Study on Time Series Forecasting Algorithm of Power Users' Electricity Charges Based on Support Vector Machine

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Abstract. When forecasting the electricity charges of power users, the accuracy of the forecast results is low because of the correlation between the actual electricity consumption time series. Therefore, the research on the time series forecasting algorithm of power users' electricity charges based on support vector machine is proposed. In order to ensure the reliability of the forecast results, the time series of electricity tariff data is decomposed from the perspectives of long-term trend, periodicity, randomness, comprehensiveness, stability and short-term. Combined with the decomposition results, the power consumption load of users at different times is regarded as the phase point in the chaotic phase space, and the chaotic characteristics of the time series data of power users' electricity consumption behavior are determined by using the maximum Lyapunov exponent. After training the support vector machine through the phase point and reconstructing the phase space of all users' electricity consumption load at different times with the help of historical load data, In the test results, the difference between the predicted results of the overall electricity bill and the actual electricity bill is always stable within 15.0 yuan.

Keywords: Support vector machine; Time series of electricity charges of power users; Decomposition treatment; Combined with decomposition; Electric load; Chaotic phase space; Maximum Lyapunov exponent;

1 INTRODUCTION

Under the background of the rapid development of society, the corresponding demand for power and energy is also showing a growing trend, which brings the most direct impact that the demand for power from power supply companies is getting higher and higher [1-3]. For power supply enterprises, one of the most important factors affecting the flow of funds is the electricity fee income. On the one hand, it is the most direct embodiment of power commodity value, on the other hand, it is also one of the important economic indicators of power supply quality evaluation of power enterprises, and it is the embodiment of operating results in monetary form [4-5]. On this basis, it is of great significance to accurately predict the time series of electricity charges,

B. K. Kandel et al. (eds.), *Proceedings of the 2023 8th International Conference on Engineering Management (ICEM 2023)*, Atlantis Highlights in Engineering 23,
https://doi.org/10.2991/978-94-6463-308-5_6

whether from the perspective of improving the economic benefits of power enterprises or realizing enterprise reproduction [6-7]. By analyzing the current situation of electricity tariff forecast, it can be seen that most power companies still have room for further improvement in the related system construction of electricity tariff forecast, and at the same time, there are obvious deficiencies in scientificity and perfection. The most direct impact brought by this is that the accuracy and effectiveness of the forecast results are difficult to meet the objective needs of power enterprise management [8-10], which has a negative impact on the stable development of power enterprises to some extent. It is extremely necessary to accurately forecast the daily, monthly, quarterly and annual electricity fee income in combination with the capital demand for maintaining the reproduction process of power enterprises. From the perspective of electricity revenue data, due to the influence of many factors, the corresponding time series has different degrees of fluctuation, and it is far from enough to predict it only by simple statistical analysis and empirical analysis. Among them, the forecasting method based on time series model can effectively forecast the trend of electricity cash flow, but the forecasting effect will obviously decrease when the electricity cash flow fluctuates under the influence of many factors. Although the method based on machine learning has high accuracy in forecasting the actual cash flow of electricity charges, its forecasting process is complicated and the application stage is difficult.

Combined with the above analysis, this paper puts forward the research on the time series forecasting algorithm of power users' electricity charges based on support vector machine, and analyzes the forecasting performance of the designed algorithm through comparative testing.

2 DESIGN OF TIME SERIES FORECASTING ALGORITHM FOR POWER USERS' ELECTRICITY CHARGES

2.1 Time series decomposition of electricity fee data

Time series data is statistical data arranged in time order. By observing the time series, we can see the changing way of the electricity charge data with time and the state of each period. The user electricity charge data is the time series data generated in the power system operating environment, and it has other characteristics except the most basic time series characteristics. In order to ensure the reliability of the forecast results, firstly, the time series of electricity fee data is decomposed and the decomposition results shown in Table 1.

Table 1. Time Series Decomposition Results of Electricity Fee Data

Serial Number	Decomposition results	characteristic	notes
1	Long term trend	The value of electricity bills will change over time, showing a slow and long-term continuous upward, downward, and flat trend of the same nature.	In recent years, with the needs of social production and daily life, the electricity consumption has increased, and the highest load power of the power grid has been increasing year by year, indicating a long-term upward trend in electricity bills.
2	Periodicity	Electricity bill data shows significant periodic changes, with similar load values at the same time point each year.	For example, on statutory holidays of each year, the electricity bill value will enter a lower level on this day.
3	Randomness	Electricity bill data may experience random, irregular, and irregular changes during certain periods, mainly caused by various random and uncertain external factors, such as politics, economy, and meteorology.	
4	Comprehensive	The changes in electricity bill data are usually caused by the superposition of multiple variables, so when predicting electricity bills, efforts are generally made to filter out uncontrollable irregular changes, highlighting their trend and periodicity characteristics.	For example, when building a prediction model, data is usually preprocessed and anomaly detected. By removing Outlier generated by abnormal events, the long-term trend and periodicity of the overall data are more obvious.
5	Stability	Load data has stability in time distribution, and there is generally no significant difference between the load data at each time point and the load data at adjacent times before and after it.	
6	Proximity	Load data has the characteristic of "near large far small", with the current load value closely related to the recent historical load value, and less related to the non periodic synchronous load value of the long-term historical time	

According to the way shown above, the time series of electricity fee data is decomposed from the perspectives of long-term trend, periodicity, randomness, comprehensiveness, stability and recency, which provides reliable guarantee for subsequent electricity fee forecasting.

2.2 Support Vector Machine-based Electricity User Electricity Fee Forecasting

This paper takes the maximum Lyapunov exponent, a parameter to judge the existence and characteristics of chaos, as the implementation basis. Among them, the larger the maximum Lyapunov exponent value, the stronger the chaotic characteristics of the time series data representing the power consumption behavior of power users. On this basis, the time series data of chaotic power users' electricity consumption behavior is set as x_i , then, based on the theory of reconstructed phase space, multi-dimensional phase space (the overall composition of power load at different times) can be established. The time series data (phase points) corresponding to the power consumption behavior of any power user in the phase space can be expressed as

$$s(t_1) = [x(t_i), x(t_i + \tau), \Lambda, x(t_i + (n-1)\tau)] \quad (1)$$

Among them, $s(t_1)$ represents phase space, and any power user is in t_1 power consumption behavior data at all times, τ represents a delay parameter, n represents the dimension of the overall composition of the electric load. On this basis, when the power load forecasting is based on the chaotic analysis support vector machine model, the specific operations in each stage are shown in Table 2.

Table 2. Power load forecasting methods based on support vector machine model

Execute steps	perform operations
step 1	Selecting the optimal delay time and embedding dimension using chaotic methods
step 2	Establish multidimensional Phase space of chaotic time series to form learning samples and predictive values
step 3	Establishing an objective function for dual optimization of user electricity load support vector machines using training samples
step 4	Establishing an objective function for dual optimization of user electricity load support vector machines using training samples
step 5	Substitute the parameter support vector machine that meets the constraint conditions into the overall power load phase feature space and calculate the corresponding dot product
step 6	Using samples to predict the load at a certain time or times in the future

According to the above-mentioned way, the phase space of electricity load of all users at different times is reconstructed with the help of historical load data, and the load situation at a certain point or a certain point is predicted, which provides a reliable basis for the subsequent electricity time series. Among them, the specific prediction mode can be expressed as follows

$$C(t_1) = \sum s_i(t_1) * c(t_1) \tag{2}$$

Among them, $C(t_1)$ express the electricity bill at the time of t_1, $c(t_1)$ express the unit price of electricity at the time of t_1. It should be noted that the unit price of electricity at different times is based on the actual power management in the forecast area.

According to the way shown above, the accurate prediction of electricity time series is realized.

3 APPLICATION TESTING

3.1 Test preparation

In the test results, in addition to the time series forecasting algorithm of power users' electricity charges based on support vector machine designed in this paper, the time series forecasting model and machine learning forecasting algorithm are also set up for comparative test in the same environment. Among them, the test environment is based on an actual power supply network, which covers a total of 1,250 power users, of which 1,231 are effective users (users with electricity consumption behavior). Among them, in the historical data, the peak value of the fade-in electricity fee is 1,365.24 yuan, and the valley value is 562.45 yuan. Due to the instability of users, the single-day electricity fee fluctuates in the range of 20.0-500.0 yuan. On this basis, firstly, the power consumption data of one month in a chain-like period and one month in a year-on-year period are obtained as training data. In the forecasting results, the electricity bill for 10 consecutive days is taken as the forecasting target, and the forecasting performance of different algorithms is analyzed by comparing with the actual electricity bill.

3.2 Test results and analysis

On the basis of the above, the development of electricity charges under different forecasting algorithms is counted respectively. Within 10 days, the forecasting results of different algorithms are shown in Figure 1.

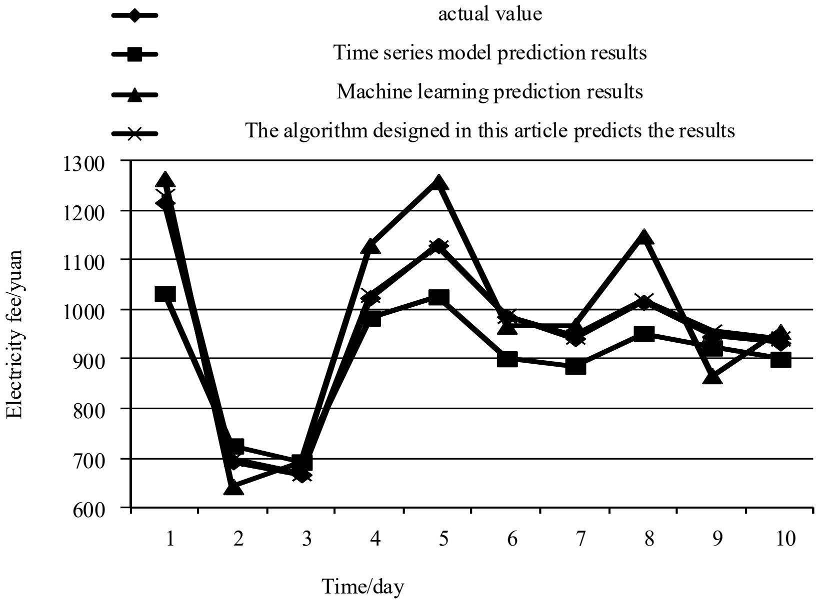

Fig. 1. Comparison chart of prediction results of different algorithms

By analyzing the test results of the three algorithms combined with the test results shown in Figure 1, it can be seen that the predicted results of different algorithms are different from the actual electricity bill, but the specific differences show different characteristics. In the test results of the time series forecasting model, the overall forecasting results show a trend higher than the actual electricity bill, in which the maximum error reaches 183 yuan (the first day of the test) and the minimum error reaches 23 yuan (the ninth day of the test). In the test results of the machine learning prediction algorithm, the overall prediction results show a trend lower than the actual electricity bill, with the maximum error reaching 134 yuan (the eighth day of the test) and the minimum error reaching 23 yuan (the tenth day of the test). In contrast, in the test results of the actual forecasting algorithm in this paper, the difference between the overall forecasting results and the actual electricity bill is always within 15.0 yuan, in which the maximum error is 14 yuan (the first day of the test) and the minimum error is only 2 yuan (the sixth day of the test). On this basis, the prediction results of different algorithms are analyzed from a macro perspective. During the 10-day test, the actual total electricity bill is 955.20 yuan, in which the prediction results of time series prediction model are higher than the actual value of 530.0 yuan, and the prediction results of machine learning prediction algorithm are lower than the actual value of 344.0 yuan. The prediction results of the algorithm designed in this paper are lower than the actual value of 54.0 yuan, which is obviously superior to the control group in accuracy.

4 CONCLUSION

Influenced by the characteristics of the actual electricity consumption form of power users, there is a big difference between the forecast of electricity charges and the actual situation, which not only affects the development of related power management, but also is extremely unfavorable to the fund management of power enterprises. In this paper, a time series prediction algorithm of power users' electricity bill based on support vector machine is proposed. After decomposing the time series of electricity tariff data from many angles, the chaotic phase space is used to analyze the user's electricity consumption load at different times, which is used as the training data of support vector machine. Finally, according to the load at the target time and the unit price state of electricity price, the electricity tariff is predicted, and the accurate forecast of electricity tariff is realized. With the help of this paper's design and research on the time series prediction algorithm of power users' electricity charges, I hope it can provide reference value for the actual capital flow management of power enterprises.

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