An aggregator-based dynamic pricing mechanism and optimal scheduling scheme for the electric vehicle charging

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High penetration of electric vehicles (EVs) in an uncontrolled manner could have disruptive impacts on the power grid, however, such impacts could be mitigated through an EV demand response program. The successful implementation of an efficient, effective, and aggregated demand response from EV charging depends on the incentive pricing mechanism and the load shifting protocols. In this study, a genetic algorithm-based multi-objective optimization model is developed to generate hourly dynamic Time-of-Use electricity tariffs and facilitate the decision making in load scheduling. As an illustrative example, a case study was carried out to examine the effect of applying demand response for EVs in Beijing, China. With the assumptions made, the maximum peak load can be reduced by 9.8% and the maximum customer savings for the EVs owners can reach 11.85%, compared to the business-as-usual case.

1 Introduction

Market demand and sales of electric vehicles (EVs) are soaring. There were 11 million registered EVs on the road worldwide by the end of 2021 (Abdelbaky et al., 2021). According to the projection, the share of EVs in the European and North American markets will be around 50% and 30% by 2030, respectively (Rezaeimozafar et al., 2021). Large-scale electric vehicle charging loads can dramatically change load demand in a short period of time, which can lead to grid instability and peak demand rise. Reinforcing the network and expanding capacity could be a possible solution to this problem, but would require huge capital investments. So using intelligent charging scheduling strategies is a more economical and feasible approach. A natural way to reduce peak loads is by controlling the charging power, but this would result in the EVs taking longer to charge (Chen et al., 2014; Zhang et al., 2018). Authors in (Gjelaj et al., 2017; McKinsey, 2018)

FIGURE 1
Optimal EV charging with demand response and dynamic pricing schemes.
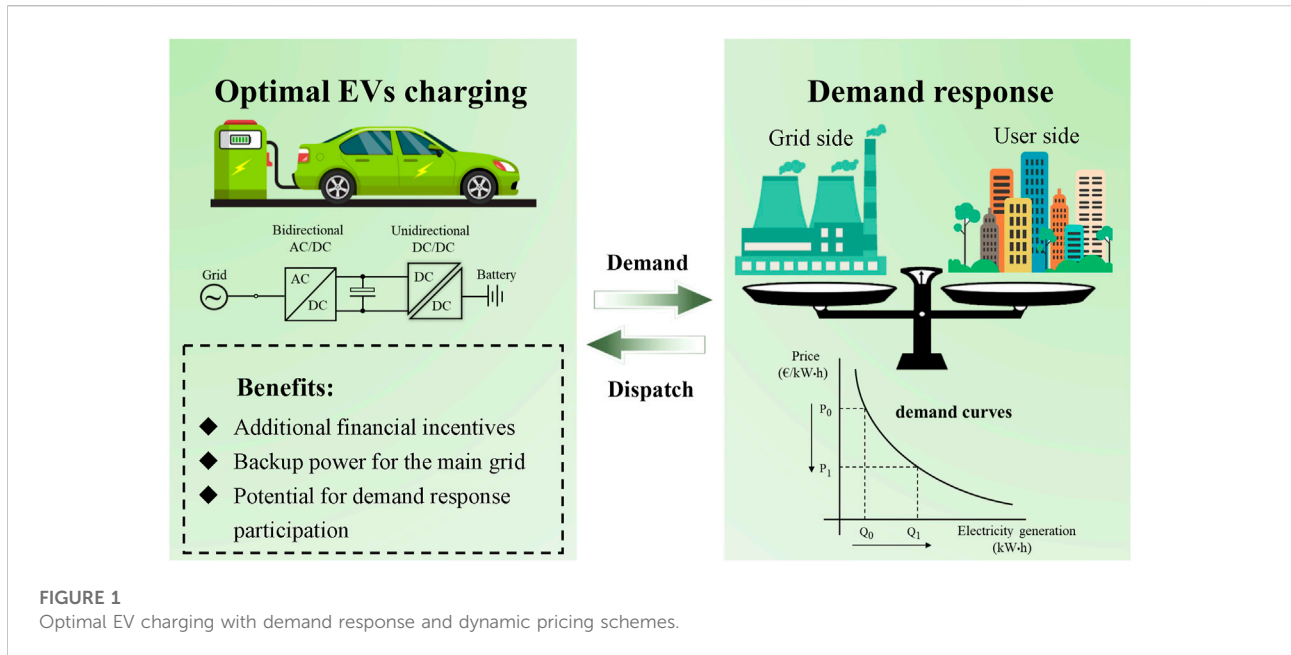
employed a stationary battery for shifting the load from peak periods to off-peak periods, which would result in more costs when building charging stations. Incentivizing customers to participate in demand response to avoid charging during peak hours by setting dynamic electricity prices is a more promising approach for application.

The time-varying-based demand response (DR) programs refer to prices that vary over the day to indirectly induce consumers to adjust their energy use patterns following dynamic electricity prices. For a given protocol, the charging stations perform DR actions to reduce energy usage during periods of peak demand, high electricity rates, system constraints, and/or emergencies. The EV owners can assess the trade-off between savings in the charging costs by advancing or postponing the charging action, against the inconvenience of adjusting their desired time slot (Zheng et al., 2019). The successful implementation DR approach on EV owners relies on two initiatives: the incentive dynamic pricing (DP) mechanism and the load shifting scheme (Zheng et al., 2021; Genis et al., 2022) as shown in Figure 1.

The DP concept in the retail electricity market refers to price the electricity dynamically based on the current and forecasted mismatch between generation and demand. The authors in (Moghaddam et al., 2019) present a dynamic pricing model to reduce the overlaps loads between residential and public charging stations by shifting loads away from the evening peak load hours. Authors in (Yu et al., 2022) formulate a dynamically updated price, which includes a discharge incentive reward and charging expense, based on the peak-to-valley time of use (TOU) tariff. The DP mechanism has shown great performance in reducing the peak-valley difference of load and improving the benefits for

the energy consumers (Wang et al., 2019). Reference (Kong et al., 2022) proposed an optimization model to manage the load in the distribution system by setting a DP to incentivize electric vehicles to charge at different locations and times. Reference (Sharma and Jain, 2019) considered DP has a low acceptance rate by EVs for being too dynamic to respond and proposed a demand response model that integrates TOU and DP by clustering dynamic tariffs. From the perspective of cost saving for car owners, reference (Zhou et al., 2020) proposed a strategy model of electric vehicle charging and discharging under DP, which considers the parking cost and the inconvenience caused by the change of charging end time of car owners.

With a proper pricing scheme, the load shifting scheme is usually formulated as a single or multi-objective optimization problem (MOOP) to optimize the charging schedules or battery State-of-Charge (SoC), where cost reduction, carbon emissions reduction, battery lifetime, peak shaving, or renewable energy consumption are included in the objective functions (Gou et al., 2021; Yang et al., 2021). To solve a MOOP, broadly used approaches include genetic algorithm (GA), particle swarm optimization, and neural network technique (Wang and Singh 2007; Kataoka et al., 2019; Limmer and Rodedmann 2019; Wenqiang et al., 2021).

Although dynamic pricing has been successfully implemented in various industries like the gasoline market, airline companies, and online retail, real-time pricing has not been widely employed in the retail electricity sector. Most of the price schemes are Time-of-Use (TOU) tariff-based, which means the utility company charges more during a certain time of day. The authors in (Abbasi et al., 2020) consider the aggregator as a price-maker in the day-ahead market by offering energy price

bids. A bidding strategy model for the EV aggregator who acts as a price-maker both in the day-ahead and real-time electricity market is established in (Gong et al., 2021). Reference (Zhang et al., 2021) uses the Stackelberg game theory to model the negotiation process of charging price and determine the congestion cost that the EV side should be allocated. In most of the previous works, the energy prices are still set in advance, and they do not fluctuate on the timescale of hours or minutes according to demand.

Given the area of dynamic TOU price-based charge scheduling of EVs is nascent, we make the following contributions: 1) generate a dynamic pricing profile that can reflect the demand changes simultaneously and trigger the EV owners to modify the original charging activity; 2) develop a GA-based optimization model to find alternative charging windows that yields the lowest electricity costs and peak-to-valley ratio in power grid; and 3) evaluate the efficiency and effectiveness of the proposed DR program.

The rest of this paper is organized as follows. Section 2.1 describes the EV driving and charging behavior model. Section 2.2 introduces the dynamic incentive pricing scheme. The GA-based optimization formulation is presented in Sections 2.3 and 2.4. Section 3 defines the case study. In Section 4, the simulation results are presented, and Section 5 concludes.

2 Mathematical models

To better model the EV driving and charging behaviors and patterns, the EVs are classified into four groups: electric bus, electric taxi (taxi/uber/lift), business vehicle, and private EV. Each EV is characterized by six parameters including the vehicle type, daily driving mileage, battery capacity, charging rate, initial charging time (the time arrive at the charging station), and the charging probability.

To generate hourly dynamic Time-of-Use electricity tariffs and load scheduling commends, a genetic algorithm-based multi-objective optimization model is described in this section.

2.1 EV behavior model

The daily driving distance of each EV is generated randomly from the predefined probability density function (PDF), as shown in Eq. 1. The PDF is generated by data fitting a set of survey data of the National Household Travel Survey in 2018, which is sponsored by the US Department of Transportation (Stats, 2017). Given the daily mileage, the initial SOC_0 and the charging duration T_C can be calculated, as shown in Eqs 2,3:

$$f_D(s) = \frac{1}{s\sigma_D\sqrt{2\pi}}exp\left[-\frac{(lns - \mu_D)^2}{2\sigma_D^2}\right] \quad (1)$$

$$SOC_0(i) = \left(1 - \frac{S(i)}{S_{max}}\right) \times 100\% \quad (2)$$

$$T_C(i) = \frac{(1 - SOC_0(i))E_{cap}}{P_{rate}\eta} \quad (3)$$

Where S is the daily mileages (km); μ_D and σ_D are the mean value and the standard deviation, respectively; i is the index for the EVs; S_{max} is the maximum driving range (km). The charging duration of EV, T_C, is determined by the initial State of Charge (SOC_0), battery capacity (E_{cap}), charging rate (P_{rate}), and the charging efficiency (η).

Based on the survey data, the EV charging behaviors are categorized by the type of EV, charging window, start time, battery capacity, charging rate, and charging probability. The electric buses operate on fixed routes on a typical workday. We assume the electric buses would have two charging windows: fast charging during the daytime and slow charging at night. There are four possible charging windows for the electric taxi, representing the daily shifts (morning, afternoon, evening, and late night). The charging activities of the business or commercial vehicles would happen during working hours and are highly random. For the private EV owners, they are more likely to charge their cars late at night and early in the morning.

The key parameters and charging characteristics of the EVs in this case study are provided in Table 1. The originally intended arrival time or the earliest time (i.e., before DR) potentially available for charging each day is generated randomly from either a normal distribution (N) with an associated mean and standard deviation or a uniform distribution (U) with a given range, using the data from Table 1. The charging probability indicts the probability that that EV presents at the charging station within that time window and has the charger plugged in (Liu and Qi, 2014). For example, for this case study (described in Section 3), the electric bus would have a 100% chance to charge between 9:00 a.m. and 4:00 p.m. at a rate of 90 kW.

2.2 Dynamic price generation model

In this study, a three-tier dynamic pricing system for EV charging is created based on the amount of electricity used; the more electricity used, the higher the charge. The first (off-peak) and second (mid-peak) tiers cover nearly 70% of EV consumption, and the third tier (on-peak) is charged for about 30% of electricity use.

To set the real-time pricing, price elasticity of demand, which is a measurement of the change in energy demand in relation to the change in utility charges for the electricity, as shown in Figure 2. It states that with a fixed amount of generation, when the price falls, the demand rises, and *vice versa*. The formula for

TABLE 1 The statistical data of EV charging events (Liu and Qi, 2014).

Type of EV	Charging window	Charging start time	Battery capacity (kWh)	Charging rate (kW)	Charging probability
Electric bus	9:00-16:00	U (9, 16)	180	90	1
	22:00-6:00	N (23, 0.5)		21	
Electric taxis	0:00-8:00	N (4, 1.3)	45	45	0.5
	8:00-15:00	N (11.5, 1.1)			
	15:00-19:00	N (16.7, 0.9)			
	19:00-24:00	N (21.5, 0.9)			
Electric business car	19:00-7:00	N (19, 2)	60	7	0.5
Private EV	0:00-5:00	N (1.5, 0.6)	45	7	0.6
	5:00-10:00	N (8.2, 6)			0.4
	10:00-17:00	U (10, 1.7)			0.4
	17:00-24:00	N (19.1, 1.7)			0.6

FIGURE 2
price elasticity of demand.

$$\begin{bmatrix} \dfrac{\partial q_1}{q_1} \\ \dfrac{\partial q_2}{q_2} \\ \cdots \\ \dfrac{\partial q_n}{q_n} \end{bmatrix} = \begin{pmatrix} \varepsilon_{11} & \cdots & \varepsilon_{1n} \\ \vdots & \ddots & \vdots \\ \varepsilon_{n1} & \cdots & \varepsilon_{nn} \end{pmatrix} \begin{bmatrix} \dfrac{\partial p_1}{p_1} \\ \dfrac{\partial p_2}{p_2} \\ \cdots \\ \dfrac{\partial p_n}{p_n} \end{bmatrix} = E_c \begin{bmatrix} \dfrac{\partial p_1}{p_1} \\ \dfrac{\partial p_2}{p_2} \\ \cdots \\ \dfrac{\partial p_n}{p_n} \end{bmatrix} \quad (5)$$

Where $\partial q_i\,(i = 1, 2, \ldots, n)$ and $\partial p_i\,(i = 1, 2, \ldots, n)$ represent the change in demand and price at the time i,q_i and p_i represent the benchmark values of demand and price at the time i. E_c represents the electricity price elasticity matrix, ε_{ij} which is the element in E_c.

The amount of load change for each time period is the amount of change in the current time period in response to the time share tariff plus the amount of movement from other time periods to this time period. Therefore, the amount of load change at the moment before and after the time-of-use tariff with n-dimensional data:

$$\Delta q_i = \sum_{j=1}^{n} \left\{ \varepsilon_{ij} \frac{q_{i0}}{p_{j0}} \left[p_{j0} - p_j \right] \right\} \quad (6)$$

Where, when $i = j$, ε_{ij} is the coefficient of self-elasticity ($\varepsilon_{ij} < 0$), when $i \neq j$, ε_{ij} is the coefficient of mutual elasticity ($\varepsilon_{ij} \geq 0$), q_{i0} is the load at the time i before the tariff change, p_{j0} is the tariff at the time j before the tariff change, p_j is the tariff at the time j after the tariff change.

calculating the elasticity of demand is expressed by the elasticity coefficient (Gou et al., 2021):

$$E_c = \frac{\partial q}{\partial p} = \frac{p_0}{q_0} \times \frac{dq}{dp} = \frac{\Delta q/q}{\Delta p/p} \quad (4)$$

Where E_c is the demand elasticity of power price; p_0 is the initial price of electricity, q_0 is the initial electric energy demand; dp is the amount of change in price over a time period, dq is the amount of change in the energy demand; p is the current price, and q is the current demand.

The EV owner's decisions or choices on the time of charging are not only affected by the price of electricity at that moment but are also correlated with the prices at adjacent moments. Therefore, the correlation relationship between electricity demand and electricity price at different periods can be expressed as:

2.3 Optimization formulation

A Multi-objective optimization problem is formulated to minimize the costs for EV owners and to minimize the peak-to-valley difference. Decision variables express the hourly price rate and the new start times for the schedulable EVs. To perform
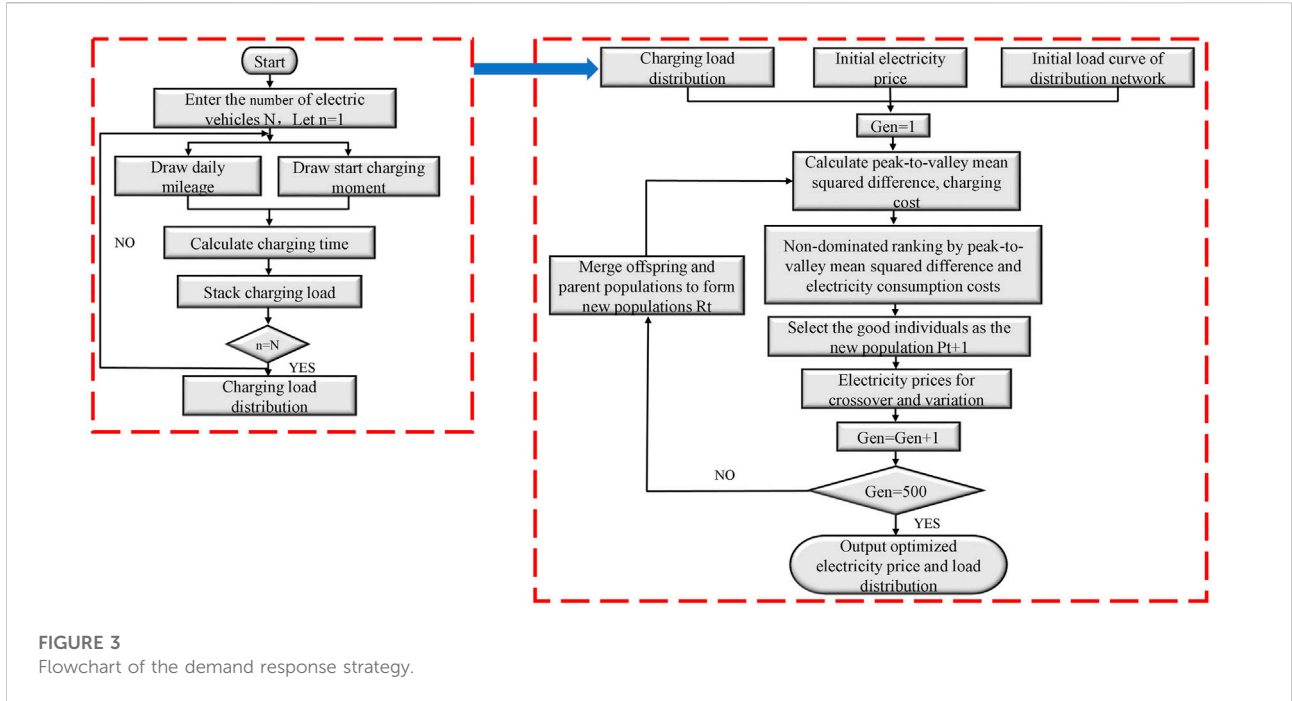
FIGURE 3
Flowchart of the demand response strategy.

the load shifting, a constrained, non-linear, MOOP has been formulated as

$$min \ [f_1(x), f_2(x)] \quad (7)$$

Where f_1 and f_2 represent the two objectives; the first objective function f_1 is defined as minimizing the electricity purchasing cost for the EV owners; the second objective function f_2 is designed to avoid the rebound effect, which may occur and create peaks greater than the original ones. Hence, to mitigate these rebounds in the middle of the load shifting procedure, the second objective function is for minimizing the peak-to-valley difference for all the time intervals.

$$f_1 = min \sum_{t=1}^{T}\sum_{n=1}^{N} E_{EV_{n,t}}^{after} \pi_t \quad (8)$$

$$f_2 = min \sum_{1}^{T} \left(E_t^{non_{ev}} + \sum_{n=1}^{N} E_{EV_{n,t}}^{after} \pi_t - \bar{E}_{s,t} \right)^2 \quad (9)$$

Where N is the number of EVs and n is the index of it; T is the number of investigated time periods and t is the index of it; E_{EV} is the amount of energy purchased from the utility; π is the real-time electricity price driven by the demand; $E_t^{non_{ev}}$ is the initial electricity load without any charging loads; and $\bar{E}_s$ is the average load over the studied time period. It is important to note that even though π_t represent the price rate at time t, it does not mean there are 96 distinct values for the price rate. In this study, one assumption is made that the TOU tariff is a three-tiered structure. Therefore, the number of possible values for π_t is three. The optimization problem is subjected to the following constraints. The total electricity consumption is the same before and after shifting, without changing the total daily amount of energy usage within the studied

horizon. $E_{EV_{nt}}^{before}$ and $E_{EV_{nt}}^{after}$ denote the total charging load of n EVs in time period t before and after the implementation of demand response, respectively. The EV charging load distribution curves before and after the implementation of demand response are shown in Figure 7, and by integrating the curves in time period t, we can obtain the total load in time period t.

$$\sum_{t=1}^{T}\sum_{n=1}^{N} E_{EV_{n,t}}^{before} = \sum_{t=1}^{T}\sum_{n=1}^{N} E_{EV_{n,t}}^{after} \quad (10)$$

The net increase of the load in a single period should be less or equal to the maximum charging capacity in the region.

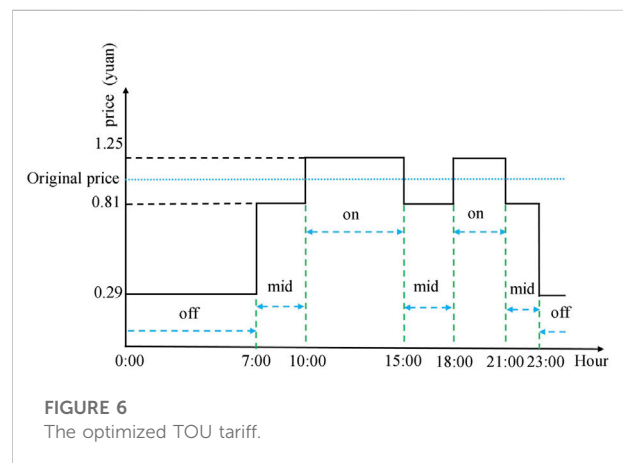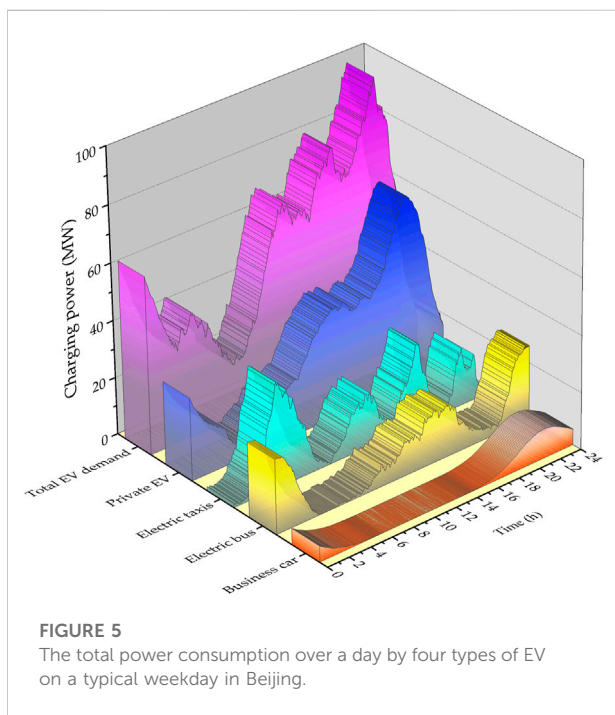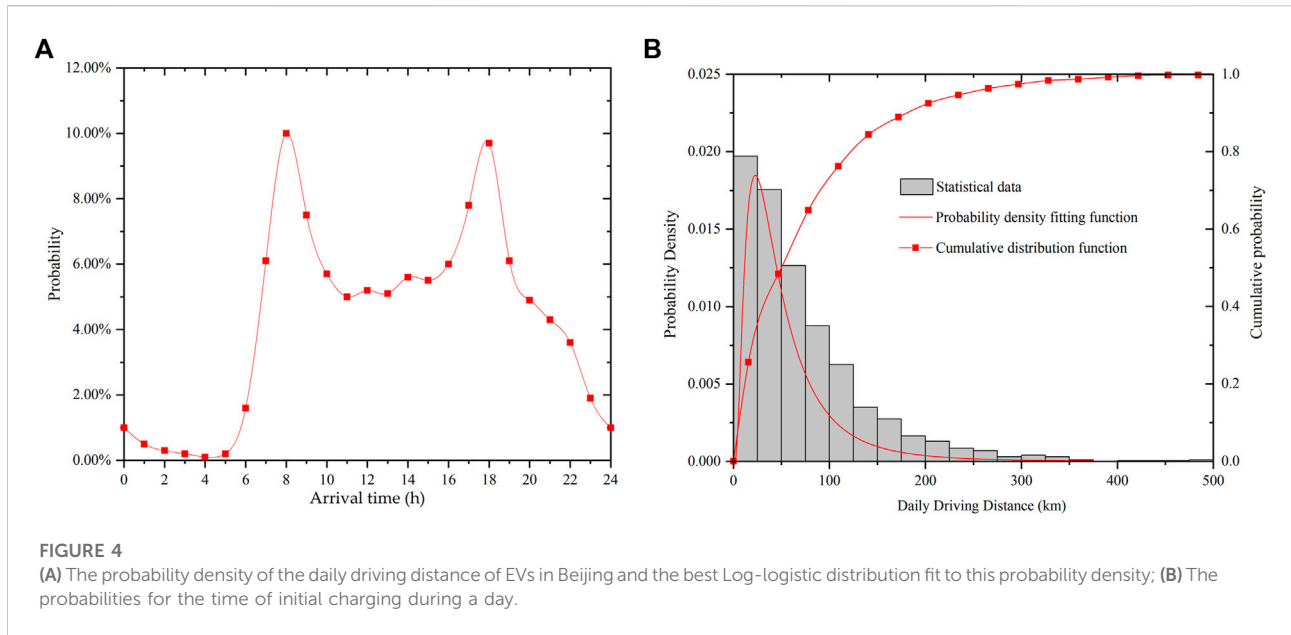$$\sum_{i=1}^{N} E_{EV_{n,t}}^{after} \leq E_{cap}^{max} \ for \ t = 1, 2, \ldots, 96 \quad (11)$$

To achieve the purpose of peak cutting and valley filling, the three-tiered dynamic pricing system makes sure the mid-peak rate (π_{mid_peak}) is lower than the on-peak rate (π_{on_peak}) and higher than the off-peak rate (π_{off_peak}). Also, the peak-to-valley rate is set to be in the range of 3–5.

$$\pi_{off-peak}(t) \leq \pi_{mid\_peak}(t) \leq \pi_{on\_peak}(t) \quad (12)$$

$$3 \leq \frac{r_{peak}}{r_{valley}} \leq 5 \quad (13)$$

To avoid the rebound effect, which means a new peak that is even higher than the original one may occur after the implementation of the DR program, the new peak must satisfy:
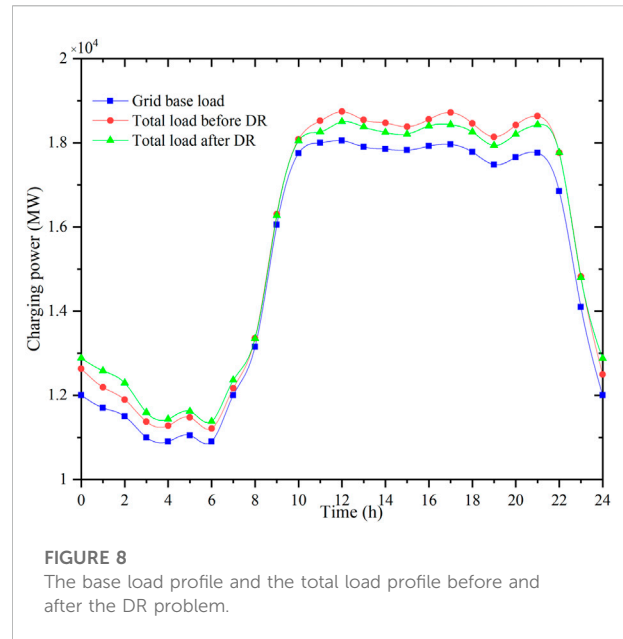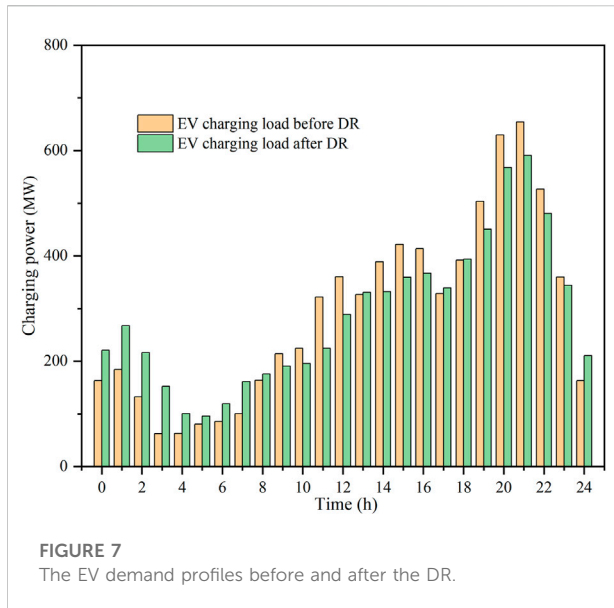
$$max_{i \in N, t \in M}\left(E_i^{after}(t) + E_i^{non_{ev}}(t)\right) \leq max_{i \in N, t \in M}\left(E_i^{before}(t) + E_i^{non_{ev}}(t)\right) \quad (14)$$

FIGURE 4
(A) The probability density of the daily driving distance of EVs in Beijing and the best Log-logistic distribution fit to this probability density; **(B)** The probabilities for the time of initial charging during a day.

FIGURE 5
The total power consumption over a day by four types of EV on a typical weekday in Beijing.

FIGURE 6
The optimized TOU tariff.

2.4 Genetic algorithm

A concise description of the GA employed in this study is described here. The chromosome composition of the genetic algorithm comprises two segments: the first 96 genes representing the real-time price vector–one element for each 15-min interval in the 24-h period; the second segment contains genes representing the new charging start times for the schedulable EVs.

The initial population of 200 chromosomes is generated randomly, and each chromosome is evaluated and sorted based on the fitness function (objective value). The linear bias parameter is determined based on the size of the population. Crossover selects genes from parent chromosomes and generates a new offspring. Within the offspring chromosome, each gene has a mutation probability of 0.33. The new offspring in the new population are evaluated and ranked in terms of the objective function value again, and the worst two chromosomes are eliminated. The newly generated population is used for the successive iterations of the algorithm until the stopping criteria of 500 total iterations. Flowchart of the demand response strategy is shown in Figure 3. The newly generated population is used for the successive iterations of the algorithm until the stopping criteria of 500 total iterations.

FIGURE 7
The EV demand profiles before and after the DR.

FIGURE 8
The base load profile and the total load profile before and after the DR problem.

3 Case study set up

The case study is based on the metropolitan area of Beijing, a region that has the fastest-growing EV markets in the world. The area of study covers about 16,000 km² and included 10 million inhabitants and 400,000 EVs in 2021. The data used are obtained from the 2021 Beijing Transportation Development Annual Report (Gou et al., 2021). The original electricity rates in Beijing are assumed to be flat and cost 1 yuan/kWh. The demand profile for electricity is from a typical workday in 2020 and was obtained from the local utility company. For the purpose of computational efficiency, we examine a case with only 40,000 EVs, which constitute 10% of the current EV fleet.

To generation and EV driving and charging profiles and solve the optimization formulations above, a total of 40,000 Monte Carlo simulations were conducted to generate a finite number of possible cases based on the probability distributions of all stochastic parameters.

4 Results

4.1 EV driving and charging patterns

The simulation results of the EV driving and charging patterns are shown in Figure 4. There is a 50% chance that the Beijing EV owners drive less than 50 km per day. The daily average driving distance is also similar to the value provided by the AAA Foundation for Traffic Safety Survey, which states that on average, Americans drive 47 km per day. The duck curve in Figure 4B shows that the initial charging time of EVs peaks around 8 a.m. and 6 p.m., which indicates that the drivers are more likely to start the charging events once they arrive at work or get back home from work. Moreover, 98% of the charging events are performed before 10:00 p.m. on workdays.

With the assumptions made in this study, the charging power drawn from the grid is presented in Figure 5. Electric buses use fast chargers during the day and the load peak happens around 2:30 p.m. Most of the electric buses stop operating at late night, therefore, the charging demand starts to increase again after 9:00 p.m. The daily load peak of electric taxis is around 4 a.m. The load curve demonstrates four peaks, which are strongly correlated with the four working shifts of taxi drivers. During the daytime working hours, most of the business EVs are either in standby mode or on the road. Therefore, the charging frequency is low. They tend to charge initially at 5 p.m., which has a distinct single-peak load shape. The private EV drivers plugged in more frequently than the other drivers. The charging load keeps increasing during the daytime till late at night. This means that even though most private EVs get plugged in after 5 p.m., the owners do not leave the charger plugged in overnight.

Figure 5 also demonstrates that the power withdrawn by the private EVs attribute the most to energy consumption. From 6 to 9 p.m., a time when energy use typically ramps up fast as most people go off duty and have their EV plugged in. The charging demand is highest at 8 p.m. and the total load profile has separate morning and evening peaks.

4.2 Real-time pricing generation

Given the charging load and the original price rate, the price elasticity matrix can be calculated and is shown in Eq 15 (Ruoyu, 2018). The key to successfully implementing TOU tariffs is aligning rates with customer demand signals. As shown in Figure 6, the optimized TOU tariff, which is solved by the NSGA-II algorithm, follows the demand trend closely. This study assigns a weight factor of 50% to each of objectives for the selection of solutions. The first tier is set at 0.29 yuan

TABLE 2 simulation results.

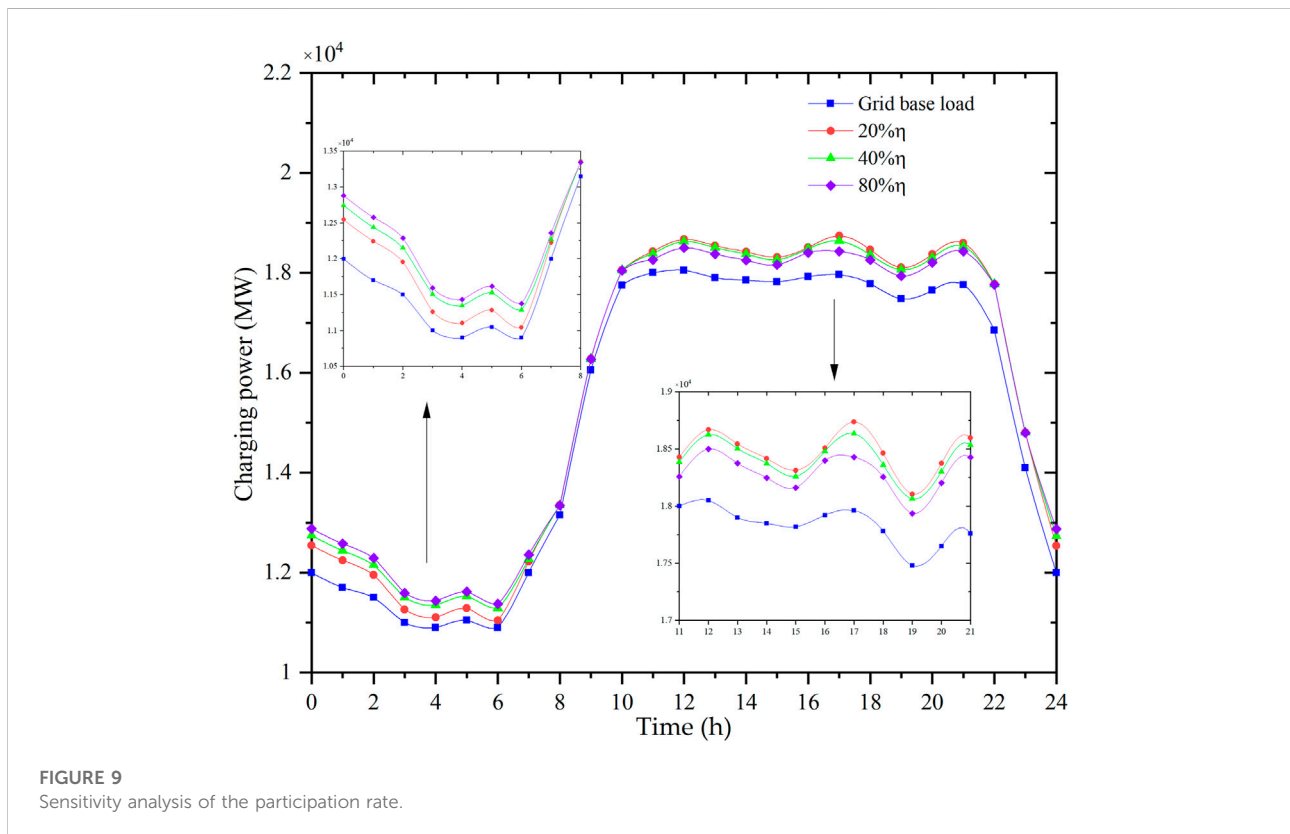| Period of time	Base load (MW)	EV load without DR (MW)	EV load with DR (MW)	Change ratio
On Peak	18,050	18,770	18,500	−1.44%
Mid Peak	16,188	16,734	16,649	−0.51%
Off Peak	10,900	11,280	11,380	+0.89%
Peak-to-valley ratio	39.61	39.98	38.49	−3.73%
Cost (million Yuan)	—	64.70	48.21	−25.49%

FIGURE 9
Sensitivity analysis of the participation rate.

($0.04) per kWh, the second at 0.81 yuan ($0.12), and the third at 1.25 yuan ($0.19). The ratio of peak-to-valley rates is 4.31, which meets the constraint set in Section 2.3.

$$E_c = \begin{pmatrix} -0.6233 & 0.3241 & 0.2305 \\ 0.3553 & -0.6166 & 0.2216 \\ 0.3215 & 0.3038 & -0.6065 \end{pmatrix} \qquad (15)$$

4.3 The effect of demand response.

Figure 7 presents the change in the hourly EV charging loads before and after the DR approach. The real-time pricing-driven load shifting reduces the peak load from 654.3 to 590.3 MW,

corresponding to a 9.8% peak reduction from the EV charging load alone. The real-time price profile has the lowest rate between 11:00 p.m. and 7:00 a.m., therefore, most EV owners would program their charging events by then.

By combining the commercial and residential hourly load profiles and the EV charging load profile, Figure 8 demonstrates the change in the total electricity loads of Beijing before and after the DR problem. The DR program can potentially reduce the peak load from 18,770 to 18,500 MW, corresponding to a 1.4% peak reduction. This DR outcome occurs because the DR approach depends on real-time pricing, and the price profile has a valley around 6:00 a.m.

The efficiency and effectiveness of the proposed method are evaluated by comparing with the case without DR on peak-to-valley ratio and average daily charging costs (Table 2). Simulation

results show that the proposed algorithm has managed to reduce the daily cost for the EV owners to 482,146 yuan, from a high of 646,955 yuan for the case without the DR program, corresponding to a 25.49% cost reduction. The positive or negative change ratios correspond to an increase or decrease in the values between the case without or with the DR problem. As shown in Table 2, the strategy reduces the on-peak and mid-peak loads by 1.44% and 0.51%, respectively.

Figure 9 shows the load profiles obtained by changing the EV owner's participation rate value from 20% to 80%. The participation rate is defined as the proportion of the EV owners that are willing to adjust the charging schedules. The results show that the peak-to-valley difference decreases as the participation rate increases, which is expected.

The scheduling optimization model was implemented using MATLAB in the WINDOWS environment on a HUAWEI MateBook D laptop computer with an Intel i5-7200U CPU and 2.5 GM RAM. The converge time is 0.72 min.

5 Discussion

The peak-to-valley ratio in the grid and the customer savings by participating in the proposed DR program confirm that with the given protocol, proper DR actions can reduce energy usage during certain periods. The genetic algorithm-based multi-objective optimization for EV charging rescheduling is feasible and efficient enough for the case study.

The results presented above are specific to the data, algorithms, and system used and may not yield comparable benefits in all scenarios. Nevertheless, the framework is general and applicable to a wide range of DR environments. Future research should focus on building a precise predictive model for the EV charging loads.

6 Conclusions

This study develops an optimization model to find the optimal TOU tariff rates and hourly schedule for EVs and analyses the influence of DR programs on the load profiles and customer cost. The presented model ensures that the TOU tariff can track the demand trends and that the optimization results meet the defined constraints. The model was tested for the city of Beijing with four types of EVs.

The simulation results indicate that the proposed DR helps transform the electricity system from a one-way, centralized power network where customers passively receive electricity to a two-way flow of information where EV owners regularly contribute to system operations. An optimal EV charging strategy could potentially attribute to reducing the slope of system ramps, firming the intermittency of renewable energy resources, and relieving congestion on the electric grid. It's essential to note that the diversity of DR products adds another level of complexity to the current electricity market. Advances in smart metering and controlling technology are required for DR to play a greater, faster, and more diverse role in addressing the emerging grid needs.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Author contributions

YL Software, Writing—original draft JZ Validation, Writing—original draft YS Writing—review and editing MS-A Writing—review and editing TJ Resources YZ Resources YZ Funding acquisition, Project administration, Writing–original draft.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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Nomenclature

Abbreviations

EV electric vehicles

DR demand response

DP dynamic pricing

MOOP multi-objective optimization

SoC state-of-charge

GA genetic algorithm

TOU time-of-Use

PDF probability density function

N normal distribution

U uniform distribution

Indices and Sets

T, t set of time periods, time index

N, i set of EVs, EV index

Parameters

T_c charging duration (h)

S the daily mileages (km)

S_{max} the maximum driving range (km)

μ_D the mean value of function

σ_D the standard deviation of function

SOC_0 the initial State of Charge (%)

E_{cap} battery capacity (kW·h)

$E_{cap}{}^{max}$ the maximum battery capacity range (kW·h)

P_{rate} charging rate (kW)

η charging efficiency (%)

q_0 the initial electric energy demand (kW)

$p0$ the initial price of electricity (yuan)

$qi0$ the load at the time i before the tariff change (kW)

p_{j0} the tariff at the time j before the tariff change (yuan)

Variables

p_i current price (yuan)

q_i current demand (kW)

E_c electricity price elasticity matrix

ε_{ij} electricity price elasticity factor

E_{EV} the amount of energy purchased from the utility

$E^{non_{ev}}$ initial electricity load without any charging loads (kW)

$\bar{E}_S$ average load over the studied time period (kW)

E_{EV}^{before} charging load before DR (kW)

E_{EV}^{after} charging load after DR (kW)

π_t real-time electricity price at time t (yuan)

π_{on_peak} on-peak rate (yuan)

π_{mid_peak} mid-peak rate (yuan)

π_{off_peak} off-peak rate (yuan)