Evaluation Method of Sports Industry Competitiveness based on Fuzzy Neural Network Model

Nan Hu[1] and Minghao Qu[2]

[1]College of Physical Education, Baicheng Normal University, Baicheng, Jilin 137000, China, hn5777@bcnu.edu.cn
[2]College of Physical Education, Baicheng Normal University, Baicheng, Jilin 137000, China, 18643682200@163.com

Corresponding author: Nan Hu, hn5777@bcnu.edu.cn

Abstract. This study proposes that the competitiveness of sports industry is reflected in three aspects: dynamic change, efficiency change and quality change. Based on these three dimensions, this paper further evaluates the competitiveness of the sports industry. Specifically, firstly, in order to overcome the problem of low fit of the traditional linear model, a fuzzy neural network model is constructed in this paper. Secondly, this paper finds that the model has good predictive validity and can effectively evaluate the competitiveness of the industry. Finally, based on the results of the model analysis, this paper points out that three aspects are needed to enhance the competitiveness of China's sports industry, including promoting the flow of labor and capital factors in the sports industry, accelerating the regional agglomeration effect of the sports industry and insisting on innovation as the power source.

Keywords: Sports industry competitiveness; neural network model; index system
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1 INTRODUCTION

The desire to engage in physical activity is inherent in human nature. However, in the past, sports did not hold any significant economic value since it was not a paid or commercial activity. It was not until sports gained validity as a form of demand and reached a certain scale that it was supported by high levels of income. In fact, when economic development reaches a certain threshold, typically above $6,500, a significant and effective demand for sports consumption begins to form. As a country progresses into the high-income stage, the sports industry becomes a key pillar industry. Over the past decade, China's sports industry has seen a faster growth in its value-added than that of the country's GDP [1].

However, as De and Wang [2] stated, previous research that has been conducted in parallel with the practice of the industry development are mostly qualitative studies on the definition of the connotation and theoretical support of high-quality development of the industry, the structural adjustment and policy guarantee, the innovation of the organizations and the optimization of the layout of the the industry, as well as the practical path and influencing factors. There is no quantitative evaluation study in this traditional research field. According to Zhuo et al. [3], the evaluation of the competitiveness mostly emphasizes the quantitative scale, but does not measure the comprehensive level including innovation capability and efficiency. Wiśniewski [4] pointed out that the evaluation indexes are also mainly focused on single aspects such as industrial transformation and upgrading, industrial competitiveness, and industrial policies. In other words, there is a lack of exploration of a comprehensive evaluation system for the industry competitiveness and a lack of suitable methods for empirical analysis of it.

Therefore, this paper draws on industrial evaluation theory to construct an evaluation index system for the competitiveness of China’s sports industry according to the basic idea of “sorting out the connotation, analyzing the logic, clarifying the construction principles, selecting evaluation indicators, determining the evaluation index system”. In other words, the theoretical logic of the evaluation index system of the competitiveness of China’s sports industry is clarified. Finally, this paper use the radial RBF method to quantitatively evaluate the competitiveness of the sports industry.

2 RELATED WORK

China's economy has entered a new phase of high-quality development, which prioritizes quality and efficiency over simply increasing economic volume. This shift emphasizes promoting quality, efficiency, and power changes in economic development, with a focus on improving total factor productivity through innovation. The Chinese government has adopted a quality-oriented, efficiency-driven, and innovation-focused model for economic development. In line with this approach, the sports industry, as one of China's key pillar industries, has also begun to emphasize high-quality development in its strategic orientation. However, there is a lack of sufficient discussion on how to evaluate the quality of the industry. Huang and Chen [5] also pointed out that it is necessary to re-examine the industry's competitiveness from the perspectives of quality, efficiency, and innovation, providing theoretical references for future growth and development.

Based on the three dimensions of quality, efficiency and innovation, this paper further constructs a comprehensive evaluation index system (Figure 1). The innovation change dimension includes two sub-dimensions of creativity dynamics and root dynamics. Specifically, firstly, the proportion of the total output value of resource- and technology-intensive industries and emerging sports industries to the total scale of sports industry can effectively evaluate the industrial structure of sports industry. New industries, new business modes and new business models of sports industry, such as sports tourism, sports competition and performance activities, sports and leisure activities, sports intermediary economic services and sports consulting, are important industries that drive the renewal of sports industry. In addition, the innovation of sports industry is also reflected in the intensity of investment in science and technology and the transformation rate of scientific and technological achievements. Secondly, resource endowment and market demand constitute the root driving force of the innovation change dimension. Resource endowment refers broadly to the degree of accumulation of resources such as land and infrastructure, while market demand is the key to determine the economic benefits of sports industry, which is important for the economic development of sports industry and stimulating the innovation ability of sports industry. Therefore, the ratio of total output value, the ratio of units, the degree of R&D investment and the ratio of effective patents are selected to reflect innovation competitiveness; the ratio of added value, the ratio of revenue of and the ratio of revenue are selected to reflect innovation competitiveness. Chen et al. [6] proposed that the innovation competitiveness is reflected by the ratio of value added, the ratio of income per unit, the ratio of the number of units, and the level of per capita sports consumption.

Previous research has focused mainly on the quantitative scale of evaluation, with a lack of emphasis on a comprehensive evaluation system. This study fills this gap by constructing a comprehensive evaluation system based on quality, efficiency, and innovation (Figure 1). The innovation change dimension consists of two sub-dimensions, namely creativity dynamics and root dynamics. To assess the industrial structure, the total output value of resource- and technology-intensive industries and emerging sports industries are evaluated. New industries, business modes, and models such as sports tourism, sports competitions and performances, sports and leisure activities, sports intermediary economic services, and sports consulting, are taken into consideration to drive the renewal of the industry. The innovation of the sports industry is also measured by the intensity of investment in science and technology and the transformation rate of scientific and technological achievements. Resource endowment and market demand are significant driving forces of innovation change. Resource endowment refers broadly to the degree of accumulation of resources such as land and infrastructure, while market demand is essential to determine the economic benefits of the sports industry. The ratio of total output value of new industries, the ratio of units of new industries, the degree of R&D investment in the industry, and the ratio of effective patents in the industry are selected to reflect innovation competitiveness. Additionally, the ratio of added value of sports industry, the ratio of revenue of major industry units, and the ratio of revenue of major industry units are chosen to reflect innovation competitiveness [6].

The dimension of efficiency change consists of two aspects: single-factor output rate and factor allocation efficiency. Efficiency is a broad concept that can be evaluated in different ways, such as technical, scale, market, production, and allocation efficiency. The efficiency of the industry can be measured by the efficiency of its main units, namely enterprises, and the efficiency change of these enterprises reflects the efficiency change of the competitiveness. This change is the process of the main unit acquiring the maximum output with a certain allocation of resources. The single-factor output rate, which is a measure of the quality of each supply factor, can reflect the overall efficiency, including the capital output rate and labor productivity of its main units [7]. By understanding the quality and output efficiency of the supply factors of the industry, the weak links in supply-side efficiency can be accurately identified, and a balance between consumption upgrading and factor supply can be achieved from the supply-side perspective, in the context of high-quality economic development. The optimal allocation of production factors should not only consider single-factor productivity, but also take into account total factor productivity, which reflects the comprehensive output level of factors such as industrial technology and industrial system. Total factor productivity is a comprehensive measure of the level of sports industry intensification and the productivity of each factor, while single-factor output rate is a reflection of the efficiency of each factor. Therefore, the single-factor output rate is represented by the resource output rate, capital output rate, and labor productivity, while the factor allocation efficiency is represented by the technological progress index, total factor productivity, and technical efficiency change index [8].

The quality change dimension of the industry includes three sub-dimensions: optimization of the industry structure, development of new spaces within the industry, and social benefits. Optimization of the industry structure refers to the process of promoting restructuring and rationalization [9]. Evaluation in this paper considers four aspects. First, the diversification index reflects the development and integration of various related industries. Second, the high-quality index refers to the development of industry structure from a low level to a high level. Third, the rationalization index refers to the correlation and synergy among sub-industries of the industry. The complementarity and synergy among the sub-industries are the key to improving the overall efficiency. Fourth, the service index is an important characterization of the service quality, with the sports service industry being a crucial part of the sports industry. The proportion is an essential indicator of the optimization of the structure. The development of new spaces refers to the infrastructure formed to meet the upgrading of consumption demand and the integration and synergistic development of related industries. This infrastructure has the characteristics of high-quality development such as the gathering of high-end elements [10]. The evaluation of the new space should consider the number, scale, and degree of industrial agglomeration. The industrial agglomeration index reflects the concentration degree of factor endowment of the same or similar industries in the spatial scope. From the perspective of high-quality development, the industry will ultimately play a role in promoting high-quality economic development through power change, efficiency change, and quality change. Based on this, the following indicators are selected to reflect the structure: diversification index, heightened index, rationalization index, and service index. The number of new spatial forms and the industry agglomeration index are chosen to reflect the degree of new space construction. The social benefits are reflected by the proportion of employment absorbed by the industry, the proportion of tax revenue, and the proportion of amount invested in the lottery public welfare fund.

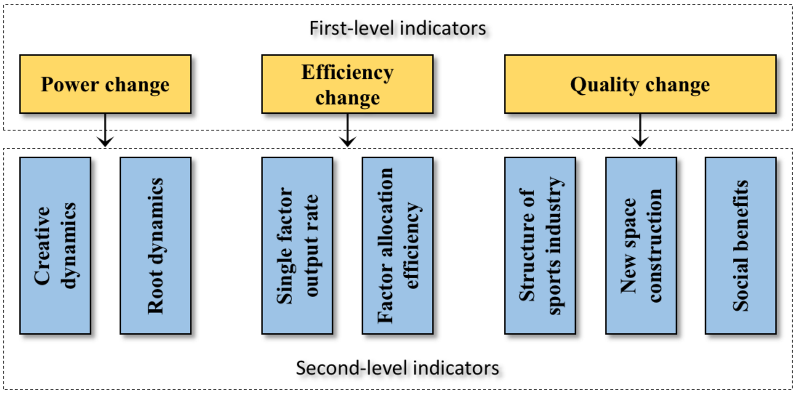


Figure 1: Sports industry competitiveness index.

3 METHODOLOGY

3.1 Influencing Factors Based on Mutual Information

Normally, selecting influencing factors can directly determine the accuracy of model building. In general, correlated variables are useful for building accurate prediction models, while redundant variables not only increase the complexity of model computation but also obscure the correlation effect between variables. In order to reduce the interference of redundant variables and build an efficient prediction model, this paper uses correlation analysis among multiple variables to determine a set of sub-variables that are most closely related to each other. In general, independent component analysis and mutual information can be used for correlation analysis of multiple variables. Mutual information, which originates from the entropy in information theory, is the amount of information lost during the transmission of a signal, and is often used to measure the closeness of multiple variables. This method can not only speculate qualitatively on the trend of the relationship between variables, but also determine quantitatively the specific numerical relationship between variables. Next, we will estimate the mutual information based on K-nearest.

3.1.1 Mutual information estimation of K-nearest neighbors

First, we need to define two continuous variables, that is, X and Y, and assume that $\mu_x(x)$, $\mu_y(y)$ and u(x, y) are the marginal and joint density functions of X and Y, respectively. According to the relevant theory of information theory, we can get as follows:

$$I(X;Y) = \iint dxdy\,\mu(x,y)log\frac{\mu(x,y)}{u_x(x)u_y(y)} \tag{3.1}$$

If the above equation I is larger, it means that the variables X and Y are more closely related and have more information in common with each other. On the contrary, if the value of mutual information I is smaller or even zero, it means that the two variables contain little information or are independent of each other.

3.1.2 Multivariate selection based on mutual information of K-nearest neighbors

The form since the input multi-variables are not restricted to linear relationships. To analyze the influence of different input variables on the amount of mutual information, we uses a feature selection algorithm based on the mutual information dimension to analyze the correlation between multi-variables, and then identify and remove the redundant and irrelevant variables. We introduce multivariate information as the evaluation criterion for selecting correlated variables, i.e., mutual information among multiple variables in a high-dimensional space, and in this method, for a given input feature variable, both the relationship with the output feature variable and the relationship with the selected feature variable are considered.

Suppose the mutual information of 3 continuous variables, which is denoted as $I(X;Y;Z)$, then it can be expressed as:

$$I(X;Y;Z) = I(X;Y|Z) - I(X;Y) \tag{3.2}$$

The antecedent becomes the conditional mutual information quantity, i.e., the amount of information obtained after the communication of variables X and Y passed under a certain condition Z is known. The conditional mutual information quantity can be expressed as:

$$(X;Y|Z) = H(X,Z) + H(Y,Z) - H(Z) - H(X,Y,Z) \tag{3.3}$$

Therefore, the conditional mutual information must be non-negative, and combined with the mutual information estimate based on K-nearest neighbors in the previous section, the conditional mutual information estimate can be written as:

$$(X;Y|Z) = \varphi(k) - < \varphi[n_{xz}(i)] + \varphi[n_{yz}(i)] - \varphi[n_z(i)] > \tag{3.4}$$

The mutual information of the continuous variables X, Y and Z can be estimated from the above equations. However, unlike the conditional mutual information, the value of the multivariate mutual information can be positive or negative. When the multi-information $I > 0$, it means that the characteristic variables X and Y are complementary; when the multi-information $I < 0$, it means that Z is a redundant variable, so when Z is added as a condition, the dependence between X and Y is reduced; when the multi-information $I = 0$, it means that the dependence between Y and Z is basically independent of X. Based on the above properties, the evaluation criteria for the selection of multi-characteristic variables are defined as follows:

$$max\{I(X;Y;Z)\} > \beta \cdot I(Y;Z) \tag{3.5}$$

X is the variable to be selected; Y is the selected variable; Z is the class variable; β is the user-defined quantity. The above equation is used to measure the dependence of variables Y and Z on variable X. When the above equation is satisfied, then X is considered as a relevant variable, otherwise it is a redundant variable.

In summary, the input variables of the algorithm are assumed to be: $U = D$ (F, C) is the training data set, F is all the input feature variables, C is the class variables; the output variables are the selected feature set S.

$$Y = \sum_{j=1}^{k} \omega_j \theta(X_i - c_j) \tag{3.6}$$

3.2 Predicting Based on RBF Network

Similar to other multi-layer back propagation networks, the radial basis network function is a 3-layer network topology with fast convergence including input, implicit and output layers, which not only has the potential to meet real-time requirements, but also can approximate continuous functions with different accuracy, and its structure is shown in Figure 2.

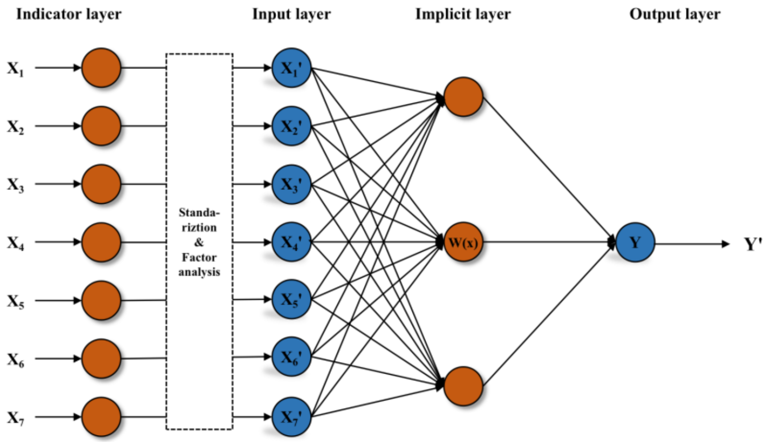


Figure 2: RBF Model.

3.2.1 Initial parameters

In the above model, the input layer is composed of sample data, and the output unit is a simple linear function activated by the hidden unit. By adjusting the parameters of the activation function, the implicit layer neurons can not only transform the low-dimensional spatial pattern into a high-dimensional space, but also convert the nonlinear mapping into a linear one. When the input sample value is closer to the center of the basis function, the activation degree of the hidden layer unit is higher and the weight is higher, so the output value of the RBF network is:

$$\theta(r) = exp(-\frac{r^2}{2\sigma^2}) \tag{3.7}$$

The basis function in this paper is represented by $\Phi(X_i-c_j)$, and the output layer is denoted by ω_j. Common basis functions include the Gaussian function, inverse S-function, and multi-quadratic function. The Gaussian function is preferred due to its applicability, simplicity, and rotational symmetry. Its expression is given by assuming σ as the variance of the radial basis function or the expansion constant, and r^2 as the distance between the sample data and the center of the basis function.

To analyze the competitiveness, a two-stage approach is employed. In the first stage, an initial prediction model is trained using the RBF network. This involves determining the centers of the nodes in the hidden layer based on an improved K-means algorithm. The center of the basis function c, expansion constant σ, and weight w are then adjusted using the gradient descent method. In the second stage, the initial model is corrected using the relative mean error to obtain a competitive final prediction model.

Although the initial prediction model for the competitiveness is obtained using the radial basis network function, different regions may have varying adaptability to this method. Therefore, the relative average error is used to reverse the initial results and obtain the final prediction model. The specific correction method involves:

$$\begin{gathered} \bar{e} = \frac{1}{m}\sum_{i=1}^{m}|\frac{y_i - y_i'}{y_i}| \\ y'' = \frac{y'}{1-\bar{e}} \end{gathered} \tag{3.8}$$

y is the actual value; *y'* is the predicted value trained by RBF network; *e* is the relative average error; *y''* is the predicted value after error correction. The model prediction process involves some steps, which is shown in Figure 3:

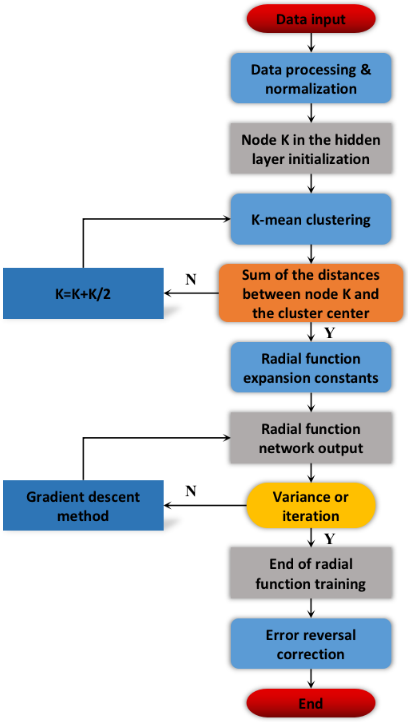


Figure 3: The flow chart of the prediction model.

4 RESULTS

K-nearest neighbor estimation mutual information was established for the seven proposed influencing factors, and the main influencing factors were screened out based on the mutual information, i.e., the Shukuru variables of the prediction model, and the identified influencing factors were creative dynamics, root dynamics, single factor output rate, factor allocation efficiency, structure of sports industry, new space construction, social benefits. Based on the topology of the RBF network, a two-stage radial basis function network was used to predict the competitiveness. We also compared the predicted values and the actual output values of the RBF model for the Yangtze River Delta sample. Figure 4 shows the predicted change curve of regional sports industry competitiveness.

The model is trained and simulated for 7 indicators, the maximum number of total samples trained reaches 50, the training sample value and the test sample value reach the best after 10 iterations, the actual output is close to the desired output (Figure 5).

Based on the simulation results, a time-series prediction of the sports industry competitiveness is made, and the results show that the predicted values fit the actual values to a high degree and are close to the linear model. The overall trend of competitiveness is consistent for different training sample (Figure 6). This paper also tested the model for both small and large samples, and the results continue to show consistent trends (Figure 7). The forecast results of natural gas production are given in Figure 8, and the models were compared and selected according to the accuracy of the forecast. the forecast results of ETS show that the competitiveness is stabilizing, which is in line with the real world.

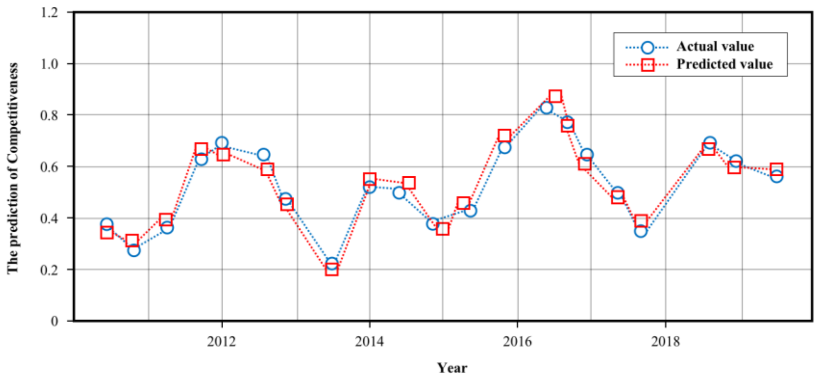


Figure 4: The prediction curve.

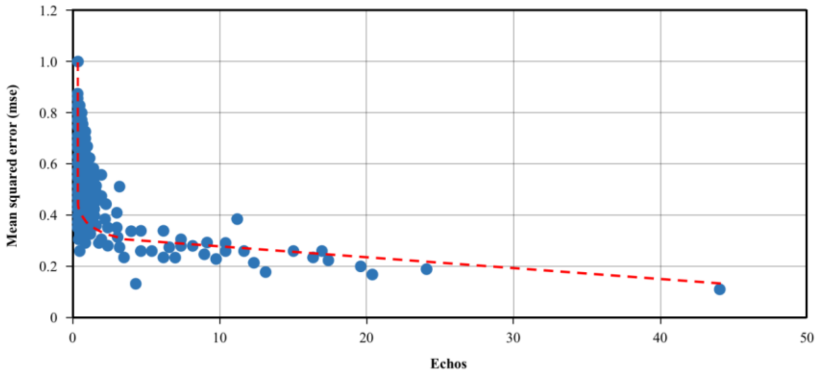


Figure 5: Neural network training curve.

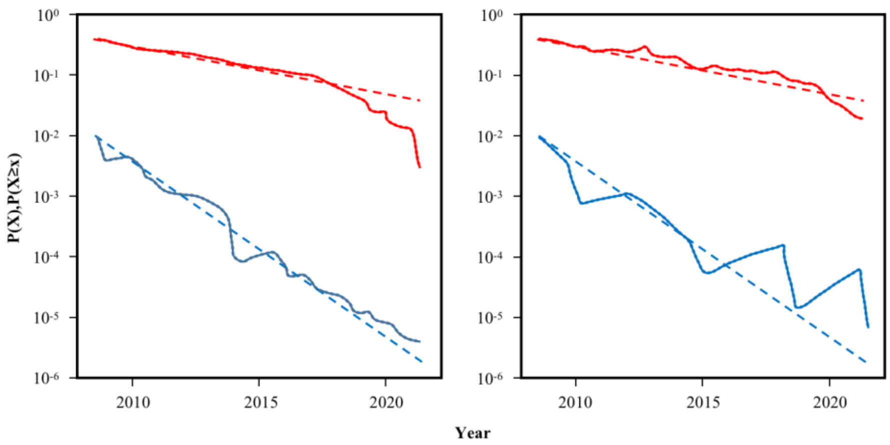
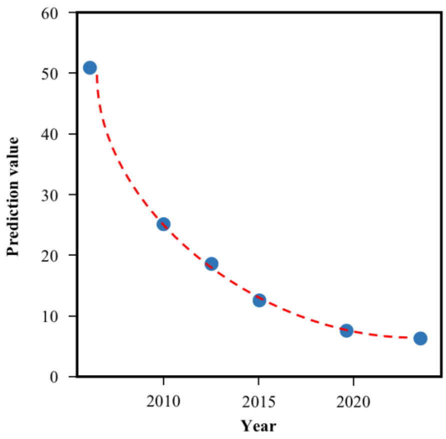


Figure 6: Time series decomposition.



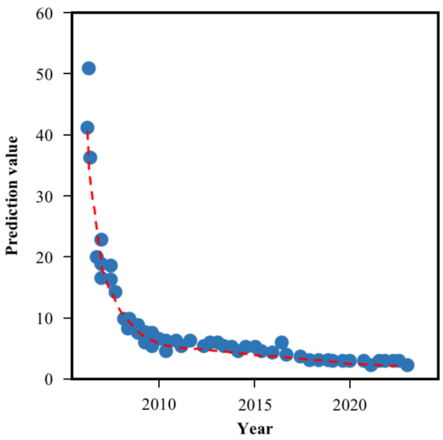


Figure 7: Non-linear prediction: (a) small sample, (b) lager sample.

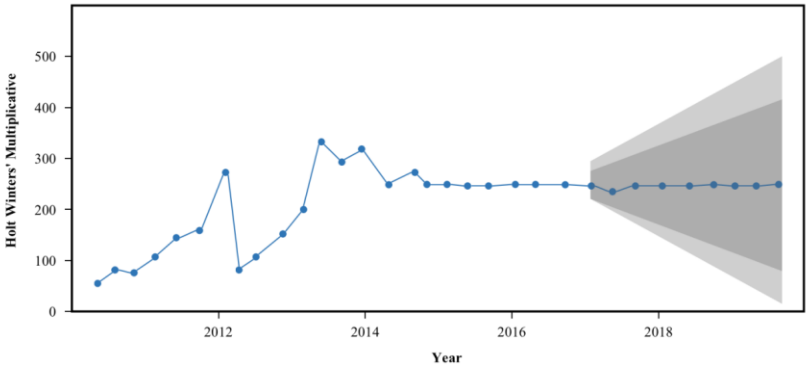


Figure 8: Sports industry competitiveness exponential smoothing model.

5 CONCLUSION

This paper constructs an evaluation index system for the competitiveness of sports industry from the perspective of power change, efficiency change and quality change, based on the logic of “development foundation - development main line - development main body”, with the industry development as the main body and basic requirements as the index selection principle. Based on this evaluation index system, the radial base neural network method was used to verify the evaluation index system. The analysis results show that our model has good predictive validity. Importantly, the government should promote sports industry clusters to enhance the competitiveness of regional industries. The important trend is industry clustering, which promotes the efficient flow of factors among regional sports industries through the development of flexible clusters among industries, integrates advantageous resources in the region, builds an intra-regional innovation system, releases the vitality of regional industries, and enhances the competitiveness of regional industries. Secondly, the sports industry competitiveness index system does not include the factor of sports consumption, which needs to be further improved, but sports consumption is an intrinsic motivation. Cities should continue to strengthen the publicity and promotion of national fitness to enhance residents' enthusiasm for sports and fitness, and at the same time introduce measures to promote residents' consumption to further drive the development of regional sports industry. Thirdly, to achieve high-quality development, the local government should tailor the development tactics based on the local conditions. In other words, they should formulate policies to promote in accordance with the actual regional economic development, and on the other hand, they should consider the integration and development with other industries. This paper also has some limitations. First, this paper does not incorporate time scales into the model, and given the dynamic changes in the sports industry, future research could consider dynamic analysis over long time spans to reveal the changing trends in the Chinese sports industry. Second, this paper does not conduct cross-regional analysis, which may limit the generalizability of this paper's model, and future research can consider different case regions to clarify the scientific validity of the model proposed in this paper. Third, the RBF NN-based model can also draw on the relevant contents of machine learning in the future to continuously improve the model.

6 ACKNOWLEDGEMENTS

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Nan Hu, https://orcid.org/0000-0003-1852-9212
Minghao Qu, https://orcid.org/0009-0008-2235-3911

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