

# Combination of Grey System and Neural Network Based Sports Achievement Forecasting Algorithm

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**Abstract**—This paper presents two novel forecasting algorithms for sports achievement based on combination of grey model and neural network: (1) GM-NN1: Firstly, the error sequence is obtained by GM(1,1) model using original data sequence of sports achievement, and then in order to gain a forecasting error sequence, the neural network is built up to train the regression of error sequence. This new model corrects the error of GM(1,1) model prediction using neural network, and its accuracy has been significantly improved. (2) GM-NN2: This model uses the partial-data sequence of the original sports achievement data to create partial-data GM(1,1) model group, and build a neural network to establish the nonlinear relationship between the fitted values and original data, the generated network estimates the forecasting development trend of the partial-data GM(1,1) model group, and achieves better results in the medium- and long-term forecast for sports achievement.

**Keywords**-sports achievement; forecasting; grey system; neural network

## I. INTRODUCTION

Physical education forecast refers to the predictor's prediction and deduction to all kinds of future or unknown factors in the field of physical education [1, 2]. Physical education forecast is not only very important to the development of physical education career, but also important to the assessment of the development trend of sports achievement. It provides scientific basis to policy-maker. How to establish a forecasting model for athletic contest achievement is an important project of tourism study. But there is not a centralized normal form for which kind of mathematics model can be used [3]. At present commonly used mathematics models are [4~6]: (1) Time sequence model: often used to predict simple, stable or periodic statistics. As for the apparent rising Chinese athletic contest achievement, the prediction result may be lower than the real one. (2) Regression model: rely too much on limited variables, and many major influential factors have been excluded from the model. The model is usually in static state. It is hard to predict the future changing trend of the self-variables that set up in the competitive achievement function. (3) Gray predictions: a linear model, however the change of the athletic contest achievement is a linear dynamic process, so it is hard for the Gray model to predict the exact change of the athletic contest achievement. (4) Delphi method: it cannot effectively reveal the relationship among various kinds of factors in physical education system, in which they interact and associate with each other, and cannot reveal the relationship between physical education system and outside environment.

Grey forecasting model is the main component of the grey system theory [7], and one of the hot research areas, which is composed of GM(1,1) model, grey Verhulst model and DGM(1,1) model, and so on. The basic principle of the grey forecasting model is that after the accumulation of the raw data, to discover previously unknown, interesting relationships among attributes from large databases, and to retrieve to initial states for simulation and forecasting. Grey combined forecasting model is one of the main research directions in the combined forecasting theory, and the organic integration of the grey model with other models is an important content in the grey combined forecasting model [8].

Neural network forecasting network is a nonlinear computing model [9, 10]. And Study ability, neural network can effectively fit any nonlinear function and its neuron realizes two fuzzy functions for fuzzy processing. Neural network with the characteristics of massively parallel processing, distribution storage, self-adaptive, fault tolerance and etc. [11~13], could be used to solve complex nonlinear problems, which can reflect the nonlinear relation among the variables of sports achievement. Therefore, we choose neural network model to combine with the grey GM(1,1) model to forecast sports achievement.

This paper proceeds as follows: Section II discusses the basic concepts of the grey prediction model and artificial neural network. Section III clarifies the contribution of the theory of copulas to the detection of the volatility and the improved model. Section IV presents the results data and Section V concludes.

## II. MODEL ANALYSIS

According to the research on neural network and grey system theory, it can be found that these two theories are similar to a certain extent. Firstly, the output results of neural network can approximate any fixed value at arbitrary precision [14]. However, because of the existing error, the output values will fluctuate around some value as a center. It can be derived that the output of neural network is a grey coefficient [15].

Meanwhile, the two theories have otherness and complementarity: The neural networks can approximate any nonlinear function at arbitrary precision, but GM(1,1) is not suitable to approximate complex nonlinear functions [16]. The accumulated sequence appeared a monotonously increasing trend, which is suitable for neural network to approximate [17]. Therefore, combine grey GM(1,1) model and neural network is feasible.

**A. GM-NN1 Algorithm**

That using GM(1,1) model to fit the original data cannot avoid the information distortion caused by positive and negative cancellation in the process of accumulative sequence of system identification [18]. Therefore, to increase accuracy, we propose a combined forecasting model based on grey GM(1,1) model and neural network 1<sup>st</sup> (GM-NN1) algorithm. The content of GM-NN1 algorithm is shown in Fig. 1: At first, we set up GM(1,1) model according to the original data, and obtain error sequence. Secondly, neural network is used to obtain forecasting error sequence by error regression analysis. At last, a new forecasting value is acquired by adding the forecasting value of GM(1,1) and the forecasting error.

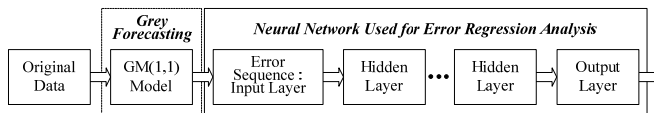


FIGURE 1. CONTENT OF GM-NN1 ALGORITHM

The mathematical description is given as follows:

For an original non-negative sequence

$$X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n)) \tag{1}$$

the reduction value sequence of  $X^{(0)}$ ,  $\hat{X}^{(0)}$ , can be obtained through utilizing grey GM(1,1) model, i.e.,

$$\hat{X}^{(0)} = (\hat{x}^{(0)}(1), \hat{x}^{(0)}(2), \dots, \hat{x}^{(0)}(k)) \tag{2}$$

To facilitate description, we make the following definitions.

*Definition 1:* when  $k = n$ ,  $\hat{X}^{(0)}$  is the fitting value of  $X^{(0)}$ , thus

$$\begin{cases} x^{(0)}(1) = \hat{x}^{(0)}(1) \\ \varepsilon^{(0)}(k) = x^{(0)}(k) - \hat{x}^{(0)}(k) \end{cases} \tag{3}$$

Let  $\varepsilon^{(0)}$  represents the error sequence of GM(1,1) model, which can be denoted as

$$\varepsilon^{(0)} = (\varepsilon^{(0)}(2), \varepsilon^{(0)}(3), \dots, \varepsilon^{(0)}(n)) \tag{4}$$

*Definition 2:* when  $k > n$ ,  $\hat{x}^{(0)}(k)$  is the forecasting value calculated by GM(1,1). Let  $k = n + m$ , then the forecasting sequence of GM(1,1) can be denoted by

$$(\hat{x}^{(0)}(n+1), \hat{x}^{(0)}(n+2), \dots, \hat{x}^{(0)}(n+m)) \tag{5}$$

where  $m$  is the forecasting steps.

The Definition 1 reflects the difference between real value

and fitting value, which exists in GM(1,1) predictions. The traditional GM(1,1) model utilizes the  $k > n$  values of the reduction sequence  $\hat{X}^{(0)}$  mentioned in Definition 2 to make predictions, without considering the changes of the error sequence, which may lead large difference into prediction. For solving the above problem, GM-NN1 algorithm is proposed, and the detail procedure is described as follows:

Step 1: GM(1,1) model calculates reduction sequence  $\hat{X}^{(0)}$ , error sequence  $\varepsilon^{(0)}$ , and prediction sequence from original data sequence.

Step 2: in order to obtain a forecasting error sequence  $\hat{\varepsilon}^{(0)}$ , a neural network is built up to train the regression of error sequence. Denote  $q$  as the forecasting steps of the neural network, i.e., the information of  $\{\varepsilon^{(0)}(k-q), \varepsilon^{(0)}(k-2), \dots, \varepsilon^{(0)}(k-1)\}$  is used to predict the error value at moment  $k$ . Consider  $\{\varepsilon^{(0)}(k-q), \varepsilon^{(0)}(k-2), \dots, \varepsilon^{(0)}(k-1)\}$  as input sample of the neural network,  $\varepsilon^{(0)}(k)$  as supervised value of the neural network. Train  $\varepsilon^{(0)}$  by the neural network. The trained neural network can be used as an effective tool for forecasting the error sequence, for example, the forecasting value of  $\varepsilon^{(0)}(n+1)$  can be obtained from the values of  $\varepsilon^{(0)}(n-q+1), \varepsilon^{(0)}(n-q+2), \dots, \varepsilon^{(0)}(n)$ . For an error sequence which needs  $m$  steps prediction, let  $\hat{\varepsilon}^{(0)}$  be the forecasting sequence from training and prediction of the neural network, thus

$$\hat{\varepsilon}^{(0)} = (\hat{\varepsilon}^{(0)}(n+1), \hat{\varepsilon}^{(0)}(n+2), \dots, \hat{\varepsilon}^{(0)}(n+m)) \tag{6}$$

Step 3: a new forecasting value is obtained while summing the GM(1,1) model prediction and forecasting error sequence, i.e.,

$$\hat{x}^{(0)}(i) = \hat{x}^{(0)}(i) + \hat{\varepsilon}^{(0)}(i) \tag{7}$$

in which,  $i = n+1, n+2, \dots, n+m$ ;  $\hat{x}^{(0)}(i)$  is the new forecasting value obtained from GM-NN1.

This new model correct the error of GM(1,1) model prediction using neural network, and its accuracy has been significantly improved, which will be verified in section III.

**B. GM-NN2 Algorithm**

In the GM(1,1) modeling procedure, it doesn't need to utilize all the data in the raw sequence, and when the data choosing manners are different, the sports achievement forecasting models have a lot of diversity. We explore partial-data sequence of the original sports achievement data to create a prediction grey area with upper and lower bounds. This area appears to be a horn with the passage of time, i.e., The longer the forecasting period, the larger the grey area, the lower the predicted precision, which is one of the main reasons that grey forecasting manner is not suitable to make a long-term

prediction. To raise the long-term predicted precision, neural network is explored to set up the nonlinear mapping relation between partial-data GM(1,1) model and original data.

For  $X^{(0)}$  and  $\hat{X}^{(0)}$  given in Eq. (1) and (2), define as follows:

*Definition 3: if GM(1,1) modeling needs at least k data, then the GM(1,1) model obtained by the former S data of  $X^{(0)}$ ,  $X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(s))$ , can be named as S-GM(1,1) model. And the former n data of reduction sequence obtained by S-GM(1,1) model is still called fitting value, and the remainder is called forecasting value.*

*Definition 4: if GM(1,1) modeling needs at least k data, and the length of  $X^{(0)}$  is  $n \geq k$ , then  $n - k + 1$  S-GM(1,1) models can be obtained, which can be named partial-data GM(1,1) model group.*

Usually, GM(1,1) modeling needs five data, i.e.,  $k = 5$ . For an original non-negative sequence with  $n$  data, we can obtain  $n - 4$  partial-data GM(1,1) models, which compose a GM(1,1) model group. The fitting and forecasting values calculating from each model in the group can be treated as approximations of sports achievement system under certain condition. The basic concept of the combined forecasting model based on grey GM(1,1) model and neural network 2<sup>nd</sup> (GM-NN2) algorithm is depicted by Fig. 2: The neural network is trained by treating the fitting value of partial-data GM(1,1) model group as inputs, and the corresponding original data as supervised values. After trained well, the neural network can predict the forecasting values of original data by inputting the forecasting values of partial-data GM(1,1) model groups.

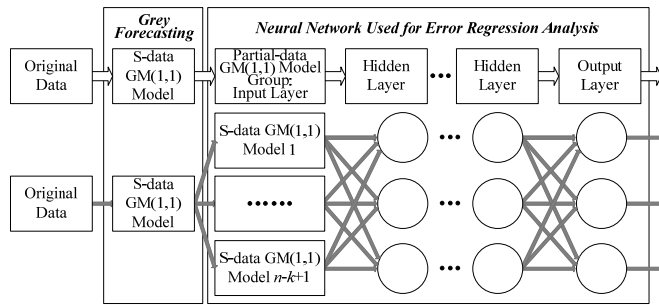


FIGURE II. CONTENT OF GM-NN2 ALGORITHM

The detail procedure of GM-NN2 algorithm is described as follows:

Step 1: Set up the S data GM(1,1) model, and obtain the partial-data GM(1,1) model groups.

Step 2: Input the fitting values of partial-data GM(1,1) model groups and set up neural network by the supervised values. The nonlinear mapping relationship between partial-data GM(1,1) model groups and original data can be reflected by the trained neural network.

Step 3: For the trained neural network, the forecasting values of the original data can be obtained by inputting the forecasting values of partial-data GM(1,1) model groups.

III. SIMULATION RESULTS

Sports achievement forecasting has very important meaning to hold the development trends of athletics sports. And it is the basic and premise of finding scientific theory of training and instructing practice of training. However, sports achievement forecasting is affected by many factors, such as level of training, personal habits, health, climate and temperature conditions. Sports achievement forecasting model must give full consideration to various factors. But some of them can be quantized while others cannot, so it's difficult to depict all the factors accurately. From the viewpoint of system theory, the forecasting model is a typical grey system in which information is known partly and unknown partly. We choose LIU Xiang's international competition record in men's 110m from 2001 to 2008 [19] as experiment samples (shown in Tab. 1), and use GM(1,1) model, GM-NN1 and GM-NN2 algorithms to analyze the former 9 values, and forecast the latter 4 values. The performances of the three manners can be compared by the real and forecasting values.

TABLE I. LIU XIANG'S INTERNATIONAL COMPETITION RECORD IN MEN'S 110M

No.	1	2	3	4	5	6	7
Notes (seconds)	13.33	13.36	13.42	13.12	13.56	13.27	13.23
No.	8	9	10	11	12	13	
Notes (seconds)	13.08	13.21	12.88	12.93	13.15	12.95	

A. GM-NN1 Algorithm

In GM-NN1 algorithm, GM(1,1) model is set up by the former 9 data, and the obtained error sequence is made regressive training. After training is completed and neural network is convergent, new forecasting values can be calculated, which are shown in Fig. 3. In this figure, we compare GM-NN1 algorithm forecasting values with GM(1,1) model forecasting and real values.

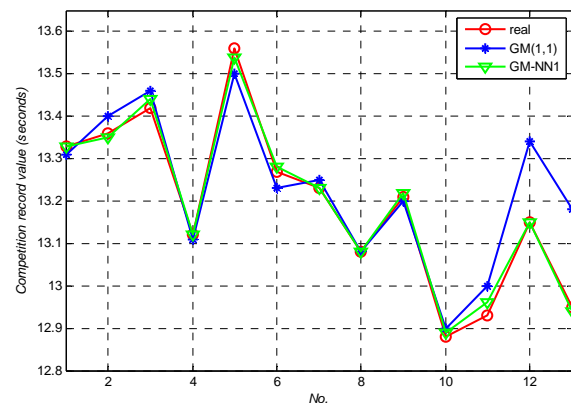


FIGURE III. COMPARISON OF GM(1,1) AND GM-NN1

As depicted in Figure. 3, for the neural network can fit test

samples accurately, the fitting values of GM-NN1 algorithm is fine, and the forecasting values of GM-NN1 algorithm is better than those of GM(1,1) model.

**B. GM-NN2 Algorithm**

In GM-NN2 algorithm, partial-data GM(1,1) model group is set up by the former 6, 7, 8, and 9 data, respectively. We use fitting data as input and original data as output to train the neural network. After training is completed and neural network is convergent, new forecasting values can be calculated, which are shown in Fig. 4. In this figure, we compare GM-NN2 algorithm forecasting values with real values and forecasting values of partial-data GM(1,1) model with 6, 7, 8, 9 data, which are denoted by GM(1,1)-6, GM(1,1)-7, GM(1,1)-8, and GM(1,1)-9.

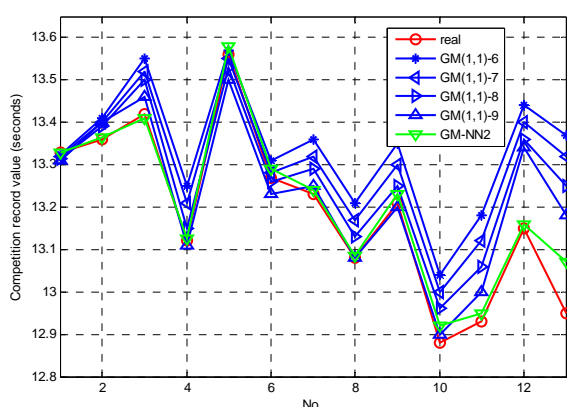


FIGURE IV. COMPARISON OF PARTIAL-DATA GM(1,1) AND GM-NN2

It can be seen from Figure. 4, the curves of partial-data GM(1,1) model group appear to be a horn with the passage of time, which proves that the forecasting time cost is larger and the precision is higher when the test samples used to set up model is more. The fitting and forecasting results show that GM-NN2 algorithm perform much better than partial-data GM(1,1) model group.

**IV. CONCLUSION**

Predictions of sports achievements have much to do with strategies for sports development. In this article, we propose two algorithms, i.e., GM-NN1 and GM-NN2, to analyze given athletic performances, and forecast new performances. The simulation results prove that our proposed algorithms perform better than the traditional model.

**REFERENCES**

[1] Wang Hui-ming, and Na A. Z., "Study of the Present Situation and Future Development of Sports Equipment and Instruments in China," 2011 International Conference on Future Computer Science and Education (ICFCSE), pp. 10 - 13, 2011.  
 [2] Chen Jingfei, "the Explanation of the Application of the Computer-Aided and Analysis Technology in the Field of Sports," 2010 International Conference on Electrical and Control Engineering (ICECE), pp. 3077 - 3079, 2010.

[3] Banjun Sun, Zhonghai Zhao, "the Management of Competitive Sports and Research on Sustainable Development of in Physical Education Institutes," 2011 International Conference on Management and Service Science (MASS), pp. 1 - 4, 2011.  
 [4] Huang Chang-mei, Shen Wei-hua, and Xiao Xiao-cong, "Gray Modeling and Tendency Studying of Track and Field Achievements of Olympics Based on Grey Prediction Theory," 2011 IEEE International Conference on Grey Systems and Intelligent Services (GSIS), pp. 419 - 425, 2011.  
 [5] Bai Kai-xiang, GaoMing, Yin Hang, Cheng Yin, and Wang Ni, "Prediction of Aerobics Achievement Basing on Neural Network," 2010 Sixth International Conference on Natural Computation (ICNC), Vol. 1, pp. 503 - 508, 2010.  
 [6] Wei Huali, Chen Li, Huang Chengjia, and Qin Chaoling, "the Grey Weight Analysis of the Influencing Factors in 400m Performance," 2011 International Conference on Future Computer Science and Education (ICFCSE), pp. 331 - 333, 2011.  
 [7] Kayacan E., Oniz Y., and Kaynak O, "A Grey System Modeling Approach for Sliding-Mode Control of Antilock Braking System," IEEE Transactions on Industrial Electronics, Vol. 56, pp. 3244 - 3252, 2009.  
 [8] Wang M. H. and Tsai H. H., "Fuel cell fault forecasting system using grey and extension theories," IET Renewable Power Generation, Vol. 6, pp. 373 - 380, 2012.  
 [9] Kabir H., Ying Wang, Ming Yu, and Qi-Jun Zhang, "High-Dimensional Neural-Network Technique and Applications to Microwave Filter Modeling," IEEE Transactions on Microwave Theory and Techniques, Vol. 58, pp. 145 - 156, 2010.  
 [10] Razavi S. and Tolson B. A., "A New Formulation for Feedforward Neural Networks," IEEE Transactions on Neural Networks, Vol. 22, pp. 1588 - 1598, 2011.  
 [11] Xiaofang Yuan, Yaonan Wang, and Lianghong Wu, "Neural Network Based Self-Learning Control Strategy for Electronic Throttle Valve," IEEE Transactions on Vehicular Technology, Vol. 59, pp. 3757 - 3765, 2010.  
 [12] Weizhong Yan, "Toward Automatic Time-Series Forecasting Using Neural Networks," IEEE Transactions on Neural Networks and Learning Systems, Vol. 23, pp. 1028 - 1039, 2012.  
 [13] Guo-Dong Li, Masuda S., Yamaguchi D., and Nagai M., "A New Reliability Prediction Model in Manufacturing Systems," IEEE Transactions on Reliability, Vol. 59, pp. 170 - 177, 2010.  
 [14] Naiming Xie and Sifeng Liu, "Research on evaluations of several grey relational models adapt to grey relational axioms," Journal of Systems Engineering and Electronics, Vol. 20, pp. 304 - 309, 2009.  
 [15] Wilamowski B. M. and Hao Yu, "Neural Network Learning Without Backpropagation," IEEE Transactions on Neural Networks, Vol. 21, pp. 1793 - 1803, 2010.  
 [16] Kao-Shing Hwang, Chia-Yue Lo, and Guan-Yuan Lee, "A Grey Synthesis Approach to Efficient Architecture Design for Temporal Difference Learning," IEEE/ASME Transactions on Mechatronics, Vol. 16, pp. 1136 - 1144, 2011.  
 [17] Atwa Y. M. and El-Saadany E. F., "Annual Wind Speed Estimation Utilizing Constrained Grey Predictor," IEEE Transactions on Energy Conversion, Vol. 24, pp. 548 - 550, 2009.  
 [18] Chang G. W. and Lu, H. J., "Forecasting Flicker Severity by Grey Predictor," IEEE Transactions on Power Delivery, Vol. 27, pp. 2428 - 2430, 2012.  
 [19] [http://en.wikipedia.org/wiki/Liu\\_Xiang](http://en.wikipedia.org/wiki/Liu_Xiang), 2013.01.26.