Optimization of Green Supply Chain Management Based on Improved MPA

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***Abstract*—With the advancement of industrialization and urbanization in the global market, the contradiction between economic development and environmental protection is becoming increasingly prominent. In response to the optimization problem, this study constructs a green supply chain network problem model with green constraints. In the second half of the iteration of the ocean predator algorithm, Gaussian mutation is used to replace the original fish swarm aggregation device effect, proposing an improved ocean predator algorithm to solve the green supply chain network model. The results demonstrated that the designed algorithm performed greater than other algorithms on all four benchmark functions. Except for the mean value of 2.17×10^{-202} when solving function 1, the other mean and standard deviation were all 0. When solving the multi-modal benchmark test function, the proposed algorithm still had the fastest convergence speed and the difference was more obvious. In small-scale testing sets, the proposed algorithm could find the best solution for the test instance, resulting in a lower total cost of 139,832.97 yuan, 148,561.28 yuan, and 147,535.81 yuan, respectively. In three different scale test sets, the proposed algorithm had the fastest convergence speed and successfully converged to feasible solutions. The research results verified the algorithm performance and its good application effect in handling green supply chain network problems, which helps optimize it.**

Keywords—Green supply chain; supply chain management; marine predator algorithm; optimization problem; fish gathering device

I. Introduction

The deepening advancement of globalization has led to an increasing emphasis on the optimization of supply chain networks, gradually becoming an important factor affecting the competitiveness of enterprises. Green Supply Chain (GSC), also known as Environmental Awareness Supply Chain, is a modern management model that comprehensively considers environmental impact and resource efficiency throughout the entire Supply Chain (SC) [1]. Gawusu et al. outlined GSC management in the context of Renewable Energy (RE) and proposed a distributed energy system network based on GSC management to establish a green management standard that can be adopted by enterprises. This study helped RE producers sell their remaining electricity built on peer-to-peer networks [2]. Lerman L V et al. addressed the unexplained importance of digital transformation in GSC management and adopted a configuration perspective of digital transformation and Supply Chain Management (SCM) to explore the contribution of intelligent GSC management to green performance. Intelligent GSC was directly influenced by global SCM and is related to green procurement activities [3]. Khan M et al. investigated the correlation between SC connectivity, information sharing, logistics acceptance, and GSC management, and proposed a new GSC management scale. This scale helped to facilitate the effective transition of traditional SC to GSC and provided a deeper understanding of the logical integration of resource-based features [4]. AlBrakat N et al. conducted a questionnaire survey on 280 participants in private hospitals to determine the practical level of GSC and its impact on the operational performance of private hospitals. The statistical analysis of the survey results indicated that GSC practices had an impact on performance, and therefore, operational efficiency could be improved by evaluating sustainability parameters [5]. Al Khawaldah R et al. established a research framework to investigate the impact of GSC on industrial companies achieving competitive advantage, using organizational duality as a mediating variable. All elements of GSC management greatly affected the competitive advantage, but green procurement had no significant impact on organizational duality [6]. Ricardianto P et al. used quantitative methods to explore the contribution of green manufacturing and distribution to improving GSC management performance and randomly selected 70 people for analysis. Green manufacturing, reverse logistics, and green distribution contributed to the successful implementation of GSC management [7].

The Marine Predators Algorithm (MPA) is a natural heuristic optimization algorithm that mimics the foraging behavior and rate strategy between marine predators and prey. It has the benefits of strong evolutionary ability, fast search speed, and strong optimization ability [8]. Housein E H et al. developed a breast cancer diagnosis and classification model grounded on hybrid CNN, improved MPA, and transfer learning for pre-detection and analysis. This model had high classification accuracy and sensitivity, which was superior to the most advanced methods currently available [9]. Abualigah L et al. proposed an optimal multi-level image segmentation threshold optimization model built on MPA and Salp Swarm to address the issue of selecting the best threshold in pixel rating and used image histograms to represent the obtained solutions. This model could effectively determine the optimal image segmentation threshold and had good image segmentation performance [10]. Jangir P et al. put forward a multi-objective MPA to artificially handle optimization problems with multiple conflicting targets, relying on elite non-dominated sorting, and tested it in various multi-objective case studies. The proposed algorithm has demonstrated good performance in solving nonlinear, unconstrained, continuous, and discrete optimization problems [11]. Abd Elaziz M et al. designed a feature selection method based on the MPA in dataset dimensionality reduction. This method combined the sine-cosine algorithm to enhance search capability and help decrease the computational workload of the classification process. This algorithm had high feature selection performance and efficiency and was superior to existing methods in classification metrics [12]. Dinh P H proposed a high-frequency component fusion rule based on maximum Gabor energy to address the issue of missing important information in input images in multi-modal medical image fusion. Using the best parameters of the MPA to synthesize low-frequency components helped ensure the output image quality. This method had good medical image fusion performance and achieved excellent performance than others [13]. Shaheen A M et al. proposed an improved MPA for the economic scheduling problem of co-generation under operating constraints of co-generation units and measured the performance of the algorithm through four testing systems. The proposed algorithm had stable convergence characteristics, which helped to reduce the total fuel cost supply and effectively improved the optimization efficiency of traditional MPAs [14].

To sum up, many experts have performed extensive research on GSC. However, existing models have been simplified to a certain extent, which has affected the practical application effect of the models and thus affected the development and optimization of GSC management. In this context, this study constructs a GSC network problem model with complex constraints and proposes an improved MPA to solve it. This study combines intelligent optimization algorithms with SCM, which is expected to provide more efficient and reliable solutions for SCM. The innovation is mainly reflected in two aspects. The first point is the introduction of new green constraints and the construction of a GSC network problem model with complex constraints. The second point is to make phased improvements to the traditional MPA to enhance its Global Optimization Ability (GOA).

II. Methods and Materials

To reduce environmental pollution from the source, this study introduces green constraints and builds a GSC network problem model with complex constraints. An improved MPA is developed to perfect GSC management for the solution problem of the proposed GSC network model.

A. GSC Network Model Construction

SCM is the process of strengthening the SC operation, from procurement to the point of sale, intending to minimize costs. This process involves planning, coordinating, controlling, and optimizing the entire SC activities, aiming to ensure that products or services can flow and be delivered to end customers with the highest efficiency and lowest cost [15]. To achieve the goals of SCM, it is necessary to optimize the SC network structure, logistics strategy, and inventory strategy. The model of GSC is shown in Fig. 1.

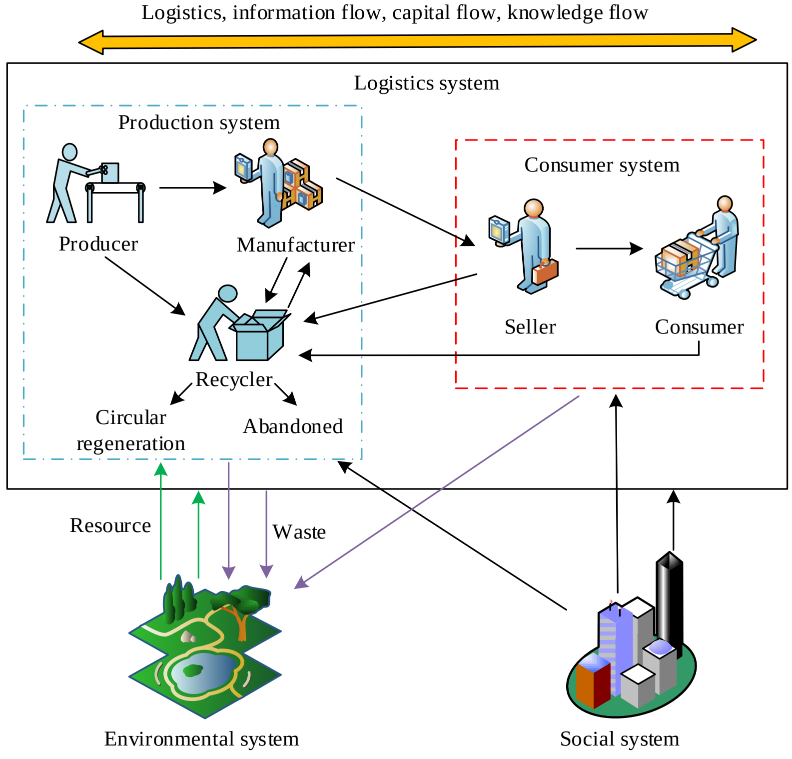


Fig. 1. The model of the green supply chain.

GSC network optimization problems usually have characteristics such as large-scale and multi-constraint. Sometimes it is necessary to consider multiple optimization objectives simultaneously, which can be divided into SC network design, SC configuration optimization, inventory optimization, and vehicle path optimization [16]. Assuming the decision vector is $x=(x_1,x_2,...,x_d)$, where d represents dimension, the mathematical modeling of the optimization problem is Formula (1).

$$\begin{aligned} &\text{minimize/ max mize } y = f(x) \\ &s.t.\quad g_i(x) \le 0, i = 1,...,m \\ &\qquad h_j(x) = 0, j = 1,...,n \end{aligned} \tag{1}$$

In Formula (1), $f(x)$ is the objective function. $g_i(x)$ and $h_j(x)$ represent in-equality and equality constraints. From the perspective of constraints, optimization problems have two categories: constrained and unconstrained. To meet the actual situation, this study fully considers various complex constraints in real life to build a GSC network model. It targets to shorten the total operating costs of the GSC while meeting all constraints. In addition, the proposed GSC network model also considers the constraints of green factors, making energy conservation and pollution reduction important goals of enterprise management. The main workflow of the proposed GSC network model can be divided into four steps. Firstly, the supplier provides the manufacturer with the raw materials required for production. Secondly, manufacturers manufacture products based on raw materials. Then, the manufacturer transports the manufactured products to the warehouse. Finally, the warehouse delivers the product to the customer. To better align with the actual situation, this study proposes four hypotheses. Firstly, the raw materials provided by suppliers are constrained by the proportion of raw materials required to manufacture a certain product. Secondly, the quantity of raw materials and products provided by suppliers, manufacturers, and warehouses cannot exceed their maximum capacity. Thirdly, the customer's demand is known in advance and can all be met. Fourthly, there is no uniqueness in the supply and demand relationship. In summary, the application scenario and workflow of the proposed GSC model are shown in Fig. 2.

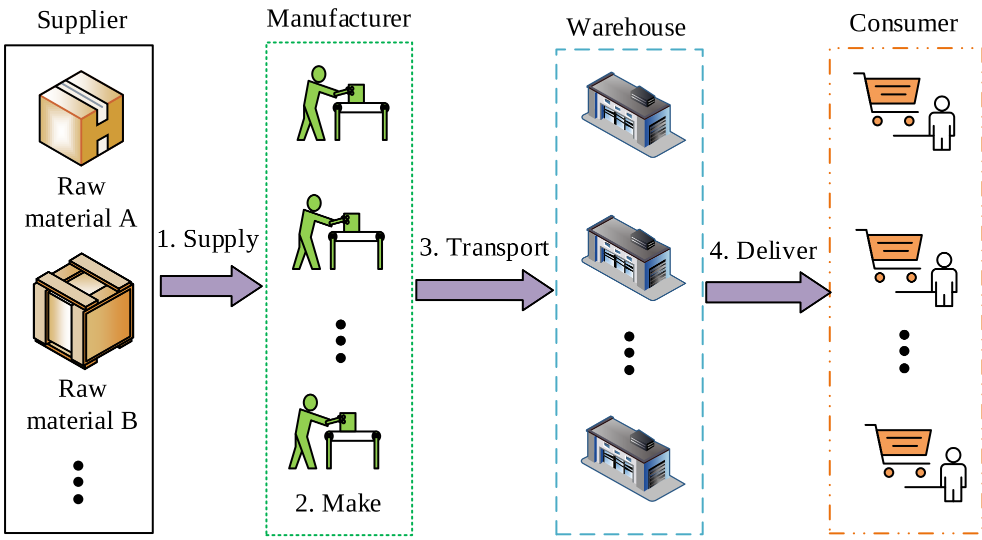


Fig. 2. Application scenarios and workflow of GSC network.

The calculation of raw material cost C_p is Formula (2).

$$C_P = \sum_{p=1}^{N}\sum_{s=1}^{S}\sum_{m=1}^{M} S_p \times Q_{sm} \tag{2}$$

In Formula (2), N represents the type and quantity of raw materials. p represents raw materials. S represents the number of suppliers who provide raw material p. s is the supplier. M is the number of manufacturers. m denotes the manufacturer. S_p means the unit price of raw material p supplied by supplier s. Q_{sm} is the quantity of raw materials p provided by supplier s to the manufacturer m. The calculation of manufacturing cost C_m is Formula (3).

$$C_m = \sum_{m=1}^{M} Q_m \times M_m \tag{3}$$

In Formula (3), Q_m and M_m are the quantity and unit cost of products manufactured by manufacturer m. The calculation of fixed cost C_f is Formula (4).

$$C_f = \sum_{m=1}^{M} M_{mt} \times M_{mf} + \sum_{w=1}^{W} M_{wt} \times M_{wf} \tag{4}$$

In Formula (4), M_{mt} represents whether manufacturer m has been selected. M_{mf} represents the fixed cost of m. M_{wt} represents whether warehouse w has been selected. M_{mf} represents the fixed cost of w. The expression of freight cost C_t is Formula (5).

$$C_t = \sum_{p=1}^{N}\sum_{s=1}^{S}\sum_{m=1}^{M} T_{sm} \times Q_{sm} + \sum_{m=1}^{M}\sum_{w=1}^{W} T_{mw} \times Q_{mw} + \sum_{w=1}^{W}\sum_{c=1}^{C} T_{wc} \times Q_{wc} \tag{5}$$

In Formula (5), T_{sm} represents the unit transportation cost of raw materials from s to m. T_{mw} represents the unit product transportation cost from m to warehouse w. Q_{mw} represents the quantity of products provided by m to w. T_{wc} represents the unit transportation cost of products from warehouse w to customer c. Q_{wc} represents the quantity of products provided by w to c. In summary, the objective function of the GSC network problem is Formula (6).

$$\min TC = C_p + C_m + C_f + C_t \tag{6}$$

In Formula (6), TC represents the total operating cost of the GSC, consisting of raw material costs, manufacturing costs, fixed costs, and freight costs. The solution to GSC network problems consists of Q_{sm}, Q_{mw}, Q_{wc}, Q_m, as well as whether suppliers, manufacturers, and warehouses are selected. To simplify the solution, an encoding scheme consisting of Q_{sm}, Q_{mw}, and Q_{wc} is designed with a dimension of $\sum_{p=1}^{N}(S\times M)+MW+WC$, where W and C represent the number of warehouses and customers, respectively.

B. GSC Management Optimization Based on Improved MPA

After building the problem model of the GSC network, this study uses the MPA to solve it. The MPA starts the search process by initializing the elite and prey matrix, aiming to search the global optimal solution [17]. The optimization process of the MPA mainly has three stages. Stage 1 is the high Speed Ratio Stage (SRS), which means that the prey moves quicker than the predator [18]. Stage 2 is the equal SRS, where the predator's speed is the same as the prey. Stage 3 is the low SRS, where the predator moves faster than the prey. The three-stage foraging diagram of the MPA is shown in Fig. 3.

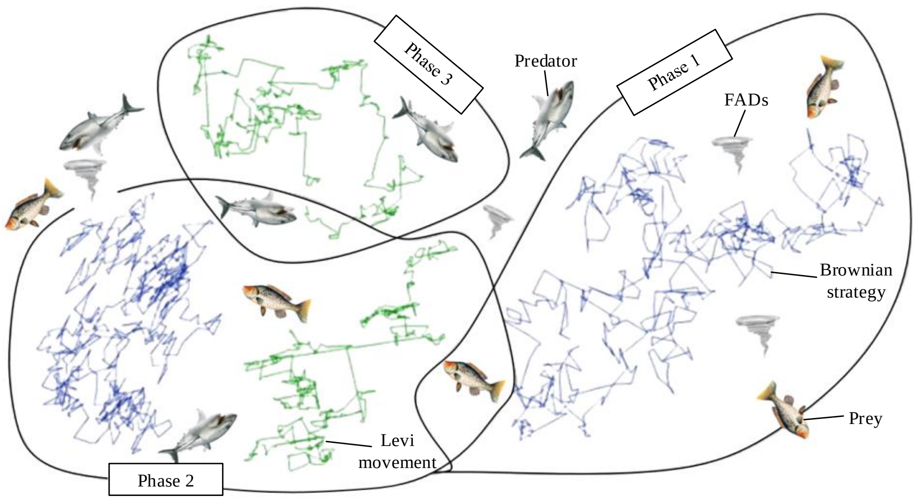


Fig. 3. Three-stage foraging diagram of MPA.

The MPA uses a random initialization approach to generate the origin population, as expressed in Formula (7).

$$X_{i,j}=b_{uj}+r_1(b_{uj}-b_{lj}) \tag{7}$$

In Formula (7), $X_{i,j}=b_{uj}+r_1(b_{uj}-b_{lj})$ means the j-th dimensional position of the i-th prey. b_{uj} and b_{lj} respectively are the upper and lower boundaries of the optimization problem model in the search space of dimension j. r_1 represents a Random Number (RN) with an interval of [0,1]. After generating the first population, the fitness of all individuals is calculated. The elite matrix $\mathbf{E}$ is composed of individuals with the best fitness, while the prey matrix $\mathbf{P}$ contains randomly generated initial solutions. Since one predator may also become the prey of another more advanced predator, it is necessary to update the elite matrix in each iteration [19]. Each predator moves according to $\mathbf{P}$, and $\mathbf{E}$ and $\mathbf{P}$ are shown in Formula (8).

$$\mathbf{E}=\begin{bmatrix} X_{1,1}^I & X_{1,2}^I & \dots & X_{1,d}^I \\ X_{2,1}^I & X_{2,2}^I & \dots & X_{2,d}^I \\ \dots & \dots & \dots & \dots \\ X_{n,1}^I & X_{n,2}^I & \dots & X_{n,d}^I \end{bmatrix}_{n\times d}, \mathbf{P}=\begin{bmatrix} X_{1,1} & X_{1,2} & \dots & X_{1,d} \\ X_{2,1} & X_{2,2} & \dots & X_{2,d} \\ \dots & \dots & \dots & \dots \\ X_{n,1} & X_{n,2} & \dots & X_{n,d} \end{bmatrix}_{n\times d} \tag{8}$$

In Formula (8), n denotes the Population Size (PoS). d is the position of each dimension. In the high SRS, the algorithm mainly performs global search, and the update of the $\mathbf{P}$ is Formula (9).

$$\begin{cases} S_i = R_B \otimes (E_i - R_B \otimes P_i) \\ P_i = P_i + pR \otimes S_i \end{cases}, \text{if } t<\frac{1}{3}T \tag{9}$$

In Formula (9), S_i represents the movement step length between prey and predator. E_i represents the elite matrix constructed by top predators. R_B represents the standard Brownian motion. $\otimes$ represents Hadamard product. P_i represents a $\mathbf{P}$ with the same dimension as the elite matrix. p represents a variable with a default value of 0.5. R represents a uniform random vector (RV) within [0,1]. t and are the current and maximum iterations. In the equal SRS, the update of the $\mathbf{P}$ is Formula (10).

$$\begin{cases} S_i = \begin{cases} R_L \otimes (E_i - R_L \otimes P_i), i=1,2,\dots,n/2 \\ R_B \otimes (R_B \otimes E_i - P_i), i=n/2,\dots,n \end{cases}, \text{if } \frac{1}{3}T \le t \le \frac{2}{3}T \\ C_F = (1-t/T)^{\frac{2t}{T}} \\ P_i = \begin{cases} P_i + pR \otimes S_i, i=1,2,\dots,n/2 \\ E_i + pC_F \otimes S_i, i=n/2,\dots,n \end{cases}, \text{if } \frac{1}{3}T \le t \le \frac{2}{3}T \end{cases} \tag{10}$$

In Formula (10), C_F represents Levi's motion, which is an RV that follows a Lévy distribution. C_F represents an adaptive parameter that gradually decreases as the iterations increase, utilized to control the predator's step size. In the low SRS, the update of $\mathbf{P}$ is Formula (11).

$$\begin{cases} S_i = R_L \otimes (R_L \otimes E_i - P_i) \\ P_i = E_i + pC_F \otimes S_i \end{cases}, \text{if } \frac{2}{3}T < t \tag{11}$$

Environmental issues like vortex formation and Fish Aggregating Devices (FADs) effects can also cause influences in marine predators behaviors, which can be considered as local optima [20]. After each iteration, the FADs effect is applied to each marine predator by perturbing the local optimal solution, with a FADs value of 0.2. The FADs effect is Formula (12).

$$P_i = \begin{cases} P_i + C_F[X_{\min} + R \otimes (X_{\max} - X_{\min})] \otimes U, r_2 \le 0.2 \\ P_i + [0.2(1-r_2) + r_2](P_{n1} - P_{n2}), r_2 > 0.2 \end{cases} \quad (12)$$

In Formula (12), U represents a binary vector containing arrays of 0 and 1. r_2 represents a uniform RN with a value range of [0,1]. r_2 and P_{n2} represent two randomly selected prey. In addition, the MPA also has a memory saving operation, which can lift the solution quality through iteration. Specifically, if the updated solution is not as good as the historical solution, the current solution will be replaced. The process of MPA algorithm is shown in Fig. 4.

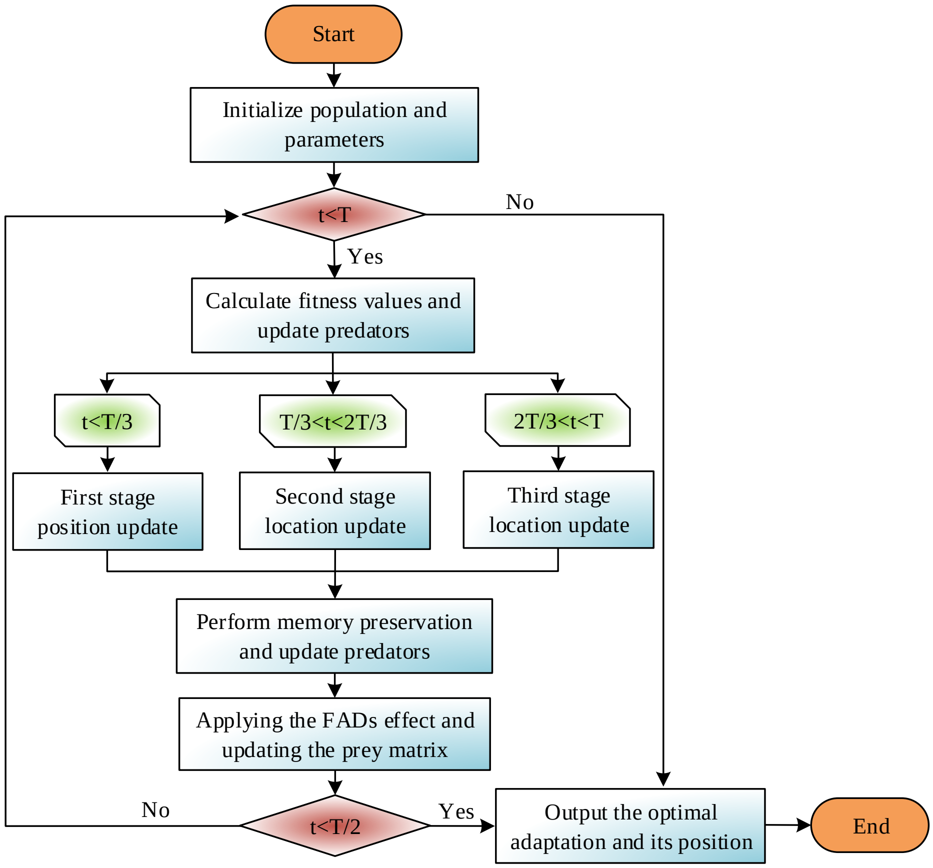


Fig. 4. The flowchart of MPA.

However, the MPA also has limited global exploration capabilities and is prone to getting stuck in local optima, so it is necessary to make phased improvements to the MPA. To increase the diversity of the population, this study applies logistic chaotic mapping to the initial population generation of the algorithm, as shown in Formula (13).

$$X_{n+1} = \mu X_n (1 - X_n) \quad (13)$$

In Formula (13), X_n represents the value generated by the n-generation chaotic sequence. μ represents the parameter, take $\mu = 4$. Refractive reverse learning is based on reverse learning and combined with the law of refraction of light to find better candidate solutions [21]. In the first stage of the MPA, this study selects prey with generally poor fitness for position updates, as shown in Formula (14).

$$P_{i,j}^* = \frac{a_j + b_j}{2} + \frac{a_j + b_j}{2k} - \frac{P_{i,j}}{k} \quad (14)$$

In Formula (14), $P_{i,j}$ is the value of the i-th prey in the j-th dimension of the current population. $P_{i,j}^*$ is the solution formed by $P_{i,j}$ through refraction reverse learning. a_j and b_j are the max and min values of the current prey population in the j-th dimension. k represents the ratio of the length of the incident light to the length of the refracted light. The Golden Sine Algorithm (GSA) can speed up the convergence. In the second stage of this study, the GSA and Sparrow Search Algorithm (SSA) are fused using the follower approach of SSA, and the fused position is updated as shown in Formula (15).

$$P_i = X_i^t + Q \exp\left(\frac{X_{worst}^t - X_i^t}{i^2}\right) \quad (15)$$

In Formula (15), X_i^t means the new position where i particles are updated according to the golden ratio after the second stage update. X_{worst}^t represents the worst global position. Q represents an RN that follows a normal distribution. The basic idea of Gaussian mutation is to randomly perturb an individual's genes, causing a certain degree of variation in the solution space, thereby enhancing the algorithm's global search ability. To avoid the MPA getting stuck in local optimum, this study uses Gaussian mutation in the latter half of the iteration to replace the original FADs effect.

The expression of the new solution $P_{i,j}$ generated after Gaussian mutation is Formula (16).

$$m(P) = P(1 + N(0,1)) \tag{16}$$

In Formula (16), P represents the current solution. $N(0,1)$ represents a normally distributed RN with an expected value of 0 and a standard deviation of 1. In summary, the process of the proposed improved MPA is shown in Fig. 5.

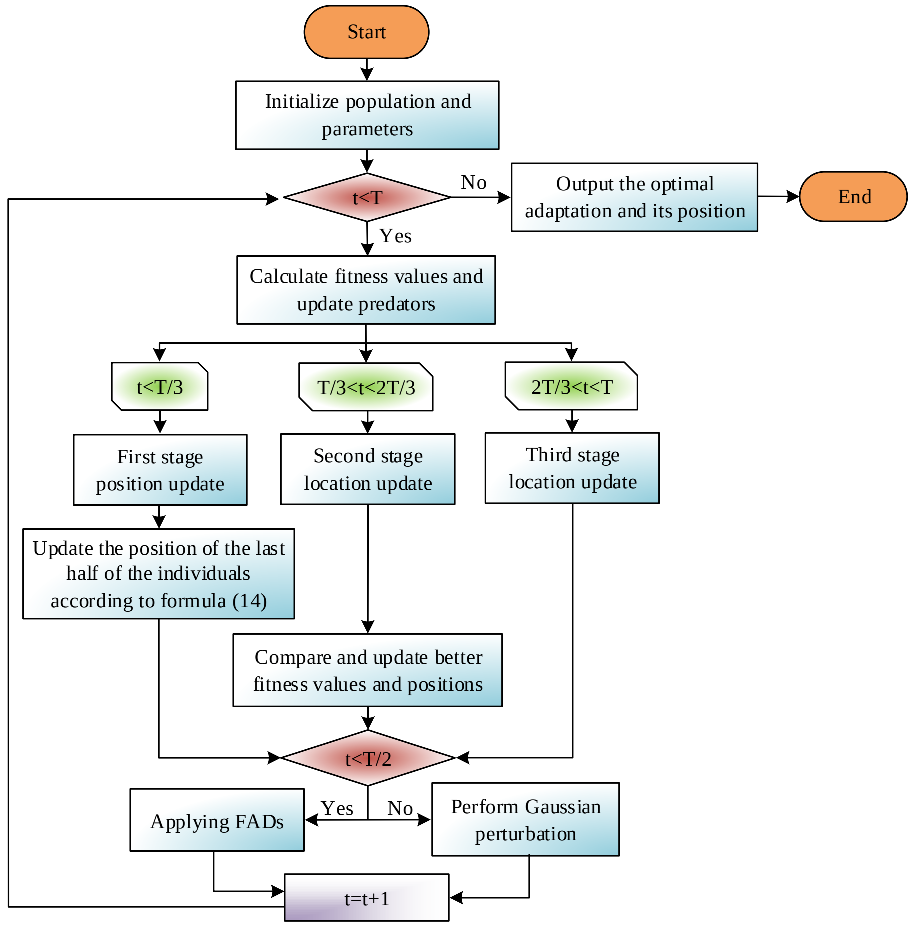


Fig. 5. The flowchart of improved MPA.

III. Results

To reduce environmental pollution in the SC, this study constructs a GSC network problem model with complex constraints and proposes an improved MPA for solving the problem of the proposed model. However, its actual application effect still requests deeper verification. This study analyzes from two points. Firstly, the performance of the improved MPA is analyzed, and then the application effect of the improved MPA in GSC management optimization is verified.

A. Performance Analysis of Improved MPA

To verify the improved MPA performance, this study conducts simulation comparative experiments using four common Benchmark Test Functions (BTFs). Among them, there are two Unimodal Testing Functions (UTF) and two Multi-Modal Testing Functions (MTF). UTF is used to verify the convergence speed, while MTF is taken to verify the global optimization performance and convergence accuracy. Table I shows the expressions for the four benchmark functions. In Table I, functions 1 and 2 are UTF, and functions 3 and 4 are MTF.

This study sets 50 PoS and the 30 benchmark function dimension. The improved MPA is compared with traditional MPA, PSO, Grey Wolf Optimizer (GWO), and SSA. The comparison results of the standard deviation and mean of the 5 algorithms are shown in Table II. The improved MPA performs better than the other four algorithms on all four BTFs. Except for the mean value of 2.17×10^{-202} when solving function 1, the standard deviation and mean of the improved MPA on the other three functions are all 0, indicating that it has good convergence accuracy. This indicates that the improved MPA has good convergence accuracy in handling single-extreme and multi-extreme problems, can find the optimal solution of the BTF, and has a small standard deviation, which has a certain feasibility and effectiveness.

The convergence process of the above five algorithms in solving the BTF is shown in Fig. 6. In Fig. 6 (a) and Fig. 6 (b), the improved MPA has the fastest convergence speed when solving UTF. When the iteration is around 420, the fitness of the BTF can reach the minimum value. In Fig. 6 (c) and Fig. 6 (d), the convergence speed of the improved MPA is still the fastest when solving MTF, and the difference is more obvious. A more optimal solution can be obtained with the least number of iterations. This indicates that the improved MPA has good convergence speed and GOA, with good optimization performance and certain feasibility and superiority.

TABLE I. EXPRESSION OF BENCHMARK FUNCTION

Number	Expression	Variable interval	Minimum value
Function 1	$f(x)=\sum_{i=1}^{n} ix_i^2$	[-5.12,5.12]	0
Function 2	$f(x)=\max\{\lvert x_i\rvert, 1\le i\le n\}$	[-100,100]	0
Function 3	$f(x)=\sum_{i=1}^{n}\left[x_i^2-10\cos(2\pi x_i)+10\right]$	[-32,32]	0
Function 4	$f(x)=\sum_{i=1}^{n}\left[x_i^2-10\cos(2\pi y_i)+10\right]$ $y_i=\begin{cases} x_i, \lvert x_i\rvert<0.5 \\ \frac{round(2x_i)}{2}, else \end{cases}$	[-5.12,5.12]	0

TABLE II. COMPARISON OF STANDARD DEVIATION AND MEAN OF FIVE ALGORITHMS

Number	Index	MPA	SSA	PSO	GWO	Improve MPA
Function 1	Standard deviation	3.46×10^{-23}	1.20×10^{-6}	7.24×10^{3}	3.07×10^{-33}	0
	Mean value	2.86×10^{-23}	5.96×10^{-7}	4.27×10^{4}	1.63×10^{-33}	2.17×10^{-202}
Function 2	Standard deviation	3.56×10^{-61}	8.49×10^{-13}	0.26	1.87×10^{-115}	0
	Mean value	6.23×10^{-62}	1.23×10^{-13}	0.63	5.02×10^{-116}	0
Function 3	Standard deviation	0	1.67×10^{-6}	27.55	2.83	0
	Mean value	0	6.33×10^{-7}	4.21×10^{2}	1.71	0
Function 4	Standard deviation	2.55	1.53×10^{-6}	3.56×10	3.30	0
	Mean value	0.45	7.53×10^{-7}	3.99×10^{2}	5.15	0

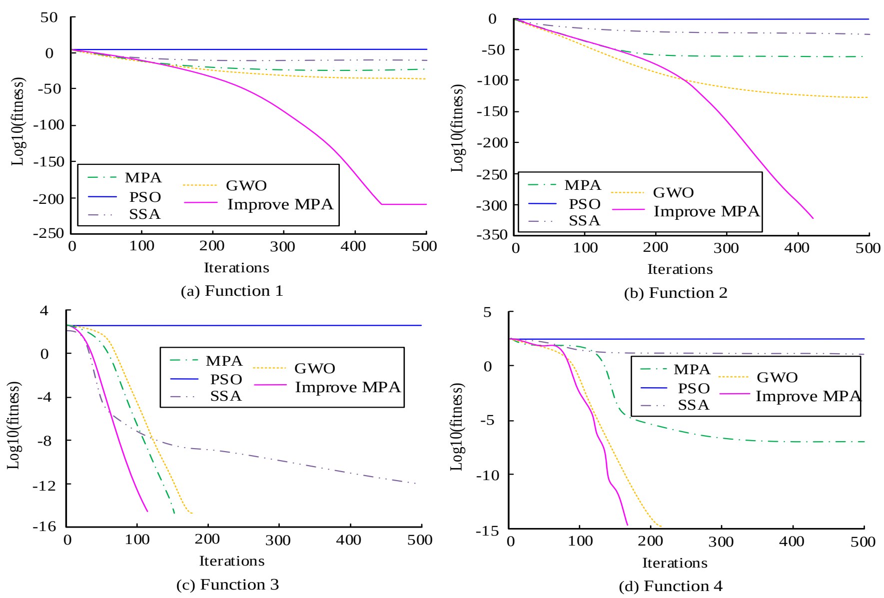


Fig. 6. The convergence process when solving BTFs.

B. GSC Management Optimization Analysis

To test the improved MPA performance in solving GSC network problems, three different scale test sets are designed. Each test set includes three test instances, all of which are obtained through random generation. Table III shows information for three test sets.

TABLE III. INFORMATION ON THREE TEST SETS

Number	Test set 1	Test set 2	Test set 3
S1	6	5	3
S2	6	4	2
M	8	5	4
W	6	5	2
C	10	6	5
Dimension	204	100	38
Run time/s	300	120	40

This study first conducts experiments on a smaller scale test set 3. The PoS and FADs are set to 150 and 0.2. The research algorithm is compared with MPA, Competitive Swarm Optimizer (CSO), and Social Learning Particle Optimization (SLPSO) [22]. Each algorithm runs independently 25 times. The best and average experimental results of the above four algorithms on test set 3 are displayed in Fig. 7. In Fig. 7 (a) and Fig. 7 (b), in a small-scale test set, the improved MPA is able to find the best solution for the test instance, with average values of 139,832.97 yuan, 148,561.28 yuan, and 147,535.81 yuan, respectively. Next are MPA and SLPSO, with CSO performing the worst. The data shows that the improved MPA can find a feasible solution to the GSC network problem with the lowest total cost, and has a good GSC management optimization effect.

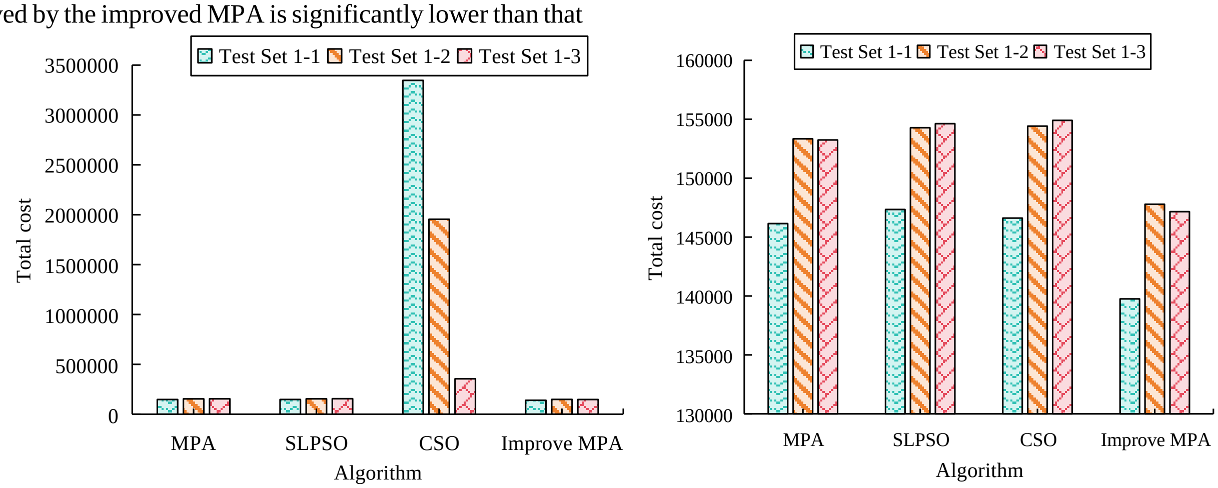
This study further conducts experiments on a medium-sized test set 2, where the CSO algorithm fails to successfully solve the GSC network problem on the instance set of small test set 2 due to insufficient performance, as exhibited in Fig. 8. In Fig. 8 (a), (b), and (c), in the three instance sets on test set 2, the total cost solved by the improved MPA is significantly lower than that of traditional MPA and SLPSO, and the results obtained are more concentrated. This indicates that the improved MPA has shown good application results in solving GSC network problems and has good stability.

To further analyze the convergence of the improved MPA, this study compares the convergence curves of the four algorithms on three test sets (Fig. 9). Fig. 9 (a), Fig. 9 (b), and Fig. 9 (c) show that, the improved MPA has the fastest convergence speed and successfully converges to feasible solutions in three different scale test sets. In small-scale test sets, it tends to converge at 15 iterations. In large-scale datasets, the other three algorithms have not successfully converged to feasible solutions. In addition, the total cost obtained by improving the MPA is significantly lower than the other three algorithms. Therefore, improving the MPA has good solving performance for GSC network problems of different scales, and can successfully converge to feasible solutions, which have certain practical application value.

To further verify the application effect of the proposed improved MPA algorithm, the research uses Hyper-volume (HV) as the evaluation index and compares it with the current progressiveness Non-dominated Sorting Genetic Algorithm II (NSGA-II), Decomposition-based Multi-objective Evolutionary Algorithm (MOEA/D) and Non-dominated Sorting and Local Search (NSLS) [23-25]. The comparison results of the HV indicators of the four algorithms in the larger test set 1 are shown in Table IV. Among the four algorithms, the improved MPA algorithm achieves the best results on all test cases, with the highest HV index of 1.57E+06.

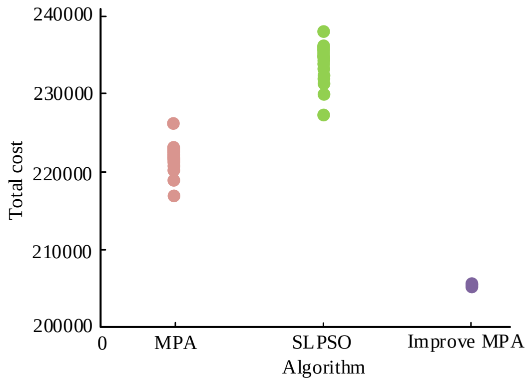
TABLE IV. COMPARISON RESULTS OF HV INDICATORS OF ALGORITHMS IN TEST SET 1

Test Examples	NSGA-II	MOEA/D	NSLS	Improved MPA
1	1.52E+06	9.80E+05	6.59E+05	1.57E+06
2	1.37E+06	8.17E+05	5.91E+05	1.42E+06
3	1.20E+06	7.26E+05	5.17E+05	1.23E+06

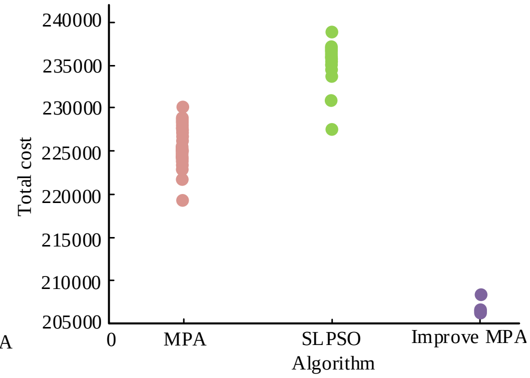


(a) Average value (b) Optimal value

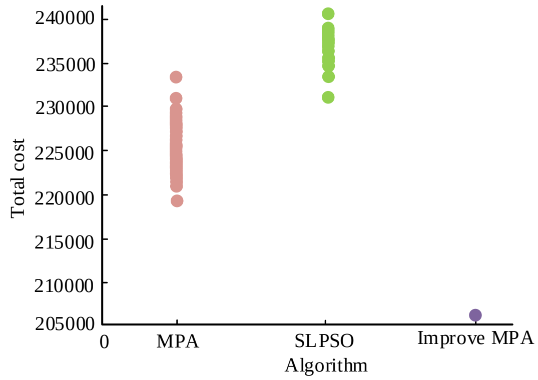
Fig. 7. Best and average experimental results on test set 3.



(a) Test Set 2-1

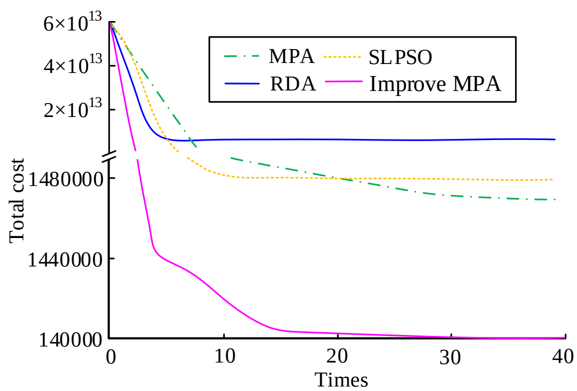


(b) Test Set 2-2

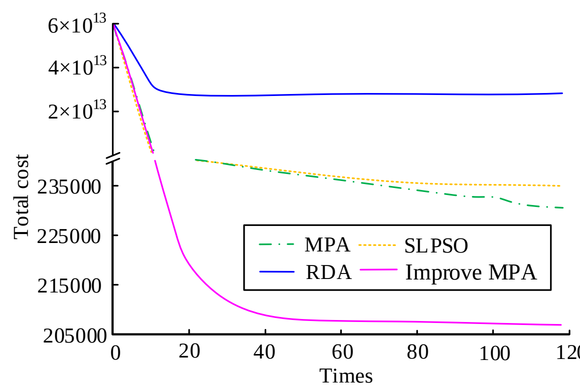


(c) Test Set 2-3

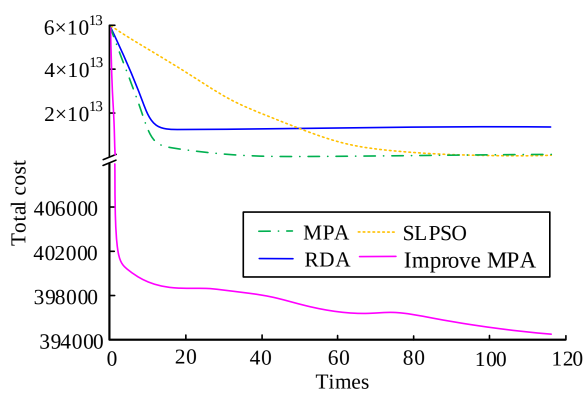
Fig. 8. Experimental results on test set 2.



(a) Test Set 1



(b) Test Set 2



(c) Test Set 3

Fig. 9. Convergence curves of four algorithms on three test sets.

IV. Discussion and Conclusion

GSC management, as a modern management model that can achieve both economic and environmental benefits, is the only way for enterprises to achieve green development. Despite the implementation of a series of policies and measures designed to encourage enterprises to engage in GSC management, the level of enthusiasm among enterprises to actively participate in this practice remains relatively low, thereby posing a significant challenge to the promotion of GSC management [26]. Previous studies have shown that establishing a GSC network model based on actual conditions and solving the model is an effective method to reduce costs and carbon emissions [27]. Therefore, to reduce environmental pollution in the SC, this study constructed a GSC network problem model with complex constraints and proposed an improved MPA for solving the model problem.

The experimental data validated that the improved MPA performed more excellently than the other algorithms on all four benchmark test functions. The standard deviation and mean of the improved MPA on the other three functions were all 0, except for the mean of 2.17×10^{-202} on solving function 1. When solving MTF, the convergence speed of improved MPA was still the fastest, and the difference was more obvious. In small-scale test sets, improving MPA could find the best solution for test instances, with average values of 139832.97 yuan, 148561.28 yuan, and 147535.81 yuan, followed by MPA and SLPSO, with CSO performing the worst. On the medium-scale test set, the total cost solved by improved MPA was significantly lower than that of traditional MPA and SLPSO, and the results obtained were more concentrated. This indicates that compared with the algorithm proposed in the study [22], the improved MPA algorithm has better application effects in solving GSC network problems, can find feasible solutions with the minimum total cost, and has good stability. In three different scale test sets, the convergence speed of the improved MPA was the fastest and successfully converged to feasible solutions. The cost of improving the MPA solution was significantly lower than the other three algorithms. In addition, the improved MPA algorithm achieved the best results on all test cases, with an HV index of 1.57E+06. The solving performance on all test cases was superior to the algorithms proposed in studies [23], [24], and [25], demonstrating certain superiority. In summary, the research algorithm has good performance in solving GSC network problems. However, the factors considered in designing the GSC network in this study are not yet comprehensive compared to the entire SC. Therefore, in future research, further consideration should be given to uncertain factors such as price fluctuations to build a more realistic and comprehensive GSC network.

V. Funding

The research is supported by Humanities and Social Science Research Project of Chongqing Education Commission, “Research on the mode and path of rural industry revitalization enabled by digital economy in the Three Gorges Reservoir Area of Chongqing”, (No. 23SKGH459)

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