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Modeling research on optimal allocation and regulation of exercise load parameters in physical fitness training combined with genetic algorithm

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SUMMARY: *In this research paper, the parameters of body ability training, that is, the quantity of exercise, the strength of exercise, the length of exercise, and the times of exercise, are defined by us as exercise load parameters. After that, we make use of the genetic algorithm to carry out the optimal distribution and adjustment of these parameters. An improved hybrid genetic algorithm (SGA) with global optimization capability was designed by combining the genetic algorithm with the simplex method, and the optimal allocation of exercise load parameters was optimally designed using this algorithm. Then NSGA-II was used as the basic search strategy to design a regulation model of exercise load parameters based on the feedback regulation mechanism. Finally, the two are combined to construct a physical fitness training prescription generation system that satisfies user preferences. It is verified that SGA and NSGA-II have better convergence and optimization performance than traditional genetic algorithms.The experimental class in University C followed the recommended program of the fitness training prescription generation system to teach physical education, and the cardiorespiratory fitness, muscular fitness, flexibility, and body composition of the experimental class changed significantly compared with that of the control class in the traditional teaching (P<0.05). 0.05).The outcome shows that the system which makes physical fitness training plans, that this paper develops by utilizing a genetic algorithm, has advantages for increasing the physical fitness of students.*

KEYWORDS: *SGA; NSGA-II; genetic algorithm; exercise load; regulation model; physical fitness training*

1 Introduction

Physical body health means the ability that human body has enough energy to finish daily work (or study) and does not have the feeling of tired out. Furthermore, this signifies the possession of an additional storage of vigor that permits individual persons to engage in amusement activities and deal with unexpected situations[1, 2]. Physical fitness training is the training to improve these abilities, including endurance training, strength training and flexibility training [3]. In physical fitness training, appropriate exercise loads can improve athletes' functional capacity and athletic performance [4]. Literature [5] emphasized the important role of load training in physical fitness training, showing that the quantification of training loads and training responses can help coaches to adopt training stimulus protocols, control stress levels, and thus improve athletes' competitive performance. Literature [6] examined the effects of load training on athletes in 1600m and 1800m races, and the experimental results pointed out that

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load training effectively improves athletes' performance, but the optimal time to compete after training varies from person to person, and is also affected by other factors.

However, in practice training, sports injuries are often caused by irrational arrangement of load parameters such as time, intensity and frequency of exercise [7, 8]. This is essentially caused by the coaches' failure to develop individualized training programs based on the athletes' own physical qualities. For this reason, literature [9] investigated the relationship between training load and musculoskeletal injuries and revealed, based on a literature review, that there is a correlation between training load and injury risk, with the subjective internal training load correlation being the most pronounced. Literature [10] demonstrated the current lack of clarity regarding the causal relationship between training load and the mechanisms of sports injuries and examined the relationship between specific training load metrics and measures, as well as the causal pathways of progressive and traumatic injuries. Literature [11] emphasized that training and competition loads are closely related to injuries, and based on this, proposed a model of injury etiology that includes the effects of sport loads and describes how the model explains the total sport load, acute, i.e., training load and injury paradox. On the training field, the physical quality of each athlete is not the same, in order to avoid sports injuries and enhance the effect of sports, optimize and regulate the parameters of sports load in physical fitness training is an inevitable choice of coaches, as an excellent optimization algorithm, genetic algorithm provides technical support to achieve this goal [12-14].

Genetic algorithm is a multi-objective optimization method, which can help to solve high-dimensional, multivariate optimization problems with and without constraints, and is a common technique to solve optimization problems in active learning [15]. It seeks to find the optimal solution that can satisfy the realistic requirements by simulating the mechanisms of “natural selection” and “genetic evolution” in nature, and the optimal solution can be the minimization sub-objective function or the maximization sub-objective function [16-18]. In the domain of body exercise training, the genetic algorithm may handle the problem of arranging load parameters, containing lasting time, strength, and times, as an optimization problem. This permits it to achieve the most optimal result and carry out dynamic changes. According to an athlete's body features, health condition, and other related factors, we can formulate a personalized load arrangement scheme. This method not only promotes the effect of the exercise but also greatly reduces the possibility of over-training and lowers the odds of getting hurt in the whole training course[19-21]. Literature [22] introduced genetic algorithm and its application in various fields, and proposed a sports training optimization model based on genetic algorithm, which was verified to have good practicability by applying it to the optimization of physical fitness training of secondary school students. Literature [23] investigated the optimization of genetic algorithms in the training programs and game strategies of basketball players, emphasizing the superiority of genetic algorithms, which are essential in order to continuously promote the growth of players and enhance team competitiveness.

To carry out appropriate distribution of the volume, intensity, duration, and frequency of exercise in the process of physical fitness training can bring about significant improvement of the training result. Under this circumstance, this paper hence defines these four affecting factors as the parameters of exercise load. It uses a genetic algorithm in order to find the most suitable numerical values of these parameters, therefore it takes NSGA-II as the basic searching method. According to the feedback adjustment mechanism, one exercise load parameter adjustment model has been established.The system which generates the physical fitness training prescription has combined these two kinds of methods. It carries out modification on exercise load parameters and body diathesis training plans according to users’ subjective feedback, hence it satisfies their training demands.

2 Modeling of optimal allocation and regulation of exercise load parameters in physical fitness training

2.1 Design of optimal distribution of motion load parameters

2.1.1 Genetic algorithms

In the genetic algorithms, each single individual represents one solution of the optimization problem. This single person is described as a series of changeable quantities, which is called a chromosome or gene string. In usual circumstances, chromosomes are given the expression by simple character or number sequences. But, other expressing methods that rely on the concrete problem can also be utilized, this process is called coding. By the continuous processes that contain selection, mating and mutation, one new group of individuals is produced. This novel generation is different from the first generation and it develops through continuous generations in a manner that enhances the whole adaptation degree.This process is been conducted in a continuous way that does not stop. Firstly, every individual entity must undergo assessment, and its degree of suitability must be calculated. After that, two individual bodies carry out mating, after which they proceed to experience mutations. Therefore, a new entity of the third generation is brought into being. This cycle continues to exist until the rule-based ending conditions that we set have been satisfied.

One eight-element group may be utilized to give definition to a heredity algorithm:

$$SGA = \left(C, E, P_0, M, \Phi, \Gamma, \Psi, T\right) \tag{1}$$

where: C - individual coding method, E - individual fitness evaluation function, P_0 - initial population, M -- population size, Φ - selection operator, Γ - symplectic operator, Ψ -- variation operator, T -- genetic operation termination condition.

2.1.2 Optimal allocation of exercise load parameters based on genetic algorithm

In this research paper, we treat parameters including exercise quantity, exercise strength, exercise lasting time and exercise times as the exercise load parameters. One genetic algorithm is then utilized to reach optimal distribution and promote the effect of body ability training.

(1) Determination of coding method

The amount of body movement, the strength of the training, the duration of the exercise session, and the frequency of exercising are expressed by the letters S_m, S_i, S_t and S_f, respectively. In this paper, we adopt the method of decimal floating-point encoding for the four parameters S_m, S_i, S_t and S_f to be optimized. Specifically, set the parameters $S_m \in \left[S_{m\min}, S_{m\max}\right]$, $S_i \in \left[S_{i\min}, S_{i\max}\right]$, $S_t \in \left[S_{t\min}, S_{t\max}\right]$, $S_f \in \left[S_{f\min}, S_{f\max}\right]$ Arrange these four decimal floats in the range of the optimization to form an individual $X(t)$.

(2) Selection of important parameters

The important parameters to be considered by the genetic algorithm are: population size N ($N = 100$ is taken in this design), crossover probability and mutation probability according to equation (2):

The important parameters which the genetic algorithm must consider are below: the population size N ($N = 100$ is taken in this design), the crossover probability, and the mutation probability according to formula (2).

$$F = 1/J \tag{2}$$

J is the objective function.

(3) Design of adaptation function

For the attainment of satisfying dynamic characteristics, under the situation that the penalty function is incorporated, this paper takes the objective function J as:

$$J = \int_0^\infty \left(w_1 |e(t)| + w_2 u^2(t) + w_3 |e(t)| \right) dt + w_4 t_u \tag{3}$$

where $e(t)$ is the dynamic system error, $u(t)$ is the output, w_1, w_2, w_3, w_4 are the weighting coefficients, w_3 and $\gg w_1$, and t_u is the rise time.

(4) Design of selection operation

This research paper uses a choosing method that is based on the size of single adaptability order to make the related choosing operation element.

(5) Design of crossover and mutation operations

The selection of crossover probability p_c and mutation probability p_m in genetic algorithm is the key to the performance of genetic algorithm, which directly affects the convergence of the algorithm. In this paper, an improved adaptive genetic algorithm is adopted so that p_c and p_m can be changed automatically with the degree of adaptation, and its p_c and p_m are specifically adjusted in accordance with as in Eq. (4):

$$p_c = \begin{cases} k_1 \dfrac{(f_{\max} - f')}{f_{\max} - f_{avg}}, f' \geq f_{avg} \\ k_2, f < f_{avg} \end{cases}$$
$$p_m = \begin{cases} k_3 \dfrac{(f_{\max} - f)}{f_{\max} - f_{avg}}, f \geq f_{avg} \\ k_4, f < f_{avg} \end{cases} \tag{4}$$

where $f_{\max}$ is the biggest fitness value which is inside the population. f_{avg} is the average fitness degree of the population in each generation. f' is the bigger fitness value between the two individuals which are about to undergo crossing. f is the individual that will have mutation has its fitness value. $k_1, k_2, k_3, k_4 \in (0,1)$.

(6) Design of simplex local search algorithm

The heredity arithmetic that this paper designs is a mixing arithmetic (SGA) which effectively puts together the heredity arithmetic and the simplex method. In the process of carrying out the introduction of the simplex method, the below two aspects are mainly considered by us:

1) the time assignment of the simplex search algorithm: When the genetic algorithm is only combined with the simplex method, the simplex search algorithm can consume the most part of the calculation time of the whole algorithm, therefore leaving only a little portion of time for the genetic algorithm. Therefore, it is hard to display the superiority that the genetic algorithm has in the aspect of the robust global search ability.Furthermore, the simple type search does not require that people get an exact solution. Hence, in the present paper, we carry out restriction

on the duration of the simplex search from two perspectives. A one aspect lies in the quantity of iteration steps of the simplex search procedure N, and the other is the probability of simplex search p_l (i.e.,putting limitation on the number of persons participating in the local searching).

2) Setting of the parameters of the simplex method: the reflection coefficient γ, the expansion coefficient α, and the search coefficient β are set as follows $\gamma = 1, \alpha = 2$, and $\beta = 0.75$.

(7) Judge whether the termination condition of the algorithm is satisfied

After that the starting crowd which is generated by the improved method is obtained through the mixed genetic operation, the population of the new generation is put again into the fitness function to carry out a process of checking and evaluation. This doing is for judging whether the algorithm's termination standard has been achieved. When the termination condition gets satisfied, the optimized solution is given out, hence the search for the optimized result comes to an end. On the opposite side, if this condition has not been reached, the working procedure will go back to circulate to carry out the operations that were mentioned above, hence until the condition for ending is fulfilled.

Figure 1 gives depiction of the utilization of the genetic algorithm in the optimization work of the algorithm implementation design process.

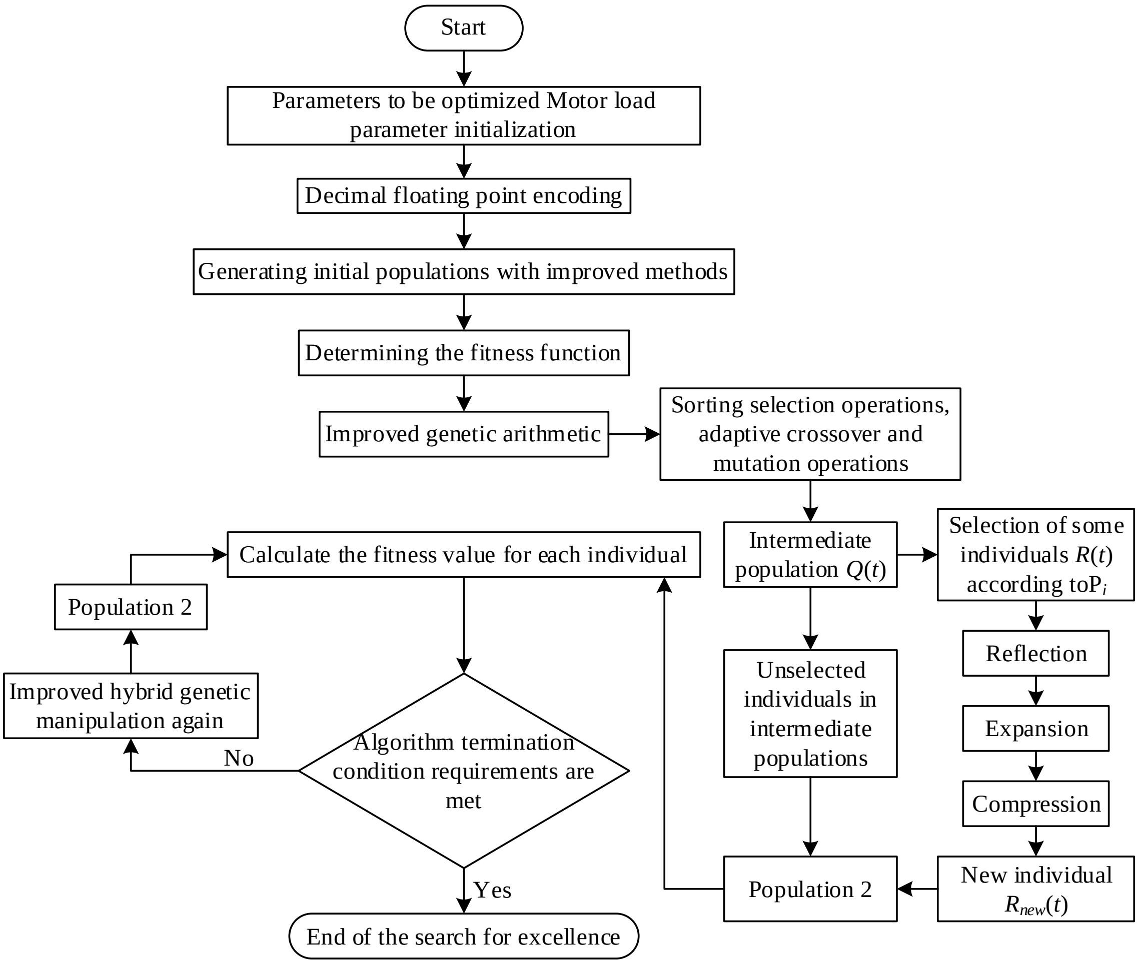

Figure 1: The optimal distribution of the motion load parameters based on GA

2.2 Modeling the regulation of exercise load parameters

In the process of physical fitness training, exercise programs and exercise parameters should be flexibly adjusted according to the actual situation. Users in the execution of the exercise process, with the surrounding environment changes may lead to the established exercise program can not be implemented, at this time the need to adjust the exercise program as far as possible, in order to meet the current user needs or sports environment.

2.2.1 Search strategy

The searching method makes certain how one should seek the best network structure in the searching space. In regard to this task, NSGA-II is utilized as the basic searching method. NSGA - II is a multi-target developing algorithm which has got the improvement from the NSGA - I algorithm. This amelioration reduces the complication of the non-dominated sorting genetic algorithm, elevates the algorithm's efficiency, hence produces solution groups with better convergence performance. First, a task encoding scheme is designed to quantize a non-numerical network structure into a string of numbers. Then, a population is initialized using random numbers, and the individuals in the population are the encoding of the above digitization. Then, the encoding result is transformed by appropriate decoding to obtain the actual represented network structure, and each individual is evaluated for fitness using a fitness function, and then high-quality individuals are selected according to the selection function to allow these individuals to genetically mutate and produce offspring.NSGA-II is a more efficient and elite genetic algorithm-based search strategy, which is improved as follows:

(1) One kind of fast non-dominated arrangement algorithm is been put forward by us.

(2) Using crowding and crowding comparison operators to select quality individuals.

(3) An elite strategy is applied to generate offspring.

As a result, the NSGA-II algorithm obtains a more uniform distribution of Pareto optimal solutions with better convergence and robustness.Furthermore, in view of the necessity that we must at the same time pay attention to the model's accuracy, the number of parameters, and the calculation work load, therefore this experiment uses a multi-objective genetic algorithm to carry out optimization. This algorithm may be expressed via the equation below:

$$Obj_{multi}\left\{\begin{matrix} \min\ f(x) = \left[f_1(x) + f_2(x) + \cdots + f_n(x) \right]^T \\ s.t. g_i(x) \geq 0, i = 0, 1, \ldots, p \end{matrix}\right\} \tag{5}$$

where $f_n(x)$ denotes different objective functions and $g_i(x)$ denotes constraint inequalities.

Nevertheless, in the actual world optimization situations, the great portion of multi-objective questions possess contradictory objectives. To concoct a fitting optimization algorithm possesses great significance. The detailed step flow of the NSGA - II algorithm is given in Algorithm (6):

$$\bar{o}^{(i,j)}(x) = \sum_{o\in 0} \frac{\exp(a_o^{(i,j)})}{\sum_{o'\in o} \exp(a_{o'}^{(i,j)})} o(x) \tag{6}$$

Define the population size as P, the total number of generations g, the number of newly generated offspring individuals S per generation and various basic operations: selection O_s, crossover O_c and mutation O_m. At the beginning of the algorithm, the population is first randomly initialized and non-dominated sorted to obtain the filtered population $P_{selected}$. Then g iterations are performed on the basis of the population $P_{selected}$, and the operations of genetic variant crossover, nondominated sorting, and merging populations are performed sequentially in each iteration, and the population P_{final} is finally obtained.

2.2.2 NSGA-II-based modeling of exercise load parameter regulation

With the accumulation of the user's exercise volume, the physical fitness of the body will gradually change, or the user's life environment causes changes in the frequency or duration of exercise, the parameters of the exercise load also need to be adjusted to ensure the smooth implementation of physical fitness training. The feedback regulation of the exercise load parameters relies on the comparison of the exercise data collected during the exercise process with the historical data, so as to find out the improvement of the user's exercise intensity, as well as the changes of the user's exercise duration and exercise frequency, and when the user's exercise intensity or exercise duration and frequency change significantly, in order to carry out adaptation toward the changing body condition or the environment of doing exercise, the solution condition parameters of the exercise load are re-set, hence the new parameters of exercise load are gotten through calculation. The adjustment model of exercise load parameters which is established on the basis of the feedback adjustment mechanism is shown in Figure 2.

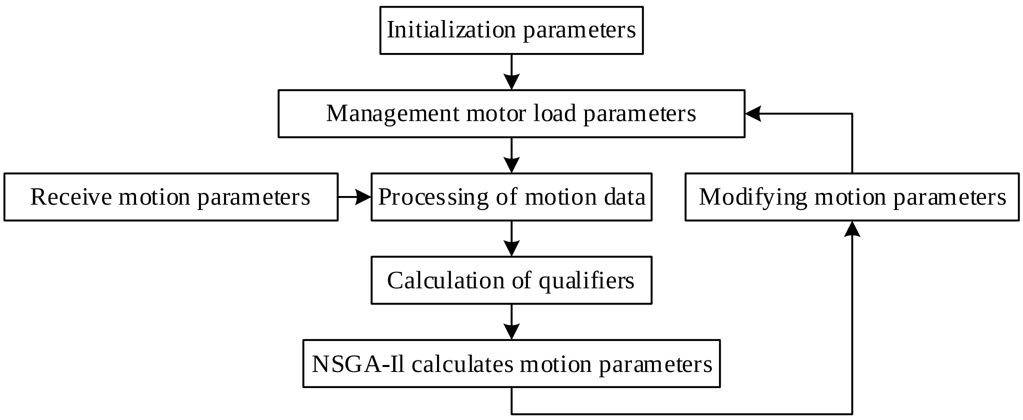

Figure 2: Based on NSGA-II's motor load parameter control model

2.3 Physical fitness training prescription generation system design

In this research article, the methods of optimizing and regulating the exercise load which were put forward in the earlier study are integrated into a system that is used for producing physical fitness training prescriptions. The structural frame of this system is displayed in Figure 3. When we carry out screening of physical fitness training programs, this work is conducted on the foundation of the user's choice for the suggested physical fitness training program,any physical fitness training plan that the user does not like we eliminate. Then, according to the user's subjective opinion feedback, the exercise load parameters and the physical fitness training plan are to be modified by us. Basing above the body fitness training formula creation system, one body fitness training project is developed and arranged to make it match what the user likes.

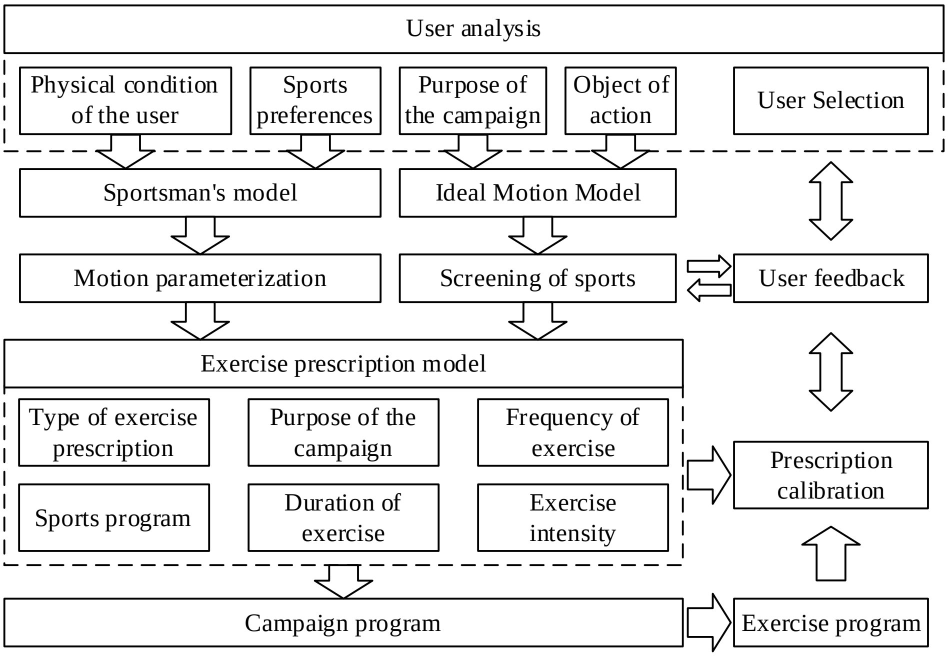

Figure 3: Body fitness can train prescription generation models

3 Empirical analysis

3.1 Performance analysis of the hybrid algorithm

For verifying the working effect of the mixture algorithm (SGA) which has united the genetic algorithm and the simplex method, just as what is narrated in 2.1.2, this article chooses the traditional genetic algorithm (GA), the particle swarm optimization algorithm (PSO), and the adaptive genetic algorithm (NAGA) to carry through a performance comparison under the identical experimental environment. The parameter setting schemes for every one of these algorithms are given in Table 1.

Table 1: Parameter setting of optimization algorithm

Algorithm	Parameter setting
PSO	$\omega_{\max}=0.8, \omega_{\min}=0.2, c_1=c_2=1$
GA	$p_m=0.02, p_c=0.6$
NAGA	$k_1=0.6, k_2=0.03$
SGA	$k_1=0.6, k_2=0.03$

Regarding the four algorithms that have been talked about above, every one of them sets the population or particle number $\mathrm{N}=100$ and the maximum iteration quantity $\mathrm{T}=300$. For evaluating the optimization abilities of these arithmetic procedures, the four-dimensional Rosenbrock function is chosen as a testing function to find out the minimum values. We here give the Rosenbrock function in what is written as Equation (7):

$$f(x)=f\left(x_1,x_2,\cdots,x_N\right)=\sum_{i=1}^{N/2}\left[100\left(x_{2i-1}^2-x_{2i}\right)^2+\left(x_{2i-1}-1\right)^2\right] \tag{7}$$

This four-dimensional function can achieve the whole domain's global minimum value 0 at one specific point $(1,1,1,1)$.

This experiment is carried out inside the four-dimensional space that has a scope from minus forty to forty. Every algorithm is carried out 50 times, and the test performance data of each algorithm is shown in Table 2. According to what we can see, the average implementation time of the SGA algorithm is longer when it is compared with the time of other algorithms. The reason for this situation is that the bringing in of the simplex method helps to make the searching behavior get an increase, which can enhance the efficiency of the global and local search, but accordingly sacrifices some algorithm running speed. However, the SGA algorithm has a better average optimal solution compared to the pre-improvement period, and the algorithm finally converges to the global minima 0 in 20 out of the 30 runs with a maximum iteration number of only 300, so it can be seen that the SGA algorithm has a better convergence as well as optimization performance, which indicates that the improvement of the genetic algorithm in this paper is effective.

Table 2: Test performance data for each algorithm

Algorithm	Average running time	Average optimal solution	Degree of convergence
PSO	0.7635	4.5216E-24	5
GA	0.7896	1.2523E-28	6
NAGA	0.8566	1.6351E-30	12
SGA	0.9633	3.0521E-31	20

3.2 Experimental Analysis of Exercise Load Parameter Regulation

(1) Data acquisition

Because the current experiment data about body ability training can not be comprehensively obtained from other platforms, therefore this paper uses the official sport contest data which is provided by Kaggle as the basic data for the experiments in this article. From the case database, we have randomly selected two cases according to each of the five sport goals: weight decrease, promotion of aerobic endurance, promotion of anaerobic endurance, increase of muscle shape, and improvement of flexibility. Furthermore, the selection work was conducted by us with a male-to-female proportion that is 1:1. In the whole, five groups of case data were chosen by us. For the purpose that information can be displayed clearly, this paper will not utilize the table form to list out all five cases one after another. On the contrary, it will make the choice to use a text-based description for explaining one of the case data sets. The main features of one case of this kind are elaborated as what follows: Case 1 includes a 27 - year - old man. His body height is 184 centimeters, and his body weight is 140 pounds. He does not have long-term diseases, and he can get basic sports equipments and places. The goal of the movement formula is to promote aerobic holding capacity. In order to obtain the most excellent effect, the exercise intensity must let the heart rate be kept at 150. For the prescription, the ideal motion time length is 42 minutes, and the suggested motion frequency is 4 to 6 times every week.

(2) Experimental results

In this paper, for the five cases selected in the above description, a single average optimization process experiment, five average optimization process experiments, and five optimal average optimization process experiments were carried out, respectively.Table 3 shows the calculation results of three different experiment values of NSGA - II and the original genetic algorithm for each of the five cases. Through checking the data got from the optimization processes of the three experiments, thus it is very clear that, when put beside the original genetic algorithm, NSGA-II has higher solution precision and can find better results.

Table 3: GA improves the calculation results of different values before and after

Case	Different value	GA	NSGA-II
Case1	Single average	1.753E+00	1.03E+00
	The average of five times	1.763E+00	1.263E+00
	The five optimal averages	1.32E+00	0.88E-01
Case2	Single average	1.774E+00	0.993E+00
	The average of five times	1.713E+00	1.088E+00
	The five optimal averages	1.382E+00	0.83E+00
Case3	Single average	1.207E+00	0.903E+00
	The average of five times	1.17E+00	0.983E+00
	The five optimal averages	0.737E+00	0.391E+00
Case4	Single average	1.179E+00	0.916E+00
	The average of five times	1.215E+00	1.02E-01
	The five optimal averages	0.755E+00	0.539E+00
Case5	Single average	1.772E+00	1.594E+00
	The average of five times	1.796E+00	1.697E+00
	The five optimal averages	1.342E+00	1.224E+00

Furthermore, in the present research paper, the numerical values of four variables that have relation to cyclic motion, that is motion strength, motion lasting time, and motion frequency, which have been calculated via GA and NSGA - II optimization method, have respectively undergone normalization processing. After that, the average numerical value of every variable after the completion of normalization was calculated for the purpose of carrying out comparison. The result situations of this comparison on the average values are shown in Figure 4. NSGA-II significantly outperformed GA in terms of exercise volume and exercise frequency on average, by 0.571 and 0.532, respectively, and slightly outperformed GA in terms of exercise intensity and exercise duration on average, by 0.111 and 0.062, respectively.

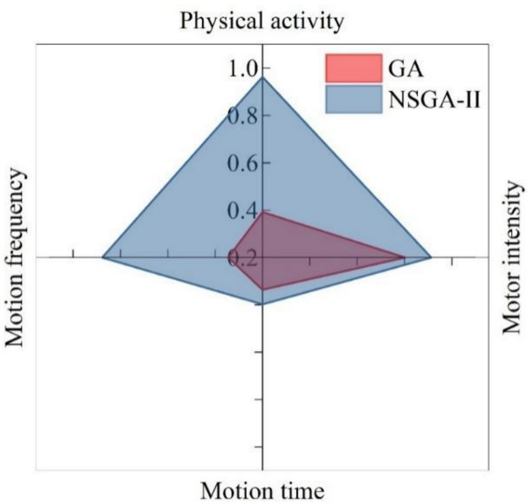

Figure 4: Mean contrast results

The numerical values of the above four parameters which are computed for the optimization of Genetic Algorithm (GA) and Non-dominated Sorting Genetic Algorithm II (NSGA-II) are each different, and they are normalized by making use of the values got from the specific case 1. After that, the average number of the differences for each physical quantity after standardization was computed with the aim for comparison. The result of this compare of the average difference numbers are shown in Figure 5. Similarly, NSGA-II is significantly better than GA in terms of both exercise volume and exercise frequency, with the mean value of difference being 0.374 and 0.277 less, respectively, and NSGA-II is also slightly better than GA in terms of both exercise intensity and exercise time, with the mean value of difference being 0.013 and 0.033 less, respectively.

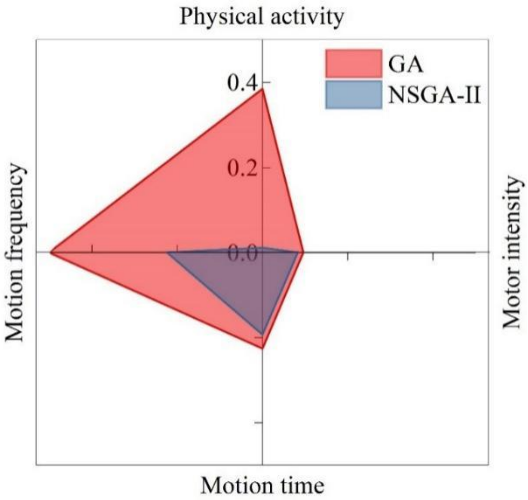

Figure 5: Mean of difference contrast results

3.3 Comparison of fitness training effects under different methods

3.3.1 Research Objectives and Methodology

The study was conducted on 400 students participating in the public physical education program at the University of C, class of 2024. This experimental study was conducted to find out whether the physical fitness training prescription generation system incorporating the optimal distribution and regulation method of exercise load parameters is effective in improving students' physical fitness.

The grouping of the experiment: The participants who are in this study have been divided into two groups. We have one experimental group, which includes 25 boy students and 25 girl students, and one control group, which also is made of 25 boy students and 25 girl students. Two groups of research objects all passed through a 12-week teaching cultivation program. The experiment group got teaching through the body ability training plan make system. At the same time, the control group accepted teaching through the traditional teaching program, and the same teacher undertook the work for both of the two groups.

Test index: 1 week before carrying out the experimental study and 1 week after the end of the experimental study, respectively, the two groups of students were tested once centrally, based on the 2014 revision of the “National Students' Physical Fitness Standard” as a passing standard.

Exercise program based on the physical fitness training prescription generation system: the experimental group fixedly arranged 30min physical fitness training content each time. The specific arrangements were as follows:

(1) 1~2 weeks were based on flexibility, endurance and strength training.

(2) 3~6 weeks, speed, strength and flexibility training.

(3) 7 to 10 weeks of speed and endurance training.

(4) 11 to 12 weeks of speed, strength and endurance training.

Each endurance training was arranged after flexibility, speed and strength training, and appropriate stretching was arranged at the end of the program.

Statistical methods: At the beginning, the data collected from the measurements have been passed through pre-processing by using Excel 2010. After that, this pre-handled data was moved into the SPSS18.0 statistics software. Regarding the data, a paired-sample T-test was utilized by us to carry out analysis on the numerical values that existed before and after the carrying out of the experiment. In addition, we have utilized an independent sample T-test to carry out the comparison between the experimental group and the control group.

3.3.2 Results and analysis

(1) Comparative analysis of the physical fitness data of the two samples before the experiment

Table Four gives a comparison of the body ability data of the two groups of samples before the experiment was carried out. We have carried out a T-test on the body healthy situation of the two groups of students before the experiment, hence the result shows that there exists no obvious difference. Because the P-value is larger than 0.05, therefore it is very clear that this experiment is able to be conducted in a way that has effect.

Table 4: The physical fitness data comparison of the previous two experiments

Gender	Test item	Experimental group	Control group	T	P
Male	Step test	71.01±9.22	70.25±8.82	1.6	>0.05
	Clapped force experiment/kg	35.52±7.22	36.02±8.06	-1.63	>0.05
	Push-ups	27.25±5.36	27.52±5.22	2.25	>0.05
	Predisposition/cm	12.36±6.42	12.39±5.36	-0.12	>0.05
	Body tester/%	17.81±6.09	17.86±7.15	2.12	>0.05
Female	Step test	52.63±5.96	56.66±7.52	-2.63	>0.05
	Clapped force experiment/kg	23.36±2.52	23.64±3.55	-1.65	>0.05
	Push-ups	17.63±2.3	16.61±5.65	1.25	>0.05
	Predisposition/cm	13.93±5.73	13.86±5.34	0.63	>0.05
	Body tester/%	17.82±8.52	18.01±5.33	-1.33	>0.05

(2) Comparison of physical fitness indicators between the experimental group and the control group before and after the experiment

1) Comparison and analysis of cardiorespiratory fitness indicators

In the exercise state, people with better cardiorespiratory endurance will continue to exercise for a longer period of time and are less likely to get tired. Therefore, the cardiorespiratory endurance will be improved after the training of the physical fitness program. In general, exercises such as walking up and down steps, brisk walking, swimming and running are beneficial for improving cardiorespiratory fitness. The comparative analysis of cardiorespiratory fitness indicators is shown in Figure 6. After 12 weeks of physical fitness practice, the students in the experimental group have significant improvement in the data of the step test, which is statistically significant difference ($P<0.05$). This indicates that physical fitness training has a significant effect on the aerobic fitness level of the students. The step test results which belong to the students of the control group have not displayed an improvement that is notable. Through we have completed a statistical analysis, therefore we obtained the result that no obvious difference existed ($P > 0.05$). When we make comparison between experimental group and control group, it is very clear that the heart-lung function of the students which are in the experimental group has obtained a very big improvement. This shows that the physical education teaching which is based on the physical fitness training prescription making system has higher efficiency in promoting the cardio-respiratory function of students than the traditional physical education class instruction.

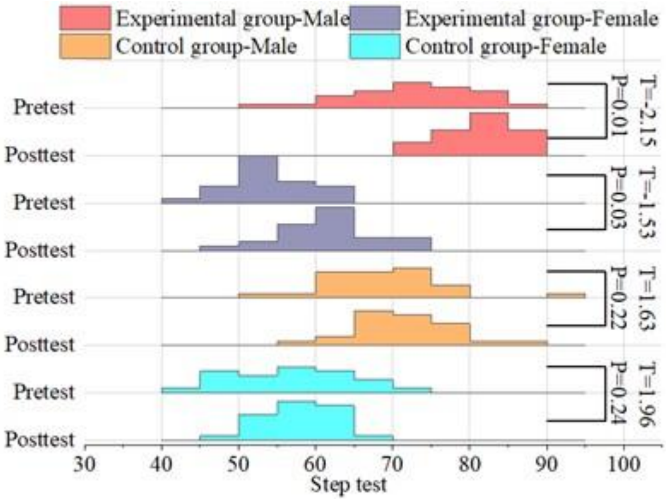

Figure 6: The analysis of the comparison of cardiopulmonary energy index

2) Comparative analysis study of muscle fitness indicators

The comparative analysis of muscle fitness indicators is shown in Table 5. After 12 weeks of physical fitness training, the test data of muscular fitness of the students in the experimental group had a big increase compared with the pre-test, and the test data of sit-ups also had a significant difference after statistical test (P < 0.05). This indicates that the physical fitness training has a significant enhancement effect on the improvement of muscular endurance and muscular strength of the students. When we make comparison between the grip strength and push-up test data of control group students and the data that got before experiment, no obvious enhancement has been found. Furthermore, after we have carried out a statistical examination, it was discovered that there did not exist an obvious difference (P > 0.05).Some people hold the view that this may act as a dependable indication that, after 12 weeks of continuous physical education class exercises, although there exists a certain level of promotion in the students' lower-limb muscle strength, the degree of this promotion is comparatively small. Furthermore, the muscle endurance capability has not obtained an obvious improvement. When we do the contrast between experimental group and control group, we discover that the muscle strength of students which are in experimental group has appeared a very notable enhancement. This shows that physical education teaching which is based on the system that generates physical fitness training prescriptions, has higher efficiency in the promotion of students' muscle function when compared with the traditional physical education classroom teaching.

Table 5: Comparative analysis of muscle fitness indicators

Gender	Test item	Time	Experimental group	P	Control group	P
Male	Clapped force experiment/kg	Pretest	35.52±7.22	<0.05	36.02±8.06	>0.05
		Posttest	38.62±5.23		36.11±7.41	
	Push-ups	Pretest	27.25±5.36		27.52±5.22	
		Posttest	32.52±7.02		28.25±6.52	
Female	Clapped force experiment/kg	Pretest	23.36±2.52	<0.05	23.64±3.55	>0.05
		Posttest	26.52±3.25		23.85±2.52	
	Push-ups	Pretest	17.63±2.3		16.61±5.65	
		Posttest	21.25±1.11		17.52±4.52	

3) Comparative analysis of flexibility indicators

The comparative analysis of flexibility indexes is shown in Figure 7. After 12 weeks of physical fitness training, the experimental group of students had a more significant increase in the level of sitting forward bending test, which was statistically significant ($P < 0.05$), and had a positive effect on the improvement of students' flexibility fitness level. In the contrast group, the result of the seated forward-bend examination displayed a small elevation. However, the degree of increase was very small. After we have carried out a statistics experiment, it has been discovered that no obvious difference exists ($P > 0.05$). This point lets us know that the traditional physical education class teaching does not have the ability to produce a good effect on the students' flexibility and body health levels.Comparing the experimental group with the control group, the flexibility fitness of students in the experimental group improved significantly, indicating that the physical education teaching based on the physical fitness training prescription generation system is more effective for students' flexibility exercise than the traditional physical education teaching.

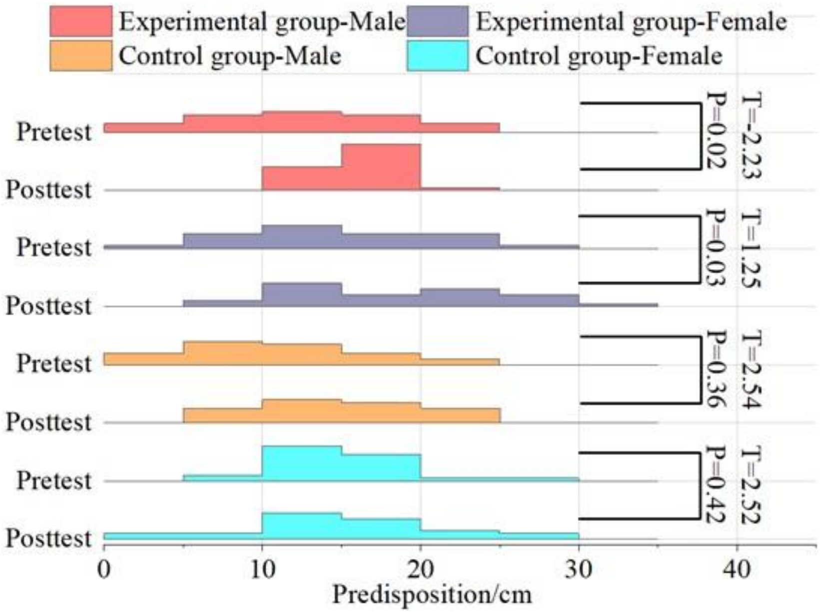

Figure 7: The flexibility index is compared and analyzed

4) Comparative analysis study of various test indicators of body composition

The comparative analysis of various test indexes of body composition is shown in Table 6. After 12 weeks of physical fitness exercise, the experimental group of students subject to body mass index and waist-hip circumference ratio did not have more obvious changes. There is no significant difference after statistical test ($P>0.05$), but the test data indicate that these two test indexes are more inclined to be rationalized. This indicates that physical fitness training has a significant contribution to the maintenance and plasticity of body shape, resulting in a significant decrease in body fat percentage, which is a significant difference after statistical test ($P<0.05$). Inside the students who belong to the control group, no obvious changes were found in the different measured data of body composition. The percentage of body fat has seen a small cut, but this cut is extremely tiny. Through the carry out of statistical analysis, it was obtained that there was no obvious significance difference ($P > 0.05$). This shows that after 12 weeks of physical education class exercises, the activity did not have obvious promotion influence on the different index numbers of body composition among the research objects in the contrast group. When we carry out the comparison between experimental group and control group, we discover that no obvious difference exists in the changes of the students' body composition between the experimental group and the control group.

Table 6: Comparison and analysis of the test indexes of body composition

Group	Body tester/%	Gender	Experimental value	T	P
Experimental group	Pretest	Male	17.81±6.09	-1.63	<0.05
		Female	17.82±8.52		
	Posttest	Male	17.01±63.1	-1.24	
		Female	18.52±5.21		
Control group	Pretest	Male	17.86±7.15	0.52	>0.05
		Female	18.01±5.33		
	Posttest	Male	17.25±5.63	0.63	
		Female	17.96±6.21		

According to the results of data inspection, after the physical fitness training plan making system is put into physical education classes, there is an obvious increase in the degree of movement abilities which students have achieved, when compared with traditional physical education teaching. Furthermore, in the course of carrying out weight management and promoting various physical characteristics, students have comprehended how to employ healthy body exercise approaches and have studied to work out scientific programs.

4 Conclusion

One system that is used for generating physical fitness training prescriptions has been gotten done developing. This system possesses the capability of carrying out optimal distribution and adjustment for the parameters of exercise load in the process of physical fitness training. When the genetic algorithm which is combined with the simplex method is used to confirm the best distribution of exercise amount, strength, continuance and frequency, the convergence of this algorithm displays an obvious advantage compared with other algorithms. But, from the average condition, this algorithm possesses a comparatively longer operation timeThe average numerical values of the differences between NSGA-II and the real motion formula on motion amount, motion strength, motion length, and motion frequency are 0.011, 0.083, 0.193, and 0.224 separately. These numerical results show that NSGA - II has better performance than the traditional genetic algorithm when it carries out the adjustment of exercise load parameters in the process of physical fitness training. That is to say, NSGA-II has more excellent capability in making the parameters of exercise load get closer to the real exercise prescription when compared with the traditional genetic algorithm. Using the system of this paper for practical teaching, the students' cardiorespiratory fitness, muscle fitness, flexibility and body composition test indexes were statistically examined, the P value is less than 0.05, while the students based on the traditional teaching method in the various indicators of the P value is greater than 0.05. This paper utilizes genetic algorithms to design the physical fitness training prescription generation system can effectively improve the students' physical fitness.

About the Author

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