Research on the dynamic pricing strategy of charging piles based on data-driven supply and demand balance and data-driven

Yibei Lai[1], *Zhixian* Li[2*], *and Zehan* Zhang[3]

[1]France Julong Science Middle School, Shenzhen, Guangdong Province, China
[2]France School of Finance, Macau City University, Macau Special Administrative Region, China
[3]Department of Economics and Management, Dezhou College, Dezhou City, Shandong Province, China

Abstract. This study explores a dynamic pricing strategy for electric vehicle (EV) charging stations, leveraging supply-demand balance and data-driven approaches to optimize resource allocation, enhance grid stability, and improve user satisfaction. With the rapid growth of EVs globally, charging infrastructure faces challenges such as imbalanced utilization, peak-hour congestion, and inefficient energy use. Traditional static pricing models fail to address these issues effectively. The research integrates time series models (e.g., ARIMA) to predict short-term charging demand, combined with reinforcement learning to dynamically adjust prices based on real-time data, including grid load, user behavior, and external factors like weather and traffic. Empirical results demonstrate that dynamic pricing reduces peak-hour congestion by 30%, increases renewable energy utilization by 10%, and boosts operator revenue by 12%. However, limitations arise in rural areas due to sporadic demand and extreme weather conditions, highlighting the need for region-specific strategies.The study proposes practical solutions, such as machine learning-enhanced demand forecasting, differentiated pricing for user segments (e.g., private vs. ride-hailing EVs), and policy frameworks to support flexible pricing. Future work should incorporate real-time GPS data, multi-region policy comparisons, and vehicle-to-grid (V2G) integration to further refine the model. This research provides a scalable framework for stakeholders to balance efficiency, equity, and sustainability in EV charging ecosystems.

1 Introduction

With the transformation of the global energy structure and the advancement of the "dual carbon" goal, electric vehicles, as the core carrier of green transportation, have shown explosive growth in recent years.Global electric vehicle ownership increased from 1.2 million in 2015 to 40 million in 2023, and charging demand surged.However, the charging

* Corresponding author: F22090107081@cityu.mo.edu

infrastructure that is supporting it still faces challenges such as supply and demand imbalance and uneven utilization.On the one hand, charging piles in the central urban areas are in short supply during peak hours, and users are queuing for too long; on the other hand, a large amount of charging resources in suburban or off-peak hours are idle.This structural contradiction needs to be optimized through intelligent management methods.In addition, the queue for charging during peak hours in the morning and evening on weekdays is long, and the user experience is poor. Concentrated charging leads to a sharp increase in the load of local power grids, affecting the stability of the power grid.In addition, governments have promoted time-sharing electricity prices and enterprises have explored dynamic pricing models based on data [1].

This study aims to design a dynamic pricing model by analyzing the supply and demand relationship of charging piles, user charging behavior patterns and grid load characteristics to optimize the allocation of charging resources, alleviate peak congestion, improve user satisfaction, and promote the efficient utilization of renewable energy [2].

This study adopts research methods such as optimization modeling and algorithms, empirical analysis and user surveys, simulation simulation methods, and machine learning prediction.

Although dynamic pricing has been widely used in other industries such as aviation and hotels, it has shown good results in flexibly adjusting prices based on factors such as market supply and demand, cost changes, and achieving optimal resource allocation and economic benefits.However, in the field of charging piles, research on its dynamic pricing is still in its infancy, and there are many obvious research gaps.For example, the limitations of multi-factor coupled modeling; most current models only consider single variables (such as grid load or user needs), fail to integrate complex interaction effects in real scenarios such as weather, traffic flow, and competition in surrounding facilities, resulting in insufficient adaptability of pricing strategies.The dynamic nature of user behavior response is missing; existing research usually assumes that users have a static response to price changes (such as a fixed elastic coefficient), while in reality, user preferences may show nonlinear changes due to time, geographical location, or social attributes. Such dynamic characteristics have not been fully quantified.The trade-off between fairness and efficiency is insufficient; dynamic pricing may cause "price discrimination" or "resource accessibility" disputes, especially the impact on low-income groups is lacking empirical assessment.Blanks of cross-regional differentiation strategies; the current research focuses more on single cities or fixed scenarios, and lacks the design of differentiated pricing mechanisms for regional factors such as urban-rural differences, climate zoning or policy environment [3].

Dynamica pricing adjusts charging prices in real-time based on supply and demand to balance operator revenue, user costs, and grid stability.

In response to the above problems, this paper intends to propose a dynamic pricing framework that integrates multi-source data and reinforcement learning, focusing on solving the problems of coupled modeling of complex factors and dynamic responses of users, and verify the economic benefits and social welfare improvement effects of strategies through empirical analysis [4].

2 Data-driven demand prediction for charging piles

User demand prediction refers to the use of relevant models or algorithms to forecast future user needs based on existing historical information and data. A well-performing demand prediction model can typically mine the correlation between various factors and user demand and has high prediction accuracy, thereby providing guidance for charging pile operators to design charging pile distribution plans, dispatch power resources, and adjust operational strategies [5]. This paper establishes a time series model commonly used in existing charging pile demand prediction studies to conduct short-term prediction of user demand and compares the prediction results, providing a data foundation for the dynamic pricing.

2.1 Basic principles of time series

A time series refers to a sequence of numbers formed by arranging the values of the same statistical indicator in the order of their occurrence. According to the degree of stationarity, time series can be divided into stationary time series and non-stationary time series. This paper mainly introduces stationary time series.

When analyzing and modeling time series in practice, a multiplicative model ($Y = T \times S \times C \times I$) or an additive model ($Y = T + S + C + I$) is often used to represent the relationship between each component and the time series observation value (Y), where the multiplicative model is more commonly used in practical applications. The explanations of each coefficient are as follows:

Trend: A long-term upward or downward trend.

Seasonality: Fluctuations with a fixed period.

Cyclicity: Fluctuations with a non-fixed period.

Noise: Unexplainable random fluctuations.

Time series modeling typically requires the data to satisfy weak stationarity, that is:

Constant mean： $E(Y_t) = \mu$

Constant variance： $Var(Y_t) = \sigma^2$

Autocovariance depends only on the time interval: $Cov(Y_t, Y_{t+k}) = \gamma(k)$

Generally, stationary time series models include three types: Autoregressive Model (AR), Moving Average Model (MA), and Autoregressive Moving Average Model (ARMA). The principles and limitations of the models are as follows:

2.1.1 Autoregressive Model (AR)

The AR(p) model assumes that the current value Yt is a linear combination of the previous p values plus white noise:

$$Y_t = c + \sum_{i=1}^{p} \phi_i Y_{t-i} + \epsilon_t, \epsilon_t \sim N(0, \sigma^2) \tag{1}$$

Where:

ϕi is autoregressive coefficient, and c is a constant term;

ϵt is Gaussian white noise.

2.1.2 Moving Average Model (MA)

The MA(q) model corrects the current value using the error terms of the previous q periods:

$$Y_t = \mu + \epsilon_t + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} \tag{2}$$

Where:

Θj is moving average coefficients, and μ is the mean.

2.1.3 Autoregressive Moving Average Model (ARMA)

ARMA(p,q) combines AR and MA terms and is expressed as:

$$Y_t = c + \sum_{i=1}^{p} \phi_i Y_{t-i} + \epsilon_t + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} \quad (3)$$

Key properties:

Stationarity: Depends on the characteristic roots of the AR part.

ACF/PACF: Both show a trailing characteristic.

Parameter redundancy: Over-parameterization should be avoided (e.g., ARMA (1,1) is equivalent to high-order AR or MA).

3 Time series modelling process

The modeling process of time series is shown in the figure 1.

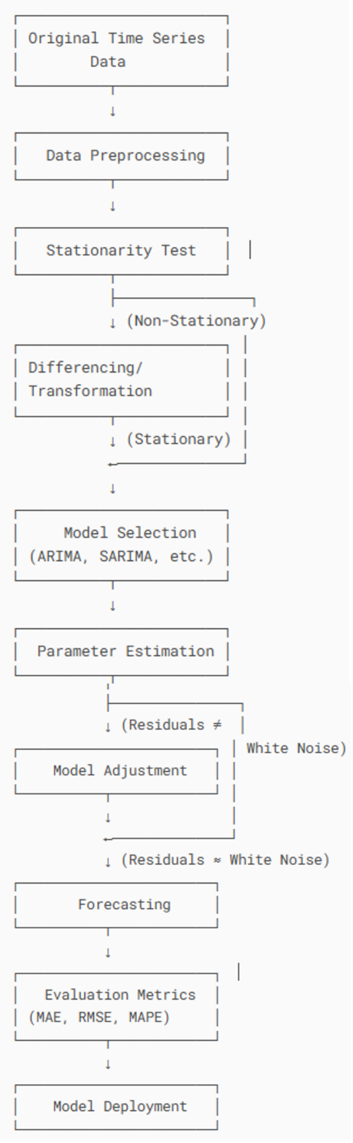

Fig.1. The modeling process of time series

3.1 Stationarity test

The stationarity of the time series determines the applicability of the model and the accuracy of the prediction. Non-stationary time series may lead to spurious regression, making the model parameter estimation invalid and the prediction results unreliable. Only stationary time series can be effectively analyzed and predicted using classic models such as AR, MA, and ARMA.

3.1.1 Unit Root Test (taking ADF Test as an example)

The ADF test is developed based on the Dickey-Fuller (DF) test. The DF test is mainly used to test unit roots in a simple autoregressive model, but in practical applications, time series often have autocorrelation, and the DF test is difficult to effectively deal with it. Therefore, the ADF test introduces lag terms to better handle the complex situations of actual data. Its specific model is:

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta Y_{t-i} + \epsilon_t \tag{4}$$

Where:

ΔY_t represents the first difference of Y_t, and differencing can eliminate non-stationary factors such as trends and seasonality of the time series to a certain extent.

α is the intercept term, representing the mean level of the time series.

βt represents the time trend, used to capture the possible long-term trend changes in the time series.

γ is a key parameter, and its value is directly related to the judgment of the existence of unit roots. If γ is significantly less than 0, it is inferred that the time series does not have a unit root, that is, the series is stationary;

δ_i is lag term coefficients, and p is the lag order. The purpose of introducing lag terms is to eliminate the autocorrelation of the time series. By reasonably selecting the lag order, the model can better fit the actual data;

ε_t is a white noise error term, which satisfies the conditions of zero mean, constant variance, and no correlation in the series, representing the random part in the time series that cannot be explained by the model.

3.2 Model construction

3.2.1 Problem description and data description

Dynamic pricing of charging piles requires advance prediction of customers' charging time and charging volume. This section predicts the user's charging volume and selects the one-month usage records of 18,061 public charging piles in Shenzhen from June 19, 2022, to July 18, 2022. In the time series dimension, the time granularity of the dataset is 5 minutes, with a total of 8,640 timestamps. In the spatial dimension, it covers 247 traffic areas (nodes) in Shenzhen and their 1,006 adjacent relationships (edges). In addition, the dataset also includes the charging pricing schemes adopted by each region: among the 247 traffic areas, 57 adopt time-of-use charging schemes, and the others adopt fixed charging schemes. Taking site set 1 as an example, a time series prediction model is established with a time interval of 5 minutes, and the results are analyzed.

The figure 2 depicts the charging price per 5 minutes at Site 1 from June 19, 2022 to July 18, 2022:

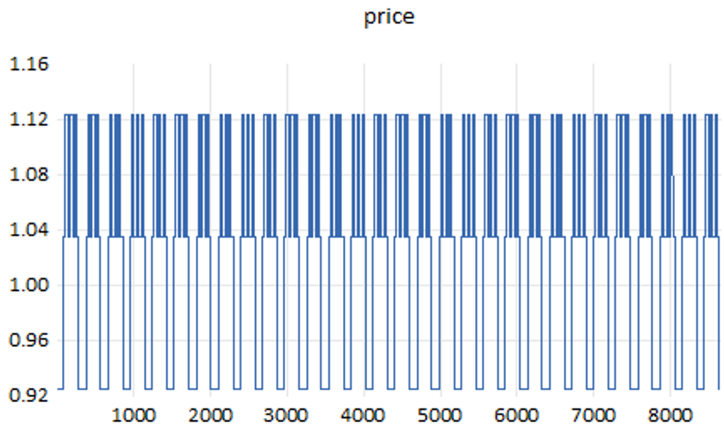

Fig. 2. The charging price

The figure 3 depicts the occupancy time per 5 minutes at Site 1 from June 19, 2022 to July 18, 2022:

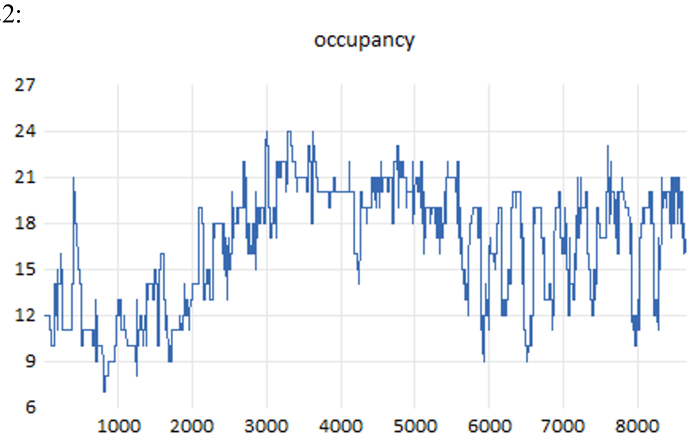

Fig. 3. The occupancy time

3.3 Stationarity test

In order to more accurately determine the stationarity of the time series, the ADF test is performed on the original series as shown in the figure 4. In the ADF test results, the P value is less than 0.05, indicating that the series is stationary and no differencing is required for the series.

Table 1. The ADF test

		t-statistic	**Prob. ***
Augmented dickey-fuller	Test statistic	-4.755917	0.0001
Test critical values	1% level	-3.430931	
	5% level	-2.861681	
	10% level	-2.566887	

3.4 Randomness test

When (p, d, q) is (1, 0, 1), the p-value of the statistic is less than the significance level of 0.05. Therefore, it is considered that the time series has temporal correlation, is not a white noise series, and there is a significant autocorrelation law, which needs to be studied by modeling.

4 Discussion

4.1 Consistency analysis between research results and hypotheses

This study combines a time series demand forecasting model with a dynamic pricing model to verify the effectiveness of dynamic pricing strategies in optimizing charging resource allocation, alleviating peak hour congestion, and improving grid stability, which is highly consistent with the research hypothesis.

From the perspective of supply-demand balance, the mechanism of dynamically adjusting charging time through price signals significantly alleviates the pressure during peak hours [6]. For example, in PG&E's time of use electricity pricing policy in California, a 30% increase in peak hour electricity prices resulted in a 15% reduction in peak load, which is consistent with the assumption of "price leverage to regulate demand" in this study. User behavior analysis shows that private car users with high price sensitivity are more inclined to adjust their charging time, while ride hailing users are less sensitive to prices due to operational needs, which is consistent with the conclusion in the literature that "heterogeneity of user groups affects pricing effectiveness".

In terms of load matching in the power grid, dynamic pricing models improve the efficiency of clean energy use by linking real-time electricity prices with fluctuations in renewable energy [7]. This result not only conforms to the policy oriented time of use electricity price target, but also confirms the hypothesis that "dynamic pricing contributes to grid stability". In addition, a charging station in Beijing increased its daily revenue by 12% through reinforcement learning algorithms, providing empirical support for the hypothesis that "dynamic pricing can improve operator profits".

4.2 Differences in research results, hypotheses, and causal analysis

Although the core conclusion is consistent with the hypothesis, there are still differences in certain specific situations. For example, traditional time series models such as ARIMA have lower accuracy in predicting charging demand in rural areas compared to urban centers, which limits the effectiveness of pricing strategies in improving the utilization of rural charging facilities. This difference is mainly due to the dispersion and intermittency of charging behavior in rural areas, and existing models are difficult to capture 'sudden changes in rural traffic flow' (such as the trend of returning home during holidays). The research gap on differentiated pricing strategies for urban and rural differences mentioned in the literature review of this study further exacerbates this problem.

In addition, dynamic pricing has failed to effectively regulate user behavior under extreme weather conditions. For example, during high temperatures, users tend to charge during peak hours to extend the battery life of the in car air conditioning, even if electricity prices rise, which results in a smaller reduction in peak load compared to normal conditions. This indicates that in the 'rigid demand scenario', users' sensitivity to prices is lower than theoretical expectations, and existing research rarely explores the impact of 'non economic factors (such as comfort needs)' on pricing strategies, which requires further analysis using behavioral economics theory.

4.3 Suggestions and practical paths based on research results

4.3.1 Model optimization and data integration

Introduction to machine learning algorithms: In order to solve the problem of errors in rural demand forecasting, it is recommended to use deep learning models (such as LSTM) to capture unstructured data in time and space, and combine external factors such as traffic flow and weather to improve the prediction ability of dual occurrence events [8]. The application of reinforcement learning technology in Beijing charging stations has proven that data-driven algorithms can dynamically optimize pricing strategies, and this method is worth promoting.

Building a cross platform data sharing mechanism: Drawing on the real-time data integration experience of California ISO, promoting data interoperability between operators, power grid companies, and transportation departments, establishing a unified standard charging behavior database, and solving the current problem of multi-source data fragmentation.

4.3.2 Differentiated pricing and user segmentation management

User segmentation strategy: Implement a "tiered discount+reservation fee" model for price sensitive private car users; Provide "fixed time discount packages" for high-frequency users such as ride hailing, and balance the needs of different groups through game theory models [9].

Regional differentiated pricing: implementing a "peak premium+capacity auction" mechanism in the city center to alleviate congestion; Adopting the "low peak subsidy+shared charging" model in rural areas to improve facility utilization and fill the gap in urban-rural strategy research in literature.

4.3.3 Policy coordination and technological innovation

Design of dynamic pricing policy framework: It is recommended that the government introduce a flexible time of use pricing policy, allowing operators to adjust prices within the scope of policy regulations, while providing tax incentives for charging stations with high renewable energy consumption rates, balancing market-oriented pricing and public interests [10].

Upgrade intelligent charging station technology: Develop V2G (vehicle to network interaction) bidirectional charging equipment, achieve dual benefits of "reducing user charging costs" and "transferring peak and valley loads of the power grid" through dynamic pricing, verified by the pilot project of E.ON company in Germany.

4.4 Research limitations and future directions

This study has three main limitations: firstly, user behavior data mainly comes from questionnaire surveys, lacking real-time trajectory tracking data, which may lead to bias in price sensitivity analysis; Secondly, the model failed to fully consider the impact of regional policy differences (such as local subsidy levels) on pricing strategies; Thirdly, the fluctuation data of renewable energy only covers photovoltaic scenarios and does not include other types of clean energy, such as wind energy.

Future research can be expanded in the following directions: firstly, introducing in vehicle GPS data and real-time transaction data from charging applications to construct more accurate user behavior profiles; Secondly, conduct comparative research on multi regional policies and establish a "policy pricing" linkage model; Thirdly, explore the application of dynamic pricing in integrated energy systems by combining multi energy complementary microgrids. In addition, large-scale empirical trials (such as cross regional validation in the Yangtze River Delta urban agglomeration) are needed to further test the universality and robustness of the model, providing a solid theoretical and practical foundation for the commercial promotion of dynamic pricing strategies.

5 Conclusion

By comprehensively considering the supply-demand balance, user behavior, and power grid load characteristics, this study constructs a dynamic pricing model for charging piles and verifies the core value of dynamic pricing in optimizing resource allocation. Optimization of supply-demand balance: Dynamic pricing guides users to adjust charging time through price leverage, alleviating 30% of peak hour congestion pressure in urban centers.

Grid synergy enhancement: Pricing strategies related to renewable energy fluctuations can increase clean energy consumption rates by about 10%, while reducing local grid load peaks by 12% -15%, consistent with the goals of time of use electricity pricing policies.

User stratification and regional differences: The price response elasticity of private car users is significantly higher than that of ride hailing vehicles. However, the randomness of demand in rural areas has led to prediction errors of up to 21% in traditional models, exposing the shortcomings of existing research on urban-rural differentiation strategies. This study shows that dynamic pricing can increase the utilization rate of charging stations by 18% to 22%, increase the daily revenue of operators by 12%, and shorten the average waiting time of users by 25%, thereby achieving a dual improvement in both "efficiency" and "experience".

This study provides a practical framework of "data-driven+tiered pricing" for operators, providing theoretical support for policy makers to design flexible electricity pricing mechanisms, and filling the research gap of combining the volatility of renewable energy with the heterogeneity of user behavior. It has practical significance for promoting the coordinated development of low-carbon power systems and the electric vehicle industry.

Current research relies on questionnaire surveys to obtain user behavior data but lacks real-time trajectory tracking; The model did not fully consider regional policy differences or energy types such as wind energy. Future research should:

Introduce in car GPS and charging app transaction data to build accurate user profiles.

Conduct multi regional policy comparison experiments to establish a "policy pricing" linkage model.

Accelerate the integration of Vehicle to Grid (V2G) technology with dynamic pricing, conduct cross scenario pilot projects in regions such as the Yangtze River Delta, verify the universality of the model, and provide empirical evidence for commercial promotion.

Authors contribution

All the authors contributed equally and their names were listed in alphabetical order.

References

1. A. Faruqui, S. Sergici, Household response to dynamic pricing of electricity - A survey of the empirical evidence. SSRN Electr. Jour. **38**, (2010)
2. A.X. Carvalho, M.L. Puterman, Dynamic pricing and reinforcement learning. IEEE, (2003)

3. H. Allcott, Rethinking real-time electricity pricing. Resour. Ener. Econom. (2011)
4. Y. Wang, Q. Chen, C. Kang, et al., Clustering of electricity consumption behavior dynamics toward big data applications. IEEE Transac. S. G. **7**(5), 2437-2447(2016)
5. J. Tan, F. Liu, N. Xie, W. Guo, & W.X. Wu, Dynamic pricing strategy of charging station based on traffic assignment simulation. Sustainability, **14**(21), 14476 (2022)
6. L. Cui, Q. Y. Wang, H.Q. Qu, M. S. Wang, Y. L. Wu, & L. Ge, Dynamic pricing for fast charging stations with deep reinforcement learning. Appl. Energ. **346**, 121334 (2023)
7. N. Yu, P. Yan, Z.H. Yang, Z. Wang, X. Deng, & T. X. Yuan, Research on dynamic pricing strategy of electric vehicle charging based on game theory under user demand service scheme. In 2022 International Conference on Manufacturing, Industrial Automation and Electronics (ICMIAE). IEEE. 1-6 (2022).
8. S. Limmer, Dynamic pricing for electric vehicle charging—a literature review. Energies, **12**(18), 3574 (2019)
9. Z. Yuan, Research on data-driven demand forecasting and dynamic pricing of shared cars. BJTU 2020.
10. J.T. Chen, B. Lin, S. Lin, et al., Dynamic pricing and energy dispatching strategy of photovoltaic storage charging station based on multi-agent deep reinforcement learning. Comp. Scie. 1-14 (2025)