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Athlete performance prediction based on time series analysis and implications for physical education and training strategies

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ABSTRACT

In this paper, time series analysis is used to monitor and predict the performance of athletes in sports training. A smooth time series model $ARMA(p,q)$ model is established, a fixed-order method based on autocorrelation function and partial correlation function is proposed, and the parameters of the model are estimated, and least squares prediction is used for model prediction. The monitoring test data of hemoglobin (HGB) in sports performance of Z athletes of a club were used as the research object, and the smooth time series test was conducted to determine the ARMA (1,1) model as the optimal time series fitting model, and the fitting effect was tested. In the application of blood oxygen saturation (BOS) index, ARMA (1,1) model can predict the trend of BOS of athlete Z with good application effect. Based on the prediction of athletes' performance by ARMA (1,1) model, this paper further proposes the integrated neuromuscular training method (INT), and integrates it with physical training will to develop the INT physical education training strategy. In the application experiment of INT physical education training strategy, the test results of the experimental group of athletes applying the INT physical education training strategy in the six events of T-test sensitive running, agility ladder, vestibular step, blindfolded one-legged standing, 30-meter sprint running, and 60-meter sprint running presented $P<0.05$, and the athletes' performance was significantly better than that of the control group.

Keywords: time series modeling, athlete performance prediction, integrative neuromuscular training, experimental approach

1. Introduction

In recent years, with the rapid change of science and technology as well as the rapid development of the sports industry, data and information have shown explosive growth, the Internet high-tech technology is in the wind, and the wave of big data is surging [1-2]. Scientific prediction methods

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integrating data analysis techniques have been widely used in various fields, and sports events have also continued to introduce a variety of prediction methods in recent years, and predicting the performance of athletes in important sports events has been increasingly emphasized by sports researchers in every country [3-6]. The development of contemporary sports, the performance of sports events and the improvement of training level rely more and more on the data analysis technology, we can make appropriate adjustments to the training methods and training content for these data, in order to improve the performance of sports in a limited period of time in the most efficient way [7-10]. Therefore, the use of scientific prediction methods to study sports competitions can help to provide assistance for athletes to win the game.

Statistics as a quantitative analysis has an increasingly important role in sports. Because the data of sports performance generally have the characteristics of time series, randomness, discrete, and the limited nature of the sample provides a great convenience for the time series analysis of data, so try to give the trend analysis of athletes' performance in sports competitions with time series analysis, and modeling processing, and then prediction and control respectively [11-15]. In statistics, the so-called time series is a series of different values of an indicator at different times, arranged in chronological order [16]. Such series, due to the influence of various contingent factors, tend to show some randomness and statistical dependence on each other, and time series analysis deals with the techniques to analyze such dependence [17-19]. In this context, exploring more effective performance prediction methods provides some theoretical reference basis for future preparation for important competitions.

In this paper, by using the time series analysis method to realize the prediction of athletes' performance, three types of smooth time series model types are proposed, namely, autoregressive model (AR), moving average model (MA), and autoregressive motion averaging model (ARMA), and the fixed-order method based on autocorrelation function and partial correlation function is used to complete the order determination of $ARMA(p,q)$, and the great likelihood estimation is proposed to be used as a parameter estimation method for the parameters of the $ARMA(p,q)$ model. Methods. The adaptability of the ARMA(p, q) model is tested by the correlation function method, and the least squares prediction method is used for model prediction. The hemoglobin (HGB) sport performance monitoring data of Z athletes of a club for the period of February 2021-August 2023 were used for time series numerical analysis, and the ARMA(1,1) model was determined to be the optimal time series fitting model. Based on the prediction of athletes' performance using the ARMA(1,1) model, integrative neuromuscular training (INT) was introduced to propose a physical education training strategy based on the principle of INT, and finally, the experimental and control groups were set up through the experimental method to carry out an empirical study of the INT physical education training strategy.

2. Athlete performance prediction based on time series analysis

Time series analysis is an important modern analytical method, widely used in the natural field, social field, scientific research and human thinking [20]. Time series is an objective record of the system's historical behavior, which contains all the information of the system's dynamic characteristics, which are specifically expressed as the statistical correlation between the observed values in the time series, and thus the statistical correlation between the numerical values in the time series can be investigated to reveal the dynamic structural characteristics of the corresponding system and its pattern of change in development.

Based on this, the present study tries to establish a mathematical model that can accurately reflect the dynamic dependencies contained in the time series through the limited length of test data, so as to monitor and predict the changes of athletes' performance indexes.

2.1 General elements of time series analysis

Time series refers to a set of numerical sequences formed by successive observations of the same phenomenon at different times. Time series analysis is the use of this set of series, the application of mathematical and statistical methods to deal with, in order to predict the future development of things.

In a mathematical sense, if a variable or a set of variables $X(t)$ in a process is observed and measured, the set of discrete ordinal numbers $X_{t1}, X_{t2}, \cdots, X_{tN}$ obtained at a series of moments $t_1, t_2, \cdots, t_N$ (t is the independent variable and $t_1 < t_2 \cdots < t_N$) is called a discrete numerical time series, i.e., a one-time sample realization of a stochastic process. Let $X(t : t \in T)$ be a stochastic process and $X_{ti}(i = 1, 2, \cdots)$ be an observation of process $X(t)$ at moment i, then $X_{ti}(i = 1, 2, \cdots)$ is called a one-sample realization, i.e., a time series.

2.1.1. Time-series variation factors. A time series is a set of data collected and organized according to the sequence of certain time intervals for a certain indicator. It is generally believed that a time series contains four types of variations, namely, trend, seasonal, cyclical and random variations, which can be characterized mathematically by the time series model:

$$Y = T \cdot S \cdot C \cdot I \tag{1}$$

Where, Y is the time series, T is the long term trend component, S is the seasonal variation component, C is the cyclical variation component and I is the random variation component.

By recognizing and analyzing the different factors of variation in the time series and testing the theoretical model against the data for fitness. It can be discussed whether the model can correctly represent the observed phenomena; portray the state of the system, so that the system can be recognized and interpreted; describe the operating law of the system, so as to achieve the purpose of recognizing the law and mastering the law; predict the future behavior of the system, so as to make use of the law; and control the future behavior of the system, so as to effectively utilize and dominate the system.

2.1.2. Types of smooth time series models:

1) Autoregressive model (AR). The mathematical model of X_t, which is known to be correlated with X_{t-1} and not directly related to behavior prior to moment $t-1$, is the one-stage autoregressive model. That is: $X_t = \phi_1 X_{t-1} + \varepsilon$; denoted as $AR(1)$, where $\{X_t\}$ is a zero-mean (i.e., centered processed) smooth series, ϕ_1 is the dependence of X_t on X_{t-1}, and ε_t is a random perturbation.

If X_t is correlated with values taken at past moments up to X_{t-p}, it needs to be portrayed using an autoregressive model of order p that includes $X_{t-1}, \cdots X_{t-p}$. The general form of the Pth order autoregressive model is:

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_p X_{t-p} + \varepsilon_t \tag{2}$$

2) Moving Average Model (MA). Knowing that the response X_t of the system is only somewhat correlated with its perturbation ε_{t-1} that entered the system at the previous moment, then a first-order moving model can be obtained. That is: $X_t = \varepsilon_t - \theta_1 \varepsilon_{t-1}$; denoted as $MA(1)$, ε_t is white noise.

If the response X_t of the MA system at moment t is somewhat correlated not only with ε_{t-1} but also with $\varepsilon_{t-j}(j = 2, \cdots, q)$, a qth order moving average model can be obtained:

$$X_t = \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots\cdots - \theta_q \varepsilon_{t-q} \tag{3}$$

Is denoted as $MA(q)$, where q is the order of the sliding average and $\theta_1, \theta_2 \ldots \theta_q$ is the weight of the participating sliding average. The corresponding series X_t is called the moving average series.

3) Autoregressive Moving Average Model (ARMA) [21]. If the current value of the sequence $\{X_t\}$, is related not only to its own past value, but also to its previous external shocks entering the system, then in characterizing this dynamic with a model that includes both its own lag term and past external

shocks, this model is called an autoregressive sliding average model, which has a general structure of $X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots\cdots + \phi_p X_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1-} \theta_2 \varepsilon_{t-2} - \cdots\cdots \theta_q \varepsilon_{t-q}$, denoted as $ARMA(p,q)$.

2.1.3. Stable time series modeling:

1) Model ordering. Since it is not possible to determine in advance how many terms of the known time series need to be used to build the estimating function, the model needs to be judged for order fixing. After determining the order, it is also necessary to estimate the parameters of the model in order to build the complete estimating function equation.

The method used in this paper is the order determination method based on autocorrelation function and partial correlation function [22]. For $ARMA(p,q)$ model, the truncated tail characteristics of its sample autocorrelation function $\{\hat{\rho}_k\}$ and sample partial autocorrelation function $\{\hat{\varphi}_{kk}\}$ can be used to determine the order of the model. The specific method is as follows.

For each q, compute $\hat{\rho}_{q+1}, \hat{\rho}_{q+2}, \ldots, \hat{\rho}_{q+M}$ (with M taken to be $\sqrt{n}$ or $n/10$), and examine whether the number of them satisfying $\hat{\rho}_k \le \frac{1}{\sqrt{n}} \sqrt{1 + 2\sum_{i=1}^{q} \hat{\rho}_i^{\,2}}$ or $\hat{\rho}_k \le \frac{2}{\sqrt{n}} \sqrt{1 + 2\sum_{i=1}^{q} \hat{\rho}_i^{\,2}}$ is 68.3% or 95.5% of M the number of them. If $1 \le k \le q_0$, $\hat{\rho}_k$ are significantly different from zero, while $\hat{\rho}_{q_0+1}, \hat{\rho}_{q_0+2}, \ldots, \hat{\rho}_{q_0+M}$ are all approximately zero, and the number of $\hat{\rho}_k$ satisfying one of the above inequalities reaches its corresponding proportion, then it can be approximated that $\{\hat{\rho}_k\}$ is a q_0-step truncated, smooth time series $\{y_t\}$ for $MA(q_0)$.

Similarly, by calculating sequence $\{\hat{\varphi}_{kk}\}$, examine whether the number of them that satisfy $|\hat{\varphi}_{kk}| \le \frac{1}{\sqrt{n}}$ or $|\hat{\varphi}_{kk}| \le \frac{2}{\sqrt{n}}$ is 68.3% or 95.5% of M. That is, it can be approximated that $\{\hat{\varphi}_{kk}\}$ is p_0 -step truncated and the smooth time series $\{y_t\}$ is $AR(p_0)$.

If there is no truncation for sequences $\{\hat{\varphi}_{kk}\}$ and $\{\hat{\rho}_k\}$, i.e., there is no p_0 and q_0 as mentioned above, then it can be determined that the smooth time series $\{y_t\}$ is an ARMA model.

2) Estimation of model parameters. After the initial identification of the model suitable for a set of sample data series, it is necessary to estimate the parameters of the model for further identification and application of the model. Therefore, regardless of the kind of time series model, the parameters of it need to be known in order to establish a complete estimation equation. The main parameter estimation methods include moment estimation, least squares estimation and great likelihood estimation.

(1) $AR(p)$ Yule-Walker estimation of model parameters [23]. For first-order autoregressive models $AR(1)$, $\hat{\phi}_1 = \hat{\rho}_1$, for second-order autoregressive models $AR(2)$, $\hat{\phi}_1 = \frac{\hat{\rho}_1(1-\hat{\rho}_2)}{1-\hat{\rho}_1^{\,2}}$, $\hat{\phi}_2 = \frac{\hat{\rho}_2 - \hat{\rho}_1^{\,2}}{1-\hat{\rho}_1^{\,2}}$.

(2) $MA(q)$ Model parameter estimates for the first-order moving average model $MA(1)$, $\hat{\theta}_1 = \frac{-1 \pm \sqrt{1-4\rho_1^{\,2}}}{2\rho_1}$, for the second-order moving average model $MA(2)$, $\rho_1 = \frac{-\theta_1 + \theta_1\theta_2}{1+\theta_1^2+\theta_2^{\,2}}$, $\rho_2 = \frac{-\theta_2}{1+\theta_1^2+\theta_2^{\,2}}$.

(3) $ARMA(p,q)$ Parameter estimation of the model. $ARMA(p,q)$ The fine estimation of the model parameters is generally done by great likelihood estimation. Due to the complexity of the model structure, the great likelihood estimation of the parameters cannot be given directly, and can only be

accomplished by iterative methods, and the iterative initial values often utilize the values obtained from the initial estimation.

3) Model adaptability test. Model adaptability refers to a time series model to explain the dynamics of the system, that is, the degree of correlation of the data series is high or low. Through the identification of the model, the model's fixed order and the model's parameter estimation, the next step is to test the model's adaptability, i.e., to determine whether the model is appropriate for describing the time series.

A fit model of a time series should completely or essentially explain the dynamics of the system such that the residual series $\{a_t\}$ in the model should be white noise series. Therefore, the model fitness test is essentially a test of whether the $\{a_t\}$ sequence is a white noise sequence, of which the main one is the independence test of the $\{a_t\}$ sequence.

Correlation function method is an important method of model fitness test, can be calculated by examining the autocorrelation function of $\{\hat{a}_t\}$ to determine the independence of the residual sequence. Let $\hat{\rho}_k$ denote the autocorrelation function of the $\{\hat{a}_t\}$ sequence, that is:

$$\hat{\rho}_k = \frac{\sum_{t=1}^{n-k} \hat{a}_t \hat{a}_{t+k}}{\sum_{t=1}^{n} \hat{a}_t^2} \tag{4}$$

If the residual sequence $\{a_t\}$ is a white noise sequence, it can be shown that $\hat{\rho}_k$ is uncorrelated and approximately normally distributed when the number of samples is sufficiently large. I.e:

$$\hat{\rho}_k \sim N\left(0,1/N\right) \tag{5}$$

Therefore, if:

$$\left|\hat{\rho}_k\right| \le 1.96/\sqrt{N} \tag{6}$$

It is then possible to accept the hypothesis of $\rho_k = 0$ at the 0.05 level of significance and consider $\{a_t\}$ to be independent.

4) Model Prediction. Let the smooth time series $\{y_t\}$ be a $ARMA(p,q)$ process, then its least squares prediction:

$$\hat{y}_t(l) = E\left(y_{T+1} \mid y_T,\ldots,y_1\right) \tag{7}$$

$AR(p)$ Model Prediction:

$$\hat{y}_t(l) = \phi_1 \hat{y}_T(l-1) + \ldots + \phi_p \hat{y}_T(l-p), l = 1,2,\cdots \tag{8}$$

$ARMA(p,q)$ Model Prediction:

$$\begin{gathered} \hat{y}_t(l) = \sum_{j=1}^{p} \phi_j \hat{y}_T(l-j) + \sum_{j=1}^{q} \theta_j \hat{\varepsilon}_T(l-j) \\ \textit{Which } \hat{\varepsilon}_T(i) = E\left(\varepsilon_{T+i} \mid y_T,\ldots,y_1\right) \end{gathered} \tag{9}$$

2.2 Empirical study of predictive time series analysis of athlete performance

2.2.1. Subjects of empirical research .An empirical study was conducted using data from the sport performance monitoring test of Z athletes from February 2021-August 2023 in a club.

2.2.2. Functionality time series analysis process. According to the principle of time series modeling, the process of designing functional time series analysis is shown in Figure 1.

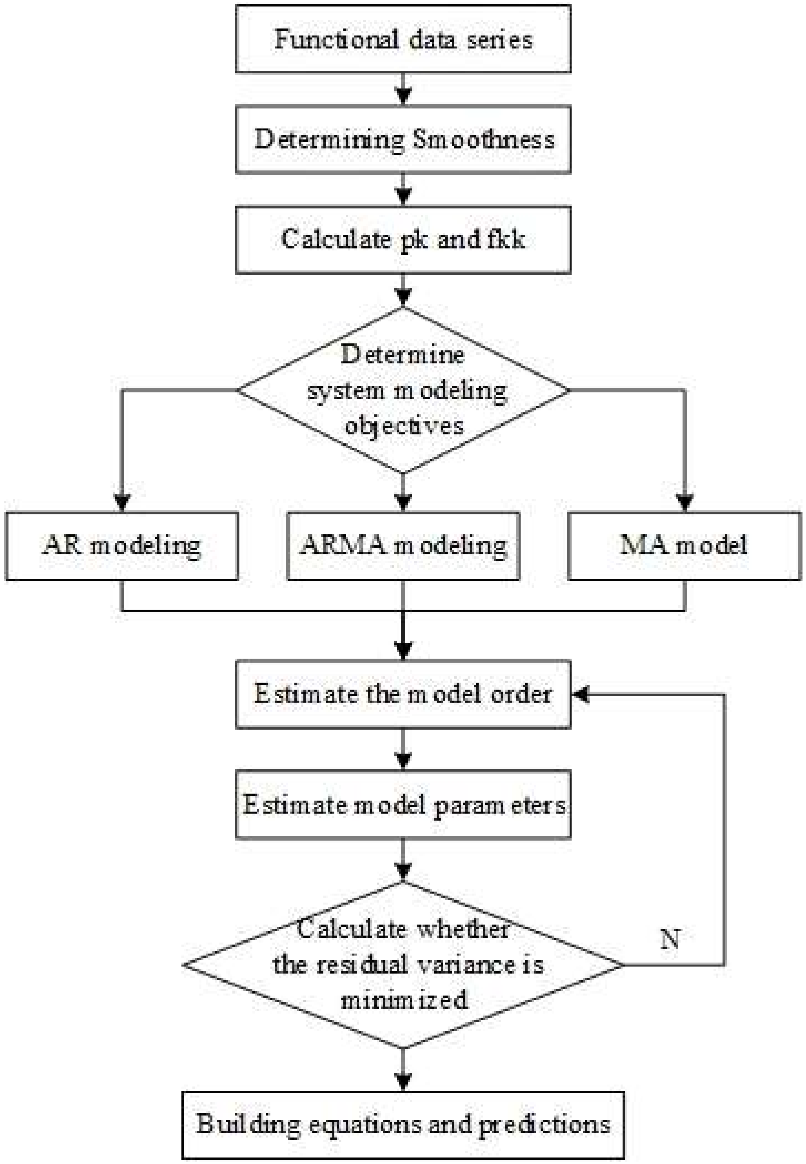
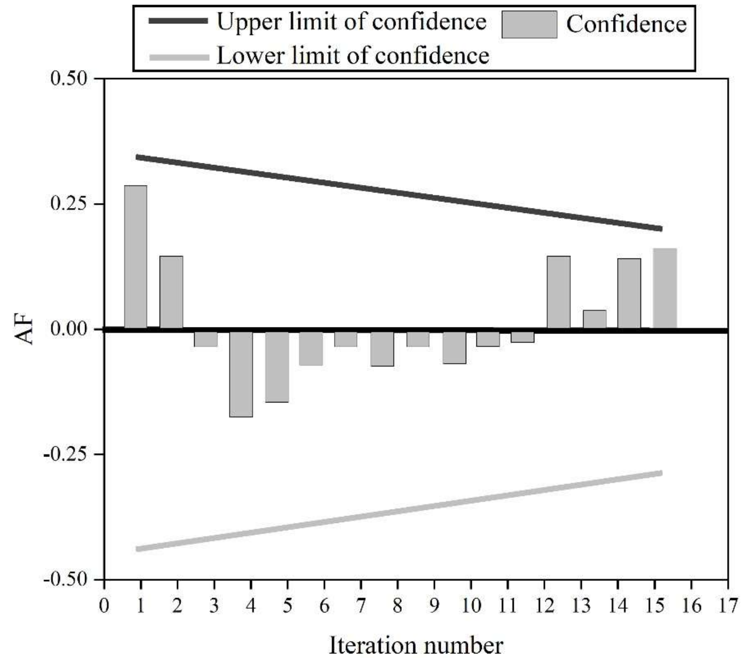


Fig. 1. Time series analysis process

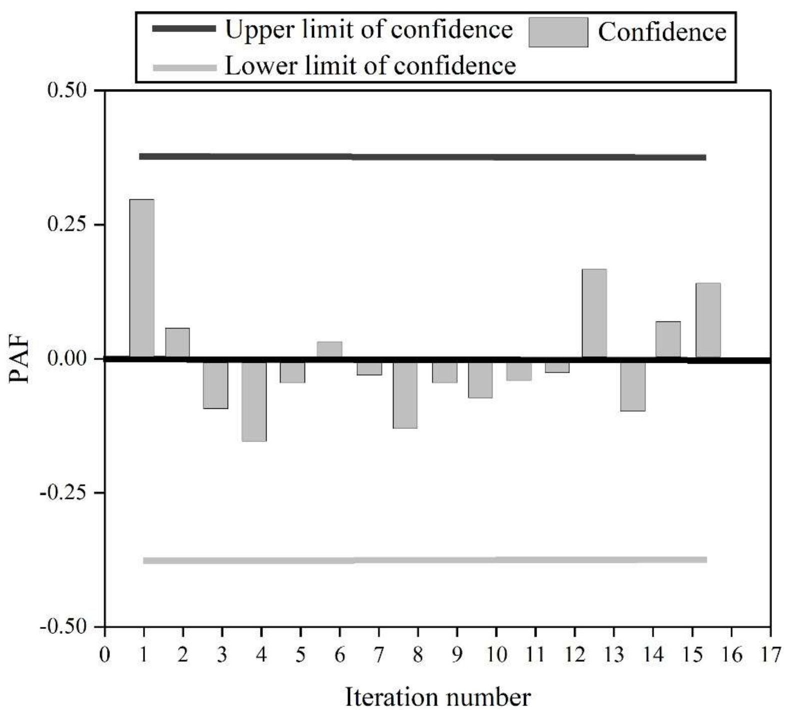
2.2.3. Analysis of the results of athlete performance prediction. In order to select the most suitable ARMA model for motor function monitoring, the smoothness test of serial data is needed in order to smooth the series. Taking athlete Z as the research object, the change of hemoglobin (HGB) corresponding to Z from February 2021 to August 2023 was selected in order to make the smoothness judgment.

1) Smooth time series test. In order to verify whether the Z*HGB level is a smooth time series, the study conducts a smoothness test for the TS of the HGB level by the judging principle of AF and PAF. The results before and after the 1st order differencing of Z*HGB can be obtained, as shown in Fig. 2. Figures (a)~(d) show the AF of Z*HGB, the PAF of Z*HGB, the AF of Z*HGB after 1st-order differencing and the PAF of Z*HGB after 1st-order differencing, respectively.It can be seen that the AF of Z*HGB gradually converges to 0 after lagging for 2 periods, and all the AFs and PAFs are in the confidence intervals after the number of iterations is more than 3. Therefore, it can be determined that the level of Z∗HGB is a stochastic smooth time series, and the corresponding AF and PAF do not change

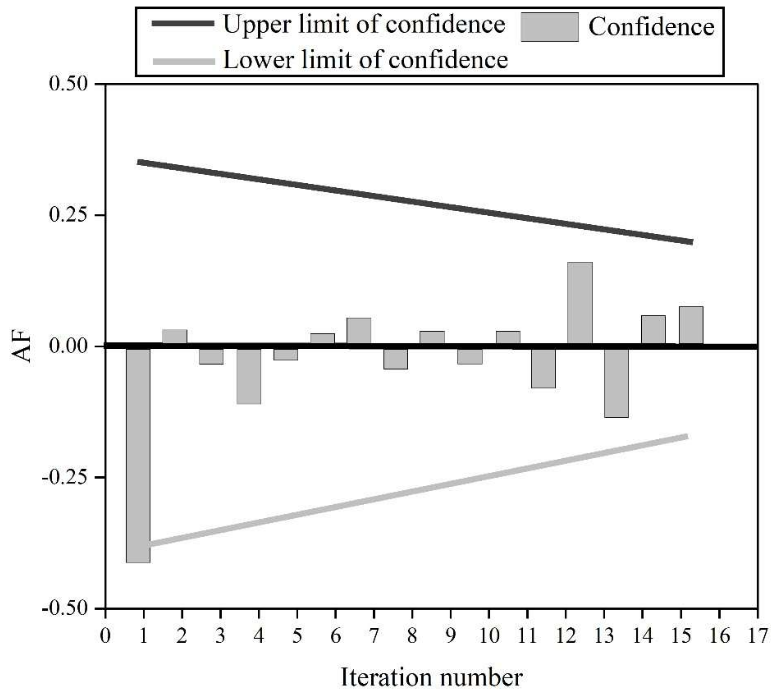
significantly after Z*HGB is differenced by the 1st order, which indicates that the time series of Z*HGB does not have a trend change.



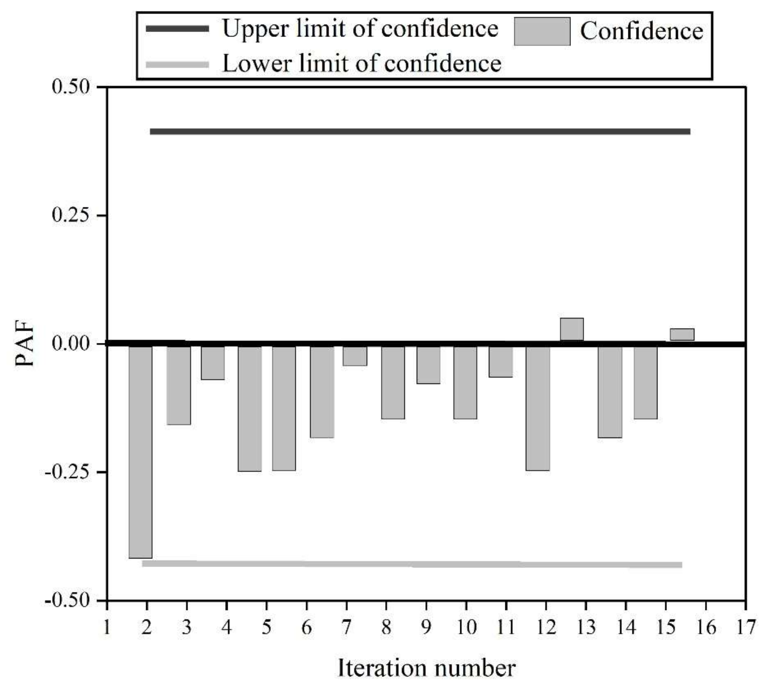
(a)AF ofZ*HGB



(b)PAF of Z*HGB



(c)AF after the first-order difference of Z*HGB



(d)PAF after the first-order difference of Z*HGB

Fig. 2. The results before and after the first-order difference of Z*HGB

In order to further make an accurate determination of the smoothness of the Z*HGB level time series, the study uses the unit root test for additional verification, and the results are shown in Table 1. As can be seen from the table, the value of the test t-statistic is -3.895275, which is smaller than the critical value at the 5% significance level, which indicates that the series is in a smooth state and can be used for modeling. After comprehensive consideration, there are three models AM(1), ARMA(1,1) and ARMA(1,2) for selection. Eviews software was used to estimate the parameters of the above models, and ARMA(1,1) was selected as the model for the HGB level, taking into account the overall fitting effect of the model, the coefficient of determination, the SC criterion and the AC criterion.

Table 1. Unit root test

-		T	P
ADF test		-3.895275	0.0264
ADF threshold	1%	3.6076618	-
	5%	-2.8758635	-
	10%	-2.5664358	-

2) Fitting effect test. After the model is determined, the short-term prediction of HGB level can be made, and the corresponding model fitting effect and residual variation results can be obtained, as shown in Fig. 3. The real value of HGB comes from the actual measurement of athletes by the monitoring system. From the figure, it can be observed that the predicted values of the ARMA model fit well with the real values, and the average real value of HGB was 154g/L, and the average predicted value was 153g/L, which indicated that the model could accurately reflect the changes of HGB levels. In addition, the residual variations of the model were small in [-1,1], which indicated that the ARMA model was fitted very well.

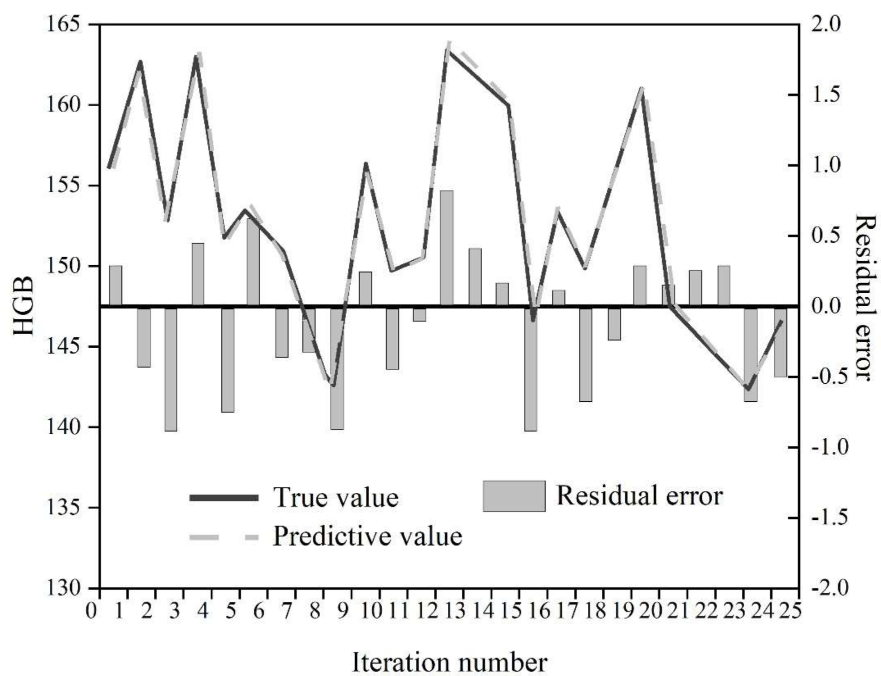


Fig. 3. Fitting effect and residual variation

3) Empirical study. In order to verify the application of the time series model ARMA(1,1) identified in this paper in practice, the training data of athlete Z in May and August 2023 for a period of 10 days in the plateau area were selected for the study. Among them, the basal heart rate (BHR) and blood oxygen saturation (BOS) in the index of motor function were selected for the study, and the results of monitoring changes in BHR and BOS of athlete Z during the training process could be obtained, as shown in Fig. 4. As can be seen from the figure, in general, Z's BHR reached the highest on the second day after arriving at the plateau for training, with an average of 53.66 beats/minute. As the number of training days increased, BHR would show a sharp decrease, and after the 6th day, BHR would show a more stable trend.The trend of BOS was opposite to that of BHR, and on the second day of training, BOS was the lowest, with an average of 92.18%, and then it would show a trend of increase, but all of

them were less than 95% in general. Based on the real-time changes in Z's physical function, the coach can make adjustments to his training and develop a personalized training plan for future training.

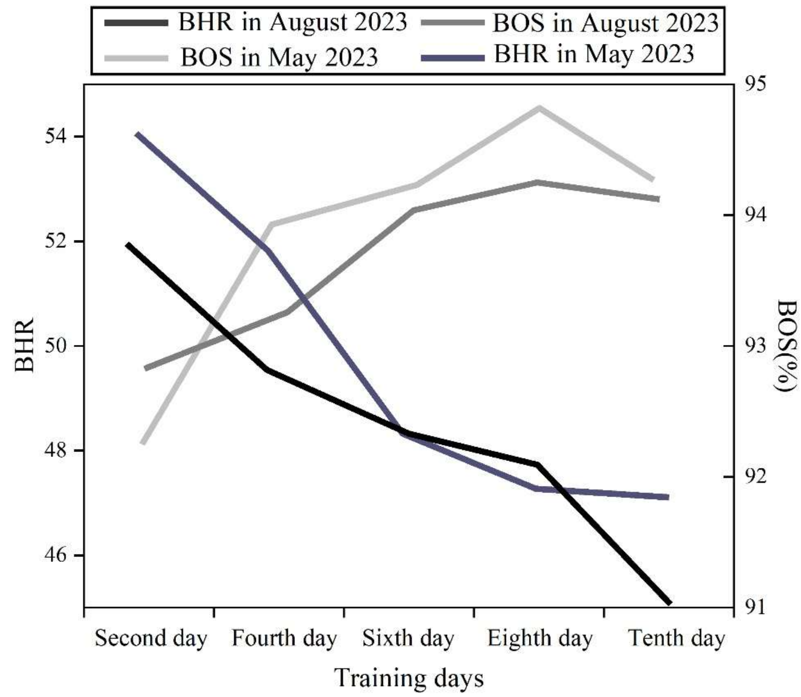


Fig. 4. Monitoring changes in BHR and BOS results

3. Physical education training strategies based on athlete performance prediction

In the previous chapter, this paper introduced time series analysis to determine the time series model ARMA(1,1) to realize the prediction of athletes' performance. In this chapter, a physical education training strategy of integrated neuromuscular training (INT) will be proposed based on the prediction of athletes' performance.

3.1 Principles of Integrated Neuromuscular Training

Integrated neuromuscular training, as an advanced training program emerging in foreign countries, has been widely applied and recognized in the international arena. Domestic and foreign scholars have formed a relatively unified understanding of the conceptual definition of this training mode. Integrated neuromuscular training (INT) is not only a conceptual training mode, but also a comprehensive physical training that complements and improves other training programs in practice [24]. It skillfully combines functional movement training with specific strength, balance, speed, agility, and hyperlength training components to provide athletes with a comprehensive and systematic training experience. Specifically, integrated neuromuscular training is a useful supplement to basic physical training. It not only focuses on the development of basic physical qualities such as strength, balance and speed, but also emphasizes the integration of functional training movements.

3.2 Physical education and training strategy development

Based on the principle of INT, this paper divides the physical education training strategy into six different parts, such as resistance training, speed and agility, etc. By formulating the relevant training strategy and applying the combination of each part, the neuromuscular control can be enhanced, which not only strengthens the training effect, but also minimizes the occurrence of sports injuries.

Resistance training can effectively improve the athletes' special sports ability and help prevent the occurrence of muscle injury. Speed training is an important factor that affects the athletes' competitive level and has an important impact on whether they can maintain a good competitive state. Sensitivity generally refers to the speed or ability to respond to a specific stimulus, which is mainly related to visual receptors and proprioception, and at the same time, it is inseparable from speed. Enhanced training is widely used for strength training, which helps to improve the muscle strength of basketball players. In addition to the above factors, athletes' performance is closely related to fatigue resistance, which relies on neuromuscular and cardiorespiratory functions to minimize the adverse effects of fatigue. This ability not only plays a key role in sports, but also has a significant impact on the prevention of injuries, which is why neuromuscular fatigue is recognized as an important factor in inducing sports injuries. In conclusion, the six components of INT should be utilized in the development of sports training strategies in order to improve athletes' performance.

4. Empirical research on INT physical education and training strategies

4.1 Research and methodology

4.1.1. Objects of study. This experiment was conducted to study the effect of INT physical education and training strategies on physical fitness as well as sports performance of athletes in a university.

4.1.2. Research methodology. The research method used in this empirical study of training strategies in INT physical education is the experimental method.

1) Purpose of experiment. To design a controlled experiment, record and compare the experimental data of the two groups of subjects, through the data to study the differences between the training program based on the INT physical education training strategy and the traditional program, and to analyze the impact of the two on the athletes' sports performance. The aim is to enrich the practical research of this theory in other neighborhoods, so as to better guide future practical activities.

2) Experimental subjects and grouping. Sixteen athletes from a college men's soccer team were used as the experimental subjects, and the subjects were informed of the relevant information in detail before starting the intervention experiment, and they could participate in the experiment only after they knew the details and expressed their willingness to cooperate. We excluded the goalkeeper position, players with short-term injuries and congenital diseases from the selection of the subjects, and all of them had a certain degree of soccer training, and had the basic physical conditions to participate in the experiment.

The 16 subjects were divided into two groups of 8 each by simple random sampling. The first group underwent 10 weeks of integrated neuromuscular training (INT) as the experimental group, and the second group underwent 12 weeks of conventional training as the control group. Both groups were trained three times a week for 90 min each time, and each training session consisted of three parts, namely, warm-up part, training part and stretching part. No other training sessions were designed to avoid injury due to fatigue, which might affect the experimental results.

3) Experimental design. In this experiment, since the integrated neuromuscular training emphasizes more on the improvement of neuromuscular innervation and proprioceptors, the high intensity and high load training methods are not emphasized in the training process, and more attention is paid to the ability of muscle control and the correct muscle force generation mode. At the same time, the lower intensity can be used to observe the state of the subjects during the training process and correct the incorrect movements and incorrect force generation pattern of the subjects in time. Therefore, the experiment was divided into two phases, the first four weeks were mainly of low difficulty, in order to form the correct movement pattern. The second four weeks were more difficult and loaded to provide a reasonable force pattern for the specialized movements.

In this paper, two enhancement training sessions are arranged in the training program in a week. On Monday, core stabilization training and strengthening training, on Wednesday, resistance training and dynamic balance training, and on Friday, speed and agility training and strengthening training. Each session was performed during the last 45 minutes of each training session, with a 90-second interval between sets. In the general physical training of the control group, speed and agility training was performed first, followed by strength training, with a 90-second interval between each set of movements.

(1) Selection of experimental indexes. In order to improve the rationality of index selection, this paper refers to the research results of previous researchers, and communicates with the relevant experts in the field of sports to design the experimental indexes reasonably with the experimental subjects and the actual situation of this study.

Indicator one, standing long jump.

Subjects stand in place, feet naturally separated, a line on the ground as the jumping line, legs bent forward to jump, after landing to measure the vertical distance between the heel and the back of the jumping line, the subject to carry out three tests, to go to the best results.

Indicator two, longitudinal jump to touch high.

Stand naturally with both feet on the ground, before jumping, raise both hands naturally, stretch the body open, record the height of the touch height in place, then jump and stomp on the ground, in the process of the body's ascent, let the arms in the air to stretch out, the palm of the hand touches the highest point of the wall. The difference between the vertical jump and the touch height was taken. Three attempts are made for each subject and the best score is taken.

Indicator III, 30-meter run test.

Take the starting point of the track as the starting line, start running with a whistle as the signal, adopt the standing starting position, each subject has two chances to take the best performance, the time is accurate to 0.01s, and the interval between the two tests is 2 minutes.

Indicator 4, 60 meters running test and 30 meters running test set up the same.

Indicator 5: Standing blindfolded.

The test subject stands naturally, and when the command “start” is heard, the left foot is raised and the eyes are closed while the tester starts the timer, and the test is over when the support foot moves or the raised foot hits the ground, and then the right foot is raised and the above test is repeated. Recordings were made in seconds, with a time accuracy of 0.01 s. Subjects were not allowed to move at the beginning of the test, and were not allowed to move their head. Each foot was tested twice, with a 2-minute rest after each test, and the best score was taken.

Indicator VI, standing long jump.

Subjects stand in place, feet naturally apart, take a line on the ground as the jumping line, legs bent and jump forward, after landing, measure the vertical distance between the heel and the back of the jumping line, subjects perform 3 tests, and go to the best score.

Indicator VII, T-test sensitive running.

The subject performs a multi-directional sensitive running test by setting up 5 different running directions and running back and forth. Each participant is given 2 chances, measured in seconds to 2 decimal places, and the best performance is recorded.

Indicator VIII, Agility Ladder.

An adjustable, movable agility ladder is constructed using ropes and straps, and the participant performs a straight run test, alternating between feet in and out of the grid to reach the finish line. Each test subject was given 2 chances, the unit of measurement was seconds, accurate to 2 decimal places, and the best performance was recorded.

(2) Experimental variable control. The independent variable, i.e., the content of integrated neuromuscular training in the experimental group and the content of traditional training in the control group.

Dependent variable, i.e., the difference between the experimental group and the control group in terms of specialized physical fitness and specialized skills.

The experimental variable, i.e., during the experimental process, the experimental group and the control group maintained the same training site and equipment. The three weekly training sessions were held on Monday, Wednesday and Friday mornings, with the last 45 minutes of the training session, and each training session was strictly in accordance with the training program. In order to ensure the consistency of the training loads of the two groups of subjects during the training process, the loads of the subjects were monitored by heart rate monitor during the training process, so that the training loads of the two groups of subjects were basically the same, and to exclude the influence of the training loads on the results of the experiments.

4.2 Findings and analysis

4.2.1. Comparative analysis of pre-laboratory test results:

1) Comparative analysis of basic information data of experimental group and control group. According to the expert's suggestion, before the beginning of this intervention experiment, the basic information test index of athletes was determined as height, weight and age, and the basic information of the experimental group and the control group was completed pre-test respectively, and the pre-test data were organized and counted, as shown in Table 2. Independent samples T-test was conducted through SPSS software, and it was found that the test results all presented P>0.05, indicating that there was no significant difference between the experimental group and the control group. Therefore, the basic information data of athletes in the experimental group and control group in the experimental pre-test have the same baseline before the beginning of this intervention experimental study, and the next stage of the experiment can be carried out.

Table 2. Basic information of athletes

Project	Control group	Experimental group	T	P
Age	20.27	20.4	0.137	0.906
Height	175.69	173.91	1.044	0.293
Weight	64.98	64.3	0.342	0.724

2) Comparative analysis of the results of the experimental group and the control group's athletic quality test. Before the beginning of the intervention experiment, the athletes were divided into four major testing modules, namely, lower extremity explosive strength module, speed quality module, sensitivity quality module, dynamic balance module. Each of the four modules corresponded to two secondary indexes, totaling eight test indexes, which were standing long jump (lower extremity explosive strength plate), vertical jump in place to touch the height (lower extremity explosive strength plate), 30-meter sprint run (speed quality plate), 60-meter sprint run (speed quality plate), T-test sensitive run (sensitive quality plate), agility ladder test (sensitive quality plate), blindfolded one-legged standing (dynamic balance quality plate), forward balance quality plate), and dynamic balance quality test (dynamic balance quality plate). Dynamic Balance Quality Plate), Vestibular Step (Dynamic Balance Quality Plate), and the pre-test of the motor qualities of the experimental group and the control group respectively, and the pre-test data were organized and counted, and the results were specifically shown in Table 3. Through the SPSS software for independent samples T-test, it was found that the longitudinal jump touch height, standing long jump, 30-meter sprint run, 60-meter sprint run, T-test, agility ladder test, blindfolded one-legged standing, vestibular step of the eight test data test results show P>0.05, indicating that the experimental group, the control group does not have a significant difference. Therefore, the athletes in the experimental group and the control group had the same baseline of athletic qualities in the pre-experimental test before the start of this intervention experimental study, and the next phase of the experiment could be conducted.

Table 3. The results of sports quality test before the experiment

Project	Group	Mean	T	P
Vertical jump touch height (m)	Control group	2.96	0.726	0.508
	Experimental group	2.92		
T-test (s)	Control group	7.31	-0.314	0.771
	Experimental group	7.44		
Vestibular step (cm)	Control group	7.41	-0.068	0.968
	Experimental group	7.44		
Blindfolded standing (s)	Control group	31.84	0.54	0.648
	Experimental group	28.41		
Standing long jump (m)	Control group	2.55	-0.174	0.952
	Experimental group	2.61		
Agile ladder (s)	Control group	5.4	-1.908	0.078
	Experimental group	6.07		
30m run (s)	Control group	4.2	-0.013	0.934
	Experimental group	4.19		
60m run (s)	Control group	7.93	0.305	0.796
	Experimental group	8.01		

4.2.2. Comparative analysis of post-experimental test results. In this experiment, after ensuring the reasonableness of the group matching of the experimental group and the control group, a 10-week training experiment was completed through the intervention of the integrative neuromuscular training model (INT). Subsequently, the experimental group, the control group of sports quality test indexes for the experimental post-test, the use of independent samples t-test to compare the experimental intervention after the experimental group, the control group of the two groups of the mean value, the specific results are shown in Table 4. It was found that in the T-test sensitive running ($T=3.027$, $P=0.005<0.05$), agility ladder ($T=2.383$, $P=0.019<0.05$), vestibular step ($T=2.503$, $P=0.012<0.05$), blindfolded one-legged standing ($T=-2.234$, $P=0.034<0.05$), 30-meter sprint running ($T= 3.042$, $P=0.001<0.05$), 60-meter sprint run ($T=3.406$, $P=0.007<0.05$) on a total of six items, the test results presented $P<0.05$, indicating that the above test indexes are significantly different. Therefore, in T-test sensitive running, agility ladder test, vestibular step, blindfolded one-legged standing, 30-meter sprint running, 60-meter sprint running above 6 sports quality test indexes, the test results of the experimental group are significantly better than the control group. In the vertical jump touch height ($T=2.065$, $P=0.052>0.05$) and standing long jump ($T=0.281$, $P=0.772>0.05$), the test results show $P>0.05$, indicating that the above two sports quality test indexes do not have significant intergroup differences between the experimental group and the control group. Therefore, both the experimental group and the control group can improve the performance of longitudinal jump touch height and standing long jump in the sports quality.

Table 4. The results of sports quality test after the experiment

Project	Group	Mean	T	P
Vertical jump touch height (m)	Control group	3	2.065	0.052
	Experimental group	2.97		
T-test (s)	Control group	7.56	3.027	0.005
	Experimental group	6.89		
Vestibular step (cm)	Control group	7.15	2.503	0.012
	Experimental group	5.17		
Blindfolded standing (s)	Control group	29.89	-2.234	0.034

	Experimental group	42.01		
Standing long jump (m)	Control group	2.7	0.281	0.772
	Experimental group	2.74		
Agile ladder (s)	Control group	5.73	2.383	0.019
	Experimental group	4.96		
30m run (s)	Control group	4.22	3.042	0.001
	Experimental group	3.96		
60m run (s)	Control group	7.96	3.406	0.007
	Experimental group	7.37		

4.2.3. Comparative analysis of test data enhancement before and after experimentation. The results of the test of the lift amplitude of the athletic quality indexes of the experimental group and the control group before and after the experiment are shown in Figure 5. The experimental group that utilized the INT training mode gained significant improvement in the eight test indexes of general athletic quality, among which the items with the largest improvement were the test indexes of dynamic balance and agility quality board, which were 47.87% improvement in blindfolded standing, 30.51% improvement in vestibular step, 18.29% improvement in agility ladder test, and 7.39% improvement in T-test, respectively. Therefore, the INT training mode can effectively improve the athletic quality and performance of athletes.

In the control group, which used the traditional training mode, only part of the indexes of the general athletic quality test were improved, and the items with the largest improvement were standing long jump by 5.88%, vertical jump touch height by 1.35%, and vestibular step by 3.51%, while the other part of the indexes of the test showed different degrees of decline, including blindfolded standing by 6.12%, agility ladder test by 6.11%, T-test by 6.11%, and agility ladder test by 7.39%. 6.11%, T-test down 3.42%, 30-meter run down 0.48%, and 60-meter run down 0.38%. Therefore, although the traditional physical training mode can improve the quality of the lower limb explosive module of the athletes, it can't fully and comprehensively develop the athletes' athletic qualities, and can't significantly improve the athletes' athletic performance.

Comprehensively, compared with the traditional physical training mode, the integrated neuromuscular training mode (INT) integrated neuromuscular training mode is more conducive to the comprehensive enhancement of athletes' athletic qualities and athletic performance.

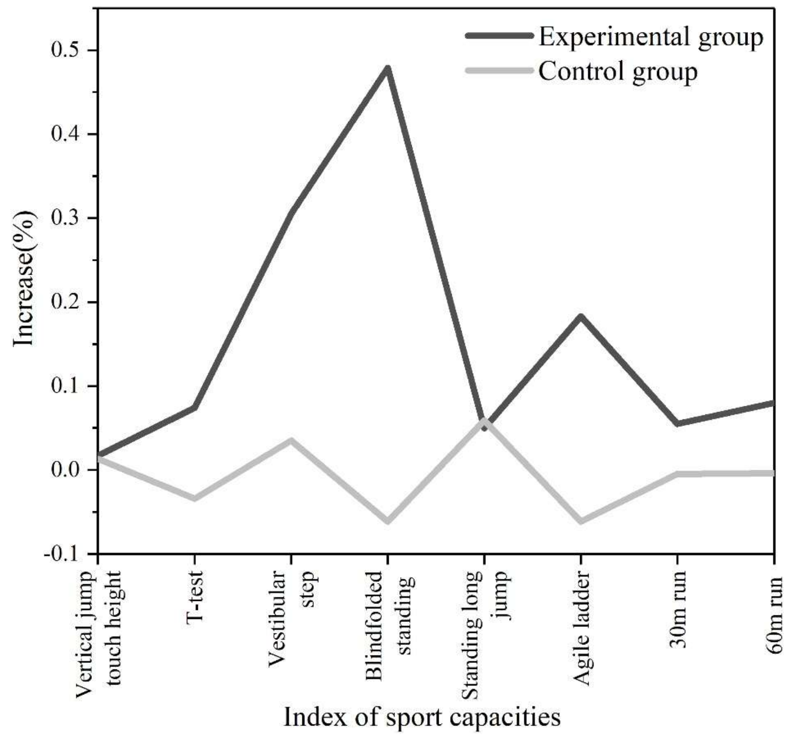


Fig. 5. The increase of test data before and after the experiment

5. Conclusion

In this paper, the general content of the time series analysis method is firstly discussed in depth, and then the monitoring test data of sports performance of Z athletes of a club for the period of February 2021-August 2023 is taken as the object of the study, and the $ARMA(p,q)$ model is determined by using the time series analysis method to predict the performance of Z athletes in sports training. In the analysis of the monitoring and prediction data of hemoglobin (HGB) of Athlete Z, the value of the test T-statistic was -3.895275,which is less than the critical value at the 5% level of significance, verifying that the series is in a smooth state. After comprehensive consideration, ARMA(1,1) was selected as the model for HGB levels. The ARMA(1,1) model was utilized for short-term prediction of HGB levels in Athlete Z. The average predicted value was 153 g/L figure, which was very close to the average true value of 154 g/L, proving the good fitting effect of the ARMA(1,1) model. The ARMA(1,1) model was applied to the prediction of basal heart rate (BHR) and blood oxygen saturation (BOS) of Z athletes, and the prediction result that the trend of BOS was opposite to that of BHR was obtained, and the application effect was better.

After determining the ARMA(1,1) model and realizing the prediction of athletes' performance accordingly, this paper further explores the training strategy of physical education, combines the integrated neuromuscular training (INT), proposes the INT physical education training strategy, and analyzes the effect of the application by using the experimental method. Before the experiment, the experimental group that applied the INT physical education training strategy to carry out physical education training and the control group that used the traditional training method did not show significant differences in the basic information data of height, weight and age, and the indexes of sports quality test (P>0.05). After the experiment, the test results in the T-test sensitive running, agility ladder, vestibular step, blindfolded one-legged standing, 30-meter sprint running, 60-meter sprint running 6 sports quality test indexes show P<0.05, the test results of the experimental group is significantly better than the control group, the test indexes have a significant difference (P<0.05). The experimental group gained significant improvement in all the indexes of motor quality test, and the most obvious indexes were blindfolded standing, vestibular step, agility ladder test, and T-test, which improved

47.87%, 30.51%, 18.29%, and 7.39% respectively compared with the preexperimental period. The control group, on the other hand, improved in standing long jump, vertical jump touch height and vestibular step indexes, and showed different degrees of decline in blindfolded standing decline, agility ladder test, T-test, 30-meter run and 60-meter run indexes. The experiment proved that the INT physical education training strategy proposed in this paper can effectively improve the athletes' sports quality and sports performance.

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