International Journal of Multiphysics
Volume 18, No. 2, 2024
ISSN: 1750-9548

Optimization Method for Experimental Identification Capability Evaluation Model Based on Improved Plant Growth Algorithm

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Abstract

The optimization problem of the experimental appraisal capability evaluation model can essentially be seen as a multi-attribute decision-making problem for decision optimization. The Analytic Hierarchy Process model and the Analytic Hierarchy Network model are the fundamental models for solving this problem. The Fuzzy Analytic Hierarchy Process model adds fuzziness to the basic model, while the Double Fuzzy Analytic Hierarchy Process model and Double Fuzzy Analytic Hierarchy Network model make greater use of fuzzy information, enhancing the applicability of the model. However, researchers have encountered issues such as the abuse of the Analytic Hierarchy Process model, failure to fully utilize fuzzy advantages, and mismatched problem characteristics in the process of evaluating experimental identification capabilities. To address the above issues, a method for selecting an experimental identification capability evaluation model is proposed based on an improved plant growth algorithm, which includes a target layer, a criterion layer, a key factor layer, and a scheme layer. The research content has important reference value for evaluating experimental identification capabilities.

Keywords: Evaluation of testing and identification capabilities, model optimization, plant growth, intelligent algorithms.

1. Introduction

The evaluation of experimental appraisal ability is an important means to grasp the foundation of experimental appraisal ability, identify the shortcomings and weaknesses of experimental appraisal ability, and provide suggestions for the development of experimental appraisal ability. However, the current model for evaluating experimental identification capabilities has the following problems in its application: (1) The Analytic Hierarchy Process model[1] has a wide range of applications due to its simple and convenient calculation, but there is a problem of ignoring the assumption of independence and being abused[2]; (2) When considering the influence and dependency relationship of factor indicators and applying the hierarchical network model[3] to solve the weight of indicators, there is a problem of unclear judgment matrix sub criteria; (3) There is ambiguity in understanding the fuzziness of the fuzzy analytic hierarchy process model[4], fuzzy hierarchical network model[5], double fuzzy analytic hierarchy process model, and double fuzzy hierarchical network model; (4) The evaluation model for experimental identification lacks comparative analysis and is often directly applied[6], ignoring the characteristics of the problem, model assumptions, etc., lacking evaluation model optimization methods, and lacking rationality in model selection. To address the above issues, the article proposes a method for selecting an experimental identification capability evaluation model that fully considers various factors based on an improved plant growth algorithm[7-10] which is a systematic and effective method for solving multi-objective optimization problems[11-15]. The research results have enriched the theory of selecting optimal models for evaluating experimental appraisal capabilities and provided methodological support for practical evaluation of experimental appraisal capabilities.

2. Multi-attribute Decision-Making Problem

In multi-attribute decision-making problems[16], $G_1, G_2, \cdots, G_m$ is the m experimental identification capability evaluation models, each with n attributes $X_1, X_2, \cdots, X_n, x_{ij}$ represents the evaluation value of the evaluation model G_i relative to the attribute X_j. The evaluation matrix can be expressed as A, where $0 \le x_{ij} \le 1$.

$$A = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & & x_{2n} \\ \vdots & & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \tag{1}$$

$\mathrm{w} = (\mathrm{w}_1, \mathrm{w}_2, \cdots, \mathrm{w}_n)$ represents the weights of each attribute, $\mathrm{w}_i \ge 0$, $\sum_{i=1}^{n} \mathrm{w}_i = 1$. The goal of decision-making is to find the most satisfactory solution among alternative solutions, and the most commonly used method is the simple weighting method.

$$\mathrm{B} = (\mathrm{w}_1, \mathrm{w}_2, \cdots, \mathrm{w}_n) \cdot \begin{bmatrix} \mathrm{x}_{11} & \mathrm{x}_{12} & \cdots & \mathrm{x}_{1n} \\ \mathrm{x}_{21} & \mathrm{x}_{22} & & \mathrm{x}_{2n} \\ \vdots & & \ddots & \vdots \\ \mathrm{x}_{n1} & \mathrm{x}_{n2} & \cdots & \mathrm{x}_{nm} \end{bmatrix}^{\mathrm{T}} = (\mathrm{b}_1, \mathrm{b}_2, \cdots, \mathrm{b}_m) \tag{2}$$

By comparing the sizes of the elements in the comparison$(b_1, b_2, \cdots, b_m)$, complete the sorting and optimization of the solutions $G_1, G_2, \cdots, G_m$.

3. Principle of Experimental Appraisal Capability Evaluation Model

3.1 Analytic hierarchy process model

Assume there are n objects $A_1, A_2, \cdots, A_n$, with weights of $w = (w_1, w_2, \cdots, w_n)^T$. The matrix A for comparing any two objects is as follows:

$$A = \begin{bmatrix} \frac{\mathrm{w}_1}{\mathrm{w}_1} & \frac{\mathrm{w}_1}{\mathrm{w}_2} & \cdots & \frac{\mathrm{w}_1}{\mathrm{w}_n} \\ \frac{\mathrm{w}_2}{\mathrm{w}_1} & \frac{\mathrm{w}_2}{\mathrm{w}_2} & & \frac{\mathrm{w}_2}{\mathrm{w}_n} \\ \vdots & & \ddots & \vdots \\ \frac{\mathrm{w}_n}{\mathrm{w}_1} & \frac{\mathrm{w}_n}{\mathrm{w}_2} & \cdots & \frac{\mathrm{w}_n}{\mathrm{w}_n} \end{bmatrix} \tag{3}$$

$$\mathrm{A} \cdot \mathrm{w} = \begin{bmatrix} \frac{\mathrm{w}_1}{\mathrm{w}_1} & \frac{\mathrm{w}_1}{\mathrm{w}_2} & \cdots & \frac{\mathrm{w}_1}{\mathrm{w}_n} \\ \frac{\mathrm{w}_2}{\mathrm{w}_1} & \frac{\mathrm{w}_2}{\mathrm{w}_2} & & \frac{\mathrm{w}_2}{\mathrm{w}_n} \\ \vdots & & \ddots & \vdots \\ \frac{\mathrm{w}_n}{\mathrm{w}_1} & \frac{\mathrm{w}_n}{\mathrm{w}_2} & \cdots & \frac{\mathrm{w}_n}{\mathrm{w}_n} \end{bmatrix} \cdot \begin{bmatrix} \mathrm{w}_1 \\ \mathrm{w}_2 \\ \vdots \\ \mathrm{w}_n \end{bmatrix} = \mathrm{nw} \tag{4}$$

Because $A \cdot w = nw$, w, n is the eigenvector and eigenvalues for matrix A. The conditions for determining the complete consistency of a matrix A are:

$$\begin{cases} \mathrm{A}_{\mathrm{ii}} = 1 \\ \mathrm{A}_{\mathrm{ij}} = 1/\mathrm{A}_{\mathrm{ji}} \\ \mathrm{A}_{\mathrm{ij}} = \mathrm{A}_{\mathrm{ik}} \cdot \mathrm{A}_{\mathrm{kj}} = \mathrm{A}_{\mathrm{ik}}/\mathrm{A}_{\mathrm{jk}} \end{cases} \tag{5}$$

Due to the complexity of objective things and the diversity, subjectivity, and one sidedness of expert knowledge, it is difficult to obtain a judgment matrix that satisfies complete consistency, especially for complex multi factor dynamic large-scale problems. The criterion for consistency testing based on the maximum eigenvalue λ_{max} is $CI = (\lambda_{max} - 1)/(n - 1)$.

In order to solve the problem of consistency testing for multi order judgment matrices with changes in matrix order, the average random consistency index is CR introduced, which is divided by the two $CR = CI/RI$ to obtain the random consistency ratio. The consistency criterion for the judgment matrixCR is that the random consistency ratio reaches 10%, that is $CR \leq 0.1$.

3.2 Hierarchical network analysis model

The Analytic Hierarchy Process model was developed to address the issue of insufficient independence between indicator factors in the AHP model. The established AHP model is shown in Figure 1, and the calculation steps are as follows: (1) Build a judgment matrix. (2) Calculate unweighted hypermatrices, element group weights, and weighted hypermatrices. (3) Calculate the limit hypermatrix W^{∞} and obtain the weights of elements under a single criterion. (4) Calculate the weights of each criterion and comprehensively calculate the final weights of each element.

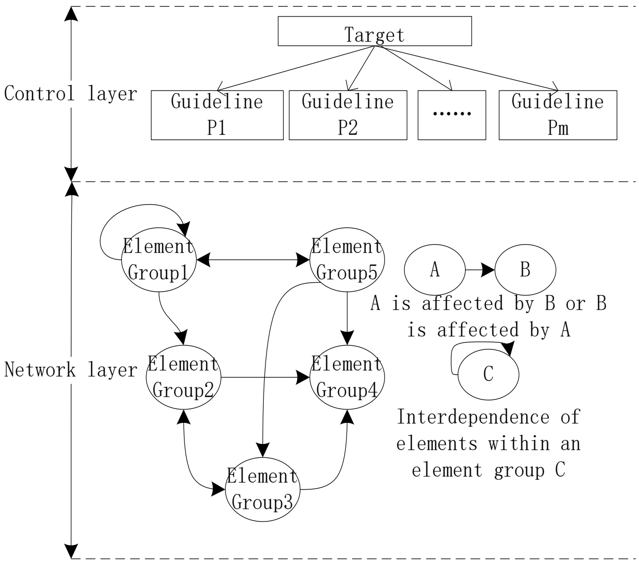

Figure 1 Typical hierarchical network analysis model structure

$$w_{ij} = \begin{bmatrix} w_{i1}^{j1} & w_{i1}^{j2} & \cdots & w_{i1}^{jn_j} \\ w_{i2}^{j1} & w_{i2}^{j2} & \cdots & w_{i2}^{jn_j} \\ \vdots & \vdots & & \vdots \\ w_{in_i}^{j1} & w_{in_i}^{j2} & \cdots & w_{in_i}^{jn_j} \end{bmatrix} \tag{6}$$

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \tag{7}$$

3.3 Fuzzy analytic hierarchy process model

Fuzzy problems with unclear boundaries often arise in decision-making[17]. Given a set of alternative options $G = (G_1, G_2, \cdots, G_m)$, the attribute set of each option $X = (X_1, X_2, \cdots, X_n)$ and the weight vector $w = (w_1, w_2, \cdots, w_n)$ of the importance of each attribute are represented by a matrix $\tilde{F}$ to represent the fuzzy attribute values.

$$\tilde{F} = \begin{bmatrix} \tilde{F}_{11} & \tilde{F}_{12} & \cdots & \tilde{F}_{1n} \\ \tilde{F}_{21} & \tilde{F}_{22} & & \tilde{F}_{2n} \\ & \vdots & \ddots & \vdots \\ \tilde{F}_{n1} & \tilde{F}_{n2} & \cdots & \tilde{F}_{nm} \end{bmatrix} \tag{8}$$

Transform the fuzzy indicator matrix $\tilde{F}$ to obtain the fuzzy decision vector $\tilde{D}=\tilde{w} \odot \tilde{F} = (\tilde{d}_1, \tilde{d}_2, \cdots, \tilde{d}_m)$. $\odot$ refers to the fuzzy aggregation operator, which compares sizes $\tilde{d}_i$ to determine the advantages and disadvantages of each scheme.

The fuzzy analytic hierarchy process model establishes a set of comments on the underlying indicators and evaluates them separately. The Analytic Hierarchy Process (AHP) model is applied to calculate the weights of each level of indicators, and the fuzzy synthesis operator is applied to calculate the evaluation membership degree of the previous level of indicators step by step[18]. Specific applications include the fuzzy analytic hierarchy process model based on fuzzy comprehensive evaluation and the fuzzy number based analytic hierarchy process model.

The steps of a fuzzy analytic hierarchy process model based on fuzzy comprehensive evaluation include: (1) establishing a set of comments $U = \{u_1 \quad u_2 \quad \cdots \quad u_m\}$, such as {excellent, good, average, poor, very poor}. (2) Establish a fuzzy membership matrix for each project attribute. The matrix elements $r_{i,j}$ represent the likelihood u_j of evaluating the indicator as a comment level, and the results are represented by the membership degree of the comment set elements. Fuzzy membership degree $r_{i,j} = f_{i,j}/\sum_{j=1}^{m} f_{i,j}$, where $f_{i,j}$ is the number of people or times the indicator A_i is evaluated as u_j a comment level, and all fuzzy membership degrees form a fuzzy membership degree matrix R. (3) Establish a judgment matrix and apply the AHP method to calculate the weights $w = (w_1, w_2, \cdots, w_n)$ of each indicator A_i. (4) The evaluation result is $B = w^{\circ}R^T$ obtained by applying fuzzy synthesis operators (such as (∧,∨)、(∨,∧), or (·,+)). (5) Realizing fuzzy results. By setting different proportional weights for the comment set, the fuzzy evaluation results are transformed into real numbers that are easier for humans to understand, and scheme comparison and selection are carried out.

The fuzzy analytic hierarchy process model based on fuzzy numbers[19] represents the elements of the pairwise judgment matrix through fuzzy numbers. When constructing pairwise judgment matrices in Analytic Hierarchy Process models, human judgment ambiguity is usually not taken into account. When experts consult and evaluate judgments, they often provide fuzzy quantities (such as the lowest possible value, highest possible value, or in the middle) instead of a definite scale value. At this time, the determined evaluation value cannot meet actual needs. Fuzzy representation can be represented by triangular fuzzy numbers, trapezoidal fuzzy numbers, and so on.

The eigenvalues and eigenvectors of the triangular fuzzy number judgment matrix are solved using the FPP method. Let the interval judgment matrix of the the indicator be represented by $A = (l_{ij}, u_{ij})$, and l_{ij},u_{ij} represent the lower and upper bounds of expert judgment opinions, respectively, $w = (w_1, w_2, \cdots, w_n)$ is the weight vector. For the consistency judgment matrix, the weight vector should satisfy: $l_{ij} \le \frac{w_i}{w_j} \le u_{ij}, i = 1,2, \cdots, n-1; j = 1,2, \cdots, n; j > i$. The triangular fuzzy number is (l_{ij}, m_{ij}, u_{ij}).

$$w_{ij}\left(\frac{w_i}{w_j}\right) = \begin{cases} \frac{\frac{w_i}{w_j} - l_{ij}}{m_{ij} - l_{ij}} & \frac{w_i}{w_j} \le m_{ij} \\ \frac{u_{ij} - \frac{w_i}{w_j}}{u_{ij} - m_{ij}} & \frac{w_i}{w_j} \ge m_{ij} \end{cases} \tag{9}$$

Transform the problem of solving weight vectors into the following programming problem:

$$\begin{cases} \lambda_{max} \\ \lambda \le w_{ij}(w), i = 1,2, \cdots, n-1; j > i \\ \sum_{i=1}^{n} w_i = 1, w_i > 0 \end{cases} \tag{10}$$

At the same time, consider the endpoint situation of triangular fuzzy numbers, $\frac{\frac{w_i}{w_j} - l_{ij}}{m_{ij} - l_{ij}} \ge \lambda$ and $\frac{u_{ij} - \frac{w_i}{w_j}}{u_{ij} - m_{ij}} \ge \lambda$, simplify the above two equations to obtain $w_j l_{ij} + w_j(m_{ij} - l_{ij})\lambda - w_i \le 0$ and $-w_j u_{ij} + w_j(u_{ij} - m_{ij})\lambda + w_i \le 0$, the expression of the nonlinear programming problem above is:

$$\begin{cases} \lambda_{\max} \\ \lambda \le w_{ij}(w), i = 1,2,\cdots,n-1; j > i \\ \sum_{i=1}^{n} w_i = 1, w_i > 0 \\ w_j l_{ij} + w_j(m_{ij} - l_{ij})\lambda - w_i \le 0 \\ -w_j u_{ij} + w_j(u_{ij} - m_{ij})\lambda + w_i \le 0 \end{cases} \quad (11)$$

The optimal solution (w^*, λ^*), w^* is the weight vector in the fuzzy feasible domain that maximizes the membership degree $\tilde{P}$, λ^* representing the consistency index.

3.4 Double fuzzy analytic hierarchy process model

The dual fuzzy analytic hierarchy process model uses fuzzy comprehensive evaluation to evaluate element indicators, applies fuzzy number principle to calculate indicator weights, and finally uses indicator weights and fuzzy membership matrix fuzzy synthesis operation to calculate the final evaluation result. This method fully exploits the advantages of fuzzy evaluation and fuzzy numbers, and through phased application, it maximizes the compatibility with complex practical situations in reality, making the evaluation results more scientific and reasonable. The disadvantage is that it cannot solve the problems of interrelated element indicators and feedback from upper and lower indicators.

3.5 Fuzzy hierarchical network model

The fuzzy hierarchical network model is a special application of the hierarchical network model, characterized by the fact that the element set is reflected through the fuzzy set. The judgment matrix is represented by fuzzy numbers, and the weight calculation adopts a method suitable for fuzzy numbers. There are two application methods for the fuzzy hierarchical network model. One is to establish a comment set for the underlying indicators, apply the hierarchical network model to calculate the weights of each level of indicators, apply the fuzzy synthesis operator to calculate the evaluation membership degree of the previous level of indicators step by step, that is, the fuzzy hierarchical network model based on fuzzy evaluation[20]. Another way is to use fuzzy numbers to represent the judgment matrix with elements as secondary criteria, and apply the method of solving eigenvalues and eigenvectors suitable for fuzzy matrix calculation[21]. This method can more scientifically process the fuzzy information of experts, and the core content is to calculate weights through fuzzy numbers.

The core content of the fuzzy hierarchical network model method based on fuzzy evaluation includes two aspects: one is to calculate the weights of various indicators through the hierarchical network model, and the other is to perform fuzzy evaluation on the underlying indicators to form a fuzzy membership matrix. After obtaining the weights of the indicators, the fuzzy hierarchical network model based on fuzzy evaluation and the fuzzy analytic hierarchy process are consistent in fuzzy processing and calculation, with the only difference being the calculation method of indicator weights.

The difference between the fuzzy number based fuzzy hierarchical network model and the fuzzy evaluation based fuzzy hierarchical network model lies in the different calculation methods of indicator weights. A fuzzy hierarchical network model based on fuzzy numbers calculates eigenvectors and eigenvalues through fuzzy matrix calculations.

3.6 Double fuzzy hierarchical network model

After obtaining the weight vectors of indicators at all levels, a fuzzy evaluation set is constructed to evaluate each underlying indicator, forming a fuzzy membership degree $r_{i,j} = f_{i,j} / \sum_{j=1}^{m} f_{i,j}$. Among them, $f_{i,j}$ is the number of people or times the indicator A_i is evaluated as the evaluation level u_j, and a fuzzy membership degree matrix is constructed. Through the fuzzy synthesis of the weight vector and the fuzzy membership degree matrix, the fuzzy evaluation result is obtained. Defuzzify the fuzzy evaluation results to obtain clear results.

4. Comparative Analysis and Optimization of Models

4.1 SWOT basic model

SWOT Strengths, (Weaknesses), Opportunities and Threats. The SWOT model can be described using matrices, as shown in Table 1

Table 1 SWOT

Internal/External	Strengths	Weakness
Opportunities	SO Strategy: Maximizing development	WO Strategy: Utilize external opportunities and avoid weaknesses within oneself
Threats	ST Strategy: Utilize one's own advantages to reduce threats	WT Strategy: Narrowing one's own weaknesses and avoiding threats

SWOT Analyze own internal and external environment to achieve a unity of avoiding your own weaknesses, leveraging your own strengths, leveraging your opponent's weaknesses, and weakening your opponent's strengths.

4.2 Comparative analysis of strengths and weaknesses

The comparative analysis of the advantages and disadvantages of the experimental appraisal capability evaluation model is shown in Tables 2, 3, and 4.

Table 2 Comparative analysis

Comparative contents	Analytic Hierarchy Process Model		Hierarchical Network Model	
	Strengths	Weakness	Strengths	Weakness
A simple problem of independent factors	Suitable for hierarchical structures with independent elements, combining qualitative and quantitative methods. The principle is simple, easy to understand, with few judgment matrices, easy to construct, easy to calculate, and a wide range of applications	The judgment matrix is constrained by the academic ability and moral level of experts, and the evaluation of experts must be objective, fair, professional, and authoritative. In reality, there are very few completely independent factors that reduce the scientificity of the results.	Applicable hierarchical structure, combining qualitative and quantitative analysis, comparative analysis is more comprehensive and thorough	Treating independent factors as non independent factors, relying on feedback relationships, determining the order of the matrix, calculating hypermatrices, weighted hypermatrices, limit hypermatrices, etc., requires a large and complex amount of computation
Complex problems with independent factors	Not suitable for complex structures, can be solved using the Analytic Hierarchy Process model with "toughness"	Treating interdependent elements as independent elements results in high coupling and reduced reliability.	Applicable to network structures with internal loops or domination	The network structure is complex, and the judgment matrix is difficult to construct and has a large number of calculations, such as judgment matrices and hypermatrices, which are complex and require a large amount of computation

Table 3 Comparative analysis

Comparative contents	A Fuzzy Hierarchical Network Model Without Fuzzy Evaluation		A Fuzzy Hierarchical Network Model Based on Fuzzy Numbers	
	Strengths	Weakness	Strengths	Weakness
Fuzzy evaluation of element indicators	Establish a set of comments, evaluate each indicator, form an indicator membership matrix, and obtain the final evaluation level based on the indicator weights. By using membership degree, the evaluation results are richer and more comprehensive	The construction of indicator membership matrix is highly subjective, and the evaluation results are obtained through the maximum membership method. In cases where there is not much difference in membership degrees, it is easy to draw uncertain conclusions	Do not establish a comment set, do not construct a membership matrix, do not perform fuzzy evaluation on indicators, adopt fixed value evaluation, and the evaluation is simple and easy to operate	The evaluation results of element indicators are single, and the comprehensive expert opinion method is not reasonable enough. The evaluation results are too single, lacking diversity and possibility
Fuzzy judgment of pairwise comparison of element indicators	Using a hierarchical network model to calculate indicator weights does not involve pairwise comparison of indicators with ambiguity. The method is relatively simple and the construction of the judgment matrix is easy	The importance of using fixed value evaluation indicators is not accurate, scientific, and reasonable enough	Emphasize the importance and ambiguity of pairwise judgment of indicators, make weight comparison analysis more reasonable, and reduce subjectivity	It is necessary to make pairwise fuzzy judgments on any two elements based on the element as a secondary criterion. The fuzzy judgment matrix has a large order and the calculation of the fuzzy matrix is complex. Once there are too many element indicators, the calculation speed is greatly reduced

Table 4 Comparative analysis

Comparative contents	Double Fuzzy Analytic Hierarchy Process Model		Double fuzzy hierarchical network model	
	Strengths	Weakness	Strengths	Weakness
Simple problems with independent factors and fuzzy evaluation of element indicators	Fuzzy evaluation of element indicators and fuzzy judgment of element indicator judgment matrix. The fuzzy judgment matrix is few, the calculation is simple, and the results are rich and comprehensive	Due to the introduction of fuzzy evaluation, fuzzy numbers, fuzzy judgment matrices, etc., which are relatively complex, their applicability is limited	Establish a set of comments, construct a membership matrix, and make thorough fuzzy judgments on pairwise element indicators	There is too much data and too many fuzzy judgment matrices, making it difficult for experts to be competent
Complex problems with independent factors and ambiguous judgments of pairwise comparison of element indicators	Not considering the issue of indicator dependency, using the Analytic Hierarchy Process model to calculate indicator weights is relatively simple	The assumption of independence of element indicators may not exist, and the evaluation basis is easily questioned, resulting in poor credibility when attributing results	Apply comment sets, fuzzy membership matrices, fuzzy numbers, FPP, etc. to comprehensively and deeply solve problems, objectively and reasonably	There are many pairwise judgment matrices for element indicators, and the processing of fuzzy numbers and calculation of judgment matrices are complex, making them unsuitable for complex large-scale problems

4.3 Improving plant growth algorithms

The common algorithm for simulating plant growth has three problems: 1) the initial point of plant growth is randomly determined; 2) The growth direction is to spread outwards, reducing search efficiency; 3) Plant growth points are selected from a set of all germination points, and the algorithm's search space rapidly expands with the expansion of multidimensional space. The core idea of the improved simulated plant algorithm is: 1) the initial point is set on the horizontal plane, and the position is the center of the maximum and minimum values of the horizontal plane evaluation data; 2) Using the weighted average method to determine the evaluation data center point, the direction of aggregation towards the evaluation data center point is determined as the plant growth direction, and the growth direction is moderately optimized during the plant growth process; 3) The set of germination points for plant growth is not a complete set, only considering the germination points of the last two branch growth, in order to improve the speed of multi-dimensional space search.

The basic steps to improve the algorithm for simulating plant growth are:

Step 1: Based on the evaluation data of experimental identification ability, set m spatial point within the bounded closed area E, with the each spatial point $Q_i = \{a_1^i \quad a_2^i \quad \cdots \quad a_n^i\}$. Set the initial optimal set node as$X_{min} = \{0 \quad 0 \quad \cdots \quad 0\}$, the objective function of the optimal set node as$F_{min} = 0$, the growth step size$l = S(E)/20$, where $S(E)$ is the area of the region E, and determine the evaluation data center point using the weighted average method.

Step 2: Randomly select a set of evaluation data $Q^0 = \{a_1^0 \quad a_2^0 \quad \cdots \quad a_n^0\}$as the simulation plant growth point and calculate its objective function $F(Q^0)$. Let $X_{min} = Q^0$, then $F_{min} = F(Q^0) = \sum_{i=1}^{m} w_i \sqrt{(a_1^0 - a_1^i)^2 + (a_2^0 - a_2^i)^2 + \cdots + (a_n^0 - a_n^i)^2}$. Based on the growth point and the evaluation data center point, determine the horizontal rotation angle $\theta$of the new branch and the vertical dispersion angle ϑ.

Step 3: Grow branche M^1in the direction $\theta$of the root node Q^0. If M^1 is not within region E, resetM^1, until the conditions are met. Select Tsprouting points$S_{M_t^1} (1 \le t \le T)$ according to the step size $l$on top $M^1$to form a set of sprouting points$S_{M^1} = \{S_{M_1^1} \quad S_{M_2^1} \quad \cdots \quad S_{M_T^1}\}$. Calculate the objective function $F(S_{M_t^1})$for each germination point, if $F(S_{M_t^1}) < F_{min}$, $X_{min} = S_{M_t^1}$, F_{min}=$F(S_{M_t^1})$.

Step 4: If $F(Q^0) < F(S_{M_t^1})$, delete from the germination point set$S_{M_t^1}$. If after calculating all the germination points, it is found that the set of germination points is empty, then repeat step 3. The remaining germination points $G1$ form a set of alternative germination points$S'_{M^1} = \{S'_{M_1^1} \quad S'_{M_2^1} \quad \cdots \quad S'_{M_{G1}^1}\}$, and the concentration of each germination point $C_{S'_{M_g^1}}$ is

$$C_{S'_{M_g^1}} = \frac{F(Q^0) - F(S'_{M_g^1})}{\sum_{g=1}^{G1} [F(Q^0) - F(S'_{M_g^1})]} \tag{12}$$

Obviously $\sum_{g=1}^{G1} C_{S'_{M_g^1}} = 1$. The higher the concentration of germination points $C_{S'_{M_g^1}}$, the greater the probability that they will become new growth points. Abstract the auxin concentration of all germination points as the number of intervals on the interval [0,1]. For example $S'_{M^1} = \{S'_{M_1^1} \quad S'_{M_2^1} \quad S'_{M_3^1}\}$, if the concentrations of auxin in three germination points are 0.3, 0.26, and 0.44, the corresponding interval numbers for the three germination points are [0,0.3], [0.3,0.54], and [0.54,1], respectively. Randomly generate an exact number δ on [0,1], and when the random number δ is in a certain interval, the corresponding germination point is a new growth point. The selection process is shown in Figure 2. If the selected result is $S'_{M_g^1}$, then let $Q^1 = S'_{M_g^1}$, $X_{min} = Q^1$, F_{min}=$F(Q^1)$.

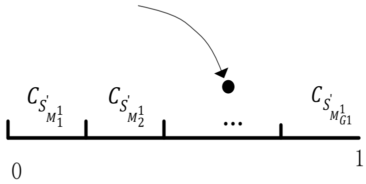

Figure 2 The process of determining new growth points

Step 5: Based on the growth point and evaluation data center point, re determine the horizontal rotation angle θ of the new branch and the vertical dispersion angle ϑ. According to $\theta$and ϑ, new branches M^2 will grow on top of Q^1. If $M^2$is not within region E, they will be reseted at a certain angle away from the evaluation data center point until the conditions are met. Select $T2$ germination points $S_{M_t^2}(1 \leq t \leq T2)$ to form a set of germination points$S_{M^2} = \{S_{M_1^2} \quad S_{M_2^2} \quad \cdots \quad S_{M_{T2}^2}\}$, and calculate the objective function for each germination point$F(S_{M_{t2}^2})$. If $F(S_{M_{t2}^2}) < F_{min}$,$F_{min}$=$F(S_{M_{t2}^2})$,$X_{min} = S_{M_{t2}^2}$.

Step 6: In order to avoid getting stuck in local minima and reduce the search space, select new long points from the set of sprouting points and on the two branches $S_{M_t^1}$ and $S_{M_{t2}^2}$. If $F(Q^0) < F(S_{M_t^1})$ or $F(Q^0) < F(S_{M_{t2}^2})$, delete $S_{M_t^1}$ or$S_{M_{t2}^2}$ from the germination point set. If after calculating all the germination points, it is found that the set of germination points is empty, then repeat step 5. The remaining germination points constitute the set of alternative germination points $S'_{M^1} = \{S'_{M_1^1} \quad S'_{M_2^1} \quad \cdots \quad S'_{M_{G1}^1}\}$ and $S'_{M^2} = \{S'_{M_1^2} \quad S'_{M_2^2} \quad \cdots \quad S'_{M_{G2}^2}\}$. Select the growth point using the idea from step 4, where the calculation formula for auxin concentration at the germination point is as follows:

$$C_{S'_{M_g^1}} = \frac{F(Q^1) - F(S'_{M_g^1})}{\sum_{g=1}^{G1}[F(Q^1) - F(S'_{M_g^1})] + \sum_{g=1}^{G2}[F(Q^1) - F(S'_{M_g^2})]} \tag{13}$$

$$C_{S'_{M_g^2}} = \frac{F(Q^1) - F(S'_{M_g^2})}{\sum_{g=1}^{G1}[F(Q^1) - F(S'_{M_g^1})] + \sum_{g=1}^{G2}[F(Q^1) - F(S'_{M_g^2})]} \tag{14}$$

Step 7: Repeat the idea of steps 5 to 6 for iteration until the number of iterations reaches the threshold or the acceptable range of changes in F_{min} and X_{min}, and the algorithm terminates. At this point, Q^{λ} is the optimal set node, where λ is the number of branches computed iteratively.

4.4 Evaluation model selection framework

For scientific researchers, it is a necessary question to choose which experimental identification ability evaluation model to use. Some evaluation models have simple principles and convenient calculations, but their shortcomings are that they do not consider the dependency and feedback effects of element indicators, which can easily lead to the absence of basic assumptions in the model and the evaluation results being easily questioned. The complex evaluation model involves pairwise comparison and judgment of indicators based on any criterion, constructing a large comparison and judgment matrix, which is a significant challenge for both researchers and domain experts. There is also a question, whether the qualitative evaluation of element indicators or the importance evaluation of pairwise judgment matrix elements are subjective evaluations, both involving whether to use the method of belonging to or not belonging to the binary set, or to use the fuzzy membership degree method. This directly leads to the question of FCE and fuzzy numbers, fuzzy sets, etc., which method to choose is a question to consider. Which evaluation model is better and better? The answer doesn't seem certain, it needs to be determined based on the individual situation of the researchers.

The established evaluation model in Figure 3 optimization method includes the target layer, criterion layer, key factor layer, and scheme layer. The goal is to find the best evaluation model that matches the problem and one's own strengths and weaknesses, while leveraging the constraints of the model's strengths. The criteria layer mainly includes analyzing one's own strengths and weaknesses based on SWOT analysis; Analyze the problem to be solved based on the characteristics of the experimental appraisal capability evaluation model and derived models; Analyze the strengths and weaknesses, difficulty of problems, and matching of model strengths and weaknesses based on SWOT-CLPV analysis; Model selection is based on comparative analysis, with principles including maximum advantage, ratio of advantages and disadvantages, minimum disadvantages, maximum leverage, and minimum vulnerability. The scheme layer refers to the evaluation model and its derivative models for experimental identification capabilities to be evaluated, and the optimal model is based on plant growth algorithms for problem solving.

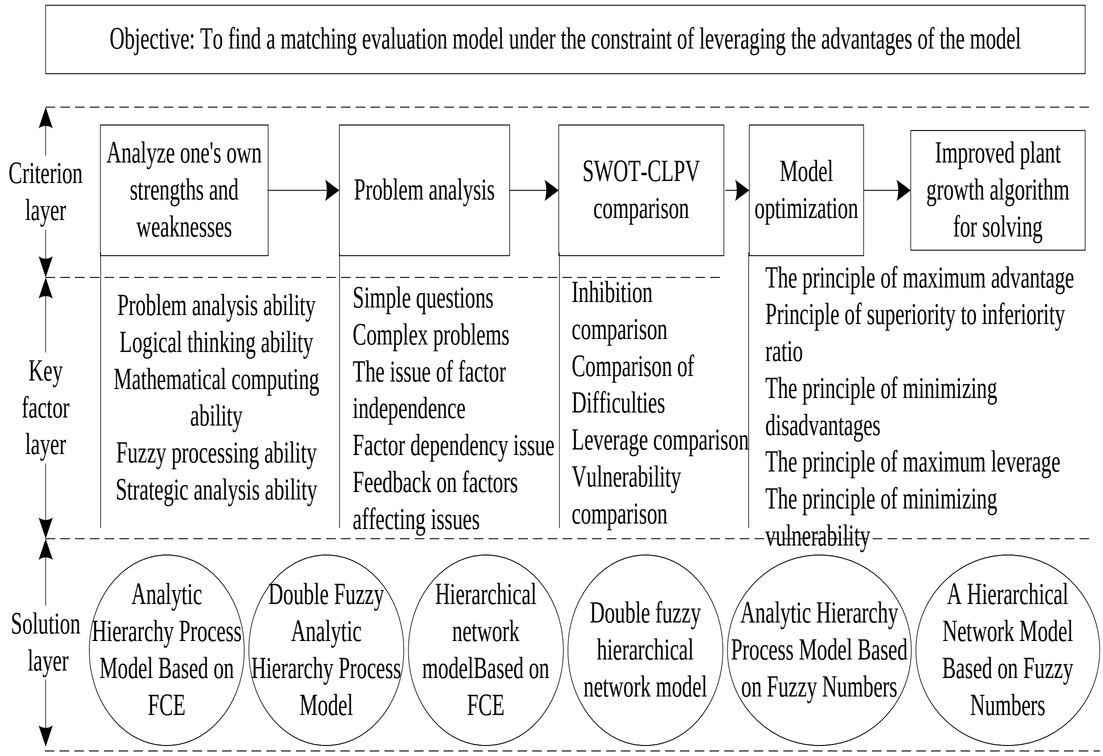

Figure3 Evaluation model selection framework

5. Conclusion

The evaluation of experimental appraisal capability is an important means to discover the shortcomings and weaknesses of weapons and equipment. Based on the analysis of the principles and advantages and disadvantages of six evaluation models, including the Double Fuzzy Analytic Hierarchy Process model and the Double Fuzzy Hierarchical Network model, and based on the Plant Growth Intelligence algorithm, this paper proposes a method for selecting an experimental appraisal capability evaluation model that includes the target layer, criterion layer, key factor layer, and scheme layer. This method can comprehensively evaluate the level of the evaluator, the difficulty of the problem, and the strengths and weaknesses of the evaluation model to select the best evaluation model. Next, it is necessary to further optimize the computational efficiency of the experimental identification capability evaluation model and improve the credibility of the evaluation results.

Acknowledgements

Fund Project: National Natural Science Foundation of China (62103425); Research on Evaluation and Adjustment of the Military Equipment Testing and Appraisal Plan (2023G0200023007); Military Graduate Program of the Whole Army (JY2023B010)

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