The Metabolism Grey Prediction Model Based on Big Data and Internet of Things Technology

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In view of the uncertainty and diversity of the metabolic grey prediction model in the prediction process, resulting in poor prediction effect, a metabolic grey prediction model based on big data and Internet of things technology is constructed.

Establish the aerobic metabolic process of human telecontrol and put forward the detection index of aerobic metabolic cycle function in human telecontrol; on this basis, use the metabolic grey prediction model analysis algorithm to determine the active intrusion intention of complex network, establish the intrusion intention attack behavior set function, establish the internal operation architecture under the technology of big data and Internet of things, and realize the construction of metabolic grey prediction model. The experimental results show that the constructed model can realize data prediction, with high confidence level and good effect.

1. Introduction

Metabolism includes material metabolism and energy metabolism. It is composed of two opposite and simultaneous processes: assimilation and alienation. Assimilation and alienation have obvious differences and close relations. Without assimilation, organisms cannot produce new protoplasm and store energy, and alienation cannot be carried out. On the contrary, if there is no alienation, there can be no energy release, and the material synthesis in organisms cannot be carried out. It can be seen that assimilation and alienation are both opposite and unified, which jointly determine the existence and continuity of organisms. In the long-term evolution process, organisms constantly interact with their environment and gradually form different types in the way of metabolism. Therefore, assimilation is a process of absorbing energy. For example, green plants use photosynthesis to convert water, carbon dioxide, and other substances in the environment into starch, cellulose, and other substances. On the contrary is alienation, that is, from the body to the external environment, the process of substances from macromolecules to small molecules is a process of releasing energy and expelling substances that organisms do not need or cannot use. The grey metabolism model is a constantly consider new information prediction model, it considers the over time one after another into the system, the effects of disturbance factors, at the same time of constantly added new information, get rid of old information in time, and make the whole system updated and the development process, more in line with the change of real world [1]. It can not only give full play to the advantages of traditional prediction models that only use a small amount of data [2, 3] but also reflect the changing trend of data, so as to further improve the accuracy of prediction results.

Big data refers to the data set that cannot be captured, managed, and processed by conventional software tools within a certain time range. It is a massive, high-growth, and diversified information asset that requires a new processing mode to have stronger decision-making ability, insight, and discovery ability and process optimization ability [4, 5]. Big data has 5 V characteristics: volume, velocity, variety, value, and veracity. Big data itself is an abstract concept [6–8]. Relying on the development of the Internet and cloud computing, big data plays an increasingly important role in the modern economy.
role in all walks of life [9]. The Internet of Things is the Internet of everything, namely, the Mobile Internet, which is no longer the link between people but machine to machine, device to device, and system to system [10]. In this regard, reference [11] proposed using big data to guide better nurse allocation strategies, using machine learning method to predict hospital discharge, discrete event simulation model to determine the needs of nurses in neonatal ICU, and using machine learning and hierarchical linear regression to connect the changing nurse allocation with the results of patients. This new study applied a unique Monte Carlo simulation model to estimate nursing needs and test different strategies to meet needs. Reference [12] proposed the mortality, disability, and recurrence rate after the first stroke, which is a study from the Chinese stroke big data observation platform. Stroke mortality, disability, and recurrence rates were investigated 12 months after the first stroke, a prospective cohort study based on national hospitals. The intravenous thrombolysis rate was 9.5%, and the intravascular treatment rate was 4.4%. The results support the hypothesis that the prognosis of stroke patients in China seems to have improved, not very bad.

Although the above research has made some progress, it is not suitable for newborn metabolism prediction. Therefore, a metabolism grey prediction model based on big data and Internet of things technology is proposed. Big data can be understood as a resource or asset. With the increasingly powerful processing capacity of computers, the more data can be obtained, and the more value can be mined. The Internet of Things is also the most critical link in an intelligent society, but it is often ignored by people. As the terminal closest to users, it is not only the front line for collecting large-scale and multidimensional user data but also the window and bridge for the effects of technology to be feedback to user experience. Big data and the Internet of things sound like them knowing you cannot have them, very “tall” smart technology, but it is closely related to many aspects of our social life, and it works from the institute to the life in every scene, related to the business analysis, data analysis, data mining, machine learning, artificial intelligence, and other fields, from pure technical research to specific application. Smart technology is everywhere. Using big data and Internet of Things technology to build a grey prediction model of metabolism has good performance.

2. Analysis of Aerobic Metabolic Function of Human Exercise

2.1. Human Telecontrol Aerobic Metabolic Process. The process of human telecontrol is mainly aerobic metabolism. Aerobic metabolic exercise refers to the endurance exercise and exercise for the purpose of enhancing human oxygen inhalation, oxygen transmission, and oxygen metabolism. The benefits of aerobic metabolic exercise are as follows: it can gradually increase the amount of oxygen absorbed by the human body during exercise. In the metabolic process, it can better consume the excess heat in the human body, so as to metabolize the excess heat in the body. In other words, in the process of human telecontrol, the amount of oxygen inhaled by the human body is basically equal to the amount of oxygen required, so as to achieve physiological metabolic balance in the process of circulation. Therefore, aerobic metabolic exercise is characterized by rhythm, uninterrupted, and long duration. Predict the data transmission according to the data transmission mode of the rule base. Construct the human telecontrol aerobic metabolism scheme and set the metabolic structure, as shown in Figure 1.

According to Figure 1, in the process of human telecontrol, aerobic metabolism is mainly the metabolism of glucose. The glucose stored in human body forms 6-P glucose through metabolic reaction with ATP and then reacts with NADP to form 6-P gluconic acid. After dehydration, it forms the intermediate 2-keto-3-deoxy-6-phosphogluconic acid and finally forms pyruvate ×2.

Pyruvate, as a main product of metabolism, can form the energy required by human functional exercise through subsequent aerobic metabolism. Through the metabolic reaction with a variety of human substances, the energy required for human movement is finally formed. The key to aerobic metabolic exercise is to master the appropriate amount of exercise, which requires not only certain competition and exercise intensity but also continuous metabolic ability.

2.2. Detection Index of Aerobic Metabolism and Circulation Function in Human Telecontrol. Based on the above analysis of aerobic metabolism process in human telecontrol, through comprehensive modeling and analysis of various factors affecting aerobic cycle metabolism in human telecontrol, a dynamic balance model of aerobic metabolism and supply is constructed to provide guidance for aerobic metabolism analysis of human telecontrol.

Based on the analysis model, the parameters affecting aerobic exercise are analyzed. When analyzing the function of human telecontrol aerobic metabolic cycle, taking 10 domestic elite athletes as the object, through long-time team competition, physical index test, training intensity, and time analysis, the physiological index test database is constructed as the research data sample of this paper. It is assumed that there is a prediction data in the data sample, and the data is located in a level. Before the assumption of information data, the standard processing method is adopted to strengthen the processing of the assumption mode, and the scheme is formulated according to the set human telecontrol aerobic metabolism structure. The execution structure is shown in Figure 2.

According to Figure 2, adjust the structural fitting angle of demand prediction, control the demand of aerobic metabolic cycle function according to the angle information, check the consistency of the analyzed data, store the tested data in the model construction system, and wait for the subsequent model design operation.

In the process of team training and competition monitoring, parameter comparison research is mainly carried out on the athletes’ shortest aerobic metabolism time, aerobic metabolism efficiency, and aerobic metabolism ratio, in order to have a good measurement and calibration for the athletes’ metabolic process and metabolic ability. In the
process of aerobic metabolism, various parameters mainly have the following functions:

1. The shortest aerobic metabolic time: it mainly reflects the time for athletes to change from anaerobic metabolic state to aerobic metabolic state and reflects the adaptability of athletes to the environment.

2. Efficiency of aerobic metabolism: it reflects the efficiency of different athletes' bodies in converting substances into energy under the condition of the same amount of oxygen inhalation. The higher the efficiency, the stronger the ability of metabolism.

3. Aerobic metabolism ratio: in the whole metabolic process, the ratio between aerobic metabolism and anaerobic metabolism reflects the composition and distribution of athletes' metabolism.

Based on the detailed test of the above indexes, the metabolic grey prediction model is constructed, and the aerobic metabolic cycle function in human telecontrol is analyzed through the evaluation of functional index. Through the above analysis, it can be seen that in the process of human telecontrol, with the process of long-distance running, irregular attenuation of respiration occurs, and the process of aerobic exercise is mixed with irregular anaerobic exercise.

2.3. Metabolic Grey Prediction Model Analysis Algorithm. Through the construction of the above human telecontrol aerobic metabolic function and evaluation parameter index system, the original sample data of athletes' aerobic metabolic function analysis and evaluation index [13, 14] are obtained. Based on the analysis method of metabolic grey prediction model, the athletes' aerobic metabolic cycle function is analyzed, and the decline characteristics of the model are used to characterize the aerobic metabolic consumption. Taking the shortest aerobic metabolism time, aerobic metabolism efficiency, and aerobic metabolism ratio as the model input parameters, the model input matrix of three parameters is constructed as follows:

\[
K_{mn} = \begin{bmatrix}
k_{11} & k_{12} & k_{13} \\
k_{21} & k_{22} & k_{23} \\
k_{31} & k_{32} & k_{33}
\end{bmatrix}.
\]

In formula (1), \(k_{11}\) represents the autocorrelation characteristic of the shortest aerobic metabolism time, \(k_{22}\) represents the autocorrelation characteristic of the effective rate of aerobic metabolism, and \(k_{33}\) represents the autocorrelation characteristic of the rate of aerobic metabolism.

The autocorrelation characteristics of the input parameters of the model characterize the stability of the model. Based on the construction of the input parameter matrix, the metabolic grey prediction model equation is obtained as follows:

\[
A_{hc} = \begin{bmatrix}
0.85 & 0.85/z_1 & 0.85/z_2 \\
1.00 & 1.00/z_1 & 1.00/z_2 \\
0.95 & 0.95/z_1 & 0.95/z_2
\end{bmatrix}.
\]

In formula (2), \(A_{hc}\) represents the characteristic equation of metabolic grey prediction model, \(z_1\) represents the correlation distance between the shortest aerobic metabolic time and aerobic metabolic efficiency, and \(z_2\) represents the correlation distance between the shortest aerobic metabolic time and aerobic metabolic ratio. The analysis process of metabolic grey prediction model is as follows:

Step 1. Initialize \(D_{dd}\):

\[
D_{dd} = \begin{bmatrix}
d_{11} & d_{12} & d_{13} \\
d_{21} & d_{22} & d_{23} \\
d_{31} & d_{32} & d_{33}
\end{bmatrix}.
\]

In formula (3), \(D_{dd}\) represents the fading factor matrix of the metabolic grey prediction model. The three autocorrelation characteristics in the matrix correspond to the parameter fading autocorrelation characteristics of the shortest aerobic metabolism time, aerobic metabolism efficiency, and aerobic metabolism ratio.

Step 2. Calculate the parameter matrix \(M\) in the grey prediction model of metabolism:

\[
M = D_{dd} \times A_{hc}.
\]

Step 3. In the metabolic grey prediction model, move forward along the same column according to the matrix distribution characteristics of the model [15, 16].

Step 4. Move to an adjacent column and calculate the fading characteristic factor of the metabolic grey prediction model, expressed as

\[
R_{ER} = S \times M \times \theta.
\]
In formula (5), $S$ represents the fading factor of the metabolic grey prediction model, and $\theta$ represents the fading parameter distribution domain of the metabolic grey prediction model;

Step 5, According to the model fading factor calculated above, move to two adjacent columns. After the new value in the model is updated, the new value represents the aerobic metabolic consumption of the current athlete [17].

Step 6, Calculate the aerobic metabolic recovery of athletes according to the recovery characteristics of fading factors and get

$$
\lambda = R_{ER} \times M + (1-R_{ER}) \times (1-M). \tag{6}
$$

In formula (6), $\lambda$ represents aerobic metabolic function index, that is, the output parameter of metabolic grey prediction model.

To sum up, by constructing the metabolic decline characteristics, take the shortest aerobic metabolism time, aerobic metabolism efficiency, and aerobic metabolism ratio as the input parameters of the metabolic grey prediction model, take the overall aerobic metabolic function index as the model output parameters, represent the aerobic metabolic consumption through the decline characteristics, and reflect the final aerobic metabolic balance through the aerobic metabolic function index.

### 3. Realize the Metabolic Grey Prediction Model Based on Big Data and Internet of Things Technology

#### 3.1. Internal Operation Architecture under Big Data and Internet of Things Technology

Under the technology of big data and Internet of things, in the process of metabolic prediction of human function, first determine the active intrusion intention of complex network [18–20], establish the set function of intrusion intention and attack behavior, and estimate the diffusion equation of active intrusion metabolism of complex network on this basis. Based on the diffusion equation, a grey prediction model of active intrusion metabolism in complex networks is constructed [21, 22].

Assuming that the metabolic diffusion feature extracted under the active intrusion of complex network is $\alpha$, the state of metabolic diffusion under the active intrusion of complex network is

$$
G_s = \frac{\beta(M_i) \times \beta_n(M_i)}{\text{con} \alpha}. \tag{7}
$$

In formula (7), $M_i$ represents the weight coefficient of each metabolic diffusion feature, and $\text{con} \alpha$ represents the observation sequence of metabolic diffusion state under complex network intrusion [23], which needs to meet the conditions of $i = 1, 2, 3, 4 \cdots$

According to the conclusions drawn from the above process, a grey prediction model of active intrusion metabolism in complex networks is constructed [24, 25]. At the same time, build the internal operations architecture, as shown in Figure 3.

According to Figure 3, in the internal operation architecture, the division of modules is not arbitrary, but should follow a certain principle, and the internal correlation of modules should be as close as possible. In this way, the divided modules have a certain independence, so as to reduce the complex calling relationship between modules and make the structure of the operating system clear. The internal parts of the module are closely linked, so that each module has independent functions.

#### 3.2. Construction of the Metabolic Grey Prediction Model

In the process of constructing the metabolism grey prediction model, based on the evaluation results of the complex network active intrusion metabolism diffusion process [26], the state transition probability value of the complex network active intrusion metabolism in the diffusion process is calculated by means of probability reasoning [27, 28]. The basic principle of time series prediction is based on the trend prediction principle. The grey prediction theory is established by using the methods of “accumulation” and “subtraction.” When there is no obvious trend in the time series, the accumulation method can be used to generate the time series with obvious trend. According to the growth trend of the series, the prediction model can be established, the influence
of grey factors can be considered for prediction, and then the “subtraction” method is used for inverse operation to restore the original time series. Based on the prediction results, a grey prediction model of active intrusion metabolism in complex networks is constructed.

Let the weight coefficient between the $j$-th complex network active intrusion metabolism diffusion state and the $i$-th diffusion direction be $D_{ji}$, and the connection parameter between the $j$ complex network active intrusion metabolism diffusion state and the $i$ diffusion direction be $E_{ji}$. Define the diffusion direction of the new generation of complex network active intrusion as

$$O = \frac{D_{ji}}{\sum_{j} D_{ji}} \times \frac{E_{ji}}{\sum_{j} E_{ji}} \times Q_j \times P_i.$$  

(8)

In formula (8), $Q_j$ represents the initial state probability distribution value in the metabolic diffusion process of active intrusion of complex network, and $P_i$ represents the metabolic diffusion random variable under active intrusion of complex network.

Let the transfer function of metabolic diffusion under active intrusion of complex network be $M_{sz}$, and the calculation formula is

$$M_{sz} = \frac{I - 1}{\sum_{j=2}^{l} f_j \times g/O}.$$  

(9)

In formula (9), $l$ represents the number of metabolic diffusion samples under complex network active intrusion, $f_j$ represents the belief conversion function of metabolism under complex network active intrusion, and $g$ represents the direction of metabolic diffusion under complex network active intrusion [29, 30].

In the process of constructing the metabolic grey prediction model of complex network active intrusion, it is assumed that $C_1$ and $C_2$ represent the compensation coefficient of metabolic diffusion prediction samples under complex network active intrusion, $x_{max}$ represents the maximum empirical weight of metabolic diffusion dependence under complex network active intrusion, and $x_{min}$ represents the minimum empirical weight of metabolic diffusion dependence under complex network active intrusion.

If the conditional probability change process of metabolic diffusion under active intrusion of complex network is stable to the direction set potential in a limited time [31, 32], the joint distribution probability of metabolic diffusion of active intrusion of complex network is obtained as follows:

$$G_{yy} = \frac{C_1 \times C_2 \times x_{min}}{x_{max} \times I_{1 \text{ max}}},$$  

(10)

In formula (10), $I_{1 \text{ max}}$ represents the observation function of metabolic diffusion under active intrusion of complex network. The objective function of metabolic diffusion of active intrusion of complex network is calculated by formula (11). The formula is

$$Z_{mb} = \arg \max \frac{Z(t) \times p_a \times P}{Z(t-1)}.$$  

(11)

In formula (11), $Z(t)$ represents the diffusion direction of complex network active intrusion metabolism at time $t$, $p_a$ represents the diffusion state set of complex network active intrusion metabolism, $P$ represents the diffusion direction set of complex network active intrusion metabolism, and $Z(t-1)$ represents the new direction of complex network active intrusion metabolism diffusion state $t - 1$ [33, 34].

According to the derivation of the above process, a grey prediction model of active intrusion metabolism in complex networks is constructed, which is expressed as

$$M_X = \arg \max P(Z_{mb}) \times G_{yy}.$$  

(12)

To sum up, by determining the set function of active intrusion intention and attack behavior of complex networks, the metabolic diffusion process of active intrusion of complex networks is estimated [35, 36]. Based on the evaluation results of metabolic diffusion process of active intrusion of complex networks, a grey prediction model of active intrusion metabolism of complex networks is constructed, and the construction of metabolic grey prediction model based on big data and Internet of things technology is realized.

4. Experimental Analysis

In order to verify the effect and feasibility of metabolic grey prediction model based on big data and Internet of things technology, simulation experiments are set up. The coding of the experiment is realized by MATLAB R2016a software platform. The hardware environment adopts Intel Core i5-3570 model 3.4GHz processor, and 8 GB installed memory, and the operating system is 64 bit Windows7 flagship. The simulation tool for data information processing is implemented in C++. 100 nodes are randomly deployed in the grey prediction model to collect metabolic information. The coverage of each sensor node is 0.93, the fixed delay of wireless sensor network routing transmission is 1.5 ms, the output carrier frequency is 6.8 kHz, and the data size is

![Figure 3: Internal operations architecture.](image-url)
Other experimental parameters are set as shown in Table 1.

Set the experimental scenario according to the parameters in Table 1 and fix the metabolic information within the prediction range of the model to prevent experimental errors caused by too small prediction range. At the same time, strengthen the prediction management of metabolism, adjust the allocation principle, execute the final prediction instruction, obtain the required prediction result data, and extract the demand analysis performance data from the prediction result data. The operation process of MATLAB software is shown in Figure 4.

According to the parameter setting in Table 1 above and the experimental operation flow in Figure 4, the metabolic grey prediction model is verified, and different methods are tested for metabolic topological grey prediction. Taking reference [11] and reference [12] as comparison methods, the confidence interval distribution of metabolic topological grey prediction is obtained, as shown in Figure 5.

According to the analysis of Figure 5, the grey prediction of metabolic topology is carried out by the model in this paper. The confidence level of data prediction realized by sensor nodes is high and has good effect, while the prediction effect of reference [11] and reference [12] is relatively poor. The reason is that this model establishes the process of human telecontrol aerobic metabolism, which can gradually increase the amount of oxygen absorbed by the human body during exercise. In the process of metabolism, it can better consume the excess heat in the human body and metabolize the excess heat in the body, so as to enhance the level of confidence.

In order to further verify the effect of the model in this paper, taking the training and competition data of 10 athletes as the data basis for the analysis of metabolic grey prediction model, the data test and result analysis were carried out. The follow-up data statistics of half a year are adopted. The interval of each test is no less than 2 hours, and each test is carried out three times, aiming at the differences caused by gender and age. The correction factor method is used to correct the error caused by individual differences, and the detailed data distribution is shown in Table 2.

Based on the sample data in Table 2, the metabolism grey prediction model function analysis experiment of aerobic metabolic function is carried out. From the experimental results and data analysis in Table 2, it can be concluded that the shortest aerobic metabolism time of male athletes is shorter than that of female athletes, mainly because men store more energy; so, anaerobic exercise is more developed. The aerobic metabolic rate varies greatly due to individual differences, which is the representation of the overall metabolism of athletes, through statistical analysis software SPSS 10.0. Different parameters are processed to obtain the correction factors under different individual differences. The results are shown in Table 3.

The unified results of aerobic metabolic function under the grey prediction model are obtained through the correction factors, as shown in Table 4.

The aerobic metabolic function of 10 athletes is analyzed by metabolic grey prediction model, and multistep iteration is carried out to obtain the error convergence curve of aerobic metabolic function analysis, as shown in Figure 6.

<table>
<thead>
<tr>
<th>Table 1: Experimental parameters.</th>
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<tbody>
<tr>
<td>Project</td>
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<td>Forecast data</td>
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<td>Database</td>
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<td>Characteristic factors</td>
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<td>Algorithm management</td>
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<td>Prediction network</td>
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1200 bytes. Other experimental parameters are set as shown in Table 1.

Set the experimental scenario according to the parameters in Table 1 and fix the metabolic information within the prediction range of the model to prevent experimental errors caused by too small prediction range. At the same time, strengthen the prediction management of metabolism, adjust the allocation principle, execute the final prediction instruction, obtain the required prediction result data, and extract the demand analysis performance data from the prediction result data. The operation process of MATLAB software is shown in Figure 4.

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The aerobic metabolic function of 10 athletes is analyzed by metabolic grey prediction model, and multistep iteration is carried out to obtain the error convergence curve of aerobic metabolic function analysis, as shown in Figure 6.

![Figure 4: Operation flow of MATLAB software experiment.](image-url)
It can be seen from Figure 6 that the error of aerobic metabolic function analysis converges rapidly and has good applicability to different individual differences, indicating that the constructed metabolic grey prediction model analyzes the characteristics of athletes’ aerobic metabolic function, and the model has good robustness.

To sum up, the accuracy of the metabolic function prediction of athletes can be achieved based on the high reliability of the Internet of things, and the reliability of the metabolic function prediction based on grey technology is good in the current application of the Internet of things.

5. Conclusions and Prospects

5.1. Conclusions

(1) The sensor nodes of the metabolism grey prediction model designed based on big data and Internet of Things technology achieve a high level of confidence in data prediction and have good effects

(2) The ratio of oxygen metabolism varies greatly with individual differences

(3) The metabolic grey prediction model was established to analyze the aerobic metabolic function characteristics of athletes, and the model had good robustness

5.2. Prospects

(1) The next step is to promote the feedback regulation of human metabolism through aerobic exercise training, so that more oxygen can be delivered to brain cells in time. Aerobic exercise can improve the level of human metabolism, effectively increase the fat burning rate, ensure the effective operation of body functions, and ensure that the body is in a healthy state

(2) Due to the reduced ability of human body to secrete antioxidants and enzymes, the level of free radicals in the body increases. Lipid alcohols such as triglycerides are easy to combine with free mineral ions in
the body, forming diseases such as obesity and hyperthyroidism. The future research content needs to carry out fat burning through aerobic exercise to promote human metabolism. In the process of aerobic exercise, skin blood vessels contract sharply, and a large amount of blood is sucked into internal organs and deep tissues to enhance human metabolism

(3) Carrying out aerobic metabolism training can improve human endurance and impact explosiveness, guide scientific group training based on metabolic grey prediction model, and promote the coordinated development of human aerobic metabolism and anaerobic metabolism, so as to improve the level of physical health

Data Availability

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Conflicts of Interest

The authors declared that they have no conflicts of interest regarding this work.

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