

Nonlinear kinetic modeling of training load and recovery cycle in martial arts sparring athletes

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ABSTRACT

The monitoring of training load and recovery cycle of Wushu Sanshou athletes is a long-term and fundamental work for sports teams. The article introduces the parameters of resting heart rate, ventricular muscle contractility, arterial wall and maximal oxygen uptake VO_{2max} as monitoring indexes, and designs a real-time monitoring method of physical training load data based on graph convolution network. Subsequently, through the flow level variables (BFL, TLQ, BRQ), flow rate variables (BFLI, BFLD, TLQI, BRQI), auxiliary variables (TT, TI, RT, RM), exogenous variables (RYN), and the causal relationship between the elements of each variable of the Wushu sparring training function monitoring system, we constructed a nonlinear system of the training load and recovery cycle of the Wushu sparring athlete Dynamics model. Using the real-time monitoring model of this paper to monitor the wushu sparring athletes, in the third minute of the experiment, the real-time monitoring system predicted that the heart rate was 90, and the adjusted heart rate using the model of this paper was 90, which was consistent with the actual monitored heart rate. It can be concluded that the model of this paper can well monitor the training load of martial arts sparring athletes. Through experimental simulation, the article concludes that both the strong physical fitness program and the strong training program can be beneficial to the training of wushu sparring athletes.

Keywords: graph convolutional network, training load, recovery cycle, nonlinear kinetic modeling

1. Introduction

Sanda sport is a non-periodic physical fitness program, which is a modern competitive sport of unarmed confrontation using the techniques of kicking, hitting, wrestling and corresponding defense in martial arts according to certain rules [1-2]. With the continuous improvement of the level of Sanshou sports, the gap between excellent athletes is getting smaller and smaller [3]. Modern competitive sparring is a very intense confrontational sport, and good physical condition of athletes is a prerequisite for giving full play to technical and tactical levels and achieving excellent results [4-5].

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Specialized training of large load sparring is an important form of training before sparring competition, and its effect will directly affect the functional state before the competition [6-7]. Therefore, it is of great practical significance to make scientific and reasonable evaluation of the load of large-load sparring special training.

Physical fitness refers to the basic athletic ability of the athlete's organism, which is one of the important components of the athlete's competitive ability [8]. The physical fitness of a sparring athlete consists of several aspects of his/her body form characteristics, body function level and the use of sports quality [9]. The body form of a sparring athlete refers to the internal and external shape of the athlete's body (composed of height, arm length, etc.). Body function refers to the function of each organ system of the body, and the level of body function mainly includes the function level of the internal organ system and the fatigue resistance and recovery ability of the body to withstand large-load exercise [10-11]. Sports quality refers to the athletes in the confrontation of a variety of sports capabilities, including speed, strength, endurance, sensitivity, flexibility and coordination. Good physical fitness quality in sporadic sports is the basis for technical and tactical training and improving athletic performance, enduring large-load training and high-intensity matches, as well as maintaining a stable and good psychological state in intense competition, which helps to prevent diseases and prolong the athletic life [12-14].

Modern sparring sports have higher and higher requirements for the comprehensive quality of athletes, physical fitness as the basic quality of athletes to play technical and tactical level, only through scientific, reasonable and systematic training, can it be improved continuously, so that the athletes can fully exert the advantages of technology and tactics in the fierce competition, play their own strengths, and finally defeat the opponent and win the game [15-18].

The article firstly proposes a real-time monitoring method of physical training load data based on graph convolutional network, introduces the parameter index system of resting heart rate, ventricular muscle contraction force, arterial wall, etc., combines with the characterization of load parameters such as maximal oxygen uptake VO_{2max} and so on, obtains the characteristic distribution model of the training load data of the wushu sporadic athlete, and realizes the monitoring of training load data of the wushu sporadic athlete. Subsequently, the real-time monitoring method of training load data proposed in this paper was tested experimentally. Then the nonlinear system dynamics model D1 design of the training load monitoring and recovery cycle of martial arts sparring athletes is carried out. On the basis of analyzing the feedback mechanism of the constituent elements of the sports training function monitoring system, the kinetic flow diagram of the training function monitoring system of martial arts sparring athletes is established to realize the simulation and regulation of the training function monitoring of martial arts sparring athletes. Finally, simulation experiments are carried out on the nonlinear dynamics model proposed in the article.

2. Methods for real-time monitoring of training load data for martial arts sparring athletes

2.1. Training load data information distribution and constraint indicators

2.1.1. Distribution of training load data information. In order to realize the real-time monitoring of training load data based on graph convolutional network, the joint feature distribution structure model of constraint variables and explanatory variables of training load data is constructed, the data characterization is carried out by using the method of on-line monitoring of cardiorespiratory function parameters, and the feature analysis model of training load data is constructed, and the parameter index system of resting heart rate, ventricular muscle contraction force, and arterial wall is introduced, combined with the maximal oxygen uptake VO_{2max} and other load parameter characterization, to get the characteristic score of training load data [19], the characteristic distribution of training load data is shown in Figure 1.

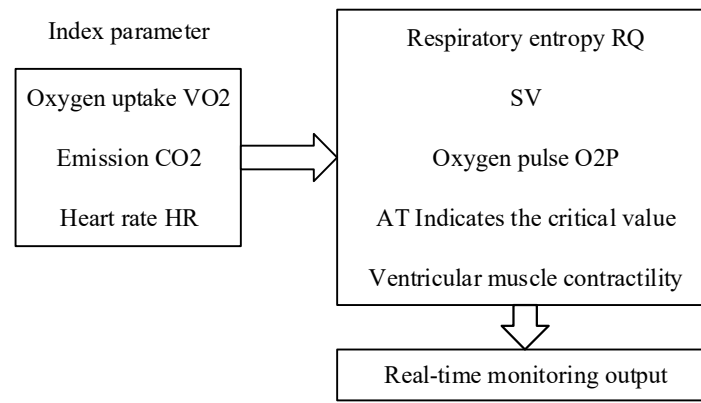


Fig. 1. Characteristic distribution of physical training load data

Using oxygen uptake VO_2 , CO_2 excretion, oxygen pulse O_2P , HR , SV , O_2P , AT threshold point, respiratory entropy RQ and ventricular muscle contractility as dependent scalars, a distribution model of the impact constraints on cardiorespiratory fitness is obtained, denoted as the model is:

$$RQ = \frac{VO_2}{SCO_2} \quad (1)$$

where, SCO_2 denotes the multi-sample fusion parameter for real-time monitoring of training load data, and the feature matching set indexed by principal component fusion and linear correlation decision making is obtained as the principal component information index of training load data:

$$S = \left\{ \frac{SCO_2 + 1}{OC}, \frac{SCO_2 + 2}{OC}, \dots, \frac{SCO_2 + n}{OC} \right\} \quad (2)$$

where, OC is the joint distribution coefficient for real-time monitoring of training load data, and redundant information filtering detection is used to obtain the undersampling resolution control parameter of training load data, which is output according to the maximum per-beat output to realize the output reliability constraint analysis of real-time monitoring of training load data.

2.1.2. Real-time acquisition of training load data. Construct the training load data real-time acquisition model, and the training load data real-time acquisition model is shown in Figure 2.

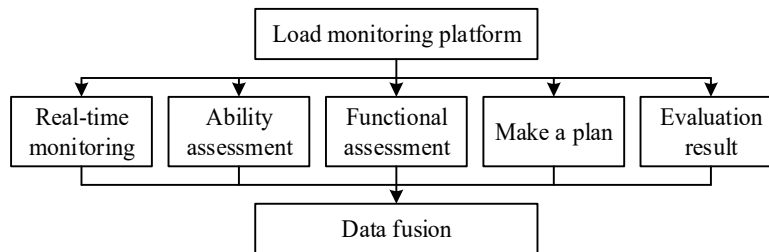


Fig. 2. Physical training load data real-time acquisition model

A regression sample fitting model of the training load data, expressed through clinical cardiopulmonary testing, was developed:

$$HR = 220 - Age \quad (3)$$

where Age is the age parameter, the maximum probability density feature analysis is used for nearest neighbor feature point matching of the training load data to obtain the statistical feature quantity for

training load data detection and fusion analysis as:

$$f_i(a, b, c) = [pc + (v_i + u_i)^2] \quad (4)$$

where $v_i + u_i$ denotes the weighting and pc denotes the test set of the training load data, the feature parameter scheduling set of the training load data is constructed under the steady state condition, and the distributed fusion of the training load data is carried out by the method of third-order autocorrelation feature matching to improve the detection and recognition ability of the training load data [20].

2.2. Optimization of real-time monitoring of training load data for martial arts sparring athletes

2.2.1. Training load data feature extraction. Different groups of physical function analysis methods are used to realize the lung function constraint parameter control and autocorrelation constraint detection of the training load data, deep learning and feature decomposition of the training load data are carried out, and the data fusion model of the training load data is constructed to obtain the multidimensional parameter detection model of the training load data as:

$$Bj = [(k(t) + 1), (k(t) + 2), \dots, (k(t) + n)] \quad (5)$$

where $k(t)$ is a discrete sample of training load data, and the regression analysis of the training load data is obtained based on the data fusion method of deep learning as:

$$S = \sum_{k=1}^{i=0} (k(t) - \omega_i(t))^2 + Bj \quad (6)$$

where $0 \leq \omega_i(t) \leq 1$. The stage involved in data fusion, based on quantitative lung function analysis, the threshold control model for training load data detection was obtained as:

$$g_{ic} = S(\beta_1, \beta_2, \dots, \beta_n) \quad (7)$$

Combined with the results of data fusion analysis, the correlation detection method of training load data was adopted, and the AT critical value point anaerobic valve was introduced to obtain the fusion rule model for real-time monitoring of training load data as:

$$E_2 = (g_{ic} + RQ)^2 \quad (8)$$

Dynamic data distribution for real-time monitoring of training load data is obtained by recording training monitoring results quickly and accurately in a timely manner.

2.2.2. Optimized output from real-time monitoring of training load data. Analyze the sugar fusion of the training load data in vivo, use the method of cardiovascular function as well as lung ventilation function exchange to realize the dynamic feature detection of the training load data, according to the results of the load test and metabolism analysis, get the feature extraction results of the training load data, and use the method of correlation dimension retrieval to establish the detection statistical feature quantity of the real-time monitoring of the training load data as:

$$U_{og} = (E_2(g_{ic} + k(t)) - Age) \quad (9)$$

The moments of the distribution of linearly mapped combinatorial features of the training load data are established, denoted as:

$$J = \left\{ \frac{Age}{U_{og}} + \frac{E_2}{RQ} \right\} \quad (10)$$

3. Practice of methods for real-time monitoring of training load data

3.1. Experimental results and analysis

3.1.1. Experimental setup. Using heart rate as the monitoring index, we focus on the dynamic feature extraction of load data and the synergistic optimization with real-time monitoring. Using a heart rate monitor as a sensor, real-time heart rate data of athletes were collected, and the acquisition frequency of the heart rate sensor was set to once per second to ensure high time-efficient monitoring of heart rate changes, and a 1-hour aerobic exercise experiment was conducted to simulate the training process. The time domain features such as the mean and standard deviation of heart rate per minute were extracted. Fourier transform was applied to extract the frequency domain features of the heart rate signal, such as the main frequency components.

3.1.2. Presentation and analysis of results. The real-time monitoring heart rate is the data obtained by performing the monitoring once in every minute, the model predicted heart rate is the prediction result obtained by the model of this paper, and the optimized adjusted heart rate is the heart rate adjusted under the guidance of the optimization algorithm. The output of the real-time monitoring system and the experimental results of this paper's model are shown in Table 1.

By extracting the time domain features, the mean and standard deviation of heart rate per minute were obtained. These features provide insight into the trend and volatility of heart rate changes. For example, in the first minute of the experiment, the mean value of heart rate was 78 and the standard deviation was 2, reflecting a more stable heart rate level. Extraction of frequency domain features through methods such as Fourier transform can reveal the frequency component of the heart rate signal. This is important for understanding the periodic fluctuations of heart rate and possible abnormalities.

The real-time monitoring system used in the experiment ensures that heart rate data is transmitted in real time at a frequency of once per second. This ensures that the system is able to respond quickly to physiological changes in the athlete. The user interface of the real-time monitoring system clearly displays information such as heart rate profiles and dynamic characterization charts. Trainers are able to visualize the athlete's physical condition and take timely action. By establishing a correlation model between dynamic features and real-time monitoring of heart rate, the system is able to adjust the model parameters in real time on the basis of continuous collection of feature data in order to more accurately predict the future state of heart rate. The genetic algorithm, as an optimization algorithm, is able to optimize the error between the predicted heart rate of the model and the actual monitored heart rate in the experiment. This makes the model's prediction more realistic. The results of the optimization algorithm were fed back to the trainer and the monitoring system through real-time adjustments. In the third minute of the experiment, the real-time monitoring system predicted a heart rate of 90, which was finally adjusted to 90 after the adjustment of the model in this paper, which was consistent with the actual monitored heart rate. From a general point of view, the synergistic effect of the dynamic feature extraction and the real-time monitoring system enables the wushu sparring trainer to have a more comprehensive understanding of the athlete's physical condition, and at the same time, through the real-time adjustment of the optimization algorithm, it realizes the precise adjustment of the training load and improves the training effect. This synergistic optimization method provides a more scientific and intelligent monitoring and adjustment means for training.

Table 1. The output of real-time monitoring system and the experimental results

Time (minute)	Real-time monitoring of heart rate	The model predicts heart rate	Optimize the recore rate after optimization
1	78	83	80

2	83	80	81
3	90	92	90
4	94	97	93
...	...	...	...
60	75	81	79

3.2. Empirical studies

3.2.1. Relevant studies on methods of objective monitoring indicators of training loads. The common monitoring method of Wushu Sanshou training volume is to count the time and distance of training, limited by the objective conditions, most researchers generally based on the training program to carry out the statistics of the relevant data, and a few researchers use tracking records of the actual training completed by the athletes. Regarding the monitoring of training intensity, at present, most of the countries with strong athletic strength have specialized load intensity evaluation standards. The division of training load intensity for martial arts sparring athletes is shown in Table 2. Based on the different energy supply substances and lactate values, the load intensity can be divided into five levels, which are anaerobic, oxygen transport, anaerobic threshold, oxygen utilization 1, and oxygen utilization 2. It is understood that the Chinese Wushu Sanshou team adopted the German Wushu Sanshou team's 6-level classification standard in the Beijing Olympic Games preparatory cycle, while the Italian 5-level standard was used in the Rio Olympic Games cycle.

Table 2. The training load intensity of martial arts disperser

Training load intensity	Energy type	Maximum heart rate%	Lactic acid(mmol/L)
Anaerobic	Glycogen	95-100	>7
Oxygen transport	Glycogen	90-95	4.5-7
Anaerobic threshold	Sugar Is The Main, Partial Fatty Acid	85-90	4.5
Oxygen utilization 1	Glycogen And Fatty Acids	75-85	2.5-4.5
Oxygen utilization 2	Fatty Acids, Some Of The Glycogen	60-75	0-2.5

Changes in physiology, athletic performance, and training loads were investigated in 20 wushu sparring athletes during 6 months of training. They were categorized into two stages: special preparation and domestic competition. The trends of external and internal loads in different stages are shown in Table 3. The external load was found to have a decreasing trend from phase 1 to phase 2, with durations and distances of 18.5 h and 147 km and 16.5 h and 125 km, respectively. On the contrary, internal load showed an increasing trend, elevating from 18 AU in phase 1 to 21.5 AU in phase 2. The study suggests that training load patterns can vary depending on the monitoring indicators and dimensions, and even yield diametrically opposed results, emphasizing the importance of monitoring both external and internal loads.

Table 3. External load and internal load trend at different stages

	Training time(h/week)	Training distance(km/ week)	Internal load(AU)
First stage	18.5	147	18
Second stage	16.5	125	21.5

3.2.2. Research on training load monitoring algorithms. In this experiment, the HR_{max} of each athlete was determined in a multistage load test, and the weekly training load was quantified using the debugged version of this paper's method based on the heart rate response and the duration of each training session, and the intensity intervals were continually adapted based on the heart rate data as the athlete's fitness improved and adapted to the load. The load fluctuations at different stages are shown in Table 4. Compared with training time, this paper's method can be more sensitive to recognize changes in training load.

Table 4. Different stages of load fluctuations

	Ours(AU)	Rowing(h week)	Resistance Training(h week)
T1	5220	78	23
T2	3895	75	25
T3	4850	77	24.5
T4	4100	76	25.5
T5	5788	79	20
T6	4800	74	28

4. System dynamics model analysis and design

4.1. General elements of system dynamics

4.1.1. Basic characteristics of system dynamics. System dynamics is based on the premise of the real world, through the system structure and function causality model, the design of feedback loops, and through computer simulation technology to carry out system analysis, system dynamics it has the following aspects of characteristics:.

- 1) The research object of system dynamics is mainly an open system. It emphasizes the viewpoint of system, connection, development and movement, and the system operation mode is determined by its internal dynamic structure and feedback mechanism.
- 2) The study of system dynamics deals with high-order, multi-variable, multi-time-varying complex systems, which can accommodate a large number of variables, generally up to thousands.
- 3) The modeling of system dynamics can be done by combining qualitative and quantitative simulation techniques. The structure of the system is recognized through a structural model that describes the causal relationship between the elements of the system.
- 4) The models established by system dynamics are canonical. The auxiliary equations may contain semi-quantitative, semi-qualitative or qualitative descriptive parts, but overall the model is canonical and the variables are categorized according to the composition of the basic structure of the system.
- 5) The modeling process of system dynamics takes advantage of the human capacity for analytical reasoning and evaluation of the system under study, and facilitates close integration between the modeler, the decision maker, and the system professional to achieve optimal or satisfactory decision making.

4.1.2. System dynamics modeling approach. The basic methods of system dynamics include causality, flow diagrams, equations, and simulation platforms. Variational equations for system dynamics:

- 1) Equation of flow level variables. The flow level variable equation is like a reservoir, which accumulates changing flow rates, with inflows causing an increase in the stock and outflows causing a decrease in the stock, and is generally represented by a difference equation:

$$LL.K = L.J + DT * (RA.JK - RS.JK) \quad (11)$$

The stream level equation essentially performs the operation of solving an integral, which can be expressed in integral form when the solution interval DT is partitioned to infinity:

$$L = L_0 + \int_0^t (RA - RS)dt \quad (12)$$

- 2) Flow rate variable equation. The flow rate equation is used to realize the control of physical flow within the system. The output of the flow rate equation controls the increase or decrease of the level variable and the physical flow between the individual flow level variables, which is a function of the stock and covariates with the general expression:

$$R \ R.KL = f(L.K, C) \quad (13)$$

- 3) Equations for auxiliary variables. The influencing factors of the flow rate variables are generally complex, and in practical systems, determining the flow rate equation with a single expression requires multiple layers of function nesting, which brings a great deal of invariance to the observation of the influence of external variables on the system [21-22]. Therefore, the rate equation is often decomposed into several independent equations, and the rate equation is supplemented by auxiliary equations.

- 4) Constant equations. The constant is the simplest form of the covariate in the system, which together with the stock determines the change in flow rate. The constant is expressed by "=", and the constant equation is to assign a value to the constant, and the generalized expression is:

$$C \ C_i = N_i \quad (14)$$

- 5) Table function. The table function generally relies on discrete points to operate, for some points not included in the table function, usually using linear interpolation method to obtain automatically.

6) Initial value equation. The initial value equation is to give initial values to the equations of the stream level variables and certain constants to be computed, and these initial values of the stream level variables determine the full state of the system required for the rate variable to change. It has a generalized expression:

$$NL_i = M_i \quad (15)$$

4.1.3. System dynamics modeling steps. The basic idea of the system dynamics modeling process is to first perform system analysis, build structural models through causality diagrams and flow diagrams, then build equation models, and then simulate and evaluate the models. The model building and simulation runs in this study apply Stella software system. Stella system is one of the dynamics modeling systems, which has a friendly graphical interface and contains 3 layers. The modeling flow of the system dynamics model is shown in Figure 3.

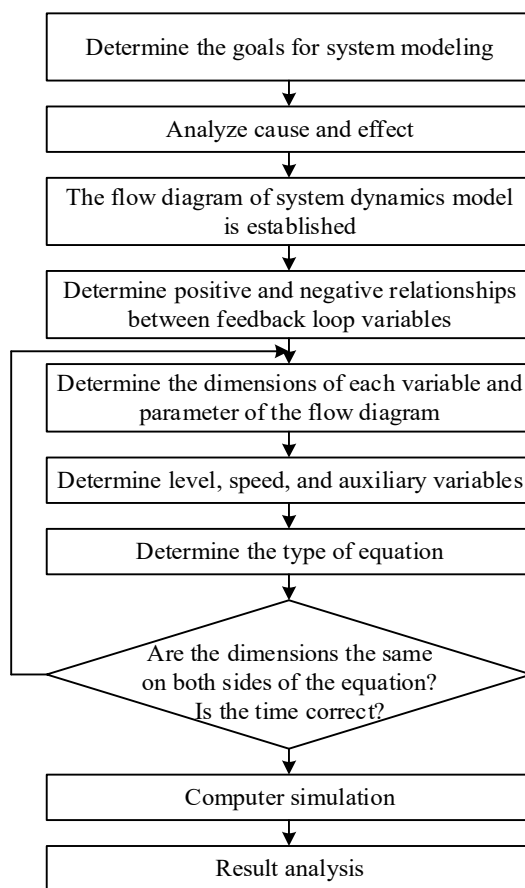


Fig. 3. Modeling process of system dynamics model

4.2. System boundary determination

The process of determining the boundaries of the system, i.e., the process of determining what important system elements the system contains. In terms of sports training function monitoring personnel, its organization includes: coaches develop and implement training plans based on training objectives. According to the training plan and arrangement of the coaches, the scientific research personnel formulate the corresponding function monitoring plan and monitor the athletes' function indexes with the actual situation of sports training and the arrangement of the events, and carry out systematic and individualized evaluation and analysis of the results of the monitoring. According to the arrangement of sports training and the injury characteristics of sports, the medical staff puts forward rationalized suggestions for the prevention of athletes' injuries, and actively diagnoses and

treats athletes' injuries and diseases. The organizational model of functional monitoring during sports training is shown in Figure 4.

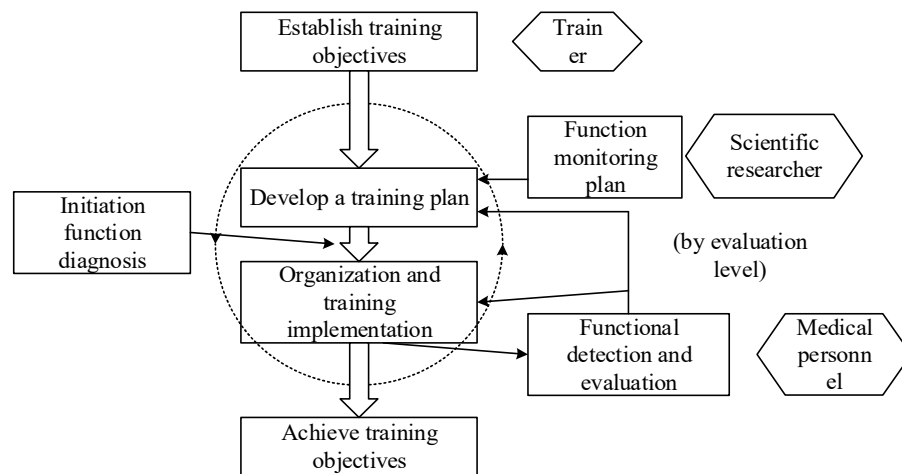


Fig. 4. Organization model of functional monitoring during exercise training

In order to make the simplification of the research problem, only three elements, function, training and recovery, which are most directly related to the monitoring of function, were selected in this study when defining the boundaries of the system. Athlete function is monitored through the system's dynamic changes of these three elements. The system structure of the sport training function monitoring components is shown in Figure 5.

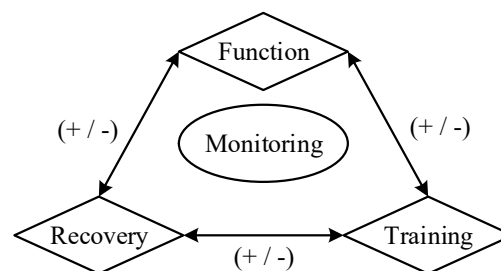


Fig. 5. Structure of functional monitoring system for sports training

4.3. System modeling

4.3.1. Determination of model variables. The model variables mainly include flow level variables, flow rate variables, auxiliary variables, additive variables, and exogenous variables. The flow level variables in this study mainly include functioning level (BFL), training volume (TLQ), and recovery volume (BRQ), flow rate variables mainly include increased functioning level (BFLI), decreased functioning level (BFLD), increased training volume (TLQI), and increased recovery volume (BRQI), auxiliary variables mainly include training time (TT), training intensity (TI), recovery time (RT), recovery measures (RM), and exogenous variables included recovery or not (RYN).

4.3.2. System model flow diagram. In the process of system modeling, it is also necessary to transform causality into system dynamics flow diagram, which is based on the causality diagram to further distinguish the nature of the variables, use more intuitive symbols to portray the logical relationship between the elements of the system, and make clear the form of the system's feedback and control law. The system flow diagram is mainly composed of symbols such as "flow level variable", "flow rate variable", "auxiliary variable", "exogenous variable" and "constant", which vividly reflects the system structure and dynamic characteristics.

The kinetic flow diagram of the athletic training function monitoring system is shown in Figure 6. The whole model consists of three flow level variables, four flow rate variables, eight auxiliary variables and graphical functions, and contains several system dynamics equations.

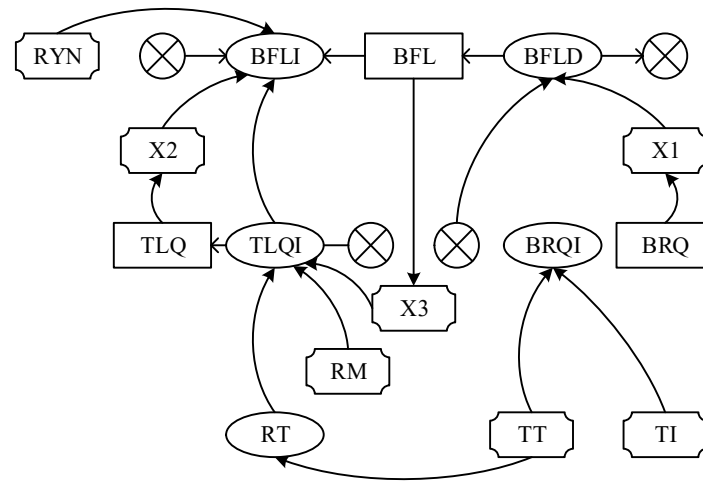


Fig. 6. Dynamic flow diagram of functional monitoring system for sports training

4.3.3. System dynamics equations. System dynamics equations are a set of mathematical relational equations that quantitatively describe the relationship between system elements on the basis of a flow diagram, which is a recursive relational equation that determines the next state from a known initial state. The system dynamics equations include: level equations, rate equations, auxiliary equations, constant equations, and initial value equations.

5. Simulation studies of nonlinear dynamics models

5.1. Data sources and parameterization

This experiment combines the cultivation cycle and characteristics of competitive sports talents, and sets the simulation base period of the simulation experiment as 2015, the simulation time as 2015-2035, and the step length as 1 year, to explore the simulation characterization of different modes, and to provide a reference for the cultivation of Wushu Sanshou athletes.

Main data sources: GDP, education expenditure, sports expenditure, sports education training expenditure, number of people and other data are mainly from the China Statistical Yearbook, China Sports Yearbook, mainly through the questionnaire survey, and the results of the survey were obtained by statistical analysis and collation. Then, based on the evaluation scale, experts were consulted for evaluation, and expert opinions were counted, and finally expert evaluation scores were integrated as the quantitative basis for the above auxiliary variables. As mentioned earlier, since the system dynamics simulation is mainly a simulation of the system development trend rather than a data operation, the data obtained by using part of the expert evaluation does not affect the effect of the simulation experiment.

5.2. System dynamics simulation analysis

5.2.1. Physical fitness-based programs. The simulation and analysis diagram of the strong physical fitness-based program is shown in Figure 7. Overall, the program can promote the training of martial arts sparring athletes to a certain extent, and the functional level (BFL), training volume (TQL), and recovery volume (BRQ) all show an upward trend. Locally, the upward trend of functioning level (BFL) was significantly higher than other state variables. This is mainly due to the fact that Program 1

emphasizes “functional level improvement” and tends to squeeze other time from high-level athletes to achieve rapid improvement in athletic training results. Although this model can quickly improve sports performance and obtain competitive benefits in the short term, the improvement of sports performance is mainly at the expense of the all-round development of high-level athletes in colleges and universities, resulting in the disconnection of “learning” and “training”, and the increasingly prominent contradiction between “learning and training”, showing a single and deformed development, and it is difficult to achieve long-term and sustainable development. In addition, the program places the recovery of high-level athletes on the back burner, making it difficult for high-level athletes to adapt to the increasingly complex technical and tactical demands of sports and slowing the development of outstanding athletic talent. In the end, the “watered-down diplomas” obtained through various point reduction policies make it difficult to adapt to the changing roles in society, thus affecting future employment. It can be seen that although the programme can achieve certain competitive benefits in a short period of time, such benefits are like drinking poison to quench the thirst and fail to realize the national goal of “cultivating athletic talents for all-round development”.

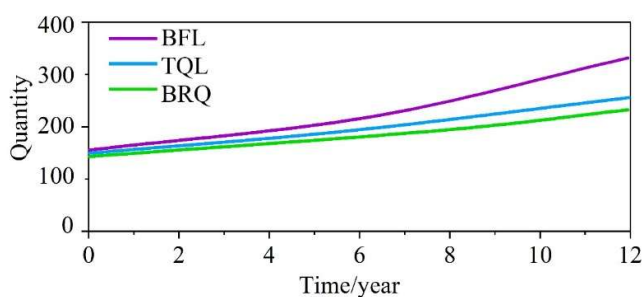


Fig. 7. Simulation chart

5.2.2. Strong training-based programs. The simulation and analysis diagram of regulating parameter program 2 is shown in Figure 8. Overall, Program 2 can promote the cultivation of wushu sparring talents, and the training volume (TLQ), functional level (BFL), and recovery volume (BRQ) all show an upward trend, but the enhancement is relatively slow. Locally, the trend of training volume (development trend is significantly higher than the trend of recovery volume). The reason for this is mainly due to the fact that Program 2 focuses on the importance of training and requires high-level athletes to follow the corresponding learning system for learning assessment. This training mode has improved the training level of high-level athletes to a certain extent. However, this training mode ignores the “special characteristics” of high-level athlete training, and the stereotyped learning system and excessive assessment requirements take up too much energy of high-level athletes, breaking the systematic and regularity of high-level sports training and competition, resulting in extremely slow improvement of sports performance.

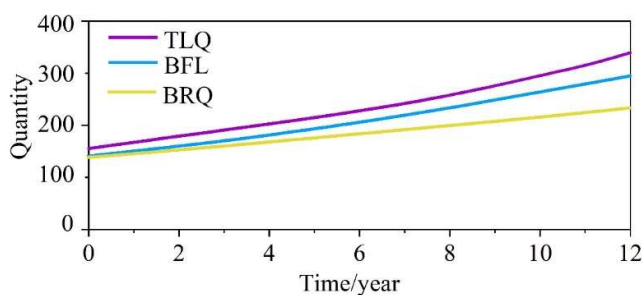


Fig. 8. Simulation chart

6. Conclusion

The article monitors the training load of Wushu sparring athletes through graphical convolutional networks, followed by the construction of a nonlinear dynamics model to further simulate different regulation parameter schemes, so as to better assist Wushu sparring athletes in sports training. The article draws the following conclusions:

At the third minute of the experiment, the predicted heart rate of this paper's model is 90, which is consistent with the actual monitored heart rate. From a general point of view, the real-time monitoring method proposed in this paper realizes the precise adjustment of training load and improves the training effect of martial arts sparring athletes.

Through the simulation experiment, it can be found that the two programs based on strong physical fitness and strong training are both healthy and scientific training modes. Under the premise of reasonable allocation of "learning and training time", the two programs can not only promote the rapid improvement of athletic performance, but also restore the physical fitness, and promote the number of excellent wushu sparring talents to continue to improve.

References

- [1] Teng, Y., Wu, H., Zhou, X., Li, F., Dong, Z., Wang, H., ... & Yu, Q. (2024). Neuropsychological impact of Sanda training on athlete attention performance. *Frontiers in psychology*, 15, 1400835.
- [2] Ren, Y. (2022). Training fatigue and recovery of Wushu Sanda athletes based on comprehensive environmental testing. *Applied Mathematics and Nonlinear Sciences*, 8(2), 845-856.
- [3] Ma, X., Sun, W., Lu, A., Ma, P., & Jiang, C. (2017). The improvement of suspension training for trunk muscle power in Sanda athletes. *Journal of Exercise Science & Fitness*, 15(2), 81-88.
- [4] Li, G., Wu, W., Zhen, K., Zhang, S., Chen, Z., Lv, Y., ... & Yu, L. (2023). Effects of different drop height training on lower limb explosive and change of direction performance in collegiate Sanda athletes. *Iscience*, 26(10).
- [5] Jin, X., & Gao, Q. (2017). Women's excellent sanda athletes' strength characteristics research. In 2016 National Convention on Sports Science of China (p. 01044). EDP Sciences.
- [6] Cho, E. H., Ko, B. G., Sung, B. J., & Lee, J. B. (2020). The comparative research of basic and professional fitness levels between national team taolu and sanda. *Korean Journal of Sport Science*, 31(2), 382-392.
- [7] Zhou, B. (2024). Sanda training program based on multi-sensor data fusion in the internet of things environment. *Internet Technology Letters*, 7(2), e470.
- [8] Jin, M. (2017). The promotion and development of martial arts sanda. In 2017 2nd international conference on education and education research (Eduer 2017) (pp. 504-507).
- [9] Bo, Y., Tao, Y., & Jiecai, Z. (2023). IMPACTS OF MUSCULAR STRENGTH TRAINING ON BOXERS' ENDURANCE. *Revista Brasileira de Medicina do Esporte*, 29, e2022_0516.
- [10] Fu, Z. (2024). Research on sanda in universities in healthy China. *Social Medicine and Health Management*, 5(1), 77-83.
- [11] Ma, J. (2017). The Research on the Application and Training Methods of Side Kick in Sanda. Executive Chairman.
- [12] Fu, Z. (2024). University Martial Arts Sanda: Developing Physical and Mental Balance. *Applied & Educational Psychology*, 5(2), 7-12.
- [13] Monteiro, J. R. F., Vecchio, F. B. D., Vasconcelos, B. B., & Coswig, V. S. (2019). Specific wushu sanda high-intensity interval training protocol improved physical fitness of amateur athletes': A pilot study. *Revista de Artes Marciales Asiáticas*, 14(2), 47-55.

- [14] Liu, Y, Li, L., Yan, X., He, X., & Zhao, B. (2023). Biomechanics of the lead straight punch and related indexes between sanda fighters and boxers from the perspective of cross-border talent transfer. *Frontiers in Physiology*, 13, 1099682.
- [15] Yao, S. (2021, February). RETRACTED: Analysis of Sanda Features Based on Big Data Analysis. In *Journal of Physics: Conference Series* (Vol. 1744, No. 3, p. 032220). IOP Publishing.
- [16] Yang, Y. (2023). Speed response after strength training in chinese boxing athletes. *Revista Brasileira de Medicina do Esporte*, 29, e2022_0661.
- [17] Jiang, X. (2023). High-intensity physical training for chinese boxing athletes. *Revista Brasileira de Medicina do Esporte*, 29, e2022_0600.
- [18] Zhang, Z., & Ding, Y. (2024). Application of Sanda-Assisted Teaching System Integrating VR Technology from a 5G Perspective. *International Journal of Advanced Computer Science & Applications*, 15(8).
- [19] Chinchin Wang, Jay S Kaufman, Russell J Steele & Ian Shrier. (2024). Target trial framework for determining the effect of changes in training load on injury risk using observational data: a methodological commentary.. *BMJ open sport & exercise medicine*(3),e002037.
- [20] Sakshi Taori & Sol Lim. (2024). Classification algorithms trained on simple (symmetric) lifting data perform poorly in predicting hand loads during complex (free-dynamic) lifting tasks.. *Applied ergonomics*104427.
- [21] Wei Han. (2024). Construction and analysis of dynamic model of discrete system of physical education teaching based on multi criteria side decision algorithm. *Advances in Computer, Signals and Systems*(1).
- [22] Beddoes Zack, Prusak Keven, Beighle Aaron & Pennington Todd. (2021). Utilizing School-based, Professional Learning Communities to Enhance Physical Education Programs and Facilitate Systems Change (Part 1). *Quest*(3),283-293.