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# Forecasting and Research on Future Steel Industry Development based on Multi-Algorithm Coupled Models

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## Abstract

**In response to the current situation where data utilization in China's steel industry is insufficient and there is an urgent need to achieve a low-carbon and smart transformation, this article initially gathers data on the development of the steel industry through literature reviews, yearbooks, websites, and other sources. It then uses a multi-algorithm coupling model to predict the industry's development scenario for the next two decades. Based on the predictive data, a high-quality development evaluation system for the steel industry is established, which will be used as a foundation to promote the early realization of industrial transformation in the steel industry.**

## Keywords

**Chinese Steel Industry; Multi-algorithm Forecasting; Coupling, Data Visualisation; High Quality Development.**

## 1. Introduction

In the current stage of the development of the steel industry, data has gradually become an intangible asset, how to better grasp the characteristics of the data, the integration of data value has become the key to enhance the competitiveness of enterprises in the steel industry. In recent years, intelligent transformation has become the trend of reform and innovation of many enterprises, but also the basis for the development of iron and steel enterprises, with the help of big data coverage, to achieve real-time data monitoring, complete visual energy, quality supervision, and constitute a set of control system in line with the development of iron and steel enterprises, as well as a comprehensive process, process, quality control platform [1]. However, China's iron and steel industry continues to promote intelligence, steel production capacity has generated a huge demand, resulting in China's iron and steel industry is facing the basic situation of production growth and high energy consumption, high pollution coexist, and its development of long-term resource and environmental constraints [2]. Therefore, the study of coupled and coordinated development has become the key to the sustainable development of the iron and steel industry.

## 2. Energy Consumption in China's Steel Industry

The steel industry, coming after the power industry, is the second largest emission industry in China, and its low-carbon transformation is critical to achieving China's dual carbon goals [3]. From 2015 to 2021, coal consumption increased year by year, reaching 730 million tons in 2021, with the steel industry's coal consumption accounting for about 17%-18% of total coal demand. However, under the dual carbon goals, industry policy has become the dominant factor in cyclical rotation, and the steel industry's energy structure adjustment must upgrade according to policy focus towards high-quality development. Coal consumption will decrease significantly with the proportion and accelerate its reduction due to this, pushing the coal industry into a long-term downward cycle [4]. With the rapid development of the downstream market, the demand for pig iron has also continued to expand. In recent years, the apparent consumption of pig iron has grown steadily. In 2021, China's apparent consumption of pig iron was 870 million tons, showing an overall trend of rising amid fluctuations. Due to China's steel production often remaining at a high level, while the growth rate of the downstream market industry slows down, weak international market demand makes export more difficult, the situation of supply exceeding demand in China's pig iron market still cannot be reversed, putting pressure on steel prices in the later period. Affected by the moderate slowdown in the economy and the slowdown in the growth rate of iron-using industries, domestic market demand for pig iron is weakening in the later period. But it is expected to continue to maintain growth [5].

## 3. Predictions for the future Development of the Steel Industry

### 3.1 Multi-algorithm Coupled Prediction of Steel Data

We composed a coupled algorithmic model based on grey forecasting, ARIMA, Lstm, Informer, BO-LSBoost, and BO-XGBoost in order to forecast a total of 12 items of steel industry data under the three secondary indicators within the framework of the assessment of the high-quality development of China's iron and steel industry, i.e., combining the years 2003-2022, the consumption of coal, the apparent consumption of pig iron, the electricity consumption of tonnes of steel, the consumption of tonnes of steel consumption, new water consumption, industry revenue, industry profit, industry profit margin, import trade volume, export trade volume, number of patents received, number of scientific researchers, and technology capital investment, and use the multi-algorithm coupling model to predict the 12 iron and steel industry data in the next 20 years.

### 3.2 Multi-algorithm Coupling Design and Prediction Results

We select the first 70 of each steel industry data during the 20 years from 2003 to 2022 as the training set, and the second 30% as the test set, and sequentially use grey prediction, ARIMA, Lstm, Informer, BO-LSBoost, and BO-XGBoost to make predictions, and observe the algorithm with the lowest RMSE in the test set of the 12 iron and steel industry data, and select the algorithm that has the lowest RMSE for it as the final prediction algorithm, and predict the future of the 12 iron and steel industry data. as the final prediction algorithm, and predict each steel industry data in the next 20 years. The following is an example of the number of accepted patents indicator to show the algorithm coupling design.

#### 3.1.1 Grey Prediction Model

Step1 Grade Ratio Test

In order to ensure the feasibility of the grey prediction model, before the formal prediction, it is necessary to carry out the level ratio test on the original series, the formula is shown below:

$$\lambda(k)=\frac{x^{(0)}(k-1)}{x^{(0)}(k)},k=2,3,\ldots,n \tag{1}$$

Calculate all the level ratios according to the formula as above, and find that they are all located in the range of tolerable coverage, the level ratio test is passed, and the subsequent prediction can be carried out.

Step2 Accumulation Generation

The original sequence is cumulatively generated sequentially to form a cumulative generation sequence.

Step3 Construct the matrix,$Y_0$,$B_0$,$C_0$.

The matrices,$Y_0$,$B_0$,$C_0$, were calculated by the following formulae, respectively.

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$$Y_0 = (x^{(0)}(2), x^{(0)}(3), \ldots, x^{(0)}(n))^T \tag{2}$$

$$C_0 = \begin{pmatrix} a_0 \\ u_0 \end{pmatrix} \tag{3}$$

$$B_0 = (-\frac{1}{2}[x^{(1)}(i) + x^{(1)}(i-1)], i = 2,3,\ldots,n \tag{4}$$

Step4 Calculate the development factor $\mathbf{a_0}$ and grey contribution $\mathbf{u_0}$.

Based on the principle of least squares, the development coefficient $a_0$ and grey role quantity $u_0$ are calculated.

Step5 Predict new data

Predict new data based on the following formulas, combined with the development coefficient $a_0$ and grey action quantity $u_0$ calculated in Step4.

Step6 Delete the old data and add the new data derived from the prediction

Repeat Step1-Step6 until the end of the prediction work.

Using matlab for prediction, the prediction result of the test set is shown in Figure.1 below, and the RMSE value of the prediction effect is 0.6472.

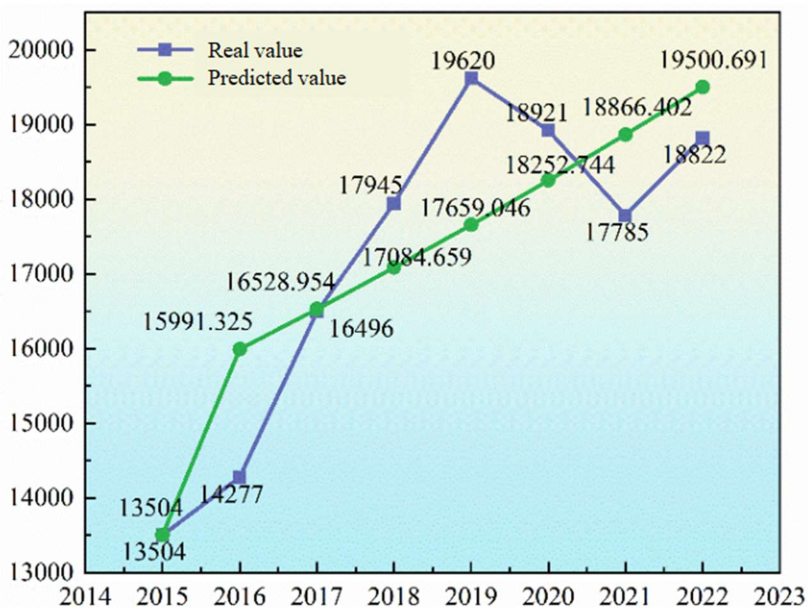


**Figure 1.** Grey prediction model test set prediction effect

### 3.1.2 ARIMA Model

Step1 Smoothness test

The premise of ARIMA model is that the time series is smooth, so before the prediction of the time series need to test the smoothness of the time series, through the first-order difference on the smoothness of the test, the results show that the ADF test is 1, the SPSS test is 0, the test is passed.

Step2 Determine the order of ARIMA model.

Based on the AIC, BIC criterion for the violence of the order, to determine the order of ARIMA calculations for (1,1,0).

Step3 residual test

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The residual test is carried out through QQ chart, the test results show that the residuals are in line with the normal distribution, and the residual test is passed.

Step4.ARIMA algorithm prediction

Using matlab for prediction,the prediction result of the test set is shown in Figure 2 above,the RMSE value of prediction effect is 0.5142.

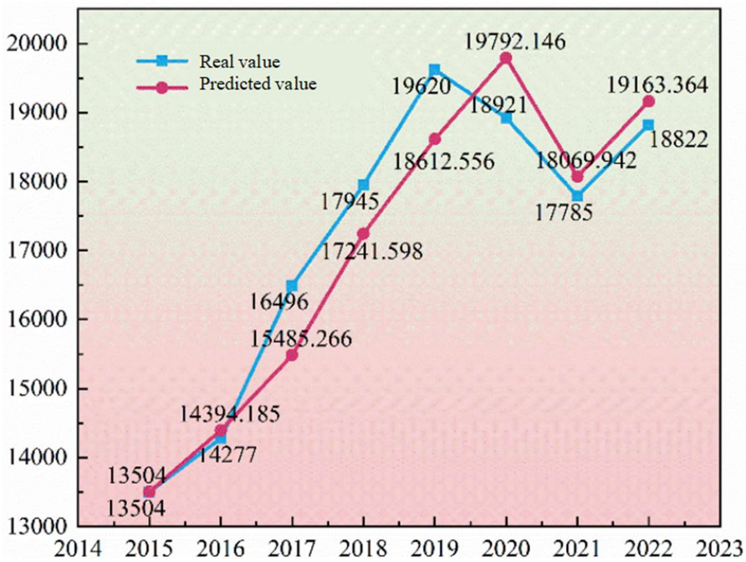


**Figure 2.** ARIMA model test set prediction effect

### 3.1.3 LSTM Model

Step1 Organise the data

Long and short-term memory neural network (lstm) for time series prediction is essentially a time series data into regression data type, followed by the establishment of regression models, to the regression model to input the past time series data, you can get to the required time series data.

Step2. Establishment of regression model

Based on the training set of data organised in Step1, the Lstm regression model is built.

Step3. Test set prediction

Through the regression model of Step2, input the time series data, predict the test set prediction results, as shown in Figure 3 below, the RMSE value of the prediction effect of the test machine is 0.1839.

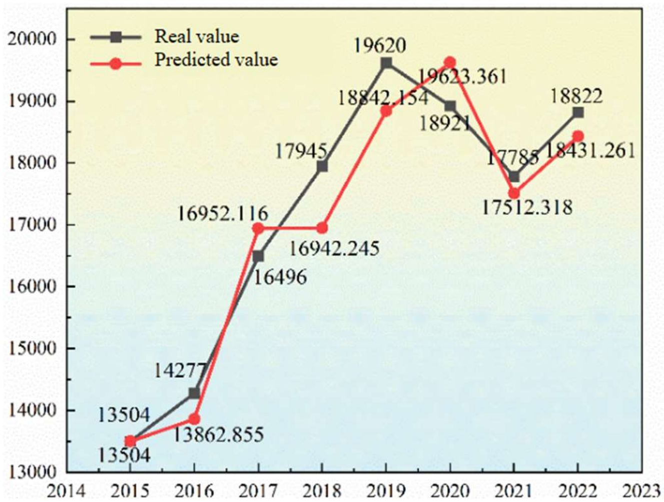


**Figure 3.** Effectiveness of test set prediction based on LSTM model

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### 3.1.4 Informer Model

Step1 Establishment of regression model

Construct the Informer model framework, combined with the training set data, establish the Informer regression model.

Step2 Test set prediction

Through the regression model of Step1, input the time series sequence data, the prediction obtained the test set prediction results, as shown in Figure 4 above, the RMSE value of the test machine prediction effect is 0.3674.

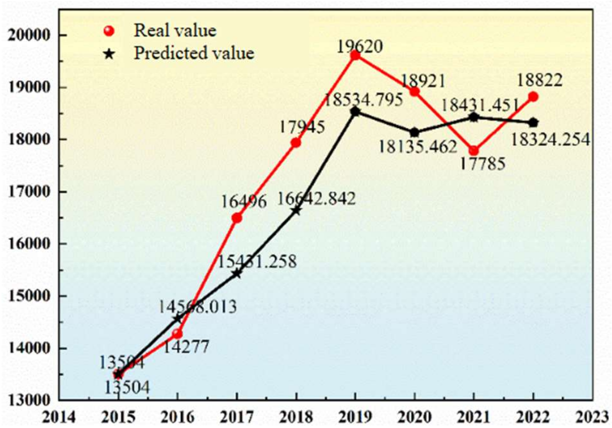


**Figure 4.** Test set prediction effects based on Informer model

### 3.1.5 BO-LSBoost model

Step1.Bayesian Orientation (BO) to solve the optimal hyperparameters

Through the Bayesian Orientation (BO), the search range of hyperparameters, box constraints, kernel function, etc. are set sequentially.

Step2. Establish the least squares tree (LSBoost) through the optimal hyperparameters.

Through the optimal hyper-parameters solved above, combined with the training set data, the LSBoost regression model is established.

Step3: Test set prediction

Through the regression model of Step2, input the time series sequence data, the prediction obtained the test set prediction results, as shown in Figure 5 below, the test set prediction effect RMSE value is 0.3594.

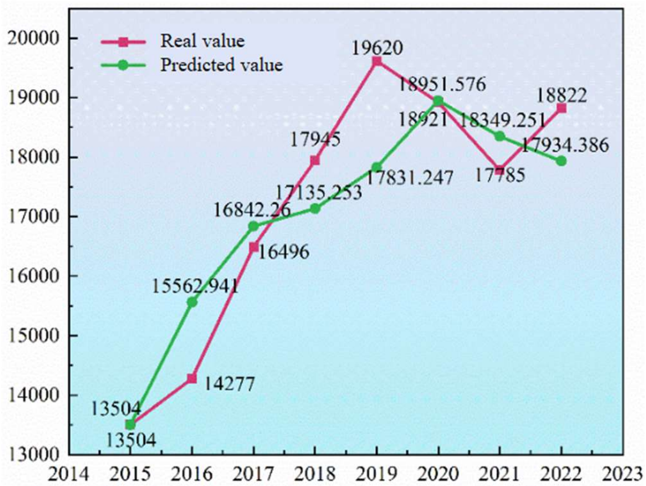


**Figure 5.** Prediction effect based on BO-LSBoost model test set

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### 3.1.6 BO-XGBoost Model

Step1.Bayesian Orientation (BO) to solve the optimal hyperparameters

Set the search range of hyperparameters, box constraints, kernel function and so on through Bayesian Orientation.

Step2.Establish the distributed gradient enhancement library (XGBoost) through the optimal hyperparameters.

Through the optimal hyper-parameters solved above, combined with the training set data, establish the XGBoost regression model.

Step3: Test set prediction

Through the regression model of Step2, input the time series sequence data, the prediction obtained the test set prediction results, as shown in Figure 7 above, the test set prediction effect RMSE value is 0.1564.

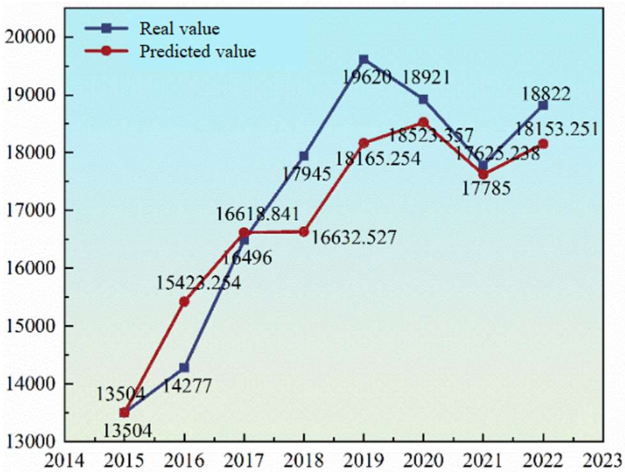


**Figure 6.** Effectiveness of test set prediction based on BO-XGBoost model

## 3.3 Select the Best Prediction Algorithm

### 3.3.1 Presentation and Analysis of Results

The RMSE values of six prediction algorithms on the test set are 0.6472, 0.5142, 0.1839, 0.3674, 0.3594, 0.1564, so the BO-XGBoost algorithm is chosen as the final prediction algorithm to predict the number of patents to be accepted in the next two decades, and the prediction results are shown in Figure 7 below:

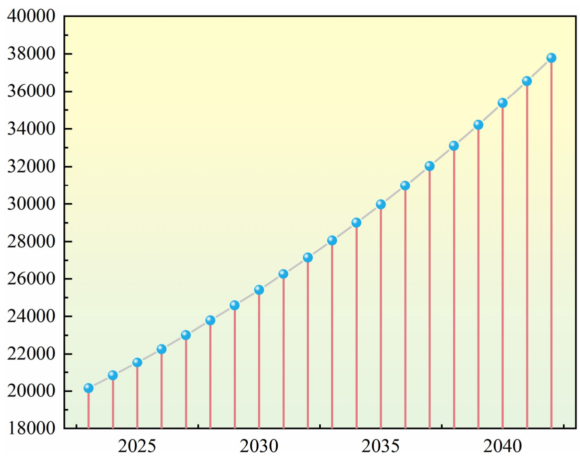


**Figure 7.** Forecast of the number of patents to be received in the next two decades

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Similarly, the other 11 indicators are analysed for prediction, and the optimal prediction algorithm corresponding to each indicator is found, and the best prediction model for the 12 steel industry development indicators is shown in the Table 1 below:

**Table 1.** The best model for each indicator

| Technological Innovation Indicators | Number of Patent Acceptance | Number of Scientific Researchers | Technical Capital Investment | Industry Revenue |
|---|---|---|---|---|
| Best Forecasting Algorithm | BO-XGBoost | Grey Forecasting | ARIMA | Lstm |
| Economic Growth Indicators | Industry Profit | Industry Profit | Margin Import Trade Volume | Export Trade Volume |
| Best Forecasting Algorithm | BO-LSBoost | Informer | BO-XGBoost | Grey Forecasting |
| Energy consumption indicators | Coal consumption | Pig iron apparent consumption | Electricity consumption per tonne of steel | New water consumption per tonne of steel |
| Best Forecasting Algorithm | Grey Forecast | BO-XGBoost | BO-LSBoost | ARIMA |

### 3.3.2 Indicator Forecast Results are Shown

The partial results of the forecast situation of the steel industry indicators are shown in the Table 2 below:

**Table 2.** Presentation of selected forecast data

| Indicators | Number of Patents Received (pieces) | Technical capital investment (Billions of Yuan) | Industry Income (Billions of Yuan) | ... | Industry Profit margin (billion yuan) | Electricity consumption (KWh/t) | Coal Consumption (billion tonnes) |
|---|---|---|---|---|---|---|---|
| 2023 | 20156 | 386.765 | 68140.43 | ... | 3.20% | 467.205 | 8.025 |
| 2024 | 20833 | 430.579 | 74631.006 | ... | -0.16% | 468.864 | 8.446 |
| 2025 | 21534 | 477.048 | 77232.389 | ... | 1.31% | 470.529 | 8.89 |
| ... | ... | ... | ... | ... | ... | ... | ... |
| 2040 | 35362 | 891.535 | 108483.89 | ... | 4.31% | 496.227 | 12.72 |
| 2041 | 36551 | 965.948 | 102483.35 | ... | 2.16% | 497.989 | 13.088 |
| 2042 | 37780 | 1044.871 | 106123.24 | ... | 6.64% | 499.758 | 13.391 |

## 4. Conclusion

Initially, by querying websites such as the National Bureau of Statistics and China Metallurgy, panel data regarding the development of the steel industry was gathered. Ultimately, a multi-algorithm coupling prediction and coupling degree analysis model was established to analyze the future development prospects of the steel industry. The following conclusions were drawn:

(1) Over recent years, with the promotion of initiatives like intelligent manufacturing and energy conservation and emissions reduction, China's steel industry has made notable progress. The industry's technological innovation capabilities have been progressively enhanced, marked by a

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growing number of associated patents and an increase in technical personnel. Resource consumption trends have stabilized, while the quantity and scale of steel enterprises have witnessed continuous expansion. China's steel industry has displayed robust dynamism, poised to sustain high-level development for a foreseeable future.

(2) The steel industry confronts certain challenges during its development process that impede its advancement. These encompass the necessity for upgrading steelmaking equipment, enhancing the competence of employees, mitigating excessive dependence on foreign ore, confronting the immense pressure for energy conservation and emissions reduction, addressing the surplus of steel production capacity, and rectifying pronounced discrepancies in loan structures. These issues fall short of fulfilling the requisites for the high-quality development of the steel industry in the future. Pertinent authorities should reinforce macro-regulation, construct and refine frameworks for resource utilization and environmental protection, augment industry competitiveness, and align with the prospective demands of steel enterprises.

(3) Via the multi-algorithm coupling prediction and coupling degree analysis model, it is discerned that steel enterprises will precipitously enter a phase of accelerated development. China's steel industry is currently cultivating a favorable coupling development rapport, predominantly propelled by industrial economy development. Subsequently, the industry will transition into a period of sustained equilibrium, characterized by pronounced accomplishments in energy conservation and emissions reduction, a substantial enhancement in innovation technology capabilities, high-level economic growth, and a considerable transformation in the landscape of industrial restructuring within the steel industry.

(4) Grounded on the outcomes derived from the model, we anticipate the forthcoming round of development in the steel industry. Recommendations are proffered to facilitate high-quality harmonized development in the realms of technological innovation, energy consumption, and economic growth within the steel industry. Endeavors are directed towards expediting the attainment of efficiency, intelligence, and eco-friendliness transformation objectives in China's steel industry.

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