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Article

Proposing an Optimal Strategy for Modernization Path Design of Vocational Education Governance Based on Multi-Objective Planning Approach

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Abstract: At present, the state urgently promotes the modernization of the governance system and governance capacity, and further improves and perfects the system of modernization of vocational education governance, which has become an important topic that needs to be urgently solved for the reform of the field of vocational education. The article analyzes the logical requirements for the modernization of vocational education governance from the connotation performance and measurement standard of vocational education governance modernization. On this basis, guided by the multi-objective optimization planning theory, a multi-objective planning model for the modernization of vocational education governance is constructed from the development goal of the modernization of vocational education governance. Then based on the GWO algorithm, the GWO algorithm is improved by introducing the chaos mapping strategy and the leading cooperation mechanism strategy, and the IMGWO algorithm is used to solve the multi-objective planning model of modernization of vocational education governance. Finally, the optimal construction path of vocational education governance modernization is proposed from the three dimensions of integration, pioneering and driving. The study shows that the IMGWO algorithm has a better overall improvement effect, has a better optimization accuracy and convergence speed compared with other comparative algorithms, and it is feasible to use it to solve the multi-objective planning model for modernization of vocational education governance. Relying on the multi-planning model of modernization of vocational education governance, it can provide decision-making guidance for the construction path of modernization of vocational education governance and better promote the development of modernization of vocational education governance.

Keywords: multi-objective optimal planning; GWO algorithm; chaotic mapping; leading cooperation mechanism; vocational education governance modernization

1. Introduction

As an important part of the national education system and human resources development, the modernization of vocational education is not only an important content of Chinese-style modernization, but also a key initiative to promote the realization of Chinese-style modernization [1-2]. And the modernization of vocational education cannot be separated from the modernization of vocational education governance as a guarantee in the process of boosting the realization of Chinese-style modernization [3-4]. In recent years, in the context of vigorously promoting the modernization of national governance and the modernization of education governance, although the modernization of vocational education governance has made great progress, it still lags behind the needs of social development, and the construction of the governance system and governance capacity does not match with the realization of the strategic requirements of a strong educational country and a strong manufacturing country [5-8]. In order to promote the early realization of Chinese modernization and the modernization of national governance, it is urgent to construct an ideal model of "modernization of vocational education governance” that is suitable for China's national conditions and put it into practice [9].

Vocational education governance is a technology and an art, which needs to change from education management thinking to education governance concept on the one hand, and needs the effective embedding and empowerment of governance technology on the other [10-11]. Nowadays, the human society is moving into the intelligent era and digital civilization, and “intelligence” has become the mark of the times. The improvement of the efficiency and effectiveness of vocational education governance mainly depends on what kind of technology is chosen, i.e., governance tools, and the choice of governance tools is directly related to governance performance [12-14]. Similarly, while intelligent technology brings positive function and value to vocational education governance, it may cause new education governance problems, from technology “empowerment” to technology “negative” [15-16]. Therefore, the innovative integration of intelligent technology and educational governance has become an important proposition of the modernization of educational governance.

Deepening the governance modernization of vocational education is not only a requirement for the reform of higher education and vocational education in the new era, but also the implementation of the reform goal of modernizing the national governance system and governance capacity. This paper proposes a multi-objective planning model for the modernization of vocational education governance based on the optimization theory of multi-objective planning, and introduces the GWO algorithm to solve the model after the improvement of chaotic mapping and the strategy of leading cooperation mechanism. Firstly, it discusses the connotation and measurement standard of modernization of vocational education, and explores the logical requirements and practical path of modernization of vocational education governance. Then the development goal of modernization of vocational education governance is taken as the objective function, and the corresponding constraints are set to construct the model of modernization of vocational education governance. Finally, the effectiveness of IMGWO algorithm in solving the multi-planning model of modernization of vocational education governance is verified and analyzed, aiming to provide support for exploring the optimal strategy of modernization of vocational education governance.

2. Knowledge of Modernization of Governance in Vocational Education

The modernization of vocational education governance is an important part of deepening the comprehensive reform in the field of vocational education and accelerating the modernization of the governance system and governance capacity of vocational education. The governance status of higher vocational colleges and universities mainly depends on what paths they take in governance, and the establishment of a governance system reflecting the characteristics of higher vocational education is a prerequisite for improving the governance capacity of higher vocational colleges and universities. Optimizing the distinctive internal governance structure is the focus of enhancing the governance capacity of higher vocational colleges and universities, and improving the smooth and efficient internal operation mechanism and execution system is the foundation of enhancing the governance capacity of higher vocational colleges and universities.

2.1. Connotation of Modernization of Vocational Education Governance

Vocational education, based on the development model of school-enterprise cooperation and industry-education integration, must work with multiple governance bodies to promote the connotative improvement of its governance capacity. Vocational education has a certain degree of openness compared with general education, and whether it can realize benign cross-border interaction and symbiosis with other education and other fields is the road to its modernization and development. To sum up, the modernization of vocational education governance studied in this paper refers to the requirements of the modernization of vocational education that the multiple governance subjects continuously adapt to the modernization of education, and under the framework of the vocational education governance system, the governance subjects set up a modernized concept of governance and continuously improve their own comprehensive quality. Under a sound and perfect institutional system, the rule of law to carry out various secondary vocational education activities, and the use of certain information technology governance means, jointly to promote the public interest of secondary vocational education as a goal of a capacity and level. Its connotation is mainly for the modernization of the concept of governance of secondary vocational education, diversification of the main body of governance, rule of law governance, standardization of the governance process, and informationization of governance technology [17].

Vocational education pluralistic governance subject is the basic force, only the pursuit of modernized governance concepts of each subject, in order to guide the ability to play correctly and effectively, this is the premise. Secondly, vocational education-related laws and regulations, institutional policies and methods are the basis of secondary vocational education governance, which is the guarantee. Once again, the standardization of the governance process of vocational education is a necessary condition, and it is the key to realize the standardization of the governance process of vocational education in order to further realize the separation of management, operation and evaluation. Finally, the use of information technology for governance in order to make vocational education governance capacity more efficient and maximize the benefits of education governance, which is the boost.

2.2. Measures of Modernization of Governance in Vocational Education

How to measure the modernization of the governance capacity of higher vocational colleges and universities and by what standard to view it are of great significance to how we can accelerate the modernization of the governance capacity of higher vocational colleges and universities and promote the development of the cause of higher vocational education. As we know, standard is the measure of things, the mark of measuring and comparing the similarities and differences between things. Since modernization is the modernization of a certain period of time and under certain conditions, the standard for measuring modernization is not absolute but relative. Coupled with the fact that modernization is a comprehensive reflection of the degree of development of a society, then the standard for measuring modernization should also be comprehensive. The modernization of governance capacity of higher vocational colleges and universities is not a simple qualitative or quantitative can be discerned, it needs to use qualitative and quantitative indicators organically combined to generalize and grasp [18].

(1) Diversification of governance subjects. The plurality of governance subjects emphasizes pluralistic cooperative governance, jointly playing the roles of government, school, market, teachers and students, and industrial enterprises (society).

(2) Systematization of governance system. The process of modernizing the governance of higher vocational colleges and universities is also the process of building the system of modern higher vocational colleges and universities.

(3) Democratization of governance. The party committee and administrative team of higher vocational colleges and universities is the effective organizer of the work of higher vocational colleges and universities, in addition to having strong leadership and playing the role of core leadership, it is more necessary to have a strong ability to perform their duties, in which democratic and scientific decision-making ability, is the first.

(4) Integration of governance means. The modernization of the governance capacity of higher vocational colleges and universities should be a comprehensive modernization of teaching, scientific research, social service and cultural construction, which is an organic, coordinated, dynamic and holistic system.

(5) Synergize the governance environment. The state and goal of modernization of governance capacity of higher vocational colleges and universities can only be truly achieved by realizing the relative balance, mutual adaptation and mutual cooperation of the forces of the four basic fields: government, market, higher vocational colleges and universities, and the society (industrial enterprises).

2.3. Logical Requirements for Modernizing the Governance of Vocational Education

(1) Strengthening the leadership of party building and building a new pattern of governance in vocational education. First, promote the systematization and normalization of party building work, and build a long-term mechanism for integrating party building into governance. Second, strengthen the construction of grassroots Party organizations and enhance political functions. Third, promote the deep integration of party building work and school-enterprise cooperation to realize two-way development [19].

(2) Serve industrial demand and explore new paths of vocational education governance. First, to realize the close docking with industrial demand, industrial colleges need to deeply participate in the key links of the industrial chain and establish a co-governance mechanism with enterprises. Secondly, to effectively serve the needs of industry, implement demand-oriented curriculum reform. Third, innovate the mode of industry-academia cooperation and promote order-oriented training.

(3) Promote digital transformation and build a new engine for industrial college governance. First, schools and enterprises will jointly build digital platforms such as “School-Enterprise Cooperation Cloud Platform”, and jointly formulate cooperation projects, talent cultivation plans and practical training arrangements. The second is to build a data-driven decision support system to enhance scientific decision-making capability.

3. Multi-Objective Planning for the Modernization of Vocational Education Governance

Modernization of national governance is an urgent task of the times facing contemporary China, and an inevitable requirement for further improving the socialist system with Chinese characteristics. As far as higher vocational colleges and universities are concerned, they need to actively deploy the implementation of the party's overall goal of comprehensively deepening reform, closely combining with their own actuality, to promote the modernization of the school governance system and governance capacity. Higher vocational colleges and universities have entered the bottleneck period from scale expansion to connotation improvement, especially at present, the national higher vocational colleges and universities are in full swing to carry out the project construction of "double-high plan", it is more necessary to promote the school from the management of the concept of governance to change, and to speed up the modernization of school governance. This will make school governance more emancipatory, optimize the top-level design, and thus promote school governance towards good governance.

3.1. Multi-Objective Planning Model for Vocational Education

3.1.1. Basics of Multi-Objective Optimization

In the study of single-objective optimization problems, for any two solutions, as long as the comparison of their corresponding objective values, you can compare the advantages and disadvantages, but in the case of multi-objective the situation is complicated, the task of multi-objective decision-making is to select from the set of non-inferiority of the solution as a satisfactory solution as the final result.

Suppose that in the education system, m objectives $f_1(X), f_2(X), \cdots\cdots f_m(X)$ need to be examined at the same time and it is hoped that all of them are as big as possible, and the optimal value of the first i objective is remembered to be, when other objectives are not considered:

$$f_i^* = \underset{X \in R}{Max} f_i(X) \tag{1}$$

$$R = \{X / G(X) \geq 0\}, G(X) = [g_1(X), g_2(X), \cdots g_i(X)]^T \tag{2}$$

Finding the multi-objective optimization within the constraint set R can be expressed as:

$$V - \underset{X \in R}{Max}\, F(X) \tag{3}$$

where $F(X) = [f_1(X), f_2(X), \cdots\cdots, f_m(X)]^T$

Consider the n -dimensional Euclidean space E_{n0} , i.e.,:

$$X = (x_1, x_2, \cdots, x_n)^T \in E_{n0} \quad RCE_{n0} \quad f(X) \in E_n \tag{4}$$

When X_0 is the optimal solution, it is denoted:

$$F(X) \leq F(X_0) \forall X \in R \tag{5}$$

When X_0 is a non-inferior solution, it means that there is no $X \in R$, there:

$$F(X) \geq F(X_0) \tag{6}$$

For each objective $f_i(x)$ in the education system, the decision maker can first determine a desired value f_i^* , and sometimes take the target value to be the optimal value that each objective can achieve, and then get the overall optimal value of each objective $F^* = [f_1^*, f_2^*, \ldots, f_m^*]^T$. Requiring all objectives to reach their respective optimal values at the same time is generally unlikely, so the vector F^* is just an ideal point for the vector function $F(X)$. So imagine how to seek a point $\overline{X}$ on R to minimize the deviation of $f(\overline{X})$ from F^* , i.e., the ideal point method, which is based on the idea of defining a mode, and finding a point as close as possible to the ideal point in the sense of this mode. That is, let the mode $\| F(X)-F^{*} \| \to Min$, for different modes can be found in different sense of the optimal point, generally defined P a mode as:

$$\| F(X)-F^{*} \|_{p} = \left[\sum_{i=1}^{m} (f_i(x)-f_i^{*})^{p} \right]^{\frac{1}{p}} = L_p(X) \tag{7}$$

$$P \in [1,\infty)$$

When $P=2$, this modulo the distance in Euclidean space, $\underset{x\in R}{Min} L_2(X)$ means that the corresponding objective value of the solution is closest to the ideal point.

When $P=1$, then:

$$L_1(X) = \sum_{i=1}^{m} \left[f_i(X) \cdots f_i^{*} \right] \tag{8}$$

We want all target values to be as close as possible to the corresponding objective values, and introducing the two-group deviation variable d_i^{+} , it is not difficult to show that $(P) Min \sum_{i=1}^{m} | f_i(X) - f_i^{*} |$ is equivalent to:

$$(P^{'}) \begin{cases} \min \sum_{i=1}^{m} (d_i^{+} + d_i^{-}) \\ f_i(X) - d_i^{+} + d_i^{-} = f_i^{*} \quad (i=1,2,\cdots,m) \\ d_i^{+} \cdot d_i^{-} = 0, d_i^{+} \ge 0, d_i^{-} \ge 0 \quad (i=1,2,\cdots,m) \\ X \in R \end{cases} \tag{9}$$

If the constraint $d_i^{+} \cdot d_i^{-} = 0$ in $(P^{'})$ is removed, we get $(P^{"})$, and we can prove that the optimal solution of $(P^{"})$ $(\overline{X}, \overline{d}_i^{+}, \overline{d}_i^{-})$ in X must be the optimal solution of (P).

In this method, when the constraint set R is the empty set, the order of successive consideration is proposed for each objective, and a number of new objective functions are made through the deviation variables d^{+} , d^{-} , and the optimal solution is sought in turn, which can be found out the negotiation scheme X , so that the deviation of $f(X)$ and f^{*} is minimized under the overall requirements of the problem.

3.1.2. Multi-Objective Planning Model for Vocational Education

According to the development plan for modernizing the governance of vocational education, the overall goal is to establish a higher education system that is compatible with the characteristics of resources, industrial structure, and economic and social development goals, with a reasonable layout and structure, good scale efficiency, and high quality of education, as well as with its own characteristics. The establishment of this model is centered on this general objective, and the main purpose of modeling is to provide the supply of various types of talents and the structure of various types of talents from the perspective of talent supply on the one hand, and on the other hand, to put forward the demand for teachers compatible with the supply of talents and to put forward the plan to improve the utilization rate of human resources.

(1) Technical manpower. Let $e_{ij}(\tau)$ denote the total number of students in grade i in τ school year j category schools, then matrix $E_j(\tau)$ denotes the flow of students in τ school year j category schools. Then:

$$E_j(\tau)=\begin{bmatrix} e_{1j} \\ \dots \\ e_{kj} \end{bmatrix}, \quad j=1,2,3,4 \tag{10}$$

where j represents the type of student and k represents the school system of the j type of school.

The student flow state model is:

$$E_j(\tau)=C_i E_j(\tau-1)+\overline{U}X_j(\tau) \tag{11}$$

where C_j is the state transfer matrix for the j class of schools, determined by the student's promotion and retention skip rate.

$$\overline{U}=[1,0,\dots,0]^T \tag{12}$$

where $X_j(\tau)$ represents the number of new students in τ school year in j type of school as a decision variable and as an input variable for the education system.

The technical manpower model of the education system for τ school year is:

$$f_j(\tau)=g_j U E_j(\tau-1)-X_{j+1}(\tau)+U_{j+1}u*E_{j+1}(\tau-1) \tag{13}$$

where g_j is the average graduation rate for schools in the j category and U_j is the average dropout rate for schools in the j category.

$$U=[0,0,\dots,0,1], U^*=[1,1,\dots,1] \tag{14}$$

The cumulative state of skilled manpower at all levels in the economy in year τ of the planning period is $Y_j(\tau)$, then:

$$Y_j(\tau)=(1-u_j)Y_j(\tau-1)+f_j(\tau) \tag{15}$$

where u_j is the natural decay rate of skilled manpower corresponding to the j level of education.

(2) Teacher flow model. Based on the student state vector and the student-teacher ratio, the need for teachers can be predicted. Let $e_{iD}(\tau)$ denote the total number of teachers at level i in the τ school year, then E_D represents the teacher flow in the τ school year. Then:

$$E_D(\tau)=\left[e_{iD}(\tau)\right] \tag{16}$$

where i stands for job title.

The teacher flow state model is:

$$e_{iD}=A_i\overline{E}(\tau) \tag{17}$$

where A_i is the ratio of teachers to students at all levels and $\overline{E}(\tau)$ is the total number of students.

A total of three objectives are set in the multi-objective planning model for modernizing the governance of vocational education, namely, the general technical manpower objective, the key professional manpower objective and the funding objective. Among them, the general technical manpower objective has a total of 20 different professional objectives, the key professional talents objective can be set according to the needs of economic construction and social development, and the funding objective mainly includes the objectives of vocational education utility fee and infrastructure fee, which is hoped to make the investment in vocational education as little as possible.

The specific constraints are as follows:

In the technical manpower target, it is assumed that the expected target value of the demand (supply) for technical manpower at the end year of the planning period is:

$$b = \{b_1, b_2, ..., b_s\} \tag{18}$$

where s is the total number of manpower categories. Let the deviation variable be:

$$D = \{d_1, d_2, ..., d_s\} \tag{19}$$

And:

$$d_i = | f_i(\text{y} - b | = \begin{cases} d_i^+, & f_i(\tau) \geq b \\ d_i^-, & f_i(\tau) < b \end{cases}, \quad i = 1, 2, ..., s \tag{20}$$

where d_i^+ and d_i^- denote the positive and negative deviations between the target value that can be achieved by the i th goal and the given expectation, respectively. Accordingly, we set up funding targets and deviations. In this education multi-objective planning model, the two main considerations are the education utility fee and the education infrastructure fee, and the funding objective is set as $\{B_1, B_2\}$.

The education utility fee is modeled as:

$$S_Y = \sum_{j=1}^{4} h_j(\gamma) \left[\frac{2}{3} u * E_j(\tau - 1) + \frac{1}{2} u * E_j(\gamma) \right] \tag{21}$$

where $h_j(\gamma)$ is the average utility cost per student in τ year j type of school.

The education capital cost (investment) is modeled as:

$$J_\tau = \sum_{j=1}^{4} P_j \notin \frac{1}{2} \left[u * E_j(\tau + 2) - u * E_j(\gamma) \right] \tag{22}$$

where ρ is the cost per square meter of infrastructure space for j type of school, and ε_j is the average infrastructure space per pupil for j type of school.

Then the constraints are:

$$f_i(\gamma + d_i^- - d_i^+) = b_i \qquad i = 1, 2, \ldots, s \tag{23}$$

$$S_Y + \eta_1^- - \eta_1^+ = B_1 \tag{24}$$

$$J_\tau + \eta_2^- - \eta_2^+ = B_2 \tag{25}$$

Combining the above analysis, the multi-objective planning model for modernizing the governance of vocational education is obtained as:

$$\begin{aligned}
&\text{lexmin} G = \{g_1(d^-, d^+, \eta^-, \eta^+), g_2(d^-, d^+, \eta^-, \eta^+), g_3(d^-, d^+, \eta^-, \eta^+)\} \\
&(d^- = \{d_1^-, \cdots, d_s^-), d^+ = \{d_1^+, \cdots, d_s^+\}, \eta^- = \{\eta_1^-, \cdots, \eta_s^-\}, \eta^+ = \{\eta_1^+, \cdots, \eta_s^+\} \\
&s.t. f_i(y + d_i^- - d_i^+ = b_i, i = 1, 2, \cdots, s \\
&S_Y + \eta_1^- - \eta_1^+ = B_1 \\
&J_\tau + \eta_2^- - \eta_2^+ = B_2 \\
&X_1(\tau) \cdots X_i(\tau) \geq 0
\end{aligned} \tag{26}$$

3.2. Algorithms for Solving Multi-Objective Planning Models

3.2.1. Mathematical Model of Gray Wolf Optimization Algorithm

The Gray Wolf Optimization (GWO) algorithm is a group intelligence algorithm inspired by the behavior of gray wolf groups in nature. Gray wolves are a kind of predator at the top of the food chain, and their life habits are group-oriented, with each group consisting of 5 to 10 wolves on average, and each wolf has its own role in the population. Therefore, their behavior strictly follows a pyramidal hierarchy, which builds the social structure of the entire gray wolf population.

Gray wolf populations engage in collective predatory actions, and their predation process mainly includes the period of enclosing the target, the period of chasing the target and the period of feeding on the target. The details are as follows:

During the siege target period, the gray wolf population will carry out the updating of each other's position. To wit:

$$D = | C \times X_p(k) - X(k) | \tag{27}$$

$$X(k+1) = X_P(k) - A \times D \tag{28}$$

where D is the distance between the individuals in the population and the target prey, k is the current number of iterations, X_p denotes the specific position of the prey, and X denotes the specific position that the individuals in the population are currently in. The mathematical formula for coefficient A and coefficient C is:

$$A = 2a \times r_1 - a \tag{29}$$

$$C = 2r_2 \tag{30}$$

$$a = 2 - \frac{2k}{k_{\max}} \tag{31}$$

where a is a linear control parameter which decreases linearly from 2 to 0 as the number of iterations increases, $k_{\max}$ is the maximum number of iterations, and r_1, r_2 are two random numbers in [0, 1].

In the gray wolf optimization algorithm, the α, β, δ wolf is the individual gray wolf that is closest to the location of the prey and assumes a leadership role in guiding the other gray wolves towards the prey during the period of chasing the target. In the abstract problem space, individual gray wolf positions are used as a proxy for the problem solution because the target position cannot be known exactly. The α, β, δ wolves represent the optimal, suboptimal, and third best solutions of the gray wolf optimization algorithm, respectively. During the predation period, the gray wolves update their positions based on where these leaders are in order to globally optimize the task. During the period of chasing the target, the position update of individual gray wolves in the gray wolf pack can be expressed according to the following equation:

$$D_\alpha = | C_1 \times X_\alpha(k) - X(k) | \tag{32}$$

$$D_\beta = | C_2 \times X_\beta(k) - X(k) | \tag{33}$$

$$D_s = | C_3 \times X_s(k) - X(k) | \tag{34}$$

$$X_1 = X_\alpha(k) - A_1 \times D_\alpha \tag{35}$$

$$X_2 = X_\beta(k) - A_2 \times D_\beta \tag{36}$$

$$X_3 = X_\delta(k) - A_3 \times D_\delta \tag{37}$$

$$X(k+1) = \frac{(X_1 + X_2 + X_3)}{3} \tag{38}$$

In Eqs. (32)~(34), C_1, C_2, C_3 constitute the three components of the vector C, and X is denoted as the position of the current solution. In Eqs. (35) to (38), X_a refers to the position of the optimal solution occupied by the α wolf in the population, X_β refers to the position of the second best solution occupied by the β wolf in the population, and X_δ refers to the position of the δ wolf in the population. position of the third best solution.

During periods of predation on prey, the gray wolf population adjusts its behavior in response to changes in the variable a. When a decreases from 2 to 0, the corresponding A value varies within the interval $[-a, a]$. When $|A|$ is less than 1, gray wolves conduct local search with a focus on predation, while when $|A|$ is greater than 1, gray wolves diffuse and conduct global search.

3.2.2. Multi-Strategy Improvement of GWO Algorithm

In order to improve the solution accuracy, stability and convergence speed of the GWO algorithm, this paper carries out 2 aspects of improvement on the basis of the standard GWO algorithm, as follows:

(1) Chaos mapping strategy

Chaos is a form of motion in nonlinear dynamical systems, which is characterized by better randomness and traversability. The use of chaotic initialization can make the initialization value as discrete as possible distribution within the preset range, effectively improving the diversity of the population. The specific steps include first generating chaotic values of specified scale, each chaotic value ranges from [0,1], and then mapping the chaotic values to the preset range of each solution to obtain the position of the initialized wolf pack. The above process can be expressed as:

$$y_{i+1} = \mu \cdot y_i \cdot (1 - y_i) \tag{39}$$

$$x_i = y_i(u_i - l_i) + l_i \tag{40}$$

where y_i is the chaotic value $y_i \in (0,1)$ of the i th solution, μ is the control parameter, when $\mu = 4$, the whole system will iterate and appear a completely chaotic state, x_i is the initialized value of the i th solution, u_i is the i th solution's maximum value, and l_i is the minimum value of the i th solution.

(2) Leading cooperative mechanism strategy

By α, β, δ providing information on the location of the prey, ω according to the instructions, organizing forces to surround and capture the target action. At this time, α in the wolf pack has the shortest distance from the target, but because ω and α still have a certain distance, there is a long time from the order to hunt to capture the prey. In the consideration of improving the strategy, if the relative distance between the prey and the individuals in the gray wolf can be shortened, then it can greatly shorten the time needed for the gray wolf to hunt, that is, to speed up the convergence of the algorithm. By applying a guiding strategy, the algorithm can converge more efficiently to the optimal solution during the iterative process. Specifically, each wolf within the pack implements a move based on the bit data of the target points α and β according to the principle of leading cooperative guidance before each move. This mechanism aims to shrink the distance between the wolf and the ideal target, and thus accelerate the convergence process toward the target solution. To wit:

$$x_i'^k = x_i + rand(0,1) \cdot (x_a^k - x_i^k) \tag{41}$$

$$x_a^k = x_i + rand(0,1) \cdot (x_a^k - x_i) + rand(0,0.3) \cdot (x_\beta^k - x_i) \tag{42}$$

where x_a^k is the location of α at the k th iteration cycle, and x_{ik}' is the location information of the i th gray wolf individual after the update.

In the GWO algorithm, each hunting method of the gray wolf is ordered by the α, β, δ 's, and the individuals can not communicate with each other and can not interact with each other for effective information, which, to some extent, will indirectly affect the convergence efficiency of the algorithm and optimization accuracy. In the article, a collaborative mechanism is incorporated upfront to pre-plan the hunting action, and other individuals x_i^* except α, β, δ will randomly select another individual x_j^* for information interaction. If the location of x_i^* is more favorable for hunting, x_j^k moves closer to x_i^k, and x_j^k moves according to equation (43). However, there is some competition among individuals in the population, and after x_j^k approaches, x_i^k moves away from x_j^k, and x_i^k moves according to equation (44). If x_i^k is in a worse position than x_j^k, the update will not be performed if the operation steps are performed in reverse and there is no reduction in the individual fitness index after the move. i.e.,:

$$x_j^{'k} = x_j^k + rand(0,1) \cdot (x_i^k - x_j^k) \tag{43}$$

$$x_i^{'k} = x_i^k + rand(0,1) \cdot (x_i^k - x_j^k) \tag{44}$$

where $x_i^{'k}$ and $x_j^{'k}$ are the location of the i th and j th individual after cooperative competition, respectively.

3.2.3. Steps to Improve the GWO Algorithm Solution

The Improved GWO algorithm (IMGWO) utilizes chaotic mapping to initialize the population, and incorporates an optimal dynamic backward learning mechanism in the iterative process, which results in a dynamic trend of the search process with the search space constantly changing. In addition, the leading and cooperation mechanism is utilized to perform the position update, which further improves the algorithm's ability to search for the optimum. The specific steps are as follows:

Step1 Set the initialized population and each parameter, including population size N, search space dimension D, iteration number t, maximum iteration number T, and upper and lower bounds of initial values.

Step2 Initialize the population using LT chaotic mapping.

Step3 Calculate the fitness of each individual gray wolf in the population, $i = 1, 2, \ldots, N$ and record the fitness values f_a, f_β and f_5 for X_a, X_p, and X_b as well as their corresponding positions x_a, x_β and x_5, order $t = 0$.

Step4 Update the parameter a according to the nonlinear control parameter policy to update the position of the i th gray wolf.

Step5 Update X_a using optimal dynamic reverse learning to produce $X_a^{'}$, calculate the fitness value $f_a^{'}$ for $X_a^{'}$ and compare $f_{a^{'}}$ with f_a if $f_{a^{'}} < f_a$ then replace X_a with $X_a^{'}$ and add the population to participate in the iteration.

Step6 Calculate the fitness values of the individuals again and reorder them so as to update the values of X_a, X_β and X_5 with the current position of α, β and δ wolf.

Step7 Determine whether the maximum number of iterations is reached, if yes, output the global optimal gray wolf position X_{best} and its fitness value $f(X_{best})$ otherwise return to Step3 for the next iteration, and the current number of iterations $t = t + 1$.

4. Multi-Objective Solutions for Modernizing the Governance of Vocational Education

In the context of the new round of vocational education reform and development, higher vocational colleges and universities are facing the dual opportunities and challenges of external economic and social transformation and their own governance transformation. In order to cope with “the great change that has not occurred in a century” and respond to the rapid development of science and technology and the reform of vocational education, this paper constructs a multi-objective planning model for the modernization of the governance of vocational education under the guidance of multi-objective planning theory. It is solved by IMGWO algorithm, aiming to provide reference for promoting the modernization of vocational education governance, and to provide reference experience for the construction of other higher vocational colleges and universities.

4.1. Performance Validation Analysis of the Algorithm

4.1.1. Comparison of Improved Algorithms in the GWO System

In order to test the effectiveness of the IMGWO algorithm proposed in this paper, six commonly used test functions (F1~F6) are selected for testing, of which F1~F3 are single-peak functions and F4~F6 are multi-peak functions. In order to verify the effectiveness of the two improvement strategies proposed in this paper to improve the performance of the GWO algorithm, the standard GWO algorithm and its improvement algorithms (RWGWO, IGWO, and SOGWO) are tested as a comparison. The result data of the comparison algorithms are taken from the related research literature, and the code is designed to conduct the experiment according to the corresponding literature parameters, and the test experimental data of the comparison are finally obtained as shown in Table 1.

Analysis of the data in the table shows that in the optimization process of the algorithms for the test function, the IMGWO algorithm in the single-peak function has a higher convergence accuracy than the RWGWO, SOGWO and IGWO algorithms in the comparison of both the mean value and the standard deviation, and at the same time it is the closest to the theoretical optimal value of the function. Among the multi-peak functions, for the benchmark functions F4 and F6, the RWGWO, SOGWO, IGWO and IMGWO algorithms are able to converge to the theoretical optimum. The IMGWO algorithm proposed in this paper is significantly faster and more accurate than the classical GWO algorithm, while the IMGWO algorithm, together with the other three state-of-the-art improved algorithms, is able to jump out of the local interference and accurately capture the global optimum. For the benchmark function F5, the solution accuracy of IMGWO algorithm is improved compared with that of GWO algorithm. The above results show that the IMGWO algorithm formed by combining the two improvement strategies proposed in this paper has strong ability to handle both single/multiple peak functions, enhances the search efficiency of the original algorithm and improves the probability of escaping from the local optimum, and is competitive among the peer improvement algorithms in the finite number of fitness evaluations.

Table 1. The comparison results of the GWO system's improved algorithms.

Algorithm	F1		F2		F3	
	Means	STD	Means	STD	Means	STD
GWO	5.682E-67	1.501E-63	2.076E-12	4.045E-12	5.176E-13	1.152E-12
RWGWO	8.915E-82	6.421E-81	6.176E-43	4.359E-42	5.521E-30	3.574E-20
SOGWO	6.035E-78	1.483E-74	5.391E-22	2.593E-22	1.184E-20	1.516E-19
IGWO	4.751E-73	9.531E-71	1.513E-20	4.021E-21	8.826E-20	1.131E-18
IMGWO	1.012E-99	3.863E-99	1.127E-68	4.969E-68	2.106E-40	3.942E-39
Algorithm	F4		F5		F6	
	Means	STD	Means	STD	Means	STD
GWO	3.372E+00	5.931E+00	1.368E+00	1.175E-01	2.514E-04	6.428E-03
RWGWO	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00
SOGWO	0.000E+00	0.000E+00	8.782E-15	0.000E+00	0.000E+00	0.000E+00
IGWO	0.000E+00	0.000E+00	1.101E-15	3.741E-15	0.000E+00	0.000E+00
IMGWO	0.000E+00	0.000E+00	4.051E-02	6.273E-02	0.000E+00	0.000E+00

4.1.2. Performance Comparison of Different Algorithms

In order to further objectively compare the performance of IMGWO algorithm, four standard objective functions, i.e., single-peak function Sphere, Rosenbrock and multi-peak function Griewank, Rastrigin, are selected for testing. Setting the spatial dimension as 20, the search range between [-120,120], the population size as 50, and the maximum number of iterations as 120, IMGWO and Particle Swarm Optimization algorithm (PSO), Whale Optimization Algorithm (WOA), Genetic Algorithm (GA), and Firefly Optimization Algorithm (SSA) were tested under the same experimental parameters, respectively, and 40 independent experiments were carried out on the objective functions. The algorithm optimization results under each test function are shown in Table 2.

From the data in the table, it can be seen that the IMGWO algorithm designed in this paper performs well on several test functions, especially on the two multi-peak functions of Griewank and Rastrigin, where the optimal value, mean and standard deviation are all the best, showing excellent optimization seeking ability and stability. Although the standard deviation is not the lowest on the Rosenbrock function, the IMGWO algorithm still shows strong optimality seeking ability, and the GA algorithm performs better on the Rosenbrock function, which has the lowest standard deviation and shows good stability, but it does not perform as well as the IMGWO algorithm on the other functions. The standard

WOA algorithm performs better on Sphere, but not as well as the IMGWO algorithm on other functions, and the PSO algorithm does not perform as well as the IMGWO algorithm on all the tested functions, and it is easy to fall into the local optimum, resulting in a higher mean and standard deviation. In summary, it can be seen that the IMPSO algorithm designed in this paper has better overall stability and better optimization seeking ability than each of the comparison algorithms, which can provide support for solving the multi-objective planning model for modernization of vocational education governance.

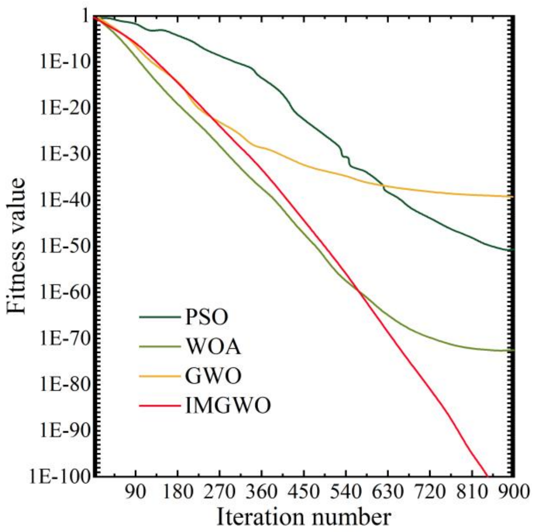
Table 2. Performance comparison of different algorithms.

Function	Algorithm	Optimal value	Means	STD
Sphere	PSO	1.712E+01	3.731E+01	9.443E+02
	WOA	1.115E-03	**2.915E-04**	**1.432E-04**
	GA	1.346E+00	1.952E+00	1.506E+01
	SSA	4.627E+00	2.241E+00	1.567E+01
	IMGWO	**0.000E+00**	1.011E+00	4.092E+01
Rosenbrock	PSO	5.483E+02	1.512E+05	3.531E+05
	WOA	2.923E+02	5.043E+02	5.884E+01
	GA	2.596E+01	2.704E+02	**6.452E-02**
	SSA	2.643E+01	2.823E+02	8.943E-02
	IMGWO	**0.000E+00**	**7.651E+00**	1.263E+01
Griewank	PSO	7.512E-03	3.334E-02	2.133E-02
	WOA	2.704E+00	1.985E-02	4.223E-03
	GA	7.075E+00	9.914E+00	1.815E+01
	SSA	4.563E+00	7.203E-03	1.246E-03
	IMGWO	**0.000E+00**	**0.000E+00**	**0.000E+00**
Rastrigin	PSO	1.801E+02	4.243E+03	2.513E+03
	WOA	2.394E+01	4.961E+02	2.676E+02
	GA	3.251E-05	1.335E+02	1.674E+02
	SSA	8.723E+00	2.934E+02	1.323E+02
	IMGWO	**0.000E+00**	**0.000E+00**	**0.000E+00**

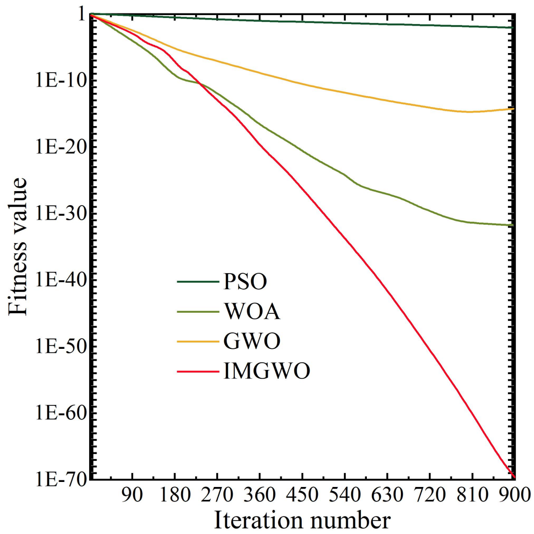
4.1.3. IMGWO Convergence Analysis

In order to express the superiority of IMGWO algorithm more intuitively, the iterative curves of the algorithms on the benchmark test functions F1~F3 are established respectively, and then PSO, WOA and standard GWO algorithms are selected as comparisons, and the convergence curves of different algorithms are obtained as shown in Fig. 1. Where Fig. 1(a)~(c) shows the convergence curves of the algorithms on the benchmark test functions F1~F3, respectively.

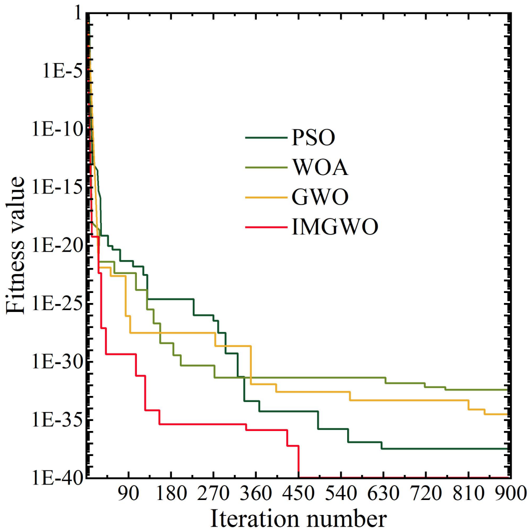
As can be seen from the figure, by analyzing the optimization curves of the single-peak test function, it can be found that the IMGWO algorithm converges slightly slower than with other algorithms in the optimization search process, but the convergence accuracy is much higher than other algorithms. It shows that the algorithm avoids falling into the local optimal solution in the initial iteration, which may lead to seemingly slower convergence speed, but in fact, it is to obtain better global search ability. And the algorithm is able to perform a more efficient local search as it approaches the optimal solution region, thus finding a more accurate solution. This helps it to achieve higher accuracy at a later stage. The experiment verifies that the IMGWO algorithm is able to obtain better solutions in the field of single-peaked function optimization, although there is a small gap in speed with other algorithms, showing its powerful optimization ability.



(a) F1



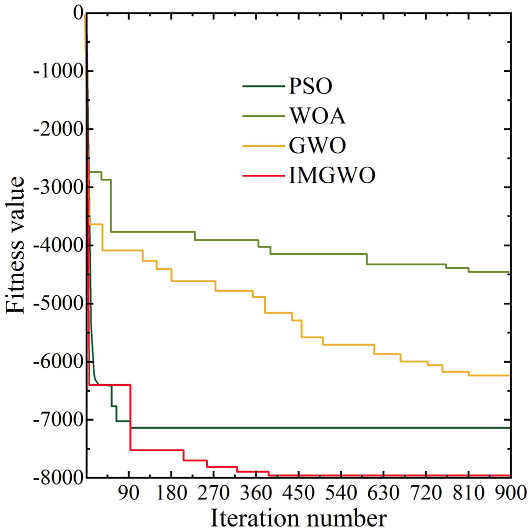
(b) F2



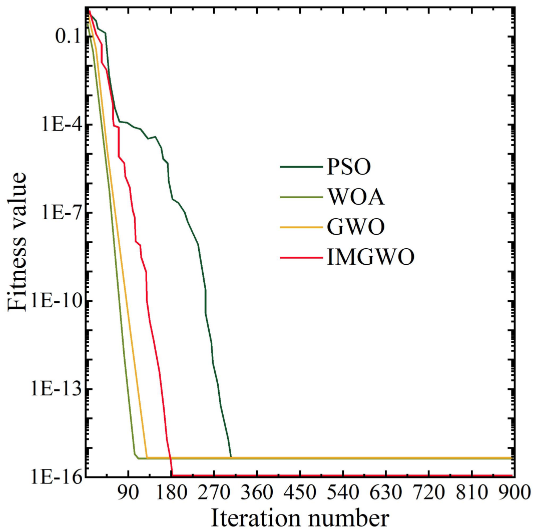
(c) F3

Figure 1. Convergence curve of different algorithms.

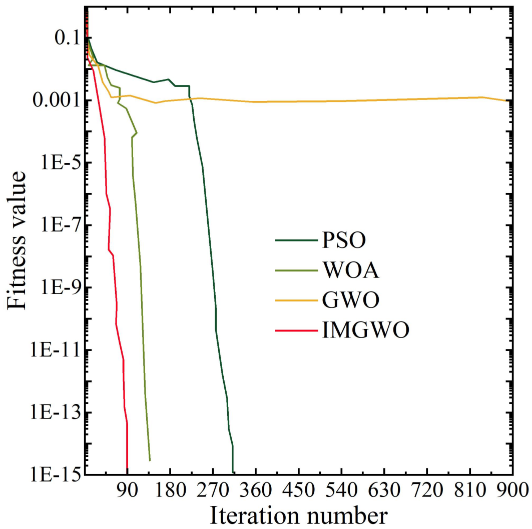
In addition, this paper also carries out convergence analysis for the multi-peak test functions F4~F6, and the specific results are shown in Fig. 2, where Fig. 2(a)~(c) shows the convergence curves of the algorithms on the benchmark test functions F4~F6, respectively. From the multi-peak test function optimization curve, F4 and F6 can be seen due to the multi-peak function has more than one extreme point, more complex than single-peak function, resulting in most of the algorithms convergence curve with the increase in the number of iterations gradually tend to flatten out, there is a certain degree of stagnation caught in the local optimal solution, thus missing the local optimal solution. The IMGWO algorithm does not fall into the local optimum in the late iteration.F5 can be seen that although PSO, WOA and IMGWO algorithms all find the optimal solution, the fitness value of IMGWO after the 180th iteration is significantly better than that of PSO iteration for the 320th time and that of WOA for the 95th time to find the optimal solution, and the IMGWO algorithm still requires fewer iterations than the other algorithms.



(**a**) F4



(**b**) F5



(**c**) F6

Figure 2. Convergence curve of different algorithms.

In summary, the IMGWO algorithm strikes a good balance between convergence speed and convergence accuracy. Although its convergence speed is slightly slower, the high-precision convergence results give it a unique advantage in the field of single-peak function optimization. This advantage makes the IMGWO algorithm feasible in practically solving the multi-objective planning model for the modernization and construction of vocational education governance, therefore, the research and improvement of the IMGWO algorithm has important theoretical and practical significance. In addition, IMGWO algorithm shows its unique advantages when dealing with multi-peak test functions. Both in terms of the ability to avoid falling into local optimal solutions and the number of iterations required to reach a converged state, the IMGWO algorithm shows its superior performance. These features make the IMGWO algorithm more efficient and accurate in solving multi-peak optimization problems, and thus valuable in practical applications.

4.2. Ablation Experiments and Rank Sum Tests

4.2.1. Comparative Results of Ablation Experiments

To better improve the original GWO, two strategies were introduced into the original GWO, namely the chaos mapping strategy and the leading and cooperation mechanism strategy. In order to verify that the combination effect is more prominent than a single strategy, a single strategy experiment is conducted and two different GWOs are developed to investigate the effect of each strategy. Among them, "H" and "Y" stand for chaos mapping strategy and leading and cooperation mechanism strategy, respectively. Fifteen different types of benchmark test functions are selected in the ablation comparison experiment, and the optimization comparison results under different strategies are obtained as shown in Table 3.

The best results are shown in bold using the proposed Gray Wolf Optimization Algorithm based on Chaos Mapping and Leading and Cooperative Mechanism Strategies (IMGWO) with other single-strategy improved Gray Wolf Optimization Algorithms, Gray Wolf Optimization Algorithm based on Chaos Mapping Strategies (HGWO), Gray Wolf Optimization Algorithms based on Leading and Cooperative Mechanism Strategies (YGWO) in the comparative experiments.

From the data in the table, it can be seen that the single strategy algorithms other than the IMGWO algorithm perform better and have higher accuracy in the single-peak test function for the HGWO algorithm, and the YGWO algorithm works better in the multi-peak test function. Each single strategy has its own strengths, and the IMGWO algorithm with all strategies combined has a significant improvement in both convergence speed and optimization accuracy compared to the other three algorithms. In conclusion, the IMGWO algorithm can obtain competitive results compared to the other algorithms, and also proves that each strategy of the IMGWO algorithm is effective.

Table 3. Comparison results of ablation experiments.

-	IMGWO		HGWO		YGWO	
	Means	STD	Means	STD	Means	STD
F1	**7.915E-318**	**0.000E+00**	5.913E-292	**0.000E+00**	7.651E-06	7.874E-05
F2	**1.015E-156**	**0.000E+00**	**4.556E-161**	**0.000E+00**	8.153E-04	7.751E-04
F3	**3.116E-293**	**0.000E+00**	9.616E-193	**0.000E+00**	1.505E-02	2.426E-02
F4	**9.316E-156**	**0.000E+00**	1.024E-148	**0.000E+00**	5.913E-04	5.237E-04
F5	**4.602E-03**	**0.000E+00**	2.876E+02	2.516E-144	4.736E-03	6.625E-03
F6	**9.674E-05**	**0.000E+00**	5.886E+01	1.643E-02	7.041E-05	9.913E-05
F7	**7.873E-05**	**7.453E-06**	7.745E-05	4.206E-02	1.236E-04	8.881E-05
F8	**-1.23E+04**	2.512E-02	-4.016E+06	8.263E-05	**1.261E+05**	**3.946E-02**
F9	**0.000E+00**	**0.000E+00**	**0.000E+00**	**0.000E+00**	2.916E-05	6.412E-05
F10	6.151E-16	1.806E-16	**4.451E-16**	**0.038E+00**	2.963E-04	2.894E-03
F11	**0.000E+00**	**0.000E+00**	**0.000E+00**	**0.000E+00**	8.875E-05	1.156E-04
F12	2.031E-06	2.931E-06	8.919E-02	8.965E-02	**8.381E-07**	**1.174E-06**
F13	3.114E-05	5.923E-05	2.935E+00	5.163E-01	**2.456E-05**	**2.316E-05**
F14	**9.982E-02**	**2.671E-11**	9.416E+00	**3.986E+00**	9.982E-02	1.174E-11
F15	**3.036E-05**	**2.876E-06**	5.283E-05	9.159E-06	3.376E-05	3.232E-06

4.2.2. Wilcoxon Rank Sum Test

The Wilcoxon rank sum test is a nonparametric statistical test capable of detecting complex data distributions. In order to evaluate the performance of IMGWO algorithm, Wilcoxon rank sum test was performed on the results of running IMGWO algorithm with other six algorithms in three types of test functions (single peaked function, multi-peaked function and fixed dimension multi-peaked function, i.e., F1~F9), and P-value was calculated. Where the significance level of 0.05 was chosen and when $P<0.05$, it can be considered as a strong validation of the rejection of the null hypothesis. "+/≈/-" is used to indicate that the algorithms are better, similar or worse than the compared algorithms, and N/A indicates that the algorithms' results are too close to make a significance judgment. Table 4 shows the results of the Wilcoxon rank sum test for the test functions.

As can be seen from the table, most of the Wilcoxon rank sum test results of the IMGWO algorithm have P-values less than 0.05, where the comparative results are (9/0/0), (6/2/1), (7/1/1), (8/0/1), (7/2/0), (9/0/0), and compared to the GWO algorithm, the other intelligent optimization algorithms and the other improved GWO algorithms, the IMGWO algorithm has a significant advantage in the performance of optimization search for the three types of test functions. It is feasible to apply it in solving the multi-objective planning model of vocational education governance modernization, which provides reliable results for further deepening the construction of vocational education governance modernization path.

Table 4. The Wilcoxon rank sum test of the test function.

IMGWO VS.	GWO		Golden SA		WOA	
	P	-	*P*	-	*P*	-

F1	1.211E-13	+	4.792E-09	+	1.216E-13	+
F2	3.025E-12	+	3.023E-12	+	3.035E-12	+
F3	3.025E-12	+	4.225E-05	-	9.923E-12	+
F4	1.154E-13	+	N/A	≈	N/A	+
F5	1.161E-13	+	N/A	≈	2.083E-09	+
F6	8.306E-04	+	1.058E-05	+	2.881E-06	+
F7	4.086E-12	+	7.894E-03	+	6.124E-10	-
F8	3.504E-04	+	3.031E-12	+	0.215E-02	≈
F9	2.626E-04	+	1.724E-06	+	4.034E-04	+
+/≈/-	(9/0/0)		(6/2/1)		(7/1/1)	
IMGWO VS.	PSO		ROLGWO		VMGWO	
	P	-	*P*	-	*P*	-
F1	1.212E-13	+	1.214E-12	+	1.212E-13	+
F2	3.023E-12	+	3.023E-12	+	3.023E-12	+
F3	3.023E-12	+	3.023E-12	+	3.023E-12	+
F4	1.212E-13	+	N/A	≈	1.174E-12	+
F5	1.212E-13	+	N/A	≈	7.443E-14	+
F6	3.024E-12	+	4.114E-08	+	6.536E-08	+
F7	1.212E-13	+	1.856E-09	+	3.115E-02	+
F8	1.584E-12	-	5.016E-03	+	9.796E-06	+
F9	7.576E-13	+	1.034E-03	+	1.545E-02	+
+/≈/-	(8/0/1)		(7/2/0)		(9/0/0)	

4.3. Practical Path of Modernization of Vocational Education Governance

Based on the multi-objective planning model of vocational education governance modernization and using IMGWO algorithm to solve it, this paper constructs the practice path of vocational education governance modernization from the three dimensions of integration, pioneering and driving after satisfying the various objective functions.

The modernization of governance in higher vocational colleges and universities needs to adhere to common governance, focusing on reforms in key areas such as democratic governance, secondary management and quality assurance. Improve the school system by taking the constitution as the unifying principle, tighten the relationship between government, school, industry and enterprise by focusing on the council, reconstruct the secondary colleges by taking the professional group as the core, and promote the internal quality diagnosis and improvement by taking the quality culture as the leader, so as to improve the school governance system and comprehensively enhance the level of school governance.

(1) Integration - Forming a new pattern of joint participation of stakeholder subjects

The main task of governance is to establish a standardized governance structure, a mutually coordinated governance mechanism, and to realize the benign interaction among stakeholders under a particular institutional framework. To get rid of the limitations of traditional school self-governance, closed governance and single governance, it is necessary to do a good job in the top-level design of the decision-making and implementation mechanisms. Adhering to the basic principles of "leadership of the Party committee, responsibility of the principal, governance by professors, and democratic management", we should promote the scientific and effective governance of the school by stakeholders with an open attitude.

(2) Pioneering - building a new system of decision-making support based on institutional research

Institutional research is a profession that provides support for the decision-making process by analyzing data through conducting systematic and scientific research on the management issues of the university in order to improve the management and decision-making level of the university, and is characterized by action research, consulting research and self-study. It is of great significance to systematically improve the quality of talent cultivation in higher vocational colleges and universities, improve the internal governance structure, and deepen the reform and development of higher vocational education by conducting institutional research.

(3) Driving - Cultivating a new culture of internal quality assurance that is self-conscious and self-motivated

Quality culture is the core of the culture of higher vocational colleges and universities, and it is the key guarantee for higher vocational colleges and universities to insist on serving the development of the society and the personality development of students. Cultivating quality culture can promote the construction of internal quality assurance system through positive guidance. Formal system is rigid constraint, informal system is flexible guidance, cultivating quality culture, so that the school running practice gradually from the mandatory norms of the system to the flexible guidance of quality culture. Through behavioral guidance, promote each unit and individual participation in quality assurance behavior from spontaneous to conscious.

5. Conclusion

This study constructs a multi-objective planning model for the modernization of vocational education governance from the theory of multi-objective planning and from the development goal of modernization of vocational education governance. And the GWO algorithm with chaotic mapping and leading cooperation mechanism strategy optimization is introduced to solve the model, and the specific performance of IMGWO algorithm is explored. From the results, IMGWO algorithm has high optimization accuracy and convergence speed, and can provide reliable algorithmic support for solving the multi-objective model of vocational education governance modernization construction. Based on the results of solving the multi-objective model of vocational education governance modernization construction, it can provide decision-making guidance for the construction path of vocational education governance modernization and further realize the transformation and development of vocational education governance modernization.

The article mainly discusses the multi-objective planning model of vocational education governance modernization and its solution, and there is a lack of relevant empirical analysis of the optimal strategy of vocational education governance modernization path, and in the future research, the application of the model in practice will be further expanded to provide a new direction for the development of vocational education governance modernization.

References

1. Larionova, A. A., Zaitseva, N. A., Anoshina, Y. F., Gaidarenko, L. V., & Ostroukhov, V. M. (2018). The modern paradigm of transforming the vocational education system. Astra Salvensis, 6, 436-448.
2. Platonova, R. I., Pankaj, V., Olesova, M. M., Osipova, V. V., Platonova, A. Z., & Evseeva, M. M. (2019). Modernization of Secondary Vocational Education System. Journal of Environmental Treatment Techniques, 7(4), 562-565.
3. Stoyanets, N., Zhao, H., & Li, G. (2020). Modernization of vocational education in the context of rural human resources development in China. Agricultural and Resource Economics: International Scientific E-Journal, 6(1), 76-90.
4. Gumenyuk, T., Kushnarov, V., Bondar, I., Haludzina-Horobets, V., & Horban, Y. (2021). Transformation of professional training of students in the context of education modernization. Studies of Applied Economics, 39(5).
5. Kovalchuk, V., Maslich, S. V., Tkachenko, N., Shevchuk, S. S., & Shchypska, T. P. (2022). Vocational education in the context of modern problems and challenges. Journal of Curriculum and Teaching, 8(11), 329-338.
6. Cañavate-Cruzado, G., Moreno-Muro, F. J., & Bueno-Delgado, M. V. (2020). Modernizing the Vocational Educational Training in the field social sciences and humanities towards the Key Enabling Technologies in the digital transformation. In EDULEARN20 Proceedings (pp. 8125-8132). IATED.
7. Vodolazskaya, N. (2019). Types and ways of modernization in a context of the international experience. Virtual Economics, 2(1), 82-94.
8. Vodenko, K. V., Komissarova, M. A., & Kulikov, M. M. (2018). Modernization of the standards of education and personnel training due to development of industry 4.0 in the conditions of knowledge economy's formation. In Industry 4.0: Industrial Revolution of the 21st Century (pp. 183-192). Cham: Springer International Publishing.
9. Loyko, O., Dryga, S., Park, J., & Palianov, M. (2015). Modern professional education in the global society: comparative study. Procedia-social and behavioral sciences, 206, 464-468.
10. Kamasheva, Y. L., Goloshumova, G. S., Goloshumov, A. Y., Kashina, S. G., Pugacheva, N. B., Bolshakova, Z. M., ... & Timirov, F. F. (2016). Features of vocational education management in the region. International Review of Management and Marketing, 6(1), 155-159.
11. Glykas, M., Bailey, O., Al Maery, M., & Al Maery, N. (2015). Process and quality management in vocational education & training (VET). International Journal of Management Sciences and Business Research.
12. Rujira, T., Nilsook, P., & Wannapiroon, P. (2020). Synthesis of vocational education college transformation process toward high-performance digital organization. International Journal of Information and Education Technology, 10(11), 832-837.
13. Beer, P., & Mulder, R. H. (2020). The effects of technological developments on work and their implications for continuous vocational education and training: A systematic review. Frontiers in psychology, 11, 918.
14. Xibin, H. A. N., Chengming, Y. A. N. G., & Qian, Z. H. O. U. (2023). Digital Transformation in Vocational Education: Present Situation, Problems, and Countermeasures. Frontiers of Education in China, 18(1).
15. Jiang, X., Xu, J., & Xu, X. (2024). An overview of domestic and international applications of digital technology in teaching in vocational education: Systematic literature mapping. Education and Information Technologies, 29(13), 16867-16899.

16. Nilsook, P., Chatwattana, P., & Seechaliao, T. (2021). The Project-Based Learning Management Process for Vocational and Technical Education. Higher Education Studies, 11(2), 20-29.
17. Qi He. (2025). The Innovation and Balanced Development Path of Education Management Mode in Remote Areas of Chongqing Driven by the Modernization of Vocational Education. Educational Innovation Research,3(2),69-74.
18. Xiaohong Shu. (2025). Construction of high quality agricultural vocational education system from the perspective of system theory. International Journal of New Developments in Education,7(2).
19. Jinling Zhao. (2024). Research on the Influencing Factors of Vocational Education in Promoting Common Prosperity under the Background of Chinese Modernization. Exploration of Educational Management,2(11).