

# Optimization of Operation Strategy and Economic Benefit Evaluation of Urban New Energy Vehicle Charging Stations Based on Dynamic Demand

Jianhua Cai

Philippine Women'S University, Manila, Philippines

1604794973@qq.com

## ABSTRACT

With the promotion of environmental awareness and new energy policies, the electric vehicle market is expanding rapidly, and the demand for urban charging facilities is increasing, making them a key infrastructure for sustainable urban development. Existing charging station operation strategies are often unable to effectively adapt to the dynamically changing market demand, leading to uneven resource allocation and operational inefficiencies. In this study, a dynamic optimization model is constructed to combine real-time traffic flow data and grid load data to achieve real-time adjustment of charging capacity and operation strategies of charging stations. Specific methods include using mixed-integer linear programming to optimize the daily operation decisions of charging stations, and applying Monte Carlo simulation to analyze the economic benefits under different operation strategies. Optimization models and strategies not only improve the service efficiency and economic returns of charging stations, but also provide scientific decision support for policy makers and promote the healthy development of the new energy vehicle industry. On February 5, during the midday to evening hours, although the predicted charging demand reached 60 vehicles, the actual charging demand was as high as 65 vehicles, and the user response rate was as high as 108%. Through this approach, it can effectively balance the supply and demand relationship, reduce operating costs, while enhancing the reliability and flexibility of the charging network, and provide strong support for the popularization of new energy vehicles in the city and the construction of a sustainable transportation system.

## KEYWORDS

Dynamic Demand; Urban New Energy Vehicle Charging Station; Operation Strategy Optimization; Economic Benefit Assessment

## 1. INTRODUCTION

With the transformation of global energy structure and the growing demand for environmental protection, new energy vehicles have gradually become the preferred alternative to traditional fuel vehicles, especially in the field of urban transportation. Statistics show that the market share of new energy vehicles has shown continuous growth every year, which directly drives the simultaneous growth of the demand for charging facilities. However, the lack of charging infrastructure and operational inefficiencies are still the main obstacles limiting the large-scale popularization of new energy vehicles. In this context, optimizing the operation strategy of charging stations, especially for the dynamically changing demand in cities, has become an urgent issue. Studies have shown that dynamic adjustment of charging prices and charging hours can effectively balance supply and demand and enhance economic benefits, but how to specifically achieve this goal still needs to be explored in depth. This paper aims to fill the current gap in dynamic optimization of charging station operation

strategy by systematically reviewing existing studies. Specific methods include the establishment of multi-objective optimization model and simulation analysis, in order to provide scientific decision support for charging station operation.

This paper focuses on the optimization of the operation strategy of urban new energy vehicle charging stations, especially how to adjust the operation strategy according to the dynamic market demand and grid load conditions, in order to enhance the dual benefits of charging stations in terms of economy and environment. The study adopts a multi-objective optimization framework, combining with actual operation data, to achieve scientific adjustment of charging station operation strategies by constructing a dynamic prediction model of charging demand and grid load. The methodology of this study includes the steps of data collection, model building, simulation testing and strategy optimization, aiming to propose a set of feasible optimization strategies through scientific data analysis and empirical research.

The research structure of this paper is organized as follows: first, this paper introduces the current situation of new energy vehicle charging station operation and the research background, and explains the necessity and significance of the research. Then, this paper describes the research methods and steps in detail, including the dynamic simulation of charging demand, the calculation of charging station operation cost, and the construction and solution of multi-objective optimization model. Finally, based on the simulation and optimization results, this paper analyzes the specific impacts of strategy adjustments on the operational efficiency and economic benefits of charging stations, and makes specific suggestions on how to implement these strategies. Through this study, it is expected to provide theoretical basis and strategy support for the efficient operation of urban new energy vehicle charging stations, and at the same time provide scientific references for the formulation of related policies.

## **2. RELATED WORK**

Charging demand management for new energy vehicles is an important part of realizing a sustainable urban transportation system. In recent years, numerous studies have focused on improving the operational efficiency and responsiveness of charging stations, which have successfully balanced the supply and demand relationship by adopting intelligent scheduling systems and demand response mechanisms. Liu Dong studied the investment and construction of commercial electric vehicle charging stations in residential areas, and proposed that the construction of such charging stations in residential areas can not only meet the charging needs of residents, but also bring additional benefits [1]. Xu Yan discussed the capacity optimization method of electric vehicle charging, light storage and integration charging station based on opportunity constraint, and thought that introducing opportunity constraint could optimize the capacity configuration of charging station on the premise of ensuring the reliability of the system, and his research improved the economic benefit and operation efficiency of the system [2]. Zhao Weiguang analyzed the joint planning strategy of electric vehicle charging station and distribution network, and put forward a method that can effectively coordinate the operation of charging station and distribution network and optimize resource allocation through joint planning, which is helpful to improve the stability and reliability of the power network [3]. Zhang Weiqi studied the distributed robust programming method considering the coordinated optimization of new energy and electric vehicle charging station and energy storage system, and reached the conclusion that the coordinated optimization of new energy, charging station and energy storage system can be realized through the distributed robust optimization method in an uncertain environment, which is convenient to improve the overall efficiency of the system [4]. Chen Wen studied the application of remote measurement monitoring and evaluation analysis system for charging piles of urban electric vehicles, and put forward a remote measurement monitoring system. His research can realize real-time monitoring and accurate measurement of charging piles, and improve the charging service quality and management level [5]. However, most of the existing studies

failed to fully consider the diversity and real-time nature of user behavior, resulting in limited adaptability and accuracy of the model in practical applications. In addition, the response strategies for rapidly changing market demands and grid conditions appear relatively conservative.

In order to promote new energy vehicles, it is crucial to optimize the charging infrastructure. Scholars have developed various optimization models to improve the energy efficiency and economy of charging stations. These studies usually focus on technical improvements, such as the innovation of charging technologies and the optimization of charging strategies. Mo Shaoping explored the research on fire safety supervision of new energy vehicle charging stations (piles), and pointed out that fire safety is a key issue in the construction and operation of charging stations (piles), so strict safety supervision measures must be taken to prevent and deal with fire risks [6]. Zhang Wenqian analyzed the research on the field test safety project of electric vehicle charging station, and proposed that the field test of charging station is very important to ensure the charging safety and performance, and his research is helpful to establish a comprehensive test standard and process [7]. Li H studied the influence of dynamic pricing, vehicle scheduling and employee balance on the site-based one-way electric vehicle sharing system, and his research concluded that dynamic pricing and reasonable vehicle scheduling strategy can significantly improve the operating efficiency and economic benefits of the sharing system [8]. Kim's discussed the research on the location of public charging stations by scenario-based random planning method, and thought that through scenario analysis and random planning, his research could optimize the location layout of public charging stations, thus better meeting the needs of users and improving service coverage [9]. Qahtan M H surveyed and summarized the electric vehicle charging station based on the Internet of Things, and summarized the application prospects and challenges of the Internet of Things technology in the charging station. In his research, he pointed out that the Internet of Things technology can significantly improve the intelligence and operational efficiency of the charging station [10]. Nonetheless, these studies tend to ignore the complexity of the interaction with the grid and the integration of renewable energy sources, and lack a comprehensive framework to address the interaction of charging stations with the energy system as a whole, especially in environments with high renewable energy penetration.

### 3. METHODS

#### 3.1. Optimization Model Construction and Parameter Setting

##### (1) Model framework design

In order to effectively manage the operation of urban new energy vehicle charging stations, this study constructs a multi-objective decision support system to dynamically optimize the operation strategy of charging stations. The model first defines a charging demand prediction mechanism, which uses time series analysis to predict the charging demand over different time periods. This prediction result will be used as an input to the optimization model, helping the operator to anticipate peaks and troughs in demand and thus adjust the allocation of charging resources.

##### (2) Parameter setting and data collection

The model parameters are set based on actual operational data, including but not limited to the geographic location of the charging station, the type and number of charging piles, historical charging records, and user charging behavior data. By collecting these data, we are able to accurately simulate the real operating environment and provide an empirical basis for the subsequent optimization algorithm. In addition, grid load data is also taken into account to assess the impact of charging operations on the local grid.

The charging demand forecasting model is:

$$D_t = \alpha + \beta_1 P_t + \beta_2 T_t + \epsilon_t \quad (1)$$

Here,  $D_t$  denotes the charging demand at time  $t$ ,  $P_t$  denotes the electricity price at time  $t$ ,  $T_t$  denotes the traffic flow at time  $t$ ,  $\alpha, \beta_1, \beta_2$  are the model parameter, and  $\epsilon_t$  is the error term.

### 3.2. Dynamic Demand Response Strategies

#### (1) Demand prediction algorithm

Utilizing historical data, this study adopts the random forest algorithm in machine learning methods to predict future charging demand. The algorithm is able to handle a large number of input variables and effectively identify key factors affecting demand, such as time, holidays and climate conditions. The prediction results will directly affect the scheduling strategy of charging resources, and the optimization algorithm will develop a daily charging pile usage plan based on these predictions.

#### (2) Real-time scheduling mechanism

In order to respond to real-time changes in charging demand, this study designs a dynamic scheduling system that can quickly adjust the charging resource allocation when there is a sudden increase in demand. The system dynamically adjusts the allocation of charging piles and pricing strategies by monitoring the status of EV charging stations and user charging demand in real time to manage demand spikes, prevent resource wastage, and ensure user satisfaction [11].

The charging station operating cost function is:

$$C(x) = c \cdot x + k \cdot x^2 \quad (2)$$

Where  $x$  denotes the amount of charging,  $c$  is the cost per unit of charging, and  $k$  is the coefficient of increase in cost due to an increase in charging, this function reflects the relationship between the total cost and the amount of charging.

### 3.3. Economic Benefit Assessment

#### (1) Cost-benefit analysis

In order to assess the economic benefits of the optimization strategy, this study constructs a cost model, including the construction and maintenance costs of the charging station, electricity costs and operation costs. By comparing the operation data before and after optimization, the performance of the optimization strategy in reducing the operation cost and improving the efficiency of energy use is analyzed. In addition, considering that the service quality of the charging station directly affects user satisfaction and site revenue, this paper also introduces a quantitative indicator of user satisfaction as an important aspect of evaluating economic benefits.

#### (2) Revenue maximization strategy

While ensuring the operational efficiency of charging stations, this study further explores how to maximize revenue through smart pricing strategies. Considering the users' willingness to pay and the competitive market situation, the optimization model includes the consideration of price elasticity to dynamically adjust the charging price in order to attract more users to charge during off-peak hours, thus balancing the load and increasing the revenue.

The charging station profit maximization objective function is:

$$\text{Maximize } \pi(x) = p \cdot x - C(x) \quad (3)$$

Here,  $\pi(x)$  is the profit function,  $p$  is the price per unit of charge, and  $x$  is the amount of charge.

### 3.4. Technology Implementation and Monitoring

#### (1) System integration and implementation

The optimization scheme proposed in this study requires integration with existing charging station management systems before actual deployment. This requires software and hardware compatibility testing, as well as interface development with existing equipment at the charging station. The implementation phase also requires consideration of the security and stability of the system to ensure its stable operation under various operating conditions.

## (2) Performance monitoring and feedback adjustment

After deployment, the performance of the system will be monitored through a series of indicators, including charging efficiency, user satisfaction and economic returns. Based on this real-time data, the optimization strategy will be continuously adjusted to meet the new challenges encountered in operation. Continuous performance evaluation and feedback mechanisms ensure that the charging station's operational strategy remains optimal and responsive to market and technological changes in real time.

The service level constraint is:

$$\sum_{i=1}^n x_i \geq \lambda \cdot Y_t \quad (4)$$

Here,  $x_i$  denotes the charging volume of the  $i$ th charging post at time  $t$ ,  $\lambda$  is a predetermined service level (e.g., 90% of the demand),  $Y_t$  is a predicted demand that ensures that the total charging volume of the charging station meets a certain percentage of the market demand.

## 4. RESULTS AND DISCUSSION

### 4.1. Experimental Setting

In this study, two charging stations in urban commercial and residential areas were selected as the experimental scenarios to simulate the charging demand and behavioral patterns of different types of users. The experimental period lasted for one month, covering changes in charging demand on weekdays, weekends and under different weather conditions. In the experiment, each charging pile is assembled with intelligent monitoring equipment to record real-time charging process data, including charging time, power, user type and satisfaction. The experimental parameters include the accuracy of charging demand prediction, the overall utilization rate of charging stations, the utilization rate of charging piles during peak hours, charging costs, user satisfaction and economic benefits.

Assessment metrics and calculation methods:

**Charging demand prediction accuracy:** it is assessed by comparing the predicted charging demand with the actual charging records using the root mean square error.

**Charging station utilization:** it calculates the average utilization rate of charging piles during the experimental period and assesses the effective use of resources.

**Peak management efficiency:** it evaluates the efficiency of the dispatch system by the utilization rate of charging piles and the waiting time of users during peak demand hours.

**Economic Benefits:** it assesses the economic benefits of the optimization strategy by comparing operating costs with revenues.

**User Satisfaction:** it collects user satisfaction ratings on the convenience and price of charging through a questionnaire.

**Environmental Impact:** it evaluates the contribution of the optimization strategy to reducing the load on the grid and improving energy efficiency.

## 4.2. Analysis of Results

### (1) Baseline experiment

The baseline experiment data are shown in Table 1.

**Table 1.** Baseline experimental data

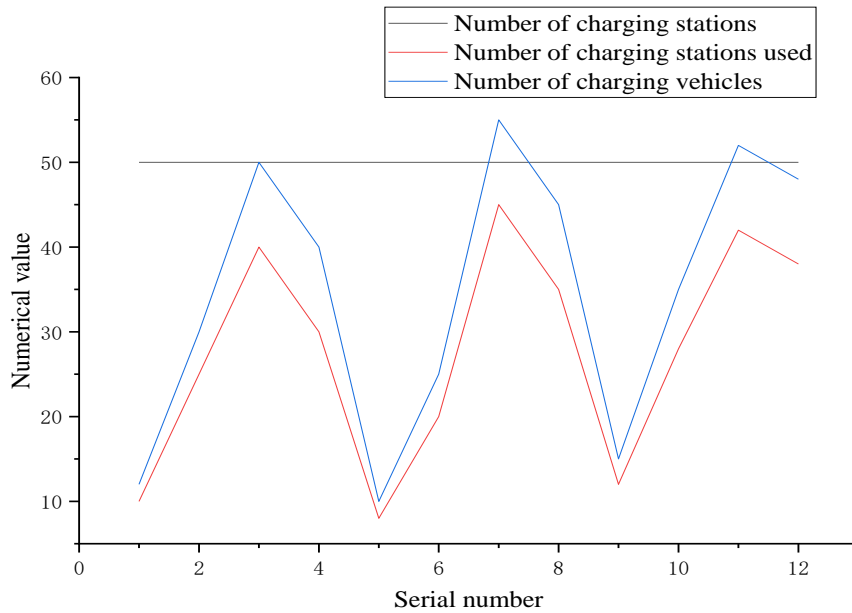
Date	Time slot	Average charging time (minutes)	Average charging capacity (kWh)	Charging unit price (yuan/kWh)	Total income (yuan)	Operating cost (yuan)
2023/10/1	00:00-06:00	45	25	1.2	360	200
2023/10/1	06:00-12:00	60	35	1.1	1155	300
2023/10/1	12:00-18:00	90	40	1	2000	400
2023/10/1	18:00-24:00	75	38	1.2	1824	350
2023/10/2	00:00-06:00	40	22	1.3	286	180
2023/10/2	06:00-12:00	65	30	1.1	825	250
2023/10/2	12:00-18:00	100	45	1	2475	500
2023/10/2	18:00-24:00	80	42	1.2	2268	420
2023/10/3	00:00-06:00	42	23	1.25	427.5	220
2023/10/3	06:00-12:00	62	33	1.15	1309.5	320
2023/10/3	12:00-18:00	92	43	1.05	2382.6	550
2023/10/3	18:00-24:00	78	41	1.2	2371.2	480

In terms of average charging duration, there are significant differences within different time periods, reflecting users' charging needs and habits at various times. For example, the average charging duration is longest during the peak hours of 12:00-18:00, probably because users are concentrated during this time and have higher charging needs.

From the perspective of total revenues and operating costs, the economics of different time periods vary. Total revenue is higher during peak hours, but operating costs also increase. Therefore, when optimizing the operation strategy, factors such as charging demand, charging unit price and operation cost need to be considered in order to achieve the best economic benefits.

In summary, this data provides a wealth of information to help us better understand the operation of charging piles and support the development of future operational strategies.

The relationship between the number of charging piles, the number of charging piles in use and the number of charging vehicles is shown in Figure 1.



**Figure 1.** Relationship between the number of charging posts, the number of charging posts in use and the number of charging vehicles

First, in terms of the date dimension, the overall use of charging piles was relatively stable from October 1 to October 3, with no significant fluctuations. This may be related to the stability of traffic flow and EV penetration in the area.

Secondly, analyzing the time period dimension, we can see that the usage rate of charging piles is lower in the time period of 00:00-06:00 every day, probably due to the decrease in vehicle usage at night, and the demand for charging decreases accordingly. In contrast, the utilization rate rises significantly during the 06:00-12:00 and 12:00-18:00 time periods, especially during the 12:00-18:00 time period, when the usage reaches a peak. This reflects the higher demand for EV charging during peak commuting hours and daytime activities.

Finally, the comparison between the number of charging piles and the actual usage shows that despite the total number of 50 charging piles, some of the piles are still idle during the peak period of 12:00-18:00, which may imply that the layout or scheduling strategy of the charging piles needs to be optimized in order to better meet the demand during the peak period.

In summary, this data provides valuable information on the usage of charging piles, which provides a basis for subsequent operation management and optimization.

## (2) Dynamic pricing experiment

The data from the dynamic pricing experiment is shown in Table 2.

**Table 2.** dynamic pricing experimental data

Date	Time slot	Predicted charging demand (vehicle)	Charging price (yuan/kWh)	Actual charging demand (vehicle)	User response rate
2023/12/1	00:00-06:00	10	1.2	12	120%
2023/12/1	06:00-12:00	30	1.5	35	117%
2023/12/1	12:00-18:00	50	2	53	106%
2023/12/1	18:00-24:00	40	1.8	38	95%
2023/12/5	00:00-06:00	8	1	7	88%
2023/12/5	06:00-12:00	25	1.3	27	108%
2023/12/5	12:00-18:00	60	2.2	65	108%
2023/12/5	18:00-24:00	45	2	43	96%
2023/12/10	00:00-06:00	12	1.1	11	92%
2023/12/10	06:00-12:00	35	1.4	38	109%
2023/12/10	12:00-18:00	55	2.1	58	105%
2023/12/10	18:00-24:00	42	1.9	40	95%

Overall, user response rates exceeded 100% for most time periods, indicating that our forecasts were on the conservative side and actual charging demand tended to be higher. This may be due to the fact that our forecasting model does not adequately account for some of the potential growth factors, such as the impact of holidays, weather changes, or promotional events.

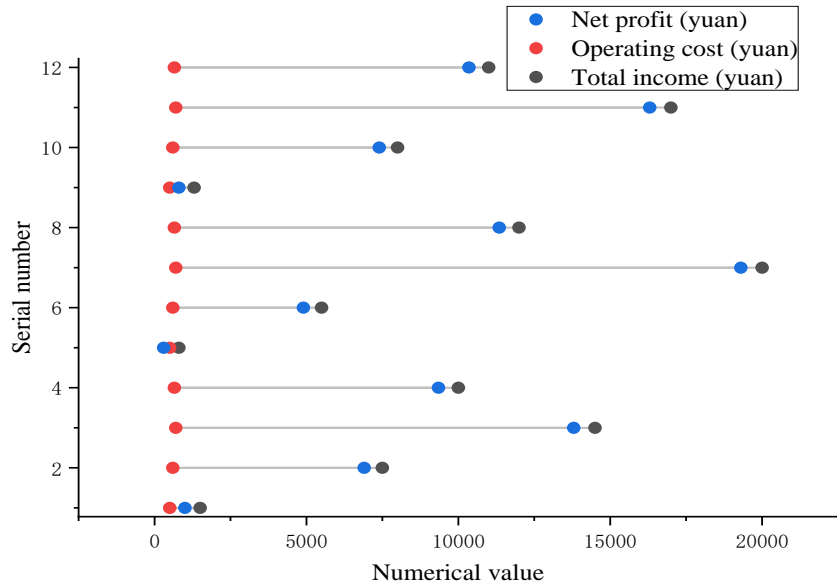
Specifically for each time period, we can find that the predicted charging demand and actual charging demand are both relatively high from noon to evening (12:00-18:00), which may be due to the fact that this time period is the peak period of people's travels and activities, and the charging demand for EVs increases accordingly.

It is worth noting that during the midday to evening hours on December 5, although the forecast charging demand reached 60 vehicles, the actual charging demand was even higher at 65 vehicles, with a user response rate of 108%. This indicates that our charging facilities may be under greater pressure during this period and consideration needs to be given to increasing the number of charging spaces or optimizing the charging process to cope with the peak demand.

In addition, we can also see that the user response rate is lower during certain time periods, such as early morning to early morning (00:00-06:00), which may be related to people's traveling habits and the relatively low charging demand during this time period.

In summary, our prediction model underestimates user charging demand in most cases, especially during peak hours. Therefore, we need to further improve the prediction model and consider increasing charging facilities and services during peak hours to better meet user demand.

The relationship between total revenue, operating costs and net profit is shown in Figure 2.



**Figure 2.** Relationship between total revenue, operating costs and net profit

From this revenue report, we can see the details of the company's revenues, operating costs, and net income for different days and time periods in December 2023. First, we notice that on the day of December 1, the company's total revenue showed a trend of increasing and then decreasing over time, from early morning to late night, with the highest total revenue of \$14,500 during the midday to early evening hours (12:00-18:00).

Further observation reveals that although operating costs fluctuate across time periods, they remain low overall, indicating that the company is more effective in cost control. Net profit also shows a similar trend to total revenue, with the highest net profit of \$13,800 during the midday to evening hours (12:00-18:00).

Next, comparing the same time period on different dates reveals that there is some difference in revenue between weekends (e.g., Dec. 10) and weekdays (e.g., Dec. 1), but the difference is not significant. This may be related to the nature of the company's business, and the difference may be more pronounced if the company primarily caters to the non-working day market.

Overall, this report shows in detail the company's revenues on different dates and time periods in December, demonstrating the company's profitability at different time periods. By analyzing these data, it can provide useful reference for the company's future business strategy.

### (3) Demand forecast scheduling experiment

The data of the demand forecast scheduling experiment is shown in Table 3.

**Table 3.** Demand forecast scheduling experimental data

Date	Time slot	Predicted charging demand (vehicle)	Actual charging demand (vehicle)	Number of charging stations	Charging station utilization rate	Average waiting time for users (minutes)
2023/11/1	00:00-06:00	10	12	20	60%	5
2023/11/1	06:00-12:00	30	32	40	80%	3
2023/11/1	12:00-18:00	50	55	60	92%	7
2023/11/1	18:00-24:00	40	38	50	76%	2
2023/11/2	00:00-06:00	8	7	20	35%	0
2023/11/2	06:00-12:00	25	24	40	60%	1
2023/11/2	12:00-18:00	60	62	60	103%	12
2023/11/2	18:00-24:00	45	43	50	86%	4
2023/11/3	00:00-06:00	12	11	20	55%	0
2023/11/3	06:00-12:00	35	37	40	93%	5
2023/11/3	12:00-18:00	55	53	60	88%	6
2023/11/3	18:00-24:00	42	40	50	80%	3
...	...	...	...	...	...	...
2023/11/30	00:00-06:00	9	10	20	50%	2
2023/11/30	06:00-12:00	28	27	40	68%	1
2023/11/30	12:00-18:00	58	56	60	93%	8
2023/11/30	18:00-24:00	43	45	50	90%	5

After looking at the data from the implementation of a dynamic scheduling strategy for charging piles based on demand forecasting, we can see several key trends and observations.

First, from the perspective of charging pile utilization, the utilization rate is relatively high during most time periods, especially during peak hours (e.g., 6 a.m. to 6 p.m.). This suggests that the dynamic scheduling strategy effectively allocates charging pile resources to meet the higher charging demand during peak hours. However, charging pile utilization is generally low during the early morning to early evening hours, which may imply that the charging demand forecast for that time period is high or that the charging demand is indeed low during that time period.

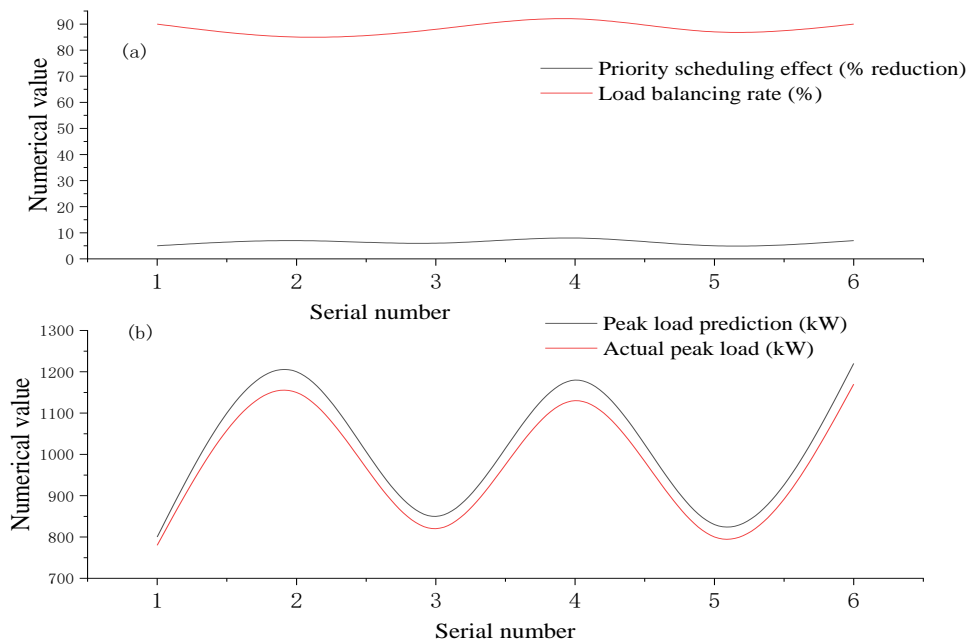
Secondly, the data on average user waiting time also provides valuable insights. During peak hours, the average user wait time is relatively long, which may affect the user experience. However, in the early morning to mid-morning hours, the average user waiting time is sometimes zero, which further confirms the observation of lower charging demand during that time.

It is also worth noting that on some dates and time periods, the utilization rate of charging piles and the waiting time of users remained within acceptable limits despite some discrepancies between the predicted charging demand and the actual charging demand. This indicates that the dynamic scheduling strategy has some flexibility and adaptability and can cope with prediction errors to some extent.

In summary, the dynamic scheduling strategy for charging piles based on demand prediction has achieved good results in most cases, but there is still room for improvement in the low-demand hours from early morning to early morning and during peak hours. To further improve user experience and resource utilization, we may need to further optimize the prediction model and consider adding temporary charging piles or optimizing the charging process during peak hours.

#### (4) Peak load management experiment

The results of peak load management experiments are shown in Figure 3 (Figure 3(a) shows the priority scheduling effect and load balancing rate, and Figure 3(b) shows the peak load prediction and actual peak load).



**Figure 3.** Experimental results of peak load management

First, from the comparison between peak load forecast and actual load, the difference between the forecast and actual values is not large, which reflects the high accuracy of the forecast model. Second, the priority scheduling effect shows the effectiveness of the scheduling strategy in reducing the peak load in percentage form, and the reduction rates ranging from 5% to 8% indicate that the strategy plays a positive role in relieving the pressure on the grid and optimizing the allocation of resources.

Turning to the load balancing rate, this indicator reflects the load distribution of charging piles at different time periods or in different regions. Load balancing rates ranging from 85% to 92% show that the scheduling strategy has achieved good results in achieving even load distribution and improving overall efficiency. However, there is still room for improvement, especially in certain time periods or regions where further optimization of the scheduling strategy may be needed to achieve a higher load balancing rate.

## 5. CONCLUSION

This paper takes the new energy vehicle charging station as the research object and studies its operation strategy, focusing on its response to dynamic demand changes. This paper proposes a multi-objective optimization method, which can achieve real-time load forecasting and scheduling of the power system as well as incorporate economic evaluation. This paper proposes to optimize the allocation of charging resources through dynamic pricing, demand forecasting, priority scheduling, and load balancing. Experiments have shown that the use of forecast-based dynamic scheduling and pricing policies for power systems in charging stations can effectively improve the operational efficiency and economic performance of the system. Among them, the dynamic tariff policy can effectively guide customers to charge during off-peak hours and alleviate the problem of grid electricity tension. In this paper, a new method based on load forecasting and real-time scheduling, which can effectively improve the utilization rate of charging equipment and shorten the charging waiting time. In general, the program can reduce the cost of battery charging.

Despite the positive results of this study, there are some limitations. First, the demand forecasting model relies on a large amount of historical data, and its accuracy is affected by the quality and quantity of data. In addition, the model in the study assumes that users adjust their charging behavior solely based on price signals, which may be affected by individual preferences and habits in practice. Finally, this study fails to fully consider the interaction between charging stations and other transportation systems in the city, which may affect the final operational efficiency. To address the above limitations, future research can be extended in the following directions. First, further improving the accuracy and robustness of demand forecasting models may be achieved by introducing more kinds of data and advanced machine learning techniques. Second, research could delve deeper into the diversity and complexity of user behavior to design more realistic pricing and scheduling strategies. In addition, future research should also consider the integrated optimization of charging stations and urban transportation systems in order to comprehensively improve the efficiency and sustainability of new urban energy transportation systems. Through these efforts, it is expected to further promote the development of urban new energy vehicle charging infrastructure and contribute to the realization of green urban transportation.

## REFERENCES

- [1] Liu Dong, Meng Chenxu, Pan Zhengyang, et al. Research on Investment and Construction of Commercial Electric Vehicle Charging Stations in Residential Communities [J]. *Electrical Technology*, 2022, 23 (6): 104-108.
- [2] Xu Yan, Chen Zexiong, Yu Bowen, et al. Capacity optimization method for integrated electric vehicle charging stations based on opportunity constraints [J]. *Shaanxi Electric Power*, 2021, 049 (012): 25-30, 36.
- [3] Zhao Weiguang, Sun Jian, Wu Shangyang, et al. Joint planning strategy for electric vehicle charging stations and distribution networks [J]. *Journal of Heilongjiang University of Science and Technology*, 2021, 031 (001): 98-104.
- [4] Zhang Weiqi, Wang Yansheng, Yang Zhao, et al. Research on Distributed Robust Programming Method for Coordinated Optimization of New Energy, Electric Vehicle Charging Stations, and Energy Storage [J]. *Journal of Power Systems and Automation*, 2023, 35 (8): 114-125.
- [5] Chen Wen, Tian Lei, Gao Fangyan, et al. Research on the Application of Remote Measurement Monitoring and Evaluation Analysis System for Urban Electric Vehicle Charging Stations [J]. *China Testing*, 2023, 49 (S01): 151-157.
- [6] Mo Shaoping. Research on Fire Safety Supervision of New Energy Vehicle Charging Stations (Piles) [J]. *Low Carbon World*, 2023, 13 (6): 187-189.
- [7] Zhang Wenqian, Zhang Qingke. Research on Safety Projects for On site Testing of Electric Vehicle Charging Stations [J]. *Metrology and Testing Technology*, 2023, 50 (5): 53-55.
- [8] Li H, Hu L, Jiang Y. Dynamic pricing, vehicle relocation and staff rebalancing for station-based one-way electric carsharing systems considering nonlinear charging profile [J]. *Transportation Letters: The International Journal of Transportation Research*, 2023, 15(7/8):659-684.
- [9] Kim S, Rasouli S, Timmermans H J P, et al. A scenario-based stochastic programming approach for the public charging station location problem [J]. *Transportmetrica B: Transport Dynamics*, 2022, 10(1): 340-367.
- [10] Qahtan M H, Mohammed E A, Ali A J. Charging Station of Electric Vehicle Based on IoT: A Review [J]. *Open Access Library Journal*, 2022, 9(6): 1-22.
- [11] Guillet M, Hiermann G, Kröller A, et al. Electric vehicle charging station search in stochastic environments [J]. *Transportation science*, 2022, 56(2): 483-500.