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Prediction and Analysis of USD /JPY Exchange Rate Based on BP Neural Network

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Abstract. One of the most important variables in the global financial market is the exchange rate, which is the ratio of change between the currencies of two countries. Moderate currency devaluation can stimulate exports, promote economic growth. This paper uses the back propagation (BP) neural network model to predict the short-term exchange rate of USD /JPY. The research result shows that the exchange rate price prediction trend is basically consistent with the real value trend, and the relative error of USD /JPY is extremely small, controlled within 0.8%, which shows that the superficial BP neural network is relatively accurate in the short-term exchange rate forecast of USD /JPY, which has a positive research impact, that is, it provides help for financial analysis. However, it has certain limitations in terms of timeliness, such as the extension of the prediction time, the prediction accuracy may decrease. Future research may need to be combined with other models and methods to improve its reliability.

1 Introduction

In the context of global economic integration, fluctuations in the exchange rates of USD /JPY have a profound impact on international trade, capital flows, and financial market stability. Accurate analysis and forecasting of exchange rates are of great significance for formulating relevant economic and financial policies also for enterprises to avoid foreign exchange risks [1]. The exchange market is a complicated system, evolving, and nonlinear dynamic system [2]. In terms of short-term forecasting, this market remains one of the most challenging [3]. Traditional forecasting methods struggle to fully capture market dynamics, and there is an urgent need for efficient forecasting models. The back propagation (BP) neural network model plays a role in improving forecasting accuracy to obtain the best forecasting results in foreign exchange rate forecasting [4]. In previous research cases, Jitian Yang analyzed the application of genetic algorithms in exchange rate prediction based on the BP neural network [5]. Both Yuanyuan Xu and Ting Cheng took RMB and USD as examples to establish regression forecasting models for exchange rates from the perspective of relevant influencing factors and conducted an exchange rate forecasting analysis [6,7]. Meanwhile, Ye Sun used data from 2005 to 2010 to establish the BP neural network model to forecast future RMB exchange rates [8]. Jingwei Deng utilized MATLAB to construct neural network functions for forecasting foreign exchange rates [9]. All these studies yielded valuable research data

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and methods. This paper will use the BP neural network model to forecast USD/JPY exchange rate, compare the forecasted values with the actual values, analyze the accuracy of the BP neural network model in forecasting exchange rates, and summarize the advantages and disadvantages in this context. This paper first introduces the research method, proceeds with project implementation, then interprets and analyzes the experimental results, and finally summarizes and outlines future prospects.

2 Research methods

2.1 Design scheme

In order to evaluate the prediction effect of the superficial BP neural network on the short-term exchange rate of the dollar against the yen, this article categorizes sample data into four types. The opening price, closing price, highest price and lowest price of the 1, 3, 5 and 10 days are the input, and the corresponding closing price of the 2, 4, 6 and 11 days are the output. Through MATLAB, a superficial BP neural network is established for training, and then the prediction experiment is carried out. Finally, the prediction effect of the superficial BP neural network in these four situations is summarized by comparing and analyzing its advantages and disadvantages in short-term exchange rate forecasting [10].

2.2 Data collection and collation

This paper collects a total of 13,847 groups of data excluding holidays from 1971/01/05 to 2024/09/06 through the website https://cn.investing.com [11]. In order to weaken the adverse effects of outlier data, the data set is also normalized [12]. According to the design scheme, this paper uses the data of the first n (n=1,3,5,10) days to train and predict the closing price of the n+1 day, so the downloaded data also needs to be reconstructed. For example, for the third type, the initial 13847*4 matrix needs to be converted into the 13842*20 matrix. Similarly, the remaining three types of reconstructed matrices can be obtained. For the four situations mentioned above, 400 datasets were picked as the testing sample, with the rest categorized into the training sample, also the corresponding test matrix and training matrix were established.

2.3 Network training and prediction

This paper uses the train function and the sim function in MATLAB to train and predict the above-mentioned BP neural network, and inversely normalize the output results of the test set to calculate its relative error with the real value.

3 Experimental process

3.1 Establish a BP Neural Network

According to the universal approximation theorem, a three-layer BP neural network can theoretically approximate continuous functions within a closed interval with arbitrary accuracy. Therefore, it is imperative to simplify the intricacies of the neural network architecture [13], this paper establishes a superficial BP neural network with only one hidden layer to train the exchange rate data of USD/JPY.

To ascertain the optimal number of nodes within the hidden layer of a neural network architecture, the paper can first use some existing empirical formulas to estimate a general range. Then, the paper selects the ideal quantity of nodes by comprehensively considering the training speed, training error, and testing error. Specifically, based on empirical formulas, this paper obtains a rough range of 4-15 for the number of hidden layer nodes of type three (with appropriate extensions in the actual implementation). By comparing the maximum relative test errors under different numbers of nodes, the paper finally adjusts the number of nodes in the hidden layer to twelve (Fig. 1) [14]. The training epochs are set to 1000, the learning rate is 0.01, and the target error is 0.000001. It is established using the newff function.

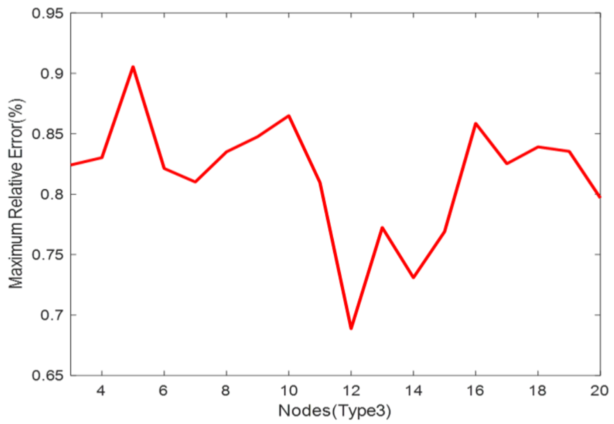

Fig. 1. The correlation between the highest relative error and the number of hidden layer nodes, type 3

3.2 Comparison experiment

Repeating the above experimental steps can obtain a superficial BP neural network for the remaining three types. In order to compare the accuracy of the superficial BP neural network in predicting the short-term exchange rate of USD/JPY, this paper has conducted 20 repeated experiments and collected the corresponding relative error mean of the test set (Table 1) and the number of training rounds (Table 2).

Table. 1 Test set average relative error

TEST SET MEAN RELATIVE ERROR				
SAMPLES	TYPE1	TYPE2	TYPE3	TYPE4
1	0.001526	0.001523	0.001619	0.001483
2	0.001597	0.001526	0.001552	0.001405
3	0.001533	0.001451	0.001566	0.001619
4	0.001474	0.001507	0.001688	0.001736
5	0.001524	0.001436	0.001706	0.001641
6	0.001467	0.001625	0.001599	0.001711
7	0.001522	0.001561	0.001435	0.001758
8	0.001505	0.001544	0.001648	0.001573
9	0.001482	0.001474	0.001623	0.001709
10	0.001465	0.001552	0.001447	0.001538

11	0.001520	0.001501	0.001597	0.001362
12	0.001527	0.001628	0.001597	0.001503
13	0.001509	0.001620	0.001546	0.001619
14	0.001508	0.001548	0.001546	0.001609
15	0.001519	0.001424	0.001564	0.001563
16	0.001688	0.001471	0.001501	0.001576
17	0.001526	0.001468	0.001559	0.001557
18	0.001519	0.001518	0.001495	0.001637
19	0.001541	0.001438	0.001468	0.001369
20	0.001562	0.001491	0.001547	0.001491
Trimmed Mean	0.001520	0.001510	0.001566	0.001577

Table 2. Training epochs

EPOCHS				
SAMPLES	TYPE1	TYPE2	TYPE3	TYPE4
1	94	204	118	81
2	136	167	47	40
3	65	102	62	108
4	112	122	74	19
5	78	108	147	16
6	152	83	280	23
7	150	22	40	241
8	175	42	172	17
9	158	53	55	72
10	25	21	182	17
11	179	53	49	34
12	39	126	18	103
13	140	24	140	161
14	457	45	56	16
15	256	144	39	55
16	463	312	82	161
17	178	66	175	66
18	62	128	93	47
19	274	120	35	58
20	62	88	25	44
Trimmed Mean	134.75	91.17	80.25	53.5

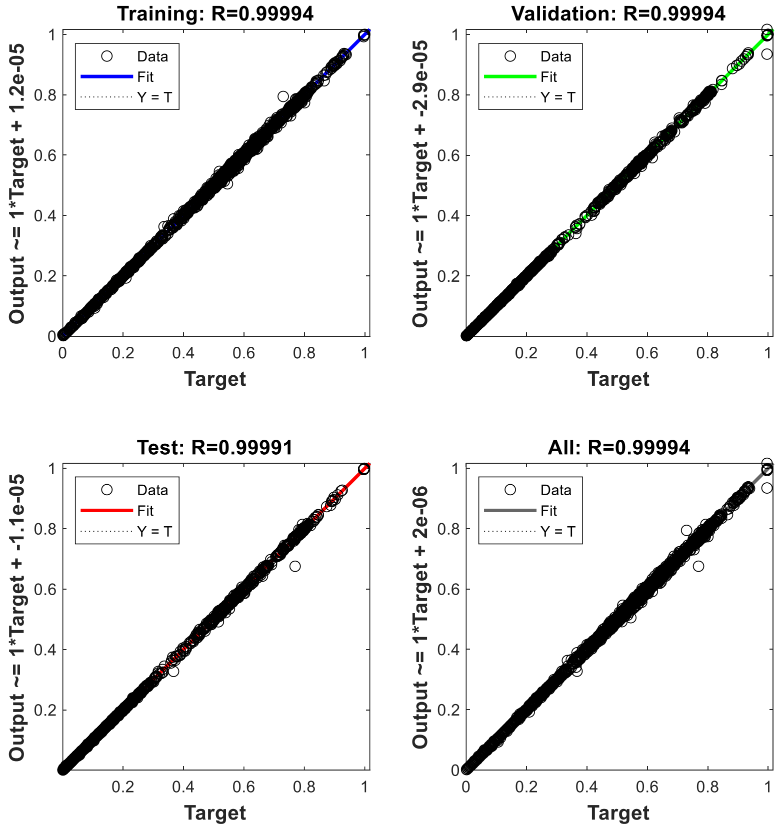

Fig. 2. Regression effect

3.3 Results and analysis

It can be obtained from Table 1 that among the four types, Type 2 has the best prediction effect, that is, the fourth-day closing price can be reliably predicated from the opening, closing, maximum, and lowest prices of the preceding three days. At the same time, the selected sample data time span also has a certain impact on the accuracy of the predicted value. If the time span for the sample data is too brief or too long, the output error will be large, so the superficial BP neural network is not suitable for long-term prediction.

It is evident from Table 2 that the number of nodes in the hidden layer is equal to the number of hidden layers when observed, the more input nodes, the more efficient the BP neural network can learn the training sample, which reduces the training cost to a certain extent.

From the above analysis, this paper finally chooses to establish a superficial BP neural network with 12 input nodes, an implicit layer, 12 nodes and 1 output layer nodes to make a more accurate prediction of the closing price of USD/JPY. Running this network has achieved a good fitting effect on the prediction of USD/JPY test set (Fig.2). It can be seen that the exchange rate price prediction trend basically coincides with the real value trend (Fig.3), and the relative error of USD/JPY is controlled within 1.2% (Fig.4), which also indicates the appropriate superficial BP neural network. The construction energy is relatively accurate in predicting the short-term exchange rate of USD/JPY, which has a certain

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credibility and is of practical application significance.

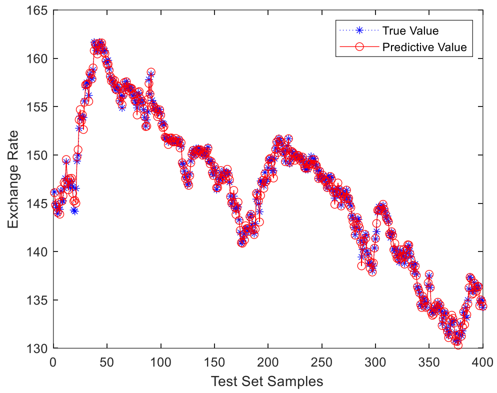

Fig. 3. The predictions of the test set

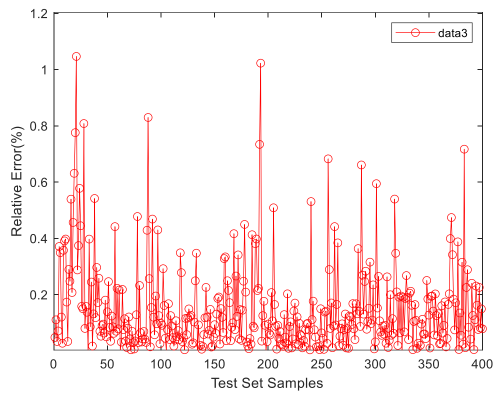

Fig. 4. Relative errors of the test set

4 Conclusion

In summary, the BP neural network prediction model shows that the exchange rate price prediction trend basically coincides with the real value trend, and the relative error of USD/JPY is small, indicating that the superficial BP neural network is relatively accurate in predicting the short-term exchange rate of USD/JPY, that is, the BP neural network shows in short-term exchange rate price prediction. It shows a certain degree of accuracy. In reality, it is conducive to having significant reference value for investors to formulate investment strategies and enterprises to carry out risk management.

BP neural network provides a powerful prediction tool in exchange rate research. However, it still has certain limitations in data processing, model hypothesis, interpretation, timeliness and algorithm optimization. For example, with the extension of the prediction time, the prediction accuracy may decrease. Future research may need to combine other models and methods, as well as more advanced optimization algorithms, like recurrent neural networks (RNN) and convolutional neural networks (CNN), to overcome these shortcomings and increase the accuracy and reliability of exchange rate forecasting by demonstrating their strong ability to process time series data.

Authors Contribution

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

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