A data-driven dynamic pricing scheme for EV charging stations with price-sensitive customers

Marta Fochesato[1*], Giovanni Gino Zanvettor[2*], Marco Casini[2] and Antonio Vicino[2]

***Abstract*— The increasing adoption of electric vehicles (EVs) has left power network providers to deal with new challenges in terms of grid stability and electricity market design. On the latter direction, a demanding problem is represented by the development of probabilistic algorithms capable of computing optimal time-varying price profiles for EVs charging stations to induce a desired aggregative behavior. Here, the inclusion of demand elasticity represents a key feature to provide usable schemes for real-world cases. In this paper, we propose an "estimate-then-optimize" framework for optimal dynamic pricing computation in the presence of price-sensitive customers. It consists of an estimation step based on nonparametric kernel methods to infer about the demand elasticity, followed by an optimization step to maximize the expected daily profit. We describe the charging process via a probabilistic framework and we show the benefits of the proposed formulation via extensive numerical experiments.**

***Index Terms*— EV charging stations, dynamic pricing, stochastic optimization, kernel regression.**

I. Introduction

Transportation sector is reported to contribute more than 30% of the total carbon emissions in Europe in 2020 [1], making it a crucial target for decarbonization strategies. Alternatives to fossil-based vehicles for private transport are therefore on the urge. The most mature technology serving as "green" alternative is represented by electric vehicles (EVs).

Given the central role of EVs in the decarbonizing transition, they have lately received a great attention from the scientific community. Indeed, the integration of an increasing number of EVs into the power grid rises several challenges: on one side, it may compromise the safety and reliability of the power grid; on the other side, it opens new questions in terms of electricty market design due to spikes in the electricity demand. Moreover, these issues are complicated by the stochastic sources arising from traffic conditions and user preferences.

Several works in the literature have focused on cost minimization and peak shaving targets during EV charging stations operations, proposing smart charging strategies, like e.g., in [2], [3]. In [4], the optimal operations of an EV charging station coupled with storage devices and uncertain renewable generation is addressed, while in [5] a parking lot energy management strategy is developed considering different driving/parking patterns. Peak load reduction problems have also been considered. For instance, valley filling algorithms are proposed in [6] and [7], while a peak shaving strategy accounting for customers dissatisfaction is presented in [8] and [9].

A parallel research line is represented by pricing algorithms for EV charging stations capable of maximizing the social welfare or the charging station profit. In particular, [10] designs a pricing scheme by exploiting game theoretic frameworks based on time-of-use concepts, while [11] considers a hierarchical two-layer model. In [12], a pricing scheme ensuring a desired profit with probabilistic guarantees is designed.

Building upon this literature, we address the problem of computing an optimal time-varying price profile for EV charging stations in the presence of price-sensitive customers. This aspect represents a novel contribution in the electricity pricing literature, especially when competitive settings are considered. The inclusion of demand elasticity ensures a more realistic description of the charging process and allows the development of more accurate optimization algorithms. On the other hand, the inclusion of this feature introduces several challenges related to the difficulty of estimating the demand elasticity from historical data. In the most general case it may be time-varying and/or present spatial correlations.

Few works are present in literature in this direction. In [13], the authors propose a conditional random field model for online estimation and refinement of the demand elasticity of EVs and link it to a profit maximization problem. Similar works are found in [14], where the parameters of the load elasticity model are assumed to be known, and in [15], where the model reduces to a typical deterministic load perturbed by a random variable. In [16], a deterministic approach to model a pricing game where the user propensity to charge is inversely proportional to the energy price is considered.

In this paper, we propose a novel algorithm to maximize the expected daily profit of an EV charging station considering price-sensitive customers. We formulate an "estimate-then-optimize" probabilistic framework, where the estimation task and the optimization task are split in two different layers to reduce the problem complexity. The contribution of this work is threefold:

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[*] These authors equally contributed to the work.
[1] Automatic Control Laboratory, ETH Zurich, Switzerland. E-mail: {mfochesato}@control.ethz.ch
[2] Dept. of Information Engineering and Mathematics, University of Siena, Italy. Email: {zanvettor,casini,vicino}@diism.unisi.it

1) full flexibility in characterizing the charging process behavior, i.e., no specific structure on the probability distributions concerning the EV uncertainties is assumed.
2) privacy-oriented approach, i.e., only the aggregate customers behavior is considered.
3) highly-scalable procedure with tractable runtimes even in presence of a large vehicle populations.

The paper is organized as follows. Section II introduces problem variables, constraints and probability distributions governing the charging process. In Section III, the estimation algorithm is described, while in Section IV, the stochastic profit maximization problem is formulated. Numerical simulations are provided in Section V to evaluate the effectiveness of the proposed procedure. Finally, conclusions and future research lines are drawn in Section VI.

Notation

The set of real numbers, non-negative real numbers, and natural numbers are denoted by $\mathbb{R}$, $\mathbb{R}^+$, and $\mathbb{N}$, respectively. We denote an n-dimensional vector as $x \in \mathbb{R}^n$. The i-th component of vector x is denoted by $x(i)$, whereas its mean value over the set of indexes $\{t, ..., t+\tau-1\}$ is defined as $\tilde{x}(t,\tau) := \frac{1}{\tau}\sum_{l=t}^{t+\tau-1} x(l)$. Estimated quantities are referred to with symbol $\hat{}$ to distinguish them from the true (possibly unknown) quantity. We define the indicator function as $\mathbb{1}_{\mathcal{X}}(x) := 1$ if $x \in \mathcal{X}$, 0 otherwise. Given an event E we define the probability associated to the occurrence of such event as $\mathbb{P}(E)$, while $\mathbb{P}(E \mid D)$ denotes the conditional probability of E given D. A random variable is denoted with bold notation $\mathbf{w}$, while a realization of such variable is denoted with plain notation w. The expected value of a random variable $\mathbf{w}$ is denoted by $\mathbb{E}[\mathbf{w}]$, whereas the expected value of $\mathbf{w}$ conditioned to the event D is denoted by $\mathbb{E}[\mathbf{w}|D]$.

II. Problem formulation

In this work an EV charging station that serves a large pool of price-sensitive customers is considered. Customers can decide whether to accept the selling price offered by the charging station and thus recharge there, or decline it and consequently recharge in other facilities. We restrict the treatment to the case where the EV charging station competes against home charging. However, the framework can be extended to handle competition against other players, i.e., other EV charging stations. We envision the following setting for the charging process: at a given time step a vehicle arrives at the charging station and it decides whether or not to accept the charging offer. Given its own energy requirement, the customer takes a decision by comparing the charging station selling price with the cost of home charging. In case of acceptance, the amount of energy to be charged will be available to the charging station and could be used to derive a dynamic pricing strategy; in case of refuse, only the time instant at which the user declines the charging offer will be available.

In such a setting, we aim at determining the optimal daily selling price profile to maximize the expected profit of the charging station. It is evident that a trade-off emerges in a price-sensitive customer scenario: in general, high selling prices are expected to lead to lower acceptance ratio (and thus fewer vehicles recharging), but higher "per-vehicle" profit. Vice versa, low selling prices are expected to lead to higher acceptance ratio, but lower "per-vehicle" profit.

The problem is formulated in discrete time setting, with sampling time Δ. The reference day is divided into T time slots, $t \in \{0, \dots, T-1\}$. We assume that the number of charging units is enough to provide charging to all incoming vehicles, and that the day-ahead price profile of the grid is available. This profile is assumed to correspond to both the price associated to home charging as well as the cost incurred by the charging station to purchase the required energy from the distribution system operator.

Given a vehicle v, let t_v^a and t_v^c be its arrival and charging time, respectively. Let us denote by $\mathbf{t}_v^a$ and $\mathbf{t}_v^c$ the random variables associated to the arrival and charging time, respectively. Moreover, we denote by $\mathbf{N}$ the random variable associated to the daily number of incoming vehicles (both accepting and non-accepting the charging). We assume that $\mathbf{t}_v^c$ and $\mathbf{N}$ have a bounded support with lower limits $\underline{t}_v^c$ and $\underline{N}$ and upper limits $\overline{t}_v^c$ and $\overline{N}$, respectively. We denote by $\mathbf{A}_v$ the Bernoulli random variable associated to the accepting event, where $\mathbf{A}_v = 1$ refers to the acceptance and $\mathbf{A}_v = 0$ to the refusal. Note that the probability distribution of $\mathbf{A}_v$ is assumed to be independent w.r.t. $\mathbf{N}$, but it depends on the selling price as reported in the next section. Finally, the quantities related to EVs are assumed to be independent and identically distributed (i.i.d.), i.e., for each vehicle one can consider the tuple $(\mathbf{t}^a, \mathbf{t}^c, \mathbf{A})$ independently from v.

We suppose to have at our disposal a historical dataset where EV charging data are gathered. Specifically, let G denote the number of days recorded in the dataset. For each day $g \in \{1, \dots, G\}$, the following data are available:

- Grid daily price profile, $c_g(t)$ for $t \in \{0, \dots, T-1\}$.
- Daily selling price profile $p_g(t)$ for $t \in \{0, \dots, T-1\}$.
- Number of incoming vehicles (both accepting and non-accepting ones) throughout the day N_g.
- For every vehicle $v_g \in \{1, \dots, N_g\}$ we assume to know its arrival time $t_{v_g}^a$, and if the customer has accepted or not the charging offer. We use $A_{v_g} \in \{0, 1\}$ to model the two cases, i.e., $A_{v_g} = 1$ if the accepting event occurred and $A_{v_g} = 0$ otherwise.
- If the v_g-th vehicle is flagged with $A_{v_g} = 1$, then its charging time $t_{v_g}^c$ is available, otherwise this information is censored.

In the following, for ease of notation, the dependence on g will be omitted when considering a single day.

The following assumptions are enforced:

A1 Vehicles are charged at constant charging power P_0.

A2 The underlying distributions governing the daily EV charging process are day-invariant, i.e., they do not change from day to day.

A3 The probability of accepting the charging offer as a function of the selling price is time-invariant over the day.

A4 For each day, vehicles starting the charging process at time t will incur a constant price equal to $p(t)$ throughout the entire charging process.

A5 For each day, the probability of accepting the charging offer decreases monotonically as a function of the selling price p according to the following index referred to as *discriminant*:

$$d_v(t_v^a, t_v^c) := \frac{p(t_v^a) - \tilde{c}(t_v^a, t_v^c)}{\tilde{c}(t_v^a, t_v^c)}. \quad (1)$$

Hereafter, dependencies on t_v^a and t_v^c of the discriminant will be omitted when clear from the context.

Assumption A1 and A2 are common in the context of EV literature; A3 is used to streamline the presentation, but is in general not restrictive. A4 is motivated by a "fairness" concept, i.e., connected vehicles are assured not to incur in a sudden price increase during the charging process. Finally, A5 introduces the function modeling the acceptance behavior of the users, similarly to that reported in [16].

Remark 1 *It is clear that in real settings the acceptance behavior depends on several variables rather than the selling price alone. However, such dependencies can be effectively embedded while computing the acceptance probability. For example, suppose that each incoming customer has his/her own urgency function (e.g., depending on battery size, user habits, etc.) characterizing the related acceptance probability together with the selling price. Then, assuming that the urgency probability distribution is known, the total probability rule can be exploited to derive an aggregate acceptance probability function which depends on the selling price only.*

III. Estimation

The goal of the estimation step is to infer about the customer sensitivity to price, i.e., the probability of accepting the recharge offer depending on the price. First, the estimation of the charging process quantities is described. Successively, the proposed nonparametric kernel-based estimation algorithm is reported.

Remark 2 *The demand behavior does not depend on the specific acceptance probability distribution of the single customers, but rather on the aggregated behavior of the pool of vehicles. Thus, the aggregated probability of accepting the charging offer will be estimated. This in turn leads to a formulation which only refers to aggregated quantities, ensuring a privacy-preserving scheme.*

A. Estimate of charging process probability distributions

In a first step, we are interested in estimating the relevant probability distributions characterizing the vehicle charging process from the available historical data.

Since the daily number of incoming vehicles (both accepting and not accepting ones) N_g is known, an estimate of the arrival time distribution of a generic vehicle v to the charging station is given by

$$\hat{\mathbb{P}}(\mathbf{t}^a = t) = \frac{\sum_{g=1}^{G} \sum_{v_g=1}^{N_g} \mathbb{1}_t(t_{v_g}^a)}{\sum_{g=1}^{G} N_g}. \quad (2)$$

Concerning the daily number of incoming vehicles, an estimate can be derived as follows

$$\hat{\mathbb{P}}(\mathbf{N} = n) = \frac{\sum_{g=1}^{G} \left(\mathbb{1}_n\left(N_g\right)\right)}{G}. \quad (3)$$

In general, when only few data are available, (3) may provide a rough estimation. As it will become clear in the following, this will not impact the accuracy of the proposed method.

By dataset construction, we do not have any information on the charging process (i.e., duration of the recharge or amount of energy recharged) for a vehicle v that does not accept the charging offer. Consequently, the estimate of the charging time distribution is based solely on those vehicles which accepted the charging offer, whose data are available. Since, the charging time depends on the arrival time, one has

$$\hat{\mathbb{P}}(\mathbf{t}^c = \tau \mid \mathbf{t}^a = t) = \frac{\sum_{g=1}^{G} \sum_{v_g=1}^{N_g} A_{v_g} \mathbb{1}_t(t_{v_g}^a) \mathbb{1}_\tau(t_{v_g}^c)}{\sum_{g=1}^{G} \sum_{v_g=1}^{N_g} A_{v_g} \mathbb{1}_t(t_{v_g}^a)}. \quad (4)$$

B. Estimate of the demand elasticity

We now illustrate the proposed method to estimate the probability of accepting the charging offer.

Definition 1 *Let $n \in \mathbb{N}$ be the number of samples available and $h(n) : \mathbb{N} \to \mathbb{R}^+ \backslash \{0\}$ be an increasing function w.r.t. n denoted as bandwidth function. A kernel function K defined as*

$$K(x, x_0) = \kappa\left(\frac{\|x - x_0\|}{h(n)}\right), \ \kappa : \mathbb{R} \to \mathbb{R}^+$$

is a weighting function which is monotonically decreasing with respect to $\|x - x_0\|$.

Examples of kernel functions are reported in Fig. 1.

The bandwidth function h in Definition 1 plays a critical role in the accuracy of the kernel regression as it regulates the smoothness of the estimate. Several works investigate the optimal selection of such parameter based on the size of the dataset (see [18] and reference therein).

Since the charging time of vehicles that have declined the charging offer is not available, an estimate of the corresponding discriminant is needed to derive an estimate of the accepting probability. In particular, we infer about

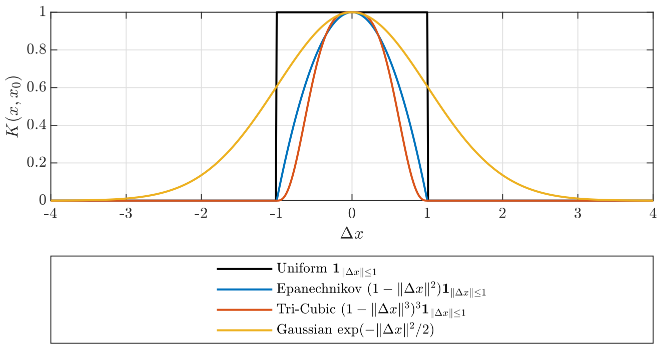

Fig. 1. Examples of popular kernel functions K where $\Delta x := x - x_0$ and $h(n) = 1,\ \forall n$.

the aggregated probability of accepting the charging offer given the value of the discriminant d as

$$\hat{\mathbb{P}}(\mathbf{A} = 1 \mid \mathbf{d} = d) = \frac{\sum_{g=1}^{G} \sum_{v_g=1}^{N_g} A_{v_g} K(d_{v_g}, d)}{\sum_{g=1}^{G} \sum_{v_g=1}^{N_g} A_{v_g} K(d_{v_g}, d) + (1 - A_{v_g}) \hat{\mathbb{E}}\left[K(\mathbf{d}_{v_g}, d)\right]}, \tag{5}$$

where $K(\cdot, \cdot)$ is a kernel satisfying Definition 1. Concerning vehicles that have declined the charging offer, their contribution is estimated by taking into account the expected value of their kernel function. Since the charging time distribution of these vehicles is the same of the accepting ones, the expectation can be computed as

$$\hat{\mathbb{E}}\left[K\left(\mathbf{d}_{v_g}(t^a_{v_g}, \mathbf{t}^c_{v_g}), d\right)\right] = \sum_{\tau=1}^{\overline{t}^c} K\left(d_{v_g}(t^a_{v_g}, \tau), d\right) \cdot \hat{\mathbb{P}}(\mathbf{t}^c = \tau \mid \mathbf{t}^a = t^a_{v_g}). \tag{6}$$

Remark 3 *In general, local kernel methods produce estimators characterized by regions with "dips" and "bumps" compromising the monotonicity of the estimate, as required by Assumption A5. To this end, the monotonicity constraint can be enforced by post-filtering the estimated function as explained in [17, Theorem 1].*

IV. Optimization

Once the estimates of the EV probability distributions described in the previous section are available, the next step focuses on deriving an algorithm for the computation of the optimal time-varying daily selling price $p(t)$, $\forall\, t \in \{0, \ldots, T\}$ to maximize the daily profit of the charging station.

The random variable related to the net cumulative profit of the charging station during a day is given by

$$\mathbf{R} = \sum_{t=0}^{T-1} \mathbf{r}(t), \tag{7}$$

where $\mathbf{r}(t)$ is the net profit related to vehicles arriving at time t. In turn, $\mathbf{r}(t)$ is defined as

$$\mathbf{r}(t) = \sum_{v=1}^{\mathbf{N}} \Delta P_0 \left(p(t) - \tilde{c}(\mathbf{t}^a_v, \mathbf{t}^c_v)\right) \mathbf{t}^c_v \mathbb{1}_t(\mathbf{t}^a_v) \mathbf{A}_v. \tag{8}$$

Actually, the cost incurred by the EV charging station to purchase the required energy from the distribution system operator (see (8)) is a wholesale price tailored for industrial customers, i.e., the charging station electricity price is a fraction of the residential one. However, this aspect does not impact either the optimization routine or the interpretation of the results in Section V, since the resulting optimization will differ only by a scaling factor.

Notice that in (8) only vehicles arriving at time t concur in determining the net profit at time t due to the presence of the term $\mathbb{1}_t(\mathbf{t}^a_v)$. The objective function is the expected value of the cumulative net profit $\mathbf{R}$, i.e.,

$$\begin{aligned} \mathbb{E}[\mathbf{R}] &= \sum_{t=0}^{T-1} \mathbb{E}[\mathbf{r}(t)] \\ &= \Delta P_0 \sum_{t=0}^{T-1} \mathbb{E}\left[\sum_{v=1}^{\mathbf{N}} \left(p(t) - \tilde{c}(\mathbf{t}^a_v, \mathbf{t}^c_v)\right) \mathbf{t}^c_v \mathbb{1}_t(\mathbf{t}^a_v) \mathbf{A}_v\right]. \end{aligned} \tag{9}$$

The last expectation in (9) is equivalent to

$$\begin{aligned} &\mathbb{E}\left[\sum_{v=1}^{\mathbf{N}} \left(p(t) - \tilde{c}(\mathbf{t}^a_v, \mathbf{t}^c_v)\right) \mathbf{t}^c_v \mathbb{1}_t(\mathbf{t}^a_v) \mathbf{A}_v\right] \\ &= \sum_{n=\underline{N}}^{\overline{N}} n \mathbb{E}\left[\left(p(t) - \tilde{c}(\mathbf{t}^a, \mathbf{t}^c)\right) \mathbf{t}^c \mathbb{1}_t(\mathbf{t}^a) \mathbf{A}\right] \mathbb{P}(\mathbf{N} = n) \\ &= \mathbb{E}\left[\left(p(t) - \tilde{c}(\mathbf{t}^a, \mathbf{t}^c)\right) \mathbf{t}^c \mathbb{1}_t(\mathbf{t}^a) \mathbf{A}\right] \sum_{n=\underline{N}}^{\overline{N}} n \mathbb{P}(\mathbf{N} = n) \\ &= \mathbb{E}\left[\left(p(t) - \tilde{c}(\mathbf{t}^a, \mathbf{t}^c)\right) \mathbf{t}^c \mathbb{1}_t(\mathbf{t}^a) \mathbf{A}\right] \mathbb{E}[\mathbf{N}], \end{aligned} \tag{10}$$

where the total probability theorem has been used in the derivation. Two main observations can be made concerning (10). First, subscript v has been removed since the EV random variables are i.i.d. and the accepting event is independent from $\mathbf{N}$, so it is sufficient to consider n times the expected value of the net profit from a single vehicle. Second, the net profit at time t can be written as the product of the expectation of the net profit provided by a single vehicle and the expectation of the daily number of incoming vehicles. Therefore, an accurate estimate of the expected daily profit strictly depends on the accuracy of $\mathbb{E}[\mathbf{N}]$, which can be better estimated than its probability distribution, especially when scarce data are available.

The expectation on the net profit of a single vehicle is computed as

$$\begin{aligned} &\mathbb{E}\left[\left(p(t) - \tilde{c}(\mathbf{t}^a, \mathbf{t}^c)\right) \mathbf{t}^c \mathbf{A} \mathbb{1}_t(\mathbf{t}^a)\right] \\ &= \mathbb{E}\left[\left(p(t) - \tilde{c}(t, \mathbf{t}^c)\right) \mathbf{t}^c \mathbf{A} | \mathbf{t}^a = t\right] \mathbb{P}\left(\mathbf{t}^a = t\right) \\ &= \sum_{\tau=1}^{\overline{t}^c} \left(p(t) - \tilde{c}(t, \tau)\right) \tau \mathbb{P}(\mathbf{t}^c = \tau | \mathbf{t}^a = t) \mathbb{P}(\mathbf{t}^a = t) \mathbb{E}\left[\mathbf{A} | \mathbf{t}^a = t, \mathbf{t}^c = \tau\right] \end{aligned} \tag{11}$$

where

$$\mathbb{E}\left[\mathbf{A} | \mathbf{t}^a = t, \mathbf{t}^c = \tau\right] = \mathbb{P}\left(\mathbf{A} = 1 \,\middle|\, \mathbf{d} = \frac{p(t) - \tilde{c}(t, \tau)}{\tilde{c}(t, \tau)}\right). \tag{12}$$

The conditional probability in (12) can be estimated in a data-driven fashion as reported in (5).

Let $\mathcal{P} := \{p \in \mathbb{R}^+ \mid \underline{p} \leq p \leq \overline{p}\}$, where $\underline{p}$ and $\overline{p}$ denote the lower and the upper bound on the selling price, respectively. We are interested in determining an optimal time-varying daily selling price profile which maximizes $\mathbb{E}[\mathbf{R}]$ with $p(t) \in \mathcal{P}$, $\forall\, t = \{0, \ldots, T-1\}$.

In general, the expected net profit $\mathbb{E}[\mathbf{R}]$ may be a nonconcave function with respect to the selling price p. Indeed, the EV accepting probability in (12) may assume any shape. Thus, the optimization procedure cannot be solved by relying on standard convex optimization tools. However, thanks to Assumption A5, the net profit at time t depends exclusively on selling price at same time step, i.e., $p(t)$. Therefore, the cumulative net profit can be maximized by optimizing the selling price at each time step separately. As a result, by exploiting (7), the optimization problem can be written as

$$\max_{\substack{p(t)\in\mathcal{P},\\ \forall t\in\{0,\ldots,T-1\}}} \mathbb{E}[\mathbf{R}] = \sum_{t=0}^{T-1} \max_{p(t)\in\mathcal{P}} \mathbb{E}[\mathbf{r}(t)], \qquad (13)$$

Notice that, at each time step only one optimization variable is involved, allowing the use of a gridding technique for the computation of (13). This allows to find the global optimum up to a given quantization error. The overall complexity of such approach depends linearly on the total number of time steps, guaranteeing low computational burden.

V. Numerical simulations

Numerical simulations have been performed to validate the proposed method. The sampling time is set to 10 minutes, while the nominal charging power for electric vehicles is 22 kW. The number of daily incoming vehicles has been modeled by a Gaussian distribution with mean 150 vehicles and standard deviation of 25. Both the arrival time distribution (Fig. 2) and the charging time distributions (Fig. 3) are modeled by means of Gaussian mixture models. Concerning customer side, the probability of accepting the charging offer as a function of the discriminant is modeled through a “decreasing-step” function, see black line in Fig. 4. This setup has been used to generate a synthetic dataset of $G = 90$ days. For each day $g \in \{1, \ldots, G\}$, the corresponding grid price c_g has been randomly sampled from the Italian electricity market [19]. Instead, the selling price p_g ha been considered constant throughout the day and it value has been randomly chosen on the basis of th energy cost to guarantee a discriminant range lying i $[-1, 4]$, resulting in a sufficiently rich dataset.

The estimated arrival time distribution is compare with the true distribution in Fig. 2, while Fig. 3 report the same comparison for a charging time distribution.

In general, the estimated probability distributions re semble the true unknown ones even for few recorded days. On the other hand, according to (10), the distribution of

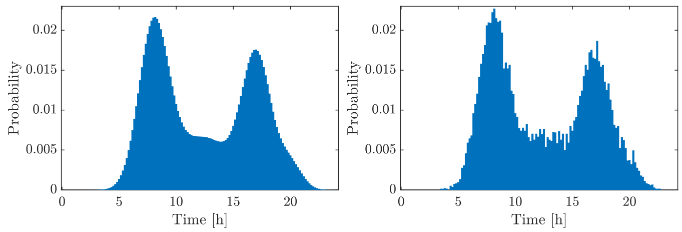

Fig. 2. True (left) vs estimated (right) arrival time distribution.

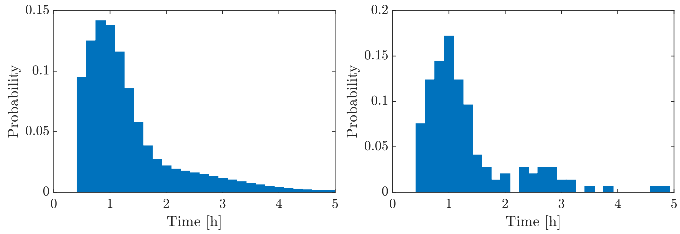

Fig. 3. True (left) vs estimated (right) charging time distribution for fixed arrival time $t^a = 47$.

the daily number of incoming vehicles does not influence the optimization as the cost function only depends on its mean. Therefore, accurate results can be obtained with few historical data; for instance, the considered small-sized dataset leads to an estimated mean of 148 incoming vehicles a day, with a relative error around 1%. Concerning the acceptance probability, Fig. 4 reports the performance of different kernel estimations w.r.t. the true function. The standard kernel regression tends to produce non-monotone estimates. However, the post-filtering procedure mentioned in Remark 3 leads to a monotone function which is in line with Assumption A5. Therefore, the latter estimator has been considered in the subsequent computations.

To validate the proposed procedure, a comparison between the optimal solution obtained with the real distributions (benchmark) and the estimated ones has been carried out. In particular, a simulation over 1000 days has been performed. For each day, the same grid price profile c has been taken into account, while different EV realizations have been considered. The optimal price profile obtained by the proposed technique is compared with the benchmark in Fig. 5. The general behavior shows a good match between the two curves. The statistics in

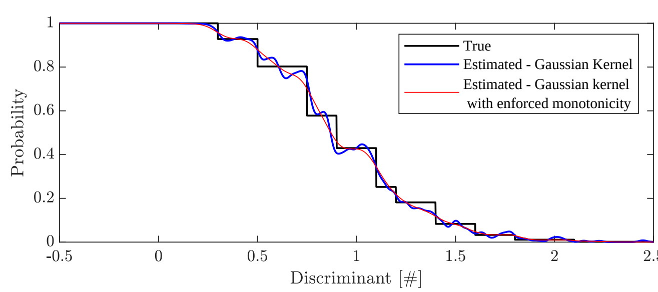

Fig. 4. True vs estimated accepting probability ($h(n) \propto 1/\sqrt{n}$).

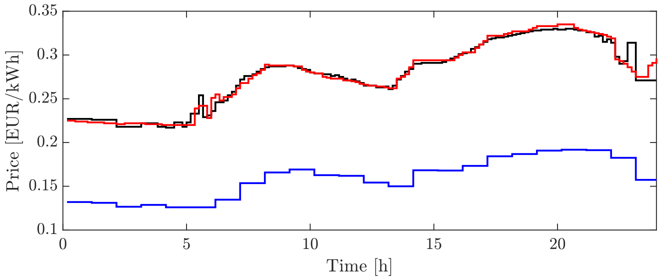

Fig. 5. Optimal price profile for one day of simulation. Black curve is the solution based on estimated probabilities, red dotted curve is the benchmark based on real distributions, blue curve is the grid price.

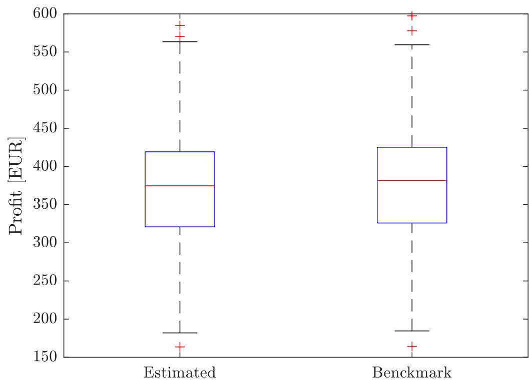

Fig. 6. Boxplot of the daily net profit over 1000 days of simulation.

terms of daily net return $\mathbf{R}$ over the 1000 simulated days are reported in Fig. 6. In this setup, the price profile computed from the estimated distributions leads to an average net profit of 372.62€ in contrast to the average daily profit of 378.29€ obtained by the benchmark. Finally, the proposed approach results tractable from a computational point of view. In fact, for each time step, the gridding exploration took on average 0.85 seconds to compute the optimal selling price over a grid of 500 prices with resolution of 10^{-3} €/kWh.

VI. Conclusions

In this paper an "estimate-then-optimize" probabilistic framework has been adopted to maximize the expected daily profit of an EV charging station with price-sensitive customers. First, a data-driven kernel-based procedure has been established to infer about the probability of accepting the charging offer given a price. Next, this information has been incorporated into a stochastic optimization program. Numerical simulations show that the proposed approach produces results showing good performance even in the presence of small datasets.

Ongoing work focuses on the extension of the framework for power signal tracking to accommodate for peak shaving/valley filling objectives, and the integration of online learning for continuous refinement of the estimated probabilities. Moreover, the proposed framework is intended to be validated in real scenarios.

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