The design of a time-of-use tariff with a demand charge for residential electric vehicle charging posts

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ABSTRACT

Time-of-use tariffs have been widely adopted to manage the charging demand of electric vehicles within residential communities. However, the growing penetration of EVs has led to challenges, particularly over-response during off-peak periods. Currently, residential consumers in China are served by the grid company at a privileged price, which excludes network tariffs. In early 2024, the National Development and Reform Commission of China issued Guideline No. 1721, requiring the implementation of "a differentiated pricing mechanism for the charging demand". Consequently, while traditional household demand remains at the favorable price, innovative tariffs tailored for residential charging posts are being encouraged to address the increasing charging demand. Drawing on international experiences in tariff design, this study proposes a time-of-use tariff with a demand charge (ToU-D) for EV charging. Under this scheme, each EV owner reserves a monthly charging capacity and pays for the consumed energy according to a ToU tariff, but is subject to a penalty energy price for the charging profile above the reserved capacity. A mixed-integer bilevel optimization model is developed, where the upper level represents the grid company aiming to minimize wholesale electricity purchase costs subject to a regulated profit rate, while the lower level represents residential consumers aiming to minimize their electricity bills. To demonstrate the model's adaptability to unbundled retail market settings, it is extended to consider network tariffs of different structures. The bilevel model is solved by transforming into a single-level one using a heuristic method that minimizes the duality gap of the lower-level problem, due to the existence of binary variables at the lower level. An empirical analysis based on realistic data reveals that the proposed tariff not only mitigates over-response issues and generates substantial economic benefits for both the grid company and EV owners overall, but also indicates that less flexible EV owners may face increased charging costs.

1. Introduction

1.1. Background

Electric vehicles play an important role in the global energy transition. By the end of 2024, China had already reached 31.4 million EVs, and by the end of July 2025, the total number of charging posts exceeded 16.6 million, approximately 74.8% of which are private residential charging posts. However, this rapid growth poses challenges to both the network capacity and the generation capacity. Time-of-use tariffs, first introduced more than half a century ago to manage residential demand (Faruqui & Sergici, 2010), have also been applied to residential charging posts in various regions (Hildermeier et al., 2023). Nevertheless, as more EVs are programmed to charge during off-peak hours, a new peak emerges due to over-response (Kamwa & Matevosyan, 2023), mainly because consumers with enabling technologies tend to have higher response rates to tariffs (Faruqui & Sergici, 2010). Interested readers may refer to Shariatzadeh et al. (2025) for a comprehensive review of the factors influencing EV users' charging behaviors. This over-response phenomenon has also been observed in some Chinese residential communities. To address this issue, new approaches to retail tariff design are required.

In the context of electricity retail pricing, two primary regulatory models generally exist (Morell Dameto et al., 2020; Beraldi & Khodaparasti, 2023). In vertically integrated utility systems, consumers are offered bundled tariffs without clear separation between tariff components. In contrast, liberalized electricity markets feature retailers that act as intermediaries between consumers and the wholesale electricity market. In such settings, retail tariffs typically

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consist of a competitive energy charge and a regulated network charge. In some cases, retailers may operate as regulated local monopolies even within a liberalized wholesale market. In liberalized markets, the most common residential tariffs are volumetric, calculated based on *kWh* consumption and often combined with a fixed subscription fee (Faruqui & Bourbonnais, 2020) to recover administrative costs. The energy tariff component can take various forms, such as a flat rate, a time-of-use tariff, or more advanced dynamic hourly pricing. The network tariff component is usually either flat or time-differentiated, while more advanced ones are being explored (Wang et al., 2023), such as peak-coincident charges (Morell-Dameto et al., 2023) and a local network capacity market (Morell-Dameto et al., 2024).

Currently, residential consumers in China are served by the grid company at a privileged price, excluding network charges, which is significantly lower than the tariffs applied to industrial and commercial consumers. However, at the start of 2024, the National Development and Reform Commission of China issued Guideline No. 1721, mandating a differentiated pricing mechanism for EV charging demand. This guideline explicitly distinguishes between traditional non-EV household demand and EV charging demand. While traditional household demand retains its favorable pricing, the guideline encourages the development of innovative tariffs specifically tailored for residential EV charging posts. In response to this policy trend, this study aims to design a new tariff scheme for residential charging posts with the following objectives:

- mitigate the over-response during off-peak hours;
- maintain consistency with the current ToU tariff structure to enhance residential consumer acceptance;
- ensure a reasonable profit for the grid company.

1.2. Literature review

A growing body of literature addresses the pricing of EV charging, especially with the development of machine learning techniques for dynamic pricing (Ban & Keskin, 2021; den Boer & Keskin, 2022). These approaches have been applied to EV charging to manage demand–supply imbalances (Narayan et al., 2022), reduce idle connection times (Zhou et al., 2025), and minimize both wait times and electricity costs (Zulfiqar et al., 2024), among other objectives. However, the majority of the studies of EV charging focus on public charging stations (Cedillo et al., 2022; Lu et al., 2022; Sheng et al., 2023; Dupont et al., 2024; Sawant & Zambare, 2024; Cui et al., 2025) or explore the nexus between the transportation system and charging stations (Wangsness et al., 2021; Kazemtarghi et al., 2024). To the best of our knowledge, research on tariff design for residential charging posts is relatively scarce, except for the paper by Zhao et al. (2020), which introduces a non-cooperative game model to establish a price for sharing a charging post to address the insufficiency of public charging stations. Although not extensively discussed in the literature, dedicated EV charging tariffs have been implemented in many countries, including the United States (Con Edison, 2025) and various European nations (Hildermeier et al., 2023). These tariffs range from relatively simple structures to more complex designs, such as standard time-of-use pricing, dynamic pricing linked to day-ahead market signals or other (near) real-time inputs. Some also incorporate interactions with network operators. Under such tariff schemes, each EV owner is typically required to install a separate residential meter exclusively for EV charging.

However, numerous works address pricing for residential consumers in general, particularly time-of-use tariffs in demand response programs. To mitigate the rebound peaks created by the synchronization of the individual residential demands, Muratori & Rizzoni (2016) create multiple sets of ToU tariffs with varied peak and off-peak periods tailored to consumers with various load curves. Venizelou et al. (2018) suggest determining ToU periods and rates through statistical analysis and hybrid optimization functions, to encourage residential consumers to alleviate power grid congestion. Dengfeng et al. (2024) concentrate on grid investments and introduce the Gaussian Mixture Model clustering algorithm to categorize ToU pricing periods, which could reduce the peak-to-valley load gap. As an extension of the traditional ToU tariff, the time-and-level-of-use tariff has been proposed (Gomez-Herrera & Anjos, 2019; Besançon et al., 2020), enabling residential consumers to reserve a variable energy capacity and charging higher prices for exceeding booked levels, while offering lower prices otherwise. The purpose is to create an incentive for consumers to respect the upper bound on their consumption. This "energy capacity" idea is similar to the concept of "demand charge" discussed and advocated by Faruqui & Bourbonnais (2020), but the latter is typically charged per billing period, such as monthly. According to Faruqui & Bourbonnais (2020), there is a misalignment between current residential tariff structures and the underlying utility cost drivers. Specifically, most residential tariffs consist of a fixed monthly charge to recover administrative costs and a variable volumetric component based on *kWh* consumption. However, the primary cost drivers for both network and generation capacity are based on *kW* demand, which is not accurately captured by purely volumetric pricing. As a result, such tariffs may fail to reflect cost causation in future power systems with higher variability and peak demand. Introducing a demand charge component represents a potential solution to aligning prices with system costs.

Demand charges are typically calculated based on a consumer's peak power consumption over a 15-minute to one-hour interval and require smart meters for implementation. Smart meters have become increasingly common among residential consumers, with rollout rates exceeding 70% in many countries (IEA, 2021; ACER, 2024). Demand charges come in two primary forms, i.e., coincident and non-coincident. A coincident demand charge is based on a consumer's peak usage during the system's overall peak period, while a non-coincident demand charge reflects the consumer's highest demand at any point during the billing cycle. Demand charges have been implemented in various contexts, including distribution network tariffs for commercial consumers in Sweden (van Zoest et al., 2021) and low-voltage network tariffs in Spain (Morell Dameto et al., 2020). With the increasing deployment of distributed energy resources, such as rooftop PV panels, the traditional volumetric network tariff has come under scrutiny. In particular, it may lead to a so-called "death spiral" in network cost recovery, as consumers with self-generation reduce their volumetric consumption while still relying on the grid for backup (Borenstein & Bushnell, 2015). In response, some utilities, such as Salt River Project in Arizona, and distribution system operators, such as Fluvius in Belgium, have mandated demand charges for consumers with rooftop PV installations as part of their network tariffs.

Building on prior research and real-world experience, this paper proposes a time-of-use tariff with a demand charge (ToU-D) for residential EV charging posts. It is developed in response to evolving policy directives of China and the growing penetration of EVs in residential communities. The demand charge proposed in this study differs from the concept in the aforementioned literature in several aspects. First, it addresses the energy component of the tariff, rather than the network component. In an energy-only wholesale market, generation capacity investment costs are typically recovered through market-clearing prices that exceed the marginal production costs. However, with increasing shares of variable renewable energy, capacity markets are expected to become a non-negligible revenue stream for ensuring generation adequacy, as discussed in Mou et al. (2023) and the references therein. A demand charge is thus a suitable mechanism for retailers to recover the costs associated with meeting generation capacity obligations. Second, rather than calculating peak demand *ex post* at the end of the billing cycle, each consumer is required to reserve a monthly charging capacity in advance. If actual consumption exceeds the reserved capacity, the excess is billed at a penalty energy price proportional to the consumption exceeding the limit. This approach introduces greater flexibility for consumers by allowing occasional exceeding with a predictable penalty charge, while still encouraging efficient charging behaviors.

Another stream of work related to our study is bilevel optimization. Many tariff design problems are represented as Stackelberg games to capture the interaction between the tariff designer and consumers, which are cast as bilevel optimization models (Mou et al., 2020). The traditional method for solving bilevel problems involves converting the bilevel model into a single-level one by appending the KKT conditions of the lower-level model to the upper-level model (Kleinert et al., 2021; Beraldi & Khodaparasti, 2023). However, our model incorporates binary variables in the lower-level problem as described in Section 2.2.1, resulting in a mixed-integer bilevel problem that precludes the application of the KKT conditions for solution. Various methodologies have been proposed to solve this type of problem (Kleinert et al., 2021), including generalized Benders decomposition (Bolusani & Ralphs, 2022) and column-and-constraint generation method (Haghighat & Zeng, 2018). But the performance of these exact algorithms is not guaranteed when the number of binary variables exceeds a few hundred. Soares et al. (2021a) propose a deterministic bounding procedure for global optimization, and numerical simulations show it can converge to high-quality global solutions within a few iterations. However, this method requires that upper-level constraints do not include lower-level variables and that lower-level constraints do not include upper-level decision variables, which is not satisfied in our model. Alternatively, Soares et al. (2020, 2021b) introduce hybrid methods that incorporate particle swarm optimization, while Ye et al. (2020) introduce a heuristic method by minimizing the duality gap of the lower-level problem, which is applied to a large-scale unit commitment problem in the context of strategic bidding in the day-ahead market. The methodology of Ye et al. (2020) is adopted to solve the proposed mixed-integer bilevel model, due to its good performance in handling large-scale problems.

1.3. Contributions and paper organization

To address the current research gaps in pricing for residential charging posts, we design a time-of-use tariff with a demand charge. The contributions of this paper are as follows.

- We develop a mixed-integer bilevel optimization model for the ToU-D tariff design, in which each consumer reserves a monthly charging capacity in advance, and any excess consumption is billed at a penalty energy price. The model is further generalized to represent different retail market settings by incorporating network tariffs.
- Through intermediate-scale case studies, we demonstrate that the proposed tariff prevents over-response, adjusts grid company profits, and mobilizes consumer flexibility. Moreover, the penalty energy price enhances consumer choice by allowing occasional exceeding with a predictable surcharge, while the demand charge still discourages excessive peak charging demand.

The remainder of this paper is organized as follows. The methodology applied in the study is described in Section 2, including the structure of the ToU-D tariff, the mixed-integer bilevel model, and the model solution procedures. The main results and findings are discussed in Section 3. We conclude the paper by summarizing the main conclusions and policy implications in Section 4, where we also present limitations and future work of the study.

2. Methodology

In this section, we first introduce the structure of the ToU-D tariff. We then formulate a mixed-integer bilevel optimization model, with the grid company represented at the upper level and residential consumers at the lower level. Next, we reformulate and solve the model. Finally, to illustrate its adaptability to unbundled retail market settings, we extend the framework to incorporate network tariffs.

2.1. Structure of ToU-D tariff

The ToU-D tariff is dedicated to EV charging posts, where each EV owner in the residential community must reserve a charging power capacity from the grid company. In contrast, household electricity demand continues to be billed under the current ToU tariff via the other meter. Following each charging session, the grid company first calculates the fee for the energy consumed based on the ToU component of the ToU-D tariff, referred to as the basic energy fee. Then, if the charging power exceeds the reserved capacity, consumers will be charged an additional penalty fee for the energy consumed above the reserved capacity [1].

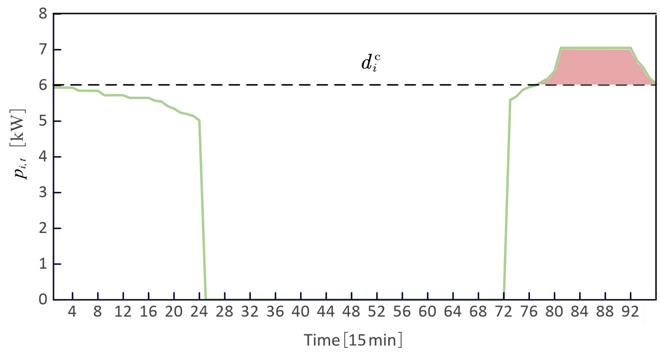


Figure 1: Illustration of the charging profile $p_{i,t}$ and the reserved capacity d_i^c.

In the ToU-D tariff, π^c is the demand charge for the reserved capacity measured by ¥/kW. The demand charge is typically calculated on a per-billing-period basis, such as monthly. π_t is the energy price of the ToU component, while π_t^{sc} is the penalty rate. As illustrated in Figure 1, for a particular EV owner i, the dashed line represents the monthly reserved capacity d_i^c and the solid curve shows the consumer's charging profile $p_{i,t}$ for a given day. The entire profile is first billed at the ToU component π_t. Since $p_{i,t}$ exceeds d_i^c in the red shaded area, it incurs a penalty fee at the rate π_t^{sc} for the consumption in the shaded area. The total fee of the EV owner i for one billing period is given by Equation

[1]There are alternative designs for the demand charge excluding the penalty. For example, the demand charge could be applied to the combined household and EV demand, or a baseline capacity (e.g., 2.5 kW) could be provided free of charge. Another option is to calculate the demand charge only during specific hours when the system peak is likely to occur, for instance, between 4 p.m. and 7 p.m. in Arizona (Arizona Public Service, 2025).

(1):

$$\overbrace{\pi^{\mathrm{c}} \cdot d_i^{\mathrm{c}}}^{\text{reservation fee}} + \overbrace{\sum_{t\in\mathcal{T}} \pi_t \cdot p_{i,t} \cdot \Delta T}^{\text{basic energy fee}} + \overbrace{\sum_{t\in\mathcal{T}} \pi_t^{\mathrm{sc}} \cdot s_{i,t} \cdot (p_{i,t} - d_i^{\mathrm{c}}) \cdot \Delta T}^{\text{penalty fee}}, \tag{1}$$

where ΔT is the duration of a time period; $\mathcal{T}$ is the set of time periods in a billing period; the binary variable $s_{i,t}$ equals 1 when $p_{i,t} > d_i^{\mathrm{c}}$, indicating additional charges at the penalty rate π_t^{sc}.

2.2. Mixed-integer bilevel optimization modeling of the ToU-D tariff

This paper assumes that residential consumers, some of whom are EV owners and others who do not own EVs, procure electricity through the grid company. Their non-EV consumption (e.g., TV, lighting, cooking, etc.), referred to as household demand, is billed under the current ToU tariff. In contrast, EV charging demand is subject to a dedicated ToU-D tariff, which aligns with current policy requirements in China, but the proposed model can be readily adapted to represent different retail markets in other regions, as discussed in Section 2.4.

Both household and EV charging demands are supplied by the grid company, which purchases electricity from the wholesale market. The electricity purchase costs include both the energy cost in the energy market and the capacity cost associated with meeting peak demand (household plus EV charging) in the capacity market due to capacity obligations. As depicted in Figure 2, the interaction between the grid company and residential consumers establishes a game-theoretic relationship, forming a bilevel optimization model. At the upper level, the grid company sets ToU-D prices to minimize electricity purchase costs while ensuring a regulated profit rate. At the lower level, residential consumers optimize their charging behaviors and capacity reservation under the ToU-D tariff set by the grid company, aiming to minimize their own charging fees. In the subsequent sections, we present the mathematical models along with their respective notations, which are also collected in Appendix A.

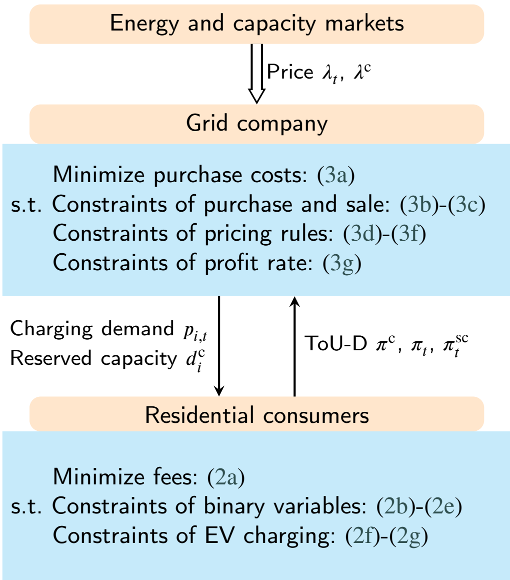


Figure 2: The bilevel model for the ToU-D tariff design. The upper-level grid company sets ToU-D prices to minimize electricity purchase costs while ensuring a regulated profit rate, while the lower-level residential consumers optimize their charging behaviors and reserved capacities under the ToU-D tariff to minimize their own charging fees.

2.2.1. The lower-level residential consumer model

We divide residential demand into household demand, and EV charging demand which are metered separately, and further assume that household demand is under the current ToU tariff. In addition, household demand profiles follow historical observed values because they are inflexible or have already reacted to the current ToU tariff. In contrast, the flexible EV charging demand is subject to the ToU-D tariff in this paper. Each residential consumer aims to minimize its electricity bill, but since each consumer is independent from other consumers, we aggregate them and minimize the total fee equivalently.

Equations (2a)-(2g) present the mathematical formulation of the lower-level problem, with the set of optimization variables denoted by $\mathcal{V}_{\text{lower}} = \left\{d_i^{\text{c}}, p_{i,t}, s_{i,t}\right\}$. The terms d_i^{c} and $p_{i,t}$ represent the reserved capacity of residential consumer i and the charging power during time period t, respectively. The term $s_{i,t}$ is a binary variable that indicates whether the charging power exceeds the reserved capacity for consumer i during t. If a particular consumer does not own an EV, these variables would be 0.

$$\min_{\mathcal{V}_{\text{lower}}} o_{\text{lower}} = \sum_{t\in\mathcal{T}} \widetilde{\pi}_t \cdot D_t \cdot \Delta T + \sum_{i\in\mathcal{I}} \pi^{\text{c}*} \cdot d_i^{\text{c}} + \sum_{i\in\mathcal{I}}\sum_{t\in\mathcal{T}} \pi_t^* \cdot p_{i,t} \cdot \Delta T + \sum_{i\in\mathcal{I}}\sum_{t\in\mathcal{T}} \pi_t^{\text{sc}*} \cdot s_{i,t} \cdot (p_{i,t} - d_i^{\text{c}}) \cdot \Delta T \tag{2a}$$

$$\text{s.t. } p_{i,t} \le d_i^{\text{c}} - s_{i,t} \cdot d_i^{\text{c}} + P_i \cdot s_{i,t}, \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \tag{2b}$$

$$p_{i,t} \ge s_{i,t} \cdot d_i^{\text{c}}, \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \tag{2c}$$

$$s_{i,t} \in \{0,1\}, \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \tag{2d}$$

$$d_i^{\text{c}} \ge 0, \forall i \in \mathcal{I} \tag{2e}$$

$$\sum_{t\in\mathcal{T}_n} p_{i,t} \cdot \Delta T = C_{i,n}, \forall i \in \mathcal{I}, \forall n \in \mathcal{N} \tag{2f}$$

$$0 \le p_{i,t} \le P_i \cdot L_{i,t}, \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \tag{2g}$$

In the objective function (2a), $\mathcal{T}$ represents the set of time periods while ΔT denotes the duration of each time period. Equation (2a) comprises four terms, including the energy fee associated with aggregated household demand D_t paid according to the current ToU tariff $\widetilde{\pi}_t$, the capacity reservation fee for charging demand paid at a rate of $\pi^{\text{c}*}$, the basic energy fee for charging demand calculated under the ToU component π_t^* of ToU-D tariff, and a penalty fee incurred if the charging demand exceeds the reserved capacity, paid at a rate of $\pi_t^{\text{sc}*}$. The rates $\pi^{\text{c}*}$, π_t^* and $\pi_t^{\text{sc}*}$ are determined by the grid company and are treated as parameters in the residential consumer model.

The constraints (2b)-(2e) ensure the accurate calculation of penalty fees above the reserved capacity by introducing binary variables $s_{i,t}$, and parameter P_i denotes the maximum charging power. Constraint (2f) ensures that the energy charged meets the consumption on day n, where $\mathcal{N}$ denotes the set of days and $\mathcal{T}_n$ represents the set of time periods on day n. The parameter $C_{i,n}$ represents the charging energy requirement for consumer i on day n, derived from historical data. Constraint (2g) limits the charging power based on the connection status of the EV to the charging post. The binary parameter $L_{i,t}$ indicates whether the EV i is connected to the charging post at time period t, so the charging power $p_{i,t}$ is limited by $P_i \cdot L_{i,t}$.

2.2.2. The upper-level grid company model

The grid company procures electricity from the wholesale market at a cost. Following generation capacity market regulations, the grid company must fulfill its capacity obligations by purchasing generation capacity based on the peak demand of aggregated residential consumers, paying the corresponding capacity costs accordingly. The grid company designs the ToU-D tariff to meet the regulated profit rate.

The equations (3a)-(3g) present the mathematical formulation of the upper-level problem, with the set of optimization variables denoted by $\mathcal{V}_{\text{upper}} = \left\{\pi^{\text{c}}, \pi_t, k, \pi_t^{\text{sc}}, d_t, d_m\right\}$. π^{c}, π_t and π_t^{sc} denote the demand charge, the ToU component, and the penalty rate, respectively, while k defines the ToU component multiplier relative to the current ToU tariff. The term d_t denotes the total demand of residential consumers during time period t and d_m calculates the maximum value of d_t.

$$\min_{\mathcal{V}_{\text{upper}}} o_{\text{upper}} = \lambda^{\text{c}} \cdot d_m + \sum_{t\in\mathcal{T}} \lambda_t \cdot d_t \cdot \Delta T \tag{3a}$$

$$\text{s.t. } d_t = \sum_{i\in\mathcal{I}} p_{i,t}^* + D_t, \forall t \in \mathcal{T} \tag{3b}$$

$$d_m \ge d_t, \forall t \in \mathcal{T} \tag{3c}$$

$$\pi^{\text{c}} \ge 0 \tag{3d}$$

$$\pi_t = k \cdot \widetilde{\pi}_t, \forall t \in \mathcal{T} \tag{3e}$$

$$\pi_t^{\text{sc}} = K^{\text{sc}} \cdot \pi_t, \forall t \in \mathcal{T} \tag{3f}$$

$$\underline{r} \cdot o_{\text{lower}} \leq o_{\text{lower}} - o_{\text{upper}} \leq \overline{r} \cdot o_{\text{lower}} \tag{3g}$$

The objective function (3a) comprises two terms, including the capacity cost for fulfilling capacity obligations in the capacity market and the energy purchase cost in the wholesale energy market, where λ^{c} is the given capacity market price and λ_t is the given energy market price. The constraint (3b) ensures the balance of purchase and demand, and (3c) calculates the aggregated peak demand of the grid company. Constraints (3d) to (3f) are the design rules for ToU-D, where the parameter K^{sc} is the multiplier to calculate the penalty rate. The constraint (3g) requires a reasonable profit rate, where o_{lower} and o_{upper} are the total revenue and total cost of the grid company, respectively. The parameters $\underline{r}$ and $\overline{r}$ give the range of the profit rate.

2.2.3. The bilevel model

The grid company offers the ToU-D tariff to residential consumers, who in turn provide information on their response to the tariff, including their reserved capacities and charging profiles. Based on this information, the grid company will further optimize the ToU-D tariff to minimize its electricity purchase costs. This situation naturally forms a Stackelberg game, and we incorporate the mathematical models from Sections 2.2.1 and 2.2.2 to develop the complete bilevel formulation that represents the game.

$$\min_{\mathcal{V}_{\text{upper}}} \ (\lambda^{\text{c}} \cdot d_m + \sum_{t\in\mathcal{T}} \lambda_t \cdot d_t \cdot \Delta T) \tag{4a}$$

$$\text{s.t. } (3b) - (3g) \tag{4b}$$

$$d_i^{\text{c}*}, p_{i,t}^*, s_{i,t}^* \in \arg \min_{d_i^{\text{c}}, p_{i,t}, s_{i,t}} \left\{ o_{\text{lower}} : (2b) - (2g) \right\} \tag{4c}$$

2.3. Model reformulation and solution

The common approach for solving a bilevel model is to transform it into a single-level model by appending the KKT conditions to the upper-level model. However, this approach does not apply to the model at hand due to the existence of $s_{i,t} \cdot p_{i,t}$ and $s_{i,t} \cdot d_i^{\text{c}}$ in (2a)-(2c). The variable $s_{i,t}$ is binary and the multiplication of $s_{i,t}$ and $p_{i,t}$ creates bilinear terms. To tackle these challenges, we first represent the bilinear terms equivalently by McCormick envelopes following Mou et al. (2020), and then transform the bilevel model into a single-level one by minimizing the duality gap of the lower level model, which has been proposed as a heuristic to deal with binaries in unit commitment problems (Ye et al., 2020). The solution process is given as follows.

Step 1: Represent the bilinear terms equivalently by McCormick envelopes

First, we express $s_{i,t} \cdot p_{i,t}$ by a new variable $x_{i,t}$, and $s_{i,t} \cdot d_i^{\text{c}}$ by $y_{i,t}$, while imposing the following constraints:

$$x_{i,t} \leq s_{i,t} \cdot P_i, x_{i,t} \geq 0, x_{i,t} \leq p_{i,t}, \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \tag{5a}$$

$$x_{i,t} \geq s_{i,t} \cdot P_i + p_{i,t} - P_i, \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \tag{5b}$$

$$y_{i,t} \leq s_{i,t} \cdot \overline{d_i^{\text{c}}}, y_{i,t} \geq 0, y_{i,t} \leq d_i^{\text{c}}, \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \tag{5c}$$

$$y_{i,t} \geq s_{i,t} \cdot \overline{d_i^{\text{c}}} + d_i^{\text{c}} - \overline{d_i^{\text{c}}}, \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \tag{5d}$$

where $\overline{d_i^{\text{c}}}$ is the upper bound of d_i^{c}, and can take the value of P_i.

Step 2: Perform linear relaxation for the lower-level model

Second, we relax the binary variable $s_{i,t} \in \{0, 1\}$ in the lower-level model to a continuous variable $s_{i,t}^{\text{s}} \in [0, 1]$, and consequently $x_{i,t}$ and $y_{i.t}$ are also renamed into $x_{i,t}^{\text{s}}$ and $y_{i.t}^{\text{s}}$, to obtain the objective function (6a) and constraints (6b)-(6p) for the relaxed lower-level model.

$$\begin{aligned}\min_{\mathcal{V}_{\text{lower}}^{\text{s}}} \ o_{\text{lower}}^{\text{s}} = &\sum_{t\in\mathcal{T}} \widetilde{\pi}_t \cdot D_t \cdot \Delta T + \sum_{i\in\mathcal{I}} \pi^{\text{c}*} \cdot d_i^{\text{c}} \\ &+ \sum_{i\in\mathcal{I}} \sum_{t\in\mathcal{T}} \pi_t^* \cdot p_{i,t} \cdot \Delta T + \sum_{i\in\mathcal{I}} \sum_{t\in\mathcal{T}} \pi_t^{\text{sc}*} \cdot (x_{i,t}^{\text{s}} - y_{i,t}^{\text{s}}) \cdot \Delta T\end{aligned} \tag{6a}$$

$$\text{s.t. } p_{i,t} - d_i^{\text{c}} + y_{i,t}^{\text{s}} - P_i \cdot s_{i,t}^{\text{s}} \leq 0, \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \qquad (\lambda_{i,t}^{\text{a}}) \tag{6b}$$

$$y_{i,t}^{\text{s}} - p_{i,t} \leq 0, \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \qquad (\lambda_{i,t}^{\text{b}}) \tag{6c}$$

$$-s^{\mathrm{s}}_{i,t} \le 0, \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \qquad (\lambda^{\mathrm{c}}_{i,t}) \tag{6d}$$

$$s^{\mathrm{s}}_{i,t} - 1 \le 0, \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \qquad (\lambda^{\mathrm{d}}_{i,t}) \tag{6e}$$

$$-d^{\mathrm{c}}_{i} \le 0, \forall i \in \mathcal{I} \qquad (\lambda^{\mathrm{e}}_{i}) \tag{6f}$$

$$p_{i,t} - L_{i,t} \cdot P_i \le 0, \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \qquad (\lambda^{\mathrm{f}}_{i,t}) \tag{6g}$$

$$x^{\mathrm{s}}_{i,t} - s^{\mathrm{s}}_{i,t} \cdot P_i \le 0, \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \qquad (\lambda^{\mathrm{g}}_{i,t}) \tag{6h}$$

$$-x^{\mathrm{s}}_{i,t} \le 0, \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \qquad (\lambda^{\mathrm{h}}_{i,t}) \tag{6i}$$

$$x^{\mathrm{s}}_{i,t} - p_{i,t} \le 0, \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \qquad (\lambda^{\mathrm{i}}_{i,t}) \tag{6j}$$

$$-x^{\mathrm{s}}_{i,t} + s^{\mathrm{s}}_{i,t} \cdot P_i + p_{i,t} - P_i \le 0, \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \qquad (\lambda^{\mathrm{j}}_{i,t}) \tag{6k}$$

$$y^{\mathrm{s}}_{i,t} - s^{\mathrm{s}}_{i,t} \cdot \overline{d^{\mathrm{c}}_{i}} \le 0, \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \qquad (\lambda^{\mathrm{k}}_{i,t}) \tag{6l}$$

$$-y^{\mathrm{s}}_{i,t} \le 0, \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \qquad (\lambda^{\mathrm{l}}_{i,t}) \tag{6m}$$

$$y^{\mathrm{s}}_{i,t} - d^{\mathrm{c}}_{i} \le 0, \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \qquad (\lambda^{\mathrm{m}}_{i,t}) \tag{6n}$$

$$-y^{\mathrm{s}}_{i,t} + s^{\mathrm{s}}_{i,t} \cdot \overline{d^{\mathrm{c}}_{i}} + d^{\mathrm{c}}_{i} - \overline{d^{\mathrm{c}}_{i}} \le 0, \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \qquad (\lambda^{\mathrm{n}}_{i,t}) \tag{6o}$$

$$\sum_{t=1}^{T_d} p_{i,t+T_d(n-1)} \cdot \Delta T - C^{\mathrm{d}}_{i,n} = 0, \forall i \in \mathcal{I}, \forall n \in \mathcal{N} \qquad (\nu_{i,n}) \tag{6p}$$

Step 3: Derive the dual problem of the relaxed lower-level model

Third, we derive the dual problem of the relaxed lower-level model to obtain the objective function (7a) and constraints (7b)-(7g). The operation $n = \lceil t/T^{\mathrm{d}} \rceil$ represents rounding up the value of t/T^{d} to the nearest integer, which finds the day that a certain time period t belongs to. T^{d} is the number of time periods in a day, e.g., $T^{\mathrm{d}} = 96$ when each period ΔT is 15 minutes.

$$\max_{\mathcal{V}^{\mathrm{d}}_{\mathrm{lower}}} \ o^{\mathrm{d}}_{\mathrm{lower}} = \sum_{t\in\mathcal{T}} \widetilde{\pi}_t \cdot D_t \cdot \Delta T - \sum_{i\in\mathcal{I}} \sum_{t\in\mathcal{T}} (\lambda^{\mathrm{d}}_{i,t} + L_{i,t} \cdot P_i \cdot \lambda^{\mathrm{f}}_{i,t} + P_i \cdot \lambda^{\mathrm{j}}_{i,t} + \overline{d^{\mathrm{c}}_{i}} \cdot \lambda^{\mathrm{n}}_{i,t}) - \sum_{i\in\mathcal{I}} \sum_{n\in\mathcal{N}} C_{i,n} \cdot \nu_{i,n} \tag{7a}$$

$$\text{s.t. } \pi^{\mathrm{c}*} + \sum_{t\in\mathcal{T}} (-\lambda^{\mathrm{a}}_{i,t} - \lambda^{\mathrm{l}}_{i,t} - \lambda^{\mathrm{n}}_{i,t}) - \lambda^{\mathrm{e}}_{i} = 0, \forall i \in \mathcal{I} \tag{7b}$$

$$\pi^{*}_{t} \cdot \Delta T + \lambda^{\mathrm{a}}_{i,t} - \lambda^{\mathrm{b}}_{i,t} - \lambda^{\mathrm{i}}_{i,t} + \lambda^{\mathrm{j}}_{i,t} + \lambda^{\mathrm{f}}_{i,t} + \nu_{i,n} \cdot \Delta T = 0, \forall i \in \mathcal{I}, \forall t \in \mathcal{T}, n = \lceil t/T^{\mathrm{d}} \rceil \tag{7c}$$

$$-P_i \cdot \lambda^{\mathrm{a}}_{i,t} - \lambda^{\mathrm{c}}_{i,t} + \lambda^{\mathrm{d}}_{i,t} - P_i \cdot \lambda^{\mathrm{g}}_{i,t} + P_i \cdot \lambda^{\mathrm{i}}_{i,t} - \overline{d^{\mathrm{c}}_{i}} \cdot \lambda^{\mathrm{k}}_{i,t} + \overline{d^{\mathrm{c}}_{i}} \cdot \lambda^{\mathrm{n}}_{i,t} = 0, \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \tag{7d}$$

$$\pi^{\mathrm{sc}*}_{t} \cdot \Delta T + \lambda^{\mathrm{g}}_{i,t} - \lambda^{\mathrm{h}}_{i,t} + \lambda^{\mathrm{i}}_{i,t} - \lambda^{\mathrm{j}}_{i,t} = 0, \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \tag{7e}$$

$$-\pi^{\mathrm{sc}*}_{t} \cdot \Delta T + \lambda^{\mathrm{a}}_{i,t} + \lambda^{\mathrm{b}}_{i,t} + \lambda^{\mathrm{k}}_{i,t} - \lambda^{\mathrm{l}}_{i,t} + \lambda^{\mathrm{m}}_{i,t} - \lambda^{\mathrm{n}}_{i,t} = 0, \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \tag{7f}$$

$$\lambda^{\mathrm{a}}_{i,t}, \lambda^{\mathrm{b}}_{i,t}, \lambda^{\mathrm{c}}_{i,t}, \lambda^{\mathrm{d}}_{i,t}, \lambda^{\mathrm{e}}_{i}, \lambda^{\mathrm{f}}_{i,t}, \lambda^{\mathrm{g}}_{i,t}, \lambda^{\mathrm{h}}_{i,t}, \lambda^{\mathrm{i}}_{i,t}, \lambda^{\mathrm{j}}_{i,t}, \lambda^{\mathrm{k}}_{i,t}, \lambda^{\mathrm{l}}_{i,t}, \lambda^{\mathrm{m}}_{i,t}, \lambda^{\mathrm{n}}_{i,t} \ge 0, \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \tag{7g}$$

Step 4: Reformulate the bilevel problem into a single-level one by minimizing the duality gap

Fourth, we introduce W as the penalty constant, and reformulate the bi-level model into a single-level one by penalizing the duality gap:

$$\max_{\mathcal{V}_{\mathrm{single}}} \ o_{\mathrm{single}} = -o_{\mathrm{upper}} - W \cdot (o_{\mathrm{lower}} - o^{\mathrm{d}}_{\mathrm{lower}}) \tag{8a}$$

$$\text{s.t. } (3b) - (3g), (2b) - (2g), (7b) - (7g) \tag{8b}$$

where $\mathcal{V}_{\mathrm{single}} = \left\{\mathcal{V}_{\mathrm{upper}}, \mathcal{V}_{\mathrm{lower}}, \mathcal{V}^{\mathrm{d}}_{\mathrm{lower}}\right\}$ denote the set of optimization variables, $(o_{\mathrm{lower}} - o^{\mathrm{d}}_{\mathrm{lower}})$ calculates the duality gap of the lower-level model. The constraints of the single-level model include all the constraints from the upper-level model, lower-level model, and its dual problem.

2.4. Extension to liberalized electricity markets

The model presented in Section 2.2 is formulated for Chinese residential consumers, who currently benefit from favorable electricity prices without network tariffs. In this section, we extend the model to liberalized electricity markets, where retail tariffs are unbundled into an energy tariff and a network tariff. The network tariff is typically regulated and determined by network operators, whereas the energy tariff may be offered by either a regulated local monopoly retailer or competing retailers.

Equations (9a)–(9d) present the ToU-D tariff design model for a regulated local monopoly retailer. In this setting, the ToU-D tariff corresponds to the energy tariff component of the retail tariff, while the network tariff component of the retail tariff is exogenously given and may include both a demand charge $\pi^{\text{net,c}}$, and a volumetric time-varying charge π_t^{net}. Note we assume that the demand charge component (if present in the network tariff design) follows the same design as the demand charge in our ToU-D tariff, which allows for exceeding with a penalty fee. It only applies to EV charging demand, while household demand only pays the volumetric π_t^{net}. The purpose is to provide an interesting analysis of the impacts of network tariffs in Section 3.2.5. Although alternative designs are possible, as discussed in footnote 1. In the analysis, we compare the proposed tariff with a retail tariff composed of a ToU energy tariff and a network tariff that includes both a volumetric time-varying charge and a demand charge, where the demand charge is based on peak demand and does not allow exceeding. In the extended bilevel model, the upper level represents the retailer, who retains the structure of the grid company. The objective function of lower-level residential consumers is augmented with the inclusion of network tariffs, as formulated below.

$$\min_{\mathcal{V}_{\text{upper}}} \ (\lambda^{\text{c}} \cdot d_m + \sum_{t\in\mathcal{T}} \lambda_t \cdot d_t \cdot \Delta T) \tag{9a}$$

$$\text{s.t. } (3b) - (3g) \tag{9b}$$

$$d_i^{c*}, p_{i,t}^*, s_{i,t}^* \in \arg \min_{d_i^{\text{c}}, p_{i,t}, s_{i,t}} \Big\{ o_{\text{lower}}^{\text{ext}} : (2b) - (2g) \tag{9c}$$

$$\begin{aligned} o_{\text{lower}}^{\text{ext}} = & \sum_{t\in\mathcal{T}} (\widetilde{\pi}_t + \pi_t^{\text{net}}) \cdot D_t \cdot \Delta T + \sum_{i\in\mathcal{I}} (\pi^{\text{c}*} + \pi^{\text{net,c}}) \cdot d_i^{\text{c}} + \sum_{i\in\mathcal{I}} \sum_{t\in\mathcal{T}} (\pi_t^* + \pi_t^{\text{net}}) \cdot p_{i,t} \cdot \Delta T \\ & + \sum_{i\in\mathcal{I}} \sum_{t\in\mathcal{T}} (\pi_t^{sc*} + K^{\text{sc}} \cdot \pi_t^{\text{net}}) \cdot s_{i,t} \cdot (p_{i,t} - d_i^{\text{c}}) \cdot \Delta T \Big\} \end{aligned} \tag{9d}$$

Another possible extension is to consider competing retailers, which would result in a multi-leader game to represent multiple retailers. Alternatively, retail market competition could be approximated by incorporating price constraints, as in Soares et al. (2021a) and Beraldi & Khodaparasti (2023). While this is an interesting direction for future research, it lies beyond the scope of the present study.

3. Case studies

3.1. Data and assumptions

This paper adopts a time resolution of 15 minutes and sets a one-month horizon as the billing period. We select the data of 100 EVs from datasets collected in a few communities in a province in eastern China. To represent a penetration rate of 20%, we scale down the residential demand curve of this province to reflect the aggregated household demand curve D_t for 500 residential households. Each EV exhibits various charging habits (e.g., arrival and departure times, number of charging sessions per week, etc.). In order to reflect the combined impact of these parameters, we define the concept of flexibility level on a one-month scale as shown in Equation (10) [2]. The flexibility levels of the 100 EVs are shown in Figure 3, which would be used for analysis on individual EVs in Section 3.2.2. Consumers are assumed to be rational, with a response rate of 100%, except in the sensitivity analysis of Section 3.2.4.

$$\text{flexibility level} = \frac{\text{accumulated connection duration - energy demand / maximum power}}{\text{the number of hours in a month}} \times 100\% \tag{10}$$

[2] At one extreme, if an EV remains connected to the charging post for the entire month with zero energy need, its flexibility level is 100%. At the other extreme, if the connection time is just sufficient to meet the energy demand at maximum charging power, the flexibility level is 0. In a normal scenario, assume an EV with a maximum power of 3.2 kW and a monthly energy demand of 200 kWh, and accumulated connection duration (the difference between the scheduled departure time and the time starting to connect to the charging post each day) of the EV is 100 hours. This results in a flexibility level of 5.21%, calculated as $(100 - 200/3.2)/720 = 5.21\%$.

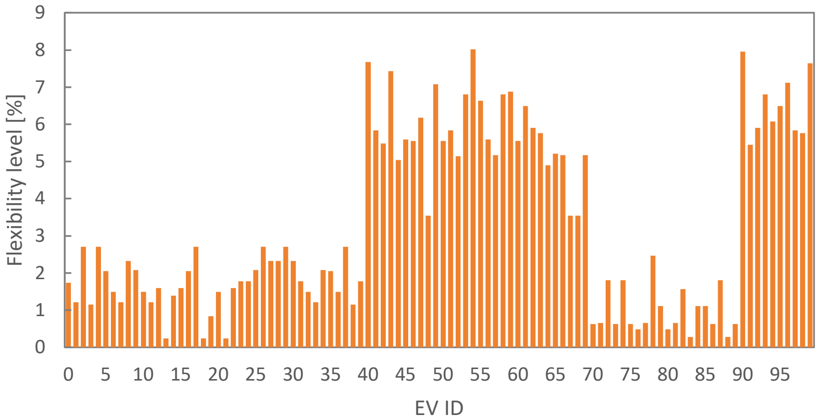


Figure 3: Illustration of the flexibility levels of 100 EVs.

The grid company procures energy from the wholesale market at time-varying prices and fulfills its capacity obligations by purchasing generation capacity from the capacity market based on its peak demand at a rate of 30 yuan per kW per month. The current time-of-use tariff consists of three segments: peak hours from 18:00 to 22:00, at 0.888 ¥/kWh; flat hours from 8:00 to 18:00, at 0.555 ¥/kWh; and valley hours from 22:00 to 8:00 the next day, at 0.385 ¥/kWh. The penalty ratio K^{sc} is set to 2 in the ToU-D tariff. The profit rate of the grid company under the ToU-D tariff is assumed to be 8-10%.

Regarding the exogenously given network tariffs, we adopt the Spanish tariff (Morell Dameto et al., 2020), scale down the values correctly, and conduct analyses on two distinct structures, as presented in Section 3.2.5.

3.2. Result analysis

As discussed in Section 2.3, we employ a heuristic method to solve the bilevel model by minimizing the duality gap of the lower-level problem. Therefore we first investigate the impact of the penalty constant W. With W ranging from 1000 to 0.001, the model is solved repeatedly to derive the relationship between W and the objective function value of the upper-level model, i.e., the purchase costs of the grid company. As depicted in Figure 4, as the penalty constant W decreases, the purchase costs initially remain constant at the maximum value of 127303 ¥, and then rapidly decrease until the penalty constant reaches 0.1, where the purchase costs approach the minimum value of 127165 ¥. Therefore, the penalty constant W is set to 0.1, and the model is solved to obtain the ToU-D tariff, where the demand charge π^{c} is calculated to be 4.77 ¥/kW, and the ToU component multiplier k is 0.50. We then conduct detailed analyses in the following aspects: the overall performance of the ToU-D tariff in Section 3.2.1, the impact of the ToU-D tariff on different types of EVs in Section 3.2.2, a sensitivity analysis on the demand charge component of the ToU-D tariff in Section 3.2.3, and a sensitivity analysis on the response rate of EVs in Section 3.2.4. These analyses focus only on the ToU-D tariff, excluding network tariffs. An assessment of how network tariffs affect both ToU-D and the current ToU tariff is presented in Section 3.2.5.

3.2.1. Overall performance of the ToU-D tariff

Figure 5 compares the aggregated residential demand curves on a typical day in different cases. In the figure, the gray dashed curve represents the household demand. The blue curve illustrates the EV demand in addition to the household demand in the scenario where EV owners charge their vehicles immediately upon arrival home, regardless of electricity prices. The orange curve illustrates the current ToU tariff case. A comparison between the orange and blue curves reveals an over-response phenomenon under the current ToU tariff, with an increase in peak demand occurring around the 22^{nd}-23^{rd} hour. The green curve displays the aggregated demand curve with EV demand under the ToU-D tariff, indicating that the over-response issue has been resolved, resulting in a 9.37% reduction in peak demand.

Table 1 compares the economic performance of the grid company and residential consumers under different tariffs. Under the ToU-D tariff, both the purchase costs for the grid company and the charging fees for residential consumers

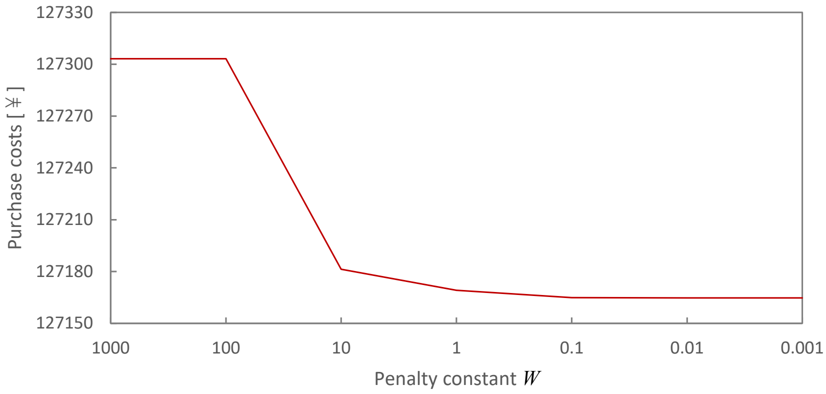


Figure 4: Evolution of the purchase costs with respect to the penalty constant.

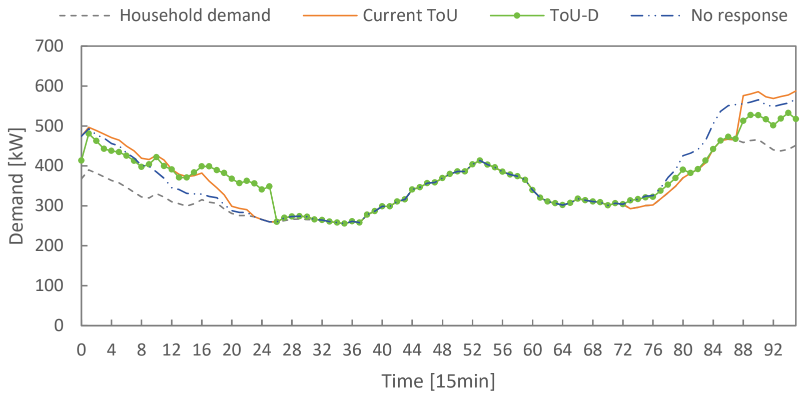


Figure 5: Comparison of aggregated demand curves in the cases of no response to prices, response to the current ToU tariff, and response to the proposed ToU-D tariff.

Table 1
Economic performance of the grid company and residential consumers under different tariffs.

	Grid company			Residential consumers		
	Costs [¥]	Profits [¥]	Profit rate	Household demand fee [¥]	Charging demand fee [¥]	Total [¥]
ToU	130938	9036	6.46%	132327	7647	139974
ToU-D	127165	11813	8.50%	132327	6650	138978
Relative change	-2.88%	+30.73%	+31.58%	0%	-13.03%	-0.71%

decrease, while the profit and profit rate of the grid company increase. Therefore, the ToU-D tariff creates a win-win situation by mitigating the over-response of EV charging.

3.2.2. *Impact of the ToU-D tariff on different types of EVs*

An individual analysis of charging fees for each EV reveals that not all consumers experience a reduction in monthly charging fees under the ToU-D tariff. Among the 100 EVs, 35 actually incur varying degrees of increased charging fees under ToU-D. Figure 6 plots the percentage change in charging fees under ToU-D (relative to the current ToU) against flexibility levels for 100 EV owners. The fitted trend line indicates a negative correlation, i.e., higher flexibility levels leading to larger relative fee reductions.

Furthermore, two representative EVs are selected for detailed analysis, with one experiencing a relatively larger percentage increase (EV88, +45.63%) and the other experiencing a relatively larger percentage reduction (EV90,

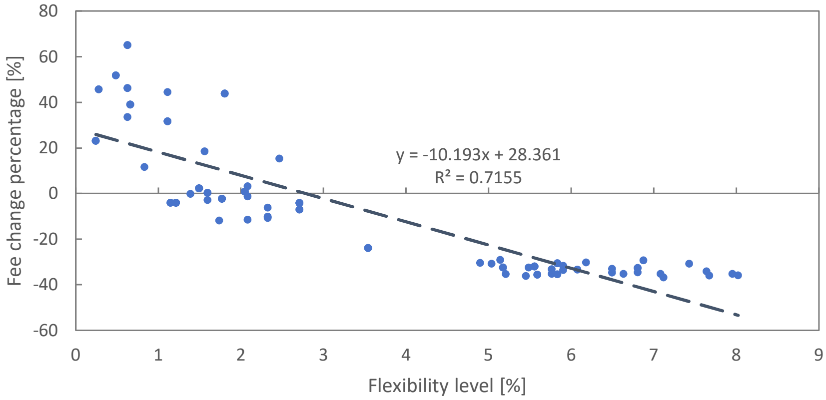


Figure 6: The percentage change of charging fees under ToU-D and the current ToU tariff with respect to flexibility level.

Table 2
Details of EV88 and EV90 in one month.

ID	Energy demand [kWh]	Connection duration [hours]	Reserved capacity [kW]	Reservation fee [¥]	Energy fee [¥]
88	116.16	15.75	6.03	28.79	36.33
90	572.00	138.50	6.80	32.43	110.11

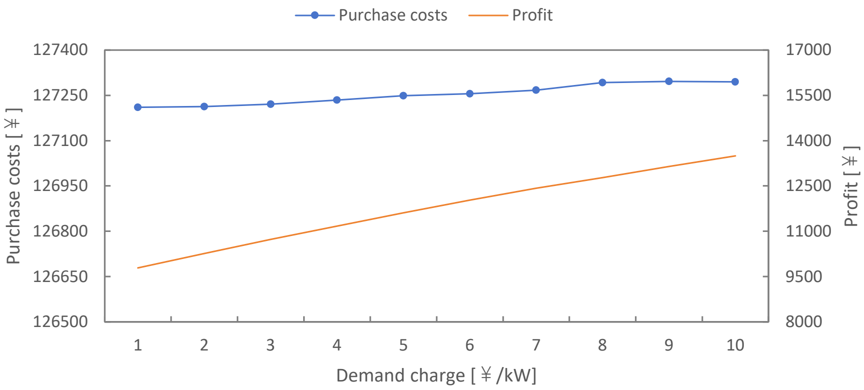
–35.27%) in charging fees. Their flexibility levels are 0.28% and 7.95%, respectively. Table 2 shows that although the two EVs have similar reserved capacities, their utilization of these capacities differs, as reflected in their monthly energy demands and connection durations. The owner of EV88 has a "poor" charging habit and does not often connect to the charging post after arriving home. The charging costs can be reduced by extending the connection duration while lowering the charging power per session. Consequently, the ToU-D tariff can incentivize consumers to adjust their charging habits by extending their charging duration and reducing the maximum charging power, thereby minimizing charging fees.

3.2.3. Sensitivity analysis on the demand charge component of the ToU-D tariff

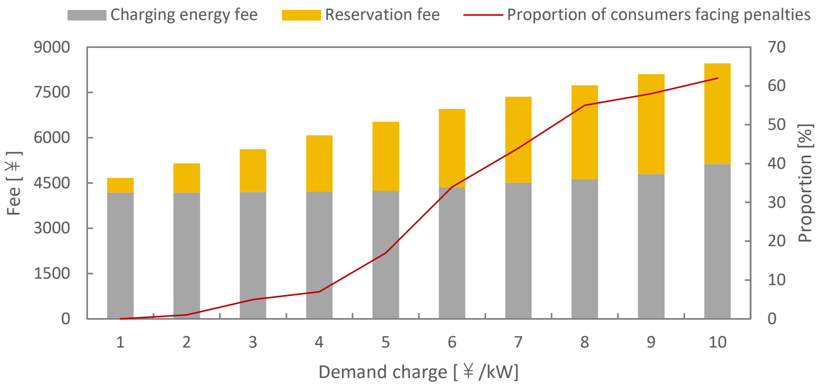
A detailed sensitivity analysis is conducted to examine the implications of adjusting the demand charge π^c within a range of 1 to 10 ¥/kW. The findings of this analysis are presented in Figure 7. Specifically, Figure 7a reveals that as the demand charge increases, the grid company's purchase costs remain relatively stable, maintained at approximately 127250 ¥, whereas its profit shows an upward trend. For residential consumers, both the total charging fee and proportion of consumers facing penalties increase steadily in Figure 7b. However, the charging energy fee (including basic energy fee and penalty fee) increases gradually, while the reservation fee initially increase steeply before stabilizing at the demand charge of approximately 8 ¥/kW. This finding suggests that in scenarios of higher demand charges, residential consumers tend to reduce their reserved capacities to minimize their charging fees, thereby resulting in a situation where charging power exceeds the reserved capacity and incurs a the penalty fee. Therefore, the demand charge plays a crucial role in guiding consumers' charging behaviors effectively and and serves as a mechanism for balancing the economic interests of both the grid company and residential consumers.

3.2.4. Sensitivity analysis on the response rate of EVs

After designing the ToU-D tariff based on a 100% response rate, we evaluate its performance under 20% and 60% realized response rates, where the responding EVs are randomly selected while the remaining EVs begin charging immediately upon arrival. Table 3 compares the economic performance of the ToU-D tariff and the current ToU tariff. The results show that the ToU-D tariff outperforms the current ToU tariff in terms of the grid company's purchase costs, residential consumers' charging fees, and system peak demand across these three response rates. However, at a 20% response rate, the ToU-D tariff yields a lower profit rate than the current ToU tariff, indicating a potential risk for the grid company if the realized response rate falls significantly short of the level assumed in the tariff design.



(a) The purchase costs and profit of the grid company with respect to the demand charge.



(b) The composition of charging fees with respect to the demand charge.

Figure 7: Sensitivity analysis on the demand charge component of ToU-D.

Table 3
Sensitivity analysis on the response rate of EVs.

Response rate	Tariff type	Purchase costs [¥]	Charging fees [¥]	Profits [¥]	Profit rate	Peak demand [kW]
20%	Current ToU	131679	10001	10649	7.48%	604
	ToU-D	130954	7396	8769	6.28%	586
	Relative change	-0.55%	-26.05%	-17.65%	-16.04%	-2.92%
60%	Current ToU	131440	8744	9632	6.83%	608
	ToU-D	129260	7008	10075	7.23%	561
	Relative change	-1.66%	-19.86%	+4.61%	+5.86%	-7.59%
100%	Current ToU	130938	7647	9036	6.46%	615
	ToU-D	127165	6650	11813	8.50%	523
	Relative change	-2.88%	-13.03%	+30.73%	+31.58%	-15.02%

3.2.5. *Impact of network tariffs*

Based on the bilevel model presented in Section 2.4 and the parameters in Section 3.1, we evaluate two different network tariff structures:

- Type 1: A time-varying volumetric tariff without a demand charge, with the volumetric rate of 0.248 ¥/kWh, 0.011 ¥/kWh and 0.003 ¥/kWh during peak, flat, and valley hours, respectively. The time-of-use periods align with the current ToU tariff definition.

Table 4
Economic performance of the retailer under various network tariffs.

Case	Network tariff	Energy tariff	Purchase costs [¥]	Profits [¥]	Profit rate	Peak demand [kW]
A0		Current ToU	130938	9036	6.46%	615
B0	None	ToU-D	127165	11813	8.50%	523
-		Relative change	-2.88%	+30.73%	+31.58%	-15.02%
A1		Current ToU	130938	9036	6.46%	615
B1	Type 1	ToU-D	127168	11813	8.50%	523
-		Relative change	-2.88%	+30.74%	+31.58%	-15.02%
A2		Current ToU	129820	10872	7.73%	583
B2	Type 2	ToU-D	127167	11813	8.50%	523
-		Relative change	-2.04%	+8.65%	+9.96%	-10.35%

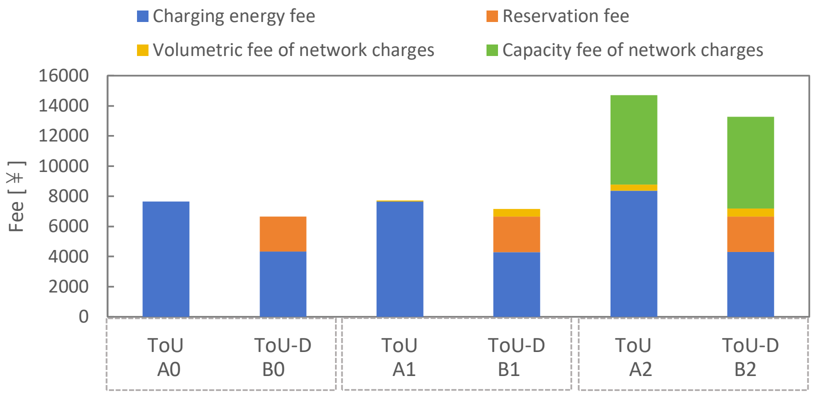


Figure 8: Breakdown of residential charging fees in different cases.

- Type 2: A hybrid network tariff including a demand charge of 12.51 ¥/kW per month, in addition to the same volumetric rate as Type 1.

Combining the two types of network tariffs with the energy tariffs yields six cases labeled A0 to B2. Table 4 presents the economic performance of the retailer across different cases, while Figure 8 provides a breakdown of consumers' overall charging fees. The demand charge of the Type 2 network tariff is implemented differently under the ToU and ToU-D energy tariffs. Specifically, in case A2, the demand charge is based on the monthly peak charging demand. By contrast, in case B2, it is applied in the same way as the ToU-D design, where charging demand may exceed the reserved capacity but is subject to a penalty.

We first evaluate the Type 1 network tariff. Comparing case A1 with A0 in Table 4, the retailer's economic performance remains unchanged. The Type 1 network tariff does not alter the segmentation of peak, flat, and valley hours, and most EVs continue to charge during valley hours, leading to over-response. Comparing case B1 with B0, the retailer's performance is also nearly identical, as the ToU-D tariff dominates the outcomes. For consumers, the total fee increases only slightly in A1 compared with A0, as shown in Figure 8, since the network tariff is just 0.003 ¥/kWh during valley hours. However, comparing B1 with A1, the share of volumetric network charges becomes larger in B1. This situation occurs because the demand charge mechanism in ToU-D discourages concentrated charging during valley hours, forcing consumers to spread charging over longer durations, including hours with higher network tariffs.

With the Type 2 network tariff, case A2 outperforms A0 for the retailer by reducing purchase costs and yielding a higher profit and profit rate, mainly due to the reduction in peak demand. However, A2 remains inferior to B2 because of differences in demand charge implementation. In A2, the demand charge is determined by the month's peak charging power, so a single emergency charging event at maximum power fixes the capacity fee for the entire month, preventing incentives for optimization in future charging sessions. By contrast, B2 allows exceeding the reserved capacity with a penalty, so after emergency events, consumers retain motivation to optimize charging within their reserved capacities.

4. Conclusions and policy implications

This paper addresses the issue of off-peak over-response in EV charging under the current ToU tariff by proposing a ToU pricing mechanism with a demand charge (ToU-D). We develop a mixed-integer bilevel optimization model to capture the game-theoretic interaction between the upper-level grid company and the lower-level residential consumers. The model can be readily adapted to include network tariffs in liberalized markets. Medium-scale EV charging datasets have been utilized to conduct case studies. In this section, we first summarize our main findings and present policy recommendations, and then discuss some limitations and future work.

First, compared to the current ToU tariff, the proposed ToU-D tariff mitigates over-response from charging demand. It results in a decrease in both the grid company's purchase costs and the overall charging fees for residential consumers. However, if the realized response rate falls significantly below the level assumed in the tariff design, the grid company faces the risk of reduced profits. Consumers with less flexible charging habits may experience an increase in their charging fees, so the ToU-D tariff incentivizes consumers to adopt more flexible charging habits. Second, sensitivity analysis on the demand charge reveals that it is a crucial factor in balancing the economic interests of both the grid company and residential consumers, as well as in influencing consumers' charging behaviors. Third, in liberalized markets with unbundled network tariffs, the ToU-D tariff is compatible with diverse network tariff designs, offering economic benefits through its mechanism of allowing for exceeding reserved capacity with a penalty.

Based on this study and our discussion with practitioners, we offer the following recommendations. First, as the EV charging demand rapidly increases in China, the low-voltage distribution system will face challenges of overloading. The traditional ToU tariff could potentially lead to an over-response, as EVs can conveniently be programmed to start charging immediately upon the start of off-peak hours. Therefore, the inclusion of a demand charge component could serve as a potential remedy. Second, for counties and regions where residential consumers do not benefit from favorable tariffs or where EV charging demand is not separately metered from household demand, the tariff should be designed to account for both the overall residential demand and the network tariff. Our study can serve as a valuable reference in this context.

The proposed model's limitations and directions for future work are discussed below. First, we adopt a heuristic method to solve the mixed-integer bilevel model; thus, the solution may not be optimal. Future work could explore more advanced algorithms, such as a value-function-based approach (Lozano & Smith, 2017), to obtain exact solutions or to quantify the economic impact of the optimality gap. Second, residential consumer tariffs are typically enforced at the local utility level and remain in effect for at least a year. However, due to computational challenges, our case studies narrow the scope of the simulation to 500 households, 100 EVs, and a one-month time horizon. A larger sample of EVs across multiple communities would provide a more representative reflection of charging behaviors. Moreover, a pilot project is essential before implementing on a large scale, particularly to measure EV response rates and mitigate the risk of profit reduction. Third, we assume that consumers maintain their original charging habits by introducing the parameter $L_{i,t}$. For instance, some may charge their vehicles daily while others opt for weekly charging sessions. The frequency of charging can be regarded as a long-term flexibility, in contrast to the short-term flexibility in adjusting the charging power. In the long run, consumers may modify their charging habits under the ToU-D tariff to reduce charging fees. This perspective requires further investigation in the trial we intend to implement. Finally, the case study shows that less flexible consumers may face higher charging fees under ToU-D, which could discourage EV adoption among risk-averse consumers. The broader implications of the ToU-D tariff for distributional equity, particularly for low-income and vulnerable consumers, as well as EV adoption, are also worth further investigation.

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CRediT authorship contribution statement

Yikang Xiao: Conceptualization, Methodology, Software, Investigation, Data Curation, Visualization, Writing - Original Draft, Writing - Review & Editing. **Yuting Mou:** Conceptualization, Methodology, Supervision, Funding acquisition, Writing - Original Draft, Writing - Review & Editing. **Bo Pan:** Data Curation. **Min Yang:** Data Curation.

Declaration

During the preparation of this work the authors used ChatGPT in order to correct language errors. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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A. Nomenclature

A.1. Sets

$\mathcal{T}$ Set of time periods

$\mathcal{I}$ Set of residential consumers with EVs

$\mathcal{N}$ Set of days

$\mathcal{T}_n$ Set of time periods on the day n, $n \in \mathcal{N}$

A.2. Variables

The variables marked with * represent the optimal solutions of the corresponding decision variables, which are treated as parameters in the relevant mathematical model.

d_i^{c} Reserved capacity of residential EV owner i, $i \in \mathcal{I}$ [kW]

$p_{i,t}$ Charging power of EV i on time period t, $i \in \mathcal{I}$, $t \in \mathcal{T}$ [kW]

$s_{i,t}$ Binary variable distinguishing whether the charging power exceeds the reserved capacity, $i \in \mathcal{I}, t \in \mathcal{T}$

$x_{i,t}$ Utilized to eliminate bilinear term $x_{i,t} = s_{i,t} \cdot p_{i,t}$, $i \in \mathcal{I}, t \in \mathcal{T}$

$y_{i,t}$ Utilized to eliminate bilinear term $y_{i,t} = s_{i,t} \cdot d_i^{\mathrm{c}}$, $i \in \mathcal{I}, t \in \mathcal{T}$

π^{c} Demand charge of the ToU-D tariff [¥/kW]

π_t ToU component of the ToU-D tariff, $t \in \mathcal{T}$ [¥/kWh]

k The multiplier relative to the current ToU tariff

π_t^{sc} Penalty rate of ToU-D, $t \in \mathcal{T}$ [¥/kWh]

d_t Total demand of residential consumers in time period t, $t \in \mathcal{T}$ [kW]

d_m The maximum value of d_t [kW]

$s_{i,t}^{\mathrm{s}}$ Relaxed variable of $s_{i,t}$, $i \in \mathcal{I}, t \in \mathcal{T}$

$x_{i,t}^{\mathrm{s}}$ Relaxed variable of $x_{i,t}$, $i \in \mathcal{I}, t \in \mathcal{T}$

$y_{i,t}^{\mathrm{s}}$ Relaxed variable of $y_{i,t}$, $i \in \mathcal{I}, t \in \mathcal{T}$

A.3. Parameters

ΔT Duration of a time period [h]

λ^{c} Capacity market price for capacity obligations per month [¥/kW]

λ_t Spot market price for energy purchase, $t \in \mathcal{T}$ [¥/kWh]

K^{sc} Penalty ratio of the penalty price for consumption exceeding the procured capacity

$\widetilde{\pi}_t$ The current ToU tariff, $t \in \mathcal{T}$ [¥/kWh]

$\overline{r}$ The upper bound on the profit rate

$\underline{r}$ The lower bound on the profit rate

D_t Aggregated household demand in time period t, $t \in \mathcal{T}$ [kW]

$\overline{d_i^{\mathrm{c}}}$ The upper bound of d_i^{c}, $i \in \mathcal{I}$ [kW]

P_i Maximum charging power of EV i, $i \in \mathcal{I}$ [kW]

$L_{i,t}$ The connection status of EV i to the charging post, $i \in \mathcal{I}$, $t \in \mathcal{T}$

$C_{i,n}$ The daily electricity consumption for consumer i on day n, $i \in \mathcal{I}$, $n \in \mathcal{N}$ [kWh]

T^{d} The number of time periods in one day

$\pi^{\mathrm{net,c}}$ The demand charge component of the network tariff [¥/kW]

π_t^{net} The volumetric component of the network tariff, $t \in \mathcal{T}$[¥/kWh]