

Retraction

Retracted: Risk Prediction of Sports Events Based on Gray Neural Network Model

Complexity

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

In addition, our investigation has also shown that one or more of the following human-subject reporting requirements has not been met in this article: ethical approval by an Institutional Review Board (IRB) committee or equivalent, patient/participant consent to participate, and/or agreement to publish patient/participant details (where relevant).

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] Z. Wang, "Risk Prediction of Sports Events Based on Gray Neural Network Model," *Complexity*, vol. 2021, Article ID 6214036, 10 pages, 2021.

Research Article

Risk Prediction of Sports Events Based on Gray Neural Network Model

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In this paper, neural network is used as a predictive network modeling method, with the support of MATLAB Neural Toolbox, based on the implementation of predictive research. A risk warning model is designed for sports events relying on neural network s to reduce the losses caused by risk accidents. First, the article introduces a literature review of sports event risk warning, combined with the sports event risk warning index system; summarizes the main advantages of using neural network and fuzzy theory; and establishes a sports event risk warning model relied on neural network. The article starts with the application of gray network in sports risk warning design, starting from the necessity of applying gray network in sports event risk warning; analyzes the risk warning model and operation process; and conducts sample data verification to verify this power of the model. Practice has proved that the application of gray neural network in sports events can play a role in risk warning.

1. Introduction

In sports events, due to the complexity of the activities and the interest of the construction unit, the internal environment is more complicated, which is very risky [1]. This kind of prediction has some advantages. It can provide athletes and coaches with clear training and competition goals and can also track and judge the development law of sports performance and the characteristics of sports development [2, 3]. To sum up, it is necessary to evaluate and predict the risks it will face and avoid risks as much as possible to avoid unnecessary losses. Sports events require relatively large costs and expenses, require high external hardware facilities, and have more roles for the distribution of related benefits. At home and abroad, there are various comprehensive environmental impacts [4]. The prediction of the sports performance to be produced based on the existing sports performance is often applied to the performance prediction of large-scale sports meets. For a sports event, if it is successfully held, then we need to predict some risks in advance, such as the instability of the event, in order to reduce the impact of related factors and ultimately reduce the risk of uncertain factors [5].

When conducting large-scale and high-level sports events such as the Olympics, the establishment of a wind direction early warning indicator system requires many qualitative indicators, and most of these indicators have nonlinear and unclear characteristics. However, because this type of prediction is based on a small amount of data, at the same time, there is a large randomness in the data generation process and many hidden influencing factors, so that there is a large uncertainty in the data information [6]. There are many factors that can affect events, and the uncertainty is strong. The traditional risk warning indicator system is mainly based on factors within a fixed range and cannot be updated in time. It is a static form with weak adaptability and difficult to comply with more and more diversified sports events [7]. It is necessary to be able to scientifically monitor the risks of sports events as the basis for the establishment of the event risk warning index system [8]. The use of parallel and decentralized processing modes greatly improves the recognition accuracy of the entire system and at the same time increases the logic robust fault tolerance rate. Therefore, this type of prediction is often difficult to ensure accuracy [9].

Using relevant literature data, this article establishes the risk events, which is based on the theory of gray neural network structure. It is proposed to split the amount of sports events during large-scale events into two independent parts, the daily part and the activity part, for prediction. The daily part has more historical data that can be used, such as time series forecasting method, neural network forecasting method, and other forecasting methods that require a longer training sequence; the active part is discrete data with fewer samples, but it is mainly related to the number of users. Predictive methods such as regression analysis method can be applied. Finally, the two independent prediction parts are merged to get the final result. At the same time, the neural network is used to approximate the nonlinear insertion method to construct the risk prediction in the time series, and the GM model and the time response function of the risk time series are established to predict the risk of giant projects. Finally, the accuracy of the prediction results is calculated through examples and the risk of sports events. The forecast has certain reference value.

2. Related Work

In the supervised summarization method, summarization is often used as a predictive value-level clustering, regression, or sequence labeling task to solve, and many supervised learning algorithms are widely used [10]. However, since most supervised learning methods require many labeled data, it is difficult to directly obtain relevant data sets in many cases, especially in specific fields. Using natural language processing and comprehension technology, we merge the generation method with information and use natural language technology to generate new summary prediction values. Generative automatic summarization methods are usually divided into the following three categories: methods based on formal semantics, phrase selection and piecing together, and deep learning sequence-to-sequence model [11].

At present, the mainstream methods of researching generative abstracts are based on deep learning to convert the problem of generative abstracts into sequence-to-sequence problems. Kim [12] used long short-term memory network as the model of the encoding and decoding (encoder-decoder) framework and used the attention model to generate the title of the risk article. The simplified version of the attention mechanism proposed by Liu et al. [13] has a better effect in solving the problem of title generation than the complicated version of the attention mechanism. Dixon and Candade [14] proposed a copy network (COPYNET) model based on the sequence-to-sequence framework, which directly extracts part of the original text content and combines it with the generated text content for the automatic summarization task to form the final abstract content, which is a very good solution. Ghasemiyeh et al. [15] solved oral word (OW) problem, which is based on the innovation of the model architecture, and used some skills in the experiment, mainly to solve the problem of how to summarize long texts. This model is also based on the sequence-to-sequence framework of the recurrent neural network

(RNN), CN/Daily Mail, New York Times data set has reached a new best result (state-of-the-art). In addition, the model is improved compared to the traditional attention mechanism. In the paper, two sets of attention mechanisms are used. In addition to the traditional attention mechanism, the attention mechanism is also used inside the decoder, and a hybrid learning is proposed. The goal is a combination of supervised learning (teacher forcing) and reinforcement learning. The sequence-to-sequence model based on convolutional neural network (CNN) proposed by Nguyen [16] can also achieve near-optimal results in text summarization tasks. The model is represented layer by layer and long-range dependence. In addition, the convolutional neural network itself has the advantage of high parallelization, so CNN training is more efficient than the automatic generation of sports risk as an emerging field.

One of the most relevant recent works is that Chou and Lin [17] use traditional predictive value features and task-specific features to build a supervised learning framework to score all predictive values in sports scripts and then combine the determinant point process (DPP) to remove redundancy and sort according to the predicted scores to get the final risk content. In addition, the author constructed a public data set, which contains the live broadcast script text and the corresponding manually edited sports risk. This article also uses this data set to take the comments on Twitter related to a sporting event as a data set. At the same time, taking into account the timing factor, the number of related tweets at a certain moment increases sharply, which indicates that the events at this moment are more important [18]. Based on this design, automatic abstracts belonging to specific fields are automatically generated based on neural network sports risks. It is a traditional research field in natural language processing, and its application objects are mainly focused on risk and social media. The current methods for solving automatic summarization problems are usually divided into the following two categories: extractive and generative [19]. Most extractive summarization methods are based on unsupervised or supervised learning. In unsupervised learning methods, feature-based ranking methods are usually based on the semantic or statistical characteristics of the predicted value, such as word frequency, predicted value position, clue words, punctuation words, vocabulary chain, rhetorical structure, and topic information [20]. Clustering-based methods usually select one or more representative sentences with minimum redundancy and maximum coverage from each subtopic to form a summary. In recent years, model-based methods have achieved good results; using predictive value to sort the algorithm extracts relevant predictive values from Twitter as a summary of sports risk and proposes a new framework to integrate sports video highlights to generate a summary of sports games [21–24].

3. Construction of Risk Prediction Model for Sports Events Based on Gray Neural Network

3.1. Basic Theory of Gray Neural Network. The so-called gray prediction refers to the prediction based on the GM (1, 1) model. It is single factor in form but full factor in essence; it

is mainly used in time series forecasting [25–27]. Gray prediction is a new type of theory established through the processing of raw data and gray models. It can make scientific and quantitative predictions of the future state by discovering and mastering the law of system development. We preprocess the original data before modeling [28, 29].

Based on the neural network, we have built a corresponding network architecture. Through data learning and training, we input the risk warning data of traditional sports events into the network. However, the prediction error is often high, especially when there are special circumstances in the system, abnormal data will appear, which will destroy the stability of the prediction data, and the prediction error will increase significantly. The matrix composed of i warning indicators of j data to be early warning is shown in the following formula:

$$(X_{ij})_{m \times n} = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{pmatrix}. \quad (1)$$

Through the accumulation and generation, the random interference of the original data is weakened, and the inherent laws contained in the system are highlighted. All the data in the matrix are standardized.

$$r(i, j) = \frac{\max(x) - x(i, j)}{x(i, j) - \min(x)} - 1, \quad (i, j = 1, 2, \dots, m). \quad (2)$$

Some eigenvalues are processed according to the following formula:

$$r(s, t) = \frac{x(s, t) - \min(x)}{\max(x) - x(s, t)} + 1, \quad (s, t = 1, 2, \dots, n). \quad (3)$$

After processing, normalize the formula (1) to get the membership matrix, as shown in the following formula:

$$R_{m \times n} = \begin{pmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{pmatrix}. \quad (4)$$

Next, perform an optimal evaluation on n data to be warned and set the relative optimization vector of the maximum risk of a sporting event as f, g :

$$f(i, j) = (f_1, f_2, \dots, f_m) = (1, 1, \dots, 1). \quad (5)$$

The relative risk relative optimization factor is n :

$$g(i, j) = (g_1, g_2, \dots, g_n) = (0, 0, \dots, 0). \quad (6)$$

W - i is the weight value of the i indicator. There are many combinations of neural network forecasting methods such as the combined gray artificial neural network model for seasonal forecasting. This method mainly considers the dual trend of seasonal time series with growth and volatility and combines the complex seasonal trends of the two trends. The problem of predictability is combined with the combined

model to improve the prediction accuracy; in addition, there is a method of first using the gray model to correct its prediction residuals. When the actual output of the neural network is close to the expected output, it can be considered that the input data training is over, and the fuzzy optimization neural network weight and threshold range are obtained at the same time.

$$y(i) = \frac{1 - w(i) \cdot (r(i, j) - g(i, j))}{1 + w(i) \cdot (r(i, j) - g(i, j))}. \quad (7)$$

To determine the value of sports event risk, we use the obtained fuzzy optimization neural network weight and threshold method application value range and perform alarm processing on related indicators.

$$x(\text{mean}) = \frac{\sum_{i,j=1}^m x(i, j) + 1}{r(i, j) - 1}. \quad (8)$$

The neural network learning process is completed by the forward calculation process and the error reversal propagation process. As the error propagation correction continues, the correct rate of the network's response to the input mode continues to rise, and finally the network reaches a balanced state within the allowable error range and automatically converges. At the same time, the neural network can be used to approximate the expected curve of the risk loss value, and then the trained network can be used for nonlinear interpolation. For the risk loss value curve, the neural network mapping is a simple one-to-one mapping model from time t to risk s . Therefore, the input and output nodes of the model are all generated as one. In the actual model establishment process, it can be known that normalization processing according to the general method will make the network convergence performance poor. Therefore, the zero averaging and the standard deviation used in MATLAB are used in giant projects with time-related risks. The data preprocessing method of 1, that is, corresponding to each input quantity, the input L group data should be zero mean and the standard deviation should be 1. The calculation method of the response is as follows: knowing that the input layer in the neural network has n nodes, corresponding to n input variables, and there are L learning samples, the original observation data X is an $n \times L$ matrix, and the processed matrix is expressed as

$$w(i, j) = \frac{x(i, j) - \bar{x}}{\sum x(i)^* x(j) + -\bar{x}}, \quad (i, j = 1, 2, \dots, m). \quad (9)$$

$w(i, j)$ refers to the equalization of risk data values through neural network interpolation. The data of the new series is called the generated number. Therefore, using generated data to establish a time series risk model for giant projects is the focus of gray theory in risk prediction, and the commonly used gray generation is cumulative generation.

3.2. Risk Prediction Algorithm for Sports Events. The risk time series method is one of the most common short-term load forecasting methods. The method adopted in this paper is to establish a model for multiple sports index sequences, and

then a series of predicted values for the original sequence can be obtained. There must be deviations between these predicted values and the original values. There is also a certain correlation between macroeconomic indicators. Therefore, the deviation relationship between the predicted value and the actual value and the relationship between the series can be regarded as the neural network model. The predicted value is used as the input sample of the neural network. The random time series forecasting model can be regarded as a linear filter, and the specific algorithm is shown in Figure 1. The value is used as the output sample, and then the network is trained to obtain the weight and threshold of the corresponding node.

The next one or more predicted values of each model of GM (1, 1) are used as the input, and the output obtained is the final predicted value. The neurons in the input layer can be determined to be solved. In general, the number of neurons in the input layer of the neural network is determined by input value. Since the risk warning index for sports events is 12, the neurons in the input layer is selected as 12 in this paper. Commonly used time series-based sports event volume analysis and forecasting models mainly include exponential smoothing model and neural network model. The neural network is the information input from the outside. This part of the input information is advanced through the weighted summation of the layer neurons and through the activation function. Finally, the output layer obtains the output of the entire network (y_1, y_2, \dots, y_n). Since there is no correlation between nodes in the same layer, the output result of each layer will only affect the output value of the next layer. The number of neurons in the output layer can be determined according to the user's requirements. When the network is used as a classifier, the neurons in the output layer generally depend on the category patterns m . The meaning of each node is a neuron, which corresponds to a transfer function, usually of the Sigmoid type. By adjusting the gray network structure, we solve problems such as nonlinear classification and finally approximate any nonlinear function.

The neural network-gray system joint model is used to generate the required isochronous moment sequence for the gray system, and the neural network is used to approximate the nonlinear interpolation method. After the restored value is obtained from the model, the accuracy of the gray model must also be tested. Usually, the small error probability P and the posterior difference ratio C are used for model accuracy test, the qualified model is used for prediction, and the actual value is used for prediction accuracy test. The node distribution is shown in Table 1. When the neural network structure is determined, the input and output sets are used to train the network to realize the given input and output mapping relationship of the network.

This method is the most commonly used method in the risk prediction of sports events. The characteristic of the method is that it does not consider the longer-term data and gives more weight to the recent data; while the index method has the advantages of both, while not discarding the past data, it gives a gradually weakening degree of influence. In other words, on the basis of the moving average method, the

index method can be developed as a forecasting method. Then determine whether the risk response plan meets the actual requirements of the event; if it does not meet the requirements, continue to develop a new plan. The state of the system is difficult to judge, the mechanism of action is unclear, and the input information of the system is also difficult to distinguish. Therefore, it is difficult to try to establish a system model with input-output relationships. But the final result of the system is that the total output data and information are more or less available. Gray theory makes full use of this information and uses the gray information to isoform the system model to suggest the internal characteristics and laws of things.

3.3. Optimization of Prediction Model Parameters. There are three main ends to make up the neural network topology, namely, input, implicit, and output. Among them, as long as the neural network contains a hidden end, it can be close to a non-breakpoint function. Therefore, the neural network can be operated in the form of many-to-many mapping. Risk assessment is the focus of the operation of the sports event risk warning model. The risk warning can be regarded as three levels, and there are three corresponding modes for the number of neural nodes. If the mathematical form is used to represent the three risk levels, from high to low, they are 100, 010, and 001. In other words, if the number structure of neural nodes at the output end is "high" and the position is "1 bamboo," it means the risk rating is high. Similarly, if it is "1" in the "medium" or "low" position, the risk rating is medium or low, it can be seen that only one "1" will appear in the structure, and the segmented flow table of sports events is shown in Table 2. The warning of sports events requires the establishment of a supervisory agency responsible for all sports events. The event conducts data analysis, dynamically monitors the entire operation of sports events, and obtains event risk warning signals.

The key link of risk warning management activities is the "alertness" forecast, and the "alertness" forecast requires the determination of early warning criteria. Early warning criteria are standards and principles for judging and evaluating the severity of the risks of large-scale sports events. It is used to determine whether an alarm should be issued and to what extent an alarm should be issued under different circumstances. The classification of risk warning levels should be reasonably determined according to the risk characteristics of large-scale sports events. It must be operability without losing its risk warning significance. The author refers to relevant literature and combines experts in the field on the risk of events. Based on the industry experience of "alertness" and its suggestions of the risk alertness that may occur during the holding of large-scale sports events, the "alertness level" of risks is divided into three levels according to the severity, namely, light alert (mainly refers to sports events with little or minimal impact), middle police (mainly refer to those that have a serious impact on sports events and require close attention by event managers and need to take corresponding measures in a timely manner), and heavy police (mainly refer to those that have a serious impact on sports

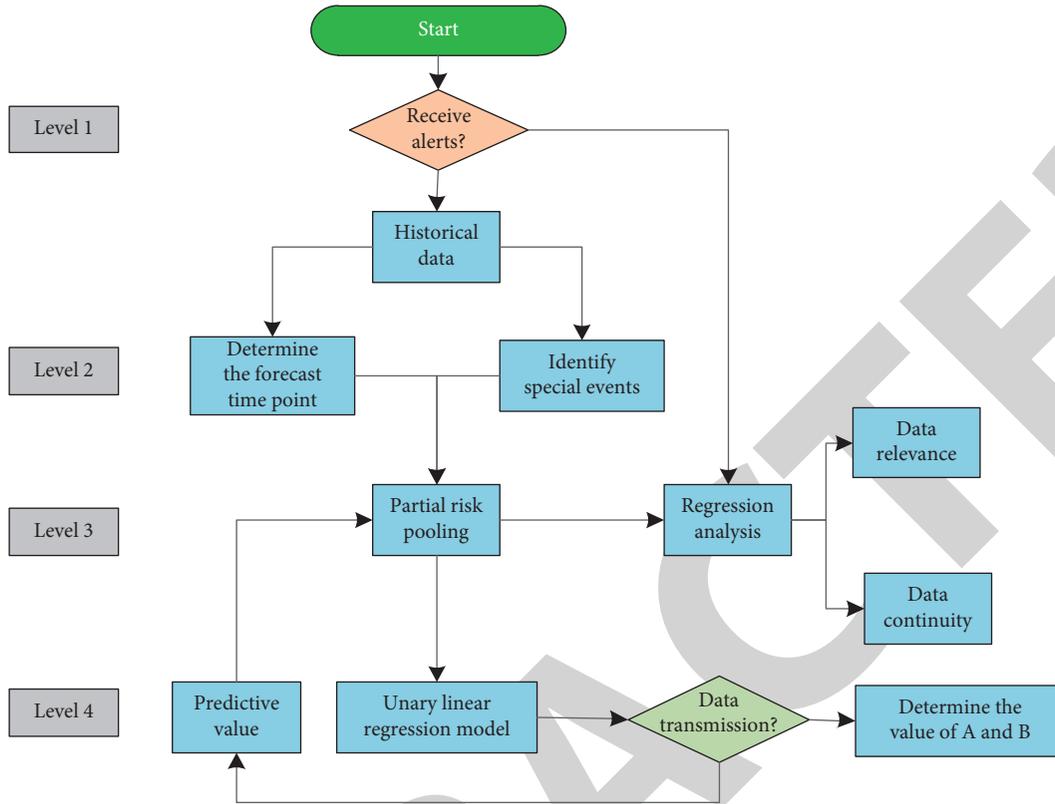


FIGURE 1: The process of risk prediction algorithm for sports events.

TABLE 1: Distribution of neural network nodes.

Node number	Distribution density	Risk rate
1	0.62	0.89
2	0.18	0.64
3	0.35	0.69
4	0.41	0.85
5	0.21	0.57

TABLE 2: Segmented flow table of sports events.

Event stage	Time	Crowd characteristics	Risk trend
Approach	2	Dispersion	Rise
Contest	2	Concentrated	Second peak
Exit	1	Concentrated	Peak

events). The impact of the event is extremely serious, and the event organizer may not be able to bear the consequences. According to the value of the risk consequence caused by the early warning indicators, different levels of alarms will be issued, so as to provide a strong basis for taking corresponding countermeasures.

In addition, the hidden end is more complex than the output end of the number of neural nodes. After analyzing the modeling process of the gray system theory method, it can be known that while the gray system model has many advantages, it also has the inevitable shortcomings of the gray system theory itself. It lacks the ability of self-learning, self-organization and self-adaptation, and the processing of

information. The ability is weak, and there are inherent shortcomings in error feedback when modeling the system. The system rarely uses deterministic information during the modeling process. Figure 2 shows the framework of the risk prediction model for events based on the neural network. If the number of hidden end neural nodes is too large, the overall neural network will be too large, which will lengthen the time and weaken the generalization ability. This affects the final risk prediction accuracy n . If the number of nodes is too small, the scale of the overall neural network will be not big, the overall modeling will not be perfect, and the accuracy will also be affected. Therefore, it is very important to control the number of hidden end neural nodes. It is necessary to ensure that the scale of the network meets the standard, while ensuring that the overall neural network scale cannot be too large, which affects the overall accuracy.

4. Application and Analysis of Sports Event Risk Forecast Model Based on Gray Neural Network

4.1. Simulation of Risk Prediction for Sports Events. Use MATLAB software to carry out the simulation training of gray network applied to the risk model of events. The software contains a toolbox dedicated to the simulation and testing of the neural network. The construction prediction and construction function can be used to learn in the network. Take 0-1 as the vector representation of the output end of the structure, so the logarithmic function is used to

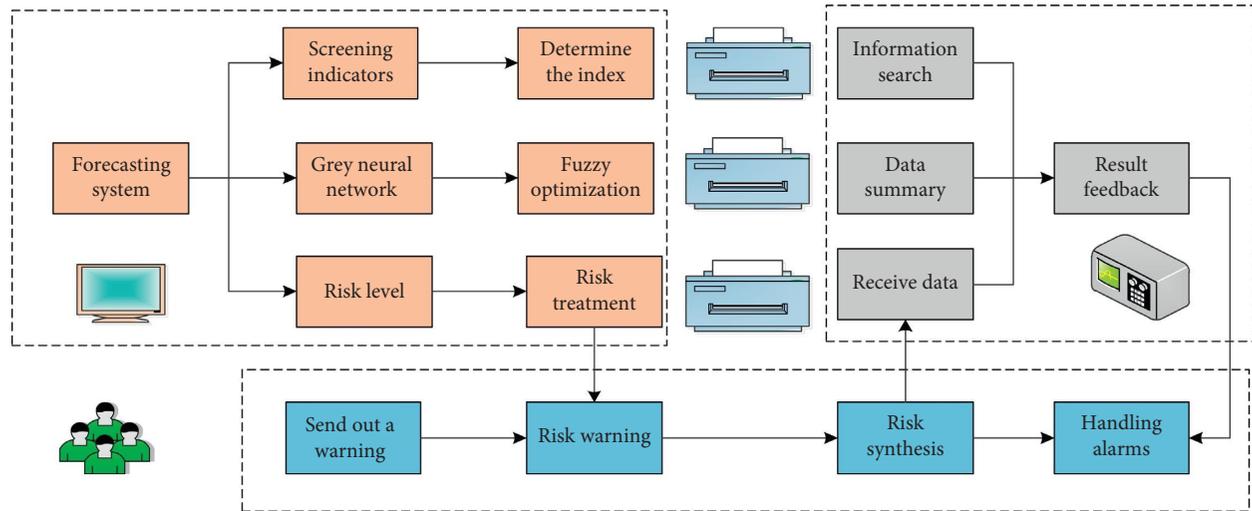


FIGURE 2: The framework of the sports event risk prediction model relied on neural network.

construct the function for the number of neural nodes at this end, as shown in Figure 3. The more complex implicit end uses the tangent function to express the number of neural nodes. The neural network uses node training function with TRAINLM as the input; the number of times is set to 2000, in order to reduce the final deviation below 0.01. When the data in the neural network is finally completed, there are 7 neural nodes at the input, and the final deviation is less than 0.01.

First, complete the neural network learning training of 8 sets of risk prediction sample data information, set the number of times until the deviation meets the standard, and then use the data as the input value to calculate the corresponding output value, and compare the output value with the theoretical data comparative analysis. The problem of risk warning for large-scale events is essentially a classification problem. Since the “alertness” is divided into three levels, this article uses the number of classification modes to determine the operation method of output neurons and designs the neurons in the layer. Use the three risk levels of (1, 0, 0), (0, 1, 0), and (0, 0, 1) in the theoretical data to detect the output value to detect whether the risk warning effect is effective. The numerical deviation distribution is shown in Figure 4. The setting of the alarm value is mainly determined based on the obtained weight and the threshold range. The comprehensive value of the risk, that is, the level of each risk, is determined first, and then the alarm value is set. After finishing the study and training, 8 out of 20 groups are used to test the relevant sports event risk warning model and check whether it is effective. This paper builds a risk warning mechanism for large-scale events relied on neural network s , uses the 12 risk indicators identified above as early warning indicators, extracts state sample data based on this, and divides the sample data into network training samples and network tests sample.

In the application analysis, the functions in the neural network toolbox provided by MATLAB7 are used to train the network. Since the elements of the output vector are 0-1, the sigmoidal logarithmic function $\log s$ is used in the selection of the function in the layer of the network. The

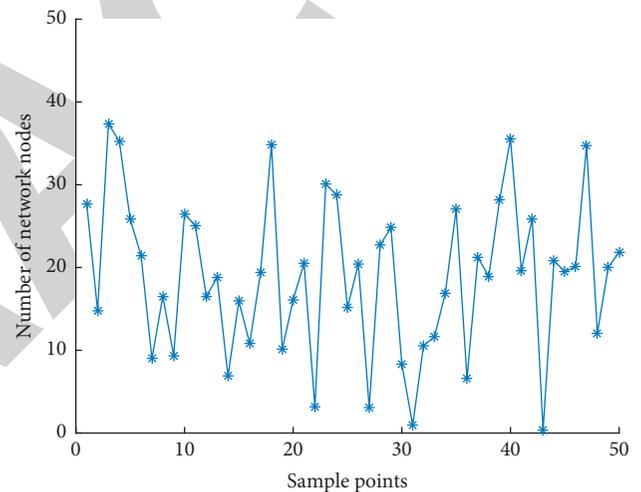


FIGURE 3: Line graph of the number of neural network nodes.

transfer function of the neurons of the network is the s -tangent function t , the number of training termination times is 2000, and the training termination error is 10–20. The training function is TRAINLM. After repeated learning and training, it is determined that the number of neurons in the network is 7. After 38 trainings, the network can meet the error requirements. The specific risk prediction value changes over time are shown in Figure 5.

4.2. Example Results and Analysis. This paper conducts a questionnaire survey to obtain relevant sample data information for the analysis of the risk warning of sports events. Analyzing the results of the questionnaire survey, 20 groups of valid sample data were obtained. Then, 20 sets of sample data are used to run the risk warning indicator level, the input value is 20 sets, and the output value obtained by one-to-one correspondence is the indicator level. The sample data obtained needs to complete self-learning and training. In order to ensure the influence of the sample data on the error of the

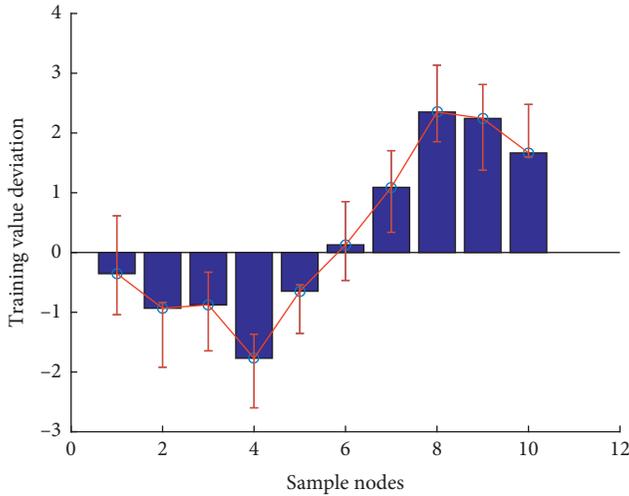


FIGURE 4: Deviation distribution of neural network training value.

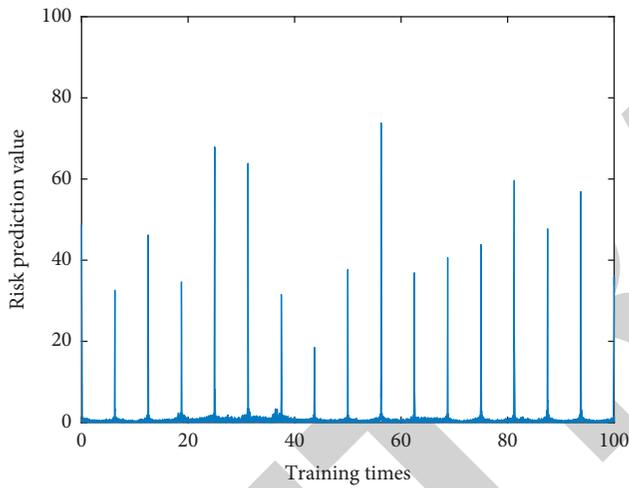


FIGURE 5: Trend of risk prediction value over time.

evaluation, the training frequency can be gradually increased in the process. Define the target output mode as (100), (010), and (001), and let them represent their respective classification modes, which means 3 risk levels, namely, heavy, medium, and light. Therefore, the number of neurons in the output layer is designed to be 3. Through the learning of training sample data, the gray network can complete the acquisition of early warning knowledge and learn a large number of internal and regular connections from it. As shown in Figure 6, the trained network model can be used as an internal basis for evaluating the risk of large-scale sports events after testing the test sample data. Finally, the warning indicator value of each sample in the detection set is directly input into the trained gray network, and the risk warning status value output by the network is compared with the actual “alertness” to judge the warning model of the completed training accuracy, so as to complete a more accurate alarm process.

Selection of Sample Data. Mainly use questionnaire surveys and expert interviews to conduct surveys and interviews with relevant experts engaged in theoretical

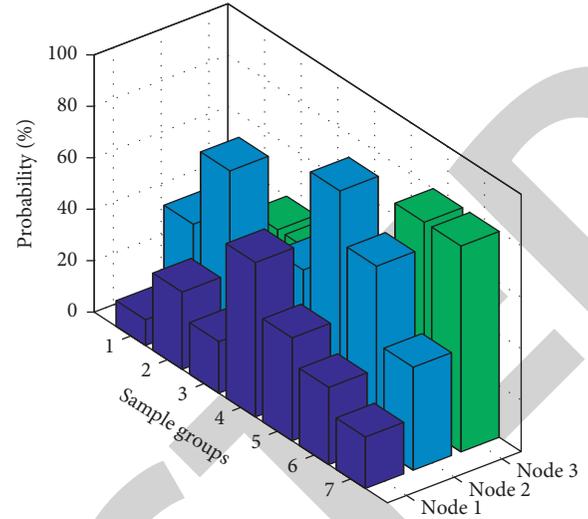


FIGURE 6: The distribution probability of sample nodes in different sports event groups.

research and management practices of large-scale sports events, and obtain 28 scoring sample data for events. Experts’ scores on 12 early warning indicators are used as input values, and their evaluation values on the level of events are used as output values. This paper selects 28 sample data with serial numbers 1–28 as training samples for learning and training and continuously increases the number of learning and training during the training process to meet the overall error requirements. After the network is trained, select 8 sample data with serial numbers 29–36 as test samples to test the model validity. Figure 7 shows the specific prediction results.

The network structure design includes the input layer and output layer design. For gray networks, there is a very important theorem; that is, for a function in any interval, it can be lied on a single layer neural network, so a 3-layer neural network can completely make any mapping. Therefore, it is ideal to use a 3-layer network in practical applications. The specific error distribution is shown in Figure 8. The neurons in the layer can be determined with the user’s requirements. To evaluate the performance of the model, the game results are split into home wins, away wins, and draws (if there is a tie), and then the standard classification matrix is used to view the number of matches correctly identified by the model. The degree of imbalance, although taking into account the generally observed family advantage phenomenon, people may see a slight tilt in favor of the family to win; in this case, classification accuracy is a reasonable evaluation method. In the case of highly imbalanced data, the curve evaluation may be more appropriate. Assuming that the defined error rate is the proportion of the number of samples misrecognized by the BP model in the total number of samples in the set, the rate of the BP network model can be obtained after training. As mentioned earlier, it is important to preserve the order of training data for sports prediction problems. It only predicts upcoming matches based on past matches, which usually involves disrupting the order of the examples. Therefore, for the

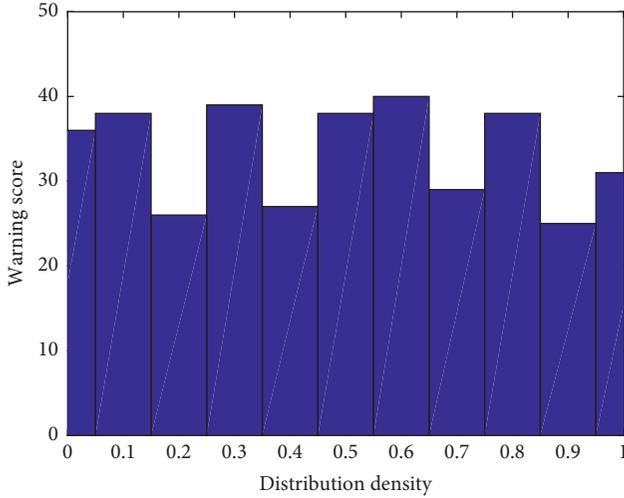


FIGURE 7: The distribution trend of risk warning value with sample density.

motion result prediction problem, cross-validation is not a suitable method to split the data into training and testing.

When the gray network is used as a classifier, the neurons generally depend on the category patterns m . Without loss of generality, the number of layer nodes can be decided by the number of output parameters of the network, and the layer nodes should be like to the kinds of objects to be classified. Through the comparison between the value of sports event traffic, it is analyzed that the error is mainly composed of the error caused by the uncorrected historical data, the error transmission caused by the error of the number of people forecast, and the error caused by unexpected events. Too many network nodes will lead to some time to predict the network and will weaken the ability and decrease the predictive ability. Except that the first part can be solved by data stabilization, there is no better solution for the errors of the latter two parts. The risk warning problem of large-scale sports events is essentially a classification problem. Since the “alertness” is divided into three levels, this article uses the number of classification modes to determine the operation method of output neurons, design 3 output layer neurons, and the target of the output modes are (100), (010), and (001), and let them represent their respective classification modes, which means 3 risk levels, namely, heavy, medium, and light. Therefore, the number of neurons in layer is designed to be 3.

As shown in Figure 9, the output value is not same as to the expected value, and the output value is closer to one of the three classification modes (0, 1, 0), (0, 0, 1), and (1, 0, 0) to decide the final calculation result of the test sample. For example, the actual output value of the sample number 32 is (0.006, 0.1411, 0.9944), which is more explicit than the other two modes, which is closer to the classification mode (0, 0, 1); therefore, the early warning result of the sample calculated by the early warning model established in this paper is a light warning, and the result analysis method is analogous to this. A simple comparison between the output results in the text and the actual situation shows that the number of

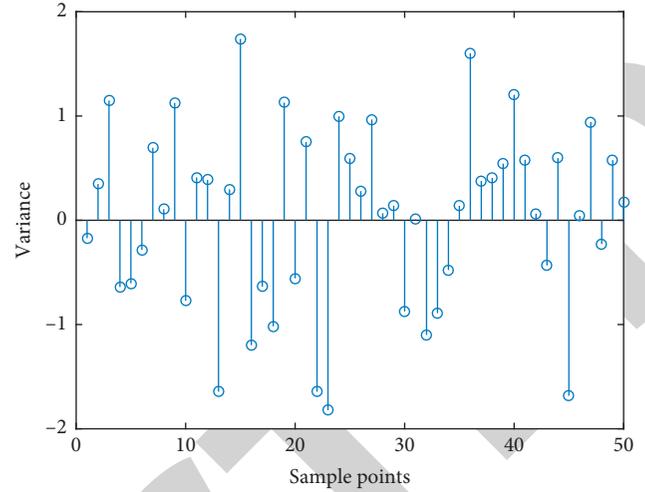


FIGURE 8: The distribution of the error of input neuron sample points.

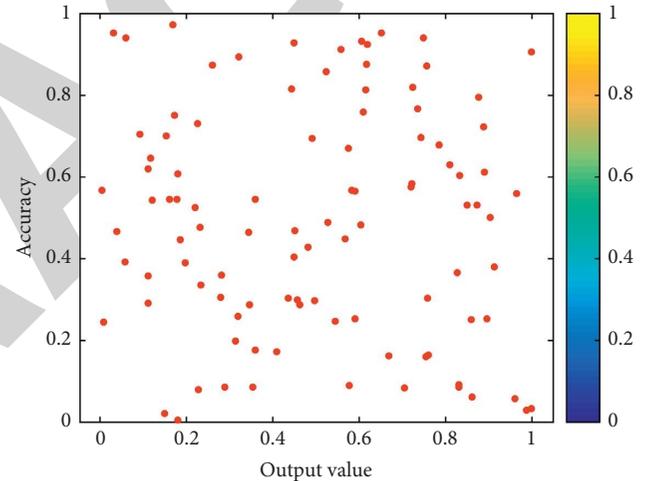


FIGURE 9: Scattered distribution of actual output value and expected value accuracy.

sample data misjudgments among the 8 test samples is one. Assuming that the defined error rate is the proportion of the number of samples misrecognized by the gray model in the total number of samples in the set, the rate of the gray network model formed after training is 12.5%, and the prediction accuracy rate reaches 87.5%. The results of the empirical research show that the large-scale sports event model relying on neural network can achieve better early warning effects.

5. Conclusion

In this article, based on the constructed sports event risk warning model, the sports events are prewarned. Focusing on neural network-based modeling and forecasting schemes, this article studies different neural network models, and considering the requirements of forecast reliability, real time, and timeliness, the network models are screened, and the training speed is compared with RBF neural network

with good generalization ability. We use MATLAB software to realize gray network model and neural network model and choose model and network model, respectively, to perform gray fuzzy neural network fitting operation on the usual results of sports events. In view of the traditional sports event risk warning indicator framework, a sound sports event risk warning indicator system is proposed, which explains the implementation process of the sports event risk warning model based on network. From the perspective of gray system theory and from the perspective of combinatorial optimization, this paper uses the concept of effectiveness to build a model suitable for forecasting of nonlinear systems, a first-dimensional recursive parallel neural network model. Finally, the empirical analysis results are obtained, the main basis for the risk warning of sports events is introduced, and the main countermeasures and related precautions for the risk warning of sports events are explained.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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