Forecasting Chinese Sports Industry Revenue from 2024 to 2030: A Comparative Model Analysis

Fang Wu[1,a,*]

[1]The High School Affiliated to Renmin University of China, Beijing, 100080, China
a. dongbeippianbei@126.com
**corresponding author*

Abstract: In the past decades, the rapid development of the sports economy has become one of the most important factors in China's economy. This research uses three mathematical models to predict the specific revenue of China's sports industry from 2024 to 2030. The Grey Theory Prediction Model and the recursive algorithm were used in previous research to make revenue forecasts. The research and comparison indicate a large difference between the real income and the predicted results of the models. This paper proposed a novel predicting method improved by the ARMAX-BP prediction model. The results show that the predicted result of ARMAX-BP is much more accurate than the first two models on the revenue forecast of the sports industry from 2010 to 2020. The prediction model can help sports investors plan their careers and investments precisely.

Keywords: BP neural network, ARMAX model, sports industry, revenue forecasting, econometrics

1. Introduction

In the past decades, the swift evolution of the sports economy has emerged as a pivotal force propelling China's economic expansion. For instance, in 2021, the average annual growth rate has reached 16.08%, and the proportion of industrial-added value to GDP during the same period has increased from 0.6% in 2012 to 1.07%. This remarkable growth can be attributed to the maturation of the sports industry and a surge in financial investments. In addition, according to the research on sports economy, the previous research on sports economy mainly focused from 1990 to 2000, and the majority of the prediction models were based on gray theory, linear regression, and chaotic dynamics model. Since 2008, China's sports industry has undergone substantial changes, particularly in the realm of "Nation-wide Sports" (universal sports participation), propelled by the 2008 Summer Olympics and accentuated by robust growth, heightened investments, and technological advancements, with the forthcoming 2022 Winter Olympics symbolizing China's enduring dedication to a dynamic nationwide sports culture. This progress has resulted in a scarcity of papers available for the in-depth analysis of the increasingly intricate data within the sports economy and industry.

In this paper, A novel BP neural network prediction model is applied. The model has Parallel Processing, distributed storage and processing, self-organization, adaptation, and storage capabilities. It can also approximate continuous functions with arbitrarily high precision. In this study, the available data were used to fully train and improve the accuracy of the model, including using GM (1,1) of grey forecasting model, recursive algorithm, and ARMAX-BP model to predict the data

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from 2008 to 2020, and the comparison of the real value and the predicted value, and finally found that ARMAX- BP model is the most accurate one and uses this model to predict the revenue of China's sports industry from 2024 to 2030. This study can fill the gap in the revenue forecast of the sports industry from 2010 to 2020 and promote the development of the sports industry in the future. This research holds significance for the general reader by providing insights that can inform better career and investment decisions, especially within the realm of sports management. For instance, as the revenue in sports management proliferates, individuals may consider pursuing careers or making investments in this specific sector.

2. Literature review

China's sports economy has undergone significant changes during the past few decades, so it is necessary to use more accurate models to predict the trend.

Previous studies have used chaotic dynamics model and nonlinear models to predict the development of the sports economy from 1997 to 2002. [1] Previous studies have also used chaotic dynamics models to forecast GDP, and grey forecasting models to forecast other industries. While these models can provide reasonable predictions and conclusions, they are unable to make more precise predictions based on the evolving sports market and have limitations in accurately analyzing the current sports market. For example, in the later periods, the predicted growth rate of income is higher than the real value. The limitation of the recursive algorithm is its lower execution efficiency despite of better explanation, especially for deep-level problems, compared to iterative loops or other simpler steps of other models. When calling the function, if the recursion depth is too large, the call stack may accumulate too much information and cause overflow errors. The second model, the grey forecasting model, has a high degree of instability [2]. Since the grey forecasting model is based on the grey forecasting model, which itself has certain uncertainties, the stability of the model is poor. Secondly, the accuracy of the grey forecasting model is limited. While it can handle cases with small amounts of data, it may be less accurate than traditional methods due to the limitations of the model itself. The sports market is influenced by several factors beyond what is considered in existing models [3]. To overcome the limitations of previous models, this study uses a more advanced ARMAX-BP, which can be used to make predictions of complex systems [4]. ARMAX-BP model can improve the accuracy and applicability of the model in the Chinese sports market. BP neural network can be used to solve nonlinear problems, and due to its multilayer structure and the introduction of nonlinear activation functions, BP algorithms can learn and model nonlinear relationships. In addition, the BP algorithm has strong learning ability and can approximate complex function relationships through appropriate network structure and parameter adjustment, which helps to solve various complex problems. Compared with the first two models, the BP algorithm is a parallel training algorithm, which can improve computational efficiency through matrix operation and vectorization calculation [5]. The trained neural network has strong generalization ability and can make good predictions for unseen samples. By considering autoregressive, moving average, and exogenous variables, the ARMAX model can capture the dynamics of time series more comprehensively [6]. By adjusting the order of AR, MA, and X, it can more flexibly adapt to the characteristics of different data, and deal with more influencing factors at the same time than the grey forecasting model and recursive algorithms. In addition, the ARMAX model uses methods such as maximum likelihood estimation to estimate the parameters, which makes the parameter optimization of the model more reliable than that of the previous model. The grey forecasting model is usually modeled with a small number of samples, while the parameter adjustment of recursive algorithms may be sensitive to initial conditions. Combining the BP neural network and ARMAX model can combine the advantages of both models and make the prediction results more accurate.

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3. Research design

The accuracy of the prediction results of the ARMAX model is higher than that of the gray theory prediction and recursion algorithms, which is reflected in the mean square deviation, R^2, and relative error. This conclusion is measured by predicting line charts and coefficients for n+1/n years. These conjectures are supported by using income and growth rates as time series to support these conjectures [7-10].

The assertion of the ARMAX model's superiority over the gray theory prediction and recursion algorithms is attributed to the constraints posed by the limited dataset. With a restricted amount of data, the ARMAX model's capacity to generate more accurate predictions is emphasized, as it is better equipped to handle the intricacies of the available information compared to the other algorithms. The limited dataset underscores the importance of employing models that can effectively extract meaningful patterns and relationships, and in this context, the ARMAX model demonstrates enhanced performance.

3.1. Dataset

The data used in this article is obtained from the financial information disclosure on the official website of the National Bureau of Statistics of China, which mainly provides research data on the final accounts of various revenues and expenditures at all levels of the sports sector in the past ten years [11]. In this study, the income of each sector is aggregated by weight, and other coefficients, such as the growth rate, are calculated from the total income to ensure the availability of data [12]. In this study, the data obtained is a chronological period, with a time range from 1991 to 2022, and sufficient data is used to ensure that the model is fully trained.

3.2. Mathematical model 1 – The GM (1,1) mode

The GM(1,1) model is the main prediction model of the grey forecasting model, and the advantage of the GM(1,1) model is that compared with the traditional model, it requires a smaller data set to obtain high-precision prediction results. As a result, it is used for forecasting research in the sports industry with fewer data years.

The basic steps of this model are as follows:

Let a primitive time series X0={INCOMEXi} where INCOMEXi is the total income of the ith year and n is the number of serial data. The second sequence, X1, is obtained by accumulating X0, to make the data more suitable for grey theory predictions.

The next step is to solve the two parameters in the model by solving the differential equation using least squares and regression analysis. (A represents the development coefficient; B represents the amount of gray action.) Predictive models

From the development coefficient and the gray effect, we can calculate the predicted value of the original time series.

3.3. Apply Mathematical Model 1 in problem-solving

In this study, MATLAB was used to establish a prediction model. Based on the original sequence, the accumulation generation sequence is constructed, and the data matrix B and data vector y are constructed to predict the data through the following steps.

Start by reading the data from the Excel file, and then select a part of the data as the original sequence x0.

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Data processing and parameter calculation: By using differential operations, the data x1 in the imported model is converted into a new data z1, and the parameter vector aa to be estimated is calculated.

b/a calculation: The values of a and b in the parameter vector aa to be evaluated are calculated using the least squares method

Data prediction: Use model parameters a and b to predict data to obtain the predicted data series X1.

Then, the data is restored, and the data is restored by the prediction sequence X1 to obtain the restored sequence simx0.

Absolute and Relative Residual Calculations: Calculate the residuals between the actual and predicted values and use them to evaluate the precision and accuracy of the model.

Correlation test: Calculate the absolute residual series and correlation coefficients, and evaluate the accuracy and prediction accuracy of the model through the

correlation coefficients.

Plot graphs to show how your true and forecasted earnings have changed.

Through steps 6 and 7, it can be judged whether the prediction accuracy of the system is accurate, and after the above check is confirmed, the above

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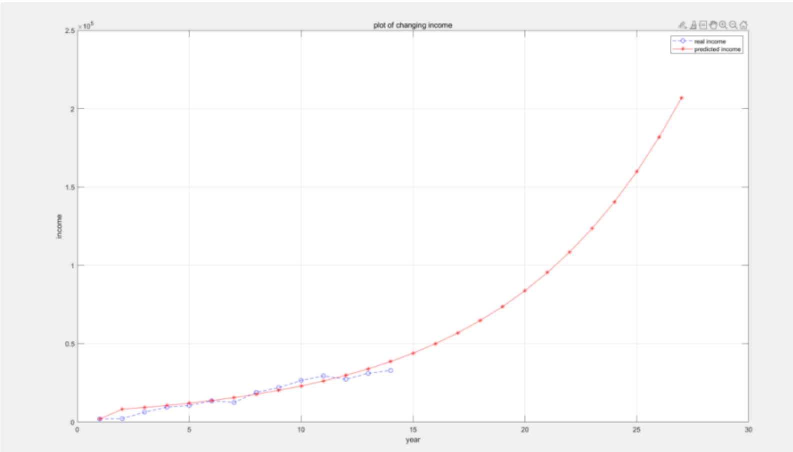

Figure 1: Chart of income prediction based on GM(1,1) model

After the model is run, it returns Fail, which indicates that the system has poor prediction accuracy by calculating the correlation degree, which indicates that this model is not suitable for this problem. In 2010 and 2022, there is a large relative error between the forecast value and the real value

3.4. mathematical model 2 – recursive algorithm

A recursive algorithm is an algorithm that solves a large problem by solving a smaller instance of a problem. The recursive algorithm has two processes, one is the invocation process, and the other is the process of passing the result upwards. In this study, the recursive algorithm was used to obtain the predicted value and perform error analysis.

The parameters of a function typically include input data and other parameters required for recursion.

The recursive function needs to set a termination condition that, when met, will stop the recursion and return the result. This is an important part of ensuring that recursion doesn't loop indefinitely.

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By reducing the size of the problem, the original problem of the recursive function can be transformed into a simpler form, and these subproblems can be solved recursively, and the problem can be broken down into smaller subproblems repeatedly by recursive calls until the termination condition is reached.

In a recursive function, the solutions of the sub-problems need to be integrated to get the solution of the original problem. This typically involves combining, computing, or otherwise manipulating solutions to subproblems.

4. Results

The following figures show the error coefficient of the recursive algorithm and the individual residuals, respectively

Linear relationship and independence: The shape of the reference illustrations in the residual case order plot is not completely randomly distributed, but uneven on the X-axis, and there is a slight curve trend, indicating that the model does not have a good linear relationship. There may be nonlinear factors that lead to the curved shape of the residual case's distribution. This suggests that there may also be a nonlinear relationship in the problem and that the predicted values lack independence

Homoscedasticity: The variance of the residuals remains constant within the range of different predicted values is homoscedasticity, and in this graph, the horizontal line across the x-axis has a conical shape, indicating that the graph may have a homoscedasticity problem. In summary, the analysis of error coefficients and residuals indicates a suboptimal linear relationship, suggesting potential nonlinear factors influencing the model. The observed conical shape in the variance of residuals graph points to a homoscedasticity issue, emphasizing the need for further model refinement to address these challenges.

5. ARMAX-BP Model

The ARMAX-BP model is a combined model that combines the ARMAX model and the BP neural network.

BP neural network is a multi-layer feedforward network model based on error backpropagation. Its structure includes the input layer, hidden layer, and output layer. Its algorithm takes the square of network error as the objective function and uses gradient descent to calculate the minimum value of the objective function. Artificial neural networks do not require mathematical equations to determine the mapping relationship between inputs and outputs in advance. The model's training and learning can obtain the closest result to the expected output value when given input values.

The basic BP algorithm includes two processes: forward propagation of signals and backward propagation of errors. When calculating the error output, it is done in the direction from input to output, while adjusting the weights and thresholds in the opposite direction. During forward propagation, the input signal acts on the output node through a hidden layer and undergoes nonlinear transformation to generate an output signal. If the actual output does not match the expected output, it enters the process of error backpropagation. Error backpropagation is the process of transmitting output errors layer by layer through the hidden layer to the input layer, and distributing the errors to all units in each layer. The error signals obtained from each layer are used as the basis for adjusting the weights of each unit. By adjusting the connection strength between input nodes and hidden nodes, as well as the connection strength and threshold between hidden nodes and output nodes, the error decreases along the gradient direction. After repeated learning and training, the network parameters (weights and thresholds) corresponding to the minimum error are determined, and the training stops. At this point, the trained neural network can handle the input information of similar samples and process the non-linear transformed information with the minimum output error on its own [11].

The ARMAX model is a statistical model used for time series modeling and forecasting. [10] It combines the influence of autoregressive (AR), moving average (MA), and exogenous variables (X) to capture the dynamics and influencing factors of time series data more comprehensively.

$$Y_t = \alpha + \Phi_1 Y_{t-1} + \cdots + \Phi_p Y_{t-p} + w_t \cdot(\mathrm{AR}) \tag{1}$$

$$Y_t = \alpha + \varphi_1 w_{t_{t-1}} + \cdots + \Phi_q Y_{t-q} + w_t \cdot(\mathrm{MA}) \tag{2}$$

The AR model and MA model combine to form ARMA model

$$Y_t = \alpha + \Phi_1 Y_{t-1} + \cdots + \Phi_p Y_{t-p} + w_t \cdot (\alpha + \varphi_1 w_{t_{t-1}} + \cdots + \Phi_q Y_{t-q} + w_t \cdot(\mathrm{ARMA}) \tag{3}$$

The ARMAX model is an extension of the ARMA model with the addition of the exogenous variable x

$$Y_t = \alpha + \sum_{i=1}^{\rho} \Phi_1 Y_{t-i} + \sum_{j=1}^{9} \psi_j W_{t-i} + \beta T X_t + W_t \tag{4}$$

The ARMAX model consists of three main components. The autoregressive part (AR) includes autoregressive coefficients, which represent the linear relationship between the current value and the value at previous moments. Moving Average Portion

(MA): Includes a moving average coefficient, which represents the linear relationship between the current value and the error at the previous moments. Exogenous Variables Part (X): Includes exogenous variables that represent external factors considered in the model. The ARMAX model adjusts these coefficients to make the model's predictions as close as possible to the actual observations while maintaining the simplicity of the model. This makes ARMAX models widely used in time series analysis and forecasting, especially for complex datasets with multiple influencing factors.

In this study, we combined the BP neural network and ARAMAX model to predict sports revenue. By integrating both models, the study aims to harness the advantages of the BP neural network's pattern recognition capabilities and the ARMAX model's proficiency in handling temporal dynamics. This combined approach is expected to offer a more comprehensive and accurate prediction of sports revenue, leveraging the strengths of each model to enhance the overall forecasting performance.

5.1. Basic Algorithm Steps

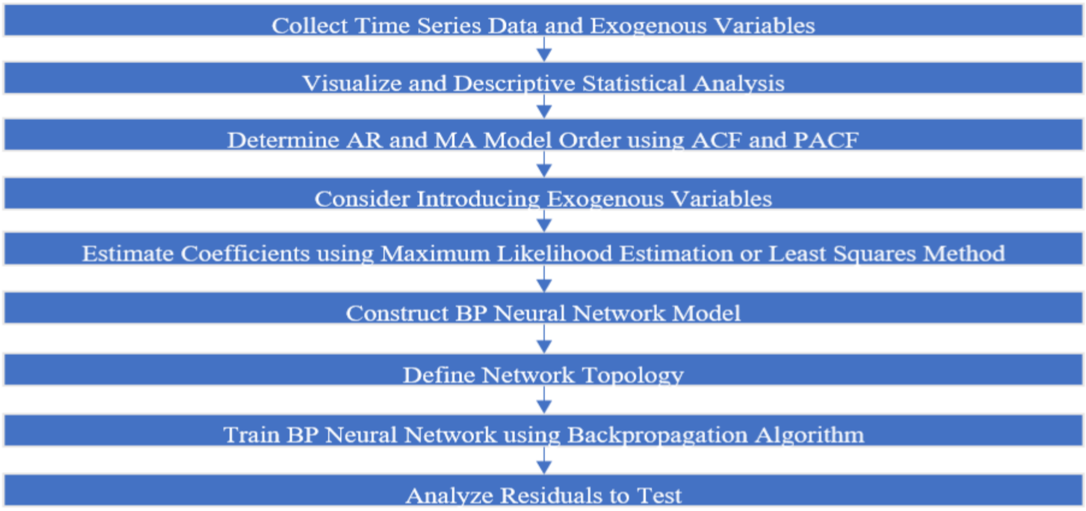

Figure 2: Flowchart of basic steps

Collect time series data and related exogenous variable data.

Visualize and descriptive statistical analysis of data to understand the characteristics and trends of data.

The order of the AR and MA models was determined by observing the graphs of the autocorrelation function (ACF) and the partial autocorrelation function (PACF). At the same time, consider whether to introduce exogenous variables.

The coefficients of AR, MA, and exogenous variables are estimated using methods such as maximum likelihood estimation or least squares method.

The exogenous variable is used as the input and the time series data is used as the output to construct the BP neural network model. Determine the topology of the network, including the number of nodes and how they are connected at the input, hidden, and output layers.

Using known time series data and exogenous variable data, the BP neural network is trained by the backpropagation algorithm to optimize the weight and bias of the network.

The residuals of the trained ARMAX-BP model were analyzed to test the goodness of fit and the stationarity of the residual sequence.

The estimated ARMAX-BP model is used to predict the future value.

BP network adds several layers (one or more layers) of neurons between the input layer and the output layer, these neurons are called hidden units, they have no direct contact with the outside world, but the change of their state can affect the relationship between input and output, each layer can have several nodes.

5.2. Specific steps of application

Data preprocessing

Since the data used is time series data, data extraction and preprocessing are required. The required part is extracted from the loaded data and stored in variables x1 and y1.

Create and estimate ARMAX models

Determine the order (na, nb, nc, nk) of the ARMAX model: AR (AutoRegression) order, X order, MA (Moving Average) order, and delay.

Use the iddata function to merge the input data x1 and the output data y1 into a single iddata object named combinedData.

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Use the armax function to create an ARMAX model and store it in a variable named model.

Get the output prediction of the ARMAX model

Use the predict function to get the output of the ARMAX model to predict ypred.

Plot a comparison of the predicted and actual output of the ARMAX model

Use the plot function to plot a comparison plot of the actual output and the predicted output of the ARMAX-BP model.

Create a BP neural network

The input data x1 and the output data y1 are normalized, and the mapminmax function is used to obtain the normalized input data pn and the target data tn, and the normalized parameters inputStr and outputStr are saved.

Use the newff function to create a BP neural network, specify the number of nodes in the input layer as 1, the number of nodes in the hidden layer as 10 and 5, the number of nodes in the output layer as 1, the activation functions as tansig and purelin, and use trainlm as the training function.

Train the BP neural network

Set the training parameters of the neural network, including displaying the training progress, momentum factor, maximum training times, learning rate, target error, etc.

The trained function is used to train the established BP neural network, and the training data pn and target data tn are input.

Predict new data

Load the new input data newInput from another Excel file.

The new input data is normalized, using the normalized parameter inputStr of the original input data (the input data of the training set).

The sim function is used to simulate the new data, and the predicted output newOutput is obtained.

To denormalize the output data, use the mapminmax function.

6. Refining of the model

At first, the experiment used the same data from 2009 to 2022 as the previous two models, but after 10,000 rounds of training, the performance of the neural network improved from 2.85 to 0.0395 with the goal of 0.001. From a statistical point of view, the final prediction result of R equal to 0.95534 is quite different from the true value, so I improve it from the following points

Augmentation of the Dataset

By augmenting the dataset capacity from the initial 13 to 32, specifically, the model configured with an expanded temporal range yielded a minimized value of 0.00095 upon execution. This marked a substantial improvement compared to the preceding training iteration. Additionally, the achieved coefficient of determination (R) was recorded at 0.99894, exhibiting a minor deviation of 0.0083 from the targeted value. Given the relatively ample provision of 30 data points, the study abstained from employing data augmentation techniques.

Parameter adjustments

By continuously adjusting the training parameters of the BP neural network in the model and comparing the difference between the model and the ideal value under different parameters, the appropriate parameters are ultimately adjusted

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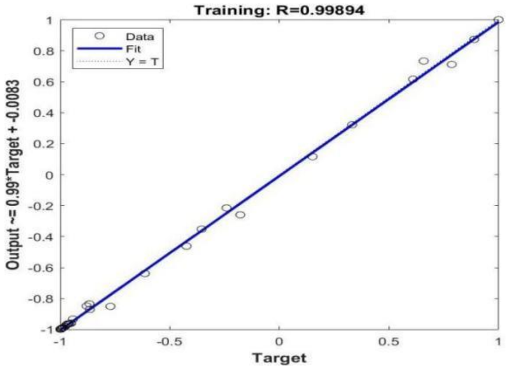

Figure 3: Regression with a large dataset

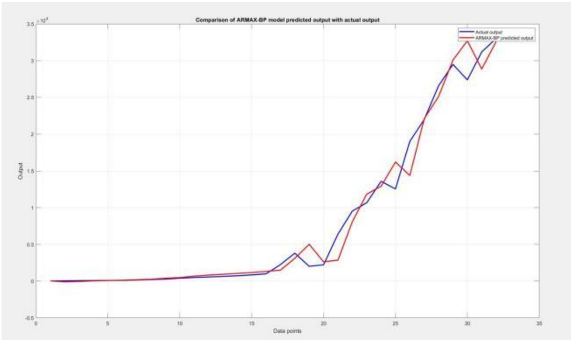

Figure 4: Preliminary sports revenue projections based on ARMAX-BP neural networks

7. Analysis of results

7.1. Model Comparison

Through a comparative analysis of the relative errors among the three models, the ARMAX-BP prediction model was computed in terms of percentage error, revealing the lowest relative error, followed by the gray theory prediction with the minimum error. Notably, the relative error of the ARMAX-BP model significantly outperformed the other two models. Additionally, the coefficient of determination (R^2) for ARMAX-BP was found to be closer to 1 than those of the alternative models. These findings suggest that the utilization of neural network training methods, particularly in the ARMAX-BP framework, proves more adept at addressing the complexities and fluctuations inherent in forecasting sports market revenue. The subsequent refinement of the ARMAX-BP projection for the aggregate revenue of the sports industry spanning from 2024 to 2034 culminated in obtaining a more accurate forecasted value.

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Table 1: the real forecast value

year	real income	prediction of ARMAX-BP (billion RMB)	relative error of ARMAX-BP(%)	prediction of Gm11 (billi on RMB)	relative error of Gm11 (%)	prediction of the recursive algorithm (billion RMB)	relative error of recursive algorithm (%)
2011	6,390.00	5,685.00	-11.03	9,362.21	46.51	9,337.69	46.13
2012	9,526.00	8,968.00	-5.85	10,651.10	11.81	10,760.22	12.96
2013	10,660.00	11,769.00	10.4	12,117.50	13.67	10,719.70	0.56
2014	13,574.00	13,695.00	0.89	13,785.80	1.56	13,413.23	-1.18
2015	12,536.00	15,094.00	20.4	15,683.70	25.1	12,652.63	0.93
2016	19,011.00	17,324.00	-8.87	17,842.90	-6.14	18,895.38	-0.61
2017	21,987.00	21,461.00	-2.39	20,299.40	-7.67	23,426.53	6.55
2018	26,579.00	24,055.00	-9.49	23,094.00	-13.1	29,200.04	9.86
2019	29,483.00	27,295.00	-7.42	26,273.50	-10.89	34,104.72	15.68
2020	27,372.00	29,773.00	8.77	29,890.60	9.2	26,970.39	-1.47
2021	31,175.00	30,113.00	-3.4	34,005.70	9	25,958.51	-16.73
2022	33,008.00	32,961.00	-0.14	38,687.40	17.21	39,186.63	18.72
2024		**33,615.00**					
2025		**34,412.00**					
2026		**35,051.00**					
2027		**35,545.00**					
2028		**35,935.00**					
2029		**36,244.00**					
2030		**36,491.00**					

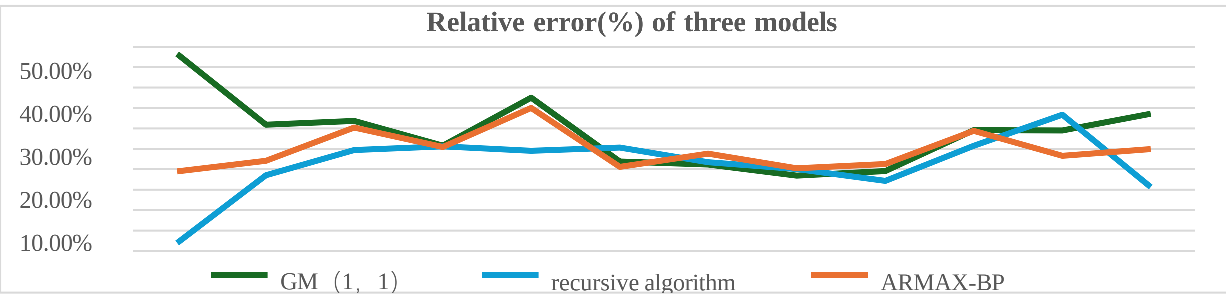

Figure 5: Relative error of three models

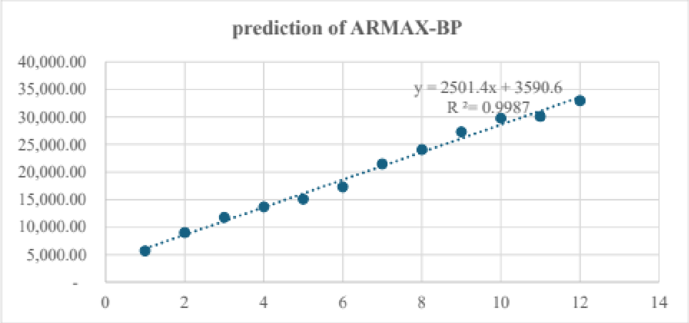

Figure 6: R^2 of ARMAX-BP

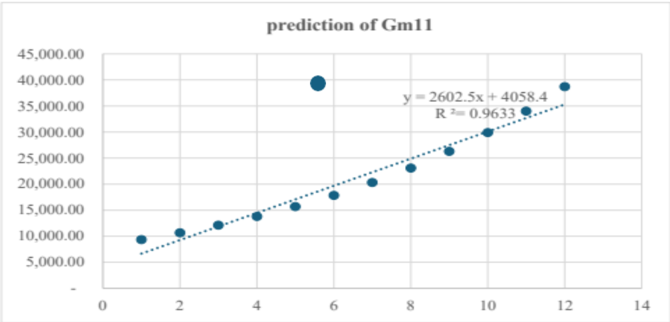

Figure 7: R^2 of GM(1,1)

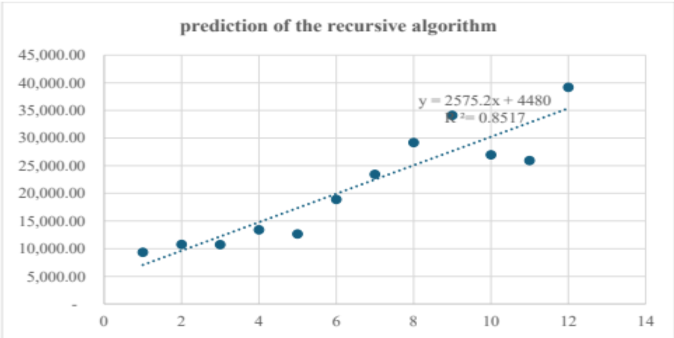

Figure 8: R^2 of recursive algorithm

7.2. Limitations

The ARMAX-BP model has certain limitations and can be improved in the future. The model has high data requirements and needs to have sufficient historical data(about 50 years) and relevant exogenous variable data. If the amount of data is small or exogenous variables are missing, the performance of the model may be limited. In addition, the BP neural network in the ARMAX-BP model has strong fitting ability, which is prone to overfitting problems in the training process. The model can perform well on specific training data, but has poor generalization ability on extended data. In future research, data augmentation and other methods can be used to improve the model's accuracy.

8. Conclusion

The accuracy of the prediction results of the ARMAX model is higher than that of the gray theory prediction and recursion algorithms. It is predicted by the model that China's sports industry is developing rapidly now and in the future with a steady growth speed. According to the model, the income of China’s sports industry in 2030 will approximately reach 36,491 billion RMB. Based on the conclusion, The government can increase financial investment in the sports industry, including the construction of sports facilities, the research, development and production of sports equipment, and the holding of sports events, to promote the development of the sports industry. Strengthen the cultivation and support of sports talents, including the training of outstanding athletes, coaches, and sports administrators, to improve the competitiveness and influence of sports in China. Through policy support and financial guidance, the promotion of the sports industry will be diversified, including sports tourism, fitness, sports training, and other fields, to expand the development space of the sports industry. Strengthen the standardized management and standardization of the sports industry, improve the quality of sports products and services, and enhance the international competitiveness of China's sports industry. Encourage the integrated development of the sports industry with culture, science and technology, education, and other fields, promote collaborative innovation between industries, and promote the cross-border development of the sports industry. To further promote the healthy development and sustainable growth of China's sports industry.

This paper introduces a novel prediction model tailored to the sports industry, conducting a comparative analysis with existing models utilized in forecasting sports industry revenue. The study encompasses a thorough examination of sports revenue trends from 2010 to 2020, enhancing the predictive model and addressing temporal gaps in prior research. The outcomes of this analysis not only contribute valuable insights for future sports industry revenue forecasting but also provide recommendations and developmental directions for governmental bodies and investors. As part of ongoing improvements, the integration of data augmentation and exploration of alternative models, such as the grey neural prediction model, are contemplated to enhance accuracy and minimize errors in the predictive framework.

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