Development forecast of special robot market based on gray correlation degree and BPNN

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ABSTRACT

Through in-depth research of China's special robot market, this paper constructs a comprehensive evaluation model, which takes into account many factors such as market size, technological innovation level, policy support, international competitiveness, application field expansion and core technology breakthrough. In the model construction, a series of indicators with important influence on the market development are selected, and the feasibility of the model is verified through the data over the years. Finally, the paper provides suggestions on market trends, technological innovation and policy making, which provides insights for decision makers, investors and researchers, and provides theoretical support for the sustainable development of the special robot industry.

Keywords: Special Robot; Market Forecast; Grey Correlation Model, BPNN

1 INTRODUCTION

The special robot market is booming due to increasing demand in various fields like chemical plants, environmental pollution control, and geological research. These robots are crucial for tasks in hazardous or inaccessible environments, enhancing efficiency and reducing risks. National policies, particularly those outlined by General Secretary Xi Jinping, prioritize robotics and intelligent manufacturing, propelling China's robot industry forward. Globally, the special robot market has seen significant growth, with sales projected to reach $20.18 billion by 2023. China's market is also expanding rapidly, with sales expected to reach 18.52 billion yuan by 2023, driven by applications in military, security, medical care, and more [1]. Technological innovation, encompassing sensors, AI, machine vision, and more, is a key driver of market development. China's research and development efforts involve universities, research institutes, enterprises, and military units, supported by national innovation platforms. Competition in the special robot market is influenced by factors like demand, technology, policy, investment, and brand influence. China faces international challenges from developed countries and experiences diversification and centralization in domestic competition [2]. This study aims to forecast the future trends of the special robot market, focusing on technological innovation and major application areas, to provide insights for policymakers, investors, and researchers, fostering sustainable industry development.

2 RESEARCH STATUS QUO

Recent research by Jiang indicates a significant acceleration in China's special robot market, with demand soaring from $820 million in 2018 to $7.8 billion in 2022. Wang Desheng underscores the vital role of the intelligent robot industry in technological innovation, industrial upgrading, and national security across various sectors [3]. Liu Yilun's literature analysis highlights the prosperous stage of the service robot market, forecasting trends toward autonomous learning, natural interaction, and multi-machine interconnection. Meanwhile, Xing Xinxin identifies ongoing growth in China's robot market alongside existing challenges, emphasizing the importance of addressing these issues for the industry's high-quality development [4-6]. These studies collectively offer insights into the current state and future trajectory of China's robot industry, serving as valuable references for further exploration of the market's evolution.

3 RESEARCH PURPOSE AND QUESTIONS

This study seeks to comprehensively analyze future trends in the robot market, focusing on key factors such as technological innovation and major application areas. By addressing specific research questions on the main factors influencing special robot development in China and forecasting the country's robot market growth, it aims to provide valuable insights for policymakers, investors, and researchers to foster sustainable industry development.

4 STUDY ASSUMPTIONS

This study is based on several key hypotheses: Firstly, the market size of special robots is influenced by both sales volume and unit price. Secondly, technological innovation in the special robot market is linked to the input-output ratio of innovation. Thirdly, government support affects the industry's innovation through the allocation of resources [7]. Fourthly, the international competitiveness of domestic special robots is tied to export volume and market share. Fifthly, the expansion of application fields depends on the number and effectiveness of scenarios and industries. Lastly, breakthroughs in core technology are associated with patent applications, scientific publications, and technological awards.

5 RESEARCH TECHNIQUE

Market indicators and influencing factors of China's special robot industry are compiled from sources like the National Bureau of Statistics and research reports, followed by correlation analysis to determine each factor's impact. This informs the development trend prediction using linear models for influencing factors and machine learning for a 10-year forecast of China's special robot industry.

6 DATA ANALYSIS

6.1 Model Preparation

The statistical results of the above indicators are as follows:

Table 1: Statistics of each indicator

year	Market Scale (100M yuan)	Tech Innovation Level (%)	Policy Support Strength (%)	International Competitiveness (%)	Application Field Expansion Index	Core Tech Breakthrough Index
2012	3.2	0.8	1.2	0.5	0.12	0.08
2013	4.5	1	1.5	0.6	0.15	0.11
2014	6.8	1.3	1.8	0.8	0.18	0.14
2015	9.6	1.6	2.1	1	0.22	0.18
2016	13.5	2	2.5	1.3	0.27	0.23
2017	18	2.5	3	1.6	0.33	0.29
2018	25	3	3.6	2	0.4	0.36
2019	34	3.6	4.2	2.5	0.48	0.44
2020	48	4.2	5	3	0.58	0.53
2021	66.5	5	6	3.6	0.69	0.63
2022	78.6	5.8	6.8	4.2	0.82	0.74
2023	95	6.8	7.8	5	0.97	0.86

Over the past decade, the domestic special robot industry has exhibited sustained market growth, with increasing levels of technological innovation, policy support, and international competitiveness, along with expanding application scope and core technology breakthroughs, highlighting its significant development potential and market competitiveness.

6.2 Analysis of influencing factors

6.2.1 Model building

This paper adopts the method of grey correlation analysis to study the specific calculation steps of the correlation between the special robot market and the influencing factors as follows:

Step 1. Determine the reference sequence and compare the sequence [8].

Take the stock index as the reference sequence;$Y = \{y(k), k = 1,2 \ldots n\}$

In 6.1, a total of 5 indicators affecting the market size of special robots are compared$X_i = \{x_i(k), k = 1,2 \ldots n\}, (i = 1,2 \ldots 5)$

Step 2. De-dimensional dimension. The reference sequence and comparison sequence are standardized according to the following formula:

$$\bar{x}_i = \frac{x_i - \min\limits_{i\in[1,n]}\{x_i\}}{\max\limits_{i\in[1,n]}\{x_i\} - \min\limits_{i\in[1,n]}\{x_i\}} \tag{1}$$

Step 3. Find the difference sequence. The difference columns between the reference and comparison columns are:$YX_i\Delta x_i(k)$

$$\Delta x_i(k) = |Y(k) - X_i(k)| \tag{2}$$

Step 4. Find the minimum difference and the maximum difference of the difference sequence.

$$\Delta_{ik}min = \min_i \min_k \Delta x_i(k) \tag{3}$$

$$\Delta_{ik}max = \max_i \max_k \Delta x_i(k) \tag{4}$$

$$\gamma_i(k) = \frac{\Delta_{ik}min + \rho\Delta_{ik}max}{\Delta_i(k) + \rho\Delta_{ik}max} \tag{5}$$

Step 5. Solve the correlation coefficient. For the reference series and the comparison series, the correlation coefficient is:$YX_i\gamma_i(k)$.

Step 6. Solve the correlation degree.

$$\xi_i = \frac{1}{n}\sum_{k=1}^{n}\gamma_i(k) \tag{6}$$

Through the above steps, we solved the correlation with the size of the characteristic robot market using gray correlation analysis [9].

6.2.2 Model solution

Through the above model, the gray correlation coefficient of each index is obtained as follows:

Table 2: List of grey correlation coefficient of each index

year	Tech Innovation Level (%)	Policy Support Strength (%)	International Competitiveness (%)	Application Field Expansion Index	Core Tech Breakthrough Index
2012	0.7893	0.7099	0.8278	0.7600	0.8620
2013	0.7546	0.6657	0.8164	0.7214	0.7987
2014	0.7204	0.6550	0.7818	0.7207	0.7844
2015	0.7059	0.6593	0.7699	0.7104	0.7553
2016	0.6929	0.6703	0.7412	0.7117	0.7366
2017	0.6657	0.6726	0.7364	0.7069	0.7091
2018	0.7201	0.7298	0.7687	0.7663	0.7402
2019	0.8258	0.8965	0.8250	0.9005	0.8236
2020	0.9052	0.8657	0.9856	0.8967	1.0000
2021	0.5585	0.5491	0.6051	0.5539	0.5982
2022	0.4916	0.4613	0.5408	0.5136	0.5433
2023	0.4120	0.3719	0.4697	0.4388	0.4452

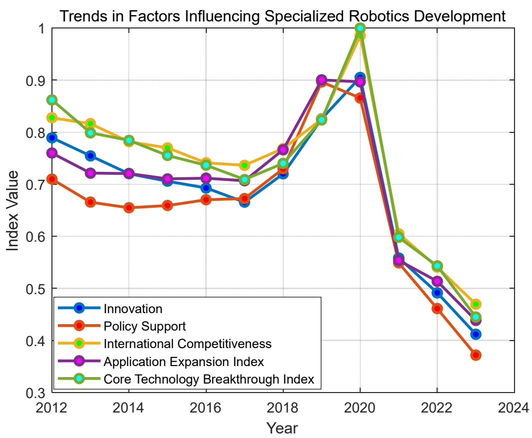

Figure 1: Visualization results of the gray correlation coefficient of each index

The domestic special robot market size has steadily grown due to technological innovation, policy support, and international competitiveness, with fluctuations in 2021 and 2022 suggesting the need for ongoing attention to these key factors for sustained market development.

Finally, the gray correlation degree of each index is:

Table 3: Gray correlation results for each indicator

Evaluation item	Correlation degree	Ranking
Domestic special robot international competitiveness (%)	0.739	1
Breakthrough index of special robot core technology	0.733	2
Expansion index of special robot application field	0.7	3
Domestic special robot technology innovation level (%)	0.687	4
Domestic special robot policy support strength (%)	0.659	5

Grey correlation analysis ranks international competitiveness as the most influential factor, followed by core technology breakthrough index, application field expansion index, and technological innovation level, while domestic policy support ranks relatively lower, aiding policymakers in devising effective strategies.

6.3 Market Forecast Analysis

6.3.1 Prediction of influencing factors

For calculation, 2011 minus all years to obtain the fitted curve as follows:

Table 4: List of fitted curves of each index

Metric	Fitting a curve	Degree of fitting
Tech innovation level (%)	$Y = 0.0352t2+ 0.0792t + 0.7136$	$R2= 0.9996$
Policy support strength (%)	$Y = 0.041t2+0.0606t +1.175$	$R2= 0.9993$
International competitiveness (%)	$Y = 0.0306t2+0.0055t + 0.4795$	$R2= 0.9993$
Application field expansion index	$Y = 0.006t^2-0.0035t + 0.1298$	$R2= 0.9992$
Core tech breakthrough index	$Y = 0.0049t^2+0.0072t +0.0725$	$R2 = 0.9999$

Finally, the next 10 years are:

Table 5: Forecast for the next 10 years for each input indicator

Year	Tech innovation level (%)	Policy support strength (%)	International competitiveness (%)	Application field expansion index	core tech breakthrough index
2024	7.6920	8.8918	5.7224	1.0983	0.9942
2025	8.7216	10.0594	6.5541	1.2568	1.1337
2026	9.8216	11.3090	7.4470	1.4273	1.2830
2027	10.9920	12.6406	8.4011	1.6098	1.4421
2028	12.2328	14.0542	9.4164	1.8043	1.6110
2029	13.5440	15.5498	10.4929	2.0108	1.7897

2030	14.9256	17.1274	11.6306	2.2293	1.9782
2031	16.3776	18.7870	12.8295	2.4598	2.1765
2032	17.9000	20.5286	14.0896	2.7023	2.3846
2033	19.4928	22.3522	15.4109	2.9568	2.6025
2024	7.6920	8.8918	5.7224	1.0983	0.9942
2025	8.7216	10.0594	6.5541	1.2568	1.1337

The prediction indicates that over the next decade, technological innovation, policy support, international competitiveness, application field expansion, and core technology breakthroughs will all experience growth, emphasizing their pivotal roles in fostering sustainable growth in the domestic special robot market and informing policymaking strategies.

6.3.2 Market Size Forecast

This study employs a Backpropagation Neural Network (BPNN) model for prediction. BPNN consists of input, hidden, and output layers, with neurons passing information through weighted connections. Activation functions like Sigmoid or ReLU introduce non-linearities, enabling complex pattern learning [10]. The core of BPNN is the backpropagation algorithm, adjusting weights to minimize output-error discrepancies through gradient descent. Learning involves feedforward and backpropagation iterations, with parameters like learning rate balancing speed and convergence. Model training uses known data to adjust weights, while testing assesses performance on unknown data, aiming for generalization. Each influencing index serves as input, mapped to domestic sales scale as the output, facilitating prediction.

Finally, the parameters of the neural network model that we selected were set as follows:

Table 6: The Bp neural network model parameter table

Parameter name	Parameter values
Data cut	0.9
Data shuffle	Deny
Cross validation	Deny
Activation function	Identity
Solver	Lbfgs
Learning rate	0.1
L2 regular term	1
Iterations	1000
Number of hidden layer 1 neurons	100

Select the relative error as the model evaluation, namely:

$$Relative\ Error = \frac{|A - B|}{|A|} \times 100\% \tag{7}$$

A is the actual value (the measured value),

B is the predicted value (model predicted value).

The final training results are:

Table 7: Test results of the BPNN model

Prediction test set result Y	Domestic special robot market scale (100 million yuan)	Fractional error

71.86478045	78.6	9%
84.88942641	95	11%

According to the above model, the prediction accuracy reaches about 90%, which can be used as the prediction of the market size.

The forecast results are as follows:

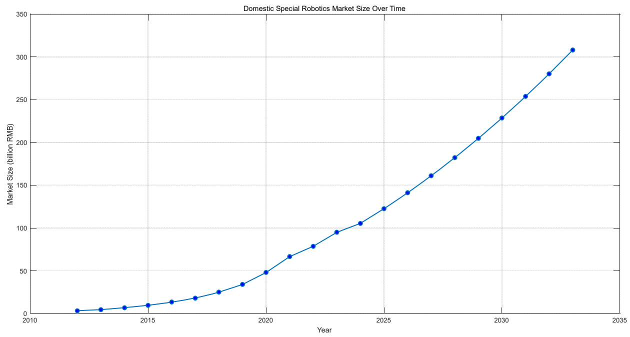

Figure 3: Forecast diagram of the market size of special robots

The neural network model predicts the domestic special robot market size with a relative error of 9% to 11% and an accuracy of about 90%, forecasting steady growth from 10.53 billion yuan in 2024 to 30.80 billion yuan in 2033. This aligns with the expectation that market growth will be driven by technological innovation, policy support, and international competitiveness. The forecast offers valuable insights for policymakers to plan future development strategies, although decision-making should consider uncertainties and real-world factors.

7 CONCLUSION

Key factors influencing the domestic special robot market scale include technological innovation, policy support, international competitiveness, application field expansion, and core technology breakthroughs, with technological innovation, policy support, and international competitiveness being primary drivers. Grey correlation analysis ranks international competitiveness highest, followed by the core technology breakthrough index, aiding policymakers in understanding factors impacting the market and formulating effective strategies. Forecasting via BP neural network suggests continual market growth over the next decade, reaching 30.80 billion yuan from 10.53 billion yuan, driven by technological innovation and international competitiveness, offering valuable insights for decision-makers to plan resources and policies for market competition.

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