assumed that the statistics of the number of daily incoming vehicles is described by a fixed distribution whose independent sampling provides realizations for different days. During each day, a similar hypothesis is enforced for the charging period (t_v^a, τ_v^f) with respect to each vehicle v. Hence, the charging process realization of a vehicle v can be drawn from the same couple of random variables $\left(t^a, \tau^f\right)$. This restriction is uniquely used to streamline the presentation; the probabilistic computations below can in fact accommodate for any daily EV behavior (for example, working days, holidays, strikes, etc.) once the corresponding probability distributions are made available. Finally, we focus on probability distributions having bounded support.

Let $E^U(t)$ be the 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 step depends only by the number of connected vehicles at that time step. Let $H(t)$ be the number of vehicles that are charging at time t. Then, the distribution of $H(t)$ 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

$$\mathcal{P}\left(H(t)=n|N=m\right) = \\ = \binom{m}{n} \mathcal{P}\left(t^a \leq t,\ t^d > t\right)^n \mathcal{P}\left(\overline{t^a \leq t,\ t^d > t}\right)^{m-n}.$$

and $\bar{N}$ denotes the upper bound of the daily number of incoming vehicles which is assumed to be known. The interested reader may refer to [16] for a detailed derivation of this probability. Finally, let us define

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

III. Receding horizon formulation

Let $\mathcal{V}(t)$ be the set of electric vehicles that are in charge at present time t,

$$\mathcal{V}(t) = \left\{v \in \mathbb{N} : t_v^a \leq t,\quad S_v(t) < E_v^f\right\}. \tag{7}$$

The set of DR requests $\mathcal{R}(t)$ to beconsidered in the optimization horizon is defined as

$$\mathcal{R}(t) = \left\{r \in \mathbb{N} : t_r^n \leq t,\quad t_r^e \geq t\right\}, \tag{8}$$

and comprises requests that have been not expired ($t_r^e \geq t$) and have been actually announced by the aggregator ($t_r^n \leq t$).

A. 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 operation cost of the charging station and comprises three terms

$$J(t) = \sum_{k=t}^{T-1} \Big(\underbrace{|\mathbb{E}[E^S(k|t)] - E^F(k)|c^d}_{\text{Deviation cost}} + \underbrace{\mathbb{E}[E^S(k|t)]c^g}_{\text{Electricity cost}} \Big) - \underbrace{\sum_{r\in\mathcal{R}(t)} \tilde{\gamma}_r}_{\text{DR reward}}, \tag{9}$$

where $\tilde{\gamma}_r$ is the decision variable concerning the reward of the r-th DR request, c^d is the unitary cost for the deviation around the profile $E^F(k)$ and c^g is electricity price of the energy purchased from the grid. In (9), all the quantities are computed according to the expected value of the energy consumed $\mathbb{E}[E^S(k|t)]$ under the information available at time t.

B. Charging station energy demand

Let $N(t) = n_a$ be the number of vehicles arrived at the charging station up to time t. The expected value of the energy demand at time $k \geq t$ is given by

$$\mathbb{E}[E^S(k|t)] = \sum_{v\in\mathcal{V}(t)} \Delta P_v(k) + \mathbb{E}[E^U(k)|t, n_a], \tag{10}$$

where

$$\mathbb{E}[E^U(k)|t, n_a] = \Delta P_0 \sum_{n=\underline{N}}^{\overline{N}} n\mathcal{P}(H(k)=n|N(t)=n_a, t_a > t). \tag{11}$$

Here the computation of $\mathcal{P}(H(k) = n|N(t) = n_a, t_a > t)$ is borrowed from [16]. Note that in (10) the term involving vehicles in $\mathcal{V}(t)$ is related to EVs whose departure time is known. Hence, the expectation operator for the energy consumed by these vehicles is not needed since concerns deterministic quantities.

C. DR constraints

For each request $r \in \mathcal{R}(t)$ the related reward $\tilde{\gamma}_r$ is constrained as follows

$$z_r^{DR} \in \{0,1\} \tag{12}$$

$$0 \leq \tilde{\gamma}_r \leq M z_r^{DR} \tag{13}$$

$$\tilde{\gamma}_r \leq \alpha_{r,d}\tilde{\delta}_r + \beta_{r,d},\ \forall d \in \{1,\dots,D\} \tag{14}$$

$$\tilde{\delta}_r \geq \delta_{r,t} z_r^{DR} \tag{15}$$

$$\tilde{\delta}_r \geq \mathbb{E}\left[\max_{k=t_r^b,\dots,t_r^e}\{E^S(k|t)\}\right] - \Delta\overline{B}_r - M(1-z_r^{DR}) \tag{16}$$

$$\tilde{\delta}_r \geq \Delta\underline{B}_r - \mathbb{E}\left[\min_{k=t_r^b,\dots,t_r^e}\{E^S(k|t)\}\right] - M(1-z_r^{DR}), \tag{17}$$

where $\tilde{\delta}_r$ is the forecast of the violation in the r-th DR period. Binary variables z_r^{DR} represent the choice of the charging station in complying with the DR request ($z_r^{DR} = 1$) or not ($z_r^{DR} = 0$). In (13) the reward is constrained to be positive, while in (14) the epigraph formulation of the DR reward is reported. In (15)-(17) the formulation of the forecast of DR violation is derived. Finally, $M > 0$ denotes a parameter that is big enough to avoid inconsistencies in the formulation, while $\delta_{r,t}$ represents the past DR violation up to time t which is defined as

$$\delta_{r,t} = \begin{cases} \max\limits_{k=t_r^b,\dots,t-1}\{E^S(k)-\Delta\overline{B}_r, \Delta\underline{B}_r - E^S(k), 0\} & \text{if } t > t_r^b, \\ 0 & \text{else.} \end{cases}$$

Note that, the constraints defined in (12)-(17) admit at least a feasible solution. In fact, it is easy to see that by setting $z_r^{DR} = \tilde{\gamma}_r = \tilde{\delta}_r = 0$, such constraints are satisfied.

Constraints defined in (16)-(17) involve the expected value of the maximum of a set of random variables whose number of elements amounts to the length of the related DR request. However, computing such expectation is not a trivial task since the energy consumed at each time step is highly correlated to the ones at previous time steps. To handle such an aspect we propose a heuristic approach. From the Jensen's inequality one has

$$\max_{k=t_r^b,\dots,t_r^e}\left\{\mathbb{E}\left[E^S(k|t)\right]\right\} \leq \mathbb{E}\left[\max_{k=t_r^b,\dots,t_r^e}\{E^S(k|t)\}\right] \tag{18}$$

$$\min_{k=t_r^b,\dots,t_r^e}\left\{\mathbb{E}\left[E^S(k|t)\right]\right\} \geq \mathbb{E}\left[\min_{k=t_r^b,\dots,t_r^e}\{E^S(k|t)\}\right]. \tag{19}$$

By using approximations introduced in (18)-(19), the overall computation results to be simplified since the expectations are computed separately. On the other hand, the performance of the receding horizon algorithm may be reduced. To deal with this issue, forecasts will be penalized by multiplicative constants $\mu_r^{high} \geq 1$ and $\mu_r^{low} \geq 1$ to approximate constraints (16)-(17) as

$$\tilde{\delta}_r \geq \mu_r^{high} \cdot \mathbb{E}[E^S(k|t)] - \Delta\overline{B}_r - M(1-z_r^{DR}) \tag{20}$$

$$\tilde{\delta}_r \geq \Delta\underline{B}_r - \mu_r^{low} \cdot \mathbb{E}[E^S(k|t)] - M(1-z_r^{DR}), \tag{21}$$

where $k = t_r^b, \dots, t_r^e$. Note that the approximations are tight if one sets those parameters as

$$\mu_r^{high} = \frac{\mathbb{E}[\max_{k=t_r^b,\dots,t_r^e}\{E^S(k|t)\}]}{\max_{k=t_r^b,\dots,t_r^e}\{\mathbb{E}[E^S(k|t)]\}} \tag{22}$$

$$\mu_r^{low} = \frac{\min_{k=t_r^b,\dots,t_r^e}\{\mathbb{E}[E^S(k|t)]\}}{\mathbb{E}[\min_{k=t_r^b,\dots,t_r^e}\{E^S(k|t)\}]}. \tag{23}$$

However, computing μ_r^{high} and μ_r^{low} as in (22)-(23) is again not tractable. Hence, we estimate μ_r^{low} and μ_r^{high} by taking into account the past peak values occurred in the most recent DR periods. The estimation procedure is reported in Algorithm 1, where μ_r^{low} and μ_r^{high} are obtained by considering the ratio between the average of the peak values of the energy consumed in the last L DR requests and the last $t_r^e - t_r^n + 1$ forecasts (i.e., $\mathbb{E}[E^S(k|t)]$ for $t = t_r^n, \dots, t_r^e$) obtained in (20)-(21). Clearly, the performance of the optimization routine depends on how many samples one considers in the estimation, as discussed in Section IV.

D. Receding horizon procedure

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

Problem 1:

$$P_v^*(t) = \arg\min_{P_v(t):v\in\mathcal{V}(t)} J(t)$$
$$\text{s.t.} \quad (1)-(4), (9)-(15), (20), (21).$$

This optimization problem is a MILP, where the number of binary variables is equal to the number of DR requests falling inside the optimization horizon. Since in real-world scenarios the number of requests per day amounts to at most few units, the proposed procedure is computationally feasible even for large-scale problem instances (i.e., large EV population and/or small discretization step).

Algorithm 2 provides a sketch of the overall receding horizon procedure. At each time step t, the procedure is based on two main steps: i) all the problem quantities

Algorithm 1: Estimation of μ_r^{high} and μ_r^{low}.

Data: For the past L requests: energy consumed $E_l^S(k)$ and forecasts $E_l^S(k|t)$, for $l = 1, \dots, L$;

set $\mu_r^{high} = \dfrac{\sum_{l=1}^{L} \max_{k=t_l^b,\dots,t_l^e}\{E_l^S(k)\}(t_l^e - t_l^n + 1)}{\sum_{l=1}^{L}\sum_{t=t_l^n}^{t_l^e} \max_{k=t_l^b,\dots,t_l^e}\{\mathbb{E}[E_l^S(k|t)]\}}$;

set $\mu_r^{low} = \dfrac{\sum_{l=1}^{L}\sum_{t=t_l^n}^{t_l^e} \min_{k=t_l^b,\dots,t_l^e}\{\mathbb{E}[E^S(k|t)]\}}{\sum_{l=1}^{L} \min_{k=t_l^b,\dots,t_l^e}\{E_l^S(k)\}(t_l^e - t_l^n + 1)}$;

return μ_r^{high}, μ_r^{low};

Algorithm 2: Receding horizon algorithm.

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

Compute $E^F(k)$ for $k = 1, \dots, T$;
Set $t = 1$;
while $t \le T$ **do**
  $n_a = |\{v : t_v^a \le t\}|$;
  compute $\mathcal{V}(t)$ as in (7);
  compute $\mathcal{R}(t)$ as in (8);
  solve Problem 1 and get $P_v^*(t),\ \forall v \in \mathcal{V}(t)$;
  $S_v(t+1) = S_v(t) + \Delta P_v^*(t),\ \forall v \in \mathcal{V}(t)$;
  $t = t + 1$;
end

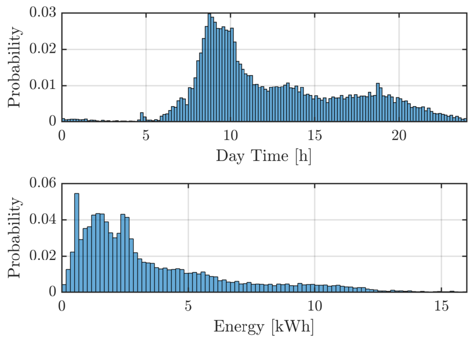

Fig. 2. Charging process distributions. Top panel: Arrival time distribution. Bottom panel: Fulfillment time distribution.

are updated on the basis of the information available at time t; ii) Problem 1 is solved and the first command of the optimal solution is applied.

IV. Numerical Simulations

To test the performance of the presented approach, simulations have been carried out by using probability distributions estimated from real data. Specifically, the ones concerning arrival time and fulfillment time have been estimated by using the historical data in [17]. The sampling time has been set to 10 minutes and experiments have been run for a duration of 100 days. Concerning EV charging, the related nominal charging power P_0 has been set to 7.4 kW, while the maximum charging power rate $\bar{P}$ has been fixed to 22 kW. Vehicles are assumed to follow the distributions reported in Fig. 2. Concerning the daily number of incoming vehicles, a Gaussian distribution with mean 175 and standard deviation 9 has been considered.

For each day, the deviation price c^d is set to 0.20 €/kWh, the grid price c^g is set to 0.05 €/kWh and 1 DR request per day has been considered. The beginning time of each request has been generated according to a uniform distribution ranging from 9 AM to 3 PM, while the related length is uniformly drawn in the interval $[9, 12]$ time steps. The charging station can be noticed of the DR request in a time window of $[0, 2]$ time steps before the request begins. For each request, the related

TABLE I
Parameters of the DR requests.

$\alpha_{r,d}$	-4	-6	-6.67
$\beta_{r,d}$	γ_r	$1.10\,\gamma_r$	$1.17\,\gamma_r$

TABLE II
Average daily cost for each estimation time window.

Number of requests	10	20	30	40	50
Average daily cost [€]	230.26	229.69	229.57	229.81	229.89

upper and lower power bounds have been set to 60% and 40% the mean value of $E^F(t)$ in the considered time interval, respectively. Finally, the maximum reward has been setup according to the formula

$$\gamma_r = k \cdot (t_r^e - t_r^b) \cdot \max_{t=t_r^b,\dots,t_r^e} \{E^F(t) - \Delta\overline{B}_r, \Delta\underline{B}_r - E^F(t)\},$$

where $k = 0.5$ €/kWh whereas three thresholds have been considered in (6), whose coefficients $\alpha_{r,d}$ and $\beta_{r,d}$ are reported in Tab. I. Note that, in this simulation setup, the notice time ranges in a small interval. This choice puts the system in stressful conditions where the charging station needs to react almost instantly to the requests of the aggregator. However, as reported in the following, the proposed procedure is capable of managing this kind of requests showing the possibility to be adapted to tertiary reserve market frameworks.

Concerning the estimation of μ_r^{high} and μ_r^{low}, they have been computed online during a simulation of 100 days. In particular, to evaluate the sensitivity of the algorithm performance with respect to L, the same simulation has been run considering a number of past requests ranging from 10 to 50 with a step size of 10. To make comparison between different time windows, the average daily cost of the proposed receding horizon algorithm (**RH**) have been taken into account. The results of such costs are summarized in Tab. II. One may note that the overall cost is not very sensitive to variations of the sample size. In the remainder, we fix the sample size for estimation to 30 requests since it leads to the lowest cost.

To validate the effectiveness of the proposed procedure, we compare its performance against three benchmarks:

- **nominal charging policy (NCP)**: all the vehicles are charged at nominal charging power rate P_0;
- **receding horizon procedure with no information (NI)**: a receding horizon algorithm which does not consider any future load forecast;
- **omniscient oracle optimization (OR)**: a one-shot optimization problem that knows the realization of all random variables. This amounts to an a-posteriori optimization performed at the end of the day. OR is clearly an optimistic, non-causal benchmark that cannot be implemented in practice.

TABLE III

AVERAGE DAILY COST FOR ALL THE STRATEGIES.

	RH	NCP	NI	OR
Cost [€]	229.57	351.39	265.29	177.79

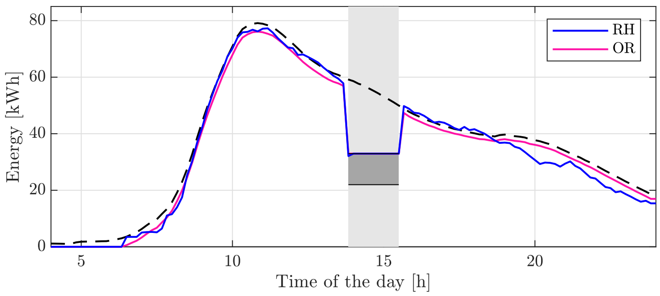

Fig. 3. Energy profiles of the charging station during day 64: energy forecast, proposed strategy and OR. The DR time interval is denoted by the gay area, while power limits are represented by the gray shaded area.

The average daily cost performance for each procedure are summarized in Tab. III. The proposed procedure outperforms the NCP and NI of about 52.04% and 15.03%, respectively. Instead, considering the algorithm behavior with respect to the OR, the obtained daily cost is on average 52.48€ above. Moreover, the number of satisfied requests amounts to 74 for the proposed procedure and to 100 for the OR. Finally, in Fig. 3 the energy profiles over one day of the charging station under the proposed procedure and under the OR benchmark are compared. In the considered day, the time when the request is noticed is exactly the same one where the DR request starts. Here, it can be noticed that the information used by the receding horizon procedure makes it possible to coordinate the EV charging in order to properly track the declared consumption profile and fulfill the DR request even if the related notice time was short. In fact, the solution obtained is fairly close to the one obtained by the OR.

Finally, thanks to the estimation procedure to compute μ_r^{high} and μ_r^{low} presented in Algorithm 1, the resulting procedure features feasible run times with nice scalability properties. The time needed to run Algorithm 2 takes on average 31 seconds per day[2].

V. CONCLUSIONS

A receding horizon approach to manage a charging station participating in DR programs has been proposed. The proposed procedure is able to exploit online information to schedule the EV charging such that the aggregated power consumption tracks the declared profile and stays within prescribed bounds during DR windows. Moreover, the approach is shown to outperform other optimization strategies that are blind to the information about the uncertainty in the charging process. Finally, the overall computational performance results to be feasible for real-time applications.

Future directions may involve the extension of the framework to energy communities or reserve market, as well as the validation of the proposed solutions in real world scenarios.

[2]Simulations run on an i7-11700K@3.6GHz with 32GB RAM.

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