Optimal Price Menu Design of Electric Vehicle Charging Stations Providing Demand Response

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***Abstract*—The proliferation of Electric Vehicles (EVs) creates new challenges for EV Charging Station Operators (CSOs) due to the increasing charging demand, but also opportunities to leverage EV user flexibility. In this work, we consider an EV CSO offering several charging power rates at different prices, and we explore the design of a price menu. In our setting, EV users are inflexible in their parking duration but flexible in terms of their energy demand, and choose the option that maximizes their welfare, i.e., their utility minus their cost of charging. We formulate the optimal price menu design problem of a profit maximizing CSO as a Mixed Integer Linear Programming problem, and we compare against the outcome of social welfare maximization. We further account for the provision of demand response by the CSO, i.e., lowering its power consumption for a certain period given a certain price for remuneration, by adjusting the price menu (in real time), so as to incent EV users to choose lower power rates. Our numerical demonstrations provide useful insights on the construction of the optimal price menu.**

***Index Terms*—Electric vehicle, charging station operator, optimal price menu design, demand response.**

I. Introduction

In view of the growing adoption of Electric Vehicles (EVs) [1], public charging stations are attracting significant attention. Their aggregate power consumption may stress the grid and its assets (e.g., transformers [2], [3]), and hence, leveraging the EV user flexibility is key to avoid costly and potentially unnecessary upgrades. An EV Charging Station Operator (CSO), with a capability to modulate its aggregate power consumption for a given period, by intelligently designing the options/services/prices offered to the EV users, can thus provide some type of remunerated demand response service and/or a non-wires solution [4] to the grid operator (e.g., [5]).

In the vast amount of literature on the scheduling and coordination of EV charging, there are only a few works [6], [7], [8], [9], [10], [11], [12], [13] considering the design of some type of *price menu* that is offered by the CSO to the EV users. Such a menu typically consists of a price that can be associated with a delay in the completion of charging [6], [7], [8], [9] (assuming that the utility of EV users depends on the delay of their departure), and/or the amount of energy that EV users receive [10], [11], [12].

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Considering the flexibility of EV users in the completion of charging, some works [6], [7], [8] propose some type of "deadline-differentiated" pricing, i.e., a price associated with a deadline. In [6], the CSO solves a profit maximization mixed integer quadratic programming problem to determine optimal prices that incent EVs to prolong their charging sessions when the cost of electricity is low. In the same spirit, [7] adds a linear penalty in the CSO aggregate power consumption, and uses block coordinated descent to solve a profit maximization problem that considers bounded rationality for the EV user deadline choice. In [8], the focus shifts to identifying optimal deadline value offers, and the CSO solves an optimal control problem, aiming at smoothing the aggregate power consumption that is associated with a convex cost for electricity. In [9] the charging intervals and corresponding prices are determined in an online fashion, considering a bound on the aggregate power consumption, and aiming at minimizing the overall delay in the completion of charging.

The aforementioned works [6], [7], [8], [9] account for the EV user flexibility in the charging deadline but not in their energy demand. Conversely, [10], [11] account for the flexibility in the energy demand but consider fixed deadlines. In a rather general setting for electric power loads [10], consumers define their energy demand for time intervals before their deadline, and pay a price that depends on the aggregate power consumption. Using a game theoretic setting, it is found that marginal cost pricing, combined with "earliest-deadline-first" charging, maximizes the CSO profit as well as the social welfare provided that the EV user willingness to charge is greater than the electricity cost. In [11], several online scheduling algorithms are proposed that maximize social welfare, in which the CSO ensures a guaranteed amount of energy upon the EV arrival and until the deadline, while taking into account constraints in aggregate power and concurrent EV charging.

In [12], the CSO offers a price menu that considers the EV user flexibility in both the energy demand and the deadline for charging. Electricity is sourced either from a local renewable energy supply at zero cost or through purchases from the grid. The optimal pricing is provided as a function of the outcome of the charging scheduling problem (cost minimization linear programming problem), both for the social welfare and the CSO profit maximization. Conversely, [13], [14] consider inflexible EV users in both the energy demand and the deadline. In [13], the CSO price menu consists of several options with different energy amounts and deadlines; the arriving EV users choose whether to charge or not depending on their utility and the charging price of the option that matches their requirements. The profit and social welfare maximization are formulated as a partially observable Markov decision process and solved through deep reinforcement learning. In [14], the charging station is modeled as a queuing network, and EV users can choose between two charging power levels that are associated with different queue lengths and prices. The CSO sets a static admission price that minimizes the "dropping rate," i.e., the proportion of EV users leaving the charging station (choosing not to charge) because of a long waiting queue.

Most of the aforementioned works require EV users to specify or provide some type of information on their parking duration (deadline) and/or their energy demand. Apart from privacy concerns, it is not unreasonable to assume that many users may not have a specific requirement for energy, and/or there may be some uncertainty in their parking duration. Furthermore, in the deadline-differentiated pricing, there may be no guarantee on the amount of energy charged if the EV user leaves sooner than expected (also not unreasonable to assume). For these reasons, we suggest a price menu that offers a guaranteed power rate for a certain price, so that EVs can choose among different power rates, thus securing a certain quality of service. In this paper, our aim is to investigate the problem of the CSO price menu design and its capability to provide demand response. We consider a CSO equipped with a large enough number of charging points, i.e., the station's capacity (in terms of charging points) does not become a limiting factor for serving EVs. We also consider EV users that view charging more as an opportunity rather than an indispensable need. Hence, the parking duration depends only on their on-site activities — see, e.g., [15] on the inelasticity of the parking demand. A profit maximizing CSO would offer a menu with different prices per power rate, which can adapt to heterogeneous requirements of EV users, using information that may be either provided by the users or obtained from the CSO statistics/data collected on its EV user utility/characteristics/behavior. Assuming a certain price for offering demand response in real time, the CSO could then dynamically adjust the price menu to reduce its aggregate power consumption.

Our main contribution is three-fold. First, we formulate the price menu design problem of an EV CSO that differentiates the options in the power rate, instead of the deadline, as a Mixed Integer Linear Programming (MILP) problem. Second, we propose a setting for the provision of demand response by the CSO, given a price for reducing its aggregate power consumption over a certain time period, by adjusting the price menu in real time. Third, we provide insights through numerical experimentation on the construction of the optimal price menu, and the trade-offs considered in terms of the CSO profits and the social welfare under different prices for electricity and demand response.

The remainder of the paper is organized as follows. Section II presents the preliminaries for the CSO and EV models. Section III formulates the price menu design problem, and Section IV describes the provision of demand response by the CSO. Section V discusses a numerical experimentation, and Section VI concludes and provides further research directions.

II. Model Preliminaries

In this section, we introduce the EV CSO offered charging options (in Subsection II-A), the utility function of EV users, (in Subsection II-B), and we define the CSO profit (in Subsection II-C) and the social welfare (in Subsection II-D).

A. EV CSO Offered Charging Options

The CSO offers a discrete set of K options, denoted by $\mathcal{K} = \{1, ..., K\}$, where option k corresponds to a constant power rate P_k and a price per energy unit (kWh) π_k. For notational simplicity, we denote the set of available options, which includes option $k = 0$ corresponding to "*not charging*," i.e., $P_0 = 0$ and $\pi_0 = 0$, by $\mathcal{K}^+ := \mathcal{K} \cup \{0\}$.

The CSO options are ordered from lowest power rate to the highest, i.e., $P_{k-1} < P_k$, $\forall k \in \mathcal{K}$, with prices that are non-decreasing with the power rate, i.e.,

$$\pi_{k-1} \leq \pi_k, \, \forall k \in \mathcal{K}. \tag{1}$$

In most of the charging stations in reality, a higher charging power is offered at a higher price, see for example [16].

B. EV Utility

Let EV class $i \in \mathcal{I}$, where $\mathcal{I} = \{1, ..., I\}$ is the set of EV classes, have (upon arrival) an initial State of Charge (SoC) denoted by e_i^0, and parking duration denoted by d_i. Let $e_i^{\max}$ denote the EV battery capacity, and e_i the SoC at the time of departure.

For brevity, we refer to EV i instead of EV class i. If EV i charges at a power rate P, its SoC at the time of departure is given by:

$$e_i = e_i^0 + P \, d_i. \tag{2}$$

Given any option k, EV i can charge at most $\min\{e_i^{\max} - e_i^0, P_k \, d_i\}$, so that the battery capacity is not exceeded. We can therefore denote the options available to EV i using a subset $\mathcal{K}_i = \{1, ..., K_i\} \subseteq \mathcal{K}$, where K_i is defined as the highest available power rate such that the battery capacity is not exceeded given the parking duration d_i.

Let U_i denote the utility of EV i, which depends on the SoC e_i at the time of departure, and is increasing and concave in e_i [17]. Essentially, increasing the SoC increases the EV utility but with diminishing returns (due to the concavity). From (2), we can express the dependency of the EV utility on the power rate P using $U_i(P)$.

Let $u_i(P_k)$ denote the marginal utility of EV i choosing option k related to power P_k, i.e.,

$$u_i(P_k) := \frac{\partial U_i(P)}{\partial P}\Big|_{P=P_k}. \tag{3}$$

Given the increasing and concave utility in e_i, which also, from (2), implies that the utility is increasing and concave in

P, the marginal utility is non-negative and decreasing in k, i.e.,

$$u_i(P_{k-1}) \geq u_i(P_k) \geq 0, \quad \forall k \in \mathcal{K}_i^+. \tag{4}$$

Eq. (4) simply states that the marginal utility is positive but decreasing in the power rate, hence, there are diminishing returns when choosing an option with a higher power rate.

C. CSO Profit

The CSO buys electricity from the grid and sells electricity to EVs. Let λ_t be the price (per kWh) at which the CSO buys electricity at time t. Let c_i denote the average cost (per kWh) over time that the CSO incurs when charging EV i, which is given by:

$$c_i = \frac{1}{d_i} \int_{\tau_i^0}^{\tau_i^0 + d_i} \lambda_t \, dt, \tag{5}$$

where τ_i^0 and $\tau_i^0 + d_i$ are the arrival and departure times, respectively of EV i.

When EV i chooses option k, the CSO charges π_k (per kWh), whereas incurs a cost c_i (per kWh). Hence, the CSO profit for charging EV i choosing option k, denoted by $\Pi_i(\pi_k)$ to indicate the dependence on π_k, is then given by:

$$\Pi_i(\pi_k) = (\pi_k - c_i) \, P_k \, d_i. \tag{6}$$

D. Social Welfare

Let $W_i(\pi_k)$ denote the welfare of EV i choosing option k, which is the difference between their utility $U_i(P_k)$, and the cost of charging at the charging station, i.e.,

$$W_i(\pi_k) := U_i(P_k) - \pi_k \, P_k \, d_i. \tag{7}$$

Note that we express the dependence of the welfare on the price π_k, whereas the dependence of the utility is on the associated power rate P_k.

EV i aims at maximizing its welfare, hence, the optimal choice, k_i^*, is given by:

$$k_i^* = \underset{k \in \mathcal{K}_i^+}{\arg\max} \, W_i(\pi_k). \tag{8}$$

Using the concavity of the utility function and the price ordering (1), one can show that for any set of options the welfare increases (in k) until the option that corresponds to the optimal choice for the EV user, and then decreases. Hence, one can find the optimal choice, with a simple search among ordered options (from the lowest power rate to the highest power rate) until the welfare begins to decrease.

The *social welfare*, $W_i^S(\pi_k)$, i.e., the sum of the CSO profit and the welfare of EV i choosing option k, is given by:

$$W_i^S(\pi_k) := \Pi_i(\pi_k) + W_i(\pi_k) = U_i(P_k) - c_i P_k d_i, \tag{9}$$

where we added the dependence on π_k, which naturally associates to the power rate P_k.

III. Price Menu Design Problem

In this section, we consider the price menu design problem of a CSO who has information on the distribution of EV users among a finite set of classes, $\mathcal{I}$. These classes and their weight over the population, denoted by θ_i for EV (class) i, can be obtained using data on the EV user behavior — see e.g., [6].

In what follows, we consider the price menu design problem under two objectives: (i) maximization of the expected CSO profit (in Subsection III-A), and (ii) maximization of the expected social welfare (in Subsection III-B). Notably, the two problems can be solved for each time period separately (no time coupling constraints), i.e., the CSO can update the price menu at each time period, assuming without loss of generality an hourly granularity (although the offered price when an EV arrives will be binding for that EV for its entire parking duration).

A. CSO Profit Maximization

The CSO expected profit is given by:

$$\mathbb{E}_{\boldsymbol{\theta}}[\Pi_i(\pi_{k_i^*})] = \sum_{i \in \mathcal{I}} \theta_i (\pi_{k_i^*} - c_i) P_{k_i^*} d_i, \tag{10}$$

where k_i^* is the optimal choice of EV (class) i that is given by (8). Hence, the CSO profit maximization problem is given by:

$$\begin{aligned} &\max_{\boldsymbol{\pi}, \boldsymbol{k^*}} \mathbb{E}_{\boldsymbol{\theta}}[\Pi_i(\pi_{k_i^*})] \text{ given by (10),} \\ &\text{s.t. (1) and (8).} \end{aligned} \tag{11}$$

The optimal choice, k_i^*, for EV user i can be modeled using a binary variable, $a_{i,k}$, $\forall i \in \mathcal{I}$, $k \in \mathcal{K}_i^+$, denoting whether EV i chooses option k (value 1, otherwise 0). The expected profit is thus given by:

$$\mathbb{E}_{\boldsymbol{\theta}}[\Pi_i] = \sum_{i \in \mathcal{I}} \sum_{k \in \mathcal{K}_i^+} \theta_i \, a_{i,k} \, (\pi_k - c_i) P_k d_i, \tag{12}$$

where we require that only one option is chosen, i.e.,

$$\sum_{k \in \mathcal{K}_i^+} a_{i,k} = 1, \quad \forall i \in \mathcal{I}. \tag{13}$$

Similarly to [6], (8) can then be reformulated using the big M method as follows:

$$\begin{aligned} W_i(\pi_k) + M^W \sum_{m \neq k} a_{i,m} \geq W_i(\pi_\ell), \\ \forall i \in \mathcal{I}, \, k, \ell \in \mathcal{K}_i^+, \ell \neq k, \end{aligned} \tag{14}$$

where M^W is a positive and sufficiently large number. With (13), constraint (14) ensures that $a_{i,k_i^*} = 1$. The idea of this constraint is that for k such that $a_{i,k} = 0$, the inequality is verified because the *lhs* second term takes a very large value (i.e., M^W). For the unique k such that $a_{i,k} = 1$, the *lhs* second term becomes equal to zero, which enforces option k to be the optimal option in terms of EV welfare maximization.

The objective function in (12) contains a product of a binary variable $a_{i,k}$ and a non-negative continuous variable π_k. Using standard big M linearization techniques [18], we can replace the product by a new, non-negative, continuous variable, say $b_{i,k}$, $\forall i \in \mathcal{I}$, $k \in \mathcal{K}_i$, so that (12) becomes:

$$\mathbb{E}_{\boldsymbol{\theta}}[\Pi_i] = \sum_{i\in\mathcal{I}} \sum_{k\in\mathcal{K}_i} \theta_i \left(b_{i,k} - a_{i,k} c_i\right) P_k \, d_i, \tag{15}$$

and add the following constraints:

$$b_{i,k} \le a_{i,k} M^{\pi}, \qquad \forall i \in \mathcal{I},\, k \in \mathcal{K}_i, \tag{16a}$$
$$b_{i,k} \ge 0, \qquad \forall i \in \mathcal{I},\, k \in \mathcal{K}_i, \tag{16b}$$
$$b_{i,k} \le \pi_k, \qquad \forall i \in \mathcal{I},\, k \in \mathcal{K}_i, \tag{16c}$$
$$b_{i,k} \ge \pi_k - \left(1 - a_{i,k}\right) M^{\pi}, \qquad \forall i \in \mathcal{I},\, k \in \mathcal{K}_i, \tag{16d}$$

where M^{π} is a positive and sufficiently large number. Constraints (16) ensure that the variables $b_{i,k}$ take the value π_k when $a_{i,k} = 1$ and 0 otherwise. Specifically, constraints (16a) and (16b) enforce $b_{i,k} = 0$ when $a_{i,k} = 0$, whereas (16a) becomes redundant when $a_{i,k} = 1$. Constraints (16c) and (16d) enforce $b_{i,k} = \pi_k$ when $a_{i,k} = 1$, and they become redundant otherwise.

Summarizing, the CSO expected profit maximization problem, $\mathbf{\Pi^{CSO}_{max}}$ is given by:

$$\mathbf{\Pi^{CSO}_{max}}: \quad \max_{\boldsymbol{\pi},\boldsymbol{a},\boldsymbol{b}} \mathbb{E}_{\boldsymbol{\theta}}[\Pi_i] \text{ given by (15)},$$
$$\text{s.t. (1), (7), (13), (14), and (16).} \tag{17}$$

Problem (17) is a MILP problem.

B. Social Welfare Maximization

Using the aforementioned binary variable $a_{i,k}$, the expected social welfare is given by:

$$\mathbb{E}_{\boldsymbol{\theta}}[W^S_i] = \sum_{i\in\mathcal{I}} \sum_{k\in\mathcal{K}_i} \theta_i \, a_{i,k} \left[U_i(P_k) - c_i P_k d_i\right]. \tag{18}$$

For practical purposes, in order to ensure a non-negative profit for the CSO (who sets the prices), we require from (15) that:

$$\sum_{i\in\mathcal{I}} \sum_{k\in\mathcal{K}_i} \theta_i \left(b_{i,k} - a_{i,k} c_i\right) P_k d_i \ge 0, \tag{19}$$

where $b_{i,k}$ are described by constraints (16).

Summarizing, the expected social welfare maximization problem, $\mathbf{W^S_{max}}$, is as follows:

$$\mathbf{W^S_{max}}: \quad \max_{\boldsymbol{\pi},\boldsymbol{a}} \mathbb{E}_{\boldsymbol{\theta}}[W^S_i] \text{ given by (18)},$$
$$\text{s.t. (1), (7), (13), (14), (16) and (19).} \tag{20}$$

Problem (20) is also a MILP problem.

IV. CSO Demand Response

In this section, we consider the case of a CSO providing demand response, by reducing the aggregate power consumption by a certain amount, during specific time periods. This reduction can be viewed as the provision of a reserve product (to be used interchangeably with demand response) — or flexibility as is often mentioned in the literature — *w.r.t.* its "usual" power consumption. Indeed, there is a long debate on how to determine such a "base case," or whether this is even possible. However, for the purposes of this paper, we can employ the outcome of the CSO profit maximization problem as the "usual consumption," upon which any reduction can be calculated. Alternatively, one can think of a day-ahead commitment on a certain power consumption (considering an expected profit maximization problem and the resulting power consumption given the "optimal price menu") and a "real-time adjustment" of the price menu to reduce the actual consumption by a certain amount. In what follows, we consider the problem for the provision of demand response through a certain reduction in the aggregate consumption during a certain time period.

For clarity, we introduce the notation in the multi-period problem, whose horizon is represented by the set $\mathcal{T} = \{1, \ldots, T\}$, assuming without loss of generality that t refers to an hourly period.

Let N_t denote the number of EV arrivals at time t, of expectation $\bar{N}_t$, and with weights per class i at hour t, $\theta_{i,t}$. For brevity, we define parameter $n_{i,t} = \bar{N}_t \, \theta_{i,t}$ representing the expected number of vehicles of class i arriving at time t.

The price menu is denoted by $\pi_{k,t}$, i.e., the prices can change every hour, assuming without loss of generality that the power rates, P_k, are parameters that do not change every hour. Still, for each time period, prices should be ordered as in (1), i.e.:

$$\pi_{k-1,t} \le \pi_{k,t}, \quad \forall k \in \mathcal{K}, t \in \mathcal{T}. \tag{21}$$

The binary variables $a_{i,k,t}$ denote whether EV i, arriving at time t, chooses option k, with:

$$\sum_{k\in\mathcal{K}^+_i} a_{i,k,t} = 1, \quad \forall i \in \mathcal{I},\, t \in \mathcal{T}. \tag{22}$$

The optimal choice of EV i, that is k^*_i such that $a_{i,k^*_i,t} = 1$, arriving at time t is given by the following constraints:

$$U_i(P_k) - \pi_{k,t} P_k d_i + M^W \sum_{m\neq k} a_{i,m,t} \ge U_i(P_\ell) - \pi_{\ell,t} P_\ell d_i,$$
$$\forall i \in \mathcal{I},\, k, \ell \in \mathcal{K}^+_i, \ell \neq k,\, t \in \mathcal{T}, \tag{23}$$

where we replaced the EV welfare by its definition — see (7).

Similarly to (16), the continuous variables $b_{i,k,t}$ verify the following conditions:

$$\forall i \in \mathcal{I}, k \in \mathcal{K}_i, t \in \mathcal{T}: \tag{24}$$
$$0 \le b_{i,k,t} \le a_{i,k,t} M^{\pi},$$
$$\pi_{k,t} - (1 - a_{i,k,t}) M^{\pi} \le b_{i,k,t} \le \pi_{k,t}.$$

The aggregate expected profit over the time horizon, using (15) and parameter $n_{i,t}$, is given by:

$$\hat{\Pi}_{\mathcal{T}} = \sum_{t\in\mathcal{T}} \sum_{i\in\mathcal{I}} \sum_{k\in\mathcal{K}_i} n_{i,t} \left(b_{i,k,t} - a_{i,k,t} c_i\right) P_k d_i. \tag{25}$$

Let $\mathcal{T}_R = \{\tau_1, \ldots, \tau_2\}$ be the set of time periods during which the CSO reduces the aggregate power consumption by a certain amount denoted by P^R_t, from the aggregate power consumption, denoted by P^{Π}_t that pertains to the solution of Problem (17), which can be solved separately for each time period.

Let indicator (parameter) $\delta_{i,t',t}$ denote whether an EV of class i arriving at time t' is connected at time t, where $t \geq t'$ — i.e., for as long as its parking duration d_i. Let variable $\hat{P}_t$ denote the expected aggregate power consumption, given by:

$$\hat{P}_t = \sum_{i\in\mathcal{I}} \sum_{k\in\mathcal{K}_i} \sum_{t'=1}^{t} n_{i,t'}\, a_{i,k,t'}\, P_k\, \delta_{i,t',t}, \quad \forall t \in \mathcal{T}. \qquad (26)$$

The reduction of the power consumption for the provision of demand response is then enforced through:

$$\hat{P}_t \leq P_t^{\Pi} - P_t^R, \quad \forall t \in \mathcal{T}_R. \qquad (27)$$

Summarizing, the CSO demand response problem, given a price λ_t^R for reducing the power consumption during hour t, is now as follows:

$$\mathbf{DR}^{\mathbf{CSO}}_{\boldsymbol{\lambda}^R}: \quad \max_{\boldsymbol{\pi},\boldsymbol{a},\boldsymbol{b},\boldsymbol{P}^R} [\hat{\Pi}_{\mathcal{T}} \text{ given by (25)}] + \sum_{t\in\mathcal{T}_R} \lambda_t^R P_t^R,$$
$$\text{s.t. (21)} - \text{(23), (26), and (27),} \qquad (28)$$

with $P_t^R \geq 0$, $\forall t \in \mathcal{T}_R$. Problem (28) is a MILP problem.

So far, we have considered the expected number of arrivals per class, $n_{i,t}$, and calculated expected profits and power consumption. One may think that the provision of demand response, i.e., the reduction in power, should be enforced with a higher probability. A simple way would be to replace the expected number of arrivals $n_{i,t}$ in constraint (26) by an appropriately-defined "worst-case" number of arrivals, during the periods $\mathcal{T}_R$ (potentially even earlier). Indeed, in a practical setting, the CSO can re-solve the problem, after each hour, and define the price menu dynamically every hour, with the information available up to that hour. However, due to space considerations, we will refrain from such settings in this first work. Future work will be directed to more elaborate robust optimization formulations and appropriate uncertainty sets as well as more dynamic settings that employ the information that becomes available during the day.

V. Numerical Results

In this section, we provide a numerical experimentation of the optimal price menu design problem. In Subsection V-A, we describe the test case (CSO and EVs). In Subsection V-B, we present the results from the profit and social welfare maximization problems, whereas in Subsection V-C, we discuss the results from the CSO demand response provision.

A. Test Case

1) CSO: We consider the provision of 4 power rates for charging: $P_1 = 2.5$ kW, $P_2 = 5$ kW, $P_3 = 7.5$ kW, and $P_4 = 10$ kW, i.e., $K = 4$. Note that we consider "low" charging rates [19] in our numerical illustrations to emphasize the fact that EVs view charging more as an opportunity than as an absolute need (which would make them less flexible or direct them to fast charging stations). However, our analysis remains relevant for higher charging rates.

TABLE I
Parameters of EV Classes

e_i^0 / d_i	**Class *i*: K_i** 1 h	2 h	3 h	4 h	Utility Parameters α_i	β_i
10 kWh	**1**: 4	**2**: 4	**3**: 4	**4**: 3	0.425	0.017
20 kWh	**5**: 4	**6**: 4	**7**: 2	**8**: 2	0.35	0.021
30 kWh	**9**: 4	**10**: 2	**11**: 1	**12**: 1	0.275	0.027

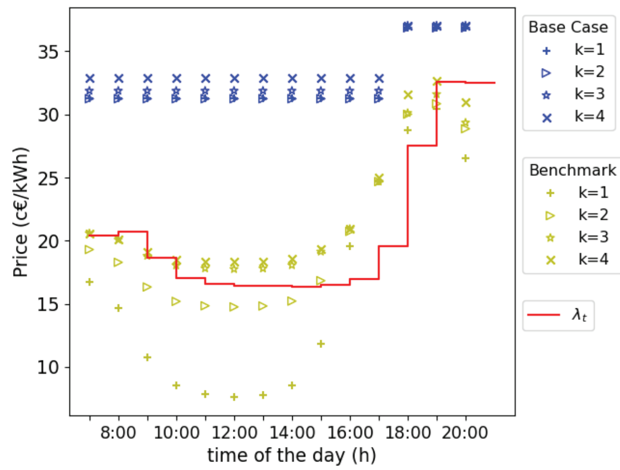

Fig. 1. Optimal price menu, Base Case and Benchmark.

2) EVs: We consider that all EVs have a battery capacity of 50 kWh, and can charge between 20% and 80%. EV classes are determined by their initial SoC and parking duration. We consider 3 different initial SoCs: 10 kWh, 20 kWh, and 30 kWh. We also consider 4 different parking durations: 1h, 2h, 3h, and 4h. Hence, in total, we have 12 EV classes, assumed to be equally distributed. EVs arrive at the charging station with a constant rate of 120 vehicles per hour, from 7am to 8pm. They share a quadratic utility function given by $U_i(P) = \alpha_i\, [\, P\, d_i - \frac{1}{2}\, \beta_i\, (P\, d_i)^2\,]$, where α_i, β_i, are positive scalars, which parameterize EV i willingness to charge while ensuring an increasing utility for practical power rates. In order to ease the exposition and interpretation of the results, we assume that scalars α_i and β_i depend only on the initial SoC, thus keeping the number of EV classes contained. Table I summarizes the 12 EV classes, the highest (in power rate) option available (K_i) for EV class i, and utility parameters. Big M values are set at 15 for M^W and 0.5 for M^{π}.

All problems were solved using CPLEX 22.1.1.0 solver.

B. Profit and Social Welfare Maximization Results

For convenience, we shall refer to the outcome of the CSO expected profit maximization problem (17), $\mathbf{\Pi^{CSO}_{max}}$, as the "Base Case," and to the expected social welfare maximization problem (18), $\mathbf{W^{S}_{max}}$, as the "Benchmark."

Fig. 1 presents the optimal price menu for the Base Case and the Benchmark, as well as the electricity price (parameter), λ_t, for comparison purposes. We observe that the Base Case optimal price menu offers higher charging prices than the electricity price (maximizing CSO profit). For the most part of the day (from 7am to 5pm), when the electricity price is low

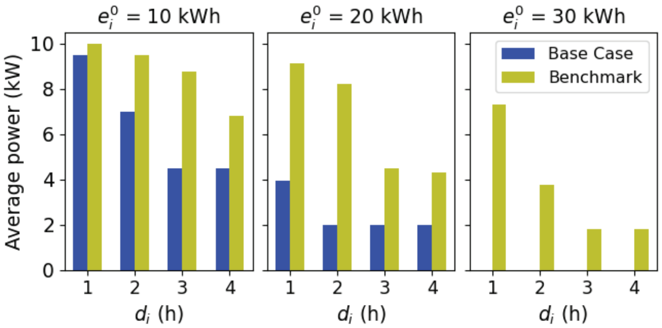

Fig. 2. Average power chosen during the day for each EV class, Base Case and Benchmark.

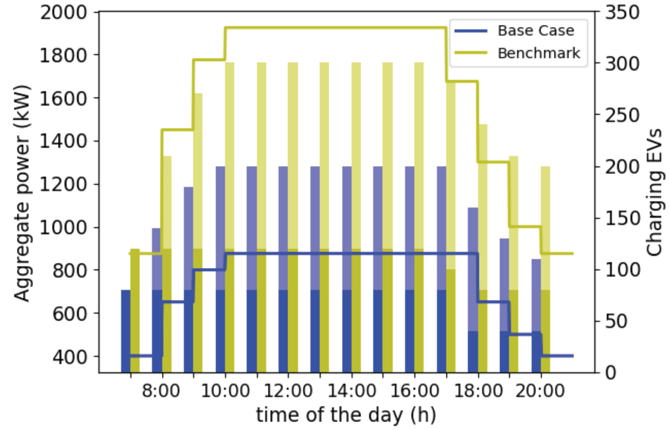

Fig. 3. Aggregate power consumption (left axis, line) and number of EVs deciding to charge (right axis, columns, lower part: EVs arriving at the hour; upper part EVs remaining from previous hours).

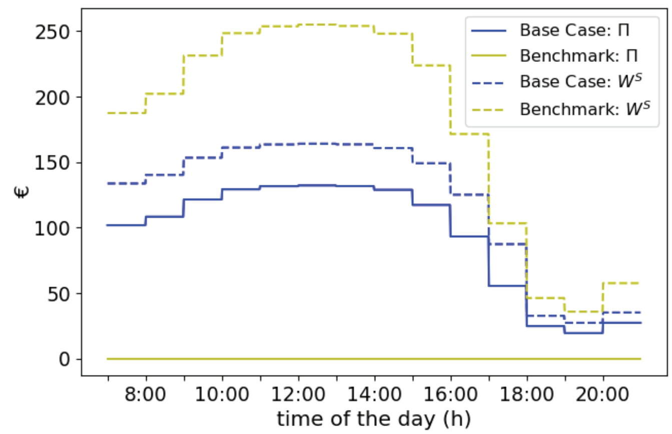

Fig. 4. Hourly profit and social welfare, Base Case and Benchmark.

(around 20 cents per kWh), the prices in the Base Case menu remain stable (spanning around 2 cents from option 1 to option 4). When the electricity price increases (from 6pm to 8pm), the prices in the menu increase and remain practically stable for all options. The shape of the Base Case menu indicates that, when the CSO maximizes its profits, the prices of the menu are not very sensitive to small changes in the electricity price. This is attributed to the fact that the price menu considers also the utility of the EV users, whose optimal choices are discrete; hence, a small increase in the offered price might result in the EVs choosing a lower power rate or even not charging. Consider for example the case of EV class 5, which chooses option 2 at 5 pm. Note that this class could choose any option, however, it chooses option 2 and not the higher power rate option 3, even though the price difference (between options 2 and 3) is only 0.625 cents; hence, this small difference in the price is enough to discourage EV class 5 from choosing option 3. The Benchmark optimal price menu in Fig. 1 exhibits a larger span during the day, with a trend of a "weighted moving average" of the electricity cost, and some prices well below the electricity price that attract EV users with a low marginal utility.

Fig. 2 illustrates the average (over the entire day) power chosen per EV class for the Base Case and the Benchmark. Unsurprisingly, the Base Case average power is lower for all EV classes, due to the higher charging prices — recall Fig. 1 compared to the Benchmark. For both, in general, the higher the parking duration and/or the higher the initial SoC, the lower the average power (due to lower marginal utilities). In fact, EV classes 9–12, with a high initial SoC (30 kWh) refrain from charging in the Base Case, since their marginal utility (of 27.5 cents per kWh) is below the lowest price in the menu (that ranges from 31 to 37 cents per kWh).

In Fig. 3, we illustrate the aggregate power consumption and the number of EVs deciding to charge, for the Base Case and the Benchmark. Clearly, the Benchmark charges more EVs compared to Base Case, and at lower prices — see Fig. 1 — thus resulting in a significantly higher power consumption, peaking at 1,925 kW, whereas the Base Case peaks at 875 kW. Recall that the average EV power consumption is also higher for the Benchmark — see Fig. 2 for the daily average — due to the lower prices compared to the Base Case. We elaborate further on the aggregate consumption shape of Fig. 3 and illustrate in Fig. 4, the hourly profit and social welfare, we observe that the Benchmark maximum social welfare (2519.22 € for the entire day) is achieved with zero profits for the CSO, and maximum welfare for the EV users. In the Base Case, the observed social welfare (821.58 € lower than the Benchmark) is primarily attributed to the CSO profits.

C. *Demand Response Results*

Using the solution of the Base Case as a "baseline" for the CSO aggregate consumption, we solve the demand response problem (28), with a 5-hour reserve period between 4pm and 9pm. We consider two cases for the reserve price, λ_t^R (constant for the entire 5-hour period): 5 and 10 cents per kW.

In Fig. 5, we present the price menu for the Base Case, and for the two values of the reserve price. For reasons that will soon become apparent, we present the 5 hours affected (4pm, 5pm, 6pm, 7pm, 8pm) as well as the previous hour (3pm). In Fig. 6, we illustrate the aggregate power consumption, for the Base Case and the two reserve prices. Considering first the lower reserve price (Fig. 5, middle), we observe that the

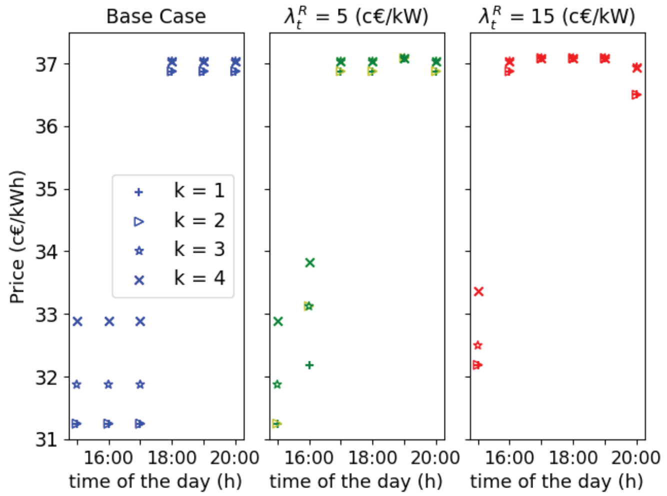

Fig. 5. Optimal price menu (3pm to 8pm): Base Case and provision of demand response (two reserve prices).

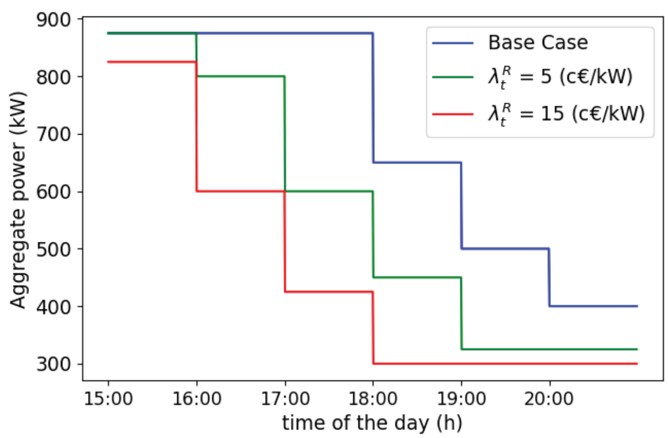

Fig. 6. Aggregate power consumption (3pm to 8pm): Base Case and provision of demand response (two reserve prices).

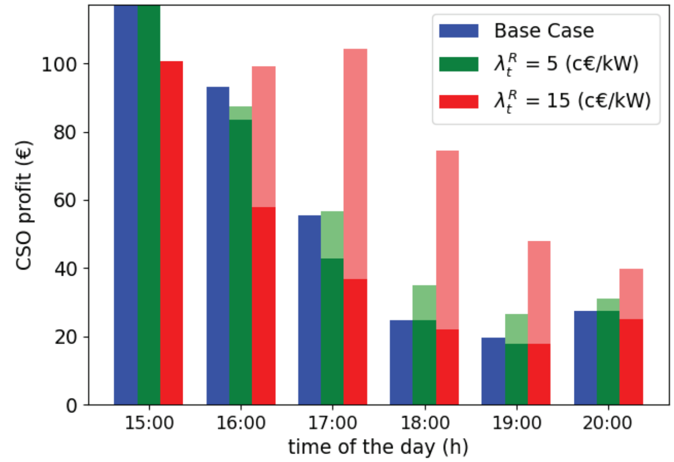

Fig. 7. CSO profit (lower part of column: profit for energy; upper part: revenue from demand response).

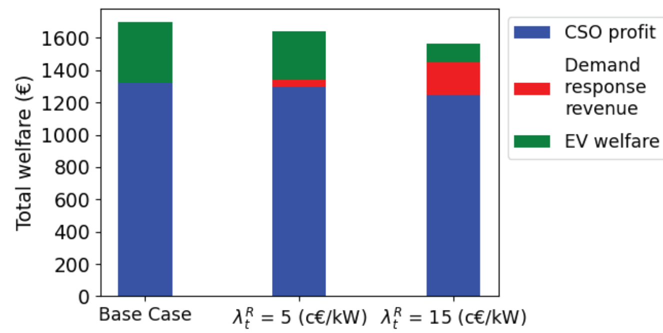

Fig. 8. Total social welfare (over the entire day) breakdown: CSO profit, revenue from providing demand response, and EV welfare (Base Case and two reserve prices).

main change *w.r.t.* the Base Case refers to hours 4pm and 5pm, when the prices increase (they span between 32 and 34 cents at 4pm, and reach 37 cents at 5pm). The reduction in the aggregate power consumption (Fig. 6, green line) is 75 kW at 4pm and 275 kW at 5pm. Note that the price menu at 6pm is the same with the Base Case, however, we still see a reduction by 200 kW, which is due to the lower amount of EVs deciding to charge in the previous hours (we remind that EVs may charge for 4 hours). The reduction drops to 175 kW at 7pm and 75 kW at 8pm because the Base Case aggregate power consumption is already low at these hours. Considering next the higher reserve price (Fig. 5, right), we observe that the prices increase earlier (slightly at 3pm, and then reach around 37 cents) achieving a higher reduction in the aggregate power consumption (Fig. 6, red line), which amounts to 50 kW at 3pm, 275 kW at 4pm, 450 kW at 5pm, 350 kW at 6pm, 200 kW at 7pm, and 100 kW at 8pm. The reduction at 3pm — before the beginning of the reserve period — is explained by the fact that a lower number of EVs that decide to charge at 3pm affects the aggregate power consumption in the hours that follow — recall the EV parking duration of up to 4 hours.

In Fig. 7, we illustrate the CSO profit for the Base Case and the two reserve prices, which includes the revenue for providing demand response. We observe that at 3pm, the Base Case and the lower reserve price yield the same profit, whereas the higher reserve price yields lower profit (see the higher prices in Fig. 5, right). This occurs in anticipation of the reserve period (as we saw in Fig. 5, right; and Fig. 6, red line), which is advantageous when the reserve price is high, e.g. 15 c€/kW. Indeed, the profit of the higher reserve price (red column) is the highest in all other hours. The profit of the lower reserve price (green column) becomes higher than the Base Case at 5pm and remains higher until 8pm.

Fig. 8 shows the breakdown of the total social welfare over the entire day into CSO profit, revenue from providing demand response, and EV welfare. The total CSO profit for the Base Case is 1,323.45 €. The total profit when providing demand response increases by 16.04 € (1.21%) for the low reserve price, and by 128.41 € (9.70%) for the high reserve price. The total social welfare over the entire day for the Base Case is 1697.64 €. Accounting for the revenues from demand response, the total social welfare decreases by 56.69

€ (3.34%) for the low reserve price, and by 131.70 € (7.76%) for the high reserve price. The total welfare of the EVs over the entire day, which is 374.19 € for the Base Case, decreases to 301.46 € for the low reserve price, and to 114.08 € for the high reserve price. Summarizing, a higher reserve price results in higher CSO profits, lower EV welfare, and lower total social welfare.

VI. Conclusions and Further Research

In this work, we considered a CSO serving EVs that are flexible in their energy demand but not in their parking duration, offering several power rates at different prices (price menu). Arguably, this CSO model could fit well public charging stations, considering the future EV adoption, where charging would be viewed more as an opportunity (e.g., in a public parking station), and charging point availability is unlikely to be a limiting factor. In this context, we formulated the optimal price menu design problem as a MILP problem, considering both a profit maximizing CSO and (as a benchmark) social welfare maximization. We further accounted for the provision of demand response by considering an adjustment of the price menu (in real time) to reduce the aggregate power consumption and benefit from a certain price for remuneration (as a type of reserve deployment). Our numerical experimentation illustrated the construction of the optimal price menu, the trade-offs considered for the CSO profit and the social welfare, and the price menu adjustment to provide demand response under different (reserve) prices.

Future research is directed to account for uncertainty in the parking duration and the EV user utility through robust optimization approaches and the construction of appropriate data-driven uncertainty sets. More elaborate price menus which might also relate to the EV SoC, as well as CSO-EV contracts for lowering the charging rate in case of demand response provision, are also interesting directions for further research. Furthermore, the literature that relates to yield management could also be relevant in the context of the CSO model, with stochastic EV arrivals that choose their power rates based on dynamic prices — see e.g., [20]. Most importantly, establishing the link between the construction of the price menus and the spatiotemporal marginal costs for delivering electricity at the charging points is key for efficient EV charging, including aggregator managed EVs [21], in an adaptive manner that accounts for the impact on the grid and its assets [22], [23].

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