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# Prediction Model of Sports Performance Based on Grey BP Neural Network

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**Abstract**

*The best annual performances of the world women's pentathlons during 2005~2013 are statistically collected in this article, and the prediction of the best performance of the world women's heptathlon in 2013 is taken as the research object. According to the best annual performances of the world women's heptathlons during 2005~2012, the sports performance prediction model composed of GM(1,1) grey prediction model and BP neural network prediction model in serial connection is established in this article, and this model is applied to predict the best annual performance of the world women's heptathlon in 2013. Through the comparison of the actual value of the best annual performance of the world women's heptathlon in 2013 and the predicted value of the model, the application of the grey BP neural network prediction model in sports performance prediction is researched and analyzed in this article. The research result shows that for the sports performance prediction problem, the grey BP neural network prediction model has the features of high prediction accuracy, simple application and strong generalization performance, and this model is also superior to single GM(1,1) grey prediction model and BP neural network model.*

**Keywords:** *Sports Performance; Women's Heptathlon; Grey BP Neural Network Prediction Model*

## 1. Introduction

With significant practical value, sports performance prediction is favorable not only for providing training objectives to the athletes, but also for providing reference to the research on the development of athletic sports. The traditional prediction methods mainly include time series method, analogy method, regression analysis method, *etc.*, The above predictions are mainly based on massive analyzable data, and the research scope is usually limited to static problems. Specifically, the sports performance prediction problem has the features of less analyzable data, strong data randomness, many influencing factors, mutual influence and complex factor relationship, so the result of the sports performance prediction, obtained by traditional prediction methods, is not ideal.

Along with the continuous development of system science, many scholars have analyzed and researched the problem about how to apply a small amount of data to effectively predict the sports performance. Therein, Yuan Jianguo (1992) has applied grey model and posterior error test method to research the single precision sports performance prediction and accordingly established the grey prediction model [1] for the national records of men's short-distance speed skating; Liu Jiang jin, *et. al*., (2005) have applied the mathematical statistics, the document literatures and other relevant methods to statistically collect the research papers regarding the application of grey theory for sports performance research during 1994~2003 in

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Tongfang full-text periodicals database and have obtained the conclusion that the application of the grey theory for the sports performance prediction in China is still in the initial stage, thus providing the reference for the application of the grey theory in the sports performance prediction in China [2]; Wang Guofan, *et al.* (2010) have applied such theories as economics and fuzzy C-mean cluster analysis to propose the improved prediction model combining the economics and the competitive sports strength difference theory and meanwhile demonstrated the sceientificity and the feasibility of the model established thereby [3]; Zhang Yu *et al.*, (2013) have taken the champion performances of 5 sports including men's 200m run in 23~30th Olympic Games as the research object to establish BP neural network prediction model and demonstrate the practicability and the accuracy of this model in the sports performance prediction [4]; Zhuang Chong (2006) has compared the accuracies of the grey prediction model and the neural network prediction model in the sports performance prediction, thus providing the reference for selecting the sports performance prediction method [5].

The best annual performances of the world women's heptathlons during 2005~2013 are statistically collected in this article in order to establish the grey BP neural network prediction model on the basis of these data. Meanwhile, the application of the model in the sports performance prediction is researched in this article through the analysis of the grey BP neural network prediction model established thereby.

## 2. Introduction to Grey BP Neural Network Model

Composed of GM(1,1) grey prediction model and BP neural network prediction model in serial connection, the grey BP neural network model established in this article not only has the functions possessed by the grey prediction model for processing small samples and poor information, but also has the features of robustness, fault tolerance, *etc.*, of BP neural network model, thus comprehensively presenting the interdisciplinary property of the grey information mining.

### 2.1. BP Neural Network Prediction Modeling Steps

Among the artificial neural network models, BP neural network model is a neural network model which is most thoroughly researched by people. According to relevant statistical information, the application of BP neural network model occupies 80%~90% of the applications of artificial neural network models. In detail, BP neural network model has a three-layer neural network structure, namely: input layer, hidden layer and output layer, wherein the layers are fully connected with each other and the connection weight values are repeatedly learned and trained through error back propagation according to the training patterns till the corresponding weight value can meet the requirements of the training patterns. Moreover, BP neural network model can approximate to any nonlinear function through the trainings already provided with training patterns and can rapidly and accurately process the problems of the nonlinear systems, thus being widely applied in the fields of function approximation, prediction, system identification, classification, data compression, *etc.*,

BP neural network model is established through the following four steps:

(1) Research problem, extract elements and collect training patterns;

(2) Set the parameters of BP neural network according to the problem;

(3) Establish training samples, input the parameters in the training samples into BP neural network system established thereby and compare the system output with the expected pattern; if any error, please execute step (4); or else, please return to step (3);

 

(4) Correct the connection weight values of various layers of the system through back propagation.

### 2.2. GM(1,1) Grey Prediction Modeling Steps

In the grey system theory, relevance space, smooth discrete function, *etc.*, are taken as the basis to define the grey derivative and the grey differential equation so as to adopt the discrete data columns to establish the dynamic model [6] of the differential equation. The corresponding grey system theory is applied in the grey prediction model in order to fully extract the obvious information and the implicit information in the small sample data and find the factor relationship. Compared with traditional probabilistic methods, the grey prediction model has certain superiority in the aspect of solving such data problems as small sample and poor information. GM(1,1) grey prediction model has the features of simplicity, wide application scope and high prediction accuracy, thus becoming one of the most widely applied grey models.

For applying GM (1,1) grey prediction model to solve the small sample data prediction problem, it is necessary to firstly extract relevant data from the problem to establish the original sequence, then check and smoothen the original sequences established thereby and adopt the eligible original sequence or the processed sequence to establish the grey model, and finally check the predicted value of the model. The specific steps are as follows:

(1) Establish the corresponding original sequence according to the problem to be solved:

$$x^{(0)} = (x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n))$$

(2) Check the original sequence, wherein the class ratio of the original sequence is as follows:

$$\lambda(k) = \frac{x^{(0)}(k-1)}{x^{(0)}(k)}, k = 2,3,\cdots,n$$

If the class ratio of the original sequence is in the interval of $(e^{-\frac{2}{n+1}}, e^{\frac{2}{n+2}})$, then the original sequence can meet the smoothness requirement and such sequence can be directly used for establishing the prediction model; or else, the translation transformation shall be implemented for the sequence.

(3) Implement AGO accumulation operation and mean value operation for the original sequence in order to respectively generate sequence $x^{(1)}$ and sequence $z^{(1)}$; meanwhile, establish the corresponding differential equations:

$$x^{(0)}(k) + az^{(1)}(k) = b, k = 2,3,\cdots,n$$

In the above formula, $a$ is the development coefficient of the model, and $b$ is the coordination coefficient of the model.

(4) Set $u = (a,b)^T$, and find the development coefficient $a$ and the coordination coefficient $b$ through the least square method $\hat{u} = (a,b)^T = (B^T B)^{-1} B^T Y$, wherein $Y$ and $B$ are respectively as follows:

$$Y = (x^{(0)}(2), x^{(0)}(3), \cdots, x^{(0)}(n))^T$$

$$B = \begin{bmatrix} -z^{(1)}(2) & -z^{(1)}(3) & \cdots & -z^{(1)}(n) \\ 1 & 1 & \cdots & 1 \end{bmatrix}^T$$

Finally, obtain the following equation through the differential equation:

$$x^{(1)}(k+1) = (x^{(0)}(1) - \frac{b}{a})e^{-ak} + \frac{b}{a}$$

(5) Verify the prediction model established thereby, namely: check whether the residual error between the sequence obtained from the above prediction model and the original sequence, the absolute relational degree and the mean square error can meet the accuracy requirements.

### 2.3. Introduction to Grey BP Neural Network Model

The grey BP neural network prediction model proposed in this article is composed of GM(1,1) grey prediction model and BP neural network prediction model in serial connection, wherein the predicted result of GM(1,1) grey prediction model is taken as the input and the actual performance is taken as the output. Meanwhile, the sample data are also established to implement the weight training for the established BP neural network. Additionally, the best annual performances of the world women's heptathlons during 2003~2013 are statistically collected in this article, wherein the performances during 2003~2011 are adopted to establish the sample data for the grey BP neural network prediction model so as to train the established neural network model. Moreover, the established prediction model is also adopted to predict the best annual performances of the world women's heptathlons in 2012 and 2013, and the predicted values are compared with the actual performances of the world women's heptathlons in above two years in order to verify the accuracy of the established prediction model.

## 3. Establishment of Grey BP Neural Network Prediction Model

The seven single sports of women's heptathlon are mutually related and various sports performances can influence each other, so it is necessary to consider the relationship among these sports during the performance prediction process. In the grey BP neural network prediction model established in this article, BP neural network model aims at comprehensively researching the mutual relationship among the sports performances while GM(1,1) grey prediction model aims at making full use of the time series of the statistical data in order to mine the temporal relationship among the data.

### 3.1. Statistical Information of the Best Annual Performances of Women's Heptathlon

As women's comprehensive sport event, women's heptathlon composed of 100m hurdles, high jump, shot, 200m run, long jump, javelin and 800m run involves run, jump and shoot sports and has high requirements for the physical quality, the psychological quality, the technical merit, *etc*. of the athletes. The best annual performances of the world women's heptathlons during 2003~2013 are statistically collected in this article, and the statistical performances are as shown in Table 1.

 

**Table 1. The Best Annual Performances of the World Women's Heptathlons During 2003~2013**

| | 100m Hurdles | High Jump | Shot | 200m Run | Long Jump | Javelin | 800m Run |
|---|---|---|---|---|---|---|---|
| 2003 | 13.18 | 1.94 | 14.19 | 22.98 | 6.68 | 49.90 | 132.12 |
| 2004 | 13.21 | 1.91 | 14.77 | 23.27 | 6.78 | 48.89 | 134.15 |
| 2005 | 12.62 | 1.91 | 12.61 | 24.12 | 6.78 | 53.07 | 134.66 |
| 2006 | 13.35 | 1.89 | 14.56 | 23.86 | 6.65 | 46.94 | 134.95 |
| 2007 | 13.15 | 1.95 | 14.81 | 23.38 | 6.85 | 47.98 | 132.98 |
| 2008 | 13.44 | 1.80 | 17.29 | 24.39 | 6.63 | 48.60 | 137.72 |
| 2009 | 12.93 | 1.92 | 14.14 | 23.25 | 6.29 | 43.54 | 132.22 |
| 2010 | 12.95 | 1.89 | 14.05 | 23.21 | 6.43 | 46.71 | 130.18 |
| 2011 | 13.32 | 1.83 | 14.17 | 23.50 | 6.61 | 52.95 | 128.04 |
| 2012 | 12.54 | 1.86 | 14.28 | 22.83 | 6.48 | 47.49 | 128.65 |
| 2013 | 13.63 | 1.86 | 13.92 | 23.93 | 6.48 | 47.90 | 131.58 |

### 3.2. Original Data Processing

Before grey BP neural network prediction model learning and training, it is necessary to implement the normalization processing operations for the total performances and the single-sport performances f the women's heptathlons in order to make all sample values in the interval of [0,1]. Afterwards, the maximum values of the single-sport performances among the best annual performances of the women's heptathlons during 2003~2013 are taken as the denominator, and the performances of the corresponding sports in other years are taken as the numerator. The data processed as above are shown in Table 2.

**Table 2. Normalization Data of the Best Annual Performances of the World Women's Heptathlons during 2003~2013**

| | 100m Hurdles | High Jump | Shot | 200m Run | Long Jump | Javelin | 800m Run |
|---|---|---|---|---|---|---|---|
| 2003 | 0.9670 | 0.9949 | 0.8207 | 0.9422 | 0.9752 | 0.9403 | 0.9593 |
| 2004 | 0.9692 | 0.9795 | 0.8587 | 0.9541 | 0.9898 | 0.9212 | 0.9741 |
| 2005 | 0.9259 | 0.9795 | 0.7293 | 0.9889 | 0.9898 | 1.0000 | 0.9778 |
| 2006 | 0.9795 | 0.9692 | 0.8421 | 0.9783 | 0.9708 | 0.8845 | 0.9799 |
| 2007 | 0.9648 | 1.0000 | 0.8566 | 0.9586 | 1.0000 | 0.9041 | 0.9656 |
| 2008 | 0.9861 | 0.9231 | 1.0000 | 1.0000 | 0.9679 | 0.9158 | 1.0000 |
| 2009 | 0.9486 | 0.9846 | 0.8178 | 0.9533 | 0.9182 | 0.8204 | 0.9601 |
| 2010 | 0.9501 | 0.9692 | 0.8126 | 0.9516 | 0.9387 | 0.8802 | 0.9453 |
| 2011 | 0.9773 | 0.9385 | 0.8195 | 0.9635 | 0.9650 | 0.9977 | 0.9300 |
| 2012 | 0.9200 | 0.9538 | 0.8259 | 0.9360 | 0.9460 | 0.8949 | 0.9341 |
| 2013 | 1.0000 | 0.9538 | 0.8051 | 0.9811 | 0.9460 | 0.9026 | 0.9554 |

In this article, the dimension-fixed and recursion-compensated GM(1,1) grey model is established on the basis of the statistical single-sport performances as follows: firstly, establish GM(1,1) grey model according to the single-sport data during 2003~2006 and predict the normalization data corresponding to the performances in 2007; then, adopt the data during 2004~2007 to predict the normalization data corresponding to the performances in 2008; similarly, obtain the predicted values of the normalization data corresponding to the performances during 2007~2011. The predicted data obtained as above are shown in Table 3.

**Table 3. Predicted Data of the Best Annual Performances of the World Women's Heptathlons during 2007~2013**

| | 100m Hurdles | High Jump | Shot | 200m Run | Long Jump | Javelin | 800m Run |
|---|---|---|---|---|---|---|---|
| 2007 | 0.9687 | 0.9658 | 0.7958 | 0.9980 | 0.9647 | 0.9003 | 0.9831 |
| 2008 | 0.9958 | 1.0037 | 0.9419 | 0.9454 | 0.9972 | 0.8353 | 0.9623 |
| 2009 | 0.9835 | 0.9197 | 1.0728 | 1.0011 | 0.9767 | 0.9331 | 1.0023 |
| 2010 | 0.9506 | 0.9536 | 0.8555 | 0.9654 | 0.8832 | 0.8011 | 0.9698 |
| 2011 | 0.9259 | 1.0053 | 0.6994 | 0.9205 | 0.9124 | 0.8361 | 0.9148 |
| 2012 | 0.9878 | 0.9190 | 0.8183 | 0.9664 | 0.9884 | 1.0928 | 0.9154 |
| 2013 | 0.9198 | 0.9384 | 0.8372 | 0.9350 | 0.9572 | 0.9385 | 0.9253 |

### 3.3. Establishment of Training Samples

In the grey BP neural network prediction model established in this article, the predicted values of the performances of the seven sports of the women's heptathlon are taken as the input of GM(1,1) grey prediction model and the actual performances are taken as the output. The training samples include seven samples, the predicted data of the grey prediction models for 2007~2011 and the actual data are respectively taken as the input and the output. The input matrix and the output matrix are respectively set as P and T:

$$P = \begin{bmatrix} 0.9687 & 0.9658 & 0.7958 & 0.9980 & 0.9647 & 0.9003 & 0.9831 \\ 0.9958 & 1.0037 & 0.9419 & 0.9454 & 0.9972 & 0.8353 & 0.9623 \\ 0.9835 & 0.9197 & 1.0728 & 1.0011 & 0.9767 & 0.9331 & 1.0023 \\ 0.9506 & 0.9536 & 0.8555 & 0.9654 & 0.8832 & 0.8011 & 0.9698 \\ 0.9259 & 1.0053 & 0.6994 & 0.9205 & 0.9124 & 0.8361 & 0.9148 \end{bmatrix}^T$$

$$T = \begin{bmatrix} 0.9648 & 1.0000 & 0.8566 & 0.9586 & 1.0000 & 0.9401 & 0.9656 \\ 0.9861 & 0.9231 & 1.0000 & 1.0000 & 0.9679 & 0.9158 & 1.0000 \\ 0.9486 & 0.9846 & 0.8178 & 0.9533 & 0.9182 & 0.8204 & 0.9601 \\ 0.9501 & 0.9692 & 0.8126 & 0.9516 & 0.9387 & 0.8802 & 0.9453 \\ 0.9773 & 0.9385 & 0.8195 & 0.9635 & 0.9650 & 0.9977 & 0.9300 \end{bmatrix}^T$$

### 3.4. Establishment of BP Neural Network Prediction Model

The neural network prediction model established in this article includes one hidden layer. As mentioned above, the neural network includes 7 inputs and 7 outputs, namely: the input layer and the output layer respectively include 7 nerve cells. Additionally, the number of the nerve cells of the hidden layer can be researched according to the following empirical formula:

$$i = \sqrt{n + m} + a \tag{1}$$

In the above formula, $n$ is the number of the nerve cells of the input layer, $m$ is the number of the nerve cells of the output layer, and $a$ is a value between 0 and 1. According to the above empirical formula, the number of the nerve cells of the hidden layer is 7.

BP neural network model includes many types of transfer functions, training functions, learning functions and performance functions. For example, the transfer functions include S logarithmic function, S tangent function, pure linear function, *etc*., the training functions include BFGS Quasi-Newton BP algorithm function, gradient BP descent algorithm function, gradient descent momentum BP algorithm function, *etc*., the learning functions include gradient descent weight learning function, gradient descent momentum weight learning function, *etc*., the performance functions include mean square error performance function, mean square error normalization performance function, *etc*., In this article, S tangent transfer function and pure linear function, gradient descent momentum BP algorithm function, gradient descent momentum weight learning function and mean square error normalization function are selected for BP neural network model. Meanwhile, for the BP neural network model, the maximum training frequency is 10,000 times, the training accuracy is 0.005 and the training display interval is 500 times.

## 4. Model Solution and Analysis

MATLAB software is adopted to train the network weight of the above established grey BP neural network prediction model through the simulation platform, the training samples and the training parameters. The weight of BP neural network is finally obtained through the repeated training for BP neural network, thus to establish the corresponding grey BP neural network prediction model. Meanwhile, the test sample data are adopted to verify the above established grey BP neural network so as to obtain the accuracy of the established samples.

### 4.1. Training Performance Analysis of Grey BP Neural Network

The established sample data and BP neural network training parameters are adopted to train the weight of the above established BP neural network. In order to analyze the training process and the model accuracy of the above established BP neural network, the training process and the training result of the grey BP neural network are researched in this article.

The training process curve of the model is as shown in Figure 1 and the training result curve of the model is as shown in Figure 2, wherein the x-coordinate in Figure 1 is the training time of BP neural network and the y-coordinate is the training accuracy of BP neural network. According to the figure, the weight training of BP neural network model is cycled for 1,518 epochs and the accuracy of the model can reach 0.00492.

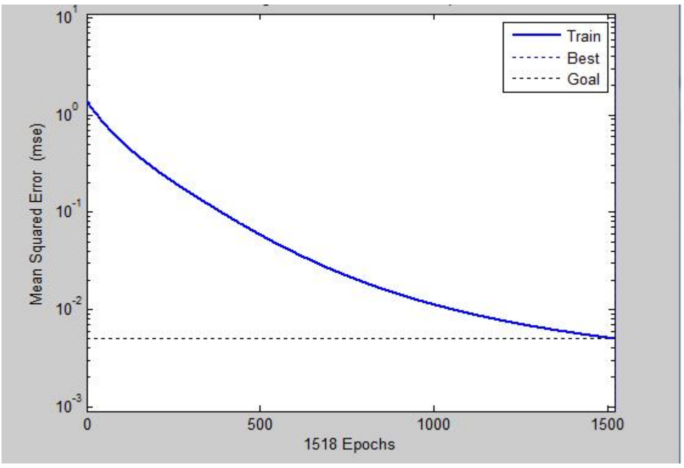


**Figure 1. Training Process Curve**

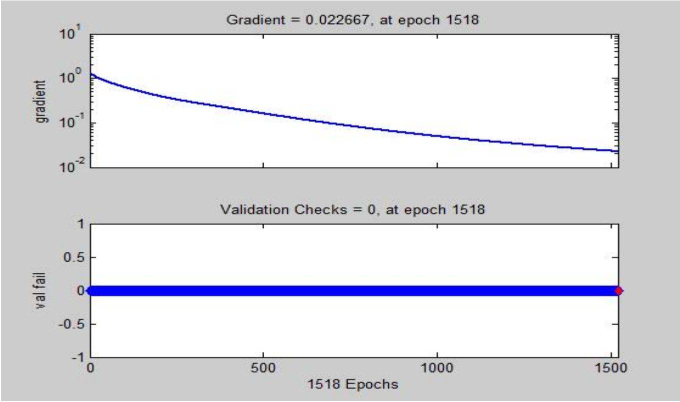


**Figure 2. Training Result Curve**

### 4.2. Accuracy Test of Grey BP Neural Network

The data for years 2012 and 2013 are taken as the test sample to test the accuracy of the established grey BP neural network prediction model. The best annual performances of the world women's heptathlons in 2012 and 2013, obtained from GM(1,1) grey prediction model, are taken as the input of the grey BP neural network prediction model. Afterwards, the output values of the grey BP neural network prediction model are compared with the best annual performances of the world women's heptathlons in 2012 and 2013 in order to research and analyze the prediction accuracy of the grey BP neural network prediction model. Specifically, the predicted data of GM(1,1) grey model for years 2012 and 2013, namely the inputs of the grey BP neural network, are respectively set as P1 and P2, and the output data of the grey BP neural network are respectively set as T1 and T2. Then, the following formulae are obtained:

$$P1 = [0.9878 \quad 0.9190 \quad 0.8183 \quad 0.9664 \quad 0.9884 \quad 1.0928 \quad 0.9154]^T$$
$$P2 = [0.9198 \quad 0.9384 \quad 0.8372 \quad 0.9350 \quad 0.9572 \quad 0.9385 \quad 0.9253]^T$$

P1 and P2 are taken as the inputs to obtain the simulation values as follows:

$$T1 = [0.9221 \quad 0.9481 \quad 0.8267 \quad 0.9411 \quad 0.9411 \quad 0.8992 \quad 0.9377]^T$$
$$T2 = [0.9238 \quad 0.9327 \quad 0.8401 \quad 0.9355 \quad 0.9591 \quad 0.9450 \quad 0.9268]^T$$

The deviation between the simulation values of the normalization data of the best annual performances of the world women's heptathlons and the actual values are compared with the actual values, as shown in Table 2.

**Table 4. Comparison Between Predicted Values and Actual Values**

| | | 100m Hurdles | High Jump | Shot | 200m Run | Long Jump | Javelin | 800m Run |
|---|---|---|---|---|---|---|---|---|
| 2012 | Actual Value | 0.9200 | 0.9538 | 0.8259 | 0.9360 | 0.9460 | 0.8949 | 0.9341 |
| | Prediction Deviation | 0.0021 | -0.0057 | 0.0008 | 0.0051 | 0.0019 | 0.0043 | 0.0036 |
| | Deviation Ratio | 0.23% | 0.60% | 0.10% | 0.54% | 0.21% | 0.48% | 0.39% |
| 2013 | Actual Value | 0.9198 | 0.9384 | 0.8372 | 0.9350 | 0.9572 | 0.9385 | 0.9253 |
| | Prediction Deviation | 0.0040 | -0.0057 | 0.0029 | 0.0005 | 0.0019 | 0.0065 | 0.0015 |
| | Deviation Ratio | 0.44% | 0.61% | 0.03% | 0.06% | 0.19% | 0.69% | 0.02% |

 

According to Table 4, the deviation ratio of the predicted value of each sport performance of the world women's heptathlons in 2012 and 2013, obtained from the grey BP neural network model, is less than 0.7%. In order to compare the accuracies of the grey BP neural network and GM(1,1) grey prediction model in the prediction of the performances of the world women's heptathlons, GM(1,1) grey prediction model is established in this article. The predicted values are as shown in Table 5.

**Table 5. Predicted Values of Grey Model**

| Year | 100m Hurdles | High Jump | Shot | 200m Run | Long Jump | Javelin | 800m Run |
|---|---|---|---|---|---|---|---|
| 2012 | 0.9648 | 0.9484 | 0.8543 | 0.9004 | 0.9347 | 0.9021 | 0.9405 |
| 2013 | 0.9697 | 0.9441 | 0.8571 | 0.9586 | 0.9276 | 0.8992 | 0.9349 |

According to the comparison between the simulation values of the established grey BP neural network prediction model and the predicted values of GM (1,1) grey prediction model, the accuracy of the grey BP neural network prediction model is significantly higher than that of GM (1,1) grey prediction model.

Meanwhile, the grey BP neural network prediction mode is adopted to recover the simulation values of the world women's heptathlons in 2012 and 2013 to obtain the predicted performance data of the world women's heptathlons in 2012 and 2013 from the model, as shown in Table 6.

**Table 6. Predicted Best Annual Performances of the World Women's Heptathlons**

| 100m Hurdles | High Jump | Shot | 200m Run | Long Jump | Javelin | 800m Run | 100m Hurdles |
|---|---|---|---|---|---|---|---|
| 2012 | 13.75 | 1.68 | 15.26 | 21.19 | 6.90 | 47.49 | 128.64 |
| 2013 | 13.10 | 1.72 | 15.32 | 22.93 | 6.62 | 53.33 | 129.50 |

## 5. Conclusion

For such comprehensive athletic sports as women's heptathlon, the sports included therein can influence each other and the sports performances thereof also have certain mapping relationship. In order to better predict the single-sport performances, it is necessary to make full use of the known data.

The grey BP neural network prediction model not only has the features of robustness, fault tolerance, *etc.*, of BP neural network prediction model, but also makes full use of GM (1,1) grey prediction model to mine the temporal relationship among the data. In the aspect of the multiple-factor prediction problems, the prediction accuracy of this model is not inferior to that of GM (1,1) grey prediction model.

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