J. COMBIN. MATH. COMBIN. COMPUT. 127b (2025) 443--459

Journal of Combinatorial Mathematics and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Combinatorial Press

Numerical simulation study of physical fitness changes in track and field athletes with different training cycles

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ABSTRACT

This paper realizes the detection of changes in physical fitness of track and field athletes in different training cycles by monitoring their sports training functions. The method used is the time series model ARMA. The athletic training function time series data were preprocessed to fit the ARMA (p,q) model, and the optimal time series fitting model was selected by examining the coefficient of determination, AIC criterion, and SC criterion. Four biochemical indexes, hemoglobin, urea, creatine kinase, and testosterone, were selected as the content of training monitoring for track and field athletes, and the ARMA(1,1) model was selected to analyze the changes in physical fitness of track and field athletes in different training cycles. Taking the hemoglobin index (HB) as an example, through the numerical simulation of the time series of HB levels of 16 track and field athletes preparing for the 15th National Games in Guangdong Province, it can be learned that the change trends of male and female track and field athletes are basically the same throughout the whole year training cycle. From the first cycle, the athletes' Hb levels began to decrease, fell to the lowest level in the third cycle, and rebounded in the fourth cycle, reaching the highest Hb level in the winter training period.

Keywords: time series modeling, functional monitoring, fitness monitoring, track and field athletes

1. Introduction

In the career development of athletes, physical training is the foundation of their continuous improvement of their own ability, especially in track and field, athletes' physical fitness has a greater impact on their performance [1-2]. Therefore, in the training process of young athletes in track and field, coaches should follow the corresponding principles of physical training, and carry out targeted training from both physical and psychological qualities to promote the overall development of young

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Received 10 August 2024; Revised 30 October 2024; Accepted 20 February 2025; Published Online 16 April 2025.
DOI: 10.61091/jcmcc127b-026

athletes in track and field [3-5]. Physical training has positive significance for young track and field athletes as a method to enhance individual organ function, motor skills and physical fitness [6]. Physical training involves the aspects of strength, speed, endurance, flexibility, coordination, and agility, and its goal is to optimize the human body structure, enhance physiological function and improve athletic ability through scientific, systematic, and holistic training methods [7-8]. At the same time, physical training focuses on enhancing muscle strength and cardiorespiratory function, and can promote the coordinated functioning of various body parts and improve the efficiency of sports, which is conducive to ensuring that athletes play at a high level in the competition [9-10]. Targeted physical training is beneficial to reduce sports injuries, enhance the physical fitness of adolescents, and improve their ability to adapt to competition [11]. The quality of good small cycle track and field training before the competition can ensure that athletes play a normal sport level during the competition [12].

In the past, the traditional track and field training cycle theory has the characteristics of long rhythm, low intensity and large cycle, which has a fundamental role in Chinese sports track and field training, but along with the continuous development of sports track and field training, the traditional track and field training theory of large cycle can not be adapted to the requirements of the modern athletic competitions, and the long rhythm of track and field training can easily cause contradictions between athletic recovery and athletic fatigue [13-15]. The theory of small-cycle track and field training has the characteristics of clear goal, short rhythm and easy recovery, and because track and field has high requirements for athletes' endurance and special strength, universities and colleges can use small-cycle track and field training to improve students' athletic level and competition endurance [16-18]. College athletes can not be like professional athletes, can be used to participate in many competitions to improve their competitiveness, they need to stand in the practical point of view, according to the rules of the game and the characteristics of the special competition in the pre-competition training of small cycle [19-20].

This study monitors and predicts changes in athletic training function of track and field athletes by using time series analysis. We propose the relevant principles of time series, complete the definition of time series, rely on time series analysis methods to establish a time series model, use Wold's decomposition theorem to decompose the sum of the series, and use the delay operator to shorthand the time series model as a $ARMA(p,q)$ model. The AIC criterion and SC criterion are proposed as the conditions for measuring the relative optimal model, i.e., when the value of the AIC function and the value of the SC function are minimized, the $ARMA(p,q)$ model can be considered as the optimal model. Taking hemoglobin index (HB) as an example, a mathematical model that can accurately reflect the dynamic dependence contained in the time series of athletic training function monitoring data was established through numerical analysis of the time series of track and field training function index data to analyze the monitoring results of the changes in the physical fitness of track and field athletes in different training cycles.

2. Biochemical indicators of physical training monitoring in track and field athletes

Excellent track and field athletes need to integrate technical and tactical, physical and intellectual abilities to play the greatest advantage in the constant 10s or even more than 10s of high-intensity intervals, track and field athletes in a short period of time, fast physical consumption, athletes only have strong physical reserves and regenerative capacity, in order to support the play of technical and tactical skills and ultimately win the game with a strong physical quality. In the daily training and pre-competition training, a very small change in the athlete's body will affect the changes in physical function, thus affecting the athlete's level of competition. Therefore, it is important to select reasonable biochemical indexes and monitor the biochemical indexes of athletes to realize scientific training and improve the performance of the competition. At present, the commonly used biochemical indexes for training monitoring and function evaluation of track and field athletes are as follows.

2.1. Hemoglobin

Hemoglobin is an iron-containing protein of red blood cells, whose function is to transport oxygen and carbon dioxide and to maintain the acid-base balance of human blood. Its function is to transport oxygen and carbon dioxide and to maintain the acid-base balance of human blood. Hemoglobin mainly reflects the oxygen supply capacity of the blood, which is closely related to the body's functional status and is an important indicator of functional evaluation (especially aerobic capacity).

2.2. Urea

Blood urea is a metabolic product of proteins and amino acids. Ammonia is released from protein and amino acid metabolism through deamidation, and ammonia is converted into non-toxic urea in liver cells, which enters the blood circulation and becomes blood urea, which is finally excreted in final urine. Under normal circumstances, urea mainly reflects the load and recovery of muscles, and its production and excretion are in dynamic balance and remain relatively stable.

2.3. Creatine kinase

For sports that emphasize speed, strength, endurance, and explosiveness, it is particularly important to monitor serum CK levels. When myocytes are not damaged, very little creatine kinase is able to permeate the cell membrane, and the measurement of serum creatine kinase activity can be used to assess the adaptation of skeletal muscle to the exercise load and the damage it has sustained. Serum CK is an important biochemical indicator for monitoring the intensity of training loads.

2.4. Testosterone

Testosterone is the most active androgen in the body. The main function of testosterone is to promote anabolism in the body, which is beneficial to the improvement of strength, speed and endurance training. Athletes in track and field events are required to have good speed and strength qualities, and the basal concentration of blood testosterone can reflect the size of the athlete's muscle strength, which is often used as an indicator for selection. Blood testosterone has been commonly used in training monitoring, and it is a kind of indicator that can effectively reflect the athletes' functional status.

3. Research Objects and Methods

3.1. Objects of study

In this paper, 16 track and field athletes from Guangdong Province who were preparing for the 15th National Games were used as research subjects. Among them, 10 are Grade 1 athletes, 6 are Grade 2 athletes, and the ratio of male to female is 1:1. The basic information of the athletes is shown in Table 1.

Table 1. Basic information of athletes

Number	Gender	Age	height(cm)	weight(kg)	Training period(year)	Athlete class
A1	Male	17	168	42.2	4	First grade
A2	Female	16	167	52.1	7	First grade
A3	Male	18	166	53.2	6	First grade
A4	Male	16	152	44.6	6	First grade
A5	Male	16	173	41.3	6	First grade
A6	Female	19	165	57.4	7	First grade
A7	Female	16	165	51.8	6	First grade
A8	Male	20	170	63.5	7	First grade
A9	Female	16	162	47.7	5	Second grade
A10	Female	20	163	53.6	6	Second grade
A11	Female	16	166	55	6	Second grade
A12	Male	19	167	51.4	5	Second grade
A13	Female	17	167	54.2	5	Second grade
A14	Male	18	158	56	5	First grade
A15	Male	16	161	51.5	4	Second grade
A16	Female	17	171	68.2	4	First grade
Average	-	17	165	52.7	5.7	-

3.2. Research methodology

In this paper, time series modeling is used as a research method to numerically simulate the physical fitness changes of track and field athletes during different training cycles [21].

3.2.1. Time Series Principles:

1) Definition of time series. A time series is an ordered set of random variables that are arranged in chronological order. Time series are so closely related to stochastic processes that they are often understood as a stochastic process. A stochastic process is also a set of ordered random variables, denoted as $\{X_t, t \in T\}$. A stochastic process is generally defined on a continuous set, and when a stochastic process is defined on a discrete set it is usually called a time series. Thus, a time series can be defined as follows.

In statistical studies, a set of random variables arranged in chronological order is often used:

$$X_1, X_2, \cdots, X_t, \cdots \tag{1}$$

Denotes a time series in a random event, abbreviated as $\{X_1, t \in T\}$ or $\{X_t\}$.

2) Preprocessing of time series

(1) Probability distribution

The statistical properties of a random variable can be characterized both by the distribution function and by the density function [22]. Similarly, $\{X_t\}$ is a family of random variables whose statistical properties can be determined entirely by their joint density function or by their joint distribution function.

For the time series $\{X_1, t \in T\}$, its probability distribution can be defined as follows.

Taking arbitrarily the positive integers m and $t_1, t_2, \cdots, t_m \in T$, the random vectors $\left(X_{t_1}, X_{t_2}, \cdots X_{t_m}\right)'$ and m are related, the joint probability distribution of the random vectors can be denoted by $F_{t_1,t_2,\cdots t_m}\left(x_1, x_2, \cdots, x_m\right)$, then the distribution function constitutes the whole:

$$\left\{F_{t_1,t_2\cdots t_m}\left(x_1, x_2, \cdots, x_m\right), \forall m \in N^+, \forall t_1, t_2, \cdots, t_m \in T\right\} \tag{2}$$

(2) Characteristic statistics

Describing the statistical characteristics of a sequence can be done by using low-order moments, which are simpler and more practical, such as the characteristic statistics mean and variance. Two characteristic statistics are described below.

In the time series $\left\{X_t, t \in T\right\}$, take $t, s \in T$ arbitrarily and define $\gamma(t, s)$ as the self-covariance function of the series $\left\{X_t\right\}$, abbreviated as ACVF:

$$\gamma(t,s) = E\left(X_t, \mu_t\right)\left(X_s, \mu_s\right) \tag{3}$$

Will $\rho(t, s)$ be the autocorrelation coefficient defining the time series $\left\{X_t\right\}$, abbreviated as ACF:

$$\rho(t,s) = \frac{\gamma(t,s)}{\sqrt{DX_t \cdot DX_s}} \tag{4}$$

In a smooth time series $\left\{X_t\right\}$, given the middle $k-1$ (here all k are greater than 1) random variables $x_{t-1}, x_{t-2}, \cdots, x_{t-k+1}$, the so-called lagged k biased autocorrelation coefficient, which can also be said to be the measure of correlation between x_{t-k} and x_t after removing the effect of the middle $k-1$ random variables, is obtained:

$$\rho_{x_{x_{t-k}}, x_t | x_{t-1} \cdots x_{1-k+1}} = \frac{E\left[\left(x_{t-k} - \hat{E}x_{t-k}\right)\left(x_t - \hat{E}x_t\right)\right]}{E\left[\left(x_{t-k} - \hat{E}x_{t-k}\right)^2\right]} \tag{5}$$

In the above equation, $Exx_{t-k} = E\left[x_{t-k} \mid x_{t-1}, \cdots x_{t-k+1}\right], x_t = E\left[x_t \mid x_{t-1}, \cdots x_{t-k+1}\right]$. This is the definition of the lagged k-bias autocorrelation coefficient.

(3) Difference operator

In the application of time series, people always want to be able to transform the non-smooth time series into a smooth time series, so that you can apply mathematical methods to it, of which the difference transform is the most commonly used transformation.

For time series $\left\{X_1, X_2, \cdots, X_N\right\}$, define its first order (backward) difference as $\left\{y_1, y_2, \cdots, y_N\right\}$, here $y_t = \nabla x_t \equiv x_t - x_{t-1}$.

Define the second order difference as:

$$\begin{aligned} \nabla^2 x_t &= \nabla\left(\nabla x_t\right) = \nabla x_t - \nabla x_{t-1} \\ &= \left(x_t - x_{t-1}\right) - \left(x_{t-1} - x_{t-2}\right) \\ &= x_t - 2x_{t-1} + x_{t-2}. \end{aligned} \tag{6}$$

Similarly, the p st order difference is defined as:

$$\nabla^p x_t = \nabla^{p-1}\left(\nabla x_t\right) = \nabla^{p-1} x_t - \nabla^{p-1} x_{t-1} \tag{7}$$

The s-period lag difference is defined as:

$$\nabla_s x_t = x_t - x_{t-s} \tag{8}$$

Clearly $\nabla\nabla_s = \nabla_s\nabla$, and for constants c, $\nabla c = 0$.

(4) AIC criterion

The minimum information criterion (abbreviated as AIC criterion) is a weighted function of the great likelihood function and the number of unknown parameters, which can be expressed as [23]:

$$\begin{aligned} AIC = & -2\ln\left(\text{Value of the great likelihood function of the model}\right) \\ & +2\left(\text{Number of unknown parameters in the model}\right) \end{aligned} \tag{9}$$

Among them, the one that minimizes the value of the AIC function $ARMA\left(p,q\right)$ model, can be considered as the optimal model.

In the $ARMA\left(p,q\right)$ model, the log-likelihood function is:

$$l\left(\tilde{\beta};x_1,x_2,\cdots,x_n\right) = -\left[\frac{n}{2}\ln\sigma_\varepsilon^2 + \frac{1}{2}\ln|\Omega| + \frac{1}{2\sigma_\varepsilon^2}S(\tilde{\beta})\right] \tag{10}$$

where $l\left(\tilde{\beta};x_1,x_2,\cdots,x_n\right)$ is proportional to $-\frac{n}{2}\ln\left(\sigma_\varepsilon^2\right)$ since $\frac{1}{2}\ln|\Omega|$ is bounded and $\frac{1}{2\sigma_\varepsilon^2}S(\tilde{\beta}) \to \frac{n}{2}$, i.e.:

$$l\left(\tilde{\beta};x_1,x_2,\cdots,x_n\right) \propto -\frac{n}{2}\ln\sigma_s^2 \tag{11}$$

In the centralized $ARMA\left(p,q\right)$ model, the number of its unknown parameters can be expressed as $p+q+1$, and in the decentralized $ARMA\left(p,q\right)$ model, the number of its unknown parameters can be expressed as $p+q+2$.

Therefore, the value of the AIC function for the centralized $ARMA\left(p,q\right)$ model can also be calculated according to the following formula:

$$AIC = n\ln\hat{\sigma}_\varepsilon^2 + 2(p+q+1) \tag{12}$$

AIC function for the decentralized $ARMA\left(p,q\right)$-model:

$$AIC = n\ln\hat{\sigma}_\varepsilon^2 + 2(p+q+2) \tag{13}$$

(5) BIC Guidelines

BIC guidelines are also known as SBC guidelines. The BIC guidelines are:

$$\begin{aligned} BIC = & -2\ln\left(value\ of\ the\ great\ likelihood\ function\ of\ the\ \mathrm{mod}el\right) \\ & +(\ln n)\left(number\ of\ unknown\ parameters\ in\ the\ \mathrm{mod}el\right) \end{aligned} \tag{14}$$

Based on the AIC criterion, the BIC criterion replaces the weights from $\ln n$ to $\ln n$, where 2 is the logarithmic function of the sample capacity. In the optimal model, the conjugate estimate of the true order is the BIC criterion.

Thus it is easy to obtain that the BIC function of the centered $ARMA\left(p,q\right)$ model is expressed as:

$$BIC = n\ln\hat{\sigma}_\varepsilon^2 + (\ln n)(p+q+1) \tag{15}$$

The BIC function for the decentralized $ARMA\left(p,q\right)$ model is expressed as:

$$BIC = n\ln\hat{\sigma}_c^2 + \left(\ln n\right)\left(p+q+2\right) \tag{16}$$

Among all the models that passed the test, the relative optimal model selected was the one that minimized both the AIC function value and the BIC function value.

3.2.2. Time series modeling. The construction of time series models relies on time series analysis methods.

Wold's decomposition theorem For any discrete smooth time series $\{x_t\}$, it can be decomposed into the sum of two series, which are smooth and uncorrelated, one of which is deterministic and the other stochastic, which may be noted as [24]:

$$x_t = V_t + \xi_t \tag{17}$$

where $\{V_t\}$ is the deterministic sequence and $\{\xi_t\}$ is the stochastic sequence.

The deterministic sequence $\{V_t\}$ represents the portion of the time series whose current fluctuations can be interpreted by the predictions of its historical information.Wold proved that the deterministic portion of a smooth time series can definitely be represented as a linear combination of the values of the historical series:

$$V_t = \sum_{j=1}^{\infty} \phi_j x_{t-j} \tag{18}$$

The random sequence $\{\xi_t\}$ represents the part of the time series whose current fluctuations cannot be interpreted by the predictions of its historical information.Wold proved that this part of the information can be equivalently expressed as:

$$\xi_t = \sum_{j=0}^{\infty} \theta_j \varepsilon_{t-j} \tag{19}$$

1) AR model. A model with the following structure is called an autoregressive model of order p, abbreviated as model $AR(p)$:

$$\begin{cases} x_t = \varphi_0 + \varphi_1 x_{t-1} + \varphi_2 x_{t-2} + \cdots + \varphi_p x_{t-p} + \varepsilon_t, \\ \varphi_p \neq 0, \\ E(\varepsilon_t) = 0, Var(\varepsilon_t) = \sigma_\varepsilon^2, E(\varepsilon_t \varepsilon_s) = 0, \forall s \neq t \\ E(x_s \varepsilon_t) = 0, s < t \end{cases} \tag{20}$$

$AR(p)$ The use of the model requires that all three of the following constraints be met simultaneously.

Condition I, $\phi_p \neq 0$. It is guaranteed that the highest order of the model is p.

Conditions II, $E(\varepsilon_t) = 0$, $Var(\varepsilon_t) = \sigma_\varepsilon^2$, $E(\varepsilon_t \varepsilon_s) = 0$, $s \neq t$. $\{\varepsilon_t\}$ is a sequence of random disturbances which are white noise sequences with zero mean.

Condition III, $E(x_s \varepsilon_t) = 0$, $s < t$. i.e., past sequence values do not affect the current random disturbance.

Omitting the restrictions in model (20), $AR(p)$ the model can be abbreviated as:

$$x_t = \varphi_0 + \varphi_1 x_{t-1} + \varphi_2 x_{t-2} + \cdots + \varphi_p x_{t-p} + \varepsilon_t \tag{21}$$

2) MA model. A model with the following structure is called a p st order moving average model, abbreviated as $MA(q)$ model:

$$\begin{cases} x_t = \mu + \varepsilon_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \cdots - \theta_q\varepsilon_{t-q} \\ \theta_q \neq 0 \\ E(\varepsilon_t) = 0, Var(\varepsilon_t) = \sigma_\varepsilon^2, E(\varepsilon_t\varepsilon_s) = 0, s \neq t \end{cases} \tag{22}$$

$MA(q)$ The use of the model requires that both of the following two constraints are met:

Condition I, $\theta_q \neq 0$. The highest order of the model is guaranteed to be q.

Condition II, $E(\varepsilon_t) = 0$, $Var(\varepsilon_t) = \sigma_\varepsilon^2$, $E(\varepsilon_t\varepsilon_s) = 0 (s \neq t)$. $\{\varepsilon_t\}$ is a random disturbance sequence which is a white noise sequence and has zero mean.

Omitting the constraints in model (23), model $MA(q)$ can be abbreviated as:

$$x_t = \mu + \varepsilon_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \cdots - \theta_q\varepsilon_{t-q} \tag{23}$$

Using the delay operator here, the centralized $MA(q)$ -model can then be abbreviated as:

$$x_t = \Theta(B)\varepsilon_t \tag{24}$$

where $\Theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$ is a polynomial in the q nd order moving average coefficients.

3) ARMA model. A model with the following structure is referred to as an autoregressive moving average model, which will be abbreviated as the $ARMA(p,q)$ model:

$$\begin{cases} x_t = \varphi_0 + \varphi_1 x_{t-1} + \varphi_2 x_{t-2} + \cdots + \varphi_p x_{t-p} \\ \quad + \varepsilon_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \cdots - \theta_q\varepsilon_{t-q} \\ \varphi_p \neq 0, \theta_q \neq 0 \\ E(\varepsilon_t) = 0, Var(\varepsilon_t) = \sigma_\varepsilon^2, E(\varepsilon_t\varepsilon_s) = 0, \forall s \neq t \\ E(x_s\varepsilon_t) = 0, \forall s < t \end{cases} \tag{25}$$

When $\phi_0 = 0$, model (24) is called the centering $ARMA(p,q)$ model. When the constraints in model (24) are omitted, the centering $ARMA(p,q)$ model is abbreviated as:

$$x_t = \varphi_1 x_{t-1} + \varphi_2 x_{t-2} + \cdots + \varphi_p x_{t-p} + \varepsilon_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \cdots - \theta_q\varepsilon_{t-q} \tag{26}$$

The constraints of the $ARMA(p,q)$ model can be referred to the AR model with the MA model.

Here the delay operator is used, then the centralized $ARMA(p,q)$ -model can be abbreviated as:

$$\Phi(B)x_t = \Theta(B)\varepsilon_t \tag{27}$$

where the p st order autoregressive coefficient polynomial can be expressed as $\Phi(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \cdots - \varphi_p B^p$, and the q rd order moving average coefficient polynomial can be expressed as $\Theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$.

If $q = 0$, model $ARMA(p,q)$ is model $\mathrm{AR}(p)$. If $p = 0$, the $ARMA(p,q)$ model is the $MA(q)$ model.

3.2.3. ARMA modeling process. The following are the steps for modeling the ARMA model.

1) Find the values of the sample ACF and PACF for this sequence of observations.

2) Fit a $ARMA(p,q)$ model based on the nature of the sample ACF and PACF.

3) Estimate the values of the unknown parameters in the model.

4) Validity testing. If the $ARMA(p,q)$ model does not pass the validity test, then go back to step 2) and re-select the $ARMA(p,q)$ model of the appropriate order to fit.

5) Model optimization. If the $ARMA(p,q)$ model passes the validity test, go back to step 2), and after fully considering all possibilities, multiple $ARMA(p,q)$ models can be built and the optimal model can be selected from among them.

6) Prediction. Use the fitted model for prediction and monitoring.

4. Findings and Analysis

4.1. Empirical study of time series model ARMA fitness monitoring

This chapter will first empirically analyze the time series model ARMA, the research method proposed in this paper, to test its performance in monitoring the fitness of track and field athletes during a certain training cycle.

4.1.1. Subject of empirical research. The athletic training function monitoring test data of 16 track and field athletes from Guangdong Province who were preparing for the 15th National Games from 2021-02 to 2023-03 were used as an empirical study.

4.1.2. Functional time series data preprocessing. Due to the influence of training program and arrangement, event time and competition location, testing personnel and testing conditions, and athletes' own special conditions, the time series data of Athletic Training Function Test (ATFT) have certain deficiencies, noises, and data redundancy. Therefore, appropriate preprocessing of the measured data is an important step in the analysis of PTF time series. In this study, the track and field athlete numbered A6 was used as an example for time series analysis of the changes in the level of hemoglobin (HB), a physical performance index of athletic training function. The changes in hemoglobin, a physical fitness test indicator, of track and field athlete number A6 from 2021-02 to 2023-03 are shown specifically in Figure 1.

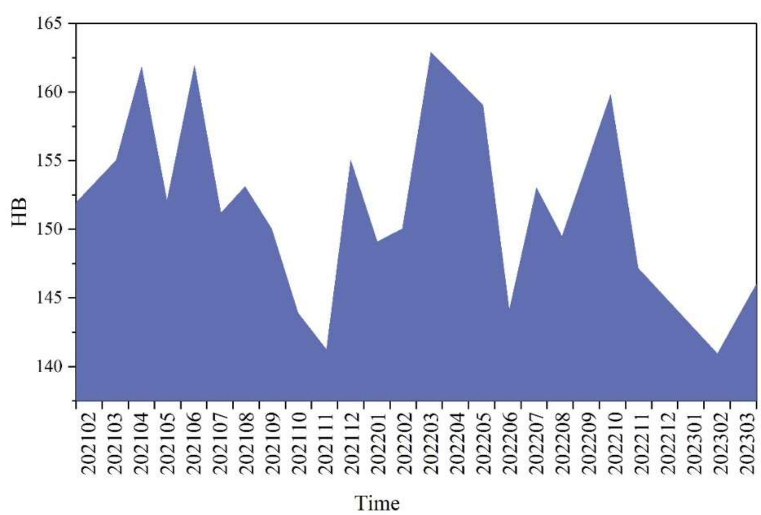


Fig. 1. Monitoring of HB

4.1.3. Identification of Functional Time Series Models. In the study, considering that the AR(p) model is a linear equation estimation, which is relatively easier than the nonlinear estimation of MA(q) and ARMA(p,q) models, the higher-order AR(p) model is commonly used in place of the corresponding MA(q) and ARMA(p,q) models when practically modeling. Therefore, in summary, the models available for the functional time series are AR(1), ARMA(1,1), and ARMA(1,2). Using Eviews software, the parameter estimation analysis of the models AR(1),ARMA(1,1), ARMA(1,2), respectively, as shown in Table 2. In the determination of the serial model, the main thing to consider is the overall fitting effect of the model, for the T-test significance level is not as strict as required in the regression equation. The adjusted coefficient of determination, AIC criterion, and SC criterion in the estimation of model parameters are all important criteria for selecting the model. The adjusted coefficient of determination mainly reflects the overall fitting effect of the model, and a better model generally requires a larger adjusted coefficient of determination, the better.The AIC criterion and the SC criterion are important reference standards for evaluating the merits of the model, which not only evaluates the merits of the model, but also takes into account the simplicity and accuracy of the model, and the AIC criterion and the SC criterion are generally required to be used for model ranking. When using AIC criterion and SC criterion for model ordering, it is generally required that the values of AIC criterion and SC criterion are as small as possible. From the table, we can get that the coefficient of determination of ARMA(1,1) is 0.235053, which is the largest among the optional models, while the values of AIC function and SC function are 5.045651 and 3.242916 respectively, which are the smallest among the optional models. After comprehensive consideration, ARMA(1,1) was selected for the HB time series model.

Table 2. Model parameter

AR(1)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	151.4109	2.06222	74.44069	0
AR(1)	0.259697	0.212064	1.853922	0.0836
R-squared	0.111587	Mean dependent var	151.659	
Adjusted R-squared	0.099482	S.D. dependent var	6.756885	
S.E. of regression	6.5681	Akaike info criterion	6.578095	
Sum squared resid	983.5481	Schwarz criterion	6.854605	
Log likelihood	-81.4742	F-statistic	3.194322	
Durbin-Watson stat	1.997062	Prob(F-statistic)	0.128843	
ARMA(1,1)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	151.1208	2.399425	62.92392	0
AR(1)	0.531662	0.545012	0.933052	0.0446
MA(1)	-0.0958	0.609525	-0.40125	0.0537
R-squared	0.148215	Mean dependent var	151.653	
Adjusted R-squared	0.235053	S.D. dependent var	6.817885	
S.E. of regression	6.675559	Akaike info criterion	5.045651	
Sum squared resid	977.1787	Schwarz criterion	3.242916	
Log likelihood	-81.2586	F-statistic	1.649285	
Durbin-Watson stat	1.95506	Prob(F-statistic)	0.232282	
ARMA(1,2)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	151.424	2.342245	64.67406	0
AR(1)	0.362232	0.21451	1.400845	0.1765
MA(2)	0.264283	0.213264	1.25052	0.2236
R-squared	0.216689	Mean dependent var	151.574	
Adjusted R-squared	0.075843	S.D. dependent var	6.844885	
S.E. of regression	6.507354	Akaike info criterion	6.676961	
Sum squared resid	948.6251	Schwarz criterion	6.825226	
Log likelihood	80.92851	F-statistic	1.929964	
Durbin-Watson stat	1.86472	Prob(F-statistic)	0.079464	

4.1.4. Functional time series model forecasting. After the model was determined, the short-term prediction of HB was carried out, and the real, predicted and residual values were specifically shown in Figure 2. It can be seen that the ARMA model is a good short-term prediction model, and the short-term prediction model of HB established in this study can roughly reflect the changes in the level of HB. However, the residuals appeared to be on the large side, in which the insufficient sampling volume is an important influencing factor, so it should be considered in combination with the athletes' recent training loads, load intensities and physical conditions in the actual application process. Meanwhile, this study only used HB as the research object to establish the time series model, and other indicators such as urea, creatine kinase and testosterone should be used to establish the time series model in the subsequent study.

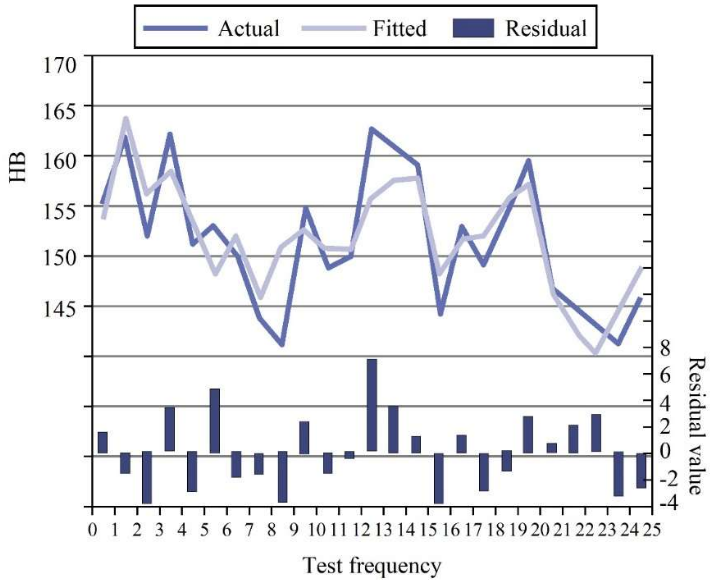


Fig. 2. Predicted real value, predicted value and residual value.

4.2. Analysis of the results of changes in training fitness of track and field athletes

In this section, the time series model ARMA will be applied to monitor the exercise function of 16 track and field athletes, the subjects of this paper, in different training cycles, and to study the changes of related biochemical indexes in different training cycles.

The annual training cycle of track and field athletes was divided into the first cycle (February~March), the second cycle (April~May), the third cycle (June~July), the fourth cycle (August~September) and the winter training period (October~January). Athletic training monitoring 1~2 times/month, according to the specific training program and the athletes' functional status, each time on Thursday 7:00~7:30 fasting to take venous blood, the test indicators include hemoglobin (Hb), testosterone (T), creatine kinase (CK), blood urea (BU).

The main instruments used were mindray BC-2600 hematology analyzer, mindray BS-220 automatic biochemistry analyzer, and MAGLUMI 800 automatic chemiluminescence detector.

4.2.1. Hemoglobin. Hb levels in male and female track and field athletes are shown in Figure 3. The trends of male and female track and field athletes were basically the same throughout the yearly training cycles. Hb levels were higher in the first cycle, then began to decrease, fell to the lowest level in the third cycle, rebounded from the fourth cycle, and reached the highest level in the winter training period. Compared with the winter training period, the Hb levels of women and men were very significantly lower in the second, third and fourth cycles ($P<0.01$). During the training process, depending on the individual track and field athletes, interventions in terms of training, diet and nutritional supplements are recommended to ensure a relatively high level of hemoglobin before the index decreases.

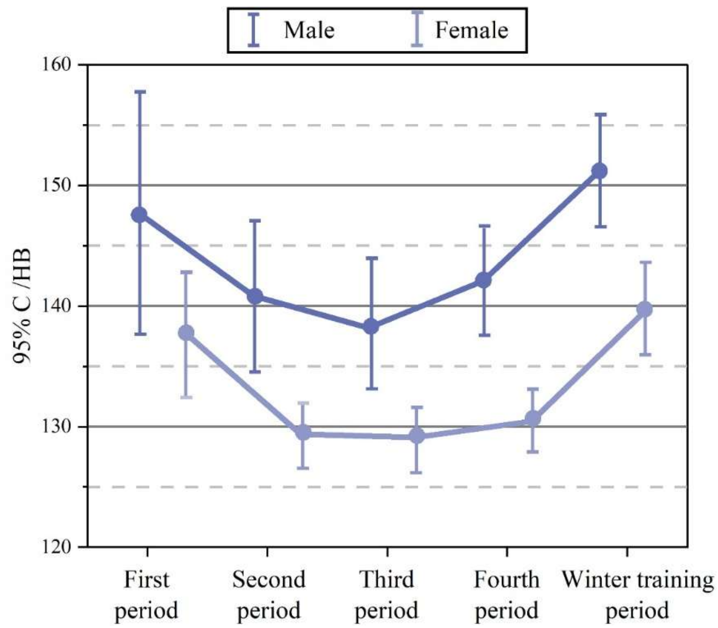
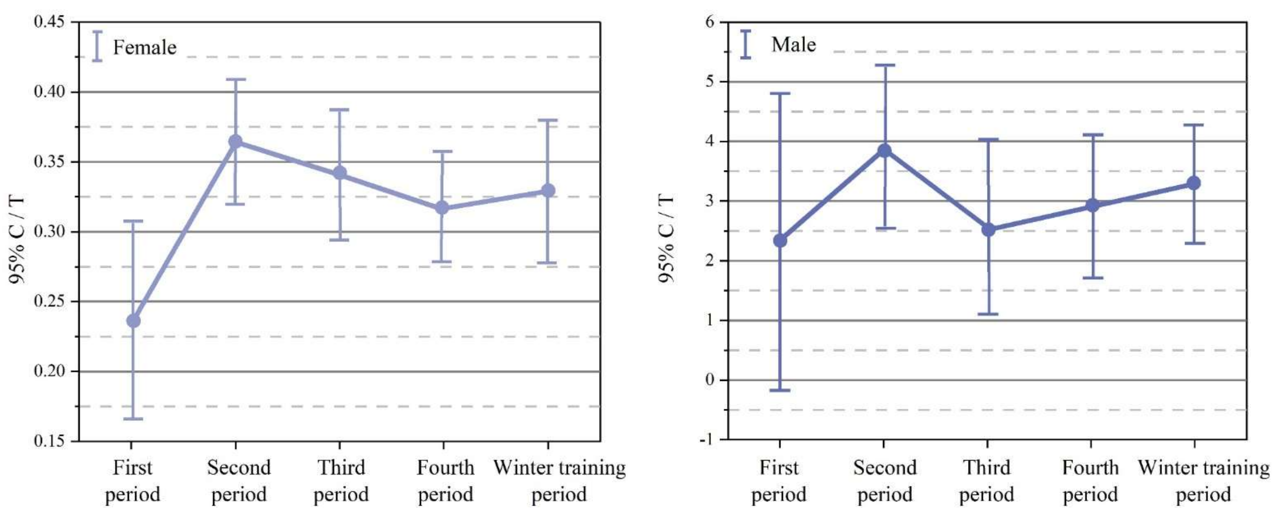


Fig. 3. HB level

4.2.2. Testosterone. The changes in testosterone in male and female track and field athletes are specifically shown in Figure 4. Figure (a) shows the changes in testosterone levels in female athletes, while Figure (b) shows the changes in testosterone levels in men. It can be seen that the first cycle T level of female athletes was the lowest during the whole year cycle, and compared with the winter training period, the T level of the first cycle was significantly reduced (P<0.05). In male athletes T levels were highest in the second cycle, but there was no significant change between training cycles (P>0.05). When testosterone decreases in track and field athletes, the athletes' physical function decreases and the overall recovery ability decreases. For excellent athletes with large testosterone decreases and slow recovery, supplementation with nutrients such as free testosterone pumps, rice bran fatty alkanol pressurized tablets candies, and ginseng sterols pressurized tablets candies can be considered to improve the blood testosterone level.



(a)Female athletes (b)Male athletes

Fig. 4. T level

4.2.3. Creatine kinase. Statistical changes of creatine kinase in the athletes in different training cycles are shown in Figure 5. The CK levels of female athletes were lower in the second cycle and winter training period, but none of them changed significantly (P>0.05) compared with each training cycle. In male athletes, CK levels were significantly higher in the second and fourth cycles compared with the winter training period (P<0.05), and there was no significant difference between the rest of the cycles compared with the winter training period. The high serum CK levels indicated that the training intensity was high and the body could not adapt to it. In addition, strength training, irrational or difficult movements, muscle strain, etc., all of them would increase the CK level abnormally. The CK level of female track and field athletes did not change much on the whole, and the changes in each cycle were relatively smooth, while male divers had higher levels in the second and fourth cycles, which might be mainly related to the athletes' technical level and the intensity of pre-competition training. The training of male track and field athletes should be reasonably evaluated and adjusted in relation to the actual training situation.

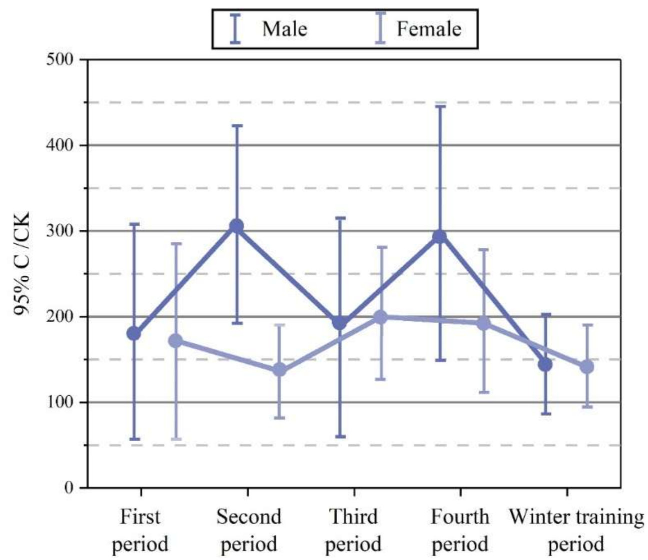


Fig. 5. CK level

4.2.4. Blood urea. The BU levels of track and field athletes are specifically shown in Figure 6. Compared with the winter training period, male athletes' third and fourth cycle BU levels were significantly lower (P<0.05), and there was no significant difference compared with the rest of the cycles. While comparing with the winter training period, the first cycle BU level of female athletes was significantly lower (P<0.05), and the third cycle BU level was very significantly higher (P<0.01). In the process of monitoring and evaluation of sports training, the abnormal increase of BU in track and field athletes should be analyzed comprehensively by considering factors such as whether the athletes' training volume was too large the day before, whether they were supplementing with protein powder nutrients, and whether the protein intake of dinner or evening meal was too high.

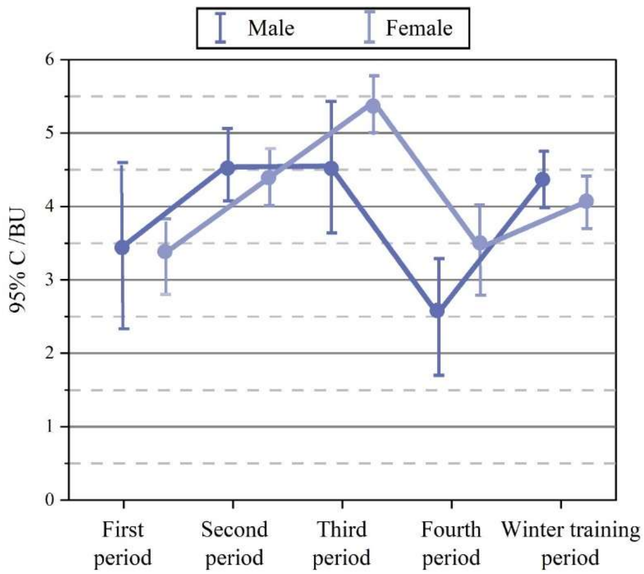


Fig. 6. BU level

5. Conclusion

In this study, 16 track and field athletes from Guangdong Province who were preparing for the 15th National Games were taken as research subjects, and the time series analysis method was used to predict the physical fitness changes of the track and field athletes, and the functional indicators such as hemoglobin, urea, creatine kinase, and testosterone during the year-round athletic training period were sampled and tested, so as to monitor the physical fitness changes of the track and field athletes in their athletic training.

Before formally carrying out the monitoring and analysis of the physical fitness changes in different training cycles of track and field athletes, the time series model ARMA was used to carry out an empirical study of physical fitness monitoring and to verify its physical fitness monitoring function. Comparing the three models AR(1), ARMA(1,1), ARMA(1,2), ARMA(1,1) model resides in the largest coefficient of determination (0.235053) with the smallest AIC function value (5.045651) and SC function value (3.242916) among the selectable models ARMA(1,1) was selected as the time-series model for this paper. The hemoglobin (HB) was used as an example for short-term prediction, and the true, predicted and residual values roughly reflected the changes in HB levels.

After completing the empirical analysis of the time-series model ARMA, the target track and field athletes were monitored for hemoglobin (HB), urea (BU), creatine kinase (CK), and testosterone (T). The HB levels of male and female track and field athletes showed the same trend throughout the yearly training cycles, being higher and starting to decline in the first cycle, dropping to the lowest level in the third cycle, and rebounding from the fourth cycle and reaching the highest level with the winter training period. T levels were lowest in the first cycle of female athletes during the whole year cycle, while male athletes' T levels were highest in the second cycle and did not show significant changes in the other cycles ($P>0.05$). In the second cycle and winter training period, CK levels were lower in female athletes, but there was no significant change between training cycles ($P>0.05$), while male athletes showed a significant increase in CK levels in the second and fourth cycles ($P<0.05$). Both female and male track and field athletes showed a significant decrease in BU levels ($p<0.05$), the former in the first cycle and the latter in the third and fourth cycles. In addition, comparing the winter training cycles, women track and field athletes had significantly lower BU levels in the first cycle ($P<0.05$) and very significantly higher BU levels in the third cycle ($P<0.01$). For the monitoring results of male and female athletes in HB level, T level, CK level and BU level, corresponding sports training interventions were proposed to ensure the physical fitness of track and field athletes.

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