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A method for weighting English education evaluation indicators based on multi-objective planning

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Abstract This study aims to construct a scientific weight allocation model of English education evaluation system to improve the scientificity and objectivity of English education evaluation. This paper constructs an English education evaluation index system containing fifteen secondary indicators and five primary indicators. Based on the defects in parameter selection of the standard projection tracing model, this paper introduces the particle swarm optimization algorithm to optimize the parameters of the model, and combines the quality evaluation mathematical model based on segmental interpolation method to assign the weights of English education evaluation indicators, which accurately reflects the contribution of each indicator. In the experimental part, this paper compares the model optimized by the particle swarm algorithm with the standard projection tracing model, and finds that the relative error of this paper's model is reduced by 0.61% compared with the standard projection tracing method, and it can effectively identify the key evaluation indicators, and identify the school leadership level as the most critical English education evaluation indicators. The study provides English education administrators and teachers with more referential evaluation information, which contributes to the scientificization and standardization of the English education evaluation system.

Index Terms English Education Evaluation System; Particle Swarm Optimization Algorithm; Projection Tracing Model; Segmental Interpolation Quality

I. Introduction

In the context of globalization, the importance of English, as a universal language, is becoming more and more prominent. English in colleges and universities is a key course for cultivating students' cross-cultural communication and exchange ability, which should resolutely reverse the tendency of one-sided test-oriented education, change the unscientific educational evaluation orientation, reintegrate and give full play to the advantages of teaching, focus on the development of students in line with international standards, and guide the students to carry out in-depth learning [1]-[3]. In response to this requirement, it is extremely necessary to study and formulate the construction of teaching evaluation index system that is up-to-date with the times.

Whether the construction of teaching evaluation index system is scientific and reasonable, to a certain extent, will directly affect the effect of teaching evaluation [4]. This is not only the ballast for the implementation of teaching reform, but also the support for boosting the transformation of teaching philosophy and teaching behavior [5]. Effective teaching evaluation will have a positive orientation and feedback effect on teachers' teaching so that teachers can adjust their teaching process in time according to the evaluation results, make remedies and corrections in time for the deficiencies and problems in teaching, and ultimately realize the effect of promoting teaching and learning by evaluation [6]-[9]. With the progress of society and science and technology, new situations, new challenges and new problems have emerged in Chinese higher education and university English education [10], [11]. How to utilize the achievements of science and technology at this stage to improve the time-consuming and inefficient problems in English education, especially constructing a set of scientific and reasonable quality assurance and assessment system for university English teaching is an urgent problem to be solved and researched to improve the quality of university English teaching [12]-[14].

This paper constructs a more scientific weight allocation model for English education evaluation system based on the projection tracing model optimized by particle swarm algorithm. This paper constructs the English education evaluation index system from five aspects: teaching resources, teaching content, teacher quality, teaching effect and teaching quality feedback. Then the particle swarm algorithm with powerful global search capability and modeling adaptability is used to solve the optimal projection direction in the projection tracing model. Finally, the quality evaluation mathematical model was constructed using segmented linear interpolation to find the function mapping relationship between evaluation data and evaluation level. After testing the excellent performance of the model in this paper with comparative experiments, the English teaching data of English majors in a university in city A was selected as the research object to verify the practical application effect of the model.

II. Model for assigning weights in the evaluation system for English language education

II. A. The construction of English education quality evaluation system

Teaching resources refer to the student classrooms, English activity rooms, student microcomputer rooms, libraries, and all kinds of English books and magazines for teachers to use and for students to expand their knowledge of English. It also includes word cards, wall charts, tape recorders and other teaching equipment to assist English teaching.

Teaching content refers to the English curriculum that teachers are prepared to design to meet the English learning level of students, including the design of questions and answers, interactive sessions, and so on.

Teacher quality includes the number of teachers, their academic qualifications, years of teaching experience, title status, and whether or not they have participated in backbone teacher training.

The teaching effect of each grade varies, with the lower grades focusing on simple phrases and easy vocabulary, the middle grades focusing on communicative phrases and common vocabulary, and the upper grades focusing on oral communication and dialogues, communicative discourse, and a certain amount of vocabulary.

At present, feedback on the quality of English teaching comes from three main sources: the district education bureau, school leaders and frontline English teachers. The school encourages teachers to share their teaching experience and listen to each other's lessons in order to complement each other's strengths. Leaders also enter the classroom from time to time to monitor the teaching activities of English teachers and students' learning. The Education Bureau requires the teaching researchers of the Teaching and Research Office to come into the school every semester to conduct regular inspections of push classes, lesson plans and assignments, and also organizes the English Teachers' Teaching Skills Competition, which stimulates the English teachers to improve their own qualities through various forms and thus improves their teaching level. However, the quality of teaching is still based on the scores of the students, especially the scores of the Unified Examination, and the horizontal comparisons of the same level of the different schools are made within the whole district.

The establishment of education quality evaluation system is a complex systematic project, scientific, comprehensive and operable are the three major principles of teaching quality evaluation system. Because the teaching quality system not only contains the setting of indicators, the follow-up also involves data collection, analysis, and therefore the realization of operability under the premise of science ahead. Combining the experience of domestic and foreign education evaluation index system and the status quo of English subject teaching, the teaching evaluation quality system was established as shown in Table 1.

Table 1: English teaching quality evaluation index system

Target layer	Criterion layer	Index layer
English education quality evaluation X	Teaching resources Y1	Network resources Z1
		Book resources Z2
		Class capacity and other hardware facilities Z3
	Teaching content Y2	Comprehensive teaching Z4
		Clear teaching goals Z5
		practicability Z6
	Teacher qualityY3	Professional ability Z7
		Teaching method Z8
		Occupational ethics Z9
	Teaching effect Y4	Students' ability to hear English Z10
		Students' ability to read English Z11
		Students' ability to write English Z12
	Teaching quality feedback Y5	Teaching quality feedback Z13
		District education bureau Z14
		School leadership Z15

II. B. Projection Tracing Model

The basic idea of PPM [15] is to map the high-dimensional data onto the low-dimensional subspace through some combination, and to find the structure and features of the original data by analyzing the structure and features of the data in the low-dimensional space, so as to achieve the purpose of analyzing and processing high-dimensional data.

(1) Linear projection

A linear projection is a way to reduce high-dimensional data to a lower-dimensional space. The matrix A of any $n \times m$ of rank n is used to represent the linear projection from R^m down to R^n dimensions, called the projection matrix or direction, where $n < m$. Then the linear projection Z of the m-dimensional random variable Y can be represented by the matrix product of the projection matrix A and the random variable Y, i.e., the following form:

$$Z = AY, A \in R^m, Z \in R^n \tag{1}$$

where A is a full rank matrix consisting of n linearly uncorrelated vectors, and the n row vectors of A must be unit vectors and mutually orthogonal.

Assume that the high-dimensional data matrix Y obeys the F distribution and the linear projection Z obeys the distribution F_A: when n is taken to be 1, A becomes of the form of a column matrix a^T, and F_a denotes the distribution when A is x^T. The eigenfunction φ of the one-dimensional projection F_a in the projection direction can be equated to the eigenfunction φ_a of F in the same direction, and there exists a mathematical relationship as shown below:

$$\varphi_a(F) = \varphi(F_a) \tag{2}$$

where φ_a denotes the eigenfunction of F and φ denotes the function of the one-dimensional projection F_a.

(2) Projection metric

Using a quantitative index to represent the data characteristics of high-dimensional data in low-dimensional space, in order to find the best projection direction, this index is called projection index.

From a mathematical point of view to define the projection index: the projection index of random variable Y in the projection direction A is the real-valued function Q on a set of n-dimensional distribution functions, denoted as $Q(F_A)$. In fact Q is some definite value that transforms the spatial function into, i.e., a generalized function on an n-dimensional space, which can also be denoted as $Q(AY)$, and denoted as $Q(a^T Y)$ when n is taken to be 1.

(3) Optimal projection direction

According to the basic idea of PPM, the key of the model is to obtain the best projection direction that can reflect the characteristics of the high-dimensional data structure. The projection direction reflects the characteristics of the data structure, and the best projection direction is the direction that reflects the most characteristics of a certain type of high-dimensional data, but also the direction that makes the most full use of data information and the most information preservation. Optimizing the projection direction is in fact to look for the best projection index in a certain sense, which is generally closely related to the actual problem.

II. C.PSO algorithm

PSO algorithm [16] is a meta-heuristic optimization algorithm with global search capability, and its basic flow is as follows.

Assume a D-dimensional search space with a particle swarm $X(x_1, x_2, \cdots, x_N)$ consisting of N particles, which are moving in the search space with a certain speed in one direction.

The current spatial position of the i th particle is:

$$x_i = (x_{i1}, x_{i2}, \cdots, x_{iD})(i = 1, 2, \cdots, N) \tag{3}$$

The i th particle is currently running at:

$$v_i = (v_{i1}, v_{i2}, \cdots, v_{iD})(i = 1, 2, \cdots, N) \tag{4}$$

Calculate the fitness value of the particle and find the current searched optimal position of the particle with the current optimal position of the whole particle swarm based on the particle fitness value.

The individual optimal position is denoted as:

$$p_i = (p_{i1}, p_{i2}, \cdots, p_{iD})(i = 1, 2, \cdots, N) \tag{5}$$

The globally optimal position is noted as:

$$p_g = (p_{g1}, p_{g2}, \cdots, p_{gD})(g = 1, 2, \cdots, N) \tag{6}$$

During each iteration, the particle updates its velocity and position information through the individual poles and global poles.

The velocity update formula is:

$$v_{id}^{(k+1)} = \omega v_{id}^{k} + c_1 r_1 \left(p_{id}^{k} - x_{id}^{k} \right) + c_2 r_2 \left(p_{gd}^{k} - x_{id}^{k} \right) \tag{7}$$

The position update formula is:

$$x_{id}^{(k+1)} = x_{id}^{k} + v_{id}^{k+1} \tag{8}$$

where $i = 1, 2, \cdots, N$; c_1 , c_2 are the learning factors; ω is the inertia weight; r_1 , r_2 are the constants of a random distribution between [0, 1]; k , $k+1$ denote the current number of iterations; v_{id}^{k} , x_{id}^{k} denote the velocity and position of the i th particle's velocity and position in the d -dimensional component of the velocity vector of the flight in the k th iteration; p_{id}^{k} denotes the d -dimensional component of the individual optimal solution of the i th particle; and p_{gd}^{k} denotes the d -dimensional component of the population optimal position.

From the above equation, it can be seen that the learning factor and inertia weight are the parameters to be set in Eq. and have a great influence on the calculation.

c_1 is used to adjust the distance of particles flying along the individual extremes, c_2 is used to adjust the distance of particles flying along the global extremes, c_1 and c_2 have a greater impact on the convergence of the algorithm, the appropriate choice of c_1 and c_2 can improve the speed of the algorithm to avoid falling into the local extremes, based on the conclusions of the research of many scholars c_1 and c_2 are generally taken as 2.

Inertia weights represent the degree of trust of the particle on its own motion state, some scholars have found that when the value of inertia weights between 0.8~1.2, the convergence speed of PSO algorithm will be larger than the ordinary range, with the increase of inertia weights algorithm convergence speed is also accelerated, in this paper, we use the linear decreasing inertia weights, the mathematical expression is as follows:

$$\omega = \omega_{\max} - \frac{k}{k_{\max}} \left(\omega_{\max} - \omega_{\min} \right) \tag{9}$$

where $\omega_{\max}$, $\omega_{\min}$ denote the maximum and minimum weights, respectively; and $k_{\max}$ represents the maximum number of iterations run.

The flowchart of the PSO algorithm is shown in Fig. 1.

II. D.Evaluation modeling

II. D. 1) Standardization of evaluation indicators

First of all, this paper sets the original data sample set as: $\left\{ x^*(i,j) \mid i = 1 \sim n, j = 1 \sim p \right\}$, where $x^*(i,j)$ is the original value of the j evaluation indicator in the sample of the i th provincial region, and n and p are the number of the samples and the number of indicators, respectively. Because the English education level of each institution is not uniform in terms of the scale and the range of variation of each evaluation index, this paper first uses the method of polar deviation to standardize the raw data when carrying out calculations, and the formula is shown below:

For the positivity indicators:

$$x(i,j) = \left(x^*(i,j) - x_{\min}(j) \right) \Big/ \left(x_{\max}(j) - x_{\min}(j) \right) \tag{10}$$

For negative indicators:

$$x(i,j) = \left(x_{\max}(j) - x^*(i,j) \right) \Big/ \left(x_{\max}(j) - x_{\min}(j) \right) \tag{11}$$

where $x_{\max}(j)$, $x_{\min}(j)$ are the maximum and minimum values of the original values of the j th indicator, respectively; and $x^*(i,j)$ is the standardized value of each evaluation indicator.

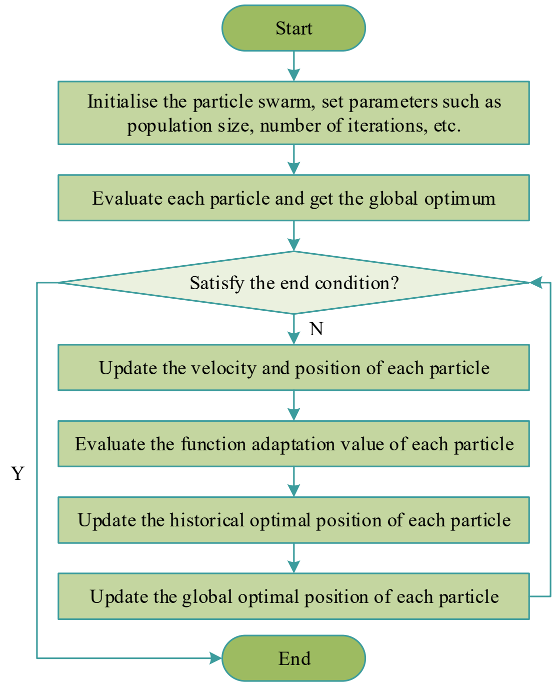

Figure 1: The basic process of the pso algorithm

II. D. 2) Constructing projection indicator functions

The projection-seeking model is to project the p -dimensional data $\left\{x^*(i,j) \mid i=1,n; j=1\sim p\right\}$ into a one-dimensional projection value $Z(i)$ with $a=\left\{a(1),a(2),\cdots,a(p)\right\}$ as the direction of the projection of the ELA grade, i.e.:

$$Z(i)=\sum_{j=1}^{p} a(j)*X(i,j)(i=1\cdots n) \tag{12}$$

The projection objective function as well as the standard deviation (S_Z) and the local density (D_Z) of the safe projection value $Z(i)$ are respectively:

$$Q(a)=S_z D_z \tag{13}$$

$$S_z=\left\{\sum_{i=1}^{n}[Z(i)-E(z)]^2 \Big/ (n-1)\right\}^{\frac{1}{2}} \tag{14}$$

$$D_Z=\sum_{i=1}^{m}\sum_{j=1}^{m}\left(R-r(i,j)\right)*u\left(R-r(i,j)\right) \tag{15}$$

where $E(z)$ is the mean of the safe projection sequence $\left\{Z(i) \mid i=1\sim n\right\}$; R is the radius of the local density, which usually takes the value of 0.1 S_Z; $r(i,j)$ denotes the distance between the samples, $r(i,j)=\left|Z(i)-Z(j)\right|$; the sign function $u\left(R-r(i,j)\right)$ is a unit step function, and the value of the function takes 1 when $R\geq r(i,j)$, and 0 otherwise.

The key of the projection tracing method is to find the best projection direction that maximally exposes a certain type of feature structure of the high-dimensional data. When the sample set of evaluation indexes is established, the projection index function $Q(a)$ only changes with the change of the projection direction a, so the projection index function can be optimized to find the optimal vector of projection methods:

$$Max : Q(a) = S_z D_z \tag{16}$$

Constraints:

$$\sum_{j=1}^{p} a^2(j) = 1 \tag{17}$$

This is a complex nonlinear optimization problem with $\{a_j \mid j = 1 \sim p\}$ as the optimization variable, which is difficult to be solved by traditional optimization methods, so the particle swarm algorithm is chosen to optimize it in this paper.

II. D. 3) Particle Swarm Optimization Projection Indicator Functions

Suppose that in a D-dimensional target search space, N particles form a swarm, where any i particle is represented as a D-dimensional vector $X_i = (x_{i1}, x_{i2}, \cdots, x_{iD})$, the position of the i th particle is x_i and the velocity is v_i, the best position experienced by the particle during its flight, i.e., the individual extreme value, is denoted as $Pbest$, and the best position experienced by the swarm of particles, i.e., the global extreme value, is denoted as $gbest$, and after randomly generating the initial positions and velocities, the particles update their own positions and velocities by keeping track of the individual extreme value and the global extreme value, and the updating formula is as follows:

$$\begin{aligned} v(t+1) = wv_i(t) + c_1 r_1(t)(pbest_i(t) - x_i(t)) \\ + c_2 r_2(t)(pbest(t) - x_i(t)) \end{aligned} \tag{18}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{19}$$

where w is the inertia weight, c_1 and c_2 are the acceleration constants, r_1 and r_2 are uniformly distributed random numbers in the range $[0,1]$, and the formulae for updating the individual extrema for each particle and the global extrema for the whole particle are as follows:

$$pbest_i(t+1) = \begin{cases} x_i(t+1) & x_i(t+1) \geq pbest_i(t) \\ pbest_i(t) & x_i(t+1) < pbest_i(t) \end{cases} \tag{20}$$

$$gbest_i(t+1) = \max\left(pbest_i(t+1)\right) \quad i = 1, 2, \cdots, N \tag{21}$$

The particle swarm projection tracing model calculation step is that the current particle position $x_i(t+1)$ is the optimal projection direction vector a, which is substituted into the calculation of the one-dimensional projection value $Z(i)$, and at the same time, the calculation of the S_Z, D_Z, and $Q(a)$, and the whole algorithm is terminated when the difference of the optimal particle adaptation value between the moment of $t+1$ and that of the moment of t is less than a set threshold value, or reaches the predefined number of iterations. operation of the algorithm. At this time, the global extreme value found by the particle swarm is the optimal projection direction a^*, and the adaptation value corresponding to the global extreme value is the maximum projection index function $Q(a)^*$, and the optimal integrated projection value $Z(i)^*$ is obtained by substituting the obtained a^* into Eq.

II. E. Mathematical model of quality evaluation based on interpolation method

In the multifactorial English education quality evaluation, it is often necessary to find the mapping relationship between the data and the evaluation level, while the data in real life is often limited, which results in the discontinuity of the mapping relationship between the data and the evaluation level, and in the evaluation of the quality of English education, it may cause the evaluation results and the evaluation level do not correspond to each other, so as to be unable to obtain the evaluation results. On the other hand, the interpolation method can effectively solve the problem of discontinuous data mapping by "simulating and generating" some new and more reliable data, so it has good applicability in the comprehensive evaluation of multi-factors. Although there are many interpolation methods, but in view of the segmented linear interpolation method [17] has a simple form, simple operation, strong quality and other characteristics, this paper intends to use segmented linear interpolation method to construct the quality evaluation mathematical model.

According to the projection value $z_0(i)$ of the standard sample set and its corresponding quality evaluation grade, the segmented linear interpolation method is used to construct the quality evaluation model:

$$Y = f(z_0) \tag{22}$$

By substituting the computed projection value $z_1(i)$ of the set of evaluation samples into the mathematical model $Y = f(z_1)$, the English education quality evaluation grade of each evaluation sample can be found.

III. Performance analysis of particle swarm optimized projection tracing model

In order to verify the arithmetic accuracy of the English education evaluation model based on the particle swarm optimization projection tracing algorithm, this paper will carry out a comparative analysis of the English education evaluation model based on the standard projection tracing method, using the sample data as well as the established evaluation indexes of the English education to carry out the calculations, and obtaining the six groups of critical projection values as 6.152, 5.284, 4.345, 3.481, 2.543, respectively. 0.000, according to the best projection value of each grade, the scatter plot of projection grade and projection value was plotted, and the relationship between projection grade and projection value of the standard projection tracing method is shown in Fig. 2, and a polynomial fitting was done to get the functional relationship between projection grade y and projection value z: y = -0.095z2 - 0.245z +5.02, and the linearity of the fit reaches 0.993.

From the calculation results, the standard projection tracing method and the particle swarm optimization projection tracing method have a high rate of calculation, can clearly distinguish the different levels of school English education levels, both models can be a better judgment of the situation of English education, and the main difference between the two methods comes from the numerical difference in the process of quantification, which is specifically embodied in the quantification of precision as well as stability of the two aspects.

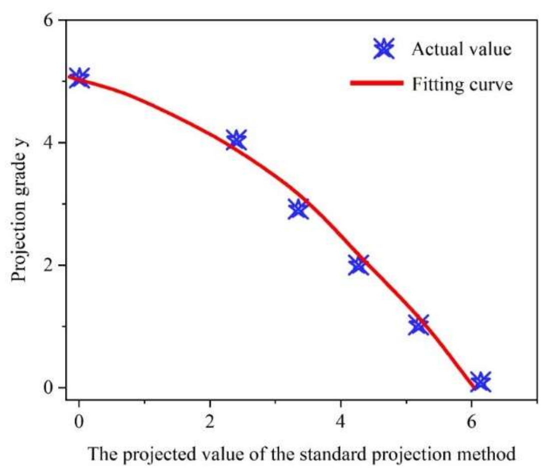

Figure 2: The relationship between the projection level and the projected value

III. A. Comparison of precision

The use of particle swarm optimization projection seeking model can effectively improve the accuracy of the English education evaluation model. The particle swarm optimization algorithm regards each optimal solution to the problem as a particle in the search space, and the position of the particle represents the potential solution in the process of solving the problem, the particle will be assigned a random solution in the initialization process, and then find the optimal solution through continuous iteration, and the current position of the particle is constantly updated through the optimal position of the particle individually and the optimal position of the whole particle swarm until the optimal solution is found. In the iterative process, the optimal position of individual particles and the optimal position of the whole particle swarm are used to update the current position of the particle until the optimal solution is found. In the solution process, a large amount of computational time is saved, which makes the computational efficiency of the evaluation model greatly improved.

Table 2 shows the comparison of the accuracy of the standard projection tracing and particle swarm optimization projection tracing models. The absolute error of the English education evaluation model using particle swarm optimization projection tracing to calculate the projection results of different grades is only 0.071, and the relative error is 3.31%, whereas the absolute error calculated by the standard projection tracing is 0.094, and the relative error is 3.92%, which shows that the model of English education grades evaluation using particle swarm optimization projection tracing method has higher accuracy. It can be seen that the model for evaluating English education grades using the particle swarm optimization projection tracing method has higher precision and is more suitable for describing the relationship between each evaluation index and evaluation grade.

Table 2: Accuracy comparison

	Standard projection method				Particle swarm optimization projection method	
Grade value	Projected value	Absolute error	Relative error	Projected value	Absolute error	Relative error
1	5.285	0.054	5.28%	5.258	-0.064	-6.64%
2	4.344	0.154	7.77%	4.382	0.081	4.16%
3	3.485	0.018	0.60%	3.475	0.075	2.44%
4	2.545	-0.204	-5.17%	2.544	-0.114	-2.92%
5	0.000	0.039	0.76%	0.000	0.022	0.40%
Mean		0.094	3.92%		0.071	3.31%

III. B. Stability Comparison

In order to describe the difference in stability between the standard projection tracing model and the particle swarm optimization projection tracing model, this paper adopts different computational methods, respectively, according to the evaluation indexes established in Chapter 2, four groups of critical samples are selected, and different projection values are obtained by calculating ten times respectively and solving for the variance, and the results obtained are shown in Table 3.

The results of comparing the variance of the projection values from sample 1 to sample 4 are 0.0013>0.0002, 0.0014>0.0004, 0.0035>0.0002, 0.0022>0.0002, from sample 1 to sample 4, the variance of the projection values calculated by using the standard projection tracing model is much larger than that calculated by using the particle swarm optimization projection tracing model, i.e., the variance calculated by using the The degree of dispersion of the projected values calculated by the particle swarm optimization projection tracing model is much smaller than the degree of dispersion of the projected values calculated by the standard projection tracing model. Therefore, it can be concluded that the particle swarm optimization projection tracing model has higher stability and is more suitable for the evaluation of English education levels.

Table 3: Model stability comparison

Degree	Standard projection method				Particle swarm optimization projection method			
	Sample1	Sample2	Sample3	Sample4	Sample1	Sample2	Sample3	Sample4
1	5.272	4.319	3.456	2.542	5.277	4.384	3.491	2.544
2	5.354	4.344	3.356	2.421	5.258	4.365	3.466	2.587
3	5.304	4.396	3.413	2.503	5.245	4.417	3.487	2.562
4	5.364	4.371	3.455	2.548	5.245	4.364	3.45	2.554
5	5.289	4.362	3.484	2.557	5.285	4.399	3.451	2.56
6	5.363	4.439	3.494	2.52	5.245	4.401	3.457	2.554
7	5.31	4.341	3.411	2.472	5.278	4.409	3.457	2.542
8	5.291	4.384	3.454	2.532	5.266	4.37	3.49	2.556
9	5.279	4.384	3.443	2.568	5.289	4.384	3.473	2.549
10	5.34	4.35	3.561	2.577	5.242	4.369	3.474	2.546
Variance	0.0013	0.0014	0.0035	0.0022	0.0002	0.0004	0.0002	0.0002

IV. Empirical studies

IV. A. Data collection and pre-processing

According to the English education evaluation model proposed in this paper, this section gradually carries out the resilience evaluation of the empirical analysis object. Firstly, the grading standards of evaluation levels of all indicators are formulated, and students majoring in English in a university in city A are selected for English education level evaluation, and different English education levels are divided into five levels: Ⅰ, Ⅱ, Ⅲ, Ⅳ and Ⅴ. Obtain the

English education evaluation data of the university. Among them, the qualitative indicators were obtained by questionnaire survey method. Quantitative indicators were obtained by consulting school management documents and other methods. The raw English education evaluation data of the empirical research subjects and the normalized data are shown in Table 4.

Table 4: Evaluation data and its normalization results

Index	Raw data	Normalization result
Z1	46.58%	0.4658
Z2	75.48%	0.7548
Z3	86.95%	0.8695
Z4	85.45%	0.8545
Z5	66.54%	0.6654
Z6	75.45%	0.7545
Z7	57.45%	0.5745
Z8	65.41%	0.6541
Z9	15.42%	0.1542
Z10	24.45%	0.2445
Z11	51.69%	0.5169
Z12	55.56%	0.5556
Z13	25.56%	0.2556
Z14	26.63%	0.2663
Z15	98.45%	0.9845

IV. B. Constructing and solving the projection seeking model

Referring to the previous research results about PSO algorithm used in multi-objective optimization, the parameters of PSO algorithm in this chapter are set as follows: the population size is set as 300, the upper limit of the number of iterative optimization calculations is 2000, the minimum computational precision is 0.000001, and the learning constants are all 2. In this paper, the upper limit of the number of population size and iterative optimization calculations is larger to ensure that the optimal solution can be found. After the program calculation, the convergence curve of the PSO algorithm is shown in Fig. 3, and according to the optimization calculation process of PSO, the optimal projection vector is quickly found in about the 120th iteration.

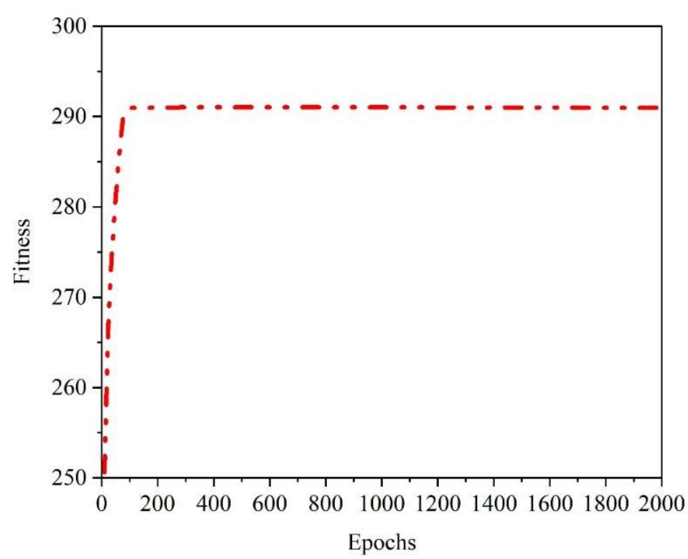

Figure 3: The convergence curve of the pso algorithm

The weights of the 15 secondary indicators were calculated as shown in Table 5. The school leadership level indicator (Z14) has the highest weight of 0.1235 and the District Education Bureau level indicator (Z13) has the lowest weight of 0.0362.

Table 5: Secondary indicator weight

Index	Weighting	Sort
Z1	0.0658	8
Z2	0.0456	10
Z3	0.0784	6
Z4	0.0452	11
Z5	0.0312	14
Z6	0.0421	13
Z7	0.0612	9
Z8	0.0885	4
Z9	0.0723	7
Z10	0.0451	12
Z11	0.0962	2
Z12	0.0785	5
Z13	0.0362	15
Z14	0.1235	1
Z15	0.0902	3

The weight of each secondary indicator can be obtained by summing up the weight of the indicator at that level, and the weights of the primary indicators are shown in Table 6. The indicator of feedback on teaching quality (Y5) has the highest weight of 0.2499, and the weight of teaching content (Y2) is the lowest, only 0.1185.

Table 6: The weight of the first level index

Index	Weighting	Sort
Y1	0.1898	4
Y2	0.1185	5
Y3	0.2220	2
Y4	0.2198	3
Y5	0.2499	1

IV. C. Mathematical model of English education evaluation based on interpolation method

Taking the best projection value of the 500 sample sets as the independent variable and the preset English education evaluation grade of the 500 sample sets as the dependent variable, the function image is plotted as shown in Figure 4. The segmented linear interpolation algorithm is used to construct the mathematical model of English education evaluation of the empirical research object, and the best projection value of English majors in this college in city A is 4.4575. Find the school's ELA evaluation level of IV.

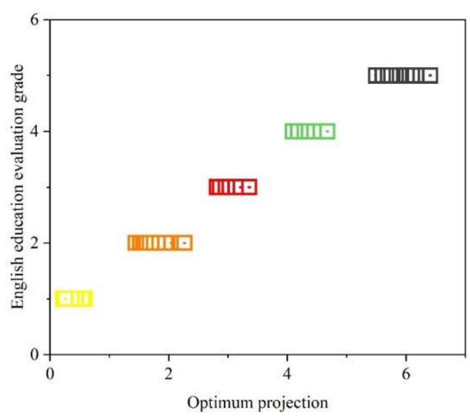

Figure 4: Map of the evaluation level and the best projection value

V. Conclusion

This paper constructs a weight allocation model of English education evaluation system based on particle swarm optimization projection tracing model and quality evaluation mathematical model.

Comparing the particle swarm optimized projection tracing method with the standard projection tracing method, the average relative error of the optimized method is only 3.31%, compared with the relative error of the standard projection tracing method which is as high as 3.92%, the method in this paper has achieved a greater degree of optimization. With a higher convergence speed, it can better meet different practical application scenarios and make a more realistic evaluation of the quality of English teaching.

In this paper, the English teaching data of a university in A city is selected as the research object, and the constructed model is applied to the evaluation of English education. The results show that the model in this paper can accurately reflect the degree of influence of each indicator on English education, so as to assign different weights to different indicators. The subjectivity of the traditional weight allocation method is overcome. The best projection value of English education evaluation of English majors in the universities studied in this paper is 4.4575, which is used to find out their English education evaluation grade as Grade IV. It provides a new idea and method for the field of English education evaluation, which has extremely important theoretical and practical value.

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