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Prediction and Analysis of Wuxi Stainless Steel MarketPrice Based on ARIMA-BP Neural Network Combination Model

Yinshan Guo[1], Chunhui Zhao[1], Xiaoxiao Qin[1], Jin Zhang[2]

[1]*School of Management, Tianjin University of Technology, Tianjin 300384, P.R. China*
[2]*Shanghai Ganglian E-Commerce Holdings Co., Ltd.*

Corresponding Authors:** ***Yinshan Guo, *School of Management, Tianjin University of Technology, Tianjin 300384, P.R.China*

Abstract: *Stainless steel is not only a high-strength and high-toughness structural material, but also an economical functional material. My country's stainless steel industry occupies a pivotal position in the fields of construction, transportation, energy, and packaging. It is also particularly important to study its price trends and internal laws. Therefore, this paper selects the price of 201 series hot-rolled and cold-rolled stainless steel and 304-series hot-rolled and cold-rolled stainless steel in Wuxi City as the research objects, and uses the time series model and BP neural network model to model them respectively, and predicts the prices of future stainless steel .Then a parallel ARIMA-BP combined model is established, and the weights of the two models are distributed by the advantage matrix method to obtain new forecast data. Comparing and analyzing absolute error and relative error, it is concluded that the accuracy of combined prediction model is higher than that of basic prediction models such as time series and BP neural network. In addition, this paper analyzes the factors influencing the fluctuations in the price of stainless steel, and the significant degree of correlation between stainless steel price and various factors is tested by the Pearson coefficient, and the possible reasons for it are explained. Finally, the future development of stainless steel is prospected.*

Keywords: *Time Series Model; BP Neural Network Model; ARIMA-BP Combined Model; Correlation Analysis*

1. Introduction

China as a major steel country, stainless steel occupies an important position in China's steel industry. Withthe increase in demand from various industries, the competition in the stainless steel industry is intensify- ing. Therefore, how China's steel enterprises to tap the internal potential, low steel prices, reasonable controlof stainless steel prices, so that enterprises can better adapt to the requirements of the market economy,is particularly important. Enterprises should strengthen the analysis and research on the overall economic efficiency of the production system to improve efficiency, while analyzing and studying how the stainless steel price market is developing and proposing a reasonable and practical model to predict the future trendof steel prices. For steel companies with a certain scale of production, it is not enough to focus only on the domestic production system, and the in-depth study of overseas study cannot be ignored. Therefore, this paper focuses on the study of the evolution of the law of stainless steel prices.

In terms of production, the data show that crude steel production of stainless steel from January to November 2021 reached 29.81 million tons. In the same period, the figure for 2020 is 27.04 million tons. This is due to the release of stainless steel production in the first half of 2021. Not only the production, from January to November 2021, China imported 2.66 million tons of stainless steel and exported 4.01 million tons of stainless steel, which is also a significant increase compared to the same period in 2020. Overall, the national stainless steel production will keep increasing [1].

In the macro environment, in recent years, a number of ideas such as "Made in China 2025", "One Belt, One Road", the green economy and so on, coupled with the upgrading of the consumer structure, for the manufacturing industry to provide a good environment to improve their own manufacturing capacity, which in turn promotes the rapid development of China's stainless steel industry. Many countries' infrastructure construction, such as high-speed rail, aerospace, new energy, etc., all of them have directly promoted China's stainless steel industry to high-quality development.

Due to the many raw materials and demand aspects of the stainless steel industry, its price changes are subject to many factors, price fluctuations trend significantly. However, since the stainless steel price has certain linear characteristics, is influencing factors such as supply and demand, raw material costs, and economic policies have non-linear characteristics. Therefore, according to these characteristics, the use of ARIMA and BP neural network, two very representative algorithm models, on the basis of which the stainless steel price portfolio forecasting model is further constructed.

Through data analysis, the growth and evolution pattern of steel prices can be derived and future prices within a certain period of time can be reasonably predicted. On the one hand, it can provide reference for large national steel companies, and on the other hand, it can make certain predictions for the market, so that the market can be prepared in advance and have some control over future prices to ensure that the price fluctuations are not too large and are controlled within a certain reasonable range. Therefore, this subject isvery theoretical and practical.

2. Literature Review

The importance of steel has become more and more important with the acceleration of the world's indus- trialization process. Whether it is the United States, which is the world's leading economy, or developing countries such as China, there are price studies on steel, including price forecasting models. The study also includes a study of factors affecting prices. Steel price forecasting has also been the subject of extensive research in the Chinese steel industry and its associated economic analysis.

In terms of international markets, Ming-Tao Chou (2012) at the 3rd International Conference on Bio-inspired Computing and Applied Innovation (IBICA) proposed to use fuzzy time series to establish a forecast model for the Asian steel price index from 1994 to 2011, and then use fuzzy time series. The Asian steel price index in 2012 is predicted, and it is concluded that the Asian steel price index in 2012 is still positive. Pascal Khoury 2013 used particle swarm optimization training (PSO) BP neural network to form an ensemble classifier to study whether there is predictability in the nature of steel manufacturers' stock price changes, and found that between 1995 and 2012 307 steel When the company's stock price uses the training metric and the Matthews correlation coefficient, it can better deal with the numerically unbalanced data set, obtain the predicted value, realize the predictability, and lay a solid foundation for the establishment of the trading model in the future. Amir Ikram 2016 used different time series ARIMA models to forecast stainless steel production in Pakistan. In the forecast results, it was found that compared with the production of the past 5 years, the steel production in 2014 seemed to be the least, and there seemed to be some problems. The production of steel was one of the largest economic sectors, and it was also directly or indirectly related to the local population and technology. We hoped to find out the problem as soon as possible or formulate relevant policies to solve the problem.

In the field of domestic research, Zou Tao (2009) analyzed the problems existing in China's steel market through the overall study of the steel industry, and made a more comprehensive exposition of the domestic steel market. For the establishment of the steel price prediction model, Wang Xuefei (2011) used the ARIMA model to make a simple prediction of the steel price, mainly analyzed the relative errors under the three ARIMA models, and selected the one with the smallest error. Zhu Yancheng (2012) and others used chaos theory and BP neural network to establish a prediction model to predict each frequency component separately, and obtained fairly accurate prediction results through the model combination method. Chen Kejun (2012) predicted long-period rebar futures price based on BP neural network of error back-propagation algorithm, which could achieve profitability. Chen Rong (2015) analyzed the steel market price based on the steel price data from January 2013 to December 2014, and successively introduced regression analysis, LASSO algorithm, and ARIMA model to analyze and predict the steel price data.

In addition, this paper also analyzes the factors that may affect the price of stainless steel. In the qualitative analysis of influencing factors, it is not simply to select the influencing factors subjectively, but to collect and analyze all possible factors as much as possible, select the influencing factors with the highest degree of relevance, and reduce subjective factors as much as possible. From 1993, Li Feng began to study the evolution of the steel price system and management mechanism. By 2010, Cui Ruixin (2010) quantitatively started with the composition and formation of steel prices, and believed that steel prices were mainly composed of profits, production costs and taxes. And he found the reasons for steel price fluctuations based on the constituent factors - macroeconomic fluctuations and supply and demand shocks. In the long run, the impact of macroeconomic fluctuations is greater. Zhou Huiqin (2018) selected the monthly data of iron ore prices from January 2013 to July 2017 for the prediction of iron ore, and established a multiple linear regression model for empirical analysis. It was found that the US dollar index, Baltic index, steel output, iron ore inventory and iron ore prices have a long-term equilibrium relationship. According to the methods of reading academic references, checking futures analysis, consulting website and interviewing authoritative experts of steel trade, this paper selects seven factors that are likely to affect steel[2].

From the domestic research situation, it can be seen that there are not many literatures that directly predict the price of steel, and most scholars only stay in the research of influencing factors, and don't go deep into the deeper direction. The influencing factors are few and incomplete, and in many studies, all of them are substituted into models, without screening, so it is easy to do useless work. In terms of model use, most of them still stay in linear regression and ARIMA time series model, and seldom use difficult methods such as combination model and machine learning, which can't achieve deeper accuracy.

This paper selects the price of 201 series hot-rolled and cold-rolled stainless steel and 304-series hot-rolled and cold-rolled stainless steel in Wuxi City as the research objects, and uses the time series model and BP neural network model to model them respectively, and predicts the prices of future stainless steel .Then a parallel ARIMA-BP combined model is established, and the weights of the two models are distributed by the advantage matrix method to obtain new forecast data. Comparing and analyzing absolute error and relative error, it is concluded that the accuracy of combined prediction model is higher than that of basic prediction models such as time series and BP neural network. In addition, this paper analyzes the factors influencing the fluctuations in the price of stainless steel, and the significant degree of correlation between stainless steel price and various factors is tested by the Pearson coefficient, and the possible reasons for it are explained.

3. BASIC FORECASTING MODEL

3.1. Time Series Model

The time series analysis method treats price changes over time as a time series, and uses its corresponding discriminative model to forecast the future by finding the change pattern of historical data. The stainless steel price forecasting in this topic is a time series model using past price data. In this paper, a differential autoregressive sliding average model is used to derive the best results for short-term forecasting of the price trend of stainless steel.

3.2. Data Source

In this paper, the daily stainless steel prices of Wuxi city from 2020 to 2022 are selected as the research object, and the prices of 201 series hot-rolled, 201 series cold-rolled, 304 series hot-rolled and 304 series cold-rolled stainless steel are predicted, where the data of Wuxi city from 2020 to 2021 are used to build the model, and since the data of 2022 are known, they can be used to calculate the error and test the model, and the data source is my Railroad Network. The following is an example of 201 series hot-rolled stainless steel for specific analysis, the original data as shown in Figure 1.

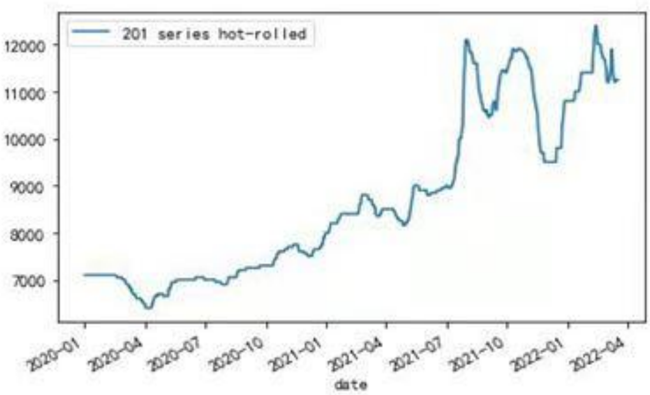

Figure1. *Price trend chart of daily 201 series hot-rolled stainless steel in Wuxi from 2020 to 2021*

As can be seen from the price trend in the figure, the price data for 201 series hot rolled stainless steel is non-stationary and always in an oscillating upward state. At this point, the non-stationary data series need to be processed and transformed into a stable series, as the variables in the model must meet the smoothness requirements. After that, the processed data also needs to be tested for smoothness to make sure it is smooth.

3.3. Stability Test and White Noise Test

The ADF unit root test was used to test the smoothness of the stainless steel price time series. After calculation, the t-statistic value is -0.6512, which is greater than the t-statistic under the 0.05 and 0.01 level tests. this indicates that the original hypothesis of having unit root exists at the 0.05 and 0.01 level of significance, i.e., it is determined that the original time series is non-stationary.

It is verified that the data pass the test of white noise and are non-white noise series.

3.4. Smoothing of the Original Series

Differencing of order d1 is generally utilized to make the time series with significant trends smooth. The series of the original time series of historical stainless steel prices after first order differencing is presented in Figure 2.

From the figure it can be seen that the series after the first difference is smooth.

3.5. Calculation of ACF, PACF

1. Autocorrelation function and partial autocorrelation function of AR(p) series[3]

The autocorrelation function is:

$$\gamma_k = \frac{\gamma_{ts}}{\sqrt{\gamma_{tt}\gamma_{ss}}}.$$

The partial autocorrelation function is:

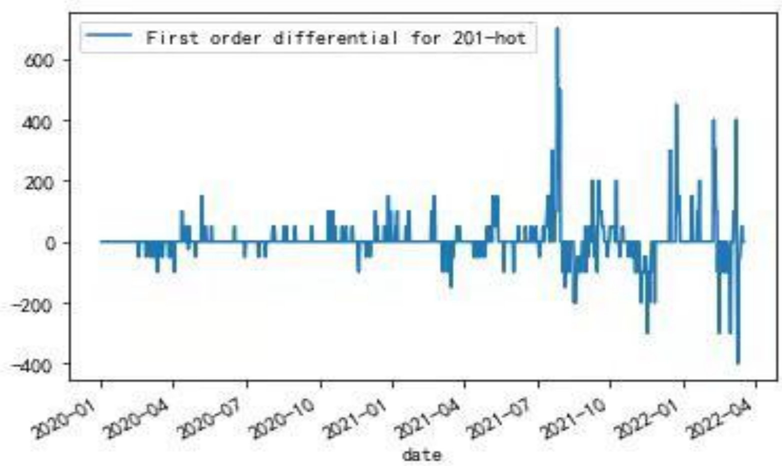

Figure2. *Price trend chart of stainless steel after first-order difference*

$$\varphi_{kk} = \begin{cases} \gamma_1 \\ \dfrac{\gamma_k - \sum_{i=1}^{k-1} \varphi_{k-1,i*\gamma_{k-i}}}{1 - \sum_{i=1}^{k-1} \varphi_{k-1,i*\gamma_{k-i}}} \qquad k = 2,3,\ldots \end{cases} \tag{1}$$

2. Autocorrelation function and partial autocorrelation function of MA(q) series The autocovariance function is:

$$\gamma_{ts} = \begin{cases} (1+\omega_1^2+\cdots+\omega_q^2)\sigma^2 & |t-s| = 0 \\ (-\omega_{|t-s|}+\omega_1\omega_{|t-s|+1}+\cdots+\omega_{q-|t-s}\omega_q)\sigma^2 & 1 \le |t-s| \le q \\ 0 & |t-s| > q. \end{cases} \tag{2}$$

where σ^2 is the variance $Var(\varepsilon_t)$ of the white noise sequence $\{\varepsilon_t\}$.The autocorrelation function is:

$$\gamma_k == \begin{cases} 1 & k=0 \\ \dfrac{-\omega_1+\omega_1\omega_2+\cdots+\omega_{q-1}\omega_q{}^2}{1+\omega_1^2+\cdots+\omega_q} & 1 \le k \le q \\ 0 & k > q. \end{cases} \tag{3}$$

The partial autocorrelation function is:

$$\varphi_{kk} = \begin{cases} \dfrac{-\omega_1+\omega_1\omega_2+\cdots+\omega_{q-1}\omega_q}{1+\omega_1^2+\cdots+\omega_q^2} & \\ \dfrac{\gamma_k - \sum_{i=1}^{k-1} \varphi_{k-1,i*\gamma_{k-i}}}{1-\sum_{i=1}^{k-1} \varphi_{k-1,i*\gamma_{k-i}}} & k = 2,3\ldots \end{cases} \tag{4}$$

3. Autocorrelation function and partial autocorrelation function of ARMA(p,q)

Both the autocorrelation and partial autocorrelation of the ARMA(p,q) sequence are tailed. If the sample autocorrelation function and partial correlation function of the time series xn are tailed, but converge to 0 quickly, then the series may be an ARMA series. When identifying (p,q), we can take (p,q) one by one as (1, 1), (1, 2), (2, 1), (2, 2)…(generally the value does not exceed 3) to try ,then estimate the parameters ,determine the model, perform a feasibility test, and finally predict future development changes.

The ACF and PCAF of the stainless steel price data in this paper are shown in Figures 3 and 4.

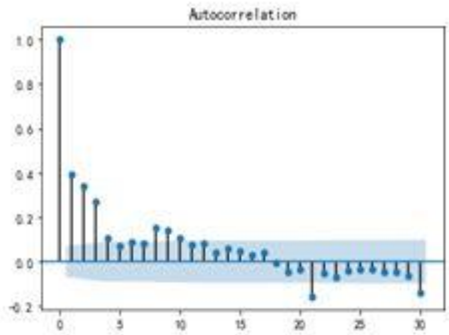

Figure3. *ACF*

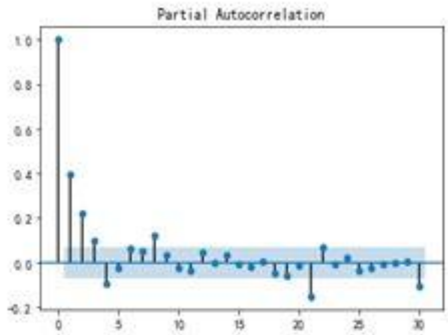

Figure4. *PACF*

3.6. Pattern Recognition

To accurately determine the type of model to use, the ARIMA (p,d,q) model is generally considered first to fit the original time series until both parameter estimation and model testing are complete, and then the appropriate model type is reconsidered.

By determining the trailing and truncated autocorrelation coefficients (ACF) and partial correlation co- efficients (PACF) of the time series, we decide which model to set in AR, MA and ARMA. The specific correspondence is shown in Table 1.

Table1. *Judgment rules of time series model*

Model	ACF	PACF
AR(p)	Decay to zero	Censored after p-order
MA(q)	Censored after q-order	Decay to zero
ARMA(p,q)	The decay tends to zero after the q-order	The decay tends to zero after the p-order

Usually, in the early stages of model ordering, it is necessary to try the sequence from low to high order. In this study, an easier process is considered by using the ARMA(p,p-1) model method, which starts with one variable p. When p is very large, the model ARMA(p,p-1) can be used to solve the model to the desired arbitrary accuracy to get it close. Also, the order of the model can be determined by comparing p and q. Regarding the determination of the model, a trial method is used. First assume a model, and then analyze and test it to find out the unreasonable part of it, and then eliminate and improve it. After a series of solutions and tests, the most suitable model for stainless steel prices is finally determined as ARIMA (4,1,1).

3.7. Model Testing

In general, in order to determine whether a model is significantly valid, it is necessary to check whether the model can extract sufficient and useful information from the data. Here, the test for white noise is used to determine whether there is valid information in the residuals. If the residual series is a white noise series, then it means that the model has sufficiently extracted the required data and there is no more valid information

in the residual series that can still be used. After the white noise test, the results show that the P-values of all the statistics of Q at the lagged period are greater than 5% at a significance level of 5%, i.e., the established model has sufficiently extracted the valid information.

3.8. Application Forecast

Since the ARIMA model is built using only past time series data, and the price of stainless steel is affected by a variety of uncontrollable factors. Under the influence of these factors, the forecasting accuracy of the established ARIMA model will gradually decrease and forecasting errors will gradually accumulate as time passes. Therefore, the ARIMA (4,1,1) model can only be used to achieve short-term forecasts.

In order to show the prediction effect of the model, we carefully compare the predicted value of stainless steel price with the real value and used two indicators, Absolute error and Relative error, to judge the prediction effect of the model.

Table2. *Price forecast of 201 series hot rolled stainless steel-ARIMA model*

Date	Actual value	Predictive value	Absolute error	Relative error
2022-03-19	11250	11247	3	0.00027
2022-03-20	11250	11249	1	8.889E-05
2022-03-21	11250	11251	-1	-8.889E-05
2022-03-22	11100	11154	-54	-0.00486
2022-03-23	11100	11158	-58	-0.00523
2022-03-24	11200	11263	-63	-0.00563
2022-03-25	11100	11168	-68	-0.00613

It can be seen from the above table that the model using ARIMA (4,1,1) has a good effect on forecasting the price of 201 hot-rolled stainless steel. During the forecast date, the relative error has never reached 1%, and the model fitting effect is good.

Similarly, according to the time sequence model of other three kinds of stainless steel price data is forecasted, and compared with the original data, the results are shown in figure 5.

3.9. BP Neural Network

Model Concepts and Features

Artificial neural network, also known as neural network, can mimic the interactive response of biological nervous system to real objects. The more layers of neural network, the stronger the learning ability. Therefore, the system can deal with the one-time function problem well. Nowadays, artificial neural network has become an important direction in science, especially in the field of prediction and control. The general BP neural network consists of three parts: input layer, implicit layer, and output layer[4].

In this paper, the stainless steel price at time t is used as the input value of the BP neural network, and the stainless steel price at time t+1 is used as the output of the network, so as to reduce the influence of random factors and improve the prediction accuracy.

Steps of Model Building

During the model building process, the input and output of the three levels can be represented as a string of vectors. Assume that the BP neural network model has n neural nodes in the input layer, p neural nodes in the hidden layer, and m neural nodes in the output layer. Then in this BP neural network there are:

(a) 201Serieshotrolling-realvalueandpredictedvaluecontrastfigure

(b) 201Seriescoldrolling-realvalueandpredictedvaluecontrastfigure

(c)304Serieshotrolling-realvalueandpredictedvaluecontrastfigure

(d) 304Seriescoldrolling-realvalueandpredictedvaluecontrastfigure

Figure5. *Comparison chart of actual value and predicted value of stainless steel price*

The connection weights between the input layer and the hidden layer: ωij; The connection weights between the hidden layer and the output layer: ωjk; Threshold of each neuron in the hidden layer: a; Thresholds for each neuron in the output layer: b.

The modeling steps are as follows:

1. Data Preprocessing

First, the given data set is divided. In this paper, the price of 201 series hot-rolled stainless steel in Wuxi City from 2020 to 2021 is still selected as the data set. Convert to a number in the interval [0,1] or [-1,1].

The initialization formula is:

$$\frac{x_i - x_{min}}{x_{max} - x_{min}}$$

2. Neural network initialization

According to the specific situation, the number of neurons in the hidden layer is determined by the formula.

$$p = \sqrt{m+n} + \alpha.$$

Among them, n is the number of neurons in the input layer, m is the number of neurons in the output layer, and α is 1-10 [5] .

3. Determination of the excitation function

In the three-layer BP neural network model, an excitation function needs to be selected for the calculation between the neurons in the hidden layer and the output layer. Generally, the sigmoid function is used as the excitation function.

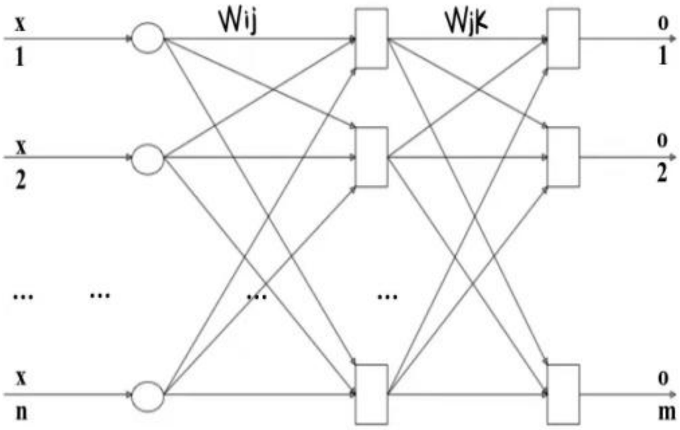

Figure6. *Neural network hierarchy diagram*

4. Compute the results of the hidden and output layersHidden layer output:

$$z_j = f_1(\sum_{i=0}^{n} \omega_{ij} x_i - a_j), j = 1,2, \dots, p.$$

Output layer output:

$$y = f_2(\sum_{i=0}^{p} \omega_{jk} z_j - b), k = 1,2, \dots, n.$$

1. Error calculation

Calculate the difference data between the actual value and the predicted value, which is recorded as the error e.

2. Update weights and thresholds based on prediction errors.

3. Determine whether the algorithm iteration can be terminated, if not, return to the step.

3.10. Prediction Results

The stainless steel price data of Wuxi city for the period of 20 to 21 years is used as the training sample, and the price data of March 19 to 25, 2022 is used as the test sample, which is input into the above BP neural network algorithm steps, and the results are obtained as follows. Figure 7 shows the comparison between the predicted and actual values of the BP neural network data set, and Table 3 shows the relative and absolute errors between the predicted data and the real data.

Table3. *Price forecasts of 201 series hot rolled stainless steel——the BP neural network*

Date	Actual value	Predictive value	Absolute error	Relative error
2022-03-19	11250	11221	29	0.00258
2022-03-20	11250	11248	2	0.00018
2022-03-21	11250	11258	8	0.00071
2022-03-22	11100	11094	6	0.00054
2022-03-23	11100	11096	4	0.00036
2022-03-24	11200	11229	29	0.00259
2022-03-25	11100	11125	25	0.00225

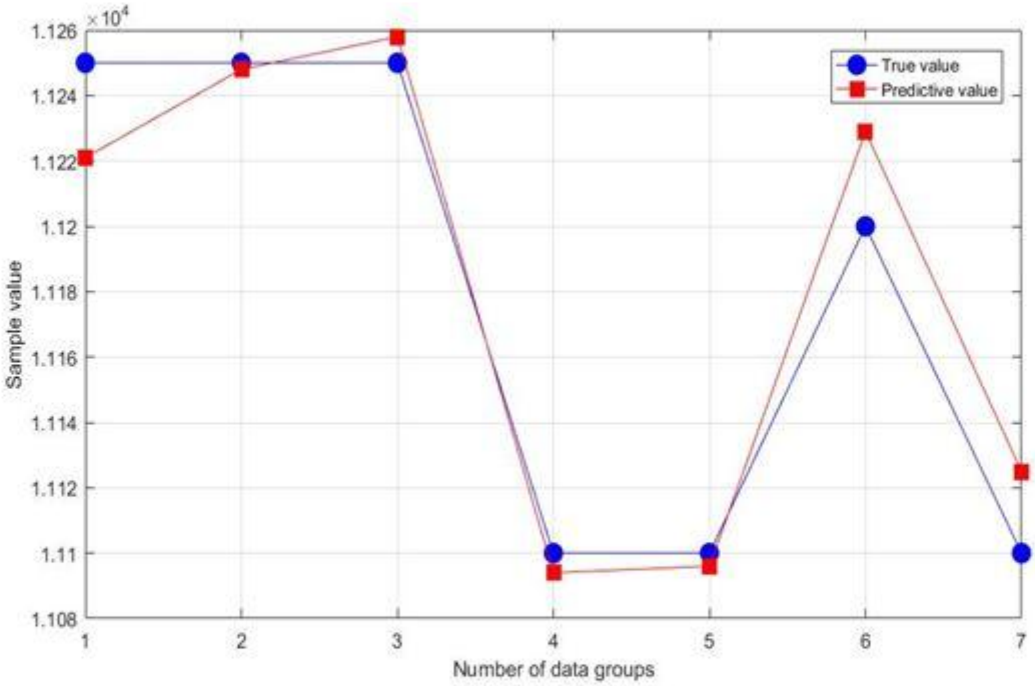

Figure7. *Comparison between the predicted value and the actual value of the BP neural network data set*

4. ARIMA-BP COMBINED PREDICTION MODEL

For the stainless steel price data information, this paper constructs a prediction model based on the combi- nation of traditional ARIMA model and BP neural network model. ARIMA model is mainly used to discover the linear part of mined data and information, while BP neural network model is used to discover the optimal control characteristics of the data and information. From the actual prediction results of ARIMA model and BP neural network model, these models are reasonable for the short-term prediction of stainless steel price data information, have certain practical value, but also have some shortcomings. The prediction of BP neural network model is not very accurate and its stability is not very strong. The relative deviation of ARIMA model is less than 1%. Therefore, in order to integrate the advantages and disadvantages of ARIMA model and BP neural network model, an ARIMA-BP composition model with weight assignment is created in the paper.

The main idea of calculating the weight of ARIMA-BP combined model is to use different prediction methods to analyze the data information of the initial time series, and then connect them with the weighted average value to assign reasonable weight to each model, and finally combine them to obtain more accurate prediction. The weight matched to each prediction model reflect the contribution of each prediction method to the final prediction result. The larger the deviation, the smaller the weight and contribution of the constituent prediction models. The predicted values of the two components are summed to obtain the predicted values of the optimized synergistic model. The improved compositional model further improves the prediction precision of the original data information model.

4.1. Determination of Combined Model Weights

The advantage matrix method is used to distinguish the predicted values of the even-numbered model thathas already been predicted. Here, ARIMA model is set as model 1, and BP neural network model is set as model 2, and the relative errors of their predicted data information are measured. The advantage matrix is:

re1=[0.02667% , 0.00889% ,-0.00889% ,-0.48649% , -0.52252% , -0.5625% ,-0.61261%];

re2 =[0.25778% , 0.01778% , -0.07111% , 0.05405% , 0.03604% , -0.25892% , -0.22321%].

According to the advantage matrix method, there are 3 times that 1 is better than 2, and the weights ω_1 = ^{3}

and $\omega_2 = \frac{4}{7}$ are determined.

4.2. Model Test

The relative errors of the three models are measured in order to better test the actual prediction effects of the combined model. Based on the data analysis in Table 4, it is observed that the relative error of the combined model ARIMA-BP is many times smaller than that of the other two models, and the reliability of the combined model is stronger. In general, the combined ARIMA-BP model is reasonable and better thanthe independent ARIMA or BP model.

Table4. *Comparison of relative errors of three models*

Date	ARIMA model	BP neural network model	Combination model
2022-03-19	0.02667%	0.25778%	0.15873%
2022-03-20	0.00889%	0.01778%	0.01397%
2022-03-21	-0.00889%	-0.07111%	-0.04444%
2022-03-22	-0.48649%	0.05405%	-0.17761%
2022-03-23	-0.52252%	0.03604%	-0.20334%
2022-03-24	-0.5625%	-0.25892%	-0.38902%
2022-03-25	-0.61261%	-0.22321%	-0.391%

4.3. Prediction of Combined Model

After determining the weights ω1and ω2, use the formula Y = ω1y1 + ω2y2 to predict the stainless steel price in the next seven days. The following picture shows the comparison of the price data of four series of stainless steel from March 26 to April 1, 2022.

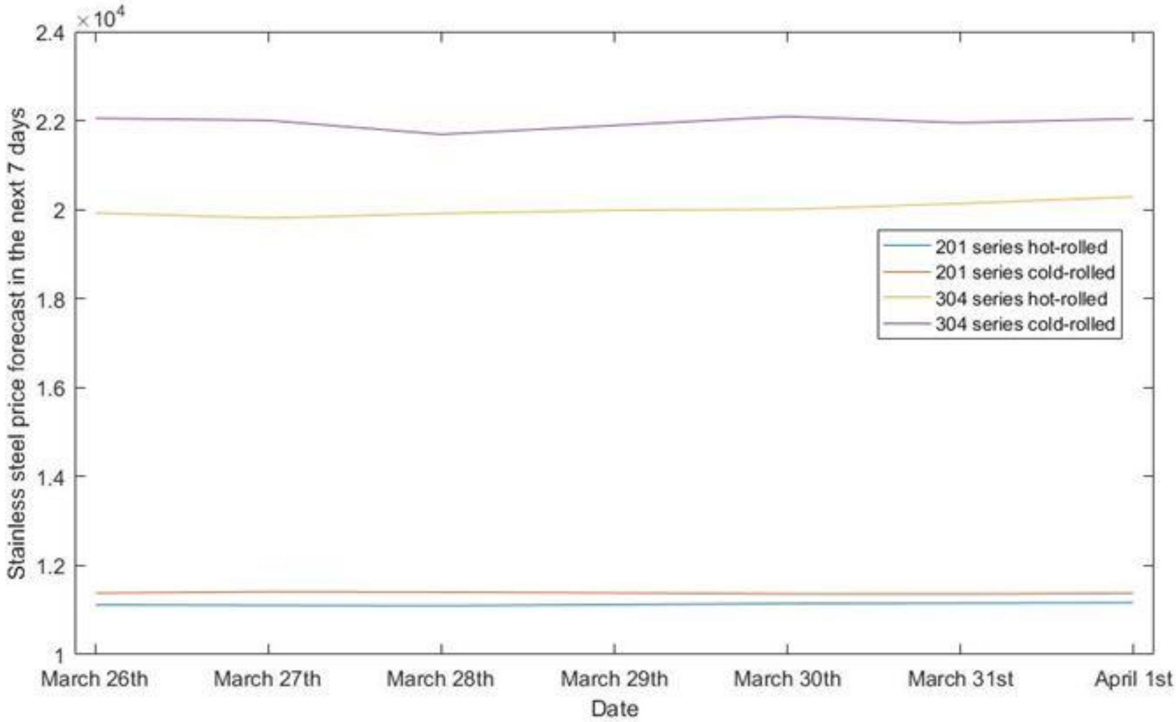

Figure8. *Price forecast chart of four series stainless steel - ARIMA-BP combination model*

5. Analysis of Factors Affecting the Fluctuation of Stainless Steel Price

5.1. Influence Factors

The iron and steel industry is a key industrial chain of social economy, which stimulates key effects in China’s modernization and urbanization. Steel price fluctuation is mainly affected by its own supply and demand, macroeconomic policy fluctuation and cost fluctuation. Scientific analysis of the impact of steel price is critical for the stable development trend of steel industry and the sustainable operation of China’s economy.

According to the methods of reading academic references, checking futures analysis, consulting website and interviewing authoritative experts of steel trade, this paper selects seven factors that are likely to affect steel. The following table shows the index system constructed[6].

Table5. *Influencing factor indicators*

Measure variable	First-level proxy indicators	Secondary proxy indicator
Stainless steel production cost	Raw materials	Ferronickel price
Stainless steel production cost	Raw materials	Ferrochrome price
Stainless steel production cost	Raw materials	Nickel ore price
Stainless steel production cost	Raw materials	Chrome ore price
Stainless steel supply and demand	Supply	Stainless steel raw output
Stainless steel supply and demand	Demand	Completed area of real estate development enterprises
Macro factors	International macro factors	RMB to USD exchange rate

5.2. Pearson Correlation Analysis

Pearson correlation coefficient is an index to measure the close degree of correlation between variables under the condition of linear correlation between them. At the same time, it can also indicate whether they are positively or negatively correlated. The larger the square root of Pearson correlation index R, the higher the correlation level between independent variable and variable. Here, it is used to measure the correlationbetween stainless steel price and its influencing factors.

Table6. *Correlation coefficient statistics chart*

Influencing factors	Pearson correlation coefficient
Ferronickel price	0.600
Ferrochrome price	-0.217
Chrome ore price	-0.596
Nickel ore price	-0.079
Stainless steel monthly output	0.110
Completed area of real estate development enterprises	0.060
RMB to USD exchange rate	-0.363

The test results show that the price of stainless steel in China is positively proportional to the price of ferronickel, the monthly production of stainless steel and the completed area of real estate development en- terprises. At the same time, the price of stainless steel is inversely proportional to the price of ferrochromium, the price of chromium ore and the exchange rate of RMB against the US dollar.

It can be seen from the inspection results that ferronickel and chromite are two factors that have a great impact on stainless steel in China. They are obviously related. These two independent variables represent, the product cost of stainless steel. Therefore, the continuous and stable development trend of stainless steel sales market can be ensured only by carrying out sales market and maintenance from the root of raw material cost.

In addition, the research results show that there is an inverse correlation between the ex-factory volume of stainless steel and the rate of US dollar against RMB, that is, with the strengthening of US dollar, the price of stainless steel decreases. The reason for this phenomenon may be that the export volume of stainless steel in China exceeds the import volume in recent years. The global steel market is usually priced in US dollars. Because the US dollar continues to fall, in order to ensure profitability, the company will continue to increase the export of stainless steel, resulting in the continuous increase of stainless steel plants with the decrease of RMB against the US dollar exchange rate.

6. Prospect

As time goes, the primary reason for the fluctuation of China's stainless steel price will also change. Moreover, the time series requires stable data, that is, it can only track the linear relationship. Once the data is unstable, it is often affected by market and other factors, and the accuracy of the time series model is prone to be greatly reduced. Therefore, in the following discussion, the initial model cannot be used all the time. In order to better create the solid model, it must be further analyzed and discussed, under the different stages, a variety of other factors that may arise on the role of China's stainless steel.

With the rapid development of modern society, stainless steel products are more and more widely used in all walks of life because of their applicability, durability, beauty and hygiene. At this stage, along with the increasingly stringent national and regional environmental protection policies, zero emission of pickling solid waste and organic waste gas of stainless steel pipe is the general trend of development. In today's pursuit of environmental protection, stainless steel products, as green products in the whole life cycle, should be transformed by new energy and new technologies. Under the vision of double control of energy consumption and "double carbon goals", it can save energy and reduce emissions, promote stable output and less pollution.

7. EPILOGUE

Due to the limitation of its own conditions, the basic prediction model may cause errors to the prediction results because of some factors when predicting the data. But the prediction accuracy will be improved by combining the models in a reasonable way, and the two will complement each other.

In this paper, the historical data of four series of stainless steel prices in Wuxi from 2020 to 2021 are intercepted as the research object. Firstly, the basic prediction model, namely ARIMA model and BP neural network model, is used for prediction. The accuracy of prediction effect is general, and there are some deficiencies. Therefore, this paper selects the parallel combination model and calculates the weight ω1, ω2 to determine the contribution of the two models in the combined model. After verification, the combined prediction model of ARIMA (4,1,1) and BP neural network is more reasonable in the prediction of time series, and the accuracy of combined prediction is better than that of basic prediction model.

However, because the information is relatively limited, the independent prediction of the 7 -day stainless steel price data is likely to cause the deviation of the entity model prediction. If the training sample is upgraded and the BP network construction is adjusted, it is likely that more accurate results will be obtained.

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AUTHORS' BIOGRAPHY

Yinshan Guo, a student, from School of Management, Tianjin University of Technology, Tianjin 300384, P.R. China.

Chunhui Zhao, a student, from School of Management, Tianjin University of Technology, Tianjin 300384, P.R. China.

Xiaoxiao Qin, a student, from School of Management, Tianjin University of Technology, Tianjin 300384, P.R. China.

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