Information Systems and Economics (2025)
Clausius Scientific Press, Canada

DOI: 10.23977/infse.2025.060101
ISSN 2523-6407 Vol. 6 Num. 1

Research on prediction technology of material price based on long- and short-term memory model

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Keywords: Long- and short-term memory model, Prediction technology, Material price

Abstract: With the rapid change of global macroeconomic condition and the adjustment of industrial structure, to carry out research on technology of dynamic prediction of power material prices is necessary. This paper uses a long- and short-term memory model to forecast the material price in order to adapt to new industrial structure and as a result to improve material price forecasting ability of power companies. The prediction experiments of material price and its fluctuation range are carried out, including the prediction experiment of electric power material benchmark price and the prediction experiment of electric power material price fluctuation range. Based on the experimental results, the prediction results of LSTM model can meet the requirements of improving the ability of material price prediction and fluctuation range prediction of power companies.

1. Introduction

Since 2021, the price of bulk commodities has risen for several times, which has a certain impact on the accuracy of the power company's material pricing and planning. Under the combined influence of multiple profit reduction factors, such as the macroeconomic downturn and the narrowing of electricity price, the operating pressure of power companies is gradually increasing, and result of a corporate profit level cut down. Currently, the Power companies are increasingly sensitive to change in material prices as the huge influence of external factors, and it is urgent to strengthen the ability of price risk control in project pricing and material purchase.

Therefore, aiming at the new industrial structure, the research on the key technology of material price dynamic prediction of power companies is carried out. In this paper, we aim to use the long- and short-term memory model to improve the technology of material price and fluctuation range prediction to reach an objective of improve the existing power company material price forecasting ability and encourage high-quality development of new power systems.

2. Literature review

In the aspect of time series prediction, the traditional prediction method adopts econometric model to carry out statistical regression. The commonly used econometric models include GARCH model and ARIMA model. For example, Zhao Guoshun in 2009 firstly used the GARCH model and

ARIMA model to make short-term prediction on the stock price volatility trend [1].

Deep learning is also introduced to forecast modelling in the field of price prediction. Zeng Lifang established BP neural network model, PCA-BP neural network model, GA-BP neural network model and ARIMA model to forecast the closing price. The GA-BP neural network prediction effect is better [2]. Ding Fangyi show that the accuracy of product price prediction results obtained by using RNN model can reach 84%, which provides a constructive basis for improving the accuracy of engineering product price prediction [3]. Further, Yuan Mingjuan, and Sun Ruoying used long- and short-term memory model to predict price trend, the experimental results show compared with the traditional prediction model, the LSTM model has better performance. [4].

Foreign research has also experienced a gradual transition from traditional model to deep learning model. In terms of traditional models, Ariyo built a stock price prediction model. The results show the ARIMA model has strong short-term prediction potential [5].

With the advent of deep learning models, researchers have begun to experiment with using neural networks to make predictions. Adebiyi tested the predictive performance of ARIMA and artificial neural network models. The results show that deep learning model is superior to ARIMA model [6]. Rather in 2015 proposed a mixed model to forecast stock returns. The experimental results show the hybrid prediction model is better than that of cyclic neural network [7]. Later, researchers further tried LSTM network. M Roondiwala et al. modelled and predicted the stock returns of NIFTY 50 by using cyclic neural network and LSTM. This result can effectively help investors, analysts or anyone who is interested in investing in the stock market to better understand the future situation of the stock market [8].

3. Methodology

3.1. Forecasting method of benchmark price of electric power materials

3.1.1. The modelling idea of prediction model

This part aims to predict the price of power materials in the next period based on the accumulated historical transaction data of State Grid Corporation and give the benchmark price fluctuation range of power materials under different risk control objectives according to the historical price fluctuation characteristics.

Benchmark price forecast is divided into three parts: task definition, model construction and test results.

Before modelling, the objective of prediction task should be clearly defined. First, it is necessary to understand the change trend of the price of power materials in the future, and second, it is necessary to provide effective riveting points for the subsequent price fluctuation range. Compared with the average or weighted average, the median monthly transaction price has good robustness and representativeness and is less affected by abnormal fluctuations. It can effectively represent the trend of the bid price and provide an effective benchmark for the price range. Therefore, this task selects the median historical transaction price as the forecast target, that is, our forecast target is the median price of the next batch of transactions.

Then, the inputs to the model need to be defined. The input of this forecast task is the historical transaction data of 80,000 kinds of materials of the company, including transaction volume, total price and quantity including tax. Based on historical transaction information, the output of the forecast task is the corresponding median transaction price.

Further, it is necessary to clarify the evaluation criteria of the model before modelling. The evaluation criteria of the model should be considered in three aspects: First, since there are many types of materials recruited by the grid company, the prices of each type of materials fluctuate in different quantities, so the model evaluation should be compatible with both high-unit price materials and low-unit price materials. Second, the total investment amount of each category of materials is different. For the materials with a high total investment amount, we require a more accurate forecast. While the total investment is low, and the historical transaction data accumulate relatively lack of materials, we can moderately relax the accuracy of its forecast; Third, the upward forecast risk of the forecast price should be less than the downward forecast risk, that is, for the same material, the risk caused by the predicted value of the price of electric power material being higher than the actual transaction value is lower than the risk caused by the predicted value of the reference price being lower than the actual transaction value. Logarithmic error is adopted as the evaluation index of the model by Normalized Weighted Root Mean Squared Logarithmic Error (NWRMSLE). Among them, normalization ensures that materials with different unit prices have the same impact; The weight is logarithmic historical investment, which ensures that the predicted value of large investment is more accurate. Taking logarithms reduces the upside risk and magnifies the downside risk of price forecasts. Finally, we need to divide the original data into training data and validation data. The model was fitted through the training set data and predicted in the test set. The merits and disadvantages of the model were evaluated by NWRMSLE. The smaller the NWRMSLE, the better the prediction effect of the model.

Prediction model construction: This part is mainly divided into two parts: feature engineering and model construction. Feature engineering is concerned with the quality of information extracted from the underlying data and determines the upper limit of the prediction of a single base model. Different base models affect the mining of basic information from different angles.

In the feature engineering part, on the basis of extracting the general time characteristics of year and month, the statistical characteristics of the mean, median and standard deviation of the trading volume, transaction price of the last batch, half a year, one year and history are extracted by sliding windows of different scales as the basis of the prediction model which is showed in Figure 1.

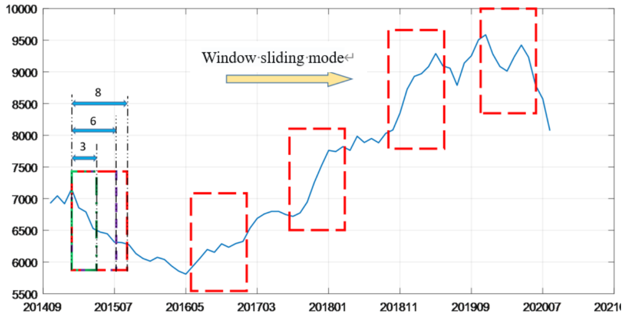

Figure 1: Sliding window extracts feature diagram

In the selection of prediction model, due to the obvious timing characteristics of material recruitment data, the long- and short-term memory neural network is selected as the base model, and pytorch, which has fast computing speed, high efficiency and can effectively support GPU parallel computing, is adopted as the model development framework, so as to ensure good performance even when the data scale continues to expand.

3.1.2. Modelling result

LSTM is a variant of recursive neural network (RNN), which was proposed by Sepp Hochreater and Jurgen Schmidhuber in 1997[9]. Gradient vanishing and gradient explosion may occur when RNN processes distant sequences, which makes it lose the perception ability of distant moments. However, the unique structure of LSTM can effectively solve the above problems in the training process of RNN. As shown in Figure 2-4, the LSTM cell unit consists of gate units and memory units.

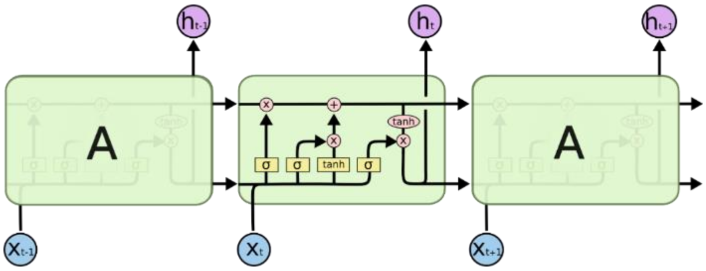

Figure 2: LSTM Structural Drawing

Where, represents the neural network layer, represents bit-by-point operation, and represents vector transmission. The key to the long - and short-term memory model lies in the transmission of cellular states along the horizontal line.

The gate unit includes input gate, output gate and oblivion gate. The specific structure is as follows:

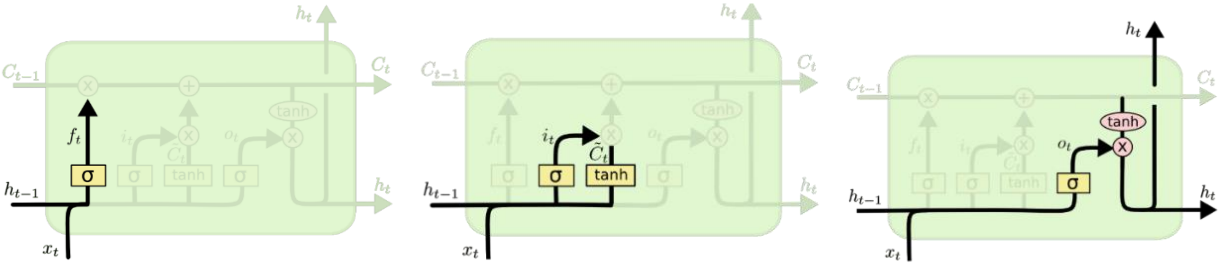

Figure 3: Oblivion Gate, Input Gate and Output Gate Structural Drawing

The entire process of memory unit is to update the state of memory unit at the previous moment, that is, to discard useless information and add new information. Figure 4 shows the structure.

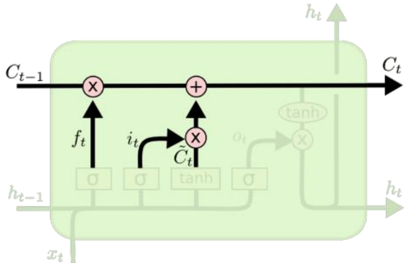

Figure 4: Memory Unit Structural Drawing

3.2. Adaptive price range calculation method

In the price prediction section, according to the accuracy principle, we need to control the error weighted logarithm square root (NWRMSLE) of the predicted price rivet point (median transaction price) as small as possible. At the same time, it is necessary to consider the upstream and downstream risks of the price range. The upward risk refers to the resistance encountered after the index breaks upward, and the greater the resistance, the greater the risk; the downward risk refers to the strength of the support force after the index breaks downward, and the stronger the support, the greater the risk; the vice versa. On the basis of considering the upstream and downstream risks of the fluctuation range, we mainly grasp the principles of inclusiveness, adjustability and adaptability in determining the fluctuation range of power materials prices. The inclusive principle means that the scheme of the price range needs to adapt to the complex data of various materials. The principle of adjustability means that the price range can realize the adjustability from wide to narrow of weak control, middle control and strong control according to the management objectives in different periods. The adaptability principle means that the price range can adjust the output adaptively according to the fluctuation characteristics reflected in the historical transaction data of each material. Based on the above requirements and principles, this project designs the scheme of reference price fluctuation range:

First, according to different management objectives, the upper and lower interval widths and corresponding quantile w of the fluctuation of forecast results were determined. In the design scheme of this project, under weak control, the quantile w_h corresponding to the upward interval is selected as 0.99995, while the quantile w_l corresponding to the downward interval is selected as 0.00005. In the case of central control, the quantilew_h corresponding to the ascending interval was selected as 0.875, while the quantile w_l corresponding to the descending interval was selected as 0.125. In the case of strong control, the quantile w_h corresponding to the upward interval is selected as 0.75, and the quantile w_l corresponding to the downward interval is selected as 0.25.

Then, calculate the w quantile $P_{m,w}$ of the average transaction price X of the material in monthly m:

$$P_{m,w} = \varphi(w,m) \tag{1}$$

Finally, assuming that the number of forward months is T and R is the risk coefficient or risk preference, the upper bound $C_{h,m}$ and lower bound $C_{l,m}$ of the price fluctuation interval predicted by monthly m are given through the index weighted average calculation, wherein the upper and lower bound $C_{h,m}$ and $C_{l,m}$ between the weak control zones are:

$$C_{h,m}=\sum_{e^{-t}}^{t=1} T \left(P_{m-t,0.99995} - P_{m-t,0.5}\right)/R_{h,m} \sum_{e^{-t}}^{t=1} T \tag{2}$$

$$C_{l,m}=\sum_{e^{-t}}^{t=1} T \left(P_{m-t,0.5} - P_{m-t,0.00005}\right)/R_{l,m} \sum_{e^{-t}}^{t=1} T \tag{3}$$

The upper and lower bounds $C_{h,m}$ and $C_{l,m}$ of the central control interval are:

$$C_{h,m}=\sum_{e^{-t}}^{t=1} T \left(P_{m-t,0.875} - P_{m-t,0.5}\right)/R_{h,m} \sum_{e^{-t}}^{t=1} T \tag{4}$$

$$C_{l,m}=\sum_{e^{-t}}^{t=1} T \left(P_{m-t,0.5} - P_{m-t,0.125}\right)/R_{l,m} \sum_{e^{-t}}^{t=1} T \tag{5}$$

The upper and lower bounds $C_{h,m}$ and $C_{l,m}$ between strong control zones are:

$$C_{h,m}=\sum_{e^{-t}}^{t=1} T \left(P_{m-t,0.75} - P_{m-t,0.5}\right)/R_{h,m} \sum_{e^{-t}}^{t=1} T \tag{6}$$

$$C_{l,m}=\sum_{e^{-t}}^{t=1} T \left(P_{m-t,0.5} - P_{m-t,0.25}\right)/R_{l,m} \sum_{e^{-t}}^{t=1} T \tag{7}$$

Since the quantile of 0.75, 0.5 and 0.25 is a statistic with strong robustness, the three values of w in this scheme are used to calculate the fluctuation range of reference price in the case of strong control, so as to determine the complex historical fluctuation of different materials simply and effectively. At the same time, this method can give differentiated weights to the interval widths in different periods by means of index weighting, which has strong adaptability to the new transaction data.

A boxplot is a statistic used to show the dispersion of a set of data. The control intensity of medium strong control, medium control and weak control approximately correspond to the median line, inner limit and outer limit of the boxplot. Under ideal conditions (the benchmark forecast price is the median, and the transaction price conforms to the overall distribution), the inclusion capacity of strong control, middle control and weak control is shown in the figure 5 below.

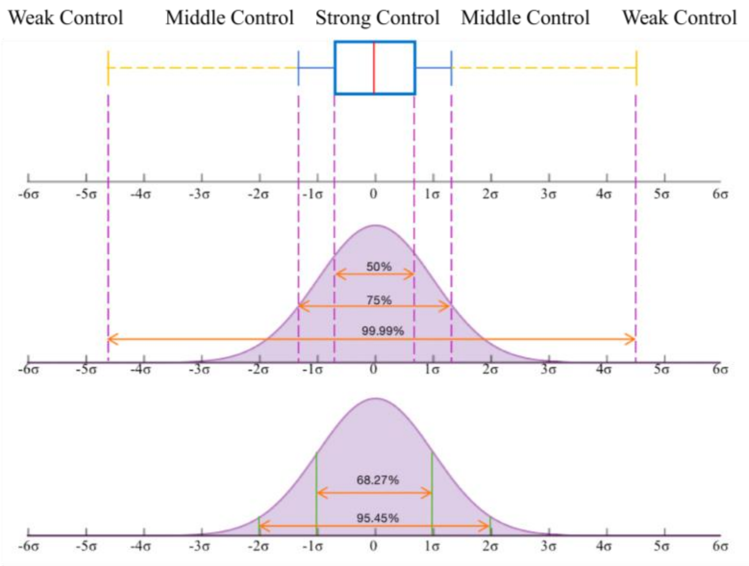

Figure 5: Box Diagram

4. Experiment result

The predicted target of this experiment is the bidding price of materials in March 2023, including 6 categories of primary equipment, secondary equipment, energy substation secondary equipment, communication equipment intelligence, device materials, instruments and instruments, 40 medium categories, 206 sub-categories, a total of 22,695 pieces of bidding data of 1,954 material codes. The training samples were 120,000 batches purchased from 2016 to December 2022. After the training and prediction of the sample data, a total of 15,543 items of material code price were obtained. Compared with the forecast target of this time, only 477 items of 181 items of material code data failed to output the result. The output rate of material code prediction results was 90.74% and that of purchase items was 98.03%. In terms of accuracy of prediction results, the actual total purchase of this forecast target is 10.744 billion yuan, the total purchase amount is 10.183 billion yuan after excluding the items that have not output forecast results, and the total forecast of reference price is 9.96 billion yuan, with prediction error of -223 million yuan and error rate of -2.19%. The classification error rate is shown in the following table 1:

Table 1: Classification presentation of the third batch of forecast results in 2022

Material Category	Total Purchase of Materials (billion)	Forecasted Total Amount (billion)	Deviation	Rate of Deviation
Primary Equipment	4.05	3.846	-0.204	-5.04%
Secondary Equipment	0.451	0.514	0.063	14.06%
Intelligent Substation Secondary Equipment	0.49	0.508	0.018	3.77%
Installation Material	4.91	4.801	-0.109	-2.22%
Communication Device	0.143	0.147	0.004	2.80%
Instrument	0.139	0.144	0.005	3.60%
Total	10.183	99.60	-0.223	-2.19%

5. Conclusion

In conclusion, according to the established research objectives, this paper introduced the long- and short-term memory model to study the material price forecasting model, algorithm and mechanism that adapt to the new industrial structure. In order to adapt to the dynamic price interval prediction scheme of electric power materials, based on the benchmark price prediction by using the long- and short-term memory model, considering the compatibility principle, adjustable principle and self-adaptability principle, and constrained by the historical price fluctuation law of materials, the reasonable boundary of the upward and downward price intervals is dynamically designed. It makes the scheme of price interval adapt to the complex data of various materials and ensures that the price interval can adjust the output adaptively according to the fluctuation characteristics reflected in the historical transaction data of each material. At the same time, it also designs the mechanism that the price interval can adjust dynamically according to the management objectives and control objectives in different periods. Based on the experimental results, the prediction results of long- and short-term memory model can meet the requirements of improving the ability of material price prediction and fluctuation range prediction of power companies.

References

[1] Zhao G.(2009). Research on Stock Price Trend Prediction Based on Time Series Analysis (Master Dissertation, Xiamen University)

[2] Zeng Lifang, Li Liping & Jiang Shaoping (2022) Stock price prediction based on BP neural network. Journal of Yunnan Minzu University (Natural Science Edition).

[3] Ding F.(2022). Price trend prediction of an engineering product based on RNN model. Science and Technology Innovation (07),77-80.

[4] Yuan M. & Sun R.(2021). Research on price prediction of agricultural commodities based on LSTM neural network. Straits Technology and Industry (11),43-47+60.

[5] Ariyo, A. A., Adewumi, A. O., & Ayo, C. K. (2014, March). Stock price prediction using the ARIMA model. In 2014 UKSim-AMSS 16th international conference on computer modelling and simulation (pp. 106-112). IEEE.

[6] Adebiyi, A. A., Adewumi, A. O., & Ayo, C. K. (2014). Comparison of ARIMA and artificial neural networks models for stock price prediction. Journal of Applied Mathematics, 2014.

[7] Rather, A. M., Agarwal, A., & Sastry, V. N. (2015). Recurrent neural network and a hybrid model for prediction of stock returns. Expert Systems with Applications, 42(6), 3234-3241.

[8] Roondiwala, M., Patel, H., & Varma, S. (2017). Predicting stock prices using LSTM. International Journal of Science and Research (IJSR), 6(4), 1754-1756.

[9] Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. Neural Computation, 9, 1735-1780.