

## Research Article

# Education Teaching Evaluation Method Aided by Adaptive Genetic Programming and Robust Scheduling

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Process mining technology aims to automatically generate process models by analyzing events, thereby assisting the design and redesign of process models. Although many process mining methods have appeared, they all have deficiencies. These methods focus on mining from the behavioral aspects described by the log, while ignoring the structural nature of the process model itself. The complexity of the process describes the simplicity and ease of understanding of the process. Higher process complexity affects the readability of the process. Genetic programming has strong robustness. Its individual representation based on tree structure can describe the special structure of the process. The introduction of process complexity fitness enables it to consider the complexity of the process model itself while mining log behavior, so as to achieve nonlinear mining of complex processes. This paper analyzes the process mining based on genetic programming and proposes process individuals based on tree structure. By realizing the combination of process complexity measurement and process mining technology, noncomplex process mining can be realized. In this paper, the process complexity is combined with the process mining algorithm based on genetic programming, and a measure of process structural complexity is proposed, which is converted into complexity fitness and introduced into the fitness function of genetic programming, to realize the use of genetic programming. The research results show that the improved new adaptive genetic programming robust scheduling algorithm provides a new idea and method for the evaluation of college sports under different sports conditions. This makes the college sports evaluation management system more intelligent and improves the rational allocation of physical education teaching.

## 1. Introduction

Physical education teaching evaluation is an important part of the physical education teaching process, and how it should be evaluated, by whom and what the content of the evaluation is, has a direct impact on the improvement of the quality of physical education teaching in colleges and universities as well as the progress and development of physical education teachers and students [1]. The current evaluation of physical education teaching in colleges and universities is mainly an online evaluation of students' teaching at the end of the semester, and students score the physical education teachers based on their classes and the teaching evaluation items set by the school and finally arrive at the physical education teachers' physical education ratings in the

semester, and this model has serious deviations and is one of the factors lagging behind the development of physical education teaching reform in schools [2]. Evaluation of physical education is an important part of the physical education teaching process. How it should be evaluated, who should evaluate it, and what the evaluation content is has a direct impact on the improvement of the quality of physical education teaching in colleges and universities as well as the progress and development of physical education teachers and students. With the rise of genetic programming robust scheduling applications, it has become possible to conduct automated physical education teaching evaluations in colleges and universities [3]. Genetic programming robust scheduling can provide a large amount of data support for physical education evaluation, making physical education

evaluation more scientific and fairer; at the same time, physical education evaluation driven by genetic programming robust scheduling can provide more timely feedback on the results of physical education evaluation. Genetic programming robust scheduling can provide a large amount of data support for physical education evaluation, making physical education evaluation more scientific and fairer; meanwhile, physical education evaluation driven by genetic programming robust scheduling can provide more timely feedback on the results of physical education evaluation. Genetic programming robust scheduling challenges the existing physical education teaching evaluation system in all aspects such as technology, system, and institution, so it is necessary to explore the construction of a college physical education teaching evaluation system that meets the requirements of the era of genetic programming robust scheduling, has reliability and operability, and truly promotes the development of students and physical education teachers.

Robust scheduling methods have been widely used for their advantages of high computational efficiency and less information required. However, robust scheduling methods usually focus on the boundary information of uncertain quantities and ignore information such as probability distribution, resulting in their decision results being often too conservative, especially in the situation where the penetration rate of renewable energy sources is increasing and the system is not flexible enough, and the overly conservative robust scheduling methods may appear to be inapplicable [4]. On the other hand, most studies in robust dispatching methods only consider the adequacy of the backup capacity allocation, while ignoring the response rate of the allocated backup, especially its continuous response capability over continuous periods [5]. This can easily lead to a system that cannot be released in time due to the limitation of response rate even though it has sufficient standby capacity, resulting in insufficient system flexibility and affecting the economy and reliability of system operation. Genetic programming is a reductive form of machine learning, where the initial goal is to design a computer program, and then this program goes on to perform a set of tasks with a training set and finally automatically constructs the best solution to the problem. Today, it is used in a wide range of applications. Genetic programming can quickly discover relationships between data and mathematical expressions through its learning and represent the relationship between the output and input variables in the form of equations. Robust scheduling methods usually focus on the boundary information of uncertain quantities and ignore information such as probability distributions, resulting in decision results that are often too conservative, especially in the situation of increasing renewable energy penetration and insufficient system flexibility, where overly conservative robust scheduling methods may appear to be unapplicable. It can be implemented in a variety of programming languages. In the beginning, genetic programming was usually implemented by Lisp language, and over some time, C language was slowly used in genetic programming. In industry, genetic programming is implemented using assembly language that can

have better performance. Currently, in the academic world, Java and C++ are the two most used languages to implement genetic programming.

The construction of uncertainty sets is one of the key points of robust scheduling algorithms; however, most traditional robust algorithms derive uncertainty sets based on experience, which does not take full advantage of big data, and the results produced are too conservative [6]. To fully exploit the information of uncertainty and take advantage of big data, it is extremely necessary to estimate the overall probability density or probability distribution based on the known samples with the help of genetic programming. The construction of uncertainty sets is one of the key points of robust scheduling algorithms; however, traditional robust algorithms are mostly based on empirical uncertainty sets, which do not take full advantage of big data, and the results produced are too conservative. To fully exploit the information of uncertainty and take advantage of big data, it is necessary to estimate the overall probability density or probability distribution based on known samples by using genetic programming. The estimation methods of probability density functions can be divided into parametric and nonparametric estimation. The parametric estimation assumes that the uncertain quantity obeys some known distribution, such as Gaussian distribution, Poisson distribution, and Weibull distribution, and then finds the parameters of the distribution based on the sample data of the uncertain quantity combined with some estimation method, such as great likelihood estimation and Bayesian estimation. However, some classical known probability density functions are mostly single-peaked, but in practice, there are often multi-peaked probability density functions. Physical education is highly random, volatile, and intermittent, and if it obeys some known distribution, it will deviate far from the actual situation, which is not conducive to the accuracy of decision making. The uncertain factors of the project environment include the uncertainty of the duration of the activity, the uncertainty of the number of resources, and the uncertainty of the content of the activity, among which the uncertainty of the activity duration is the most common. The more the uncertainty factors in the project, the more complex the project scheduling process. Nonparametric estimation, on the other hand, is a direct estimation of the actual distribution of an uncertain amount of sample information, which can reflect the overall probability density more realistically, with histograms, kernel density estimation, and K-nearest neighbor estimation. It can be used to estimate univariate and multivariate probability density functions [7]. However, kernel density estimation has the disadvantage of being sensitive to data outliers, and the method tends to overestimate the true probability density even when no outliers are present. To better deal with this problem, an improved kernel density estimation method, the robust scheduling algorithm, has been derived on this basis. The robust scheduling algorithm is a weighted kernel density estimation; that is, a weight is assigned to each kernel function, but this weight is variable. Outliers are assigned smaller weights during the iterative solving process, which weakens the effect of outliers on the

probability density and greatly improves the accuracy of the probability density estimate. The solution of the robust scheduling algorithm involves a minimum value optimization problem, the solution of which is the required probability density function, and, therefore, it cannot be solved by a general solver solution. The current physical education evaluation in colleges and universities is mainly based on the students' evaluation of teaching on the Internet at the end of the semester. Students score according to the physical education teacher's class and the teaching evaluation items formulated by the school. Finally, the physical education teacher's physical education teaching score in this semester is obtained. This model has serious deviations, which is one of the factors that lag the reform and development of physical education teaching in schools. The kernel functions are classified as uniform kernel functions, triangular kernel functions, gamma kernel functions, Gaussian kernel functions, etc., but the type of kernel function does not significantly affect the probability density estimation. The main influence on the performance of the robust scheduling algorithm is the smoothing parameter in the kernel function. The larger the smoothing parameter, the smoother the probability density curve, and the smaller the smoothing parameter, the more volatile the probability density curve, neither of which truly reflects the probability density information.

## 2. Related Works

At present, the research on the application of genetic programming in the field of educational big data has also received increasing attention from researchers at home and abroad. In response to the phenomenon that adaptive genetic programming has poor stability and is easily trapped in locally optimal solutions, scholars have improved it from several perspectives. Cheng T. et al. improved the linear type of crossover and variation operators to ensure that the crossover rate and variable rate of individuals with maximum fitness in the population are not equal to zero to avoid the problem of local optimality of the algorithm [8]. The genetic crossover and variation operators took larger crossover and variation values for near-optimal individuals to improve the search speed of the algorithm and took smaller crossover and variation values for near-optimal individuals to avoid the convergence of the algorithm to a local optimum [9]. Virgolin et al. used the "sigmoid function nonlinear adjustment crossover and variation operator" to ensure that when the difference between the maximum fitness individual and the average fitness value in the population is large, it is still possible to maintain a faster convergence speed while not converging to a local optimum solution [10]. The above-improved method reflects that, for the high complexity of the scheduling problem, the general mathematical algorithm is difficult to solve and can be borrowed or referred to as the logical thinking method in operations research to calculate the optimal solution of the scheduling problem in a hierarchical and step-by-step manner. In conclusion, in the realistic problem of solving the optimal scheduling solution of the scheduling problem,

there are many constraints influenced by relevant factors, the variables of the operational process are many and complex, and there is a close connection between the NP-complete problems.

Based on von Neumann's maximum-minimum law, the statistician Wald proposed an optimization decision criterion with the initial idea of robust optimization to achieve the selection of optimization strategies by comparing the results under the worst realization of uncertainty. After nearly 20 years of development of the foundation period, robust optimization methods have entered the fast track of rapid development and gradually formed a complete set of uncertainty optimization theory systems [11]. By constructing a bounded uncertainty set to characterize the perturbation of uncertainty, robust optimization gives the optimal decision result under the worst case of uncertainty set. Due to its excellent computational efficiency and high reliability of decision results, robust optimization methods have been widely used in system stochastic scheduling decisions, and a robust scheduling theory system has been formed [12]. With the rapid development of artificial intelligence technology, intelligent production scheduling research has been promoted to provide new technical means for the development requirements of intelligent manufacturing. The genetic programming robust scheduling challenges the current physical education evaluation system in terms of technology, system, and system. Therefore, it is explored to build a robust scheduling system that meets the requirements of the genetic programming era, has reliability and operability, and truly promotes students. It is extremely necessary to develop a physical education teaching evaluation system in colleges and universities with physical education teachers. The current research on production scheduling systems based on knowledge engineering has acquired greater achievements, which can not only make up for the shortcomings of algorithm simulation and mathematical linear programming, but also be able to perform fuzzy reasoning and comprehensive heuristic search on knowledge base according to optimization objectives and system state, reduce complex computation time, obtain the best scheduling method, and improve the capability of online decision making manufacturing system. The intelligent scheduling system based on knowledge engineering can adapt to the development trend of globalization, integration, and intelligence of modern intelligent manufacturing enterprises, highlighting the advantages of high quality, low cost, high efficiency, and speed in the future manufacturing industry, and can be widely used in various fields in the future.

In recent years, machine learning has developed rapidly and is widely used in data analysis and data mining, where genetic programming is one of the common algorithms for machine learning, and there have been many studies on genetic programming [13]. The error and outlier identification algorithm is used to find a better model of remote sensing big data, to achieve the analysis and mining of remote sensing big data [14]. In 1976, scholar Smith proposed two teaching strategies based on experience, which are content-restricted strategy and non-content-restricted

strategy. These two strategies have important implications for teaching and have achieved significant results in teaching. However, research on instructional strategies leaves something to be desired, such as the ambiguity of the concept of instructional strategies [15]. Following Smith's groundbreaking research on teaching strategies, in 1985, Gagne had a deeper inquiry into teaching strategies, along with an exploration of effective teaching strategies. He emphasized the role of teachers in guiding and supervising students during the teaching process and divided teaching strategies into two categories: management strategies and instructional strategies. In addition, Gagne shows that flexible choice of management strategies and clever use of instructional strategies can achieve good teaching results, and experienced teachers can adopt the right teaching strategies promptly according to the different situations of students and be adaptable.

### 3. Research on the Evaluation Model of College Physical Education Based on Genetic Programming Robust Scheduling Algorithm

*3.1. Genetic Programming Robust Scheduling Algorithm System Modeling.* Genetically programmed populations of individuals are created randomly and then evolve through genetic manipulation until a termination condition is reached to stop. There are various forms of genetic manipulation; the main ones used are gene duplication, mutation, and crossover. Each of these will be described next. One of the crossovers and mutation processes of genetic programming gene duplication refers to the selection of individuals in some contemporary populations that can be directly duplicated into the next generation of populations without any genetic manipulation. The selection of individuals depends mainly on the value of the fitness function, and the higher the value of the fitness function, the higher the probability being selected [16]. The mutation is the process of randomly selecting mutation nodes on an individual to produce a new individual. The specific process is to first generate a random mutation node on the individual, then randomly generate a new subtree, which is generated in the same way as the initial individual, and, finally, delete the subtree under the mutation node and replace it with a new subtree, thus generating a new individual. The original individual is  $(4.29 T) + \text{Tan}(-1.31 S)$ , and the mutation point is the operator "+" and then the subtree under the "+" node  $(4.29 T)$  is to be deleted and replaced by the newly generated subtree as soma (PS, T) instead, so the newly generated individual is  $S + \max(PS, T) + \text{Tan}(-1.31 S)$ . Forking is the process of selecting two individuals as parents, randomly generating an intersection in everyone separately, and then the subtrees under the intersection of the two individuals are exchanged to generate new individuals. Taking Figure 1 as an example, the subtree under the intersection of individual 1 is  $(4.29 + T)$  and the subtree under the intersection of individual 2 is  $\max(PS, T)$ , then the two subtrees are cross-transformed, and two new individuals are generated, respectively.

Use the Gap Char class in the toolkit to implement the genetic operations of replication, mutation, and crossover in genetic programming. The property syntax Tree data type of the Gap Char class is Expression, which refers to the individual in the program, i.e., the syntax tree; the data type of context is Context, which includes terminal sets and non-terminal function sets; the fit Funs data type is Fitness < Gap Char, Double>, which refers to the fitness of the individual; random data type is Random. The Gap Char class implements the crossover (), mutate (), and clone () methods through the three parameters syntax Tree, context, and fit Fun's crossover, mutate, and copy genetic operations. In this paper, the mutation is divided into seven cases, which are mutation triggered by random changes in functions, mutation triggered by random changes in children, mutation triggered by random changes in nodes to children, mutation triggered by reversing the set of children, mutation triggered by root node growth, mutation triggered by generating a new tree of the syntax tree, and mutation triggered by replacing the whole syntax tree by any subtree [17]. The set of functions in genetic programming is a combination of basic mathematical notations. In this paper, these mathematical symbols are used as a search space and are randomly combined with a terminal set consisting of data sets and constants, while feedback is provided through the data set to produce the optimal solution after a certain number of evolutionary operations and iterations. The selection of function sets generally follows certain rules: first, adequacy: the selection of function sets should be able to adequately represent the data set; second, the principle of validity: the combination of function sets and data sets must produce individuals that meet the syntax requirements; control the number of function sets: too many function sets will reduce the speed and efficiency of evolution. However, there is no fixed set of functions, different data sets need to set different sets of functions, and the user needs to define and figure out for themselves. Most of the studies in the stick scheduling method only consider whether the allocation of spare capacity is sufficient but ignore the response rate of the configured spare, especially its continuous response capability in continuous periods. This easily leads to the fact that even if the system has sufficient spare capacity, it cannot be released in time due to the limitation of the response rate, resulting in insufficient system flexibility and affecting the economy and reliability of system operation.

$$\text{RMSE} = \sqrt{M \sum_{i=1} (Ap_i + Sp_i)}. \quad (1)$$

*3.1.1. Genetic Programming Adaptation.* The design of genetic programming parameters requires the determination of control parameters such as initial population size, probability of genetic operands of genes, maximum depth of tree in genetic programming, initialization population mode, and a maximum depth of initialized population. And the selection of control parameters cannot be decided concerning one factor, and for complex optimization

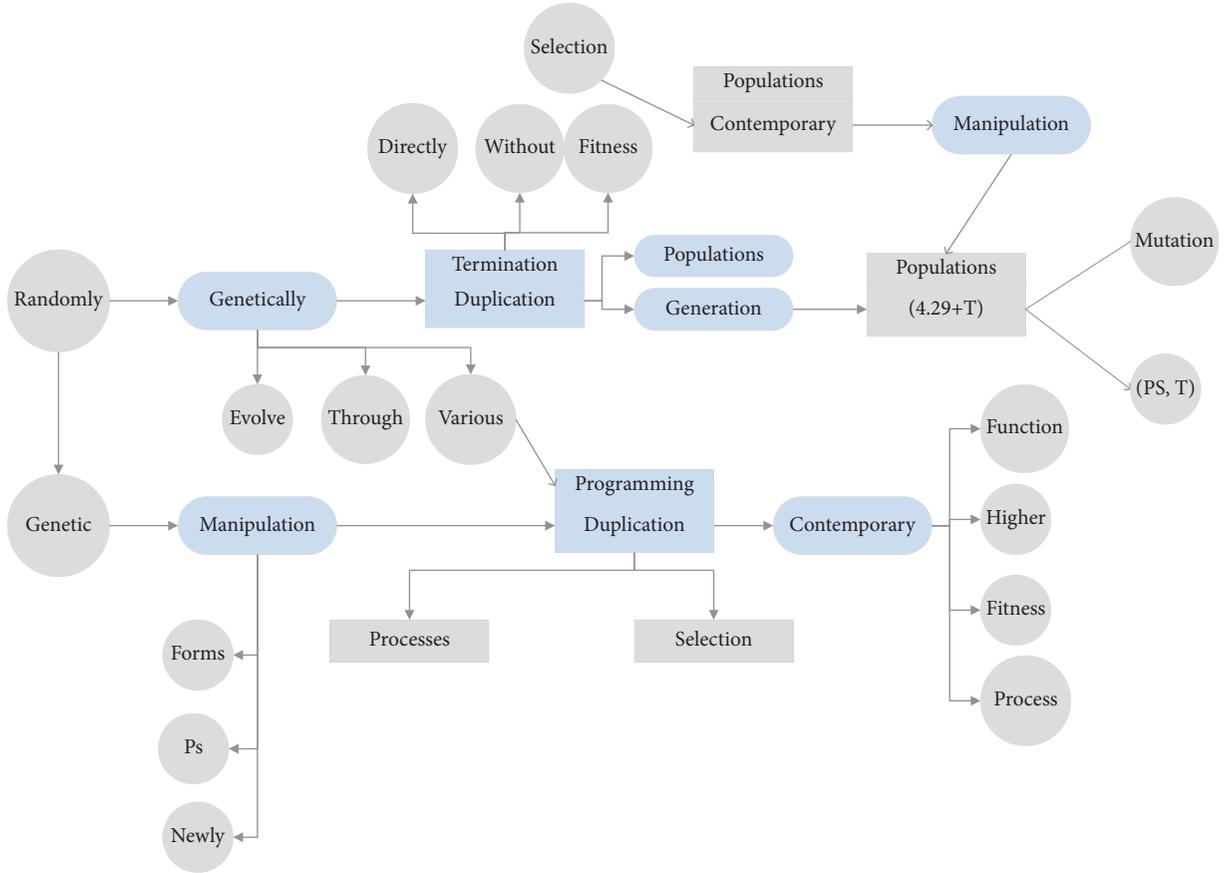


FIGURE 1: Crossover process.

problems, multiple factors need to be compared for optimization to ensure the best optimization results. In terms of fitness selection, for models with multiple perturbations, this paper uses two different fitnesses to combine: one is the least-squares fitness used to eliminate the difference between the output of the evolutionary target system and the output of the individual model; the other is the structural fitness used to limit the structural complexity of the iterated individuals, and calculating the structural fitness in genetic programming, due to the need for iterative genetic iteration operations, is easy to produce a large number of the other that is the structural fitness, which is used to limit the structural complexity of iterated individuals. To reduce the complexity of the individual structure during genetic programming, structural fitness needs to be reoptimized. The least-squares adaptation represents the output error of the individual model, combining the evolved individual model and the optimization objective, for which the same input parameters are set if the output of the evolved individual model is  $y_{\text{Individual}}(t)$ , and the output of the system is  $y_{\text{Individual}}(i)$ , and then the least-squares adaptation is

$$f_L = \sum_M \left( \frac{y_{\text{Individual}}}{y_{\text{Individual}}} t + i \right)^2. \quad (2)$$

During the operation of the algorithm, everyone is collapsed into the simplest differential polynomial form, and if  $Nt$  is the number of terms contained in the simplest

polynomial and  $Ni$  denotes the maximum allowed number of terms, then the structural fitness is defined as

$$\text{factor} = \left\{ \frac{\sqrt{Nt - Ni}}{\sqrt{Nt + Ni}} \right\}. \quad (3)$$

It follows that when the number of terms of the simplest polynomial of the structural fitness function is less than or equal to the allowed range of terms of its polynomial, the structural fitness is equal to the least-squares fitness of the output error of the evolved individual model: when the number of terms of the simplest polynomial of the structural fitness function is greater than the allowed range of terms of the polynomial, the structural fitness is 10 times the least-squares fitness, at which point the error is magnified by a factor of 10. It is guaranteed that the structure size of evolved individuals does not exceed the maximum range, causing individuals within the range to undergo preferential evolution and eliminating evolved individuals beyond the maximum range.

$$f_t = \frac{f_L + \text{Factor}}{\sqrt{f_{LS}}}. \quad (4)$$

The combination of least-squares fitness and structural fitness is an effective improvement to the common genetic programming algorithm. The combination of the two fitness's effectively limits the infinite reproduction of individual structures in the evolutionary process, reduces the use

of computer memory resources, successfully solves the time complexity problem, and effectively improves the efficiency of algorithmic operations. Genetic programming can quickly discover the relationship between data and mathematical expressions through its own learning and express the relationship between output and input variables in the form of equations. It can be implemented in a variety of programming languages. At the beginning, genetic programming was usually implemented by Lisp language. After a period of development, C language was slowly applied to genetic programming. The size value of the fitness function is used to evaluate the performance of individual evolution, where the smaller the value of the fitness function, the better the performance of the individual obtained, and the greater the probability that the individual will be selected to the next generation population, and the population evolved by genetic programming will be increasingly superior. The steps of genetic programming fitness evaluation are as follows: the GP is represented as a binary tree, the individuals evolved by the GP are expressed as tree rules, and the binary tree of individuals is traversed in the middle order to obtain the general expression of the rules. Multiple perturbation rules are case-matched with the standard model to automatically generate scheduling rules that can be used as having the highest priority level. If the performance of the initial scheduling rule does not meet the scheduling requirements, the scheduling rule is automatically generated based on genetic programming, and the next genetic operation is performed until the optimal scheduling rule is generated. Scheduling rule results from reaching the termination condition.

**3.1.2. Genetic Programming Operands.** The genetic operands of GP are selection, crossover, and mutation. The selection strategy method uses random roulette selection, in which the best individuals with high probability are randomly selected from the population with a certain probability, and the individuals with small fitness values are compared with each other and saved to the new population. The crossover operation uses a binomial tree crossover method, which randomly selects a recombination method between the subtrees of two parents to automatically generate a new generation of individuals. Variation operation generally has two types of variation: node variation and subtree variation; this paper mainly selects node variation, a randomly selected node from the individual tree to make a judgment whether the node element is an operator or an operand and after the judgment is completed, a randomly selected element from the function set or terminator set is selected to replace the initial node element. To ensure that the best individuals in each generation of the population can be retained in the new generation, genetic programming uses the elite retention strategy approach. During the genetic programming process, the genetic programming operation is performed to optimize the new generation population by assigning the probability values of the corresponding genetic operators to the selection operator, crossover operator, and variation operator. The termination control condition in

the iterative process of genetic programming is generally used as a termination condition through a determined number of iterations. The flowchart for the automatic generation of rules for genetic programming is shown in Figure 2.

Uncertainties in the project environment include uncertainty in the duration of activities, uncertainty in the number of resources, and uncertainty in the content of activities, with uncertainty in the duration of activities being the most common. The more project uncertainties there are, the more complex the project scheduling process is. In this paper, we only consider robust scheduling under activity duration uncertainty. In the iterative solution process, outliers will be assigned smaller weights, which weakens the influence of outliers on the probability density and greatly improves the accuracy of probability density estimation. The solution of the robust scheduling algorithm involves a minimum optimization problem. The solution of this problem is the required probability density function, so it cannot be solved by a general solver. The modeling and processing of active duration uncertainty can be described by fuzzy numbers, interval numbers, random factors, etc. In this paper, the active duration is considered as a random factor in the study, so it is necessary to estimate its probability distribution in the analysis, and the forms of the probability distribution of the actual active duration are commonly normal, uniform, P-distribution, exponential distribution, etc., but in the actual project, it is difficult to get the exact probability distribution of activity duration, which is very difficult and is generally based on the historical data of the actual project, using statistical principles to make predictions of the probability distribution. The specific method is as follows: invoke the coefficient of variation in statistics, make qualitative assumptions about the probability distribution of the activity, and exclude some unlikely probability distributions. Define the coefficient of variation  $a = \sqrt{V(x)}/E(x)$ , whose estimated value is

$$a_n = \frac{\sqrt{S^n + 2}}{X^n}. \quad (5)$$

**3.2. Evaluation Model Design for Physical Education in Colleges and Universities.** According to the analysis of the results of the previous survey on the current situation of physical education evaluation in colleges and universities, the suggestions of interview experts, the principles of evaluation system design, combined with the characteristics of the era of big data, the preliminary design of physical education teacher teaching evaluation index system, and student physical education teaching evaluation index system, respectively, the evaluation index system is divided into three parts: primary indicators, secondary indicators, and indicator descriptions, among which the physical education teacher teaching evaluation index system contains the evaluation index system that is divided into three parts: primary indexes, secondary indexes, and index descriptions [18]. The importance of each indicator in the evaluation system was determined by using SPSS statistical software to implement parametric analysis on the computer according

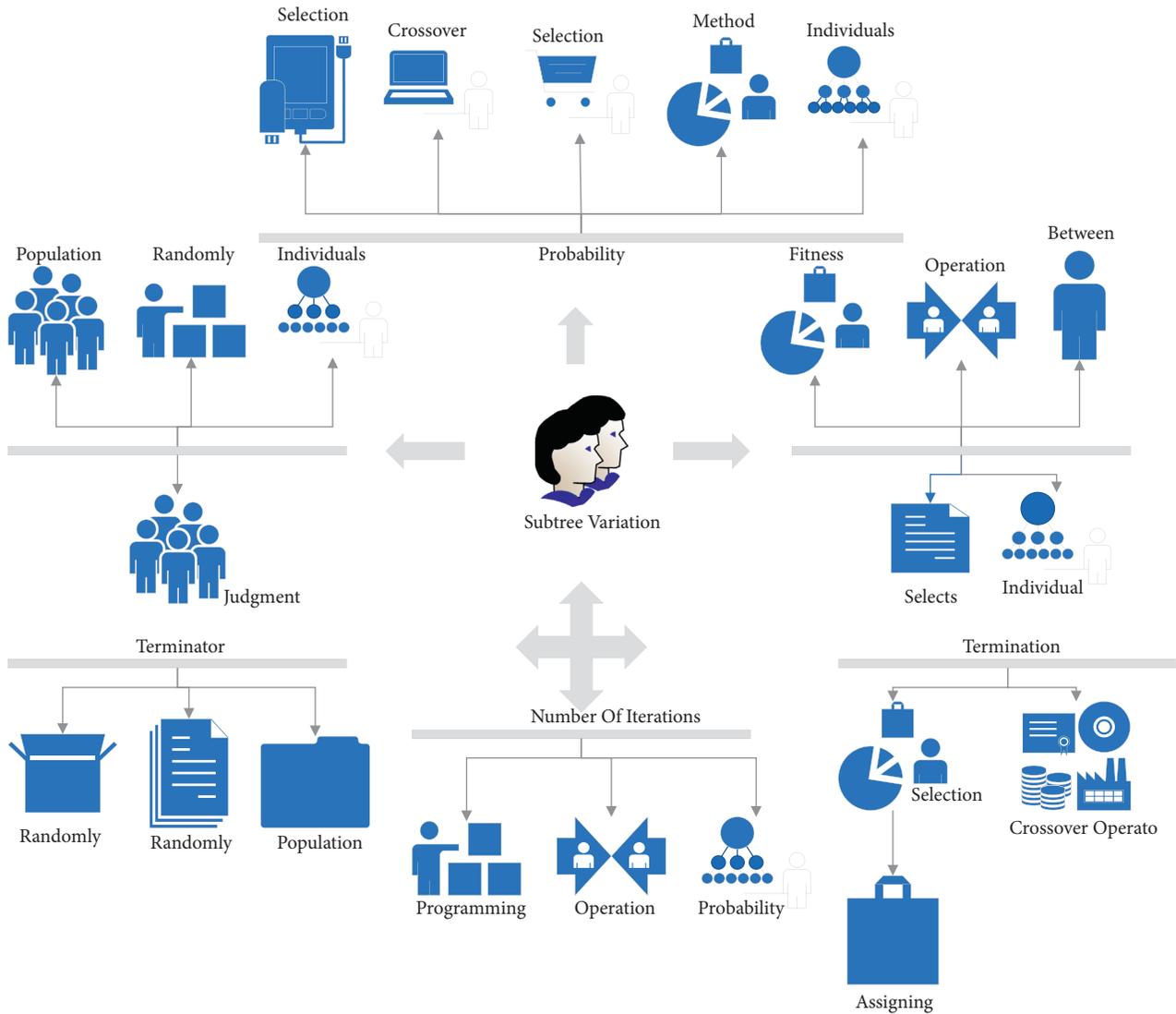


FIGURE 2: Flowchart of automatic rule generation for genetic programming.

to the assigned values of 22 experts. The expert motivation coefficient refers to the response rate of the expert consultation form, and the higher the value of the promised rate, the higher the expert motivation, and the formula is as follows:  $J = n/N$ , where  $N$  is the number of all experts, and  $n$  refers to the actual number of participating experts. The two evaluation indicator rounds of distribution and recovery, the recovery rate, and an efficiency rate of two rounds are 100%, 100%, and 90.91%, 100%, respectively, so the coefficient of expert motivation is high and meets the needs of this study. The coefficient of variation refers to the degree of coordination of experts, and the smaller the coefficient of variation, the higher the degree of coordination. The coefficient of variation  $>0.25$  is considered as a low level of coordination. The calculation formula is

$$S = \frac{\sqrt{1/n + 1}}{\sum (X_j + M_l)^2} \quad (6)$$

The Kendall's Harmony Coefficient,  $W$ , is a test of the consistency of the results of the experts' evaluations of the indicators; the larger the value of  $W$ , between 0 and 1, the higher the consistency. The  $p$ -value represents the significance test of Kendall's Harmony Coefficient:  $p > 0.05$ , the results are not consistent; the opposite is consistent. The formula is as follows:  $N$  denotes the number of indicators evaluated,  $K$  denotes the number of experts participating in the evaluation,  $S$  denotes the sum of the sums  $R_i$  of the grades evaluated for each indicator evaluated and the sum of the squares of the deviations from the mean of all these sums  $R_i$ , and  $T_i$  denotes the correction factor.

$$S_R = \sum_n^{i=1} R_i^2 + \frac{1}{n} \left( \sum_{i=1}^n R \right) \quad (7)$$

According to the analysis of the status of implementation of college teaching evaluation, the process of college physical education teaching evaluation is designed in the context of

big data application, the main users are teaching managers, teachers, and students, and the evaluation process includes data collection, data analysis, evaluation result output, and result feedback, as shown in Figure 3. Crossover and mutation process of genetic programming Gene duplication refers to the selection of individuals in some contemporary populations, which can be directly copied to the next generation of populations without any genetic manipulation. The selection of individuals mainly depends on the value of the fitness function. The higher the fitness function value, the greater the probability of being selected. Mutation refers to the process of randomly selecting mutation nodes on an individual to generate a new individual.

- (1) Data collection: data collection is the final entry of evaluation data after a new item has been created, based on the item category, the evaluation method that has been specified, etc. In this study, leaders, physical education teachers, and students entered physical education evaluation data from the campus web platform, while having the ability to add, modify, delete, and other operations. The main data collected are the basic information of physical education teachers (name, teaching experience, gender, etc.), the basic information of students (name, gender, school number, grade, major, etc.), and the physical education evaluation information of leaders, teachers, and students, which are stored into the database according to a unified format, and the database saves the entered evaluation data in time to ensure the smooth evaluation analysis at a later stage.
- (2) Data processing and analysis: under the background of big data application, the data collected in the process of college physical education evaluation, we can apply big data-related technology for processing, apply the big data-related technology to in physical education evaluation, integrate and analyze the collected data, deep mining, obtain a large amount of information, make the evaluation results more scientific and objective, and have certain application value [19]. Data mining is usually used in big data to process data, and data mining contains many algorithms, such as decision tree classifier C4.5, K-mean algorithm, support vector machine, Apriori algorithm, maximum expectation estimation algorithm, Page Pank algorithm, AdaBoost algorithm, K-nearest neighbor classification algorithm, plain Bayes algorithm, classification, and regression tree algorithm. Our data mining process in the evaluation process of physical education can be summarized in three stages: data preparation, data mining, and analysis of results.
- (3) Result in output and feedback: there is an essential link after the end of the evaluation; that is, the feedback link and evaluation without feedback link are incomplete. Physical education evaluation must function through the final feedback, and the lack of

feedback in physical education evaluation will lose its proper meaning and function. Physical education teaching evaluation in colleges and universities can take advantage of the convenience of the network in the era of big data and the popularity of mobile intelligent terminals to provide timely feedback to teaching managers, physical education teachers, and students through online feedback to improve the feedback effect to achieve the purpose of physical education teaching evaluation. The test results are shown in Figure 4.

#### 4. A Genetic Programming Robust Scheduling Algorithm Based Evaluation Model for College Physical Education

*4.1. Evaluation of Physical Education in Colleges and Universities to Achieve.* Assessment and evaluation in the physical education classroom should be more quantitative, using diagnostic, process, and summative assessments in a rational way. Diagnostic assessment is set at the beginning of the gymnastics course to diagnose the actual situation of each student, i.e., the “longboard” and the “shortboard.” This not only allows changes to be made to the original teaching plan, with different requirements for each student, to facilitate the smooth implementation of the teaching content, but also provides an objective and fair evaluation of the students, motivating them to continuously improve themselves and enhance their gymnastics level. Process evaluation is a kind of evaluation carried out in the process of teaching gymnastics, after diagnostic evaluation, after diagnosing the level of each student, and then a kind of assessment evaluation based on their learning ability and degree of progress, process evaluation, can help students find out problems and correct them, which is carried out at the same time with the teaching content and teaching plan [21]. Summative evaluation is conducted at the end of each semester and is a kind of evaluation, after all teaching contents and teaching plans are completed, and it is a summative evaluation for each student, as well as the final assessment of the whole gymnastics course. Process evaluation is a kind of evaluation carried out in the process of teaching gymnastics. After diagnostic evaluation, the level of each student is diagnosed, and then an assessment evaluation is carried out based on his or her learning ability and degree of progress. Process evaluation can help students identify problems and correct them, and it is carried out simultaneously with the teaching content and teaching plan. The use of the above three assessment and evaluation mechanisms is more able to better grasp the students’ learning situation, has also timely feedback on the teaching content and teaching plan, and is an objective test for the students’ ability improvement. The assessment content of the general physical education courses in 10 physical education colleges and universities can be divided into five aspects: sports technology assessment, sports skills assessment, theory assessment, physical quality assessment, and usual assessment, and the most used is also summative. Very little diagnostic and process assessment is involved.

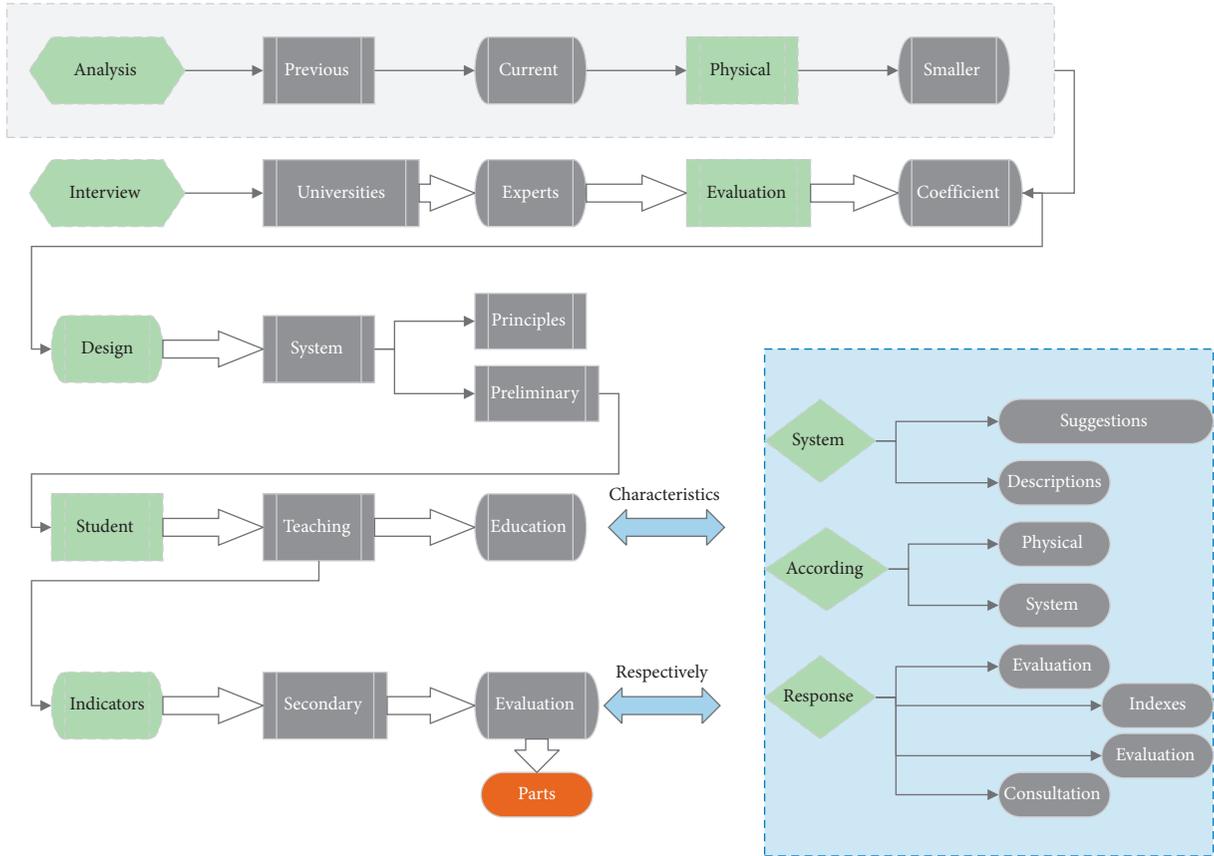


FIGURE 3: Evaluation process of physical education teaching in colleges and universities.

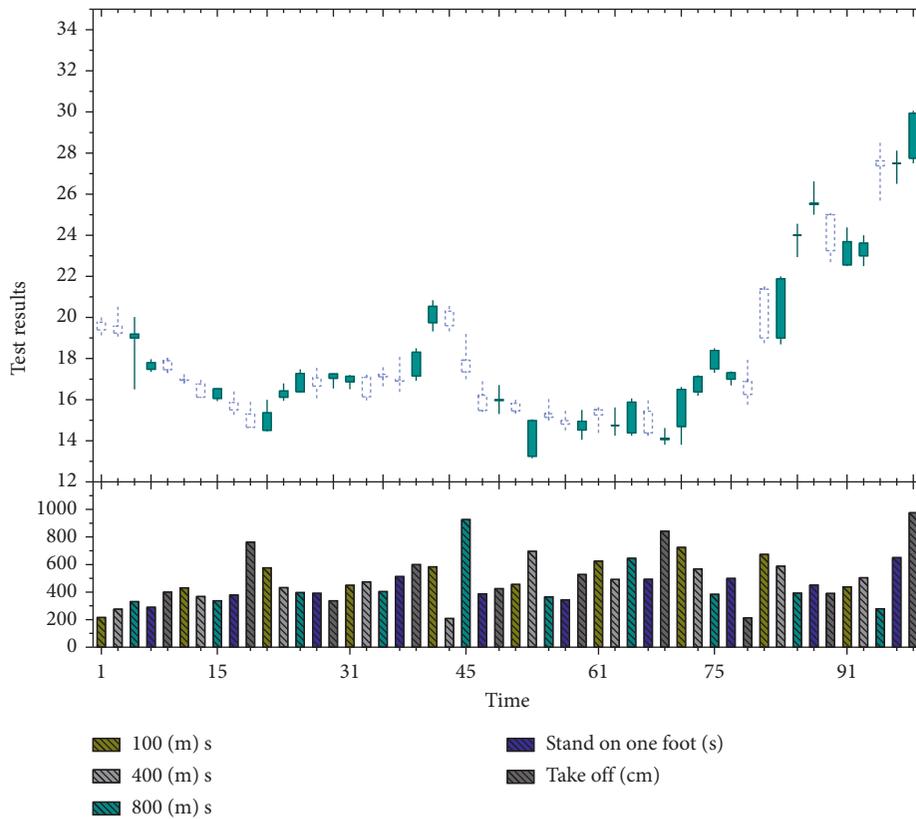


FIGURE 4: Test results.

The main body of physical education option class learning evaluation in colleges and universities is still mainly teacher evaluation, accounting for 83.33% of the overall proportion, and a few teachers use teacher evaluation + student mutual evaluation, accounting for 16.67% of the overall proportion, mainly reflected in the final set of skills examination, and most teachers will take the group as a unit for aerobics group choreography examination, so the members of each group give scores to the members of other groups and participate in the students' mutual evaluation, which can exercise the students' aerobics appreciation ability. 46.67% of teachers think it is feasible for students to participate in learning assessment in aerobics option classes, 36.66% think it is feasible for students to participate in learning assessment, and the remaining 16.67% are not sure. This shows that most teachers in the general universities in Kunming have a supportive attitude; they believe in their students and in their students' ability to self-monitor and monitor others. The case is shown in Figure 5.

To complete the practical application of the improved novel genetic programming robust scheduling algorithm in physical education evaluation, we analyze the problems existing in physical education, establish the mathematical model of the physical education system, and then design the physical education evaluation system, including the development environment of the system to the overall architecture design and the database design. Finally, the functions of the physical education evaluation system are realized, including the description of the physical education home page menu and the setting of the physical education evaluation rules to complete the physical education evaluation results while realizing the management of the physical education evaluation. The physical education evaluation system with the new improved adaptive genetic programming robust scheduling algorithm is applied for system testing. From the functional test as well as the performance test and compatibility test of the system, the stability of the physical education evaluation is verified, the user requirements are met, the goal of the physical education evaluation system is achieved, the rational allocation of teaching resources and the completion of the physical education evaluation plan are improved, and the physical education teaching management system in colleges and universities is promoted. The system tends to be intelligent. The experimental results compared before and after the improvement are shown in Figure 6.

**4.2. System Analysis of Genetic Programming Robust Scheduling Algorithm.** As the size of the project increases, the differences between the algorithms become apparent, with BasicChaining being the least effective algorithm. It is worth noting that the algorithm proposed by Artigues (2003), although aiming only to build a feasible resource network without considering any robustness goal, outperformed BasicChaining and MaxCC algorithms in the J50 project. The reason for this is that the procedure always considers the resource providers for a given activity in the same order (i.e., starting time increments). Thus, the resource providers for a given activity may be more similar for

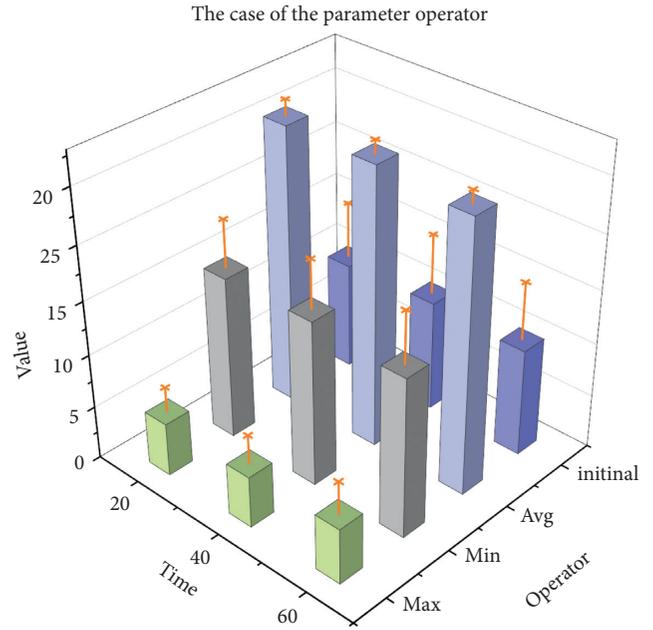


FIGURE 5: The case of operators with parameters.

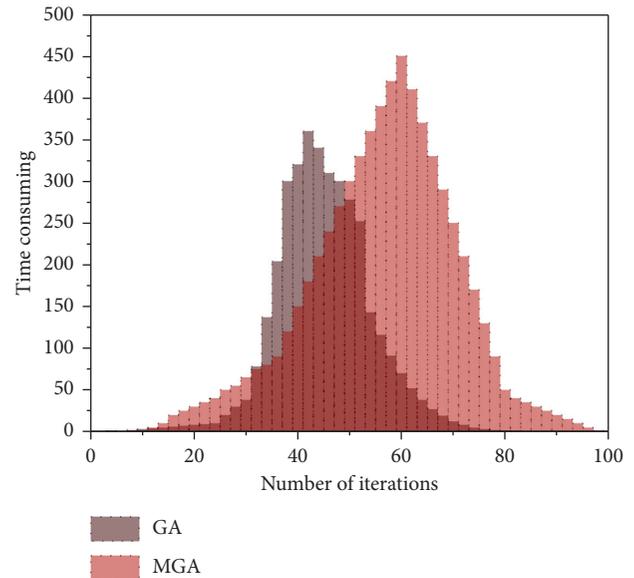


FIGURE 6: Experimental tests comparing the time required.

different resource types. In contrast, the BasicChaining and MaxCC procedures select the first resource provisioning activity for a given activity and resource type in a random manner, which typically leads to more resource dependencies between activities when considering multiple resource types [20]. In contrast, the algorithm proposed in this paper not only prioritizes the immediately preceding activities in the original network when selecting forward activities, but also adds the forward activities corresponding to the unavoidable arcs to the set of preferred resource activities. It also prioritizes the activities with low hazards to establish resource constraints with the specified activities to further reduce the impact on the stability of the network.

Both the resource allocation algorithm and the obtained resource flow network using this paper exhibit generally better robustness than other algorithms in simulation experiments. In small projects (e.g., the J10 project team), the differences in the robustness of each algorithm are small, and the advantage of the RFAP algorithm is not obvious, with only a 3% reduction in SC values, a 0.6% reduction in APZ values, and a reduction in NPC values of no more than 1 compared to the results of the algorithm with the worst relative performance. This is because the key to the RFAP algorithm is the selection of the forward activities, and when the project size is small, the activities' backward subnetwork complexity, as well as the right-shift able idle time, does not differ much, and multiple activities are randomly selected when performing the allocation of resources, so the improvement over the existing algorithm is small. Under the background of big data application, the data collected in the process of physical education teaching evaluation in colleges and universities can be processed by applying big data-related technologies. Mining and obtaining a large amount of information make the evaluation results more scientific and objective and have certain application value. But as the size of the project increases, the gap between the algorithms increases, and in the J50 project group, the RFAP algorithm outperforms the existing algorithm for all metric values, and compared to the worst solution for each metric, the RFAP algorithm has a 10.5% reduction from the SC value, a 47.1% improvement in the TPCP value, a 0.4% reduction in the value, and a reduction in the NPC value of almost 8. This indicates that the present algorithm is better at improving the robustness of medium and large project's robustness, is more advantageous, and can be further built upon to generate robust buffer plans.

$$S_j = \frac{S_j(J)}{a_j + \text{float}(J)} \quad (8)$$

In practice, regardless of the dataset for which it was run, most of the individuals in the population will start missing diversity in the later stages of optimization as they tend to form the same tree structure. Therefore, we only use it to synthesize a feature, and often selecting the first few genetic programming trees that perform well and visualizing those reveals that the overall structure of the genetic programming tree is pretty much the same, except for some branch and leaf nodes. This is the dilemma of current evolutionary algorithms; if a tournament algorithm is chosen, the overall population will certainly tend to be increasingly similar as it evolves towards potential local optima, very much in line with the perception of the natural world, but at the same time giving up more possibilities as a result. This is especially true in the case of evolutionary algorithms for tree-symbolic programs like genetic programming. So, multiple runs of GPFC-TPOT will produce different results as the initial state of the population differs at the time of initialization as shown in Figure 7.

The data-driven robust optimization method overcomes the drawbacks of conventional robust optimization methods that are too conservative. To verify the superiority of the data-driven robust optimization method and show the

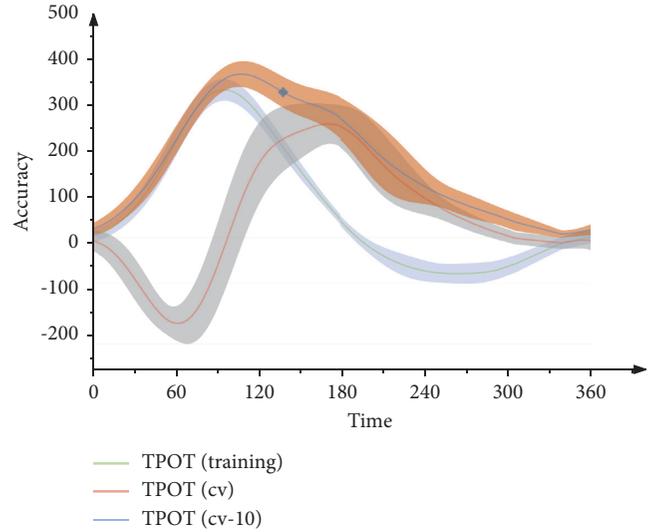


FIGURE 7: Experimental data showing.

difference between data-driven uncertainty sets and conventional uncertainty sets, the actual operations of the conventional robust optimization method and the data-driven robust optimization method based on kernel density estimation and robust kernel density estimation are compared and analyzed, regardless of the dataset at which it is targeted, most of the individuals in the population at the later stages of optimization will start to lose diversity because they tend to form the same tree structure and start missing diversity. Therefore, we only use it to synthesize a feature, and often selecting the first few genetic programming trees that perform well and visualizing those reveals that the overall structure of the genetic programming tree is pretty much the same, except for some branch and leaf nodes. This is the dilemma of the current evolutionary algorithms; if a tournament algorithm is chosen, the overall population will certainly tend to be more similar as it evolves towards potential local optima, very much in line with the perception of the natural world, but at the same time giving up more possibilities as a result. In order to verify the superiority of the data-driven robust optimization method and show the difference between the data-driven uncertainty set and the conventional uncertainty set, the conventional robust optimization method and the data-driven robust optimization method based on kernel density estimation and robust kernel density estimation are compared and analyzed. During the actual operation of the optimization method, no matter which data set it is aimed at, in the later stages of optimization, most of the individuals in the population tend to form the same tree structure and begin to lose diversity. This is especially true in the case of evolutionary algorithms for tree-symbolic programs like genetic programming. Figure 8 was an experimental test comparing the time required.

Purely genetically programmed feature synthesis (the process of searching for an initial model without a prior TPOT) cannot evolve the population because it cannot bind the fitness values of the population and thus cannot optimize the feature tree. Taking a step back, even if binding to a

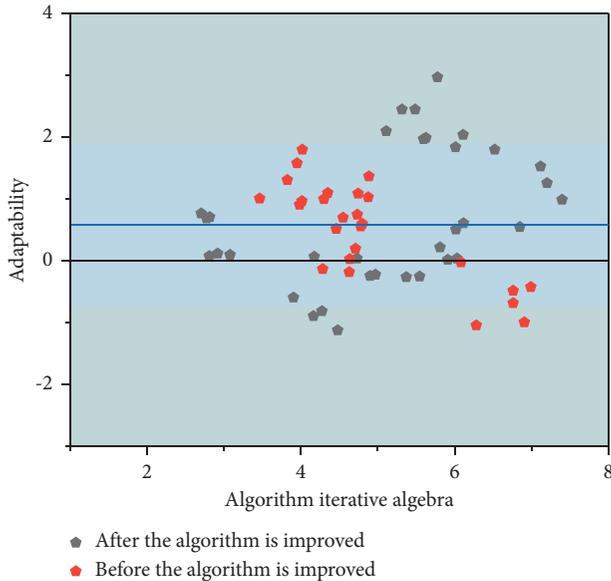


FIGURE 8: Comparison of experimental results before and after improvement.

particular model could evolve the feature synthesis tree, it is difficult for us to decide that the feature synthesis tree is good. For example, for a given dataset, there are multiple models such as SVM, NN, and KNN with accuracies of 93%, 96%, and 67%, respectively. In this case, it is pointless to explore the KNN-based accuracy to evolve the feature synthesis tree; after all, the model itself is just not suitable. And Auto ML methods such as TPOT can solve this problem precisely.

## 5. Conclusion

The evaluation of physical education in colleges and universities has many problems such as single subject and mode, simple and vague indicators, unscientific methods, lack of individuality in standards, imperfect guarantee mechanism, and unsound feedback mechanism, which largely deviates from the original purpose of physical education evaluation, which has much to do with the long-standing centralized and unified administrative management system in education. This study combines the knowledge related to the genetic programming robust scheduling algorithm to determine the evaluation indexes, which basically can reflect the various elements of the physical education process, and the distribution of index weight coefficients is more scientific and reasonable, and the physical education evaluation system of colleges and universities constructed by the exploration has certain objectivity and scientific compared with the current system, so it is feasible to apply big data to the evaluation of physical education in colleges and universities. The subjects of college physical education evaluation in the context of genetic programming robust scheduling algorithm application include physical education teachers, students, peers, and personnel of physical education teaching authorities, and the evaluation index system consists of physical education

teachers' teaching evaluation index system and students' physical education teaching evaluation index system. The construction of the evaluation system of physical education in colleges and universities should be combined with the characteristics of the era of genetic programming robust scheduling algorithm, and the evaluation process includes four major links: data collection, data analysis, result output, and result in feedback; data collection should be comprehensive, data analysis methods should be scientific, result output should be accurate, and result in feedback should be timely and open, and each link is an indispensable part of the physical education evaluation process.

## Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

## Conflicts of Interest

The authors declare that they have no known conflicts of interest or personal relationships that could have appeared to influence the work reported in this paper.

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