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Incentivizing Electric Vehicle Charging Flexibility for Demand Response via Price Menu Approach

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Abstract—This study considers a Charging Station Operator (CSO) that participates in Demand Response (DR) services and, in return, receives remuneration from the Electric Vehicle Aggregator (EVA). To participate in DR, the CSO requires flexibility from Electric Vehicle (EV) users, which typically concerns charging deadlines or energy demands. In this model, EV users are flexible with their charging deadlines but have fixed energy demands. To incentivize this flexibility, the CSO offers EV users a menu of charging options, where each option specifies a charging deadline and its corresponding charging price. The price menu design problem is formulated as a Mixed Integer Quadratic Programming problem, where the CSO aims to maximize its profit and the user selects the option from the menu that maximizes its utility. The numerical results provide valuable insights into the optimal price menu design and the ideal remuneration from the EVA to the CSO.

Index Terms—electric vehicle, charging station operator, bilevel optimization, price menu, demand response.

I. INTRODUCTION

As the world fights to reduce carbon emissions and shifts to sustainable energy, Electric Vehicles (EVs) have become a key solution for decarbonizing the transportation sector [1], aligning with international climate goals and national decarbonization targets [2].

The growing adoption of EVs [3] brings opportunities and challenges to the power grid. One important opportunity is leveraging EVs as flexible resources to provide services to the power grid, such as frequency regulation services [4], [5], and Demand Response (DR) services [6], [7]. To encourage EVs to participate in such services, the Electric Vehicle Aggregator (EVA) or the Charging Station Operator (CSO) requires a certain level of flexibility from EV users. To incentivize this flexibility, several studies propose a menu-based pricing mechanism, such as in [6], [8], [9], and [10].

In [4] and [5], both studies explore the profitability of EVs providing regulation services while ensuring the reliability of the power system. In [4], the authors present a Mixed Integer Linear Programming (MILP) model that integrates power system security constraints and accounts for the un-

certainty in market prices and EV driving patterns through a scenario-based stochastic approach. The model also considers Vehicle-to-Grid (V2G) operations. In contrast, the model in [5] considers only unidirectional charging (V1G). The authors propose a bilevel optimization framework: the upper level determines the global operation of EV aggregation in the day-ahead energy and frequency regulation markets, while the lower level determines individual EV charging schedules under the control of an EVA. On the other hand, [6] and [7] focus on the participation of EVs in DR services, assuming that EVs are flexible in their energy demand but inflexible in their departure time. In [7], a multi-leader multi-follower Stackelberg game is formulated to investigate the interactive behaviors between multiple EVAs and EVs. In this article, EVAs must meet a minimum participation requirement set by the distribution system operator while ensuring that each EV reaches its minimum state of charge before departure. In contrast, in [6], the authors propose a price menu mechanism to explore the flexibility of EVs in their energy demand. The CSO offers multiple charging power rates with their corresponding prices, without requiring a minimum quantity to participate in DR. The problem is then reformulated as a MILP model to compute the optimal price menu. In [8], [9], and [10], the authors employ a menu-based pricing mechanism to gain flexibility from EV users, in their departure time or battery usage, and to maximize the CSO profit, without integrating participation in ancillary services.

In the aforementioned articles, none proposes a price menu aimed at gaining flexibility from EV users in their charging deadlines to enable participation in DR. The main contribution of this work is to address this gap. Another contribution is the incorporation of a penalty term in the cost function of the CSO for exceeding a subscribed power, as defined in its contract with the electricity supplier, a parameter not previously studied in the literature. This parameter introduces a coupling constraint between EVs, adding complexity to the model.

The remainder of the paper is organized as follows. A detailed description of the problem is provided in Section

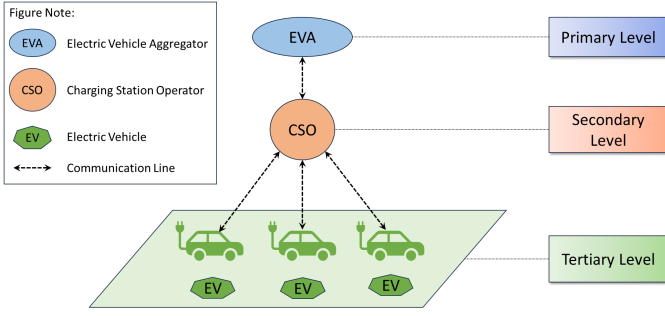


Fig. 1: Trilevel structure between EVA, CSO, and EVs.

II. The models of the price menu, the EV, and the CSO are presented in Section III. Numerical results are presented in Section IV, and the conclusion is given in Section V.

II. PROBLEM DESCRIPTION

DR programs are designed to encourage users to adjust their electricity consumption in response to dynamic market signals, such as time-varying electricity prices or incentive payments, particularly during periods of high generation costs or compromised grid reliability [11]. By reducing demand during peak hours, these programs help to avoid costly peak generation and reduce associated emissions. As a flexible resource, EVs contribute to DR by adjusting their charging power to help balance the load [12].

This study considers a CSO responsible for managing EV charging operations and acting as an intermediary between EVs and EVA for DR services. To help with load balancing, the EVA incentivizes the CSO to reduce charging loads during peak hours, i.e., to participate in DR. The CSO schedules and manages EV charging to provide DR services for EVA. To reduce charging loads, the CSO requires flexibility from EV users, either in their energy demands or their charging deadlines. In this work, EV users are assumed to be flexible with their charging deadlines but have fixed energy demands. To encourage this flexibility, the CSO offers EV users a menu of charging options, where each option specifies a charging deadline and its corresponding charging price per kWh, where shorter charging deadlines are priced higher than longer ones. This pricing structure is designed to motivate EV users to accept longer charging deadlines.

Fig. 1 illustrates the trilevel structure between the agents in the proposed model. At the primary level, the EVA publishes an incentive price per kWh to the CSO. At the secondary level, the CSO determines its optimal load reduction strategy, communicates it to the EVA, and sets a price menu for the EV users. At the tertiary level, EV users choose a charging deadline based on the prices offered by the CSO.

III. SYSTEM MODEL

In this section, the price menu is defined in Section III-A, the EV choice model is introduced in Section III-B, and the objective of the CSO is presented in Section III-C.

A. Price Menu Model

At each EV arrival, the CSO constructs a price menu for the arriving EV user, defined as:

$$\mathcal{K} = \{0, 1, \dots, K\},$$

where each option $k \in \mathcal{K}$ represents a charging price C_k (in €/kWh) and an associated charging deadline τ_k (in time slots). The charging deadline τ_k is computed as:

$$\tau_k = T^{base} + k, \quad \forall k \in \mathcal{K}, \quad (1)$$

where T^{base} represents the shortest charging duration required to meet the energy demand of the EV and is computed as follows:

$$T^{base} = \lceil \frac{E}{\xi p^{max} \Delta t} \rceil, \quad (2)$$

where $E \in \mathbb{R}_{\geq 0}$ (in kWh) is the energy demand of the EV, $p^{max} \in \mathbb{R}_{\geq 0}$ (in kW) is the maximum power of the Charging Point (CP) to which the EV is connected, Δt is the time step of the system, and $\xi \in]0, 1]$ is the charging efficiency of the EV. For simplicity, ξ is assumed to be the same for all EVs.

To encourage EV user to accept longer charging deadline, the menu \mathcal{K} is constructed such that a shorter charging deadline is associated with a higher charging price, i.e. for any $k, k' \in \mathcal{K}$:

$$k < k' \Rightarrow C_k > C_{k'}. \quad (3)$$

If an EV user selects option $k \in \mathcal{K}$, their corresponding departure time is τ_k : leaving before τ_k does not guarantee that the CSO has met the EV energy demand, while leaving after makes option $k+1$ more attractive due to its lower price.

B. EV Choice Model

Let $\mathcal{I} = \{1, \dots, I\}$ be the set of EVs arriving at the charging station during a day. Each EV $i \in \mathcal{I}$ makes its choice from the price menu by comparing the overall utility $W_{i,k}$ of each option $k \in \mathcal{K}$. For an EV $i \in \mathcal{I}$ and an option $k \in \mathcal{K}$, the overall utility $W_{i,k}$ is defined as:

$$W_{i,k} = U_{i,k} - C_{i,k} \xi^{-1} E_i, \quad (4)$$

where $U_{i,k}$ (in €) represents the utility of EV i with respect to its energy demand E_i (in kWh) and the charging deadline τ_k associated with option k . $C_{i,k}$ (in €/kWh) is the charging price for option k , and ξ is defined in Section III-A.

In this model, it is assumed that all EV users are rational and choose the option from the menu that maximizes their overall utility. Specifically, each EV $i \in \mathcal{I}$ chooses option k_i^* such that

$$k_i^* = \arg \max_{k \in \mathcal{K}} W_{i,k}. \quad (5)$$

C. CSO Model

The CSO proposes a personalized price menu for each EV user. This menu is constructed every time a new EV arrives at the charging station and is offered to the arriving EV. The CSO designs the price menu by maximizing its profit, i.e., by maximizing the revenue from EV charging and the remuneration received from the EVA for participating in

DR, while minimizing the electricity cost and the penalty for exceeding the subscribed power p^{sub} . The price menu design problem is solved in an online setting, i.e., at each EV arrival, using a sliding window approach. Therefore, when EV $i \in \mathcal{I}$ arrives at the charging station at time t_i with an energy demand E_i , the price menu design problem is formulated as follows:

$$\max_{\substack{C_{i,k} \in \mathbb{R}_{\geq 0} \\ \forall k \in \{1, \dots, K\}}} \sum_{\substack{j \in V_{t_i} \\ j \neq i}} C_{j,k_j^*} \xi^{-1} E_{t_i}^j + C_{i,k_i^*} \xi^{-1} E_i - C^{CSO}(k_i^*) \quad (6a)$$

s.t. (5),

$$C_{i,k} \geq C_{i,k+1}, \quad \forall k \in \{0, \dots, K-1\}, \quad (6b)$$

where the charging price¹ $C_{i,k}$ (in €/kWh) for the arriving EV i for choosing option k is the decision variable for all $k \in \{1, \dots, K\}$. For $j \neq i$, C_{j,k_j^*} (in €/kWh) is the charging price for EV² j for choosing option k_j^* , $E_{t_i}^j$ (in kWh) is the remaining energy demand for EV j at time t_i , V_{t_i} is the set of EVs whose energy demand is not met at time t_i , and $C^{CSO}(k)$ is the optimal value of the following optimization problem, representing the cost for the CSO when the arriving EV $i \in \mathcal{I}$ chooses option $k \in \mathcal{K}$:

$$\min_{\substack{(p_t^{exc})_{t=0}^T \\ (p_t^j)_{t=0, j \in V_{t_i}}^T \\ p_t^{DR} \in \mathbb{R}, \forall t \in \mathcal{T}}} \sum_{t=0}^T \sum_{j \in V_{t_i}} c_t p_t^j \Delta t + \sum_{t=0}^T c_t^{exc} p_t^{exc} \Delta t - \sum_{t \in \mathcal{T}} r_t p_t^{DR} \Delta t \quad (7a)$$

$$\text{s.t. } p_t^j \in [0, p_j^{max}], \quad \forall t \in \{0, \dots, T\}, \quad j \in V_{t_i}, \quad (7b)$$

$$p_t^{exc} \in [0, p_{agg}^{max} - p^{sub}], \quad \forall t \in \{0, \dots, T\}, \quad (7c)$$

$$p_t^i = 0, \quad \forall t \geq T_i^{base} + k, \quad (7d)$$

$$p_t^j = 0, \quad \forall t \geq T_j^{dep}, \quad j \in V_{t_i}, \quad j \neq i, \quad (7e)$$

$$\sum_{t=0}^T p_t^j \Delta t \geq \xi^{-1} E_{t_i}^j, \quad \forall j \in V_{t_i}, \quad (7f)$$

$$p_t^{exc} \geq \sum_{j \in V_{t_i}} p_t^j - p^{sub}, \quad \forall t \in \{0, \dots, T\}, \quad (7g)$$

$$p_t^{ref} - \sum_{j \in V_{t_i}} p_t^j \geq p_t^{DR}, \quad \forall t \in \mathcal{T}, \quad (7h)$$

where the exceed power p_t^{exc} (in kW) at time $t \in \{0, \dots, T\}$, the power p_t^j (in kW) delivered to EV $j \in V_{t_i}$ at time $t \in \{0, \dots, T\}$, and the power p_t^{DR} (in kW) provided by the CSO for DR at time $t \in \mathcal{T}$ are the decision variables. The other parameters of the model are as follows: T is the number of time slots in the discretized time horizon, \mathcal{T} is the set of time slots when the CSO is required to participate in DR, c_t is the electricity price (in €/kWh) at time t , c_t^{exc} is the penalty cost (in €/kWh) for exceeding the subscribed power p^{sub} at time t , r_t is the remuneration from the EVA to the CSO for

¹The charging price $C_{i,0}$ for option $k=0$, which represents the option with the shortest charging duration, is assumed to be the same for all EVs.

²For $j \neq i$, C_{j,k_j^*} is known because EV j arrived before EV i , and the option k_j^* chosen by EV j is known.

participating in DR at time t , p_j^{max} is the maximum power (in kW) of the CP to which EV j is connected, p_{agg}^{max} is the maximum aggregated power (in kW), p_t^{ref} is the baseline (in kW) at time t . The baseline is defined as the solution to (6)-(7) when the remuneration $r_t = 0$ for all t . T_j^{dep} is the departure³ time of EV j .

Constraint (6b) ensures that the charging prices of the menu decrease with respect to the charging deadline. Constraint (7b) represents the charging rate limit. Constraints (7d), (7e), and (7f) ensure that the charging demand of each EV is met before its departure time. Constraints (7c) and (7g) define the bounds and the formula of p_t^{exc} . Constraint (7h) defines the deviation of the power consumption from the baseline. If p_t^{DR} is negative, the CSO does not participate in DR and pays a penalty; otherwise, the CSO participates in DR and receives remuneration.

The optimal choice k_i^* of the arriving EV i can be modeled using a binary variable $a_{i,k}$ for all $k \in \mathcal{K}$, denoting whether EV i chooses option k (value 1, otherwise 0). To solve the bilevel problem (6), it is reformulated into a single-level problem using the big- M method, as in [9]. Therefore, (6) is reformulated as follows:

$$\max_{\substack{C_{i,k} \in \mathbb{R}_{\geq 0} \\ a_{i,k} \in \{0,1\}, \\ \forall k \in \mathcal{K}}} \sum_{k \in \mathcal{K}} a_{i,k} \left(\sum_{\substack{j \in V_{t_i} \\ j \neq i}} C_{j,k_j^*} \xi^{-1} E_{t_i}^j + C_{i,k} \xi^{-1} E_i - C^{CSO}(k) \right) \quad (8a)$$

$$\text{s.t. } C_{i,k} \geq C_{i,k+1}, \quad \forall k \in \{0, \dots, K-1\}, \quad (8b)$$

$$W_{i,k} + \sum_{q \neq k} a_{i,q} M \geq W_{i,k'}, \quad \forall k \neq k', \quad (8c)$$

$$\sum_{k \in \mathcal{K}} a_{i,k} = 1, \quad (8d)$$

where M is a very large positive number⁴. With (8d), (8c) ensures that $a_{i,k_i^*} = 1$. The idea of (8c) is that for k such that $a_{i,k} = 0$, the inequality is verified because $\sum_{q \neq k} a_{i,q} M$ takes a very large value. For k such that $a_{i,k} = 1$, $\sum_{q \neq k} a_{i,q} M$ becomes equal to zero, which enforces option k to be the optimal option that maximizes the overall utility of EV i . By replacing $W_{i,k}$ with its expression (4), (8) is formulated as a Mixed Integer Quadratic Programming (MIQP) problem, which CPLEX can solve.

IV. NUMERICAL RESULTS

In Section IV-A, the main parameters of the system are described. In Section IV-B, a sensitivity analysis is presented to determine the ideal remuneration from the EVA to the CSO, as well as the optimal price menu design.

³For $j \neq i$, the departure time of EV j is already known because it arrived before EV i , and the option k_j^* chosen by EV j is known. Therefore, to adjust for the new time horizon, which starts with the arrival time t_i of EV i , a change of variable is applied.

⁴It can be computed by bounding $W_{i,k}$.

A. Study Case

The time horizon is set to one day, discretized into 24 time slots ($\Delta t = 1$ h). Electricity price data from the EPEX-SPOT market in France [13] for 6 March 2025 is used. EV energy demands are generated using a Gaussian distribution with a mean of 25 kWh and a standard deviation of 4 kWh. EV arrival times are generated using a uniform law between 9 a.m. and 6 p.m., as in [14]. The CSO is assumed to have an unlimited number of CPs and is required to participate in DR during periods of high load on the power grid and high electricity prices. In this study, it corresponds to the period from 5 p.m. to 12 a.m.. The utility of EV i for choosing option k is given by $U_{i,k} = aE_i - \theta k^2$, as in [15], where a represents the willingness of the EV user to pay for the fastest charging and is set to 0.39 €/kWh, and θ denotes the sensitivity to charging delay and is set to 0.1. The other parameters of the system are given in Table I.

TABLE I: Parameter Settings

Definition	Notation	Value
Maximum power of each CP (kW)	p^{max}	7
Charging efficiency	ξ	0.9
Penalty cost (€/kWh)	c_t^{exc}	0.5
Charging price for option $k = 0$ (€/kWh)	C_0	0.4
Length of the menu	K	4
Big- M	M	45

B. Sensitivity Analysis

In this section, a sensitivity analysis is performed on three parameters: the subscribed power p^{sub} , the EV arrival frequency (AF), and the remuneration from the EVA to the CSO. Each result represents an average over 100 simulations, where each simulation differs in the energy demand and arrival time of EVs. The subscribed power is set to three values $p^{sub} \in \{80, 150, 200\}$ kW. The EV AF varies from 9 to 108 EVs per day (i.e., from 1 EV per hour to 1 EV every 5 minutes). The remuneration from the EVA to the CSO is constant throughout the day, varying from 0 to 1 €/kWh with a step size of 0.1.

Fig. 2 illustrates the amount of energy that the CSO contributes to DR services with respect to the remuneration from the EVA. For all EV AFs, this contribution increases with remuneration. Higher remunerations incentivize the CSO to participate more in DR. For all values of p^{sub} , there is a threshold beyond which the CSO cannot contribute more energy, regardless of the remuneration. This is because the CSO must satisfy the energy demands of EVs, or the CSO has completely stopped charging during the DR period and therefore cannot further reduce its load. From this figure, the EVA can determine the ideal remuneration to offer to the CSO. For example, if the CSO expects 108 EVs a day and has a $p^{sub} = 200$ kW, the EVA can achieve a 200 kWh contribution to DR from the CSO by offering a remuneration of 0.3 €/kWh. Moreover, there is no benefit in offering more than 0.5 €/kWh, since the contribution of the CSO remains unchanged for a remuneration greater than 0.5 €/kWh. The contribution of the CSO also depends on p^{sub} . For a low EV

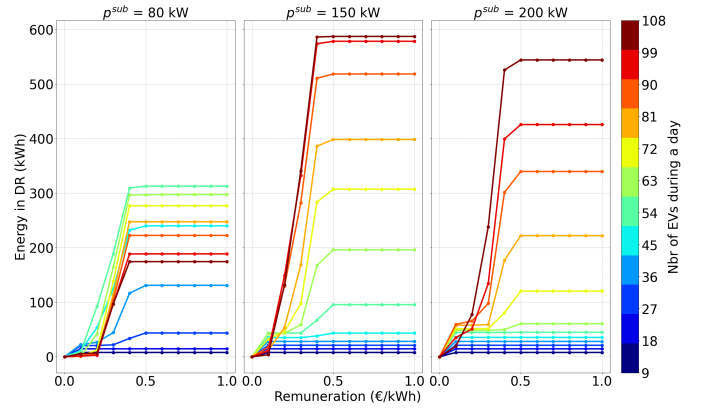


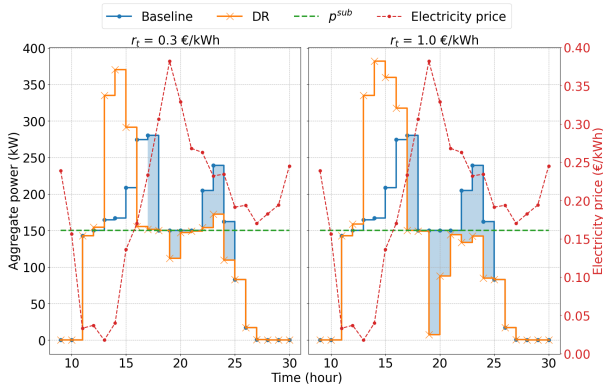
Fig. 2: Energy contributed by the CSO to DR for different EV AF and remuneration levels. For a low EV AF (blue curves) and high p^{sub} , the CSO has little incentive to participate in DR. Similarly, for high EV AF (red curves) and low p^{sub} , the CSO has little incentive to participate in DR.

AF (blue curves), if p^{sub} is high, the CSO has little incentive to participate in DR. This is because a high p^{sub} allows the CSO to avoid a penalty and charge EVs during low-cost periods. Participating in DR requires shifting the charge, which leads to higher costs. Since the remuneration is not attractive enough to offset the increased cost, the CSO has little incentive to engage in DR. Additionally, for high EV AF (red curves) and low p^{sub} , the CSO is more likely to exceed p^{sub} and pay a penalty. If the remuneration is not high enough to offset this penalty, DR participation may be unattractive. From Fig. 2, it is possible to identify the best p^{sub} value among the three tested that encourages the CSO to participate more in DR. For example, with 108 EV AF, $p^{sub} = 150$ kW appears to be the most effective. Therefore, Fig 3 focuses on this configuration, presenting the aggregate power consumption, the average number of EVs per option, the average charging price for an EV, and the CSO profit.

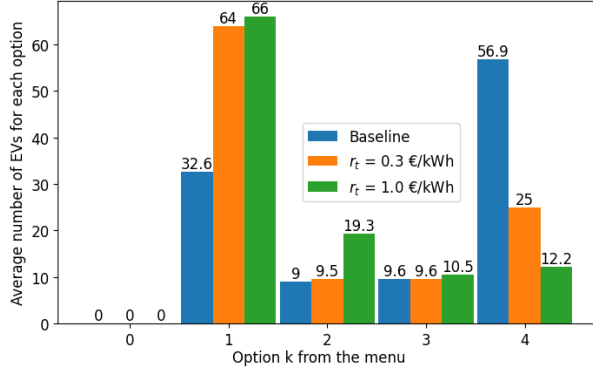
In Fig. 3a, with DR, the CSO shifts part of the charging load before the DR period (i.e., before 5 p.m., which is 17 h) to benefit from the remuneration offered by the EVA, and to take advantage of lower electricity prices compared to those after midnight. Additionally, as the remuneration increases, the CSO contributes more to DR; this is reflected in the increasing area between the blue and orange curves during the DR period, from 340.8 kWh to 587.21 kWh, i.e. a 72% increase, as also shown in Fig. 2.

To maximize its profit, the CSO is incentivized to have EVs choose earlier deadlines for two reasons: first, since part of the charging is shifted before the DR period, the CSO no longer requires significant flexibility from EV users, just one hour is sufficient; second, charging prices decrease with longer charging deadlines, making earlier deadlines more profitable. Therefore, as shown in Fig. 3b, the average number of EVs choosing the option 4 has decreased by 79%, while the number of EVs choosing the option 1 has increased by 102%.

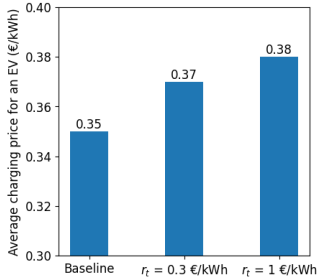
As a result, Fig. 3c shows that the average charging price



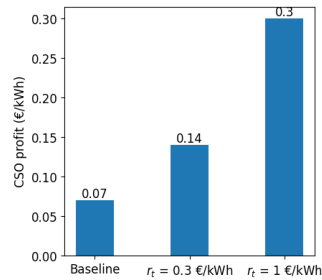
(a) Aggregate power during the day (in kW).



(b) Repartition of EVs across charging options based on the remuneration parameter.



(c) EV average charging price (in €/kWh) for different remuneration levels.



(d) CSO profit (in €/kWh) for different remuneration levels.

Fig. 3: 108 EVs per day for $p^{sub} = 150 \text{ kW}$.

per EV increases with remuneration, as EVs choose the earlier options that have higher charging prices.

Finally, Fig. 3d shows that the CSO profit increases with remuneration. For $r = 1 \text{ €/kWh}$, the CSO profit is more than triple that of the baseline case. While DR helps the CSO to increase its profit, a question arises: How should this gain be redistributed to EV users to help lower their charging prices? This question will be addressed in future work.

V. CONCLUSION

This study considered a CSO serving EVs that were flexible in their charging deadlines but had fixed energy demands. The CSO offered a price menu with several charging deadline options, each associated with a different price. Moreover, the

CSO participated in DR services and received remuneration from an EVA. The price menu design problem is formulated as a MIQP problem, considering both a profit maximization for the CSO and overall utility maximization for the EV. The numerical results revealed that there was an ideal level of remuneration from the EVA to the CSO. Moreover, with DR, the CSO no longer required significant flexibility from EV users. This depended on model parameters such as the EV arrival frequency and the subscribed power. In general, the results were sensitive to the parameters of the model. Furthermore, the CSO benefited from DR as its profit increased. Therefore, in future work, an important goal will be to identify an effective way to redistribute the remuneration gained by the CSO to EV users to minimize their charging costs. Another direction will be to consider a setting in which the EVA is connected to multiple CSOs, each with its own characteristics, such as the number of CPs, whether the infrastructure is public or private, and the EV arrival frequency. EV behavior will also be heterogeneous, reflecting variations in utility functions and user preferences.

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