Chapter 20
On the Value of Orderly Charging in Improving Power Grid Resilience

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Abstract The increase of Electric Vehicle (EVs) adoptions has achieved a double harvest of environmental and economic benefits and brings an extra burden on the urban power grid. To this end, efforts have been made to optimize chargers' location and power scheduling to mitigate the adverse impacts of increasing EVs. However, the long duration and high cost of chargers installation curbs further EVs adoption, which also triggers less charging accessibility for urban EV travel. In practice, the low utilization rate of charging piles leads to high idle rates, which motivates charging aggregators to incorporate demand response (i.e., orderly charging in our context) into traditional charging services. In such a context, we attempt to uncover economic and environmental benefits created by orderly charging in the scenario of private charging piles for self-use. The results reference the operation management of personal chargers in the community and the orderly charging scheduling of EVs.

Keywords Demand response · Orderly charging · Multi-objective optimization · Charging sharing

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Introduction

EVs with good environmental and economic benefits have been rapidly developed and utilized worldwide. Governments of various countries have formulated plans to develop new energy vehicles and introduced support and incentive policies on the supply side. On the demand side, residents gradually adopt EVs. The global sales and proportion of new energy vehicles are increasing yearly.

However, as private EV ownership increases, so does the need for charging. The global EV sales bucked the trend against the backdrop of the new crown epidemic causing total car sales to fall by one-fifth in 2020, 43%, reaching over 3 million [1]. The charging conduct of EVs is random. This random and disordered charging method will affect the operation and maintenance of the power grid system to a certain extent. The report issued by the State Council pointed out that it is necessary to coordinate the charging and discharging of new energy vehicles, and power dispatching needs. Then comprehensively use policies such as peak and valley electricity prices to achieve efficient interaction between EVs and grid energy [2].

Due to the lack of daily operation management of private charging piles, there is an imbalance between the supply and demand of personal charging piles. The possession rate of pure private EVs is only 55% [3], and the existing private charging piles are used less frequently, an idle rate of about 75% [4]. Therefore, it is essential to design a community personal charging pile operation model for the orderly charging of EVs. It can meet the needs of multiple stakeholders, such as community grids, charging service providers, and EV users. The orderly charging operation mode dynamically adjusts the time and place of charging demand based on the total load of the power grid and the unit's operational data in different periods. It is capable of power grid peak shaving and valley filling.

This paper aims to promote the orderly charging of EVs, balance supply and demand, and conduct research on EV charging demand scheduling. The specific contributions of this paper are summarized as follows. Firstly, we explore the impacts of *Orderly charging service* on two sides. For community grids, it can reduce load fluctuation and improve power grid operation safety. For users, it can decrease the charging cost and enhance the charging economy of users. Secondly, A multi-objective optimization model is developed to solve the orderly scheduling problem of EVs. The goal of the model is to minimize grid load fluctuation and user charging costs. Furthermore, an efficient computation technique includes operational research theories and methods such as statistical modeling, nonlinear programming, multi-objective optimization, and linear weighting, providing a reference for other scholars and related research on modeling and solving strategies.

The remainder of this paper is organized as follows: Section "References" reviews the related literature on EV's demand response strategies and orderly charging scheduling, Section "Problem Description and Formulation" prepares the data, Section "Orderly Charging Scheduling Model" explains the algorithm for solving this problem, and Sections "Numerical Study" and "Conclusions and Future Work" are the result and conclusion.

References

Our work contributes to strengthening the literature on sustainable operations management to improve the orderly charging scheduling of EVs. Therefore, two related literature streams are discussed: demand response strategies for EVs and orderly charge scheduling.

Regarding the electricity price of EVs, Monfared et al. [5] proposed that an EV's charging choice is made in reaction to information such as charging location, charging time, and charging price, i.e., modifying its charging behavior to promote charging satisfaction based on the charging information. At present, many scholars discuss the issue of EV charging scheduling below the time-of-use pricing mechanism. In the orderly charge scheduling problem, Choi et al. [6] raised that the pricing incentive model is frequently used to plan the charging requirements of EVs, and it comprises charging subsidies, time-of-use electricity prices, and real-time electricity prices. Lin et al. [7] optimized the schedule to shift energy demand from peak to valley. Gong et al. [8] used the price elasticity coefficient to create a demand-price response model for EV charging loads. Limmer and Rodemann [9] introduced a dynamic time-sharing pricing optimization framework that considers consumer choice uncertainty.

Regarding EV charging scheduling, Daryabari et al. [10] put forward that an EV's charging load is essentially a dispatchable and movable power demand; the charging power can be changed during the charging start and end periods. The economic benefits for many parties, such as the power grid and EV users, can be achieved by systematically managing EVs' charging behavior. As for the orderly charging optimization model, the objectives usually include minimizing the power loss of the grid, the peak-to-valley difference, the charging cost of the user, and maximizing the security of the distribution network. Tao et al. [11] developed a model intending to minimize grid load fluctuations, maximize user charging capacity, and solved it using a linear weighting method. To describe grid pricing uncertainty, AhmadiNezamabad et al. [12] proposed an interval optimization method and solved a dual-objective model with ϵ constraints to obtain the Pareto solution.

Different charging circumstances usually result in some contrasts in the charging characteristics of EVs, with community charging being the most common. Kapustin and Grushevenko [13] pointed out that when the community grid is connected to EVs on a large scale, the peak value of the EV charging load will overlap with the peak value of the conventional electricity load. Gong et al. [14] developed a genetic algorithm to solve a nonlinear programming model for the orderly charging of community EVs based on a dynamic peak pricing mechanism.

In addition to considering a single subject objective, some studies also consider the interests of the grid, users, or aggregators. Wang et al. [15] developed an orderly charging and discharging model for EVs in urban residential areas to minimize total power load variance and lowering power grid costs. Nimalsiri et al. [16] built a quadratic programming model that considered user economics and distribution network security restrictions.

Although there are numerous research results on the orderly charging scheduling of EVs, the optimal charging strategy is still worthy of further discussions, such as considering different application scenarios, the charging frequency of EVs, and the scheduling time. Therefore, this paper will fully consider the price incentive effect of time-of-use electricity prices and specifically study EVs' orderly charging in community scenarios.

Problem Description and Formulation

There are two major problems in the operation and management of charging piles: the disordered charging mode seriously impacts the power grid; the other is that the low level of process and control leads to an imbalance between supply and demand.

Therefore, we build the time-of-use electricity price mechanism for EV charging. The peak-valley electricity price difference is used to guide EVs to charge when the electricity consumption is low to stabilize the load fluctuation of the community power grid.

Model Assumptions

(1) We assume the start of charging is returning to the community that day, and the end is leaving the community the next day. According to the US national household travel survey (NHTS) on domestic cars in 2001, Taylor et al. [17] concluded that the home time of private EVs approximately satisfies the normal distribution. The EV charging start time is t, the expected value $\mu_s = 17.47$, and the standard variance $\sigma_s = 3.41$. The probability density function when the EV starts to charge is:

$$f_s(t) = \begin{cases} \frac{1}{\sqrt{2\pi}\sigma_s}\exp\left[-\frac{(t+24-\mu_s)^2}{2\sigma_s^2}\right], & 0 < t \leq \mu_s - 12 \\ \frac{1}{\sqrt{2\pi}\sigma_s}\exp\left[-\frac{(t-\mu_s)^2}{2\sigma_s^2}\right], & \mu_s - 12 < t \leq 24 \end{cases}. \tag{20.1}$$

Similarly, the end of charging time of the EV also conforms to the normal distribution, the expected value $\mu_e = 7.92$, the standard variance $\sigma_e = 3.24$, and the probability density function is:

$$f_e(t) = \begin{cases} \frac{1}{\sqrt{2\pi}\sigma_e}\exp\left[-\frac{(t-\mu_e)^2}{2\sigma_e^2}\right], & 0 < t \leq \mu_e + 12 \\ \frac{1}{\sqrt{2\pi}\sigma_e}\exp\left[-\frac{(t-24-\mu_e)^2}{2\sigma_e^2}\right], & \mu_e + 12 < t \leq 24 \end{cases} \tag{20.2}$$

EV charging power is related to mileage, battery capacity, and charging frequency. The user travel mileage conforms to the log-normal distribution [17]. The daily mileage of an EV is d, the expected daily mileage is μ_D, the standard variance is σ_D, and the probability density function is:

$$f_D(d) = \frac{1}{\sqrt{2\pi}\sigma_D d}\exp\left[-\frac{(\ln D-\mu_d)^2}{2\sigma_d^2}\right]. \tag{20.3}$$

(2) This article is based on the average mileage of 10,912 EVs in Beijing on weekdays in 2019. The expected value of its probability density function is $\mu_D = 2.77$, and the standard variance is $\sigma_D = 0.77$. Assuming that the charging frequency is once a day, d_i represents the daily mileage of EV i, and W_i is the power consumption per 100 kms of the EV:

$$D_i = \frac{d_i W_i}{100} \tag{20.4}$$

Table 20.1 The division results of the peak-to-valley period based on the K-means clustering algorithm

Time	Time-division (No EV, EV penetration rate 20%)	Time-division (EV penetration 30, 40%
peak	17:00–22:00	15:00–22:00
flat	8:00–16:00; 23:00–1:00	8:00–14:00; 23:00–1:00
valley	1:00–7:00	1:00–7:00

Table 20.2 Optimal time-of-use electricity price mechanism under different penetration rate

Time	Penetration—electricity price		
peak	20%–0.25	30%–0.25	40%–0.25
flat	20%–0.5615	30%–0.6010	40%–0.6233
valley	20%–0.7228	30%–0.7520	40%–0.7966

(3) EV charging data from Monte Carlo simulations are applied in our case study. We assume a community of 400 households, each with one private car. This paper sets the EV penetration rate at 40% and lets both ω_1 and ω_2 be 0.5. For ease of calculation, we set $S_i^{\min}$ to a constant value of 10%, at which point there are 26 EVs available for orderly charging. However, EV users have individual differences in the lower limit of acceptable SOC.

(4) We believe that the community charging period can be divided into three segments. Then, we use the K-means clustering algorithm to divide the peak, flat and valley periods. The clustering results are shown in Table 20.1:

We assume that the model adopts the time-of-use pricing mechanism. Through simulation, we obtained the optimal time-of-use electricity price mechanism in each period of the community under different EV penetration rates. The results are shown in Table 20.2:

Parameter

The notations applied in our model are listed in Table 20.3.

Orderly Charging Scheduling Model

Model Formulation

For the community power grid system, we want to minimize grid load variance for community grid systems. It is related to the charging power e_{it} of each EV, as shown

Table 20.3 List of notations

Indices and sets	
$i \in I$	Set of EV with private piles in the community
$i \in I_o$	Set of EV with orderly charging on the day
$i \in I_d$	Set of EV with out-of-order charging on the day
$i \in I_u$	Set of EV not charging for the day
$t \in T$	Set of all time, t is the start time, Δt is the length of the period
$t \in T_i$	Set of time when the EV i connects to the charging pile,$T_i = [t_i^a, t_i^d)$
Parameters	
$e^{\max}$	Maximum charging power of the EV. Maximum output power of the charging pile
$S^{\max}$	SOC upper limit
B_i	Battery capacity of the EV i
W_i	Electricity consumption per 100 km of the EV i
$S_i^{\min}$	SOC lower limit of the EV i
$S_i^{\exp}$	Expected SOC at the end of charge of the EV i
S_i^{ini}	SOC status when leaving the community on the day of EV i
t_i^{arr}	Time to start charging of EV i
t_i^{dep}	Time to end charging of EV i
d_i^1	Estimated mileage of EV i on the day
d_i^2	Estimated mileage of EV i on the following day
L^{limit}	Community transformer power limits
z_t^B	Conventional charging load of the community at time t
$z_t^{EV_d}$	Charging load of the disorderly charging EV set at time t
p_t	Electricity price at te t
Intermediate variables	
$z_t^{EV_o}$	Charging load of orderly charging EV set at time t
z_t	Total charging load in the community at time t
$\overline{z}$	Average daily charging load in the community
Decision variables	
e_{it}	EV charging power of i at time t

in the formula (20.5):

$$f_1 = \min_e \frac{1}{\mathrm{T}} \sum_{t \in T} (z_t(e) - \overline{z}(e))^2 \tag{20.5}$$

The grid load includes the regular electricity load of the community z_t^B, the disordered charging $z_t^{EV_d}$, and the ordered charging $z_t^{EV_o}$, as shown in the formula (20.7), the daily average load $\overline{z}(e)$ is determined by e in (20.8):

$$z_t^{EV_o}(e) = \sum_{i \in I} e_{it}, \quad \forall t \in T \tag{20.6}$$

$$z_t(e) = z_t^B + z_t^{EV_d} + z_t^{EV_o}(e), \quad \forall t \in T \tag{20.7}$$

$$\overline{z}(e) = \frac{1}{T} \sum_{t \in T} z_t(e), \quad \forall t \in T \tag{20.8}$$

For EV users, we hope to transfer the charging time and power to the low electricity price. The objective function is to minimize the total charging cost of the user, such as formula (20.9):

$$f_2 = \min_e \sum_{i \in I} \sum_{t \in T_i} e_{it} p_t \Delta t \tag{20.9}$$

The charge EV return to the community is $S_i^{arr} = S_i^{ini} - \frac{d_i^1 W_i}{100 B_i}$, and charge capacity is $\frac{\sum_{t \in T_i} e_{it} \Delta t}{B_i}$. Their sum should be greater than the expected EV charge and smaller than the upper limit of the state of charge of the EV, as shown in constraint (20.10). Constraint (20.11) denotes the community transformer power limits. The sum of the daily electricity and charging load is kept within the power limit of the community grid transformer L^{limit}. Constraint (20.12) indicates that the charging power should be greater than 0 and not exceed the upper limit. It is not charged if it equals 0. We assume that if the car owner does not return to the community, the charging power is 0, as shown in the formula (20.13):

$$S_i^{exp} \leq S_i^{arr} + \frac{\sum_{t \in T_i} e_{it} \Delta t}{B_i} \leq S^{\max}, \quad \forall i \in I \tag{20.10}$$

$$z_t(e) \leq L^{limit}, \quad \forall t \in T \tag{20.11}$$

$$0 \leq e_{it} \leq e^{\max}, \quad \forall i \in I, \forall t \in T_i \tag{20.12}$$

$$e_{it} = 0, \quad \forall i \in I, \forall t \notin T_i \tag{20.13}$$

Therefore, the orderly charging scheduling model for community EVs is as follows:

$$f_1 = \min_e \frac{1}{T} \sum_{t \in T} (z_t(e) - \overline{z}(e))^2$$

$$f_2 = \min_e \sum_{i \in I} \sum_{t \in T_i} e_{it} p_t \Delta t$$

$$s.t., (10) - (13).$$

Solution Approach

We solve the multi-objective optimization problem using a linear weighted summation method. First, normalize the two objective functions. Then, assign the weighting coefficients to the optimization objective ($\omega_1 + \omega_2 = 1$). The final single-objective minimization problem is obtained as (20.14):

$$\min f = \omega_1 \frac{f_1}{f_1^{\max}} + \omega_2 \frac{f_2}{f_2^{\max}} \tag{20.14}$$

$$s.t., (10) - (13).$$

Numerical Study

Data Descriptions: Monte Carlo Simulation

We use the Monte Carlo simulation method to simulate the total load curve of the community power grid under disordered charging. We use 20, 30, 40% penetration rates of EVs and 100% deployment rate at private charging piles for simulation. According to Eqs. (20.1), (20.2), and (20.3), the charging start time t_i^{arr}, end charging time t_i^{dep}, and daily mileage d_i of the EV are randomly generated. At the same time, based on Eq. (20.4), the vehicle battery capacity B_i and the power consumption W_i per 100 km are randomly set to calculate the daily charging demand D_i of the EV. In order to prevent the rapid aging of EV batteries, Han et al. (2020) proposed that the EV's state of charge should not be less than 10% and exceed 95% of the rated capacity [18]. The acceptable lower limit of SOC $S_i^{\min}$ is set to 10%, and the expected state of charge S_i^{exp} of the EV after each charge is set to 95%. The SOC upper limit $S^{\max}$ for EVs is 100%. As it leaves the community, the daily EV state S_i^{ini} will be randomly generated between $\left[S_i^{ini} + \frac{d_i^! W_i}{100 B_i}, 95\%\right]$.

After that, we delete unreasonable data records. In addition, the study in this chapter divides a day into 24 time periods T, and the time length Δt is taken as 1. The maximum output power $e^{\max}$ of each charging pile is set to 7 kWh. According to Wang and Yang (2009), the maximum output power of the community distribution transformer L^{limit} is set to 1020 kW, and the daily load z_t^B of the conventional electricity consumption in the community adopts the typical daily load data [19]. We generate community EV charging needs randomly and run 100 simulations. According to simulation results shown in Fig. 20.1, When EVs' penetration rate increases, the peak-to-valley difference between grid load and the total load peak also increases.

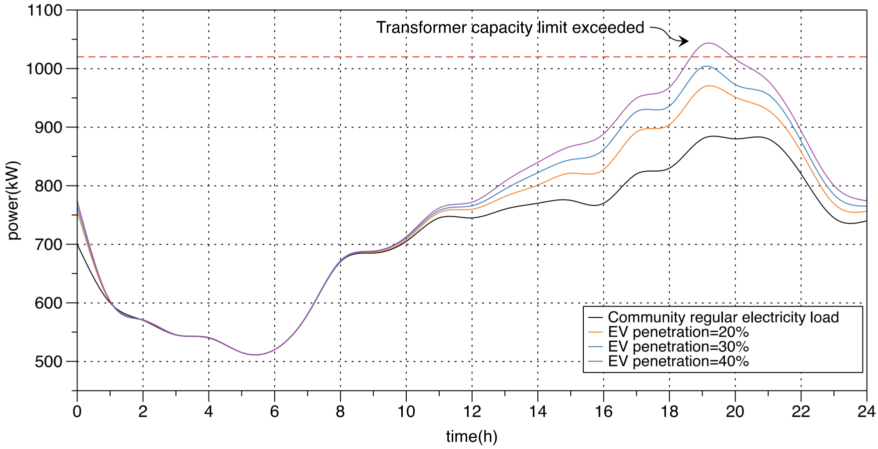

Fig. 20.1 The total load of the community grid under the disordered charging

Orderly Charging Scheduling Policy Performance

Observation

The results showed that the total charging cost of EVs was reduced from 641.37¥ to 364.67¥. The reason is that ordered charging achieves the peak-to-valley transfer. In Fig. 20.2, the charging time and the total charging power of EVs in disordered and ordered charging modes are shown. Based on this, we can conclude that the orderly charging strategy of EVs can reduce the charging costs of users.

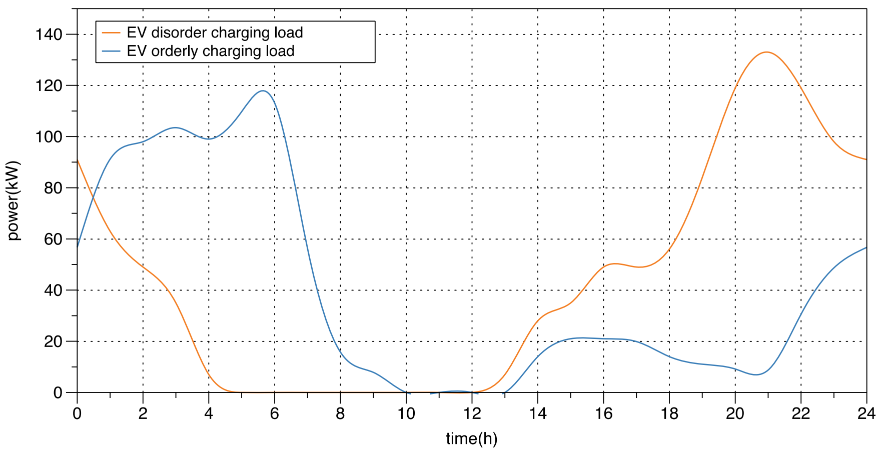

Fig. 20.2 Comparison of orderly charging and disorderly charging loads of EVs

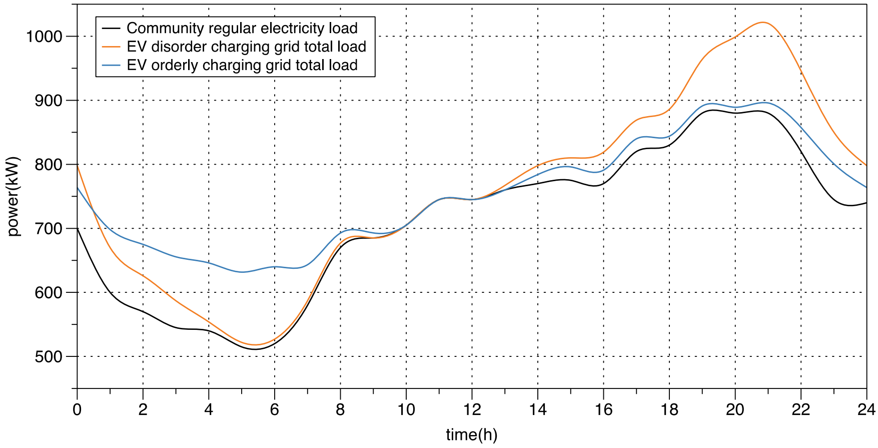

Fig. 20.3 Comparison of orderly charging and disorderly charging total loads of EVs

Observation

The community power grid's total load is calculated, as shown in Fig. 20.3. According to the findings, the orderly charging strategy reduces the grid's peak load by 12.65%, increases the valley load by 21.02%, reduces the peak-valley difference by 47.93%, and reduces the load variance 65.92% to the disordered charging mode of EVs. It is worth noting that, when compared to conventional energy load, the grid load's peak-to-valley difference is decreased by 28.96%, and the load variation is reduced by 49.54% once the orderly charging approach is adopted. It can be seen that the orderly charging mode of EVs can cut peaks and fill valleys, stabilizing load fluctuations. In addition, although the direct benefit to the grid is reduced, the peak load is reduced by 128.98 kW. The total benefit increases. We conclude that the orderly charging strategy of EVs can effectively realize the peak shaving and valley filling of the community power grid and improve the economic benefits of power grid operation.

Influence of Objective Function Coefficients

This section explores the influence of different objective weight coefficients on the results. We assign different weight coefficients to the two objective functions and plot the results in Fig. 20.4. It can be seen that with the increase of the weight coefficient ω_1 for minimizing the power grid load variance, the power grid load variance shows a decreasing trend, the value range is between 7700–7750 kW^2, and the user charging cost is increasing from 362¥ to 374¥. However, the overall degree of change in both is not significant.

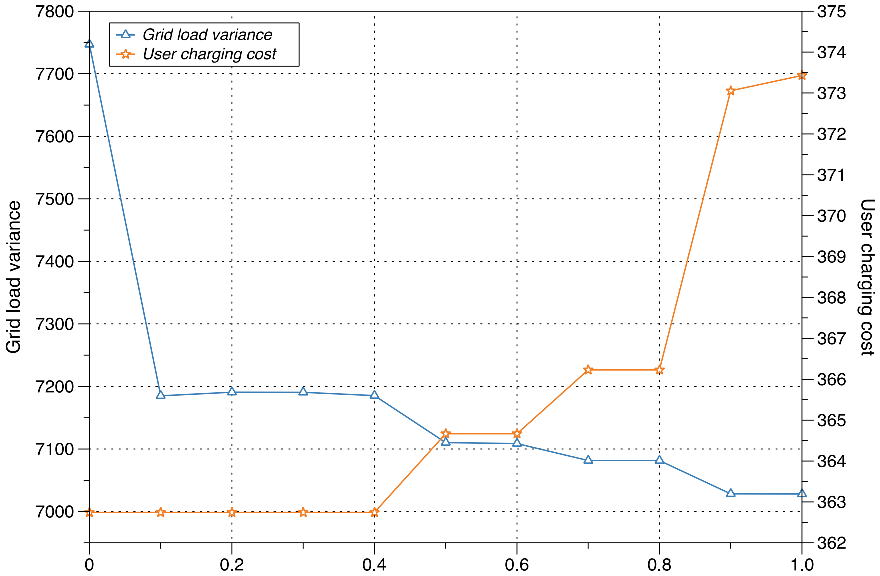

Fig. 20.4 Influence of different target weights on grid load variance and user charging cost

When $\omega_1 = 0$, the grid load variance is not considered. It is observed that the grid load variance (7746.88 kW^2) has been dramatically reduced compared with disordered charging (14091.12 kW^2). In the same way, when $\omega_1 = 1$, the user charging cost is not considered, the user charging cost (373.43¥) is also significantly reduced compared with the disordered charging (641.37¥).

Then, as ω_1 increases from 0 to 0.1, the grid load variance decreases from 7746.88 to 7185.06 kW^2. Then, when the value of ω_1 is in the range of 0.1–0.4, grid load variance and user charging cost variation are not apparent. When $\omega_1 = 0.5$, that is, when the weights of the two objective functions are the same, the grid load variance decreases to 7110.30 kW^2, and the user charging cost increases to 364.67¥. Subsequently, when the value of ω_1 changed from 0.8 to 0.9, the user charging cost increased the most, reaching 373.05¥.

We conclude that a single-objective optimization model that only considers f_1 or uses f_2 can reduce grid load variance and user charging costs. However, taking the two as the objective function and setting reasonable weight can better realize the trade-off between the power grid operation security and the user's charging economy.

Conclusions and Future Work

As EVs grows, the demand for charging rises year after year. The random and disorderly EV charging mode will harm the grid system's operation. Meanwhile, the lack of routine operation and management of private charging piles in the community results in charging pile idleness and a supply–demand mismatch. Therefore, this paper addresses the above problems by proposing an orderly EV charging scheduling strategy based on relevant research. The specific research results of this paper are as follows:

(1) In the design of the community's private charging piles' operation mode, this paper first uses the Monte Carlo simulation method to predict the disordered charging process of EVs and demonstrate the impact of disordered charging on the community power grid. Second, the K-means clustering algorithm separates the orderly charging period of EVs into peaks, flats, and valleys. Then the time-of-use pricing strategy is calculated for diverse EV penetration rates.
(2) We develop a multi-objective nonlinear programming approach to reduce EV charging costs and grid load changes. Then, it is transformed into a single-objective optimization model using a linear weighting method. The findings suggest that our orderly charging technique can reduce power grid load volatility and user charging costs. If the target weight is set reasonably, the trade-off between the safety of power grid operation and the economic demand for users' charging can be better achieved.

Furthermore, our method can also be applied to other electrically-powered industrial operations. Many aspects of EV scheduling and robustness optimization require more exploration in the future:

(1) The data source for the model provided in this paper is typical electricity grid load data from a single community. The community's actual conventional power grid load statistics can be employed for further investigation. Moreover, the time-of-use tariff strategy is usually implemented on a city basis. In the future, the research can be applied to a larger area.
(2) This paper uses the linear weighting method to obtain relevant management inspiration when solving the multi-objective optimization model. In the future, when dealing with more realistic scenarios, we can try combining methods, constraint methods, and genetic algorithms.

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