An improved Grey prediction model and the application in college sports information management system

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Abstract

The sports elective course is an important means for college students to exercise their physical education and quality education. Because the students can choose the elective courses voluntarily online, teachers and colleges cannot learn the number of the students who choose the sports elective courses before the deadline. In this paper, we propose an improved GM (1, 1) prediction model to forecast the number of the students who take part in the sports elective courses and apply this model in the college sports information management system. Firstly, this paper puts forward the Grey prediction model with time parameter. Then, this paper studies the constructing mechanism and the modelling characteristics of this model. At last, we use the improved GM (1, 1) model to forecast the number of students who select the college sports elective courses in college sports information management system. High precision of the fitting and forecasting are obtained in the experiment while the result verifies the validity of the model.

Keywords: Grey precision model, college sports information management system, sports elective course

1 Introduction

In recent years, the development of the quality education is fast and powerful in China. In order to enrich the extracurricular life of college students, many universities set up the sports elective course. The main aim of the sports elective course is to improve the physical quality. In addition, the main means of physical education curriculum is the physical exercise. Sports elective course exercises the students comprehensively. At the same time, sports elective course can enhance the physical fitness of students, promotes the students' health and improves the physical quality of college students through the rational exercise. The sports elective course is one of the important ways to implement the quality education and cultivate an all-round development of the talents.

With the development of the computer technology, the college information management system becomes more and more popular. In the meantime, students select the course by college information management system online. Because the college students can choose the elective courses voluntarily and they can also deselect the courses online before the deadline, teachers could not ensure the number of students who take part in the sports elective course. It makes a lot of trouble for the institutes and teachers arrange the curriculum planning. To solve this problem, we propose an improved $GM(1,1)$ and apply in the college sports information management system to predict the number of the students who participate in the sports elective course.

At present, there are little literatures to forecast the number of students who participant in the sports elective course. In this paper, we use the improved Grey forecasting model to predict the number of students who select the sports elective course. The Grey prediction theory is an important part in the Grey system theory which is established by the scholars of China. It becomes a significant research branch in the prediction theory. According to the accumulation of the sequence, the Grey prediction theory excavates the inherent regularity of the data sequence to reveal the future development trend. The Grey $GM(1,1)$ model is the core model of the Grey prediction. It has a higher precision for fitting and forecasting the combined series which have the Grey exponential rule. Therefore, $GM(1,1)$ model has an extensive research background.

Grey model is an important branch of Grey system theory [1-3], since it was pioneered by professor Deng in 1982. In order to enhance the model precision, scholars have been researching new modelling technology in practice. The results demonstrate that the selection of background value, the manner of accumulated generating and the mode of original data are the main factors which influence the precision of Grey model. Thus, some methods for improving model precision are presented correspondingly. Li and Dai [4] improved the model predictive precision by modifying the initial value. Tseng et al. [5] and Wang et al. [6] proposed a hybrid grey model to forecast series with seasonality, applying the ratio-to-moving-average method in order to calculate the seasonal indexes and remove the seasonal factor. For

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oscillatory sequence, Qian and Dang [7] used accelerating translation transformation and improved smoothness by weighted mean generating and modelling finally. Zeng and Xiao [8] improved original data smoothness with the power function. Dang et al. [9, 10] constructed a new class of weakening buffer operator and strengthening buffer operator by using the buffer operator axiom for shock disturbed data sequence. Papers [11, 12] also researched accumulated generating. Rao et al. [13, 14] established hopping model and phase model and studied the matrix form for solving model parameters. Peng [15] established generalized unequal interval Grey forecasting model, and presented the matrix form for solving model parameters. For background value-building, Tan [16] improved the background value for equal interval sequence and unequal interval sequence; Literature [17] thought that the actual systems are usually fractional order. Literatures [18] studied the stability of fractional order system and its controllability and objectivity. The Grey forecasting model has been proposed as a promising alternative to time-series forecasting [19, 20].

On the basis of the existing researches, this paper put forward a Grey prediction model with time parameter. According to the Grey prediction theory, we structure a new Grey prediction model which is suitable for time sequence. Then, we study the constructing mechanism and the model characters. At final, we apply this model to forecasting the number of college students who select the college sports elective courses. When teachers' entry the college sports information management system, they can select the number of the students who participant in the sports elective courses each year as the samples. As the results, they can get the predicting outcomes. The numerical experiment shows that this method has high accuracy. The structure of this paper is as follows. The first part is introduction. The second part is the generation of the operator. The third part is the $GM(1,1)$ model. The fourth part is the construction of the Grey $GM(1,1,t^{\alpha})$ model with time power form. The fifth part is the characteristic of the $GM(1,1,t^{\alpha})$ model. The sixth part is the computer simulation and the last part is the conclusion.

2 The generation of the operator

2.1 ACCUMULATED GENERATING OPERATOR AND REGRESSIVE GENERATING OPERATOR

We suppose that the original sequence is:

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

where, n is the dimensionality, $X^{(0)}$ is the Grey sequence. $n\geq 1, x^{(0)}(i)\geq 0$

We define the new sequence

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

where $x^{(1)}(k)=\sum_{i=1}^{k}x^{(0)}(i)$, $X^{(1)}$ is said to be the one order accumulated generating operation series of $X^{(0)}$, namely $X^{(1)}=AGOX^{(0)}$.

If we accumulate the Equation (1) for r orders, we can get:

$$x^{(r)}(k)=\sum_{i=1}^{k}x^{(r-1)}(i). \tag{2}$$

If $x^{(0)}=x^{(1)}(k)-x^{(1)}(k-1)$, $X^{(1)}$ is said to be the one order regressive generating operation series of $X^{(0)}$, namely $X^{(1)}=IAGOX^{(0)}$

If we accumulate the Equation (1) for r orders, we can get $x^{(r-1)}=x^{(r)}(k)-x^{(r)}(k-1)$.

2.2 INVERSE ACCUMULATED GENERATING OPERATOR

We suppose that $X^{(0)}=\{x^{(0)}(1),x^{(0)}(2),...,x^{(0)}(n)\}$ is n-dimensions nonnegative descending sequence:

$$x^{(0)}(i)\geq x^{(0)}(i+1), i=1,2,...,n-1. \tag{3}$$

We define the new sequence:

$$X^{(1)}=\{x^{(1)}(1),x^{(1)}(2),...,x^{(1)}(n)\},$$

where $x^{(1)}(k)=\sum_{i=n}^{k}x^{(0)}(i)$.

It is the reverse accumulation generation sequence:

$$x^{(0)}=x^{(1)}(k)-x^{(1)}(k+1). \tag{4}$$

We can learn that $x^{(1)}$ is a monotonous drop sequence. When $x^{(0)}$ is a nonnegative monotonic function, $x^{(1)}$ have a tendency of monotonic decrease after reverse accumulation.

2.3 INDEX ACCUMULATED GENERATING OPERATOR

We suppose that the original sequence is:

$$X^{(0)}=\{x^{(0)}(1),x^{(0)}(2),\cdots x^{(0)}(n)\}, \tag{5}$$

where, n is the dimensionality, $X^{(0)}$ is the Grey sequence. $n\geq 1, x^{(0)}(i)\geq 0$.

We define $x^{(0)}(k)=be^{a(k-1)}, k=1,2,...,n$. We call this type as homogeneous discrete exponential function and we define:

$$x^{(0)}(k)=Be^{a(k-1)}+C, k=1,2,...,n,\ a,b,B,C\in R. \tag{6}$$

We can know that:

$$-a = In\left(1-\frac{b}{B}\right) \quad (7)$$

and:

$$B=\frac{be^a}{e^a-1}, C=\frac{b}{1-e^a}. \quad (8)$$

If $x^{(1)}(1)=x^{(0)}(1)=b$ and:

$$\frac{b}{1-e^a}=\frac{u}{a}. \quad (9)$$

We can get:

$$x^{(1)}(k)=\left(x^{(0)}(1)-\frac{u}{a}\right)e^{a(k-1)}+\frac{u}{a}, \quad (10)$$

$$x^{(1)}(t)=\left(x^{(0)}(1)-\frac{u}{a}\right)e^{a(t-t_0)}+\frac{u}{a}. \quad (11)$$

3 *GM*(1,1) model

We introduce the most classic Grey model $GM(1,1)$. The first 1 means that there is one variable in this model and the other one means that we use first order differential equation.

The mean ideal of the $GM(1,1)$ is as follows. We set $X^{(0)}=\{x^{(0)}(1),x^{(0)}(2),...,x^{(0)}(n)\}$ is the original sequence and get:

$$X^{(1)}=\{x^{(1)}(1),x^{(1)}(2),...,x^{(1)}(n)\}, \quad (12)$$

where $x^{(1)}(k)=\sum_{i=1}^{k}x^{(0)}(i)$. We call the a first order linear ordinary differential equations is the albino differential equation of $GM(1,1)$:

$$\frac{dx^{(1)}}{dt}+ax^{(1)}=b. \quad (13)$$

The differential form is:

$$x^{(0)}(k)+az^{(1)}(k)=b, \quad (14)$$

where, a is called the development coefficient which represents the development state of the prediction value. b is called the Grey action quantity and it represents change contained in the data. a,b is the first order parameter bag of $GM(1,1)$ model: $[a,b]^T=(B^TB)^{-1}B^TY_n$, where:

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

$$Y_n=\left[x^{(0)}(2),x^{(0)}(3),...,x^{(0)}(n)\right]^T. \quad (15)$$

Background value is:

$$z^{(1)}(k+1)=\frac{1}{2}[x^{(1)}(k)+x^{(1)}(k+1)], k=1,2,...,n-1.$$

The discrete solution of $GM(1,1)$ is:

$$\hat{x}^{(1)}(k+1)=(x^{(0)}(1)-\frac{b}{a})\cdot e^{-ak}+\frac{b}{a}. \quad (16)$$

The reducing value is:

$$\begin{aligned}&\hat{x}^{(0)}(k+1)=\hat{x}^{(1)}(k+1)-\hat{x}^{(1)}(k)=\\&(1-e^a)(x^{(0)}(1)-\frac{b}{a})\cdot e^{-ak}, k=1,2,...,n.\end{aligned} \quad (17)$$

We suppose that $\bar{x}^{(r)}(k)$ is the fitted value of the $x^{(r)}(k)$ and we define $q^{(0)}(k)=x^{(0)}(k)-\bar{x}^{(0)}(k)$ as the residual of $x^{(0)}$ at time k.

$$\begin{aligned}S_1^2&=\frac{1}{n}\sum_{i=1}^{n}(x^{(0)}(i)-\bar{u}_1)^2\\S_2^2&=\frac{1}{n}\sum_{j=1}^{n}(\bar{x}^{(0)}(i)-\bar{u}_2)^2\end{aligned}. \quad (18)$$

$\bar{u}_1$ is the mean value of the original sequence and $\bar{u}_2$ is the mean value of the predicted sequence. The ratio is $C=\frac{S_2}{S_1}$ and the probability is:

$$P=P\{\left|q^{(0)}(k)-\bar{q}\right|<0.6945S_1\},$$

where $\bar{q}$ is the mean value of the residual error sequence. We define the prediction accuracy of good, qualified, just the mark and unqualified according to P and C. The value of P and C are shown as Table.1

TABLE 1 Residual inspection standard of *GM*(1,1)

The level of prediction accuracy	*P*	*C*
good	>0.95	<0.35
qualified	>0.8	<0.5
just the mark	>0.7	<0.65
unqualified	≤0.7	≥0.65

4 The construction of the Grey $GM(1,1,t^{\alpha})$ model with time power form

Definition 1: We assume $X^{(0)}=(x^{(0)}(1),x^{(0)}(2),...,x^{(0)}(n))$. We call $X^{(1)}=(x^{(1)}(1),x^{(1)}(2),...,x^{(1)}(n))$ as the first-order accumulated generating sequence (1-AGO) of $X^{(0)}$, where $x^{(1)}(k)=\sum_{i=1}^{k}x^{(0)}(k),k=1,2,...,n$, we call $Z^{(1)}=(z^{(1)}(2),z^{(1)}(3),...,z^{(1)}(n))$ as the proximate mean generation sequence of $X^{(1)}$:

$$Z^{(1)}(k)=\frac{1}{2}(x^{(1)}(k),+x^{(1)}(k-1)),k=2,3,...,n\ . \tag{19}$$

Definition 2: Assuming $X^{(0)},X^{(1)},Z^{(1)}$ as the **Definition 1**, we call $x^{(0)}(k)+az^{(1)}(k)=bk^{\alpha}+c$ as the basic form of $GM(1,1,t^{\alpha})$, where α is a nonnegative constant. We call $\frac{dx^{(1)}}{dt}+ax^{(1)}=bt^{\alpha}+c$ as the winterization equation of $GM(1,1,t^{\alpha})$.

Theorem 1: Assuming $X^{(0)}$ a non-negative sequence:

$X^{(0)}=(x^{(0)}(1),x^{(0)}(2),...,x^{(0)}(n))$,

where $x^{(0)}(k)\geq 0,k=1,2,...,n$. $X^{(1)}$ is 1-AGO of $X^{(0)}$. $Z^{(1)}$ is the proximate mean generation sequence of $X^{(1)}$. If $\hat{\gamma}=[a,b,c]^{T}$ is the parameter list and:

$$Y=\begin{pmatrix}x^{(0)}(2)\\x^{(0)}(3)\\\vdots\\x^{(0)}(n)\end{pmatrix},\ B=\begin{pmatrix}-z^{(1)}(2)&2^{\alpha}&1\\-z^{(1)}(3)&3^{\alpha}&1\\\vdots&\vdots&1\\-z^{(1)}(n)&n^{\alpha}&1\end{pmatrix}. \tag{20}$$

The least square parameter estimation of $x^{(0)}(k)+az^{(1)}(k)=bk^{\alpha}+c$ about $GM(1,1,t^{\alpha})$ model satisfies $\hat{\gamma}=(B^{T}B)^{-1}B^{T}Y$.

Proof: taking data to the $GM(1,1,t^{\alpha})$ model $x^{(0)}(k)+az^{(1)}(k)=bk^{\alpha}+c$, we can get:

$$\begin{array}{l}x^{(0)}(2)+az^{(1)}(2)=2^{\alpha}b+c,\\x^{(0)}(3)+az^{(1)}(3)=3^{\alpha}b+c,\\\vdots\\x^{(0)}(n)+az^{(1)}(n)=n^{\alpha}b+c\end{array}.$$

$Y=B\hat{a}$ is a set of estimates for *a*, *b* and *c*. Substituting $-az^{(1)}(k)+bk^{\alpha}+c$ with $x^{(0)}(k)$, $k=2,3,...,n$, we can get the error sequence $\varepsilon=Y-B\hat{a}$. Assuming:

$$s=\varepsilon\cdot\varepsilon^{T}=Y-B\hat{a}^{T}(Y-B\hat{a})=$$
$$\sum_{K=2}^{N}(x^{(0)}(k)+az^{(1)}(k)-bk^{\alpha}-c)^{2}.$$

The *a*, *b*, *c* which make the *s* minimum is as follows:

$$\frac{\partial s}{\partial a}=2\sum_{k=2}^{n}(x^{(0)}(k)+az^{(1)}(k)-bk^{\alpha}-c)z^{(1)}(k)=0,$$
$$\frac{\partial s}{\partial b}=-2\sum_{k=2}^{n}(x^{(0)}(k)+az^{(1)}(k)-bk^{\alpha}-c)=0,$$
$$\frac{\partial s}{\partial c}=-2\sum_{k=2}^{n}(x^{(0)}(k)+az^{(1)}(k)-bk^{\alpha}-c)k^{\alpha}=0.$$

From the above equations, we can get *a*, *b* and *c*. By $Y=B\hat{a}$, we get:

$$B^{T}B\hat{\gamma}=B^{T}Y,\hat{\gamma}=(B^{T}B)^{-1}B^{T}Y\ . \tag{21}$$

From above, we can be obtain:

$$\hat{\gamma}=\begin{pmatrix}a\\b\\c\end{pmatrix}=(B^{T}B)^{-1}B^{T}Y\ . \tag{22}$$

Theorem 2: We assume $\hat{\gamma}=[a,b,c]^{T}=(B^{T}B)^{-1}B^{T}Y$ for B and Y which referred in **Theorem 1**. Therefore, the time response function of the winterization equation $\frac{dx^{(1)}}{dt}+ax^{(1)}=bt^{\alpha}+c$ is as follows:

$$x^{(1)}(t)=be^{-at}\int e^{at}t^{\alpha}dt+\frac{c}{a}.$$

In the model $GM(1,1,t^{\alpha})$, the time response sequence of $x^{(0)}(k)+az^{(1)}(k)=bk^{\alpha}+c$ can be get discretely by the time response function of the winterization equation.

5 The characteristic of the $GM(1,1,t^{\alpha})$ model

Theorem 3: When $\alpha=0$, the model $GM(1,1,t^{\alpha})$ changes to $x^{(0)}(k)+az^{(1)}(k)=bk^{0}+c=b_{0}$. That is, $GM(1,1,t^{\alpha})$ degrades to the $GM(1,1)$ model. If *B* and *Y* are referred as the **Theorem 1** $\hat{\gamma}=[a,b,c]^{T}=(B^{T}B)^{-1}B^{T}Y$. We can get the time response function of the winterization function $\frac{dx^{(1)}}{dt}+ax^{(1)}=b_{0}$ is as follows:

$$x^{(1)}(t)=\left(x^{(1)}(1)-\frac{b_{0}}{a}\right)e^{-a(t-1)}+\frac{b_{0}}{a}.$$

1) The time response sequence of the $GM(1,1)$ model $x^{(0)}(k)+az^{(1)}(k)=b_{0}$ is as follows:

$$\hat{x}^{(1)}(k+1)=\left(x^{(1)}(1)-\frac{b_{0}}{a}\right)e^{-ak}+\frac{b_{0}}{a},k=0,1,2,...,n.$$

2)The reduction value:

$$\hat{x}^{(0)}(k+1)=\hat{x}^{(1)}(k+1)-\hat{x}^{(1)}(k)=$$
$$(1-e^{a})\left(x^{(0)}(1)-\frac{b_0}{a}\right)e^{-ak},k=1,2,...,n.$$

Property 1: From the **Theorem 3**, we can know that the $GM(1,1,t^{\alpha})$ model adapts the sequence modelling, which has the approximate non-homogeneous exponential rule $x(t)\approx ce^{at}$ when $\alpha=0$.

Theorem 4: When $\alpha=1$, the $GM(1,1,t^{\alpha})$ model changes to $x^{(0)}(k)+az^{(1)}(k)=bk+c$. That is, $GM(1,1,t^{\alpha})$ changes to $GM(1,1,t)$. If B and Y are referred as the **Theorem 1**, $\hat{\gamma}=[a,b,c]^{T}=(B^{T}B)^{-1}B^{T}Y$.

1) The time response function of the winterization function $\frac{dx^{(1)}}{dt}+ax^{(1)}=bt+c$ is as follows:

$$x^{(1)}(t)=\left(x^{(1)}(1)-\frac{b}{a}-\frac{ac-b}{a^{2}}\right)e^{-a(t-1)}+\frac{b}{a}t+\frac{ac-b}{a^{2}}.$$

2) The time response sequence of the $GM(1,1,t)$ model $x^{(0)}(k)+az^{(1)}(k)=bk+c$ is as follows:

$$\hat{x}^{(1)}(k+1)=\left(x^{(1)}(1)-\frac{b}{a}-\frac{ac-b}{a^{2}}\right)e^{-ak}+\frac{b}{a}k+$$
$$\frac{ac-b}{a^{2}},k=0,1,2,...,n.$$

3) The reduction value:

$$\hat{x}^{(0)}(k+1)=\hat{x}^{(1)}(k+1)-\hat{x}^{(1)}(k)=$$
$$(1-e^{a})x\left(^{(0)}(1)-\frac{b}{a}-\frac{ac-b}{a^{2}}\right)e^{-ak}+\frac{b}{a},k=1,2,...,n.$$

Property 2: From the theorem 4, we can know the $GM(1,1,t)$ model adapts the sequence modelling which has the approximate non-homogeneous exponential rule $x(t)\approx ce^{at}+bd$ when $\alpha=1$.

Theorem 5: When $\alpha=2$, the $GM(1,1,t^{\alpha})$ model changes to $x^{(0)}(k)+az^{(1)}(k)=bk^{2}+c$. That is, $GM(1,1,t^{\alpha})$ changes to $GM(1,1,t^{2})$. If B and Y are referred as the **Theorem 1**, $\hat{\gamma}=[a,b,c]^{T}=(B^{T}B)^{-1}B^{T}Y$.

1) The time response function of the winterization function $\frac{dx^{(1)}}{dt}+ax^{(1)}=bt^{2}+c$ is as follows:

$$x^{(1)}(t)=\left(x^{(1)}(1)-\frac{a^{2}b+a^{2}c-2ab+2b}{a^{3}}\right)e^{-a(t-1)}+$$
$$\frac{b}{a}t^{2}-\frac{2b}{a^{2}}t+\frac{2b+a^{2}c}{a^{3}}.$$

2) The time response sequence of the $GM(1,1,t^{2})$ model $x^{(0)}(k)+az^{(1)}(k)=bk^{2}+c$ is as follows:

$$x^{(1)}(t)=\left(x^{(1)}(1)-\frac{a^{2}b+a^{2}c-2ab+2b}{a^{3}}\right)e^{-ak}+$$
$$\frac{b}{a}k^{2}-\frac{2b}{a^{2}}k+\frac{2b+a^{2}c}{a^{3}},k=0,1,2,...,n.$$

3) The reduction value:

$$\hat{x}^{(0)}(k+1)=\hat{x}^{(1)}(k+1)-\hat{x}^{(1)}(k)=$$
$$(1-e^{a})\left(x^{(1)}(1)-\frac{a^{2}b+a^{2}c-2ab+2b}{a^{3}}\right)e^{-ak}+$$
$$\frac{2b}{a}k-\frac{(a+2)b}{a^{2}},k=1,2,...,n.$$

Property 3: From the **Theorem 5**, we can know, the $GM(1,1,t^{2})$ model adapts the sequence modelling, which has the approximate non-homogeneous exponential rule when $\alpha=2$, $x(t)\approx ce^{at}+bt+d$. When α gets other value, we can research the time response sequence and the related properties of the $GM(1,1,t^{\alpha})$ according to the specific value. In the practical application, when selecting the Grey model $GM(1,1,t^{\alpha})$ with time power item, we can eliminate the parameters a, b and c in the model by using the Grey derivative information coverage principle. Then, we can get the expression of the original data series about the parameter α. Therefore, we ensure the value of α and give the optimization steps of α by using the intelligent algorithm.

6 Computer Simulations

When teacher entry the college sports information management system, they choose the numbers of the students who select the sports elective courses for each year as the samples. Then, they fit the samples. If the fitting precision is high, we predict the number of participants. The flow is as follows (Figure 1).

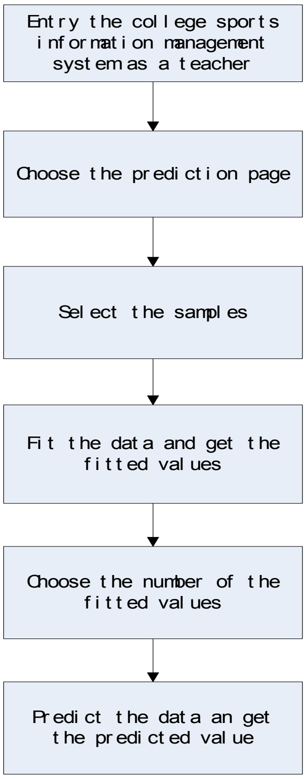

FIGURE 1 The Prediction Process of $GM(1,1,t^{\alpha})$ Model

We choose the numbers of the students who take part in the ports elective course for ten years from a college. We fit the data of first 7 years as the samples set and get the fitted values. The other data of next 3 years are compared with the predicted values.

We fit the data and get the fitted values. Then we calculate the error of the two columns of the values. The results are as shown in Table 2.

TABLE 2 The error of the actual values and the fitted values

N7	Year	Actual values	Fitted values	Error
1	2001	413	413	0.00%
2	2002	495	479	-3.23%
3	2003	560	540	3.59%
4	2004	532	538	1.21%
5	2005	581	584	0.516%
6	2006	627	635	1.2%
7	2007	663	661	-0.302%

Form Table 2, we can find that the actual values and the fitted values are almost the same. The fitting effect is good. From the 7 samples, we see that the most error is 3.59% and the error becomes smaller as the number of the samples increases. The fitting of the data achieves a good result. So, we can make prediction next.

As the good result of fitting data, we predict the values for next 3 samples by $GM(1,1,t^{\alpha})$ model. Then, we calculate the error between the actual values and the predicted values. The results are shown in Table 3.

TABLE 3 The error of the actual values and the fitted values

N3	Year	Actual values	Predicted values	Error
1	2008	742	748	0.808%
2	2009	859	864	0.58%
3	2010	916	927	0.10%

From Table 3 we can see that the actual values and the predicted values are exactly similar. This means that the prediction has obtained the good effect. The $GM(1,1,t^{\alpha})$ model applying to the aerobics performance prediction is feasible and effective.

7 Conclusions

The computer technology and the network technology become more and more popular. These technologies are applied to many fields, including the college sports information management system. Colleges introduce this system to manage the information and the students better. Through college sports information management system, it is convenient for students to select or deselect the courses before deadline, especially the sports elective course.

The main objective of the sports elective course is to improve the physical quality while its primary means is the physical exercise. Due to the uncertainty of enrolment, the institutes and the teachers could not arrange the rational curriculum planning. In order to forecast the number of the elective courses, we do below work:

1) we propose the Grey prediction model with time parameter;
2) we also study the constructing mechanism and the model characters;
3) we apply this model in college information management system. The experimental results show that this method has high accuracy. It also has a broad application and a practical background.

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