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Intelligent optimization algorithms empower multi-objective optimization configuration models for innovation and entrepreneurship education resources.

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Abstract The traditional way of resource allocation often lacks scientific and systematic, and is difficult to adapt to the needs of modern education development. The rapid development of artificial intelligence technology provides new technical means and solutions for the optimal allocation of educational resources, and multi-dimensional and multi-objective resource allocation optimization can be realized through intelligent algorithms to improve the efficiency and quality of education. This study constructs a resource allocation optimization model for innovation and entrepreneurship education based on multi-objective particle swarm algorithm, and evaluates the resource allocation efficiency through DEA method and Malmquist index model. The study establishes an evaluation system containing input indicators such as human resources, material resources and financial resources, and output indicators such as talent cultivation, scientific research and social services, and uses the multi-objective particle swarm algorithm to solve the resource allocation optimization problem. Taking 10 colleges and universities in G city as the research object, the BCC model and Malmquist index are used to analyze the innovation and entrepreneurship resource allocation efficiency statically and dynamically from 2018 to 2022. The results show that the HV value of this paper's algorithm is 0.56225, which is better than 0.55219 of SPEA2DE and 0.53897 of NSGA-III; the average value of the comprehensive efficiency of innovation and entrepreneurship of the universities in G city in 2018-2022 is 0.902; 3 out of 10 universities reach DEA effective, with a ratio of 30%; and the average value of the index of the total factor productivity change is 0.999.The study shows that the multi-objective particle swarm algorithm has good performance in the optimization of innovation and entrepreneurship education resource allocation, and can provide scientific support for the decision-making of resource allocation in colleges and universities.

Index Terms Multi-objective particle swarm algorithm, Innovation and entrepreneurship education, Resource allocation, Optimization model, DEA method, Malmquist index

I. Introduction

With the development and change of society, innovation and entrepreneurship education in colleges and universities is increasingly receiving widespread attention [1]. Innovation and entrepreneurship is an important force to promote social progress and economic development, and students who cultivate innovation and entrepreneurship awareness and ability will become the backbone of future social development [2]. As the cradle of cultivating talents, colleges and universities shoulder the important task of providing students with innovation and entrepreneurship education, in order to better serve students, colleges and universities need to constantly explore the way of innovation and entrepreneurship education, and take the optimization of resource allocation as an important direction of research [3], [4].

Resource allocation is of great significance in innovation and entrepreneurship education in colleges and universities [5]. As a knowledge base and resource center, colleges and universities have abundant advantageous resources such as faculty strength, scientific research foundation and practice platform. In turn, innovation and entrepreneurship education needs the support of a variety of resources, such as project funding, mentor guidance, enterprise cooperation, etc [6], [7]. Therefore, how to optimize and utilize these resources so that they can play a maximum benefit has become an important topic for innovation and entrepreneurship education in universities, and the application of AI makes the optimization of resource allocation for innovation and entrepreneurship education possible [8]-[10]. Firstly, AI can intelligently match high-quality educational resources according to students' learning and personalized needs, which not only improves students' learning interest and enthusiasm in innovation and entrepreneurship, but also maximizes the value of educational resources [11]-[13]. Secondly, AI education can use big data and data mining technology to analyze and evaluate the use of different innovative and entrepreneurial educational resources, realize the reasonable distribution and reuse of resources, and avoid the waste and repeated use of resources [14]-[16].

This study adopts a systematic research method, firstly constructs the input-output index system of innovation and entrepreneurship education resources and establishes a multi-objective resource allocation optimization mathematical model. Then the multi-objective particle swarm algorithm is applied to solve the optimization model, and its effectiveness is verified through algorithm performance comparison. Finally, the BCC model in the DEA method is used for static efficiency evaluation, and the Malmquist index model is used for dynamic analysis to comprehensively assess the optimization effect of resource allocation. Through the combination of theoretical modeling and empirical analysis, we strive to provide scientific decision support tools and practical optimization schemes for the allocation of resources for innovation and entrepreneurship education in colleges and universities.

II. Optimal modelling of multi-objective resource allocation for innovation and entrepreneurship education

II. A. Construction of Educational Resources Evaluation Indicator System

Educational efficiency is one of the indicators of educational achievement. The optimal allocation of resources for innovation and entrepreneurship education in colleges and universities involves how to reasonably allocate the limited resources of colleges and universities to obtain the maximum educational output with the minimum input of the unit in terms of educational efficiency. Considering that the educational system is a complex system with multiple inputs-multiple outputs, the relationship between inputs and outputs is difficult to quantify and measure, so to improve the efficiency of innovation and entrepreneurship education and optimize the allocation of resources, it is necessary to firstly construct the innovation and entrepreneurship education resources index system and multi-objective optimization mathematical model.

In order to construct the input-output index system of educational resources, we choose the indexes of input and output of innovation and entrepreneurship education resources, and focus on the two questions of “the support pattern of innovation and entrepreneurship education in colleges and universities” and “whether the above evaluation index system can completely support innovation and entrepreneurship education in colleges and universities”. Education” and ‘whether the above evaluation index system can completely support innovation and entrepreneurship education in colleges and universities’, the input-output index system of innovation and entrepreneurship education resources in colleges and universities is constructed as shown in Table 1.

Table 1: Innovation and entrepreneurship education resource investment

Primary indicator	Secondary element	Tertiary measure
Education resource input	Human resources	The number of teachers who are part-time
		Number of administrative teachers
		The number of external teachers with the enterprise background
	Material resources	The total cost of instruments is worth RMB per million yuan
		Practice platform room area/square meter
		Education base area/square meter
	Financial resources	Special funding investment/million yuan
Education resource output	Talent culture	The number of education students
		Students start business situations /
		To receive the event of the competition of the provincial level
	Scientific research	The number of academic papers, the number of works and the total number of subjects
	Social services	The transformation value of science and technology/million yuan

II. B. Multi-objective optimization analysis and model construction

II. B. 1) Multi-objective optimization analysis

In order to optimize the allocation of resources for innovation and entrepreneurship education in colleges and universities, the following two objectives are proposed.

(1) Enhance the utilization efficiency of innovation and entrepreneurship education resources. That is, to organize limited resources to maximize educational output.

(2) Improve the efficiency of innovation and entrepreneurship education resource allocation. That is, to maximize the ration of educational resources on each input resource, while also taking into account the complexity and

specificity of each resource, the degree of impact on educational outcomes, so that each resource is effectively allocated to the most adapted aspects.

II. B. 2) Multi-objective optimization model construction

(1) Innovation and entrepreneurship education resources utilization efficiency. Innovation and entrepreneurship education resources in colleges and universities are affected by multiple factors, and its allocation problem belongs to non-simple linear allocation, and the ultimate goal is to maximize the educational results, i.e., innovation and entrepreneurship education resources utilization efficiency is the ratio of education output to education input, and its expression is:

$$U=\frac{\sum_{i=1}^{m}\mu_j O_j}{\sum_{i=1}^{n}\varphi_i I_i} \tag{1}$$

where, i,j denotes educational resource elements and educational outcome elements, respectively. O_j, I_i are the amount of educational resources output and input, respectively. φ_i, μ_j are the weights of each educational resource input indicator, output indicator respectively. The larger the value of U, the larger the ratio of inputs to outputs, the higher the utilization efficiency of educational resources, and the more reasonable the combination of educational production factors, and vice versa.

(2) Innovation and entrepreneurship education resource allocation efficiency. According to the input-output index system of innovation and entrepreneurship education resources in colleges and universities, five innovation and entrepreneurship education resources allocation efficiency indexes are constructed sequentially, such as the area of teaching and auxiliary rooms, the area of education base per student, the total number of books per student, the number of computers per student, and the value of teaching instruments and equipment per student. The expression of the objective function of the i th innovation and entrepreneurship education resource allocation of the k th university is:

$$\begin{gathered} A_{ki}=\frac{X_k+\Delta X_k}{S_k}(k=1,2,\cdots,K) \\ s.t. A_{ki}<1(i=1,4) \\ 0\le A_{ki}\le 1(i=2,3) \\ A_{ki}>1\left(i=5,6,7\right) \end{gathered} \tag{2}$$

where, S_k is the number of students in the k th university. X_k and ΔX_k denote the k th university innovation and entrepreneurship of various resource elements of the average value of students and the amount of change, respectively.

II. B. 3) Construction of the objective function model

Considering the objective functions together, the multi-objective optimization function for innovation and entrepreneurship resource allocation [17] is obtained as:

$$\max U_k=\frac{\sum_{j=1}^{m}\mu_j O_j}{\sum_{i=1}^{n}\varphi_i I_i} \tag{3}$$

$$\max F_k=\sum_{i=1}^{n}\varphi_i A_{ki}, k=1,2,\cdots,k \tag{4}$$

where, $\max U_k$ is the maximum possible value that should be sought for the efficiency of utilization of educational resources in each university. $\max F_k$ is the efficiency of allocation of educational resources in each university should seek the maximum possible value.

II. C.Multi-objective particle swarm algorithm

The basic idea of particle swarm algorithm is that each solution of the optimization problem is called a particle, and a fitness function is defined to measure the superiority of each particle solution. Each particle according to their own and other particles "flight experience" swarm travel, so as to achieve the purpose of searching for the optimal solution from the whole space.

Let the position of the i th particle in n -dimensional space be $X_i = (x_{i1}, x_{i2}, \cdots, x_{in})$. The best position it has experienced (the best adapted value) is denoted as $X_{Pi} = (x_{p_i 1}, x_{p_i 2}, \cdots, x_{p_m})$, and the individual optimal value it corresponds to is denoted as P_i. The best position experienced by all particles of the population is denoted as $X_G = (x_{g1}, x_{g2}, \cdots, x_{gn})$, and its corresponding global optimum is denoted as P_g. The velocity of particle i is denoted by $V_i = (v_{i1}, v_{i2}, \cdots, v_{in})$. Its formula is:

$$v_{id}^{k+1} = uv_{id}^{k} + c_1 r_1 (xp_{id}^{k} - x_{id}^{k}) + c_2 r_2 (xg_{d}^{k} - x_{id}^{k}) \tag{5}$$

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \tag{6}$$

where $i = 1, 2, \ldots, m; d = 1, 2, \ldots, n$.

Where m is the number of particles in the particle swarm. n is the dimension of the solution vector. c_1, c_2 are positive constants, usually taken as 2.0. r_1, r_2 are random numbers between [0, 1]. k is the number of iterations. w is the inertia weight, adjusting its size can change the strength of the search ability. In order to keep the particle velocity from being too large, an upper velocity limit $v_{\max}$ can be set, and $|v_i| > v_{\max}$ is taken when $v_{i1} = v_{\max}$.

The elementary particle swarm algorithm has good performance in single-objective optimization problems, but the algorithm cannot be directly applied to the multi-objective problem solving process, because the elementary particle swarm algorithm needs to update its own position by tracking the individual extremes P_i and global optimums P_g to find the optimal solution when performing the search. These two extremes are relatively easy to determine in single-objective optimization problems, while they are difficult to determine in multi-objective optimization problems. Therefore, the selection of the individual extremes P_i and the global optimum P_g is a key problem to be solved by transforming the elementary particle swarm algorithm into the multi-objective particle swarm algorithm (MOPSO) [18].

The essential difference between the multi-objective particle swarm algorithm and single-objective optimization problem is that in the multi-objective optimization problem, each objective function is constrained by each other, and the increase or decrease of a certain objective function will inevitably lead to the decrease or increase of the other objective functions, while the units of the individual objective functions are often inconsistent. Therefore, the solution of multi-objective function optimization is usually not the only parametric solution, but a non-inferior solution set, called the Pareto solution set, and the elements in the set are called Pareto optimal solutions. Multi-objective optimization problems not only require the algorithm to have good convergence, but also ensure the uniformity of the distribution of the resulting non-inferior solutions. The multi-objective particle swarm algorithm solves the above two requirements well, the algorithm constructs an archive population to save all the non-inferior solution sets obtained in each iteration process, through the archive population, it can prevent the loss of the non-inferior solutions obtained, so as to ensure the convergence of the algorithm. In order to solve the uniformity of the distribution of non-inferior solution sets, the method proposes the concept of crowding distance. After constructing the archive population and the crowding distance, the solution with the largest crowding distance can be selected as the optimal solution in the multi-objective optimization problem. Taking the two-objective function ($y_1(x)$ and $y_2(x)$) optimization problem as an example, the steps to seek the optimal solution of Pareto are as follows.

Step 1: Initialization. Read in the original data and randomly generate the velocity V_i and position X_i of each particle, assuming that the initial velocity of each particle is zero.

Step 2: Calculate the adaptation values of each particle corresponding to the two objective functions $y_1(x)$ and $y_2(x)$, respectively.

Step 3: Find the individual extremes P_{1i} and P_{2i} and the global extremes P_{1g} and P_{2g} for each particle of the objective function $y_1(x)$ and $y_2(x)$, respectively, over the range of variations of the control variables.

Step 4: Create an archive population A, store the non-inferior solutions obtained in Step 3 into A, compute the crowding distance of each non-inferior solution in the archive population A, denoted as d_i, and arrange each non-inferior solution in descending order by the crowding distance d_i.

Step 5: Update the velocity and position of each particle. Update the velocity and position of each particle separately in the archived population A in sorted order, and then continue from step 3 to update the individual extremes and global extremes.

Step 6: Update the archive population A and determine whether the constraints are satisfied, if so, end the process. Otherwise, go to step 2 to continue the iteration until the constraints are satisfied.

II. D. Methods for evaluating the optimization of resource allocation for innovation and entrepreneurship education

II. D. 1) DEA methodology fundamentals

Due to the complex functional relationship between the selected input and output indicators, it should also ensure that the evaluation results have accuracy and reference, therefore, this paper applies the BCC model and Malmquist index model [19] in the DEA method [20] to evaluate the optimization efficiency of innovation and entrepreneurship education resource allocation. The evaluation system established under the DEA method is characterized by multi-inputs and multi-outputs, and it is able to technically realize the evaluation of efficiency effectiveness. The following are the advantages of the DEA method listed below:

First, it is not necessary to set the shape of input and output production functions before establishing the DEA model, and the DEA method is able to analyze the efficiency of optimizing the allocation of resources for innovation and entrepreneurship education in decision-making units with complex production relations, which makes it convenient to overcome the technical difficulties arising in the activities.

Secondly, the weights of relevant inputs and outputs do not have to be calculated in advance under the DEA model, but the weights of the model are naturally derived from the data, which largely reduces the influence of subjective human factors and makes the data results more informative.

Thirdly, the results of DMU calculated under the DEA method will not be affected by changes in the units of variables, and there is no requirement of unit limitation on the parameter data of decision-making units, only the consistency of the units of input and output data is needed to be ensured, so that changes in the units of any of the input and output data will not have any impact on the efficiency results.

II. D. 2) BCC model for evaluating technology effectiveness

It is set that the evaluation system has n decision-making units $DMU_j(l \le j \le n)$ and each DMU_j has m kinds of input variables and s kinds of output variables as follows:

$$\begin{aligned} & x_j = (x_{j1}, x_{j2}, \cdots x_{jm})^T \rangle 0, j = 1,2\cdots n; \\ & y_j = (y_{j1}, y_{j2}, \cdots y_{js})^T \rangle 0, j = 1,2\cdots n \\ & \text{and } x_{ji} \rangle 0, y_{jr} \rangle 0, i = 1,2\cdots m, r = 1,2\cdots s \end{aligned} \tag{7}$$

x_{ji} is the amount of inputs to the i type of input by the j th decision unit. y_{jr} is the amount of output from the j th decision unit for the r th type of output. x_{ji} and y_{jr} are known data, either historical or actually observed.

The pairwise rule is applied to determine the validity of DMU_{j0} to obtain the C2R model:

$$(D) = \begin{cases} Min\theta \\ s.t.\sum_{j=1}^{n}\lambda_j x_j + s^- = \theta x_0 \\ \sum_{j=1}^{n}\lambda_j y_j - s^+ = y_0 \\ \lambda_j \ge 0 \quad j = 1,2\ldots,n \\ s^+ \ge 0, \quad s^- \ge 0 \quad \theta \text{ Unconstrained} \end{cases} \tag{8}$$

(1) When $\theta = 1$ and $S = S^+ = 0$, the decision-making unit j_0 is valid for DEA, that is, DMU_0 is valid for DEA, that is, in an economic system composed of n decision-making units, the input x_0 will obtain the optimal output y_0, where S^+ represents the "deficit" of the output, and S·represents the "excess" of the input.

(2) When 0=1 and $S- \ne S^+ \ne 0$, the decision unit DMU_0 is weakly effective for DEA, i.e., to keep the original output y_0 unchanged in this economic system consisting of n decision units, it is necessary to reduce the S-(excess) of the inputs x_0. To keep the input x_0 constant, the output must be raised by S^+ (a deficit).

(3) When $\theta < 1$, the decision-making unit DMU_0 is DEA ineffective, i.e., in an economic system consisting of n decision-making units, it is possible to decrease the θ proportionally to the original input x_0 while keeping the original output y_0 constant. The effective decision units DMU_0 are connected to form an efficiency frontier, which

is used as a benchmark for measuring efficiency, and then analyze the “input redundancy” and “output deficiency” of each non-DEA effective decision unit DMU0.

The C^2R model is the most basic of DEA models, which is based on the assumption of constant returns to scale, which is often inconsistent with reality. Besides, the C^2R model can only make a judgment on the effectiveness of DMUs, and cannot judge whether they are purely technologically effective. Adding the condition of variable returns to scale, the research has come up with BCC model, in which the comprehensive technical innovation efficiency = pure technical efficiency × scale efficiency, which can judge the pure technical efficiency, and can also analyze the technical effectiveness and scale effectiveness of decision-making units, and the BCC model formula is as follows:

$$(D)=\begin{cases} Min[\theta-\varepsilon(e^t s^- + \hat{e}^T s^+)] \\ \sum_{j=1}^{n}\lambda_j x_j + s^- = \theta x_0 \\ \sum_{j=1}^{n}\lambda_j y_j - s^+ = y_0 \\ \sum_{j=1}^{n}\lambda_j = 1 \\ \lambda_j \geq 0, j=1,\ldots,n \\ s^+ \geq 0, s^- \geq 0, \theta \ Unconstrained \end{cases} \tag{9}$$

Through the BCC model can find out the pure technical efficiency value, specific evaluation of innovation and entrepreneurship education resource allocation optimization of the inputs whether to achieve effective use, to meet the requirements of the minimum input or the maximum output, the greater the value of pure technical efficiency indicates that the use of input factors more efficient. The efficiency value derived in the C2R model is the comprehensive technical efficiency, so we can introduce the scale efficiency, scale efficiency represents whether the ratio of output inputs is appropriate, to determine the DMU scale reward situation, the ratio is high representing the scale is appropriate, the productivity is large: when $\sum_{j=1}^{n}\lambda_j > 1$, i.e., scale reward is in a decreasing state. When $\sum_{j=1}^{n}\lambda_j = 1$, i.e., the returns to scale are in optimal returns. When $\sum_{j=1}^{n}\lambda_j < 1$, i.e., the returns to scale are in an increasing state.

II. D. 3) Malmquist exponential modeling

The Malmquist index is based on the concept of a nonparametric distance function and is used in conjunction with the DEA methodology when describing the efficiency of technological innovation in production with multiple input-output variables. It does not need to state specific behavioral criteria, and uses panel data to dynamically analyze the changes of each decision unit in different periods.Fare et al. use the geometric mean of the Malmquist productivity index in periods t and (t+1) to construct the M-index of the productivity change from t to (t+1), and further analyze it from the perspective of fluctuation of comprehensive technical efficiency, fluctuation of pure technical efficiency, fluctuation of scale efficiency and fluctuation of technical progress to find out the influences on the total factor productivity of the decision unit and to find out the effects of the total factor productivity of the production unit on the technical innovation efficiency. fluctuation perspective analysis, to find out the key factors affecting the ineffectiveness of total factor productivity of decision-making unit.Malmquist index is calculated by the ratio of distance function, which is the inverse of technical efficiency, and defines the Malmquist index of productivity progress of the decision-making unit in the period of t and period of t+1 (TIEC) as:

$$TIEC_l^{t+1} = M_{t,t+1} = \frac{D_{t+1}^V(x_{t+1},y_{t+1})}{D_t^V(x_t,y_t)} \times \left[\frac{D_t^V(x_t,y_t)}{D_t^C(x_t,y_t)} \times \frac{D_{t+1}^C(x_{t+1},y_{t+1})}{D_{t+1}^V(x_{t+1},y_{t+1})}\right] \times \left[\frac{D_t^C(x_t,y_t)}{D_{t+1}^C(x_t,y_t)} \times \frac{D_t^C(x_{t+1},y_{t+1})}{D_{t+1}^C(x_{t+1},y_{t+1})}\right]^{\frac{1}{2}} \tag{10}$$

Total factor productivity fluctuations $(TFPC)$ under the Malmquist index model are categorized into technical progress fluctuations $(TECHCH)$ and integrated technical efficiency fluctuations $(EFFCH)$, which are further categorized into pure technical efficiency fluctuations $(PTEC)$ and scale efficiency fluctuations (SEC). We define the distance function under changes in returns to scale as $D_v(x,y)$. The distance function with stable and constant returns to scale is: $D_c(x,y)$. $\frac{D_{i+1}(x_{i+1},y_{i+1})}{D_i(x,v)}$ is the combined technical efficiency fluctuation $(EFFCH)$, the extent of the effect of technological inefficiency, and $PTEC<1$ suggests a decline in pure technical efficiency. $\frac{D_t^v(x_t,y_t)}{D_t^c(x_t,y_t)} \times \frac{D_t^c(x_{t+1},y_{t+1})}{D_t^c(x_{t+1},y_{t+1})}$ refers to the analysis of whether there is any waste of input factors in the optimization of innovation and entrepreneurship education resource allocation from the perspective of resource allocation, which can also be said to be the catching-up effect of the DMU on the production frontier, $EFFCH>1$ indicates that the decision-making unit is closer to the production frontier surface, and $EFFCH<1$ indicates that the decision-making unit is farther away from the production frontier surface. $\frac{D_{t+1}^v(x_{t+1},y_{t+1})}{D_t^v(x_t,y_t)}$ is the pure technical efficiency fluctuation $(PTEC)$, which refers to pure technical inefficiency pairwise modal efficiency fluctuation (SEC), and it is used to determine whether the decision unit is at the optimal production scale, $SEC>1$ indicating that scale efficiency provides rise.

For technical progress fluctuations $(TECHCH)$, reflecting the degree of production technology changes. The results calculated through the Malmquist model can accurately identify the key factors affecting the ineffectiveness of total factor productivity of decision-making units, which facilitates decision-makers to further propose more targeted strategies. Therefore, this paper selects the Malmquist index model to dynamically evaluate the optimization efficiency of innovation and entrepreneurship education resource allocation.

III. Example analysis of optimizing resource allocation for innovation and entrepreneurship education

This paper evaluates the resource allocation efficiency of innovation and entrepreneurship education in colleges and universities from 2018 to 2022, and takes City G as an example, and selects three undergraduate colleges and universities in City G that have won the Top 50 Typical Experienced Colleges and Universities for Innovation and Entrepreneurship of the country, and three public undergraduate colleges and universities other than the Top 50 Typical Experienced Colleges and Universities as well as three private undergraduate colleges and universities and one national “double high “A total of 10 representative colleges and universities were selected for comparative study.

III. A. Algorithm performance and resource allocation optimization effect

This chapter adopts the algorithm of this paper to carry out simulation experiments, which simulation test data comes from the educational decision support platform of G city, and adopts the multi-objective optimization model of educational resource allocation under the optimization model of multi-objective resource allocation for innovation and entrepreneurship education constructed by this paper solving.

Table 2 shows the HV values obtained by the four algorithms in this model for 40 runs, and from the data in the table, it can be seen that the relationship between the mean values of HV obtained by this paper's algorithm, MOEA/D-DDE, SPEA2DE, and NSGA-III algorithms after 40 runs of experiments is as follows: HV (this paper's algorithm) > HV (SPEA2DE) > HV (NSGA-III) > HV (MOEA /D-DE). It can be shown that the diversity of Pareto non-dominated solutions obtained by this paper's algorithm in this model is significantly better than that of MOEA/D-D-DE, SPEA2DE, and NSGA-III.

Table 2: Calculation results of the HV indicator in the model

Obj	M	D	This algorithm	MOEA/D-DE	SPEA2SDE	NSGA-III
My_fitness2	20	92	0.56225	0.52112	0.55219	0.53897
			0.38489	0.28445	0.37846	0.36414
			0.48655	0.43512	0.47565	0.44878

From the population size the appropriate fitness function can be selected to obtain the results of this paper's algorithm in solving the high-dimensional multiple university districts' educational resource allocation. Since this chapter is a simulation experiment on each per pupil index, it is necessary to multiply the results of the allocation by the number of students enrolled in each district for the optimized resource allocation results of each university district. For the allocation model of educational resources in university districts its optimization results are shown in Table 3.

Each line in the table represents a university district resource allocation optimization results, showing the optimization results of resource allocation under the university district resource mutual aid model, followed by the university district 1 as an example, respectively, for the allocation of five educational resources results for detailed elaboration:

(1) The current area of teaching and auxiliary rooms in University District 1 (A) is 9,431 square meters, and after the simulation experiment, the area of teaching and auxiliary rooms that need to be newly allocated to University District 1 (newA) is 12,938 square meters, so the total area of teaching and auxiliary rooms in University District 1 is 22,369 square meters after the optimization of the allocation of the total area of teaching and auxiliary rooms.

(2) The current educational base area (D) of University Area 1 is 273 square meters, and after the simulation experiment, the new educational base area (newD) that needs to be allocated to University Area 1 is 1,601 square meters, therefore, the total area allocation of the educational base of University Area 1 is 1,877 square meters after optimization.

(3) The current total number of books (B) in University Area 1 is 195,198, and after the simulation experiment, the total number of books (newB) that need to be newly allocated to University Area 1 is 147,779, therefore, the total number of books in University Area 1 is 342,977 after optimization of book allocation.

(4) The current total number of computers (C) in University District 1 is 520, and the total number of computers (newC) that need to be newly assigned to University District 1 after the simulation experiment is 618, so the total number of computers in University District 1 after the allocation optimization is 1138.

(5) The current value of instructional equipment (E) for University District 1 is 492 yuan, and the new value of instructional equipment (newE) that needs to be assigned to University District 1 after the simulation experiment is 618 yuan, so the optimized value of instructional equipment assigned to University District 1 is 1,110 yuan.

Table 3: The configuration model of the education resource is optimized

	A	D	B	C	E
1	22369	1874	342977	1138	1110
2	25139	1899	326390	1029	1212
3	33289	2183	443330	1600	1739
4	33047	3431	401180	2156	1444
5	33207	2804	328174	1182	725
6	27016	1887	345808	1256	2164
7	20201	1270	200207	794	1382
8	29723	1965	319976	1182	1284
9	17174	956	397491	1222	1451
10	23555	2563	274154	1147	1541

Box plots can be used to more intuitively judge the biased information of the data. Figure 1-Figure 5 shows the comparison chart before and after the average value of resource allocation in the university district, the average area of teaching and auxiliary space per student in the university district, the average area of education base per student in the university district, the average area of teaching and auxiliary space per student in the university district, the average number of books per student in the university district, the average number of computers per student in the university district, and the average value of teaching instruments per student in the university district before the allocation are about 4.1, 0.50, 105, 0.50, 0.43, which is about 7.2, and the area of the education base is 1.00, 121, 0.75 and 0.49, respectively.

Through the above analysis, for the optimization of each index in the allocation of educational resources in university districts under the optimization model of this paper, it can provide decision-making support in carrying out the allocation of educational resources in university districts, in order to obtain the allocation plan with scientific theoretical support.

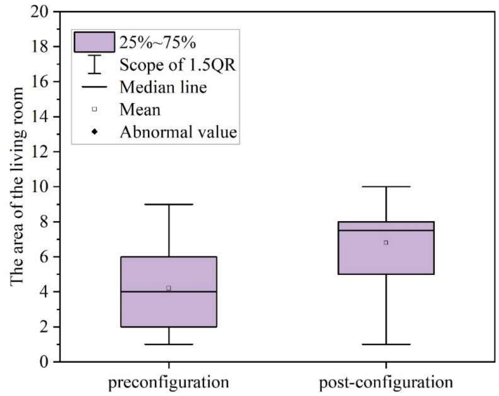

Figure 1: The area of the living room

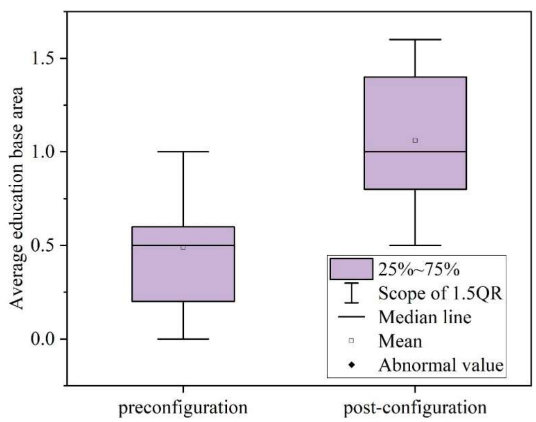

Figure 2: Average education base area

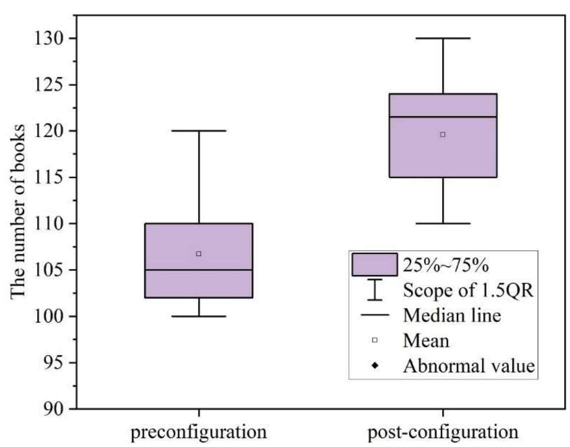

Figure 3: The number of books

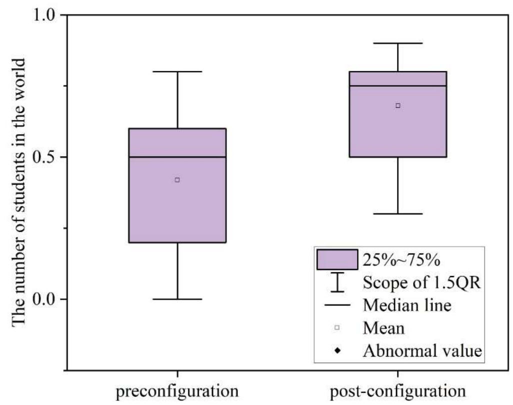

Figure 4: The number of students in the world

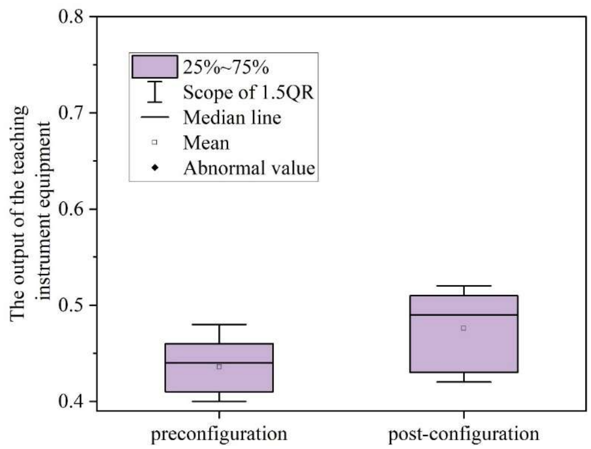

Figure 5: The teaching instrument sets the value

III. B. BCC model static analysis

Using DEAP2.1 software, the panel data of innovation and entrepreneurship resource allocation in universities in G city from 2018 to 2022 are analyzed for comprehensive efficiency, and the results are shown in Tables 4 and 5. Note: "drs" indicates diminishing returns to scale. "irs" denotes increasing returns to scale. "-" indicates constant returns to scale. Colleges 1-3 are selected as national innovation and entrepreneurship typical experience colleges. Colleges 4-6 are public undergraduate colleges. Colleges 7-9 are private undergraduate colleges. College 10 is a national "double-high" vocational college.

In the process of analyzing the efficiency of innovation and entrepreneurship resource allocation in G city colleges and universities, the comprehensive technical efficiency value is a key indicator, which can be used to measure the effectiveness of resource allocation in the process of innovation and entrepreneurship education in G city colleges and universities by measuring the ratio of innovation and entrepreneurship resource inputs to the outcome outputs, and the closer the value of which is to 1, the higher the efficiency of resource allocation is.2018-2022 G city The average value of the comprehensive efficiency of innovation and entrepreneurship in colleges and universities is 0.902, which does not reach the DEA effectiveness. In addition, the comprehensive efficiency of innovation and entrepreneurship resource allocation in each university in 2022 also has a large difference. On the whole, the overall efficiency of resource allocation is the best in the colleges and universities selected as national innovation and entrepreneurship typical experience, followed by public colleges and universities outside the top 50 and national "double-high" vocational colleges and universities, and is worse in private colleges and universities. 3 colleges and universities among 10 colleges and universities have reached the DEA, with a proportion of 30%, indicating that these colleges and universities have achieved the innovation and entrepreneurship comprehensive efficiency of 0.902. 30%, indicating that the innovation and entrepreneurship education resources of these colleges and universities are optimally configured, and the combination of inputs and outputs has reached the optimal effect. 3 public undergraduate colleges and universities, 3 private colleges and universities, and 1 national "double-high" vocational college and university failed to reach the DEA, indicating that the innovation and entrepreneurship resource inputs of the 7 colleges and universities are not effectively utilized and should be more reasonably allocated to teachers, staff, and vocational colleges. The use of teachers, venues and funds should be more reasonably deployed to achieve the optimal allocation of resources for innovation and entrepreneurship.

Table 4: Resource allocation efficiency and decomposition

Year	Integrated technical efficiency(EFFCH)	Pure technical efficiency(PECH)	Scale technology efficiency(SECH)	Scale compensation
2018	0.859	0.858	0.857	drs
2019	0.885	0.885	0.888	drs
2020	0.891	0.89	0.891	irs
2021	0.931	0.931	0.932	irs
2022	0.946	0.942	0.945	irs
Mean value	0.902	0.901	0.903	-

Table 5: 2022 university innovation and entrepreneurship resource allocation

School number	Integrated technical efficiency(EFFCH)	Pure technical efficiency(PECH)	Scale technology efficiency(SECH)	Scale compensation
1	1.000	1.000	1.000	-
2	1.000	1.000	1.000	-
3	1.000	1.000	1.000	-
4	0.899	0.915	0.988	irs
5	0.995	1.000	0.995	irs
6	0.998	1.000	1.000	drs
7	0.855	0.869	0.888	irs
8	0.845	0.854	0.869	irs
9	0.859	0.878	0.857	irs
10	0.812	0.891	0.888	-
Mean	0.926	0.941	0.949	

III. C. Dynamic analysis of the Malmquist index

Malmquist index analysis of innovation and entrepreneurship resource allocation data of universities in G city from 2018 to 2022 using DEAP2.1 software can dynamically reflect the dynamic change of total factor productivity of resource allocation; the results of the analysis are shown in Tables 6 and 7.

The average value of the total factor productivity change index (TFPCH) of innovation and entrepreneurship resource allocation in universities in G city in 2018-2022 is 0.999, and the percentage of decline is 0.1 percentage points. Among them, the total factor productivity change index (TFPCH) is greater than 1 in 2 years, 2020-2021 and 2021-2022, and the growth proportion reaches 6.5 percentage points and 8.8 percentage points respectively. In terms of the specific decomposition indicators, the technical efficiency change index has a smaller magnitude, the technical progress change index has a larger magnitude, and the change trend of the total factor productivity index is consistent with the change trend of the technical progress change index, indicating that the total factor productivity index of innovation and entrepreneurship resource allocation in the universities of G City is mainly affected by the change of technical progress.

The total factor productivity index of 6 colleges and universities in 2018-2022 is greater than 1, with a proportion of 60%, including 3 colleges and universities selected as national innovation and entrepreneurship typical experience, 2 public undergraduate colleges and universities outside of the top 50, and 1 national “double-high” vocational college, and the proportion of growth in the total factor productivity index of these colleges and universities is the highest at 17%. The total factor productivity index of these colleges and universities increased by the highest percentage of 17.5 percentage points. It shows that the allocation efficiency of innovation and entrepreneurship education resources in these universities is improving year by year, mainly due to the improvement of technical efficiency. In addition, the total factor productivity indexes of universities 6, 7, 8 and 9 are less than 1, showing negative growth, of which the lowest is only 0.775, with a decrease ratio of 22.5 percentage points. Analyzed in terms of growth factors, the decline in the index of technological progress changes is the main reason for negative growth.

Table 6: Total factor productivity changes and decomposition results

Year	Technical efficiency change(EFFCH)	Technological change(TECH)	Pure technology efficiency change(PECH)	Scale efficiency(SECH)	Total factor productivity change(TFPCH)
2018-2019	0.964	0.899	0.944	1.023	0.866
2019-2020	1.021	0.956	0.987	1.035	0.977
2020-2021	1.056	0.997	1.000	1.066	1.065
2021-2022	1.052	1.032	1.005	1.056	1.088
Mean	1.023	0.971	0.984	1.045	0.999

Table 7: Resource allocation of full factor productivity changes and decomposition

School number	Technical efficiency change(EFFCH)	Technological change(TECH)	Pure technology efficiency change(PECH)	Scale efficiency(SECH)	Total factor productivity change(TFPCH)
1	1.095	1.078	1.000	1.094	1.175
2	1.015	1.005	0.936	1.088	1.022
3	1.145	0.998	1.078	1.062	1.136
4	1.013	0.992	1.000	1.013	1.005
5	1.025	0.984	1.000	1.022	1.088
6	1.013	1.014	1.000	1.013	0.984
7	1.000	0.877	1.000	1.000	0.877
8	0.958	0.945	0.955	1.000	0.874
9	0.889	0.845	0.844	1.052	0.775
10	1.022	0.977	1.000	1.023	1.005
Mean	1.018	0.972	0.981	1.037	0.994

IV. Conclusion

By constructing an AI-enabled multi-objective resource allocation optimization model for innovation and entrepreneurship education and conducting empirical analysis, this study draws the following main conclusions:

The multi-objective particle swarm algorithm shows significant advantages in the optimization of resource allocation for innovation and entrepreneurship education, and the mean value of HV obtained by this paper's algorithm after 40 running experiments is 0.56225, which is significantly better than the 0.52112 of the MOEA/D-DDE algorithm, which proves the effectiveness of the algorithm in solving multi-objective optimization problems.

From the evaluation results of resource allocation efficiency, there are obvious differences in the development level of innovation and entrepreneurship education in colleges and universities in G. The resource allocation efficiency of colleges and universities selected as the typical experience of national innovation and entrepreneurship is the highest, while the allocation efficiency of private colleges and universities is relatively low.

The static analysis shows that the average value of comprehensive technical efficiency reaches 0.902 in the period of 2018-2022, but it still has not reached the fully effective state of DEA, indicating that there is still room for improvement in resource allocation.

The results of the dynamic analysis show that the average value of the total factor productivity change index is 0.999, in which 60% of colleges and universities have achieved positive growth, and technological progress is the main factor affecting the change in total factor productivity.

The deep integration of artificial intelligence technology and educational resource allocation provides a new path to improve the quality of innovation and entrepreneurship education, and through scientific model construction and algorithm optimization, it can realize the precise allocation and efficient use of educational resources, and provide important theoretical support and practical guidance for the reform and development of innovation and entrepreneurship education in colleges and universities.

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