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Optimization of Fuzzy Topological Symbiotic Structure Based on Fuzzy Analytic Hierarchy Process

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In order to overcome the poor performance of the traditional fuzzy topological symbiotic structure optimization method, a new fuzzy topological symbiotic structure optimization method based on Fuzzy AHP is proposed. This method uses a particle swarm optimization algorithm to initialize particle swarm uniformly and randomly in the feasible region of fuzzy topology, selects the non inferior solution particles as the "elite solution set", and allocates the fitness value of the non-inferior solution particles in the elite set by niche technology. According to the information of fuzzy topological symbiosis structure, the information exchange of fuzzy topological symbiosis structure is realized by fuzzy analytic hierarchy process. The objective value of the function is calculated, and the optimization result of the fuzzy topological symbiosis structure is solved by using a genetic algorithm. The experimental results show that the optimization performance of the proposed method is better than that of the traditional method, improving which can improve the performance of the fuzzy topological symbiosis structure.

Keywords: Fuzzy Analytic Hierarchy Process, Fuzzy Topology, Symbiotic Structure Optimization, Elitist Solution Set, Non Inferior Solution Particle, Niche Technology

1. INTRODUCTION

In the real world, due to the complexity of the relationship between things, the randomness and fuzziness of objective existence, and the insufficiency of the phenomenon, there are problems of imprecision, incompleteness and uncertainty when people understand things. Uncertainty generally exists in the fields of economy, engineering, environment, social science and business management. Fuzzy set, rough set, vague set, probability theory, fuzzy set theory and interval mathematics are commonly used mathematical tools to deal with uncertainty problems, but these theories have some defects (Ma et al., 2017).

For this reason, Molodtsov analyzed the above theory and put forward the concept of a soft set based on a parameter set. It was pointed out that the reason for the deficiency of the above theory might be the inadequate use of parameter tools. At present, soft set theory has been successfully applied to many fields, such as operational research, measurement theory, game theory, comprehensive evaluation of enterprise competitiveness, text classification, data mining, evaluation of rural land use rights, processing of credit data, prediction of foreign trade import and export volume, medical diagnosis, flood prediction, decision-making and so on. At the same time, the theory of soft set is also improving. The current development trend of soft set theory can be roughly divided into four areas: First, continue to explore the properties of soft set itself, such as defining new operations, proposing subclasses of the soft set, etc.; Second, combine the soft set with existing methods to deal with uncertainty, such as: fuzzy soft set, bipolar fuzzy soft set, soft fuzzy rough set, interval fuzzy soft set, etc.; Third, In regard to the soft set, all kinds of algebraic structures are discussed, such as fuzzy soft group, fuzzy super group, soft semi ring, soft implication algebra and soft BCK algebra. All kinds of topological structures

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are also discussed concerning the soft set, such as soft topology, fuzzy soft topology and (L, m) - Fuzzy (E, K) soft topology. On this basis, as a special L-fuzzy soft set, fuzzy topology has also been studied by many scholars. Fuzzy topology is an important branch of topology, being the combination of lattice theory, topology, fuzzy mathematics, category theory and computer science. This kind of topology is characterized by a distinct topological structure, which is integrated into the ordered structure to give the characteristics of hierarchy (Ahmed et al., 2020; Mardiana-Jansar and Marlia, 2020; Fengwei and Xiuqing, 2019). Therefore, this theory has attracted the attention of many scholars and has achieved fruitful research results (Zheng et al., 2018). In 1968, Chang introduced the theory of fuzzy sets into topology and put forward the concept of i-topology. Goguen extended the lattice value background of fuzzy topology from unit interval I to a completely distributive lattice L with reverse order correspondence, called l-topology. l-topology has some shortcomings, for example, constant mapping (the common mapping between sets) is not necessarily continuous, so the projection of product is not necessarily open mapping. Therefore, on the basis of l-topology, Lowen introduces constant value mapping (fuzzy set), which is an open set, and calls this fuzzy topology Lowen type topology, also commonly called full layer l-topology (Xu et al., 2018). After Wang Guojun, a Chinese scholar, put forward the theory of topological molecular lattice in 1979, he established the point topological theory in a broader framework with the tools of molecules, distant domain and order homomorphism.

An important feature of fuzzy topology, is that not only is the set of fuzzy topology fuzzy, but the topology itself is also fuzzy (Hesamian et al., 2017). The double fuzziness of this topology can make studying it more complex, leading to many topology concepts not being defined accurately. For fuzzy topology, the most important research topic is the optimization of its symbiotic structure. Due to the poor performance of traditional optimization methods, a fuzzy topology symbiotic structure optimization method based on Fuzzy AHP is proposed.

2. OPTIMIZATION METHOD OF FUZZY TOPOLOGICAL SYMBIOTIC STRUCTURE

2.1 Multi-Objective Optimization of Fuzzy Topological Symbiotic Structure

2.1.1 Single Optimization Objective Function

Based on the fuzzy analytic hierarchy process, the multi-objective optimization of fuzzy topology is carried out. Firstly, the particle swarm optimization algorithm is used to uniformly and randomly initialize the particle swarm in the feasible region of fuzzy topology, and the non-inferior solution particles are selected as the “elite solution set”. Niche technology is used to allocate the fitness value of the non-inferior solution particles in the elite set, and the larger the aggregation degree, the smaller the fitness of the particles, as the “elite solution set”, the basis for selecting the optimal position of a group in the English solution set. The implementation of niche technology in the PSO algorithm is as follows:

In order to maintain the diversity of the population and create the evolution environment of the niche, the shared function reflecting the similarity between individuals is used to adjust the fitness of each individual in the population, so as to ensure that in the later evolution process of the population, the algorithm can select and operate according to the adjusted new fitness (Kikuchi and Yu, 2017). In the particle swarm optimization of multi-objective optimization, a group optimal location must be selected from the “elite solution set”, so the selection operation needs to be used.

The shared function is a function that represents the degree of close relationship between two individuals in a group, which can be recorded as $S(d(i, j))$, where $d(i.j)$ represents a certain relationship between individual x_i and individual x_j. The Hamming distance between particles or between individual genotypes can be defined as $d(i.j)$, and its calculation formula is as follows:

$$d(i, j) = \|x_i - x_j\| = \sqrt{\sum_{k=1}^{n}(x_{ij} - x_{jk})^2} \tag{1}$$

In the formula, n represents a positive integer; k represents the number of particles; x_{ik} represents the k-th x_i; x_{jk} represents the k-th x_j.

Then the shared function $S(d(i, j))$ is defined according to $d(i, j)$, that is, the shared function is defined by the Hamming distance between particles. To create a niche environment, $S(d(i, j))$ can be defined as:

$$S(d(i, j)) = \begin{cases} 1 - \left(\frac{d(i,j)}{\sigma_{niche}}\right)^{\alpha} & d(i, j) < \sigma_{niche} \\ 0 \quad other \end{cases} \tag{2}$$

In the formula, σ_{niche} is the distance parameter between niches, which is the niche radius; and α is an adjustment parameter. The closeness between individuals is mainly manifested in the similarity between particles or between individual genotypes (Wang et al., 2019). When the distance between two individuals is relatively close, the shared function value is larger; similarly, when the distance between two individuals is increased, the shared function value is smaller.

The sharing degree is a measure of the sharing degree of an individual in the “elite solution set”. It is defined as the sum of the sharing function values between the individual and other individuals in the group. The sum of the sharing function $S(i)$ is expressed as:

$$S(i) = \sum_{j=1}^{M} S(d(i, j)) \tag{3}$$

In the formula, M represents the total number of individuals considered, which is the group size in the “elite solution”.

After calculating the sharing degree of each individual in the “elite solution set”, the fitness of each individual is calculated according to the following formula. The larger the fitness is, the greater the chance of being selected is, and the niche can then be realized in the particle swarm optimization algorithm (Han et al., 2017).

$$Fit(i) = \frac{1}{S(i)} \tag{4}$$

In the formula, $Fit(i)$ represents individual fitness.

2.1.2 Multi-Objective Optimization Function

When fuzzy analytic hierarchy process is used in multi-objective optimization in order to solve the real optimal solution et in the multi-objective optimization problem, it is necessary to constantly generate and update the "elite solution set", or non-inferior solution set, in the iterative process of particle swarm optimization. The total number of non-inferior solutions in "elite solution set", that is, the capacity of "elite solution set", can be given in advance (Li et al., 2017). In the iterative formula of PSO, there are two problems: the selection of individual optimal position and group optimal position. For the selection of an individual's optimal position, the general approach is to compare the advantages and disadvantages of the individual's current particle and its historical optimal position P_i. If the current particle is better, it will replace P_i with it; if P_i is better, keep P_i unchanged; if the two cannot compare the advantages and disadvantages, it will replace P_i with a probability of 50% (Lu et al., 2018).

According to the fitness calculated by Formula (4), an individual in the "elite solution set" is selected as the historical optimal position P_g of the group by the proportional roulette probability method. After each iteration, m new particles are obtained, and the non-inferior solution is selected according to the dominant relationship, which is added to the original "elite solution set", and then the inferior solution is deleted to form a new "elite solution set". If the total number of non-inferior solutions in the "elite solution set" exceeds the capacity of the "elite solution set", then some individuals with small adaptability need to be removed (Saad et al., 2017). In this way, after many iterations, the "elite solution set" is increasingly closer to the actual optimal solution set of the fuzzy topology multi-objective optimization problem. Among these, the "optimal solution" should be selected from many non inferior solutions, such as dealing with the historical optimal position p_g experienced by the group. Thus, the capacity of the "individual elite solution set" can be expanded to be greater than 1.

When there are contradictions among the optimization objectives, it is the case that there is such an optimal solution that may make one objective function very small, but also make the other objective functions very large, this may still be a real optimal solution of the original multi-objective optimization problem. At this time, it is necessary to find the optimal solution set for the decision-maker to select one from the optimal solution set. In the process of using the optimization algorithm to find the optimal solution set, a way to avoid such individuals from joining the "elite solution set" must be found, that is, when calculating individual fitness, the information of each objective function of the optimization problem needs to be added. If the value of each objective function corresponding to an individual varies greatly, the individual fitness value will be smaller, as shown in the following formula:

$$Fit(i) = \frac{1}{S(i) + c \max\limits_{1\le k,1\le p}\left\{\left|\frac{f_k(x_i)}{f_k^0} - \frac{f_l(x_i)}{f_l^0}\right|\right\}} \tag{5}$$

In the formula, p represents the total number of objective functions to be optimized in the multi-objective optimization problem; f_k^0 represents the maximum value of the k-th objective function in the "elite solution set"; in the same way, f_l^0 represents the problem of balancing the order of magnitude difference of each objective function value and normalizes it; C represents a constant, which is used to balance the problem that the difference between the sharing degree and the objective function value is too great; f_k represents the k-th objective function; f_1 represents the order of magnitude of the value of the l-th objective function.

Therefore, a new criterion for evaluating the advantages and disadvantages of the whole non inferior solution set can be obtained according to the optimization algorithm, which can be called the "practicability" criterion, and its calculation formula is defined as:

$$PR = \frac{\sum_{i=1}^{M} pr_i}{M} Fit(i) \tag{6}$$

In the formula, PR represents the "practicality" standard; M represents the total number of individuals in the "elite solution set"; pr_i represents the "practicality" of individual x_i, which can be defined as:

$$pr_i = \begin{cases} 1 & \max\limits_{1\le k,l\le p}\left\{\left|\frac{f_k(x_i)}{f_k^0} - \frac{f_l(x_i)}{f_l^0}\right|\right\} \le C_{pr} \\ 0 & other \end{cases} \tag{7}$$

In the formula, C_{pr} represents the parameter, which needs to be determined according to the actual optimization problem. Generally, it can be selected as the average value of all individuals in the "elite solution set" of all objective functions, namely:

$$C_{pr} = \frac{\sum_{i=1}^{M}\sum_{k=1}^{p}\frac{f_k(x_i)}{f_k^0}}{Mp} \tag{8}$$

After the objective optimization function is constructed, the information exchange of the fuzzy topological symbiosis structure is carried out.

2.2 Information Exchange of Fuzzy Topological Symbiotic Structure

2.2.1 Get Symbiotic Structure Information

The information of the fuzzy topological symbiosis structure is obtained through the artificial bee colony algorithm, including star topological symbiosis structure information, ring topological symbiosis structure information, wheel topological symbiosis structure information, tetrapoly topological symbiosis structure information and von Neumann topological symbiosis structure information, as shown in Table 1 (Zhang et al., 2019).

The corresponding figure of fuzzy topological symbiotic structure information is shown in Figure 1 (Osyczka et al., 2017).

Table 1 Fuzzy topological symbiotic structure information.

Serial number	Information type of topological symbiotic structure	Content
1	Point to multipoint topological symbiotic structure information	All nodes are interconnected and can communicate with each other. The algorithm of application structure has fast convergence speed, but it is easy to fall into local extremum.
2	Ring topology symbiosis structure information	Each individual only communicates with two adjacent individuals, and the neighborhood of the ring structure overlaps each other, which is conducive to information exchange and ultimately makes the algorithm converge to a solution. However, the information flow transfer rate in the whole network structure is slow, so the algorithm convergence speed is also slow. When compared with the star structure, the individual can cover most of the search space.
3	Information of wheel topology symbiosis structure	Each individual is isolated from each other; with only one individual as the focus of the whole group and all information transmission is conducted by this individual.
4	Information on symbiotic structure of tetrapoly topology	All individuals are divided into clusters. The individuals in the cluster are star like and are connected with each other. Between clusters, each cluster is regarded as a whole and is connected by two nodes in the cluster.
5	Von Neumann topological symbiosis structure information	All individuals form a network structure. Each individual is connected with four individuals. Von Neumann structure has been applied to many experiential learning problems, and has shown good performance.

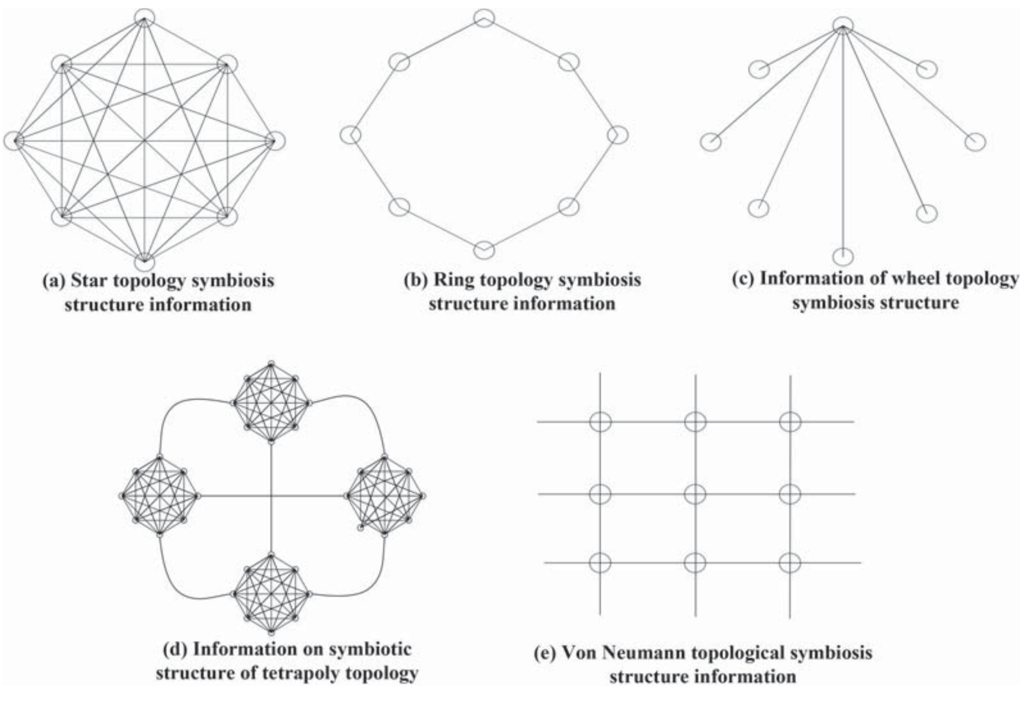

Figure 1 The graph corresponding to the information of fuzzy topological symbiotic structure.

From the analysis of Table 1 and Figure 1, it can be seen that among the five kinds of fuzzy topological symbiotic structure information, the information of tetrameric topological symbiotic structure is the most complex and the most difficult to be optimized. Therefore, the next step is to carry out information exchange processing for the information of tetrameric topological symbiotic structure to complete the optimization of the fuzzy topological symbiotic structure.

2.2.2 Structural Information Exchange

Information exchange of the fuzzy topological symbiosis structure is implemented by using the obtained information of the tetrapoly topological symbiosis structure (Derikvand et al., 2017). The ant colony optimization algorithm is needed in the process of information exchange. In the ant colony algorithm, as an agent, the artificial ant can not only optimize the information according to the guidance of the artificial pheromone trajectory, but also make full use of the heuristic information based on the problem. In addition, there are important mechanisms in the ant colony optimization algorithm, that is, pheromone volatilization and background behavior. Forgetting is a kind of advanced intelligent behavior. As a form of forgetting, the pheromone on the path will volatilize continuously with time, which will enable the artificial ant to explore new space, in order to avoid falling into the local optimal solution in the process of information exchange. Background behavior includes the process of nearest neighbor search and the collection of global information. Ant colony optimization algorithm is a kind of constructive heuristic optimization algorithm based on population. When combined with other methods, such as nearest neighbor search and tabu search, it can produce better results of information exchange. In addition, by dynamically collecting heuristic information based on the problem itself in the process of solution construction, the ant colony will be guided to conduct a finer search in the high-quality problem space, in order to improve the information exchange.

Suppose that the distance (similarity) between information exchange objects σ_i and σ_j can be expressed as $d(\sigma_i, \sigma_j)$ by Euclidean distance, if the two information are similar, then $d(\sigma_i, \sigma_j) = 0$, however, if the two information are not similar, then $d(\sigma_i, \sigma_j) = 1$, the two-dimensional similarity matrix of ant movement can be constructed by a similarity calculation.

If there are multiple ants repeatedly picking up and dropping information in this matrix at the same time, at the time of t, the ants find the information exchange object σ_i at the position of ρ, then the local density can be calculated as:

$$f(\sigma_i) = \begin{cases} S^{\frac{1}{2}\sum \sigma_i \left[\frac{1-d(\sigma_i,\sigma_j)}{2}\right]} & f > 0 \\ 0 & otherwise \end{cases} \tag{9}$$

In the formula, $f(\sigma_i)$ represents the local similar density, $\sigma_i \in Grid_{s\times s}(\rho)$, the neighborhood area of position element ρ is $(s \times s)$. The probability of ants picking up information and dropping information is expressed as $p_p(\sigma_i)$ and $p_d(\sigma_i)$ respectively, therefore the formula is as follows:

$$p_p(\sigma_i) = \left(\frac{k_1}{k_1 + f(\sigma_i)}\right)^2 \tag{10}$$

$$p_d(\sigma_i) = \begin{cases} 2f(\sigma_i) & f(\sigma_i) < k_2 \\ 1 & f(\sigma_i) \geq k_2 \end{cases} \tag{11}$$

In the formula, k_1 and k_2 are information exchange threshold constants.

According to the ant's picking up and putting down the information of the symbiotic structure, the communication of the information of the symbiotic structure of fuzzy topology is completed, which lays the foundation for the optimization of the symbiotic structure of fuzzy topology.

2.3 Optimization of Fuzzy Topological Symbiotic Structure

2.3.1 Programming Implementation of Optimization Process

The genetic algorithm is used to optimize the fuzzy topological symbiosis structure. In the process of optimization, the finite element analysis is needed to calculate the value of the objective function. ANSYS software is used for the finite element analysis. Using the parametric design language provided by ANSYS, the command flow of program execution is compiled (Walls et al., 2017). Using the APDL programming language, parametric modeling, parametric loading and parametric processing can all be realized. The whole process of parametric finite element analysis can therefore be realized (Hahn et al., 2017). ANSYS can run the command flow of APDL directly in the foreground or in a background mode. If it runs in the background mode, it is very suitable for other programs to call ANSYS. When dealing with the structural topology optimization, the main program is the iterative process of the algorithm, which is programmed using the MATLAB language. Because the calculation of the objective function value needs to get the node displacement equivalent of the structure, which needs to be obtained through the ANSYS software, the main program needs to call ANSYS during the operation process through command statements (Mohamed and Isaac, 2017).

Because MATLAB 6.5 does not support paths with spaces when calling functions, the above statement assumes that the default installation path is not used when installing ANSYS, as the default installation path of ANSYS does contain spaces (Cho et al., 2017). It is important to input the command stream file, as shown in Figure 2:

In the process of command flow processing, some data needed by the MATLAB program, such as node displacement, are written into a file for MATLAB to obtain, so as to calculate the value of objective function (Liu et al., 2018). After obtaining the value of the objective function, it is optimized with constraints, not only to reduce the objective function in the iterative process, but also to pay attention to the feasibility of the solution. In order to simplify the optimization process of the constrained optimization problem, the following ideas need to be adopted in order to construct the algorithm: transforming constrained optimization problem into unconstrained optimization problem, transforming nonlinear programming problem into linear programming problem and transforming complex problem into simple problem. The penalty function method is adopted, as it is the most widely used method to deal with constraints. Its basic idea is to transform the constrained optimization problem into a series of unconstrained optimization problems through the Sequential Unconstrained Minimization Technology, which is convenient for this application. The specific method is to add a penalty term in the objective function that can reflect whether the design variable satisfies the constraint, so as to form an unconstrained generalized objective function, so that the algorithm can then find the optimal solution of the problem under the effect of the penalty term (Xu et al., 2017; Ganim and Rief, 2017).

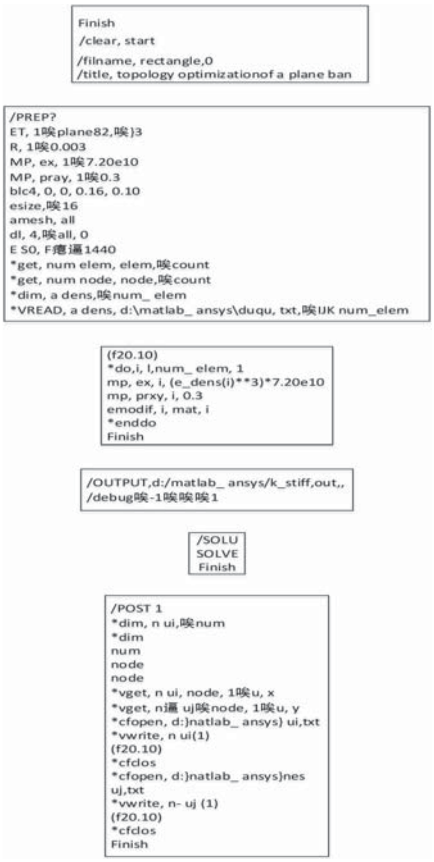

Figure 2 Command stream file entered.

2.3.2 Realization of Fuzzy Topological Symbiosis Structure Optimization

After information exchange and command stream file processing, the fuzzy topological symbiosis structure is optimized based on the genetic algorithm. In the optimization of fuzzy topological symbiotic structure, in order to reduce the discontinuity of plane elements on the basis of satisfying the displacement constraints, the mathematical model is constructed as follows:

$$\begin{gathered} \min l(x) = M \\ s.t\delta_{\max} < \delta_0;\ N_D = 0 \end{gathered} \tag{12}$$

In the formula, $l(x)$ represents the mathematical model function; M represents the quality of the optimized fuzzy topological symbiosis structure; $\delta_{\max}$ represents the maximum displacement in the fuzzy topological symbiotic structure; δ_0 represents the allowable displacement in the structure; N_D represents the number of discontinuities in the structure.

In order to make the optimization process more convenient and eliminate the influence of different constraints on structural optimization, the dimensionless processing of mathematical model functions is carried out, the concept of a penalty factor is introduced, and the optimization process is transformed into an unconstrained solution problem:

$$\min g(x) = \lambda\,[\delta_{\max}/\delta_0 - 1] + (N_D + N_H) \tag{13}$$

In the formula, $g(x)$ represents the modified mathematical model function; λ is the penalty factor.

In order to guide the structural optimization using the genetic algorithm, it is necessary to satisfy the constraints of the fuzzy topological symbiotic structure in the optimization process, so that all the plane elements in the structure remain continuous after optimization. The unconstrained function of fuzzy topological symbiosis structure is then:

$$H(x) = \sum_{m \in V} \frac{L(x)}{S_p} \cdot \min g(x) \tag{14}$$

In the formula, S_p is the unconstrained limiting factor, $L(x)$ represents the structure optimization guide function.

Based on the unconstrained function of structural optimization, the topology optimization function is constructed as follows:

$$\eta(x) = \frac{1}{x} \sum_{i=1,j=1}^{x} [H(x) - \mu]^2 \tag{15}$$

In the formula, μ represents the limiting factor of topology optimization.

The multi-objective optimization function is solved using the topology optimization function to obtain the optimization result of the fuzzy topology symbiosis structure

$$Y(x) = C_{pr} \cdot \left(\sum_{i=1,j=1}^{x} \frac{w_t}{1 + \eta(x)^2} + \sum_{i=1,j=1}^{x} \frac{w_t}{\eta(x)^2 - 1} \right) \tag{16}$$

In the formula, w_t is the optimization weight.

Through the above calculation process, the optimization of the fuzzy topological symbiosis structure is realized.

Figure 3 Simulation environment.

Table 2 Specific information of simulation environment.

Environmental type	Development tool	Edition
Operating system	Windows 7	spl
Data base	Oracle	10.0
IDE	MyEclipse	6.0
The server	Tomcat	6.0
Server language environment	Jdk	1.6
Client locale	Flex	4.0
Plug-in unit	Twaver	-

Table 3 Hardware configuration of the platform.

Serial number	Hardware	To configure
1	CPU	Intel P4 2.66GHz
2	Hard disk	65G
3	Memory	512MB

Table 4 Software configuration.

Serial number	Name		Explain
	Device name	Analog computer	
1	Simulation computer	Windows XP operating system	Version 2002
		Net Logo	4.1.3 version
2	Platform computer Mobile terminal platform	Operating system	Windows 7
		Java runtime environment	JDK 1.7
		Application server	Tomcat 7.0
		Data base	MySQL 5.
3	Mobile terminal platform	Android Smartphone	Android 4

3. EXPERIMENTAL VERIFICATION

3.1 Experimental Environment

In order to verify the performance of the fuzzy topological symbiotic structure optimization method based on Fuzzy AHP, a comparative experiment is carried out. MATLAB is selected as the simulation software to build the simulation environment, as shown in Figure 3, and the specific information of the simulation environment is shown in Table 2.

The simulation platform of the experiment is then built, and the hardware configuration of the platform is shown in Table 3.

The configuration of the software is shown in Table 4.

The API interface setting information of the simulation experiment platform is shown in Table 5.

In order to ensure the fairness and contrast of the experimental results, the traditional fuzzy topological symbiotic structure optimization method is compared with the fuzzy topological symbiotic structure optimization method designed in this paper. Among them, the traditional optimization methods of fuzzy topological symbiotic structure include the optimization methods based on decision tree construction, component matrix and matrix splicing. The optimization rate and efficiency of each fuzzy topological symbiotic structure optimization method are compared.

Table 5 API interface setting of simulation experiment platform.

Serial number	API interface	Interface specification
1	ReadOctMatrix	Read matrix from file
2	OctMatrix	Array (vector) initialization matrix
3	ones, zeros	All 1, all 0 matrix
4	WriteOctMatrix	Write matrix to file
5	as.matrix	Convert matrix to matrix in R
6	%*%	Matrix multiplication
7	+, −, *, /	Matrix addition, subtraction, scalar multiplication and division
8	t	Matrix transposition
9	apply	Applying user defined functions to matrices
10	cbind2	Joining two matrices into a matrix by columns
11	sum	Calculate the sum of all elements of a matrix

Table 6 Optimized performance test results.

	Method based on building decision tree (%)	Method based on component matrix (%)	Method based on matrix splicing (%)	Proposed method (%)
One time experiment optimization rate	82.29	80.25	73.24	92.09
Secondary experiment optimization rate	79.32	80.19	79.61	91.08
Optimization rate of three experiments	83.19	72.19	74.32	94.68
Optimization rate of four experiments	81.09	76.29	79.21	97.19
Average optimization rate	81.4725	77.23	76.595	93.76

3.2 Comparison Results of Optimization Rate

The experimental results of the optimization rate of three traditional fuzzy topological symbiotic structure optimization methods and fuzzy topological symbiotic structure optimization methods based on Fuzzy AHP are shown in Table 6.

The experimental results of the optimization rate of fuzzy topological symbiotic structure based on decision tree construction, component matrix, matrix splicing and fuzzy topological symbiotic structure optimization based on fuzzy analytic hierarchy process are made into experimental graphs for data analysis, as shown in Figure 4.

According to the optimization performance test results in Table 6 and Figure 4, the optimization rate of the fuzzy topological symbiosis structure optimization method based on Fuzzy AHP is higher than that of the traditional fuzzy topological symbiosis structure optimization method, which fully shows that the optimization performance of the fuzzy topological symbiosis structure optimization method based on Fuzzy AHP is better than that of the traditional fuzzy topological symbiosis structure optimization method.

3.3 Optimization Efficiency Comparison

In order to further verify the optimization performance of the proposed method, taking the optimization efficiency as the experimental comparison index, the proposed method is compared with the three traditional methods and the comparison results are shown in Figure 5.

Analysis of Figure 5 shows that the optimization efficiency of the proposed method is higher than that of the three literature comparison methods with the increase in experimental time. The optimization efficiency of the decision tree building method and the matrix splicing method is higher at the beginning of the experiment, but with the increase of time, the optimization efficiency of the method continues to decline. The optimization based on the component matrix method has increased, however the highest efficiency is still below 90%. The optimization efficiency of the proposed method continues to rise, and the maximum optimization efficiency can reach 95%. Therefore, the proposed method has high optimization efficiency.

4. CONCLUSION

In order to improve the optimization performance of the fuzzy topological symbiotic structure, a fuzzy topological symbiotic structure optimization method based on fuzzy analytic hierarchy process is proposed. The following conclusions are proved from both theoretical and experimental aspects. The method has a high optimization rate and structural sensitivity. Specifically, compared with the optimization

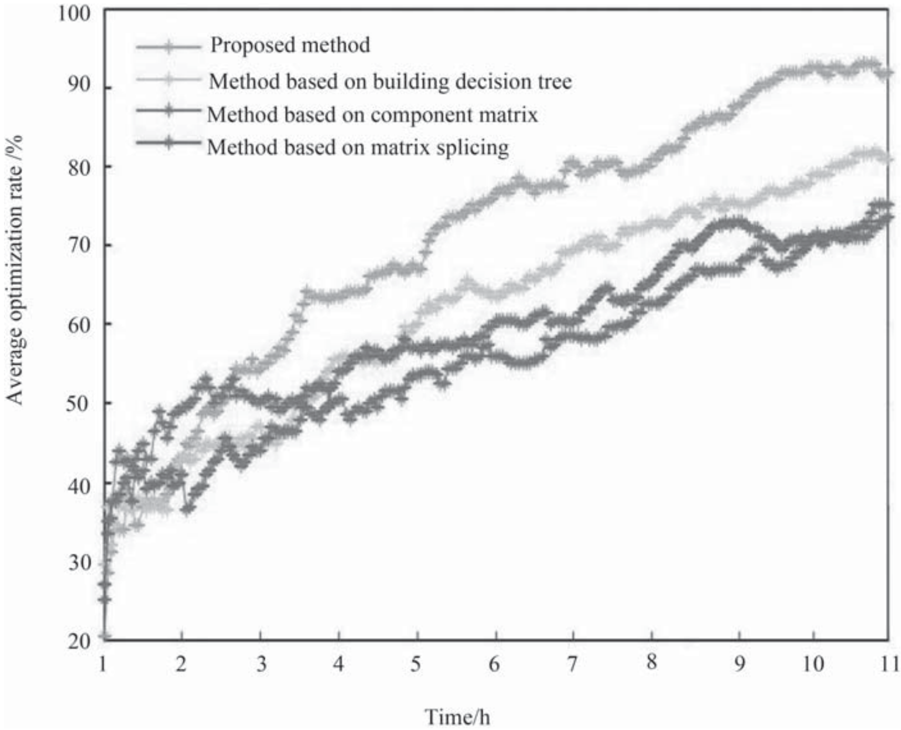

Figure 4 Experimental results of optimization rate.

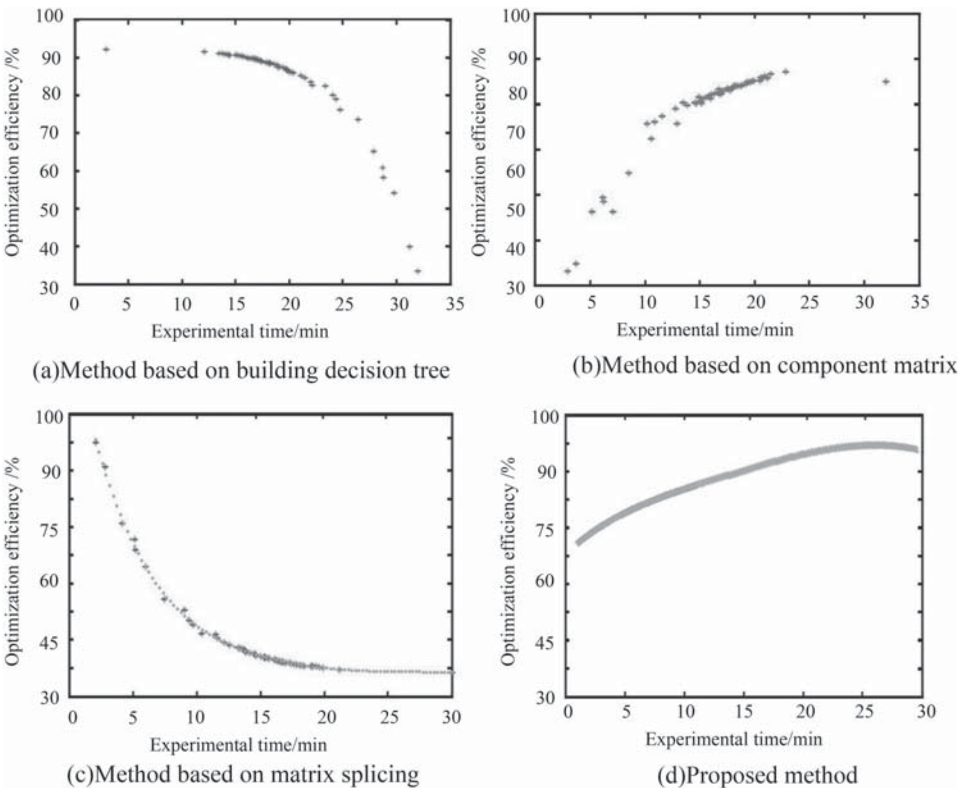

Figure 5 Comparison results of optimization rate.

method based on decision tree construction, the optimization rate of the proposed method is greatly improved; compared with the optimization method based on matrix splicing, the optimization efficiency of the proposed method is significantly improved. Therefore, it fully shows that the optimization method based on Fuzzy AHP can better meet the requirements of fuzzy topological symbiotic structure optimization.

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