

Economic Simulation and Evaluation of Electric Vehicle Charging and Discharging under Time-of-Use Pricing

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Abstract: In the context of China's ongoing experimentation with time-of-use (TOU) tariffs, electric vehicles (EVs) can serve not only as clean transportation but also as behind-the-meter distributed storage. This paper proposes a quantitative method to evaluate the economic benefits of EV charging and discharging. Battery capacity is partitioned into a "safety zone" and an "active zone": the safety zone guarantees mobility demand, while the active zone is dedicated to TOU arbitrage and vehicle-to-grid (V2G) interaction. The proposed framework jointly accounts for discharge revenue, electricity purchase cost, and battery degradation cost, while embedding practical constraints such as station power limits and heterogeneous user behavior. A long-horizon iterative accounting scheme is developed and solved through Monte Carlo simulation to compare pricing mechanisms and battery sizes. Results show that flexible TOU pricing unlocks substantially higher economic potential than fixed tariffs; expanding battery capacity yields nonlinear gains in net benefit; and under the proposed strategy an EV fleet exhibits pronounced peak-shaving and valley-filling capability, providing both economic value and grid support. The findings can inform TOU tariff design and the deployment of V2G programs.

Keywords: Electric Vehicles; Charging–discharging Scheduling; Time-of-use (TOU) Tariff; Vehicle-to-grid (V2G); Charging Load.

1. Introduction

Modern socioeconomic development still relies heavily on fossil fuels, and the long-term, large-scale use of fossil energy has imposed severe environmental impacts worldwide. Electric vehicles (EVs), as a clean-energy transportation option, feature fast charging and inherent energy storage capability. Under certain conditions, an EV can be regarded as a form of distributed energy storage on the user side [1]. As one of the world's largest EV markets, China has experienced rapid growth in EV sales over the past decade, opening new opportunities for power-system flexibility and energy efficiency improvement [2].

Globally, some countries have shortened the electricity-price regulation and evaluation cycle from monthly settlement to intra-day updates as frequent as every four hours or even every 30 minutes [3]. In China, many cities and regions are experimenting with more fine-grained and flexible pricing schemes, but adoption remains uneven. For example, southern cities such as Guangzhou have begun to link EV charging prices to market competition and regional load levels, whereas many northern cities, including Beijing, still apply relatively fixed tariffs, in some cases with an almost flat price throughout the day.

Existing research on EV participation in power-system regulation has mainly focused on reducing grid loading, promoting local renewable-energy consumption, and achieving peak shaving and valley filling. For instance, Ref. [4] optimizes EV charging/discharging behavior using a hybrid genetic algorithm and grey wolf optimizer (GA-GWO), reducing the load-variance within a residential area and improving grid stability. Ref. [5] proposes delaying or temporarily suspending EV charging at peak demand to support system stability. Ref. [6] compares EVs under orderly charging and discharging with conventional fuel vehicles

under carbon trading and shows that optimized EV scheduling can reduce regional carbon emissions and mitigate load fluctuations. Ref. [7] develops an expanded carbon-emission model and a carbon-oriented pricing mechanism, where automakers obtain optimal carbon quota trading volume and price. Ref. [8] proposes a dedicated wind–solar–storage scheme for EVs, prioritizing renewable usage and feeding energy back to the grid via charging/discharging, thereby increasing local renewable utilization and integrating intermittent generation into the main grid. Ref. [9] introduces real-time pricing into a wind–solar–storage priority framework and applies a game-theoretic approach to derive optimal prices over time, achieving both minimum user cost and improved grid stability, hence maximizing social welfare. Ref. [10] establishes a bi-level spatiotemporal scheduling model that assigns EVs to the nearest charging station spatially and minimizes charging time and cost temporally.

Overall, prior studies have demonstrated the distributed-storage value of EVs by examining the degree and mechanism of EV participation in grid operation. With technological advances—especially the maturation of vehicle-to-grid (V2G) technologies—the financial attribute of EVs is becoming increasingly important. A social-welfare maximization framework can balance supply- and demand-side benefits while ensuring supply–demand equilibrium, and it is among the effective approaches for designing real-time pricing strategies [11]. This study takes the EV's financial attribute as the core idea, encourages users to shift electricity consumption patterns via orderly EV scheduling, and quantifies the economic and energy value that EVs can create.

Motivated by stepped TOU tariffs, we propose an EV charging/discharging scheduling model that maximizes the vehicle owner's net welfare. The main contributions are:

1) Energy-zone design: Based on typical household mobility demand, battery capacity is divided into a "safety

zone" and an "active zone". The safety zone secures daily travel needs, while the active zone is independently used for TOU arbitrage and V2G interaction. Considering the fragmented, multi-trip, and hard-to-statistically-aggregate nature of real-world driving behavior, daily mobility energy demand is digitized and deducted once from the safety zone.

2) Practical constraints: Randomness in charging power and duration is introduced to emulate limited daytime charging resources and uncertainty in user availability, making the scheduling outcomes closer to real operating conditions.

3) Long-horizon iterative accounting: A unified accounting system covering discharge revenue, purchase cost, and battery degradation cost is built. Monte Carlo sampling is performed to compare long-term effects under different tariff mechanisms and battery capacities.

With this model, we verify that TOU price elasticity can substantially increase owner welfare and that EV fleets offer system-level value in peak shaving and valley filling. The results provide implications for tariff policy, pricing design, and the promotion of V2G programs.

2. EV Charging and Discharging Scheduling Model

The main target group in this study is salaried commuters with relatively stable daily routines. In most cases, this population follows regular commuting patterns between workplace and home, with fixed working hours. A 2017 U.S. Department of Transportation survey provides similar evidence: 14% of household vehicles are unused on a given day; 80% are used no more than two hours per day; and 83.7% travel within 97 km per day [12]. Like conventional vehicles, most EVs remain idle for long periods after charging and have relatively small daily driving demand, implying that their storage value is not fully utilized.

We adopt a widely observed "three-peak/three-valley" TOU tariff pattern in China as the pricing foundation. Although tariffs differ across regions due to local policies and load conditions, extensive field investigation suggests that many regions can be approximated by a three-peak/three-valley daily price curve (Figure 1).

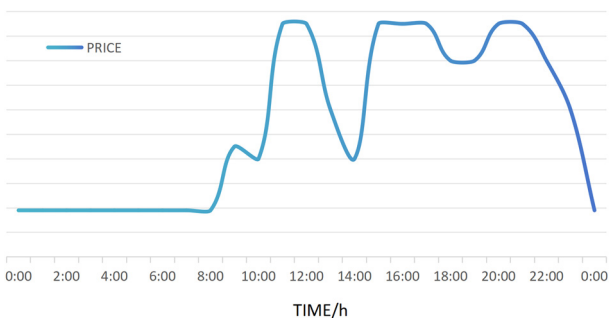


Figure 1. Three-peak/three-valley TOU tariff profile

Under such a tariff, owners are incentivized to sell stored energy during high-demand (high-price) periods and to charge during low-price periods ("charge low, discharge high") to maximize arbitrage profit. In particular, overnight hours usually exhibit the lowest price and long duration, making them the preferred charging window. In contrast, the morning, noon, and evening peaks are dominated by production and residential demand; EV usage demand is relatively low during these periods, while many EVs are

parked, creating opportunities for earning revenue through charging and discharging.

Therefore, an owner charges the EV in the residential area overnight, drives to the workplace in the morning, and returns home after work. In the workplace area, the EV performs at least one charging/discharging action according to the prevailing tariff; in the residential area, the EV may also discharge during the evening peak depending on remaining energy. Due to infrastructure and V2G limitations, we assume that all discharged energy within the studied integrated park can be effectively absorbed and consumed.

2.1. Partitioning of Battery Energy and State Evolution

2.1.1. Energy Partition

As a transportation asset, an EV's mobility function is the primary requirement [13]. To guarantee daily travel demand and facilitate quantification, battery energy is divided into a safety zone and an active zone. The active zone is the only portion allowed to participate in discharge for revenue in the proposed framework, whereas daily travel energy is entirely supplied from the safety zone.

$$C_T = C_S + C_A \quad (1)$$

$$S_T = S_S + S_A \quad (2)$$

Among them C_T , C_S and C_A are the total battery capacity, the safety-zone capacity, and the active-zone capacity, respectively; S_T , S_S and S_A are the remaining energy of the full battery, the safety zone, and the active zone, respectively.

2.1.2. Energy Evolution

The active-zone energy is dedicated to TOU arbitrage or V2G ancillary services. Its state evolves from the previous time step plus charged energy minus discharged energy, and the resulting state is carried forward in subsequent loops.

$$S_A(d, t+1) = S_A(d, t) + \Delta E_c(d, t) - \Delta E_d(d, t) \quad (3)$$

where $S_A(d, t)$ denotes the remaining active-zone energy (state of charge, SOC) at time slot t on day d ; $\Delta E_c(d, t)$ is the energy charged into the active zone during the slot; and $\Delta E_d(d, t)$ is the energy discharged from the active zone during the slot (kWh).

To satisfy capacity limits, the S_A is bounded by:

$$0 \leq S_A(d, t) \leq C_A \quad (4)$$

The safety zone covers the EV owner's daily travel consumption. Daily driving mileage is stochastic [14]. In this study, a random function is used to limit daily mobility demand to within 20% of total battery capacity. For example, for a 70 kWh EV, 20% corresponds to about 14–15 kWh, which is sufficient for most household travel. For computational simplicity, the mobility energy is deducted once at the final time index of each day, and the remaining safety-zone energy is used as the initial state of the next day.

$$S_s(d+1,1) = S_s(d,M+1) = \max\{S_s(d,M) - U(d,0)\} \quad (5)$$

where $S_s(d,M)$ is the last time index of day d , and $U(d,0)$ is the travel energy demand on day d .

The S_s is bounded by:

$$0 \leq S_s(d,t) \leq C_s \quad (6)$$

2.2. Cost and Revenue Functions

This paper focuses on the economic benefits created by EV charging and discharging. Under the proposed scheme, total profit is determined by three components: discharge revenue, charging cost, and battery degradation cost.

2.2.1. Discharge Revenue

Multiple discharge events may occur. Each discharge revenue equals the product of the selling price and the actual discharged energy. To better reflect real discharge conditions, a current-loss (efficiency) coefficient is introduced [15].

$$R_d(d,t) = p_d(t) \times [\eta \times \Delta E_d(d,t)] \quad (7)$$

Where $R_d(d,t)$ is the discharge revenue at time t on day d ; $p_d(t)$ is the electricity selling price at time t ; $\Delta E_d(d,t)$ is battery-side discharged energy; and η is an efficiency (loss) coefficient.

2.2.2. Charging Cost

Because the battery is partitioned into a safety zone and an active zone—and the safety zone is replenished only when the price is at the daily minimum—charging costs are discussed separately: active-zone charging cost and safety-zone replenishment cost.

The active-zone charging cost is analogous to the revenue formulation, but since energy flows from the grid to the battery, the efficiency treatment differs.

$$F_c(d,t) = p_c(t) \times \left[\frac{\Delta E_c(d,t)}{\eta} \right] \quad (8)$$

where $F_c(d,t)$ is the active-zone charging cost at time t on day d ; $p_c(t)$ is the purchase price at time t ; and $\Delta E_c(d,t)$ is battery-side charged energy.

The safety-zone replenishment cost depends on the energy gap between the safety-zone capacity and the remaining safety-zone energy after deducting mobility demand; larger travel demand leads to higher replenishment cost.

$$F_s(d) = \begin{cases} p_c(t) \times \frac{C_s - S_s(d,M)}{\eta}, & S_s(d,M) < C_s, \\ 0, & \text{otherwise} \end{cases} \quad (9)$$

where $F_s(d)$ is the safety-zone replenishment cost on day d .

2.2.3. Battery Degradation Cost

Frequent charging and discharging accelerates battery aging; therefore, degradation cost is indispensable. A direct

and widely used approach is to allocate battery wear cost to the unit energy throughput. We introduce a degradation coefficient k_{deg} (CNY/kWh) and compute degradation cost based on charging and discharging throughput [16].

$$F_a(d,t) = \alpha \times [\Delta E_c(d,t) + \Delta E_d(d,t)] \quad (10)$$

Where $F_a(d,t)$ denotes degradation cost at time t on day d ; α is the battery degradation coefficient.

2.3. Net Profit Accounting

To quantify the economic benefits of EVs as distributed storage for peak shaving and valley filling, we design a loop-based net-profit accounting model. Starting from the first-day profit and energy states, the model iterates to evaluate long-horizon outcomes.

2.3.1. Single-day Profit

Daily profit equals total discharge revenue in the active zone minus total charging cost and total degradation cost. The per-slot profit and daily profit are computed as:

$$\begin{aligned} R(d,t) &= R_d(d,t) - F_c(d,t) - F_a(d,t) \\ &= p_d(t) \eta \Delta E_d(d,t) - p_c(t) \left[\frac{\Delta E_c(d,t)}{\eta} \right] \\ &\quad - \alpha [\Delta E_c(d,t) + \Delta E_d(d,t)] \end{aligned} \quad (11)$$

$$R(d) = \sum_{t=1}^M R(d,t) - F_s(d) \quad (12)$$

Where $R(d,t)$ is the profit at time t on day d , and $R(d)$ is total profit of day d .

2.3.2. Multi-day Cumulative Profit

Multi-day cumulative profit is obtained by summing daily profits:

$$R_T = \sum_{d=1}^N R(d) \quad (13)$$

Where R_T denotes the cumulative profit over D simulated days.

2.4. Constraints

To ensure feasible operation of the above model, the following constraints are imposed.

2.4.1. Charging/Discharging Exclusivity

For each EV, energy transfer is allowed in only one direction at any time; simultaneous charging and discharging is not permitted:

$$\Delta E_c(d,t) \times \Delta E_d(d,t) = 0 \quad (14)$$

2.4.2. Top-up Charging Rule

In addition to scheduled overnight charging, an EV may perform opportunistic top-up charging when a daytime price valley occurs, thereby increasing available energy for subsequent discharge and improving owner welfare. We adopt the following rule: if the electricity price drops significantly and the active-zone SOC is below 90% of its capacity, the EV performs top-up charging using the maximum available charging power.

$$\Delta E_c(d,t) = \begin{cases} \min\{Q_c(d)\Delta t(t), C_A - S_A(d,t)\}, & S_A(d,t) < 0.9C_A \\ 0, & \text{otherwise} \end{cases} \quad (15)$$

$$\Delta E_d(d,t) = 0 \quad \forall t \in \emptyset \quad (16)$$

Where $Q_c(d)$ is the available charging power on day d , $\Delta t(t)$ is the effective charging duration in slot t .

2.4.3. Practical Uncertainty in top-up Charging

In practice, top-up charging power and duration are affected by stochastic station resources (e.g., available plugs, station power capacity) and user behavior (e.g., available time). To capture this uncertainty, random derating coefficients are used to modify the ideal maximum power and charging time: the charging power follows 50%–100% of the rated maximum, and the charging duration follows 70%–100% of the theoretical low-price duration. As a result, some EVs may be unable to reach the desired top-up level even if they intend to charge, leading to day-to-day variability in discharge energy and revenue.

$$Q_c(d) = \xi Q_{\max}^c, \tau_c(d) = \theta \Delta t_c(d) \quad (17)$$

$$0 \leq \Delta E_c(d) \leq \min\{Q_c(d)\tau_c(d), C_A - S_A^1(d)\} \quad (18)$$

$$S_A^2(d) = S_A^1(d) + \Delta E_c(d), 0 \leq S_A^2(d) \leq C_A \quad (19)$$

Where ξ and θ are random coefficients for power and time, respectively; Q_{\max}^c is the maximum charging power available for the vehicle within d days; $\tau_c(d)$ and $\Delta t_c(d)$ denote actual and theoretical top-up duration; $S_A^1(d)$ and $S_A^2(d)$ are the active-zone SOC at the start and end of the top-up event.

2.5. Integrated Objective

Based on the above partitioning, revenue/cost functions, and constraints, the integrated scheduling objective is to maximize the EV owner's net welfare while guaranteeing mobility demand. The objective can be written as:

$$\max Z = \sum_{t=1}^T (p_d(t) \cdot E_t^d - p_c(t) \cdot E_t^c) - F_a \quad (20)$$

where E_t^d and E_t^c denote discharged and charged energy at time t on day d , respectively; battery degradation cost over the entire scheduling cycle F_a is embedded as in Eq. (10).

Overall, Eqs. (1)–(2) define the energy partition, Eqs. (3)–(6) describe state evolution, Eqs. (7)–(13) quantify revenues and costs, and Eqs. (14)–(19) impose feasibility constraints, forming the final objective in Eq. (20).

3. Model Solution Procedure

This study aims to formulate an EV charging/discharging strategy aligned with real-world TOU tariffs and to quantify its economic benefit and peak-shaving performance. The workflow (Figure 2) is as follows. First, battery energy is partitioned into a safety zone and an active zone: the former serves rigid mobility demand, while the latter supports TOU arbitrage and V2G interaction. Second, daily initial SOC is generated via stochastic simulation of mobility demand. Third, a price-driven rule set guides the EV owner to perform charging/discharging actions to obtain profit. During operation, when both EV state and electricity price indicate room for top-up charging, the model executes top-up under the practical uncertainty constraints described above. By iterating over a long horizon, the framework quantifies how battery size, charging power, and TOU tariff design affect owner profit and the amount of mobilized energy.

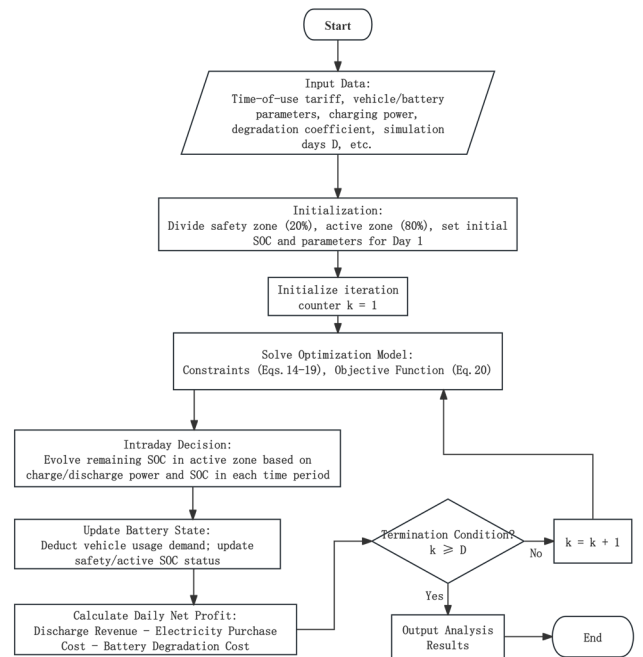


Figure 2. Model solution workflow

4. Simulation Study

The proposed approach is a rule-driven long-horizon simulation. Based on real TOU tariffs, the battery is partitioned into safety and active zones and an integrated scheduling framework is built. Electricity purchase/sale and battery degradation are jointly accounted for to close the loop in both energy and cash flow. To better reflect real EV usage, uncertainties in travel demand, station power, and available time are incorporated. Monte Carlo sampling is conducted over an annual horizon to obtain realistic fluctuating profit and energy trajectories. Key indicators such as net profit and purchased/sold energy are then computed to compare pricing mechanisms and evaluate robustness. The full process is implemented in MATLAB with a clear and reproducible script structure.

4.1. Parameter Settings

To satisfy model requirements, the following parameter settings are used:

1) By default, 20% of battery capacity is reserved as safety energy to satisfy daily travel demand [17]. This portion does not participate in frequency regulation or arbitrage. Other EV

parameters are listed in Table 1.

Table 1. EV parameters

Parameter	Value	Parameter	Value
Battery capacity (kWh)	70	Selling price (CNY/kWh)	0.8
Max charging power (kW)	30	Degradation cost (CNY/kWh)	0.05
Max discharge power(kW)	10	Charge-discharge efficiency (%)	95

2) To compare profits under different pricing mechanisms, we simulate monthly average stepped TOU tariffs at a charging station in a district of Guangzhou and a district of Beijing. The corresponding price curves are shown in Figure 3.

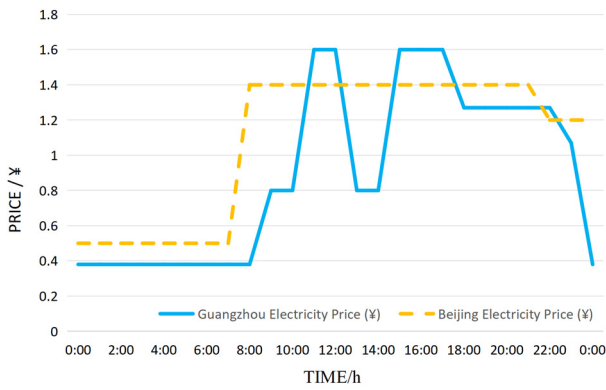


Figure 3. TOU tariffs used in simulation

4.2. Scenario Design

To demonstrate the economic feasibility of the proposed scheduling model and to examine the effect of TOU price elasticity on owner profit and grid operation, two scenarios are considered:

- Scenario 1: A 70 kWh EV is used as the baseline to compare the model’s profit under the current pricing mechanisms in Guangzhou and Beijing.
- Scenario 2: A forward-looking setting for the EV industry. A 200 kWh EV is considered (Table 2), and the more advantageous tariff pattern identified in Scenario 1 is used for future projection.

Table 2. EV parameters in Scenario 2

Parameter	Value	Parameter	Value
Battery capacity (kWh)	200	Selling price (CNY/kWh)	$0.7 \times$ charging price of the same period
Max charging power (kW)	60	Degradation cost (CNY/kWh)	0.05
Max discharge power(kW)	20	Charge-discharge efficiency (%)	95

The simulation yields multiple outcomes under stepped pricing, including owner economic benefit and load-smoothing effects. The following analysis focuses on (i) direct owner profit and (ii) peak-shaving performance from the grid perspective.

4.3. Results and Discussion

4.3.1. Comparison between Guangzhou and Beijing

Owner economic benefit is defined as net profit, i.e., total revenue minus charging cost and battery degradation cost. Daily travel demand uncertainty and practical charging constraints introduce randomness into the initial SOC of day $n+1$ and the post top-up SOC during idle periods. To ensure credibility and reflect realistic variability, we conduct one-year simulations for both regions. Daily net profit is illustrated in Figure 4, while cumulative revenue and cost components are shown in Figure 5.

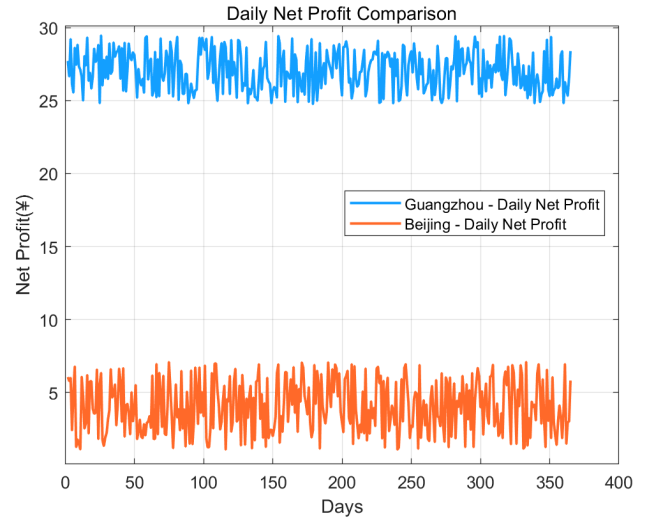


Figure 4. Daily net profit comparison

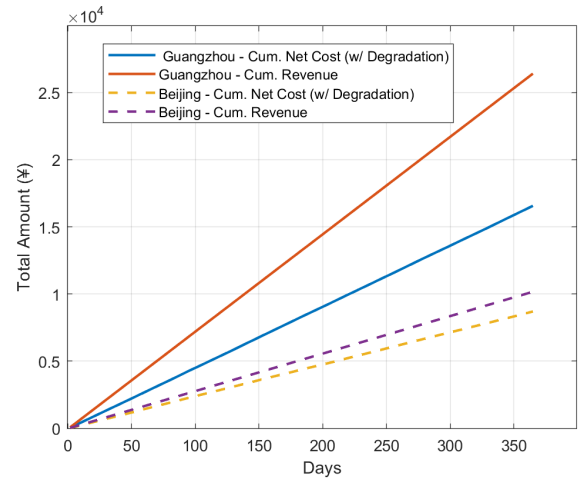


Figure 5. Comparison of cumulative indicators

Table 3. Summary of indicators

Indicator	Guangzhou	Beijing
Total net profit (CNY)	9844.4	1469.8
Profit per capacity (CNY/kWh/day)	0.38636	0.057684
Charging cost (CNY)	0	0
Total sold energy (kWh)	13443	1869.2
Total purchased energy (kWh)	13549	1902.4
Average daily net profit (CNY/day)	27	4.0

Over the annual iteration, clear differences emerge. With a 70 kWh battery, EV owners in Guangzhou typically obtain a daily net profit of about 25–30 CNY, whereas Beijing owners—constrained by a more fixed selling policy—show daily net profit fluctuating mostly within 0–5 CNY. In both regions, cumulative costs (including degradation) remain

below selling revenue; however, Guangzhou exhibits a much larger gap between cumulative revenue and cost, and significantly higher cumulative selling revenue. This indicates that Guangzhou's more flexible pricing is more favorable for owner economic benefit, thereby confirming the advantage of responsive TOU pricing. Table 3 summarizes key indicators.

4.3.2. Forward-looking Projection

Based on Scenario 1, flexible pricing is found to be more beneficial for EV owner economics. We therefore use the Guangzhou tariff as the baseline and consider a reasonable future upgrade of EV parameters. To compare annual profit distributions under different battery capacities, kernel density estimation (KDE) and the empirical cumulative distribution function (CDF) are employed.

KDE visualizes distribution shape and mean location (Figure 6).

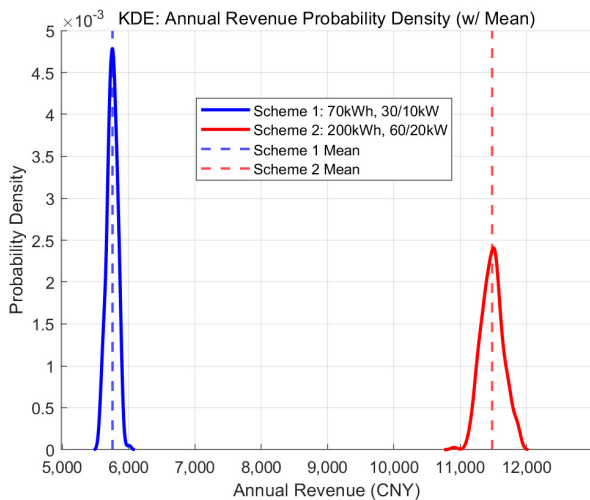


Figure 6. KDE of annual profit under different capacities

The CDF indicates the probability that a random outcome does not exceed a given value. Q10 denotes the 10th percentile (i.e., 90% of outcomes are above this value), Q50 is the median, and Q90 is the 90th percentile. By annotating Q10, Q50, and Q90, one can directly observe the lower bound, typical level, and upper quantile (Figure 7).

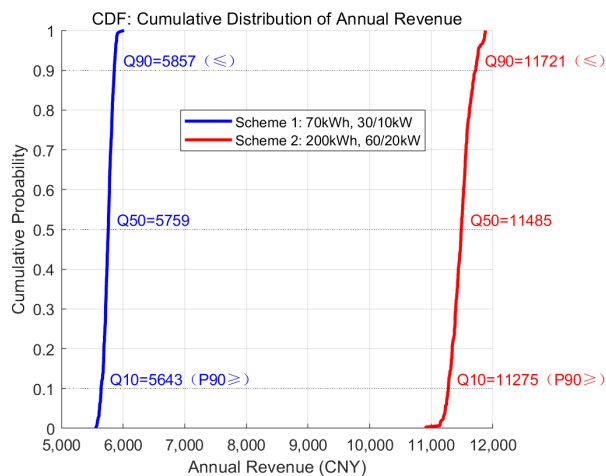


Figure 7. CDF of annual profit under different capacities

The one-year iteration shows that owner profit increases substantially when battery capacity and charging technology improve. Specifically, for a 70 kWh EV, under the assumption that owners do not pay additional charging cost in the

configured scheme, annual income has a 90% probability of lying between 5640 and 5854 CNY. For a 200 kWh EV, annual income has a 90% probability of lying between 11275 and 11721 CNY. Because the safety zone is fixed at 20% of total capacity in this study, larger capacity does not necessarily imply higher mobility demand. In practice, the safety-zone setting can become more flexible as battery capacity grows, suggesting potential for even higher profit.

4.3.3. Load-smoothing

Grid stability and owner profit represent the supply and demand objectives in power-system optimization. In addition to quantifying owner profit, we examine whether the proposed charging/discharging behavior aligns with price signals to support peak shaving and valley filling. Using the 70 kWh EV as an example, the charging/discharging power profile and its correspondence with TOU price are shown in Figure 8.

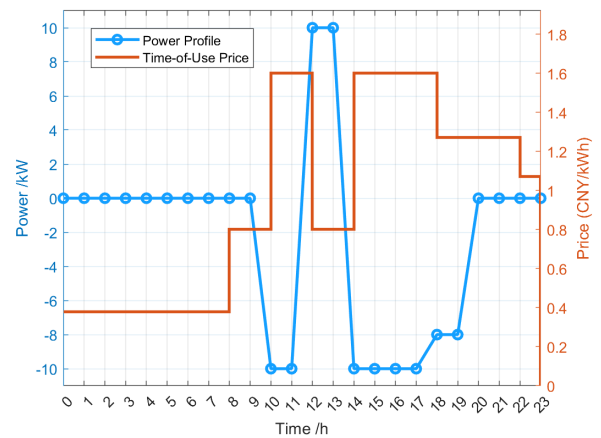


Figure 8. Power profile versus TOU price

When the price reaches a peak, the EV discharges; when the price is at a valley, the EV charges. Discharging power is represented as negative, and charging as positive. The sign of power closely follows the rise and fall of the price, indicating the feasibility and practicality of the proposed strategy.

Further quantification indicates that, with a 70 kWh battery, one EV can cumulatively discharge about 72.2 kWh per day. According to data collected in Ref. [18], a simplified park consisting of one manufacturing enterprise, one commercial plaza, and one residential community with a total population of approximately 2000 can have a daily base load of about 7200 kWh. If 100 schedulable EVs exist in the park, they can reduce grid energy by approximately 7200 kWh, accounting for 9.2% of the total park load and providing significant support to system balance and stability.

Table 4. Comparison of charging/discharging energy under different configurations

Battery capacity (kWh)	Daily discharged energy per EV (kWh/vehicle)	Daily charged energy per EV (kWh/vehicle)
70	≈ 72.2	≈ 75.6
200	≈ 190	≈ 200

5. Conclusion

Under a three-peak/three-valley TOU pricing environment, this paper develops an EV charging/discharging scheduling model that maximizes owner welfare. By partitioning battery capacity into a safety zone and an active zone, the model balances rigid mobility demand and TOU arbitrage

opportunities. A long-horizon iterative evaluation framework is established by jointly accounting for discharge revenue, purchase cost, and battery degradation.

Three main conclusions are obtained. (1) Flexible stepped TOU pricing substantially enhances the economic potential of EVs. Under flexible pricing, average V2G net benefit is far higher than under fixed tariffs, highlighting the decisive role of price elasticity in owner welfare. (2) Expanding battery capacity yields nonlinear gains in profit. Comparisons between different capacities under the same strategy indicate considerable room for further profit growth as EV technology progresses. (3) Fleet-scale effects are pronounced. By quantifying daily discharged energy, the peak-shaving and valley-filling capability of EVs is demonstrated, and increasing EV participation can effectively alleviate operational pressure in power systems.

Overall, this study demonstrates the value of TOU pricing and orderly scheduling from the perspectives of both owner profit and grid coordination. Future work can integrate more detailed mobility modeling and improvements in bidirectional charging infrastructure to achieve a better balance between economic performance and decarbonization.

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