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Study on China's manganese resource demand from 2024 to 2035 based on GM-SVR method

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Manganese is a strategic mineral resource primarily utilized in iron and steel metallurgy. As the world's largest consumer of manganese, China's future demand for this resource is crucial for its economic and social development and industrial planning. This paper focuses on manganese demand in China's iron and steel sector, establishing a combined grey prediction model and support vector regression model (GM-SVR) to forecast China's crude steel output from 2024 to 2035. Based on this output, we estimate manganese resource demand from 2024 to 2035 using the steel-to-manganese ratio. We employ qualitative and quantitative analyses to project manganese resource needs for this period by applying the "S" shape law and sectoral demand forecasting methods. These three methods indicate a gradual decrease in China's manganese demand, with projections of 12.86 million tons in 2025, 11.76 million tons in 2030, and 10.64 million tons in 2035. Despite the yearly decline in demand and tightening environmental policies, the overall need for manganese in China remains substantial. Therefore, increasing investment in manganese ore exploration is essential, as well as enhancing research and development in application technologies, optimizing the structure of manganese-related industries, and improving green growth and resource management.

KEYWORDS

manganese resources, "S" shaped law, grey support vector machine model, crude steel production, sectoral demand forecasting method

1 Introduction

As a strategic metal, manganese is extensively used in iron and steel production, metallurgy, batteries, and the chemical industry. It is an essential bulk raw material for industrial processes, prompting countries worldwide to categorize manganese as a key mineral. In 2023, China accounted for 64% of global manganese consumption, making it the largest consumer of manganese resources. The growth of China's manganese resource industry is crucial for the overall development of the global manganese sector. A healthy Chinese manganese industry significantly influences the advancement of manganese resources worldwide. Manganese is a critical raw material for steel production, with 90% of China's manganese consumption used in this sector. As a deoxidizer and desulfurizer, which removes oxygen and sulfur impurities during iron and steel smelting, manganese enhances the mechanical properties of steel. It improves strength without significantly reducing ductility. Therefore, manganese consumption plays a pivotal role in China's steel industry.

Previous studies on manganese resources mainly focus on the types of global manganese ore deposits, their reserves and distribution, production, consumption, and trade (Wang, et al, 2019; Sun et al., 2020; Ren et al., 2022; Sun et al., 2022; Guo et al., 2024). However, more research literature on manganese resource demand forecasting needs to be conducted. The inverted 'U'-shaped law was utilized to predict manganese consumption in a previous study, which posited that China's consumption of manganese resources would peak between 2016 and 2017 (He, 2020). Currently, standard methods for predicting mineral resource consumption include the "S" shape law prediction method, which relates *per capita* resource consumption to *per capita* GDP ("S" shape law prediction method) (Wang et al., 2015; Gao et al., 2019; Zhang, 2019), the sectoral demand forecasting method (Wu, 2021; Wu et al., 2021; Wang et al., 2024), the trend analogical analysis forecasting method (Zhang et al., 2024), mathematical model forecasting method (Wu et al., 2021; Zhang et al., 2024), and a combination of modeling and machine learning techniques (Ren et al., 2021; Ai et al., 2023; Wang et al., 2023; Zhou et al., 2024). China consumes 90% of its manganese in iron and steel metallurgy, and manganese demand can be predicted using the linear relationship between crude steel output and manganese consumption (He, 2020). Standard methods for predicting crude steel output include the "S"-shaped law of mineral resources consumption, ARIMA, and support vector machine (SVR) model (Wang et al., 2015; Ge, 2017; Liu, 2020; Wang and Gao 2020). Support Vector Machine (SVM) models effectively address nonlinear issues and are suitable for small sample datasets, offering higher model accuracy (Ge, 2017). However, the manganese demand forecasts do not account for changes in manganese consumption across different sectors. As manganese consumption in the new energy sector grows rapidly, its share of China's overall manganese consumption is expected to rise in the coming years (Zhang, 2022). Sectoral demand forecasting involves a detailed analysis and prediction of each sector (Wu, 2021; Wang et al., 2024) to enable more accurate forecasting of future manganese consumption.

In this paper, based on previous research and manganese consumption big data, the manganese consumption structure as well as the consumption situation in China is studied. Furthermore, the potential shortfall of manganese consumption in various fields is analyzed. A support vector machine (SVM) model is constructed for crude steel production forecasting, and the correlation between the model's eigenvalues and the accuracy of the prediction error is investigated. The model's performance is verified through the mean absolute error (MAE), the root mean square error (RMSE), and the coefficient of determination (R^2). Based on the model prediction results and the strong correlation between manganese consumption and crude steel production, future crude steel production is predicted from a macroeconomic perspective using a combination of the gray forecasting model and the support vector machine (SVM) model (GM-SVR). Based on the forecast results of China's crude steel production from 2024 to 2035 using the support vector machine (SVM) model, combined with the relationship between crude steel and manganese consumption, it is suggested that future manganese consumption will exhibit a downward trend. China's crude steel production has already shown a decreasing trend. When analyzing China's manganese consumption sectors, the iron and steel industry remains dominant, while the battery sector exhibits an upward trend. Consequently, overall manganese consumption in China is expected to decline in the future. Based on a combination of qualitative and quantitative analysis, with the S-shaped curve law prediction results as a reference, three prediction methods are employed: the sectoral demand forecast method, the S-shaped curve prediction method, and the linear ratio between steel and manganese consumption. These methods are used to predict China's manganese demand from 2025 to 2035. The average value of the three prediction results is calculated to enhance the reliability and stability of the forecasts. Furthermore, recommendations are provided based on the future supply and demand situation.

2 Data sources and methods

1980–2035 China's urbanization rate from United Nations; Population data for each country from 1980 to 2035 from UN World Population Prospects; GDP *per capita* data for each country from 1980 to 2035 from World Bank, International Monetary Fund, Oxford Economics, and the National Bureau of Statistics (NBS); data on the total value of China's secondary industry and the total value of the construction industry for 1980–2023 are from the NBS; Data on China's manganese demand for 2000–2023 are from the USGS, IMNI, JOGMEC, and data on manganese consumption in other countries are from IMNI, national statistical or mineral authorities, or for this paper the calculation of apparent consumption.

Manganese consumption in five developed countries—the United States, Germany, Japan, South Korea, and the United Kingdom—has already peaked. As a developing country, China has seen its manganese consumption stabilize. The *per capita* manganese consumption in these developed nations is used as a reference to predict China's future trend in *per capita* consumption. A total of six countries—namely the United States, Germany, Japan, South Korea, the United Kingdom, and China—were selected to forecast manganese consumption in China from 2024 to 2035 using the "S" shape law forecasting method.

The urbanization rate, GDP *per capita*, output value of the construction industry, output value of the secondary industry, and population number were selected as eigenvalues for grey correlation analysis related to crude steel output from 1980 to 2023. A grey support vector machine model (GM-SVR) was employed to predict these eigenvalues, which were then used as inputs for forecasting crude steel output from 2024 to 2035. This output, combined with the linear ratio of steel to manganese, enabled the derivation of manganese demand in China for the same period.

We examined the proportion of manganese consumption across various sectors, including iron and steel metallurgy, batteries, and chemicals, while assessing future consumption trends. The sectoral demand forecasting method was utilized to analyze and predict China's manganese demand in different fields from 2024 to 2035.

A comparative analysis of the results from the "S"-shaped law forecasting method, the sectoral demand forecasting method, and the GM-SVR model was conducted to validate and

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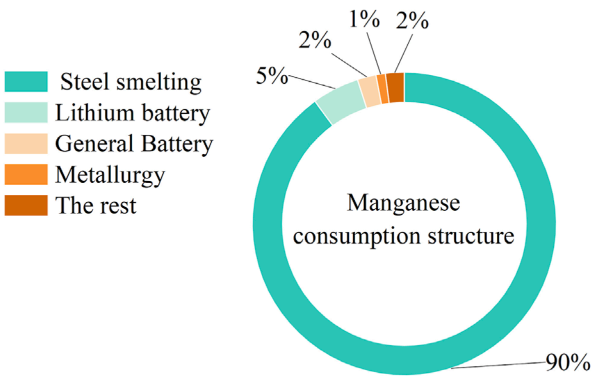

FIGURE 1
Updated consumption structure of manganese resources (Source: IMNI).

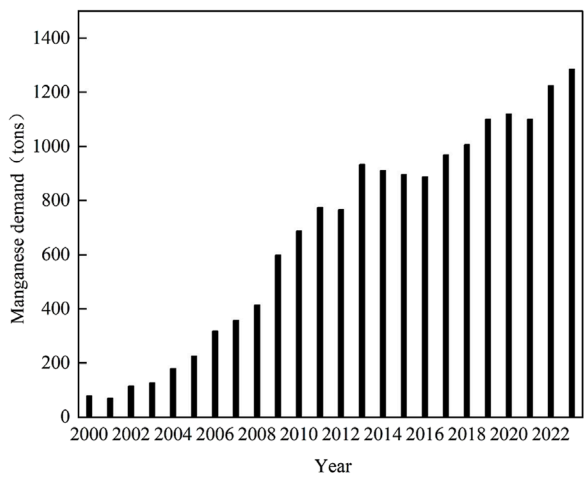

FIGURE 2
Chinese manganese demand, 2000–2023.

refine the determination of manganese demand in China for 2024 to 2035.

3 Consumption of manganese resources

3.1 Consumption structure

Consumption structure of manganese in China (Figure 1). Manganese consumption in China is predominantly concentrated in iron and steel metallurgy, accounting for 90% of total usage. The remaining 10% is distributed as follows: 5% in general batteries, 1% in lithium batteries, 2% in the chemical industry, and 2% in other applications. Manganese serves primarily as a deoxidizer, desulfurizer, and alloying element within the iron and steel sector. For example, during the steelmaking process, manganese efficiently eliminates oxygen and sulfur, enhances the chemical purity and overall quality of steel, and reduces non-metallic inclusions, which negatively affect steel performance. These improvements thereby enhance the mechanical properties and corrosion resistance of steel. In battery applications, it is chiefly utilized as a negative agent in dry batteries and as a positive electrode material in power batteries. In recent years, significant technological advancements have accompanied rapid development in new energy vehicles. This has resulted in a year-on-year increase in the installed capacity of power batteries, driving substantial growth in manganese demand for these applications.

3.2 Manganese consumption

Since 2000, China's rapid industrial development has significantly increased domestic manganese demand, rising from 780,000 tons in 2000 to 12.86 million tons in 2023—an increase of over 15 times (Figure 2). However, with the transformation and upgrading of China's industrial landscape and the gradual peak of iron and steel demand, the growth rate of manganese demand is expected to slow considerably and trend downward over time.

4 "S" shaped pattern prediction

4.1 Definition

The Global Strategy Research Center of the Chinese Academy of Geological Sciences has developed a prediction model based on the "S" shape law. This paper utilizes the historical trajectory of *per capita* manganese consumption in selected countries to forecast China's future manganese demand by comparing it with consumption levels at similar stages of development (using GDP *per capita* as an evaluation index, 1990 GK USD). The selected countries include the United States, the United Kingdom, Germany, Japan, South Korea, and China, focusing on *per capita* manganese consumption and GDP *per capita* (Figure 3). The *per capita* manganese consumption in the United States, the United Kingdom, Germany, and Japan—countries recognized as the developed nations—has peaked. Manganese consumption primarily occurs in the iron and steel metallurgy sector. Since the start of the 21st century, China has also focused its primary manganese consumption on iron and steel metallurgy. However, the usage of manganese in new energy lithium batteries has been growing rapidly in recent years, now accounting for 1% of the total consumption structure. The late start of industrialization for developing countries means that the *per capita* manganese consumption of developed countries remains a significant point of comparative reference.

4.2 Predicted results

According to data on *per capita* manganese consumption in the United States, Germany, Japan, the United Kingdom, and South Korea, the *per capita* manganese consumption of the developed countries peaked at 9,000–13,000 dollars. South Korea, a later developed country, peaked when the *per capita* GDP in the latter developed country reached 18,000–19,500 dollars. China, a rising economy after South Korea and Japan, has the most similar development trend. Concerning the peak *per capita* manganese

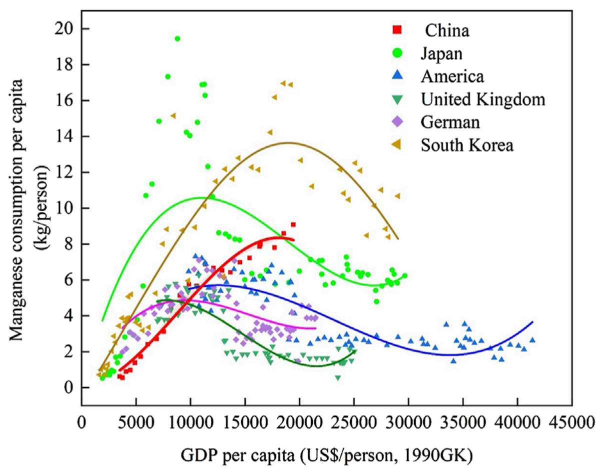

FIGURE 3
Manganese consumption *per capita versus* GDP *per capita* in a typical developed country.

consumption in Korea, it can be determined that China's *per capita* manganese consumption peaks when its *per capita* GDP reaches 18,000–19,500 dollars. In 2023, when China's *per capita* GDP reaches 19,425 dollars, the *per capita* manganese consumption will gradually enter the peak value of 9.02 kg and then slowly decline. By analogizing with the declining trend of *per capita* manganese consumption in developed countries after the peak of manganese consumption, according to the high position of *per capita* manganese consumption, the "S" shape is divided into high and middle "S" shapes. According to this, China's future *per capita* manganese consumption is projected. Among them, the high "S" shape is mainly typified by Japan and South Korea, categorized as the neutral scenario; the medium "S" shape countries are mainly typified by Germany and the United States, categorized as the optimistic scenario. The GDP *per capita* and Mn consumption *per capita* for the two scenarios are summarized in Table 1.

Neutral scenario. The "S" shaped curve of *per capita* manganese consumption in Korea and Japan is the main analogy for forecasting the downward trend of manganese consumption after reaching the peak. Mn demand peaks in Korea and Japan in 2004–2006 and 1972–1975, respectively. Optimistic scenario. It is mainly predicted by analogy with the downward trend of manganese consumption *per capita* in the United States and Germany after reaching the peak of the "S" curve, and the United States and Germany reached the peak of manganese demand in 1961–1964 and 1965–1968, respectively. According to the development trend after the peak of manganese consumption in different countries, China's future trend of manganese consumption *per capita* is predicted, and the prediction results are shown in Table 2.

5 Gray support vector machine model prediction

5.1 Support vector machine model

SVR is often used as an algorithm to solve small-sample, nonlinear regression problems and is one of the classical machine learning models (Ma et al., 2023). In the SVR model, the projection of low-latitude nonlinear eigenvalues into high-latitude space is converted into a linear regression function by a kernel function (Meng et al., 2022). The training samples $M = \{(x_1, y_1), (x_2, y_2), \cdots, (x_n, y_n)\}$. The prediction function is defined in Equation 1 where x is the input eigenvalue, and $f(x)$ is the output eigenvalue.

$$f(x) = w \cdot \varphi(x) + b \tag{1}$$

Where w is the hyperplane weight vector and b is the deviation vector.

The mathematical expression of the loss error ε is given in Equation 2.

$$\min \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\left(\xi_i + \hat{\xi}_i\right) \tag{2}$$

C is the penalization factor that ξ_i. There is a correlation between $\hat{\xi}_i$ and the slack variables.

The constraints are given by Equations 3–5:

$$y_i - [w \cdot \varphi(x_i)] - b \le \varepsilon + \xi_i \tag{3}$$

$$[w \cdot \varphi(x_i)] + b - y_i \le \varepsilon + \hat{\xi}_i \tag{4}$$

$$\xi_i \ge 0, \hat{\xi}_i \ge 0 \tag{5}$$

Where $\varphi(x_i)$ is the kernel function.

The prediction function is defined in Equation 6.

$$f(x) = \sum_{i=1}^{n}(a_i + \hat{a}_i)K(x_i, x) + b \tag{6}$$

Where a_i and $\hat{a}_i$ are Lagrange multipliers and $K(x_i, x)$ is the kernel function of the SVR model, with its mathematical expression defined in Equation 7.

$$K(x_i, x) = \exp\left(-\frac{\|x_i - x\|^2}{2g^2}\right) \tag{7}$$

Where g are the kernel function parameters.

5.2 Gray prediction model

The grey forecasting model GM (1,1) is suitable for forecasting data with incomplete information and small samples (Yao et al., 2009). In this paper, SPSSPRO software is used to forecast the total value of the secondary industry from 2024 to 2035 for the characteristic value.

5.3 Eigenvalue selection and correlation analysis

As an important indicator of a country's economic development level, GDP *per capita* has a close relationship with crude steel production. Usually, crude steel production is equal to the sum of domestic crude steel consumption and exports. Although exported

TABLE 1 GDP per capita and manganese consumption per capita for typical countries in the two scenarios. (The neutral scenario represents South Korea and Japan, while the optimistic scenario represents the United States and Germany.)

Sight	Reference country	Peak GDP per capita ($/person, 1990GK)	Peak per capita manganese consumption (kg)
Neutral scenario	South Korea Japanese	18,000–19,500 11,000–11,300	13.7 10.6
Optimistic scenario	America	12,000–13,000	5.7
	German	9,000–10,300	4.9

TABLE 2 China's manganese consumption per capita 2024-2035 "S" shaped pattern forecast results.

Year	Optimistic scenario		Neutral scenario	
	Manganese consumption per capita (kg/person)	Manganese demand (tons)	Manganese consumption per capita (kg/person)	Manganese demand (tons)
2024	9.06	1,291	9.07	1,293
2025	9.03	1,286	9.00	1,283
2026	8.95	1,274	8.87	1,262
2027	8.83	1,256	8.65	1,230
2028	8.68	1,232	8.36	1,187
2029	8.49	1,204	7.99	1,134
2030	8.28	1,172	7.57	1,071
2031	8.11	1,146	7.20	1,017
2032	7.94	1,120	6.80	959
2033	7.78	1,095	6.39	899
2034	7.64	1,072	5.97	837
2035	7.53	1,053	5.55	776

steel products are not consumed domestically, they are also part of the national economy (Wang, 2018). The population size flanks the future changes in demand for housing, transportation, infrastructure construction, etc., affecting the increase or decrease in crude steel demand. Crude steel production is an important indicator of the output value of the secondary industry (Le et al., 2009), which mainly includes construction and industry, and is an important area of crude steel consumption. The urbanization rate is an important indicator of a country's urbanization level, and the urbanization rate has an important impact on the change of steel demand in the steel market. The construction industry is an important area of crude steel consumption (Le et al., 2009). The relationship between these characteristic factors and crude steel production is not linear (Le et al., 2009). Therefore, forecasting China's future crude steel production needs to be combined with multiple factors.

5.3.1 Limitations of correlation analysis

The correlation analysis exhibits insufficient consideration of external factors, particularly the impact of policy interventions and technological advancements: policy influence: the implementation of the "Dual Carbon" policy goals (carbon peaking and carbon neutrality) has imposed restrictions on energy-intensive industries, leading to a decline in crude steel production. This regulatory shift may decouple traditional economic indicators from steel demand. Technological progress: the widespread adoption of electric arc furnace (EAF) steelmaking technology has reduced reliance on traditional blast furnaces. This technological shift could weaken the correlation between secondary industry output and crude steel production, as EAF processes prioritize scrap steel recycling over raw material-intensive methods (Chen et al., 2024).

The data of GDP *per capita*, urbanization rate, population, the output value of secondary industry, the output value of construction

TABLE 3 Gray correlation analysis results of crude steel production.

Eigenvalue (math.)	Relatedness	Rankings
GDP per capita	0.997	1
urbanization rate	0.985	2
demographic	0.984	3
Secondary sector output	0.923	4
Construction output	0.778	5

industry, and crude steel production are dimensionless (initialized), the discrimination coefficient is 0.5, and the results of grey correlation analysis are shown in Table 3.

5.3.2 Eigenvalue analysis

The correlation degree is evaluated and ranked for the five feature objects; the value of the correlation degree is between 0 and 1, and the larger the value is, the stronger the correlation between it and "crude steel production." From the above table, it can be seen that for the five characteristic values, GDP *per capita* (GK USD) has the highest value (correlation: 0.997), followed by urbanization rate (%) (correlation: 0.985), population (billion) (0.984), output value of the secondary industry (billion) (0.923), and the value of output value of the construction industry (billion) is only 0.778, because the secondary industry includes both the construction industry and the industrial industry. Comparing the correlation between the output value of the secondary industry and the correlation between the output value of the construction industry, it is more appropriate to select the output value of the secondary industry, and this paper selects the eigenvalues with a correlation degree of 0.9 or more, which is conducive to a more accurate prediction of the model. Therefore, GDP *per capita*, urbanization rate, population, and output value of secondary industry are selected as input eigenvalues of the SVR model.

5.4 Gray support vector machine model prediction

5.4.1 Data preprocessing

First, a support vector machine model (SVR) is constructed to normalize the input features, including GDP *per capita*, urbanization rate, population, and the total value of the secondary industry, to avoid potential inaccuracies during model construction. Subsequently, the input features (GDP *per capita*, urbanization rate, population, and total value of the secondary industry) and the output feature (crude steel output) from 1980 to 2023 are divided into a training set and a test set in a 7:3 ratio to train the model.

5.4.2 Model parameter selection

The trial and error method is employed to set the parameters of the Support Vector Regression (SVR) model, with the penalty factor set at 2. The radial basis function (RBF) is selected due to its strong capability to handle nonlinearities, as well as its robust stability and generalization abilities. The parameter for the RBF is set at 1.2, and the loss function is configured at 0.01. Following the completion of parameter tuning, the model is evaluated.

5.4.3 Model validation

Using the sample data on GDP *per capita*, population, urbanization rate, and output value of secondary industry from the test set, the Support Vector Regression (SVR) model is employed to derive the crude steel output. The results are then compared with the actual data to assess the validity of the SVR model.

5.4.4 Model performance evaluation

As a critical component of model usability assessment, this study employs the coefficient of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE) to evaluate the model's performance. MAE quantifies the differences between predicted and observed values, particularly by disregarding the impact of negative deviations. RMSE measures the model's error in quantitative predictive analysis, while R^2 quantifies the correlation or collinearity between predicted and actual values. Through the training of the SVR model, the test set yields an R^2 of 0.992, an MAE of 0.018, and an RMSE of 0.223. Similarly, the training set achieves an R^2 of 0.994, an MAE of 0.015, and an RMSE of 0.235. Both the training and test sets exhibit R^2 values greater than 0.99, with MAE and RMSE values being closely aligned, demonstrating that the SVR model possesses high predictive accuracy and strong generalization capabilities.

By integrating with the gray model, the issue of missing future values of input feature values in the single SVR model is addressed. Based on the excellent SVR model, the fitting degree between the actual and predicted values of crude steel production from 1980 to 2023 is visually processed, as shown in Figure 4. This demonstrates that the SVR model has a good fitting degree.

5.4.5 Input Characteristics of the SVR Model

Data encompassing *per capita* GDP, population, and urbanization rates spanning the period from 2024 to 2035 were aggregated. The projected values of China's secondary industry output for the same timeframe were forecasted utilizing a Grey Prediction Model, which demonstrated an average relative error of 5.701% and a posterior difference ratio of 0.007. This indicates that the model achieved commendable fitting performance and high precision. The primary factors influencing crude steel demand between 2024 and 2035, along with the corresponding data, are presented in Table 4.

China's 2024–2035 *per capita* GDP, population, urbanization rate, and secondary industry output value forecast data as the eigenvalue input SVR model to derive the 2024–2035 crude steel production.

The consumption of manganese in China is closely intertwined with its crude steel production, as steel production serves as the primary driver of manganese demand. Approximately 90% of manganese consumption occurs in the iron and steel metallurgy sector. By utilizing the steel-to-manganese ratio—defined as the ratio of manganese demand to crude steel output—we can estimate China's manganese consumption from 2024 to 2035 and project future trends in manganese demand.

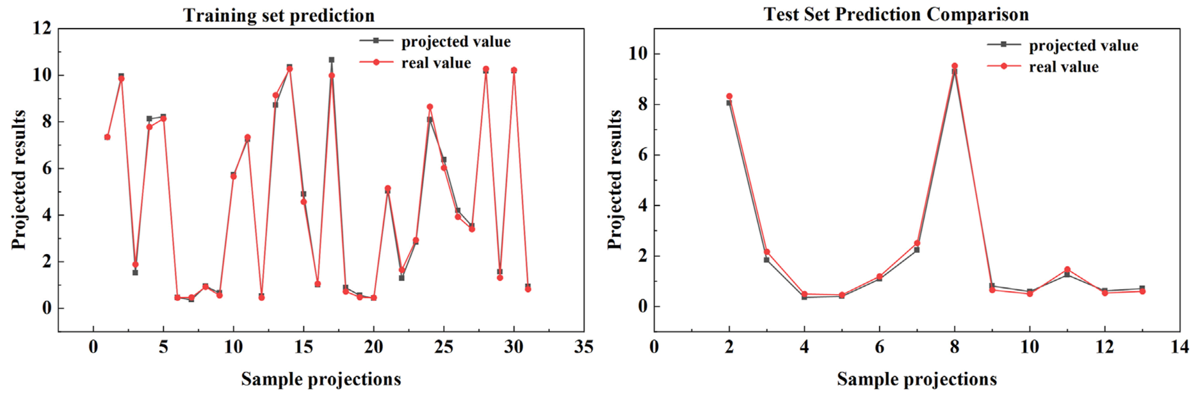

FIGURE 4
Fitting comparison between true values and predicted values of the training set and test set in the SVR model.

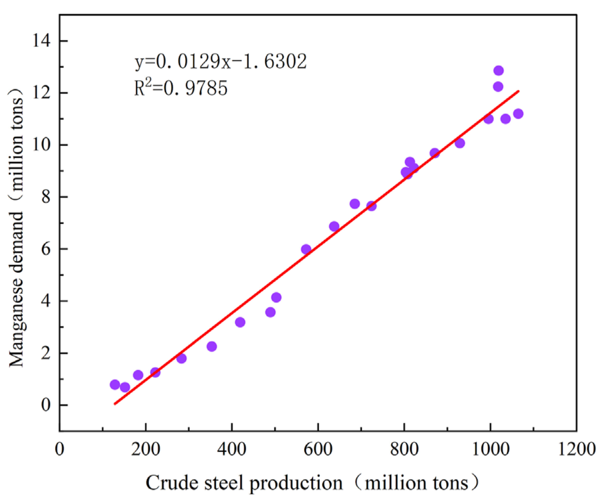

FIGURE 5
The steel-to-manganese proportion of China's crude steel output in relation to manganese demand from the year 2000–2023.

Critical value detection via change point detection (Pelt algorithm). In the critical value analysis of the steel-manganese ratio, the Pelt algorithm is employed to detect structural mutation points in the time series, with the core formula presented in Equation 8.

$$Total\,Cost = \sum_{i=1}^{K+1} Cost\left(y_{t_i,\ldots\ldots,t_{i+1}}\right) + K \times \beta \tag{8}$$

K is the number of variable points, y_(t_i …t_(i+1)) is the data segment in the time interval [ti,ti+1), β is the penalty coefficient, which controls the sensitivity of the number of variable points, and Cost (y_(a …b)) is the cost of fitting the data segment y_(a …b) fitting cost.

Cost (y_(a …b)) represents the segmented cost formula:

$$Cost\left(y_{a\ldots\ldots b}\right) = \sum_{t=a}^{b-1} \left(y_t - \mu\right)^2 \tag{9}$$

μ is the mean value of the segment.

In the relevant study, in order to balance sensitivity and stability and avoid the model's over-reliance on data noise, we empirically set the parameter β to 2.5 based on the 95% confidence interval. Phased statistics: phases were divided by the critical year of detection, and means, standard deviations, and Bootstrap 95% confidence intervals were calculated.

The critical detection years revealed significant turning points in 2008 and 2019. An analysis of the steel-to-manganese ratio across these three stages was conducted, and the 95% confidence intervals for the steel-to-manganese ratio values in each stage were calculated (Table 5), showing a steady increase in the steel-to-manganese ratio throughout the three stages. Based on the steel-manganese ratio of crude steel production and manganese demand from 2000 to 2023, the formula for the steel-manganese ratio is: y = 0.01289x - 1.63025966 (Figure 5). The goodness of fit R^2 is 0.9785, indicating good reliability. According to the steel-manganese ratio, the coefficient is 12.98 kg of manganese per ton of steel. Considering the overall perspective, the future steel-manganese ratio is in a relatively stable upward stage, with a steel-manganese ratio of 12.9 kg of manganese per ton of steel. The results for China's crude steel production and manganese demand from 2024 to 2035 are shown in Table 6.

6 Sectoral demand forecasts

The sectoral demand forecast method mainly analyzes and predicts the consumption situation of manganese resources in various fields. Based on the consumption situation of manganese resources, this paper mainly analyzes the iron and steel metallurgy field and battery field, and the battery field is divided into the general battery field and lithium battery field.

6.1 Iron and steel metallurgy

Iron and steel metallurgy, as the largest consumer of manganese, is mainly used in construction, machinery manufacturing, automobile manufacturing, shipbuilding, household appliances, and other consumer sectors (Ren et al., 2022). Under the transformation and

TABLE 4 China's GDP per capita, population, urbanization rate, and secondary industry output projections, 2024–2035.

Year	GDP per capita (GK dollars)	Population (billions)	Urbanization rate (%)	Secondary sector output (billion)
2024	20,116	14.25	65.54	516,815
2025	21,133	14.24	66.48	545,740
2026	21,996	14.23	67.38	575,502
2027	22,899	14.22	68.25	606,125
2028	23,845	14.20	69.07	637,634
2029	24,835	14.18	69.87	670,055
2030	25,871	14.16	70.63	703,415
2031	26,698	14.13	71.35	737,740
2032	27,556	14.10	72.04	773,059
2033	28,447	14.07	72.70	809,400
2034	29,373	14.03	73.32	846,792
2035	30,336	14.00	73.92	885,267

TABLE 5 Critical year division stages, means, standard deviations, 95% confidence intervals.

Phase	Average value	Standard deviation	95% confidence intervals
Phase 1 (2000-2008)	0.65	0.11	[0.59, 0.71]
Phase 2 (2009-2019)	1.10	0.03	[1.08, 1.12]
Phase 3 (2020-2023)	1.14	0.10	[1.06, 1.23]

upgrading of infrastructure construction and the "double-carbon" policy, China's crude steel demand gradually peaked. It shows a downward trend, and the industry's output decreases yearly. It can be seen through the prediction of the GM-SVR model that the crude steel output will be 1013.96 million tons in 2025, 922.18 million tons in 2030, and 828.1 million tons in 2035. Crude steel output of 828.10 million tons. According to the in-depth report of the manganese industry in the metal industry, the average manganese content in steel is 1.1%, which leads to the Chinese manganese demand in 2025, 2030, and 2035 11.15 million tons, 10.14 million tons and 9.11 million tons respectively.

TABLE 6 China's crude steel production, manganese demand, 2024–2035.

Year	Crude steel production (tons)	Manganese demand (tons)
2024	102,225	1319
2025	101,396	1,308
2026	100,349	1,295
2027	990,02	1,277
2028	970,29	1,252
2029	95,062	1,226
2030	92,218	1,190
2031	90,223	1,164
2032	88,080	1,136
2033	86,801	1,120
2034	84,371	1,088
2035	82,810	1,068

6.2 Battery sector

Manganese is used in batteries, which are divided into lithium batteries and general batteries (Ren et al., 2022).

In the realm of lithium batteries, the consumption landscape has witnessed a surge in manganese usage amidst the rapid development of new energy sources. Manganese plays a pivotal

TABLE 7 China's manganese demand analysis, 2024–2035.

Year	Baseline scenario	Optimistic scenario	GM-SVR prediction combined with steel-manganese ratio	Sectoral demand projections	Consolidated manganese demand(tons)
2025	1,283	1,286	1,308	1247	1280
2030	1,071	1,172	1,190	1155	1172
2035	776	1,053	1,068	1063	1061

role, predominantly serving as a key component in the cathode materials of power batteries. Presently, manganese's application is chiefly concentrated in lithium manganate and ternary material compositions for lithium battery cathodes. Data sourced from the CITIC Securities Research Department indicates that lithium manganate comprises 61% manganese, whereas ternary materials contain 10.6% manganese. Currently, the manganese content in nickel manganese acid lithium batteries, phosphate manganese iron lithium batteries, lithium-rich manganese-based batteries, and sodium-ion batteries is minimal. Nevertheless, it is anticipated that as market penetration escalates in the future, the demand for manganese will experience a corresponding upswing. Forecasts provided by Bloomberg New Energy Finance (BNEF) and the China Securities Research Department project the global installed capacity of power batteries to attain 1300 GWh, 2,600 GWh, and 4,500 GWh by the years 2025, 2030, and 2035 respectively (CITIC Securities, 2022), translating to manganese utilization of 316,000 tons, 673,000 tons, and 1,242,000 tons for these respective years. Predictions by Zhang et al. (2024) estimate that the capacity of power batteries in China will escalate to 931 GWh, 1241 GWh, and 1551 GWh by 2025, 2030, and 2035 respectively. Through estimation grounded on the capacity of power batteries in China relative to the globally installed capacity of power batteries, the anticipated manganese consumption in Chinese power batteries is poised to reach 226,300 tons, 321,200 tons, and 428,100 tons by 2025, 2030, and 2035 respectively. Dry batteries mainly dominate the general battery field, and common dry batteries include ordinary zinc-manganese dry batteries, alkaline zinc-manganese dry batteries, magnesium-manganese dry batteries, lithium-manganese dry batteries, and nickel-cobalt-manganese automobile batteries (Xu et al., 2023). With the continuous development of electric vehicles and renewable energy storage, the importance of manganese in lithium batteries will further increase. In contrast, the attention and growth potential of the general battery market is relatively small, so the short-term prediction of manganese used in the field of general batteries in the future will remain at about 610,000 tons.

6.3 Chemical and other fields

Manganese in the chemical field is mainly used to prepare a variety of manganese salt oxidizers and disinfectants, etc., with specific applications such as water treatment chemicals and other chemicals, automotive primers, colorants for bricks, frits, glass, textiles and ceramic tiles, powder coatings, artist's glazes, and cosmetics (Ren et al., 2022). In the short term, the development trend of manganese in the chemical field is stable, and the short-term forecast of manganese consumption in the chemical field in the future remains stable at 240,000 tons.

Manganese consumption in other fields, such as electronics, environmental protection, building materials, agriculture, etc., is very small. In the field of electronics, it is mainly used to make soft magnetic materials; in the field of environmental protection, it is mainly used as a purifying agent for automobile exhausts, industrial wastewater, and drinking water; in the field of building materials, it is mainly used as a coloring and fading agent for building materials; and in the field of agriculture, it is used to produce fertilizers and pesticides (Ren et al., 2022; Xu et al., 2023). The quantity of manganese used in these fields maintains a stable development trend, and it is predicted that China's consumption of manganese in other fields will remain stable in the future, which will be about 240,000 tons.

Sectoral Demand Forecasting for Manganese: Key Focus Areas. The sectoral demand forecasting for manganese primarily focuses on predictive analysis of its consumption in two key areas: the iron and steel metallurgy sector, which represents the primary consumption domain, and the battery sector, which is a rapidly growing consumption field. These sectors are critical for understanding both current and future manganese demand trends. In contrast, the chemical industry sector and other sectors exhibit limited data availability regarding manganese consumption due to their relatively low share in total manganese usage and stable demand patterns. These sectors are characterized by minimal short-term fluctuations, making them less significant for near-term predictive analysis.

Utilizing the departmental demand forecasting methodology, it is projected that China's consumption of manganese resources will amount to 12.47 million tons, 11.55 million tons, and 10.63 million tons for the years 2025, 2030, and 2035 respectively.

7 Analysis of the forecast results

In the course of this research, due to the time limitation of the crude steel production data utilized in the model, there exists a certain degree of variability in the forecasting results. Therefore, it is advisable to acquire more updated data to further refine and enhance the precision of the SVR (Support Vector Regression) model's predictions. Regarding the forecast of manganese demand, the GM-SVR (Gray Model - Support Vector Regression) model incorporates multifactor predictions from a broad perspective, considering both the steel-to-manganese ratio and the departmental demand forecast methodologies, thereby further improving the accuracy of future manganese demand forecasts in China. Limitations of the GM-SVR Model: The model's predictive performance is heavily influenced by sudden external factors, such as natural disasters and political crises, which can significantly impact the forecasted crude steel production. This study's prediction model struggles to account for these abrupt extrinsic variables.

The 'S' shaped curve forecasting approach, together with the GM-SVR (Grey Model - Support Vector Regression) model incorporating the steel-to-manganese ratio forecast and the departmental demand forecast, are employed to project China's manganese demand for the period spanning 2024 to 2035, as presented in Table 7. With reference to the 'S' shaped curve for anticipating China's manganese demand, this study analyzes the forecasting outcomes of the GM-SVR model when amalgamated with the steel-to-manganese ratio and departmental demand. The forecasting outcome of the GM-SVR model when integrated with the steel-to-manganese ratio bears resemblance to that of the optimistic scenario. By synthesizing the forecasting results of the three methodologies, this paper adopts the mean value as the more scientifically grounded forecast for China's manganese demand from 2024 to 2035. Specifically, China's manganese demand in the years 2025, 2030, and 2035 is projected to reach 12.86 million tons, 11.76 million tons, and 10.64 million tons respectively. He, (2020), has forecasted that China's manganese demand in 2025 and 2030 would amount to 10.2 million tons and 9.39 million tons respectively. The forecasted trends exhibit a descending pattern, which aligns with the findings of this research.

8 Conclusion and recommendations

(1) This study utilizes three forecasting methodologies, specifically the 'S' shaped curve forecasting approach, the GM-SVR (Grey Model - Support Vector Regression) model integrated with the steel-to-manganese ratio forecasting technique, and the departmental demand forecasting method, to anticipate China's manganese requirements for the timeframe spanning 2024 to 2035. The forecasting results derived from these three approaches demonstrate a strong level of agreement, with the predicted manganese demand in China for the years 2025, 2030, and 2035 being 12.83 million tons, 11.76 million tons, and 10.64 million tons respectively.

(2) China's manganese demand of 12.86 million tons in 2023 has entered the peak period of manganese consumption. In the future, China's steel demand will gradually decline, decreasing manganese consumption in iron and steel metallurgy. The development of power battery technology and the gradual increase of the penetration rate of new manganese-based anode materials cause manganese consumption in lithium batteries to increase yearly. However, the growth rate of the battery field is not as fast as that of the iron and steel metallurgy field, so manganese demand in China will show a slow downward trend in the future.

Based on the manganese demand in China, the following recommendations are made:

(1) Strengthening technological research and development and technological upgrading in the field of manganese resource application. Strengthen the research and development and upgrade of manganese ore mining, processing, and metallurgical technologies, improve the utilization rate of manganese resources at home and abroad, and reduce energy consumption. Strengthen manganese ore and manganese product recycling technologies and improve the utilization rate of secondary resource recycling. Encourage enterprises, scientific research institutions, and universities to cooperate in industry-university research to enhance the development and innovation of manganese-related industrial technologies.

(2) Optimize the structure of the manganese industry and enhance the overall value of the manganese industry. China is highly dependent on the iron and steel industry, and manganese accounts for a high proportion of its consumption. We should extend the industrial chain, increase the research and development of manganese products in new energy sources, new materials, and other high-tech fields, encourage diversified development, increase the added value of manganese products, and gradually get rid of the industrial development pattern of "importing resources and exporting low-end products."

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Author contributions

XZ: Data curation, Formal Analysis, Software, Writing–original draft, Writing–review and editing. XH: Writing–review and editing. HF: Data curation, Writing–review and editing. LL: Writing–review and editing. QL: Writing–review and editing. GL: Writing–review and editing. BD: Writing–review and editing. HZ: Writing–review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

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References

Ai, X., Li, S., and Xu, H. (2023). Wind speed prediction model using ensemble empirical mode decomposition, least squares support vector machine, and long short-term memory. *Front. Energy Res.* 10, 1043867. doi:10.3389/fenrg.2022.1043867

Chen, Z., Tian, B., Jiang, X., Wu, W., Wei, G., and Zhu, R. (2024). Advances and prospects in low-carbon, high-efficiency, and intelligent smelting technologies for electric arc furnaces. *iron steel* 59 (09), 167–183. doi:10.13228/j.boyuan.issn0449-749x.20240285

CITIC Securities (2022). in *-depth report on the manganese Industry in the metal sector* (Beijing, China: CITIC Securities).

Gao, X., Wang, A., Liu, C., Liu, G., and Yan, K. (2019). Expanded S-Curve Model of a Relationship Between Crude Steel Consumption and Economic Development: Empiricism from Case Studies of Developed Economies. *Nat. Resou. Res.* 28: 547–562. doi:10.1007/s11053-108-9406-3

Ge, S. (2017). *Research on China's total crude steel consumption forecasting model based on BP neural network and support vector machine*. (master's thesis.) Southeast University, Nanjing, China.

Guo, X., Lu, Y., Zhang, Q., Ren, J., and Cai, W. (2024). The geological characteristics, resource potential, and development status of manganese deposits in Africa. *Minerals* 14(11), 1088. doi:10.3390/min14111088

He, H. (2020). Exploration of manganese consumption pattern and forecast of future manganese demand in China. *China Min.* 29 (5), 7–11. doi:10.12075/j.issn.1004-4051.2020.05.024

Le, Y. (2009). *Research on the evaluation system of economic utilization and safety and security of manganese resources*. (PhD dissertation.) Wuhan University of Technology, Wuhan, China.

Liu, X. (2020). Forecasting crude steel production in new China based on ARIMA and GM(1,1) models. *West. Leather* (08), 87. doi:10.20143/j.1671-1602.2020.08.069

Ma, B., Liang, Q., Jia, Y., and Xu, Y. (2023). High-temperature flow stress prediction of 7050 alloys based on BPNN, SVR, and RF models. *J. Heat Treat. Mater.* (03), 196–204. doi:10.13289/j.issn.1009-6264.2022-0396

Meng, Z., Sun, H., and Wang, X. (2022). Forecasting energy consumption based on SVR and Markov model: a case study of China. *Front. Environ. Sci.* 10, 883711. doi:10.3389/fenvs.2022.883711

Ren, H., Liu, M., Wang, Z., Wu, H., and Mao, J. (2022). Security of manganese resources and industrial chain in China. *Chin. Eng. Sci.* 24 (03), 20–28. doi:10.15302/j-sscae-2022.03.003

Ren, M., Dai, J., Zhu, W., and Dai, F. (2021). Combined modeling for iron ore demand forecasting with intelligent optimization algorithms. *Gospod. Surowcami Mineralnymi-Mineral Resour. Manag.*, 21–38. doi:10.24425/gsm.2021.136293

Sun, H., Wang, J., Ren, J., Zhang, W., Tang, W., and Wu, X. (2020). Current status of global manganese resources and suggestions for sustainable development in China. *Mineral Prot. Util.* 40 (06), 169–174. doi:10.13779/j.cnki.issn1001-0076.2020.06.023

Sun, K., Zhang, Q., Zhu, Q., Jiang, S., Ren, J., and Sun, H. (2022). Global manganese ore resource characteristics and supply/demand pattern. *Mineral. Explor.* (04), 371–387. doi:10.20008/j.kckc.202204001

Wang, A., and Gao, C. (2020). Outlook of China's energy and important mineral resources dem-and. *Chin. Acad. Sci. Proc.* (03), 338–344. doi:10.16418/j.issn.1000-3045.20200107001

Wang, A., Wang, G., Chen, W., Yu, W., Yan, K., and Yang, H. (2015). S-curve model of relationship between energy cnsumption and economic development. *Nat. Resou. Res.*24 (1), 53–64. doi:10.107/s1153-014-9234-z

Wang, A., Wang, G., Deng, X., Zhou, F., An, H., Zhong, W., et al. (2019). Security and management of China's strategic critical mineral resources in the New Era. *Bulletin of National Natural Science Foundation of China*.33(2), 133–40. doi:10.16262/j.cnki.1000-8217.2019.02.006

Wang, J., Tian, G., Tao, Y., and Lu, C. (2023). Prediction of Chongqing's grain output based on support vector machine. *Front. Sustain. Food Syst.* 7, 1015016. doi:10.3389/fsufs.2023.1015016

Wang, X. (2018). *Research on bauxite resource product demand forecast and countermeasures in China Master's thesis*. Beijing: China University of Geosciences.

Wang, X., Liu, C., Wang, A., Liu, J., and Jia, X. (2024). Development and utilization status and the future demand forecast of molybdenum resources in China. *Multipurp. Util. Mineral Resour.* 45 (4), 69–75. doi:10.3969/j.issn.1000-6532.2024.04.010

Wu, Q. (2021). "Demand forecast for titanium mineral products in China, 2021-2035 Master's thesis, China University of Geosciences,". Beijing. doi:10.27493/d.cnki.gzdzy.2021.001014

Xu, Y., Dong, Z., Wang, C., and Zhang, L. (2023). The miraculous and low-profile manganese: a "supporting role" in social life. *Geol. Mineral Deposits* (06), 1310–1318. doi:10.16111/j.0258-7106.2023.06.014

Yao, T., Liu, S., and Xie, N. (2009). On the properties of small sample of GM(1,1) model. *Appl. Math. Model.* 33 (4), 1894–1903. doi:10.1016/j.apm.2008.03.017

Zhang, J. (2019). "Study on lead demand forecast and supply structure in China, 2020-2035 Master's thesis, China University of Geosciences". Beijing. doi:10.27493/d.cnki.gzdzy.2019.000587

Zhang, Y. (2022). Analysis of advantages and disadvantages under the new policy of safety and environmental protection in China's manganese mining industry and research on the development path. *China Manganese Ind.* (06), 21–25. doi:10.14101/j.cnki.issn.1002-4336.2022.06.004

Zhang, Z., Pan, Z., and Che, D. (2024). Analysis of lithium supply and demand situation from 2024 to 2035 based on the characteristics of lithium deposits and resources in China. *China Min. Ind.* (06), 26–44. doi:10.12075/j.issn.1004-4051.20241183

Zhou, W., Zhan, C., Zhang, Z., Ruan, S., and Cheng, J. (2024). A multi-scenario demand forecast of raw nickel ore in China based on a combined gray GM-BP neural network model. *Resour. Industries* 26 (02), 53–66. doi:10.13776/j.cnki.resourcesindustries.20231123.001