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# Optimization of Higher Education Talent Cultivation Path with Multi-Objective Ant Colony Algorithm Empowered by New Quality Productivity

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**Abstract** This paper constructs a pyramid structure hierarchical model through fast non-dominated sorting and adaptation grading, realizes intra-layer competition and collaboration, and finds the optimal frontier. Combining entropy weight method and fuzzy comprehensive evaluation, the influence weights of external environment and individual ability are quantified, and a multi-objective optimization model of higher education talent cultivation path is established. The improved ant colony algorithm is introduced to enhance the global search capability of multi-objective optimization by using the state transfer rule and pheromone updating mechanism. Through the practice of higher education talent cultivation path optimization, as well as multi-algorithm comparison experiments, the optimization effectiveness of this paper's method is verified. The results show that: using the method of this paper to determine the optimization of higher education talent cultivation path is divided into 3 stages, and the probability of achieving ability cultivation in each stage is 0.4, 0.3, 0.3, respectively. The method of this paper takes between 150-200ms to run in 5 test functions, and only needs a small number of iterations to get a stable fitness value. Using the method of this paper to continuously optimize the training path, the students' employment rate, the rate of obtaining professional-related certificates, and the enterprise satisfaction rate are increased by 14%, 36%, and 11%, respectively.

**Index Terms** pyramid structure, intra-layer competition strategy, entropy weight method, multi-objective ant colony algorithm, cultivation path optimization

## I. Introduction

As an important intersection of science and technology and talent, education is a positive contributor and key driver of the development of new quality productivity. Along with the development of new quality productivity, innovative models such as digital intelligence technology as the core and the integration of a wide range of applications of artificial intelligence are reshaping the traditional education ecology and teaching mode [1]. In this wave of change, in order to promote the high-quality development of higher education, the teaching methods of college teachers, the learning experience of students, the management mechanism of the school and the educational evaluation system are facing continuous and deep transformation and upgrading [2], [3]. In the face of this new trend of educational development, colleges and universities should actively adapt, take the initiative, accelerate the pace of transformation of education digital intelligence, innovation-driven development, and promote the overall progress of education [4], [5]. Focus on the new quality of education force construction of higher education power, requiring universities to stand up to the tide, based on the great rejuvenation of the Chinese nation and the world's strategic situation and the world's century-old change, in the development of the new quality of productivity to reflect the new advantages, to provide new momentum, open up new areas. The development of new quality productivity, education innovation is the key variable, talent training is the core element [6]. Education is a fertile ground for the growth of talents, shouldering the important responsibility of cultivating talents of new quality productivity, enhancing the human capital of the society and the quality of all people, and improving the productivity of the society [7], [8]. Education is the source of innovation generation, as a strategic support to improve social productivity and comprehensive national power, scientific and technological innovation needs top-notch talents to promote, and talent cultivation relies on the high-quality development of education to realize [9], [10]. The integration of education, science and technology and talents is the key support to promote the development of new quality productivity, and the construction of a strong higher education country is the intrinsic demand and inevitable path for the development of new quality productivity [11], [12]. At present, the construction of a strong educational country is closely integrated with the development needs of Chinese-style modernization, and the synergistic development of education, science and technology and human resources has become a widely recognized concept [13]. How to organically integrate the new quality productivity with the traditional education ecology and empower the transformation of higher education with digital intelligence requires in-depth exploration of the developmental changes and practical paths of higher education.

The essence of new quality productivity is advanced productivity, which can crack the main problems faced by high-quality development in the new development stage of the new era.Liu, S. examined the new talent cultivation mode of AI-enabled innovative electromechanical control professional education, which accelerates the cultivation of high-quality talents in the context of new quality productivity, and is conducive to the promotion of the speed of social informatization development [14]. He, L. and Deng, F. Integration of workplace curriculum, competition and certification models into the talent cultivation system strengthens the outcomes of big data talent cultivation under the perspective of new quality productivity and promotes the integration of industry and education, thus enhancing the quality of education [15]. Zhao, Y. et al. proposed an innovative path to cultivate management accounting talents in line with the needs of the times in terms of faculty, curriculum design as well as teaching content, which provides useful exploration and inspiration for the optimization method of education in the context of new quality productivity [16]. Mi, Y. explored the digital and intelligent talent cultivation system of financial education empowered by the new quality productivity, which closely connects the education mode with the needs of the times and promotes the cultivation of financial talents with both digital skills and innovative thinking, so as to promote the high-quality development of the financial industry [17]. Mengli, L. I. et al. proposed the establishment of a big data database of scientific and technological talents oriented to the new quality productivity, which can help to stimulate the overall effectiveness of digital talent cultivation and governance by empowering the talent workflow through the use of big data and artificial intelligence technologies [18]. Yin, C. and Wen, D. construct an innovative talent cultivation path for internationalization strategy from the perspective of new quality productivity, and put forward feasible suggestions from the aspects of curriculum construction and training plan, which can help to improve the quality and international competitiveness of vocational education [19]. It is evident that Numeracy plays a key role in the paradigm shift of higher education, which is not only a way to break out of the status quo, but also a way to innovate.

The development of new quality productivity cannot be separated from the personalization and efficiency optimization of talent cultivation path. This paper focuses on the multi-objective synergistic optimization of higher education talent cultivation path. By constructing a hierarchical competition mechanism and multi-objective model, combined with entropy weight method and fuzzy comprehensive evaluation system, the dynamic balance of talent cultivation quality and innovation ability is realized. Intelligent multi-objective ant colony algorithm is introduced to search for the global optimal solution and improve the optimization accuracy. Determine the optimized solution set of higher education talent cultivation path through feasibility analysis, and calculate the probability of ability cultivation. Compare the performance of this paper's method with the same type of optimization algorithm in the benchmark function. Investigate the quality of higher education talent cultivation under cultivation path optimization and analyze the effect of cultivation path optimization based on the method of this paper.

## II. Higher education personnel training path optimization technology realization

This chapter focuses on the core objective of higher education talent cultivation path optimization, and proposes a fusion framework of hierarchical competition strategy based on pyramid structure and optimization model introducing multi-objective ant colony algorithm.

### *II. A.Intra-layer competitive strategy based on pyramid structure*

Since the multi-objective optimization problem involves several sub-objectives, which are constrained by each other or even contradict each other. Therefore, for the multi-objective optimization problem, this chapter proposes a hierarchical mechanism and a competitive strategy for the population.

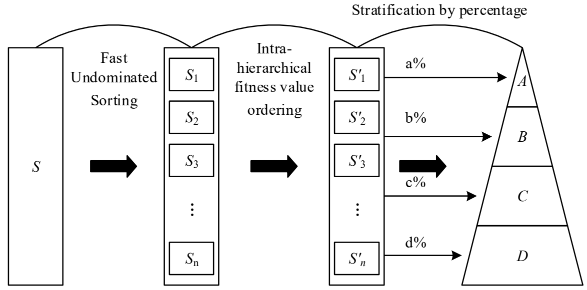



Figure 1: Hierarchical pyramid process

Firstly, the population is graded by the fast non-dominated sorting method, then the individuals within each level are sorted in ascending order according to the fitness value, and finally the individuals in each level are stratified according to the pyramid structure based on the proportion of individuals in each level. Figure 1 shows the pyramid stratification process.

1) Fast non-dominated method of sorting. The population $S$ is graded into $\{S_1, S_2, \cdots\}$ based on the dominance of solutions;

2) Intra-hierarchical fitness value sorting to obtain a new set $S_i'$;

3) Stratification based on pyramid structure. Stratification based on percentages to form a pyramid structure.

After the calculation of tiers and fitness values by the fast non-dominated sorting method, each individual possesses two attributes, which can be utilized to compare the advantages and disadvantages of any two individuals. If two individuals belong to different tiers, the individual with small tier is superior to the individual with large tier; if two individuals are in the same tier, the individual with small fitness value is superior to the individual with large fitness value. Here we define the individual with a small fitness value to be the superior individual given a non-dominated hierarchy.

In the pyramid structure, each level focuses on a different task and has a different strategy. Each layer is described below according to the evolution of the pyramid from bottom to top.

Exploring potentially superior individuals in a larger area is the core task of the exploratory layer, which aims to transport the discovered superior individuals to the upper layer, and in order to avoid the whole population falling into a local optimum, the layer adopts a diversity strategy, i.e., the generation of new individuals needs to be sufficiently randomized. Therefore, the rule for the generation of new individuals in the exploration layer is defined as follows:

$$X(n+1) = X(n) + r_0 \times \delta \tag{1}$$

The passing layer is the bridge between the exploration layer and the exploitation layer, with both cultivation and screening abilities, and the randomness of the passing layer is given a certain limit. Because different layers correspond to different tasks, the radius of searching for new individuals is different. Therefore, it is necessary to cultivate the individuals passed up, and the cultivation operation can reduce the chance that these individuals will be eliminated when they first enter the new environment and improve the efficiency of collaboration. After completing the cultivation operation, all the individuals in the passing up layer are iteratively updated, and new individuals are generated as shown in equation (2):

$$X(n+1) = X(n) + r \times \delta \tag{2}$$

Which decreases with the number of iterations as shown in the following equation:

$$r = r_0 \times \alpha^n \tag{3}$$

The individual hatching formula of this layer is

$$X = X(n+1) + \sum_{i=1}^{m} \lambda_j \left( X^{j1} - X^{j2} \right) \tag{4}$$

Where $X$, $X(n+1)$ are defined as in Eq. (1), $X^{j1}$, $X^{j2}$ denote the individuals that make the $j$ th sub-objective optimal and sub-optimal in the current generation, respectively, and $\lambda_j$ denotes the weights of the accelerating effect on individuals for each sub-objective function. Figure 2 shows the competitive process within the delivery layer.

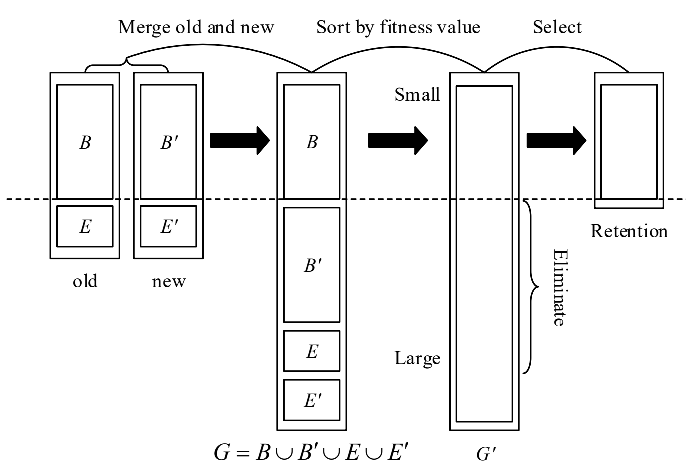



Figure 2: Competition process within the transfer layer

where $B$ denotes the set of old individuals in this layer, let its size be $p$, $E$ denotes the set of individuals passed up from the lower layer, $B'$ denotes the new individuals generated after the individuals in $B$ undergo the update operation and the hatching operation, $E'$ denotes the new individuals after the individuals in $E$ undergo the hatching, updating, and then hatching operation in sequence, and $\bar{B}$ denotes the new individuals retained in this layer after competition. Individuals retained after competition in this layer. The competition process within the transmission layer is as follows:

1) Merge the set of old individuals $B$, $E$ with the set of new individuals $B'$, $E'$;

2) Arrange them in ascending order of fitness values;

3) Retain the first $p$ individuals with small fitness values and eliminate the remaining individuals.

Finally, individuals are selected to be transported to the upper layer using a single elite roulette strategy.

The core task of the mining layer is to deep mine the region around the best individuals and update the individuals in the layer according to Eq. (2). Then a competitive operation is performed on the new and old individuals and the individuals transported up. Figure 3 shows its competition process.

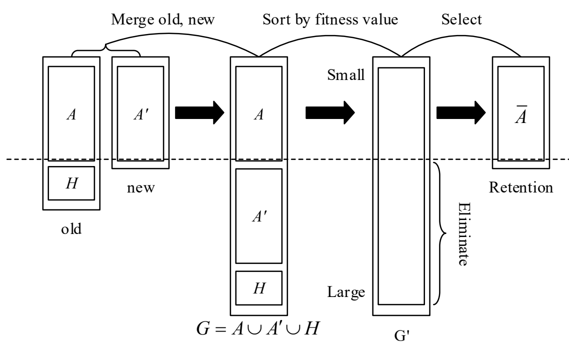



Figure 3: Competition process within the production zone

where $A$, $H$ and $\bar{A}$ are defined in the same way as $B$, $E$ and $\bar{B}$, respectively, and $A'$ denotes the updated population. Because the individuals in the exploitation layer are relatively good and competitive, no cultivation operation is performed on the individuals lost from the lower layer, so that the individuals received in that layer directly compete with the new and old individuals to enhance the convergence speed.

### *II. B.Multi-objective Optimization Model Construction for Innovative Higher Education Talent Cultivation*

The entropy weight method can determine the weight of each indicator, but because the construction of microenvironment is a relatively complex and idiosyncratic process, the establishment of the model should comprehensively consider the influence of external factors and the quality of the students themselves on two levels, to meet multiple optimizable objectives.

Firstly, considering the influence of external factors, the second-level indicators in the sample are then weighted by entropy weighting method, and the multi-objective optimization model of each influencing factor is established by combining the weights of the first-level indicators. Because the optimization model should consider the relationship between the quality of innovative talent cultivation and the factors of innovative talent cultivation, and make the results of the optimization model calculation satisfy the weight value of the first-level indicators as much as possible.

The multi-objective optimization model of higher education innovative talent cultivation is constructed with the quality of higher education innovative talent cultivation as the dependent variable and the influencing factors as the independent variables:

$$\begin{cases} Y_j = w_{9(j-1)} + w_{9j-8} + \cdots w_{9j} \\ Z_j = x_{9(j-1)} + x_{9j-8} + \cdots x_{9j} \\ T_j = Y_j Z_j - W_j \times 36 \\ F(x_1, x_2, \cdots\cdots x_{45}) = \sum_{i=1}^{45} (x_i \times w_i) \\ s_2 \geq F(x_1, x_2, \cdots\cdots x_{45}) \geq s_1 \\ 1 \leq s_i \leq 5 \\ \sum_{i=1}^{45} w_i = 1 \end{cases} \tag{5}$$

In Eq. (5), $Y$ denotes the sum of the weights of the secondary indicators corresponding to each primary indicator; $W$ denotes the weights of the primary indicators that have been obtained; $F$ denotes the total score; $w_i$ denotes the weight of the $i$ th indicator; $x_i$ is the score of the $i$ th indicator; and $i$ denotes the serial number of the secondary indicators; $j$ denotes the serial number of the first-level indicator; $Z$ denotes the sum of the scores of the second-level indicators corresponding to each first-level indicator; and $T$ denotes the difference between the total weighted scores of each first-level indicator after optimization and the total weighted scores of the first-level indicators that have been obtained.

The total score is proportional to the quality of higher education innovative talents training. The evaluation scores of each secondary index in the questionnaire are divided into 1~5, each representing very non-conformity, relatively non-conformity, uncertainty, relatively conformity, and very conformity. For the quality of innovative personnel training is also divided into five levels from 1 to 5, at the same time, in the model solving process, it is assumed that $S_1 = 4$ and $S_2 = 5$, i.e., the quality of innovative personnel training is in the range of 4-5 and the closer the result is to 5, the better, which is the optimization goal one.

If the score of each secondary indicator is 5, then in the case of each primary indicator covering 8 secondary indicators, the total score of each primary indicator is 40 and is not affected by weighting. So in the above difference equation $\tau$ set the original total score of the first-level indicators are 40 and on this basis require the optimization of the total score of the first-level indicators with weights and the total score of the weights of the first-level indicators with the above difference $T$ the smaller the better, this is the optimization goal two.

Secondly, taking into account the impact of the differences in students' own innovative ability on the cultivation of innovative talents in higher education, it is necessary to qualitatively evaluate the innovative ability of students, and then combined with the above factors affecting the cultivation of innovative talents, it is possible to target a certain group of students in colleges and universities to carry out “tailored to the needs of the student group”, and it is possible to more objectively and accurately build the microenvironment for the cultivation of innovative talents. Innovative talent cultivation micro-environment. As the evaluation index system of innovative talents is a multi-level complex system, some of the index factors are fuzzy. In this regard, a second-level fuzzy comprehensive evaluation system is established to realize the assessment of students' personal innovative development. The specific steps are as follows:

Step1 Establish the factor set of comprehensive evaluation

The factor set is the set containing all the factors affecting the evaluation object, usually denoted by $U$, $U = \{u_1, u_2, \cdots, u_n\}$. The own factors affecting students' innovative development situation are divided into two levels from outside to inside.

Step2 Establish the evaluation set of comprehensive evaluation

Evaluation set is a collection of evaluation results, denoted by $V$, $V = \{v_1, v_2, \cdots, v_m\}$. The set of comments on the innovative development of students combining the sample of questionnaires in the context of the actual situation is: $V = \{\text{Excellent } v_1, \text{Good } v_2, \text{Moderate } v_3, \text{Poor } v_4, \text{Very poor } v_5\}$.

Step3 Determine the weight of each factor

Utilizing the results of entropy weighting method, compare and get 4 first-level factors weight matrix $A = [0.2, 0.1, 0.4, 0.3]$. Similarly, the weight matrix of the second-level factors for each belonging first-level factor is obtained as:

$C_1 = [0.3, 0.4, 0.3]$, $C_2 = [0.2, 0.3, 0.5]$, $C_2 = [0.2, 0.3, 0.5]$.

$C_3 = [0.3, 0.4, 0.3]$, $C_4 = [0.5, 0.5]$.

Step4: Determine the single-factor fuzzy evaluation matrix

Fuzzy statistical method is used to determine the affiliation function, based on the results of the questionnaire survey, using the affiliation frequency to define the degree of affiliation. The single-factor fuzzy evaluation matrix is obtained after the results are organized and counted:

$$R = \begin{bmatrix} r_{111}, r_{112}, r_{113}, r_{114} \\ r_{121}, r_{122}, r_{123}, r_{124} \\ \cdots \\ r_{ij1}, r_{ij2}, r_{ij3}, r_{ij4} \\ \cdots \\ r_{3k1}, r_{3k2}, r_{3k3}, r_{3k4} \end{bmatrix} \begin{bmatrix} U_{11} \\ U_{12} \\ U_{ij} \\ \cdots \\ U_{k3} \end{bmatrix} \begin{pmatrix} i = 1, 2, 3, 4 \\ j = 1, 2, \cdots, k \end{pmatrix} \tag{6}$$

In Eq. (6), $r_{ij}$ is the affiliation degree of an evaluation level $m$ of an indicator factor $U_{ij}$ in the indicator layer, $m = 1, 2, 3, 4, 5$.

Based on the fuzzy evaluation matrix, the fuzzy transformation leads to $B = A \cdot R = \left[b_1, b_2, b_3, b_4, b_5\right]$. Then normalize $B$ to get $B' = \left[\frac{b_1}{b}, \frac{b_2}{b}, \frac{b_3}{b}, \frac{b_4}{b}, \frac{b_5}{b}\right]$, where $b = \sum_{i=1}^{5} b_i$, on which the composite evaluation value can be calculated.

### *II. C.Multi-objective ant colony algorithm*

The ant colony algorithm utilizes the positive feedback mechanism between ants and the pheromone guidance strategy to gradually find the optimal solution in the search space. Ant colony algorithm has obvious superiority in solving typical combinatorial optimization problems, such as traveler's problem and vehicle path problem, and the shared bicycle scheduling problem is also a typical class of vehicle path problem, which all involve path planning and resource matching. And in this problem, it is necessary to optimize 2 objectives of total demand unsatisfaction and scheduling cost at the same time, so the multi-objective ant colony algorithm is used to solve the problem, and it is improved according to the characteristics of the model.

#### II. C. 1) State Transfer Probability Rules

The ants use the state transfer probability rule to calculate the access probability of all accessible dispatch points when choosing the next dispatch point to visit. Let the whole ant colony contains $p$ groups of ants, each group of ants contains $q$ ants (indicating that there are $q$ cars involved in scheduling), the total number of ants is $u = p \times q$, and the number of scheduling points is $a$, and the ants will choose the line with a certain probability, and the state transfer probability of defining the ants' movement is shown in Eq. (7), in which $p_{ij}^n$ is the state transfer probability of the $n$ th ant to move from scheduling point $i$ to the scheduling point $j$ of the state transfer probability. Each group of ants has 1 weight $\lambda$, which guides the ants to search in different directions, $\lambda = c / p(c = 1, 2, \cdots, p)$, and the inverse of the distance is generally chosen as the heuristic function in the common ant colony algorithm, and in this paper, the heuristic functions are $b_{ij}$ and $\eta_{ij}$, $b_{ij} = \left|r_j\right|$, $\left|r_j\right|$ is the actual adjustable metric of scheduling point $j$, $\eta_{ij} = 1/d_{ij}$, and $d_{ij}$ is the distance between scheduling point $i$ and scheduling point $j$, $\tau_{ij}$ is the pheromone concentration on the path from scheduling point $i$ to scheduling point $j$, $\alpha$ is the informativeness factor, $\beta$ is the heuristic function factor, and $J_n$ is the set of scheduling points that are accessible to ant $n$.

$$p_{ij}^n = \begin{cases} \dfrac{(\tau_{ij})^\alpha \cdot (b_{ij})^{\lambda\beta} \cdot (\eta_{ij})^{(1-\lambda)\beta}}{\sum\limits_{s \in allow_n} (\tau_{is})^\alpha \cdot (b_{is})^{\lambda\beta} \cdot (\eta_{is})^{(1-\lambda)\beta}}, j \in J_n \\ 0, j \notin J_n \end{cases} \tag{7}$$

#### II. C. 2) Rules for updating the pheromone matrix

When all ants have finished visiting, the pheromone matrix needs to be updated, and all non-dominated solutions are used to update the pheromone, designing multiple pheromone matrices, each responsible for 1 cycle. Each update ensures that the pheromone concentration is within the $[\tau_{\min}, \tau_{\max}]$ interval, where the minimum pheromone concentration increases the exploration ability and the maximum pheromone concentration guides the ants to choose. Each pheromone matrix update rule is defined in Eqs. (8) to (10).

$$\tau_{ij}(\delta+1) = \begin{cases} (1-\rho) \cdot \tau_{ij}(\delta) + \Delta\tau_{ij}, \tau_{\max} > \tau_{ij}(\delta+1) > \tau_{\min} \\ \tau_{\max}, \tau_{ij}(\delta+1) \geq \tau_{\max} \\ \tau_{\min}, \tau_{ij}(\delta+1) \leq \tau_{\min} \end{cases} \tag{8}$$

$$\Delta\tau_{ij}^n = \begin{cases} 1 - 0.5 \times \dfrac{z_1 - \min z_1}{\max z_1 - \min z_1} - 0.5 \\ \times \dfrac{z_2 - \min z_2}{\max z_2 - \min z_2}, j \in J_n \\ 0, j \notin J_n \end{cases} \tag{9}$$

$$\Delta\tau_{ij} = \sum_{n=1}^{u} \Delta\tau_{ij}^n \tag{10}$$

where: $\rho$ is the degree of pheromone volatilization; $\Delta\tau_{ij}^n$ is the pheromone concentration increased by the release of pheromone by the $n$ th ant in the path from scheduling point $i$ to scheduling $j$; $\Delta\tau_{ij}$ is the increase in pheromone concentration due to the release of pheromone by all ants on the path connecting scheduling point $i$ to scheduling point $j$; $z_1$ is the total demand unsatisfaction per ant; $z_2$ is the cost per ant; $\min z_1$ and $\max z_1$ are the minimum and maximum total demand unsatisfaction for each group of ants, respectively; $\min z_2$ and $\max z_2$ are the minimum and maximum cost for each group of ants, respectively.

#### II. C. 3) Fast non-dominated sorting

In a multi-objective optimization problem, the objectives constrain each other, and the improvement of 1 objective is often at the cost of losing other objectives, so the solution of a multi-objective optimization problem is usually a collection of nondominated solutions-Pareto solution set, nondominated solutions means that no other solutions can be found, whose function values are no worse than the nondominated solutions on all the objectives and whose values are at least 1 better value on at least 1 objective. Fast Undominated Sort divides the set of solutions into different undominated hierarchies by traversing each solution in the solution space and comparing their dominance to each other. Solutions in the same tier are non-dominated to each other, and solutions in higher tiers can dominate solutions in lower tiers. The 1 set of non-dominated solutions in the highest tier, which are not dominated by other solutions, constitutes the Pareto optimal frontier.

## III. Optimizing the practice of training pathways for higher education personnel

This chapter carries out the specific practice and optimization feasibility study of cultivation path optimization based on the proposed technical framework. And judge the performance advantage of this paper's method by comparing with other optimization algorithms. The quality of talent cultivation before and after the implementation of the optimization path scheme is tracked to verify the application value of this paper's method.

### *III. A. Feasibility analysis of training path optimization*

#### III. A. 1) Pathway development

In this section, 250 talents are firstly taken as samples from the talents cultivated by the two different cultivation paths before and after the optimization proposed in this paper, and the quality characteristics of the sample group are measured, and the sample mean and sample variance of each ability index obtained from the measurement are used for parameter estimation, so as to derive the parameters such as the innovativeness of the quality characteristics of the talents in different cultivation paths. In order to verify the feasibility of the cultivation path as well as the multi-objective optimization model of this paper, take the higher education talent cultivation plan from 2016 to 2023 as an example, and analyze the total number of people in demand for higher education talents and the elimination rate of the cultivation of local colleges and universities in each year of the cultivation period from 2016 to 2023. The comprehensive calculation gets that the cultivation path of this higher education talent is an anisotropic bi-objective path problem. Further, three sets of feasible solutions of this problem are found, which are K=1, K=2, and K=3. Table 1 shows the initial non-inferior solutions of the cultivation path of higher education talents from 2016 to 2023. Where r denotes the number of higher education talents cultivated by each local institution in year i, which is used to supplement the higher education talent demand in year i+4, and t denotes the number of higher education talents cultivated by the university itself in year i (with a cultivation cycle of 4 years), which is used to supplement the higher education talent demand in year i+1 (with a cultivation cycle of 1 year). Missing data represent the demand for talent development that was not carried out by the institution under study in that year of the training pathway.

Table 1: Initial non-inferior solution of talent training path from 2016 to 2023

| Year | K=1 | | K=2 | | K=3 | |
|---|---|---|---|---|---|---|
| | r | t | r | t | r | t |
| 2016 | - | - | 16000 | - | 26000 | - |
| 2017 | - | - | - | - | 21151 | - |
| 2018 | 7351 | - | 22500 | - | 22500 | - |
| 2019 | - | 26000 | - | 10000 | - | - |
| 2020 | 24800 | 27000 | 24800 | 27000 | 24800 | 6849 |
| 2021 | - | 17149 | - | - | - | - |
| 2022 | - | 25300 | - | 25300 | - | 25300 |
| 2023 | - | - | - | - | - | - |
| Composite mean | 0.7714 | | 0.7701 | | 0.7687 | |
| Composite proportion | 0.6964 | | 0.7086 | | 0.7207 | |

The choice between multiple sets of non-inferior solutions depends largely on the preferences of the decision maker of the training pathway. Due to the consideration of the demand change factor in the implementation of the path, the flexibility of adjustment of different training modes needs to be taken into account in the formulation of the path. Since the training cycle of t-mode trainees is shorter, and their flexibility to cope with the adjustment of the program is higher, it can be considered that the path can be used as much as possible when choosing the feasible solutions of the path under the requirement of meeting a certain percentage of the number of people of medium and high level. From Table 1, it can also be seen that the feasible solution with K=3 has the largest comprehensive proportion of 0.7207, so it can be chosen to divide the cultivation path under the t-mode into 3 phases, i.e., the baseline phase, the gradual development phase, and the rapid development phase.

#### III. A. 2) Multi-objective optimization of training pathways

Further calculate the probability of realizing the development of 4 innovative capabilities by using the multi-objective optimization model introducing the multi-objective ant algorithm in t-mode for the optimization of the cultivation path in this paper, and ultimately to cultivate higher education talents to improve the quality of innovation and obtain the development of the 4 innovative capabilities.

Table 2 shows the parameters of the 3 stages of higher education talent cultivation.A1-A4 represent the 4 innovative capabilities to be ultimately cultivated and obtained. Among the 3 stages to be experienced by the talent cultivation path, the optimization solution using the multi-objective optimization model introducing the multi-objective ant algorithm finds that the realization probability of cultivating talents' innovation ability varies in each stage. Overall, the probability of realizing innovation ability A1 of talents cultivated in the benchmark stage is the largest, reaching 0.44, and the most difficult one is the cultivation of innovation ability A2, with a probability of only 0.14. Comprehensively calculating the probability of realizing the optimal ability cultivation in the three stages are: 0.4 in the benchmark stage, 0.3 in the gradual development stage, and 0.3 in the rapid development stage, respectively.

Table 2: Parameters of the three stages of higher education personnel training

| | Year | A1 | A2 | A3 | A4 |
|---|---|---|---|---|---|
| Reference stage | Gh+1 | 0.44 | 0.14 | 0.21 | 0.21 |
| | Gh+2 | 0.44 | 0.14 | 0.21 | 0.21 |
| | Gh+3 | 0.44 | 0.14 | 0.21 | 0.21 |
| | Gh+4 | 0.44 | 0.14 | 0.21 | 0.21 |
| | Gh+5 | 0.44 | 0.14 | 0.21 | 0.21 |
| Progressive development stage | Gh+1 | 0.44 | 0.14 | 0.19 | 0.23 |
| | Gh+2 | 0.38 | 0.15 | 0.21 | 0.24 |
| | Gh+3 | 0.36 | 0.13 | 0.23 | 0.28 |
| | Gh+4 | 0.30 | 0.14 | 0.25 | 0.31 |
| | Gh+5 | 0.29 | 0.16 | 0.26 | 0.29 |
| Rapid development stage | Gh+1 | 0.29 | 0.14 | 0.21 | 0.36 |
| | Gh+2 | 0.27 | 0.14 | 0.23 | 0.36 |
| | Gh+3 | 0.26 | 0.14 | 0.25 | 0.35 |
| | Gh+4 | 0.24 | 0.14 | 0.27 | 0.35 |
| | Gh+5 | 0.22 | 0.14 | 0.28 | 0.36 |

### *III. B. Performance comparison with other optimization algorithms*

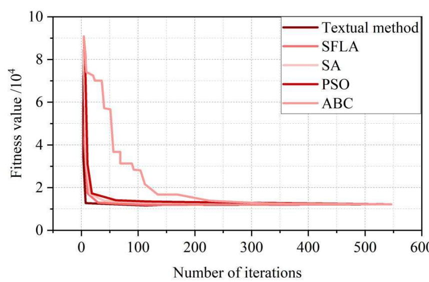
From the previous section, it is found that the multi-objective optimization model introduced into the multi-objective ant colony algorithm in this paper can realize the optimization of higher education talent cultivation paths and calculate the final optimal cultivation path. In order to further judge the application advantages of this paper's method, three aspects of stability tests were carried out on this paper's method: Based on the same population size, maximum iteration frequency and maximum running frequency, the convergence speed and search optimization accuracy of this paper's method, Frog Hopping Algorithm (SFLA), Simulated Annealing Algorithm (SA), Particle Swarm Algorithm (PSO), and Artificial Bee Colony Algorithm (ABC) are compared among five benchmark test functions, and thus verified that this paper's optimization method still has superiority.

In order to test the characteristic differences between the proposed method and other traditional methods, the number of populations is assumed to be 35, the maximum iteration time is 550ms, and the running time is recorded. The mean (mean), standard deviation (std.dev) time consumed (time) of the optimal simulation results are used as the computational performance measures.

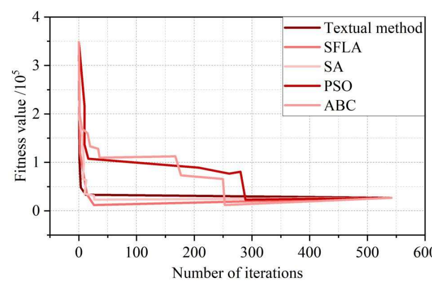
Table 3 shows the performance comparison results of this paper's method with other optimization algorithms. As can be seen from Table 3, taking the optimal mean as a measure, the optimal mean of this paper's method is the largest compared to the comparison algorithms among the five test functions. At the same time, the standard deviation and time consumption of this paper's method are also the smallest. The time used by this paper's method in the five test functions is between 150-200ms. Combined with the optimal mean and standard deviation, this paper's method has the best search and optimization results in the benchmark functions, and the overall stability is optimal.

Table 3: Compared results of textual method and other optimization algorithms

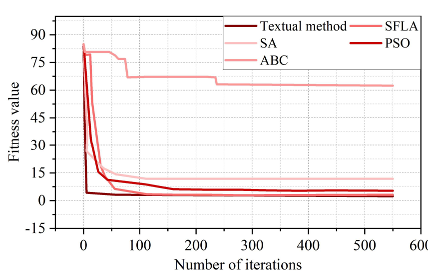
| Reference function | Index | Textual method | SFLA | SA | PSO | ABC |
|---|---|---|---|---|---|---|
| F1 | Mean | 1.8133E-01 | 1.7351E+04 | 1.7386E-07 | 1.7536E+01 | 1.7588E+02 |
| | Std.dev | 1.7132E-01 | 1.7628E+04 | 1.7408E-07 | 1.7666E-04 | 1.7610E+02 |
| | Time | 198ms | 228ms | 236ms | 231ms | 227ms |
| F2 | Mean | 2.9495E-03 | 2.7955E+01 | 2.0919E-08 | 2.6255E-09 | 2.7158E-04 |
| | Std.dev | 1.2219E-03 | 1.5521E+01 | 1.4327E-11 | 1.5947E-02 | 1.4757E+01 |
| | Time | 158ms | 165ms | 185ms | 171ms | 190ms |
| F3 | Mean | 4.1855E+04 | 3.3957E+00 | 3.2247E-03 | 3.7427E-05 | 4.0045E+00 |
| | Std.dev | 1.1290E+04 | 1.1508E+00 | 1.1698E-03 | 1.1917E+01 | 1.1787E+01 |
| | Time | 200ms | 219ms | 228ms | 231ms | 228ms |
| F4 | Mean | 5.7915E+00 | 5.0486E+01 | 5.3979E-01 | 5.0843E+03 | 5.3340E-02 |
| | Std.dev | 1.4523E+00 | 1.5729E+01 | 1.4745E-01 | 1.5997E+01 | 1.6991E-03 |
| | Time | 159ms | 178ms | 176ms | 183ms | 178ms |
| F5 | Mean | 1.9871E+02 | 1.5708E+04 | 1.6107E+03 | 1.5989E+01 | 1.6155E+06 |
| | Std.dev | 2.0121E+02 | 2.2088E+04 | 2.4356E+03 | 2.9814E+03 | 3.3347E-05 |
| | Time | 178ms | 189ms | 184ms | 187ms | 196ms |



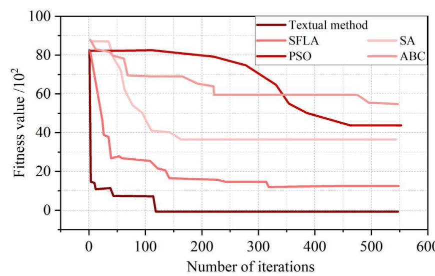
(a) F1



(b) F2



(c) F3



(d) F4

Figure 4: Run comparison iterations

Fig. 4 shows the comparison iterations between the method of this paper and the classical optimization algorithm running on F1-F4 functions. The horizontal coordinate is the number of iterations and the vertical coordinate is the fitness value. As can be seen from Fig. 4, except for the F4 function, this paper's method can obtain a stable fitness value in the running computation of the other three benchmark functions with roughly only about 10 iterations, which is much better than the comparison algorithm. In the F4 function, even though it is difficult to run, the method in this paper basically obtains a stable fitness value after 110 iterations. Compared with the fluctuation amplitude of the other four types of algorithms, the method in this paper is more stable and the iteration speed is faster. When dealing with multiple objective optimization problems, the method in this paper is able to take care of more objective tasks at the same time, and in the test, the convergence accuracy and robustness show good advantages, and after many iterations of optimization, its search efficiency will also be enhanced and improved. This also shows that the method of this paper can well find the optimization scheme of higher education talent cultivation path and achieve the ultimate goal of talent quality cultivation improvement.

### *III. C. Investigation of the cultivation effect of the optimization pathway*

The method of this paper is used to solve the optimal solution for the higher education talent cultivation path of a university, and the freshmen majoring in industrial Internet are selected to carry out a four-year optimization program experiment. At the end of the experiment, the relevant researchers conducted in-depth data collection and processing for the optimization results of the talent cultivation path of the industrial Internet major in this university. The data covered key indicators before and after the optimization, including the employment rate of students, the acquisition rate of students' professional-related certificates, the results of the enterprise satisfaction survey, the results of the student satisfaction survey, and the number of teachers' scientific research achievements. The quality of higher education personnel training is measured through these indicators. These data were collected over a six-year period, specifically divided into the year before pathway optimization, the first year of pathway optimization, the second year of pathway optimization, the third year of pathway optimization, the fourth year of pathway optimization, and the year after pathway optimization. The time of concern spans the pre-entry, college career and post-graduation year of the students in this major, which can reflect more comprehensively the quality of students' talent cultivation before and after the optimization of the path of higher talent education.

Table 4 shows the comparison between the students' employment rate and the acquisition rate of professional-related certificates. Figure 5 shows the results of the enterprise satisfaction survey before and after path optimization. Through the comparative analysis, the improvement of higher education talent quality and employment brought by path optimization can be clearly seen. Analysis of Table 4 shows that the employment rate of students has continuously increased from 83% in the year before path optimization to 97% in the year after path optimization, with an increase of 14%; the rate of obtaining professional-related certificates has also increased from 41% to 77%, with an increase of 36%. Combined with the enterprise satisfaction survey in Figure 5, it is found that the enterprise satisfaction rate of students before and after the optimization of the training path has increased from 74% to 95%, with an increase of 11%. Combining the student employment rate, professional-related certificate acquisition rate and enterprise satisfaction before and after the optimization of cultivation path, it can be judged that using the method of this paper to find the optimization scheme of cultivation path can get the optimal solution to improve the quality of higher education personnel cultivation effectively. Combining the method of this paper to optimize the cultivation path helps colleges and universities to enhance their talent cultivation ability, so that higher education talents can get better achievements in both study and employment.

Table 4: Comparison between employment rate and certificate acquisition rate

| Year | Employment rate (%) | Certificate acquisition rate (%) |
|---|---|---|
| Path optimization the previous year | 83 | 41 |
| Path optimization Year 1 | 89 | 50 |
| Path optimization year 2 | 92 | 58 |
| Path optimization Year 3 | 94 | 63 |
| Path optimization Year 4 | 95 | 70 |
| Path optimization after one year | 97 | 77 |

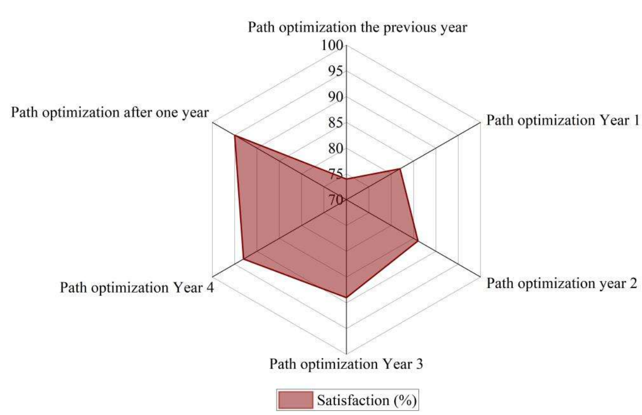



Figure 5: Enterprise satisfaction before and after route optimization

## IV. Conclusion

This paper is based on multi-objective optimization strategies and intelligent algorithms, etc., to achieve the optimization of higher education talent cultivation path. In the algorithm comparison test, the running time of the five benchmark functions of this paper's method is no more than 200ms, and only about 10 iterations are needed in most of the functions to obtain a stable fitness value. The method of this paper is better than the traditional optimization algorithm in convergence speed and stability. In the practice of higher education talent cultivation path optimization, the optimized student employment rate, certificate acquisition rate and enterprise satisfaction rate are increased to 97%, 77% and 95% respectively, and the quality of talents is improved. The multi-objective hierarchical optimization technique in this paper has application value in the optimization of higher education talent cultivation path, which helps to promote the accurate cultivation of talents in colleges and universities. In the future, the long-term dynamic adaptability of this method can be further studied and optimized to enhance the corresponding ability of path optimization and promote the intelligent cultivation of higher education talents.

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