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Research on Supply Chain Optimization Path and Economic Benefit Enhancement of Manufacturing Enterprises Based on Intelligent Algorithm

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Abstract Aiming at the supply chain path optimization problem of manufacturing enterprises, this paper constructs a multi-objective model based on the total cost of supply chain and carbon emission. Based on the traditional ant colony algorithm, the hybrid ant colony algorithm incorporates the uniparental genetic algorithm to improve the convergence speed of the algorithm and save computing resources. The example experiment verifies that the uniparental genetic hybrid ant colony algorithm outperforms the basic ant colony algorithm and the chaotic ant colony algorithm. A residential construction enterprise project in X province is selected as the research object, and the uniparental genetic hybrid ant colony algorithm is used to realize the multi-objective optimization of assembly building supply chain cost-carbon emission. The optimal total cost and carbon emission of the supply chain solved by this paper's method are 1196101 yuan and 252721 kgCO_2 respectively, which are better than that of the chaotic ant colony algorithm. The optimization of the assembly building supply chain with both economic and environmental benefits is realized, which provides decision-making guidance for the production plan of assembly building supply chain.

Index Terms Multi-objective model, Ant colony algorithm, Uniparental genetic algorithm, Supply chain path optimization

I. Introduction

With the acceleration of global economic integration, manufacturing enterprises are facing the pressure of rising costs while coping with market uncertainties, resource shortages and increasingly stringent environmental policies [1], [2]. In this context, the competition among manufacturing enterprises has become increasingly fierce, and more and more leading enterprises in the industry are constantly upgrading and optimizing their supply chain networks in order to be able to excel in the fierce competition [3]-[5]. As one of the important components of resource consumption and promotion of social development, the design of supply chain network has become a hot issue that focuses on countries around the world.

Traditional cost control methods are no longer sufficient to cope with the modern complex supply chain structure and technological environment, and the modern cost control system needs to be combined with diversified means such as supply chain management, informatization system and lean production to achieve the maximization of enterprise benefits [6]-[8]. All parties in the traditional supply chain network, such as material suppliers, product manufacturers, transporters of inventory and retailers, operate independently, and they have their own goals, which sometimes conflict with each other [9], [10]. Therefore, how to construct a more rational and efficient supply chain network model has received much attention from academics, and the speed of information exchange and processing is increasingly important in the data era [11], [12]. At the same time, how to widely apply technologies such as the Internet of Things, big data and information platforms to some manufacturing enterprises to improve operational efficiency and bring economic benefits has also been highly valued by academics [13], [14].

Some scholars have proposed relevant cost control models to help enterprises reduce production costs and thus improve the market competitiveness of their products. Liao, J. and Lin, C. show that the optimization of job shop supply chain scheduling in manufacturing enterprises will have a direct impact on the production efficiency and resource utilization of enterprises, and propose to combine particle swarm optimization algorithm and simulation computing platform to solve the optimal scheme of job shop supply chain, which provides theoretical references to the production process of manufacturing enterprises [15]. Tian, Q. and Guo, W. proposed a graph-based cost-optimization allocation model for manufacturing supply chain networks to provide decision support for manufacturing system and supply chain reconfiguration for manufacturing enterprises facing large-scale production and manufacturing demands by fully considering cost, risk and other factors [16]. Ehtesham Rasi, R. and Sohanian, M. integrated economic, social and environmental dimensions into the process of supply chain network design and optimization in manufacturing firms, and used multi-objective genetic algorithms and multi-objective particle swarm algorithms to solve the constructed mixed-integer linear programming models in order to obtain a supply chain design solution that maximizes the sustainability index [17]. Chong, J. W. et al. designed a deep reinforcement learning approach for apparel supply chain optimization, and the proposed Soft Actor-Critic model can achieve efficient inventory management while meeting sales and production demands, thus helping manufacturing companies to obtain high economic benefits [18]. Nezamoddini, N. et al. constructed a risk-based supply chain optimization framework that combines artificial neural networks with stochastic optimization models for solving the challenges faced by electronics supply chains such as fuzzy customization demands, shorter life cycles, and high inventory costs to provide the most economically efficient strategies for supply chain stakeholders [19]. Although the supply chain optimization models based on intelligent algorithms proposed in the above studies play an important role in assisting the decision-making of manufacturing enterprises, most of the models only consider the economic benefits of single products and materials. Since the production process of manufacturing enterprises involves a large number of inputs such as raw materials, labor, equipment and energy, and the waste in any one of these processes may lead to an increase in cost and erosion of the profit margin of the enterprise, further research is necessary.

This paper studies the supply chain path optimization problem of manufacturing enterprises, constructs a multi-objective supply chain optimization model based on multi-objectives, and solves the model using the improved ant colony algorithm. The model fully considers the carbon emissions and total supply chain costs generated during the production and construction phases of manufacturing projects. The uniparental genetic hybrid ant colony algorithm is utilized to improve the stability of the algorithm on the basis of improving the computational performance. Case experiments are conducted to verify the performance of the algorithm in three aspects, namely, optimization ability, reliability and convergence speed, stability and robustness. Practical cases are used to explore the effectiveness of the algorithm in solving the multi-objective model of total supply chain cost and carbon emission.

II. Supply chain optimization path model

II. A. Model assumptions

The raw materials of the enterprise are supplied by several suppliers in different regions, and the products are sold to customers in different regions. The supply chain network includes raw material logistics, organization of production, product distribution, etc [20], the specific structure is shown in Figure 1.

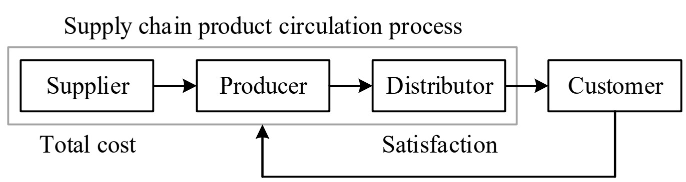


Figure 1: Schematic diagram of supply chain structure

Modeling assumptions are made for the supply chain with the following known conditions:

(1) Loss costs and maximum capacity of raw material suppliers.

(2) Geographic locations of raw material suppliers and distributors.

(3) The quantity of products ordered by customers and their satisfaction with the products.

(4) Mode and cost of transportation of raw materials and products.

(5) Carbon emission index of raw material suppliers and product distributors.

II. B. Objective function

II. B. 1) Cost objective function

The total supply chain cost can be expressed as:

$$C_1 = \sum_{i=1}^{I} X_i C_{i0} + \sum_{j=1}^{J} Y_j C_j + \sum_{i=1}^{I}\sum_{j=1}^{J} X_{ij} S_{1ij} + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{t=1}^{T} Q_{jlkt} S_{2jlkt} \tag{1}$$

In Eq. (1), i represents the manufacturer, $i=1,2,\cdots,I$, j represents the distributor, $j=1,2,\cdots,J$, l represents the product variety, $l=1,2,\cdots,L$, k represents the customer, $k=1,2,\cdots,K$, t represents the mode of transportation, $t=1,2,...,T$, X_i represents the output of the raw material manufacturer, C_{i0} represents the production cost of the manufacturer i, Y_j represents the distribution volume of the distributor j, C_j represents the distribution cost of the distributor j, X_{ij} represents the amount of product shipped by the manufacturer i to the distributor j, S_{li} represents the unit transportation cost of the manufacturer i to the distributor j, and Q_{jlkt} represents the distributor j The quantity of goods l from t to customer j by shipping, S_{2jlkt} represents the unit shipping cost of l of goods l from distributor j to customer k by shipping t.

II. B. 2) Carbon emission objective function

In this paper, the whole process of a manufacturing project is divided into four stages: planning, production, construction and operation. The carbon emissions generated in the production and construction phases account for about half of the whole cycle and are the main source of the whole project cost. Therefore, in order to guarantee the diversity and completeness of the study of the supply chain body, the accounting scope of the manufacturing project supply chain is delineated and defined into five stages, namely, the production stage, the transportation stage, the component production stage, the component transportation stage and the construction stage.

Based on the five stages of the project: production stage (CE_1), transportation stage (CE_2), component processing stage (CE_3), component transportation stage (CE_4) and construction stage (CE_5), the total carbon emissions of the project supply chain are calculated as shown in equation (2). Based on the carbon emission coefficient method, the carbon emissions of the five stages of the supply chain of the project are measured separately, and the total carbon emissions of the supply chain of the project are calculated as shown in equation (2):

$$F_{CE} = CE_1 + CE_2 + CE_3 + CE_4 + CE_5 \tag{2}$$

Eq:

F_{CE} - total supply chain carbon emissions.

CE_1 - production carbon emissions in the supply chain.

CE_2 - transportation carbon emissions in the supply chain.

CE_3 - Carbon emissions from component processing in the supply chain.

CE_4 - Carbon emissions from transportation of components in the supply chain.

CE_5 - carbon emissions from construction in the supply chain.

(1) Production Phase

Within the supply chain of the project, the carbon emissions calculated in the production phase (CE_1) mainly include the carbon emissions generated by the raw material suppliers providing various types of prefabricated components factory, and a large amount of energy and materials will be consumed in the production process. The usage amount can be obtained by checking the bill of quantities, in addition, in the actual production process, even under the premise of saving and rational use of materials, it is still inevitable to produce a certain amount of material loss. Therefore, in order to calculate carbon emissions more accurately, add a loss factor to be corrected, and the consumption rate can be obtained by querying the quota. The details are shown in equation (3):

$$CE_1 = \sum_{j=1}^{n} U_j^{pc} \times (1+\theta_j) \times f_j \tag{3}$$

where j - number of species, U_j^{pc} - total amount of the jth species supplied by the raw material supplier to the precast plant, (t/m³), θ_j - material loss rate, f_j - CO_2 emission factor of the j th species, (kgCO_2e/t).

(2) Transportation Phase

The carbon emissions generated by the transportation phase of the project come from the energy consumed by the means of transportation in the process of transporting the components to the component factory. The weight, the choice of transportation mode and the distance of transportation are the key factors affecting the carbon emissions in this phase. Therefore, in order to accurately calculate the carbon emissions of (CE_2) in the transportation phase of the manufacturing project, Equation (4) is used for calculation:

$$CE_2 = \sum_{j=1}^{n}\sum_{k=1}^{n} U_j \times (1+\theta_j) \times D_{j,k} \times f_k \tag{4}$$

k - number of types of transportation modes, $D_{j,k}$ - average transportation distance for the j th k th mode of transportation, (km), f_k - carbon emission factor for transportation distance per unit weight for the k th mode of transportation, ($kgCO_2e$/t·km).

(3) Component processing stage

In the component processing stage, the carbon emission mainly comes from the power and energy consumed by all kinds of machinery, machineries and equipments in operation, and the machinery and equipments used in the component production process of this project mainly include oil sprayer, concrete mixer, concrete vibration uncoverer, smoothing machine, autoclave kiln and so on. In addition, from the point of view of staffing, precast component factory as a labor-intensive industry, the reasonable allocation and scheduling of workers also has an impact on carbon emissions. There is no uniform standard for the current labor carbon emission factor, and this paper refers to a large number of literature and selects the average value as the carbon emission factor, with a value of 0.460$kgCO_2$/(man-workday). Therefore, the carbon emission (CE_3) of the component processing stage of the project mainly originates from the energy consumed by the operation of personnel and the operation of mechanical equipment in the production process. The specific calculation formula is shown in (5):

$$CE_3 = \sum_{i=1}^{n} T_i \times S_i \times f_j + \sum_{j=1}^{n} R_j F_r \tag{5}$$

S_i - power of the i th machinery operation, (kw), T_i - the use time of the i th kind of machinery operation, (h), f_i - carbon emission factor of energy consumption of the i th machinery, ($kgCO_2e$/unit), R_j - number of workers required for the j th process, (man-days), F_r - carbon emission factor for personnel activities, ($kgCO_2e$/person-workday).

(4) Component transportation stage

The boundary of carbon emission calculation of component transportation stage is from the beginning of loading prefabricated components in the factory to the end of unloading in accordance with the established position, and the process of transportation to the construction site by means of transportation. Considering the vertical transportation, the use of mechanical energy consumption is more comprehensive consideration of transportation routes, transportation vehicle selection and other factors, to avoid the loss of cost of secondary transportation. The specific carbon emissions at this stage (CE_4) formula shown in (6):

$$CE_4 = \sum_{k=1}^{n} (L_k \times W_c) \times f_k \tag{6}$$

L_k - Average distance of transportation of precast components under the k type of transportation, (km), W - weight of precast concrete required for the manufacturing project supply chain to undertake the project, (t), f_k - Carbon emission factor for transportation distance per unit weight under the k th mode of transportation, $kgCO_2e$/(t·km).

(5) Construction phase

The main carbon emissions during the construction phase originate from the energy consumption of construction machinery and equipment as well as the operation of the labor force. Although the water and electricity consumption in the office and living area of the construction site also generates a certain amount of carbon emissions, the amount is relatively small compared to the carbon emissions directly generated in the construction operation, and this part of carbon emissions is not considered in this paper. The formula for calculating carbon emissions from energy consumption of machines and labor activities during the construction phase is similar to that of the component processing process. By applying the construction quotas, it is possible to determine the model, number, and number of shifts of construction machinery required for different processes, as well as the number of man-days required for each process. Based on these data, Equation (7) is used to calculate the carbon emissions during the construction phase of a manufacturing project (CE_5):

$$CE_5 = \sum_{i=1}^{n} T_i \times S_i \times f_j + \sum_{j=1}^{n} R_i F_r \tag{7}$$

S_i - power of operation of the i th construction machine, (kw), T_i - time of operation and utilization of the i th construction machine, (h), f_i - carbon emission factor of energy consumed by the i th type of machinery, (kgCO2e/unit), R_i - the number of workers required for the i th type of construction machinery, (man-days), F_r - carbon emission factor for personnel activities, (kgCO2e/person·workday).

II. B. 3) Overall objective function

In this paper, two core objectives are selected for optimization: one is to strive to achieve the minimization of carbon emissions, and the other is to pursue the minimization of costs, and we strive to select the optimal combination of solutions that can meet the requirements of carbon emission minimization as well as the minimization of costs.

The previous five stages of the manufacturing project assembly building supply chain division, the establishment of the carbon emission objective function formula as shown in (8), (9):

$$\min F_{CE} = \sum_{i=1}^{5} CE_i \tag{8}$$

CF_{CE} - total supply chain carbon emissions, CE_i - supply chain carbon emissions at each stage.

$$\min F_C = \sum_{i=1}^{5} C_i \tag{9}$$

F_C - total supply chain cost, C_i - supply chain cost at each stage.

II. C.Constraints

(1) The production of a manufacturer i in the supply chain cannot exceed the upper limit of that manufacturer's production:

$$X_i \le A_{i,\max} \tag{10}$$

In Eq. (6), $A_{i,\max}$ denotes the upper limit of the production volume of the manufacturer i.

(2) The maximum sales volume of distributor j cannot exceed the upper limit of the sales volume of that distributor:

$$Y_j \le B_{j,\max} \tag{11}$$

In equation (7), $B_{j,\max}$ denotes the upper limit of the sales volume of distributor j.

(3) The goods l sold from distributor j to customers by all modes of transportation cannot exceed the maximum sales volume of distributor j.

(4) All sales from distributor k to customer k by all modes of transportation cannot exceed the maximum quantity demanded by that customer.

(5) The product l sold by distributor j to customer k by mode of transportation t cannot exceed the maximum volume of that mode of transportation.

III. Model solving based on improved ant colony

III. A. Optimization of Ant Colony Algorithm

Based on the problem of low computational efficiency and poor convergence of ant colony algorithm in solving the multi-objective optimization problem of carrier paths [21], this time, we use the uniparental genetic hybrid ant colony algorithm to provide high algorithmic stability based on the improvement of computational performance.

Let the number of ants in the nest be R, the set of elements to be optimized be D, and $D\varphi_i$ be the i th element in D. In order to obtain the initial solution of the population, let the number of all optimization parameters in this transportation model be n, and the element φ_i in D has K sub-elements. The pheromone of element j in the initial solution can be expressed as $\zeta_j(D_{\varphi_i})(0)$.

To distinguish the probability magnitude of different values, the parameters of ant t are calculated as shown in equation (12):

$$K(\zeta_j^t(D\varphi_i)) = \frac{\zeta_j(D\varphi_i)}{\sum_{i=1}^{n}\zeta_j(D\varphi_i)} \tag{12}$$

Elements from the set D_{φ_i} with large probability are selected and adjusted as shown in equation (13). The $\Delta\zeta_j(D_{\varphi_i})$ denotes the information increment on the element φ_i, i.e., the sum of all pheromones passing through this element, and is computed, as shown in Eq. (14):

$$\zeta_j(D\varphi_i)(t+\Delta) = \zeta_j(D_{\varphi_i})(t) + \Delta\zeta_j(D_{\varphi_i}) \tag{13}$$

$$\Delta\zeta_j(D_{\varphi_i}) = \sum_{k}^{R}\Delta\zeta_i^k(D_{\varphi_i}) \tag{14}$$

Repeat the above process up to the iteration count threshold, or so that each ant obtains a unique element and the initial solution of the algorithm is solved.

III. B. Uniparental Genetic Hybrid Ant Colony Algorithm

After obtaining the initial solution, the traditional ant colony algorithm still requires genetic operations, i.e., the use of selection operator, crossover and mutation operator. Problems such as excessive algorithm complexity and premature convergence often occur in the crossover operator. To solve this problem, for the established transportation path model, based on the basic ant colony algorithm, the uniparental algorithm is integrated to improve the convergence speed of the algorithm. The overall framework of the algorithm is shown in Figure 2.

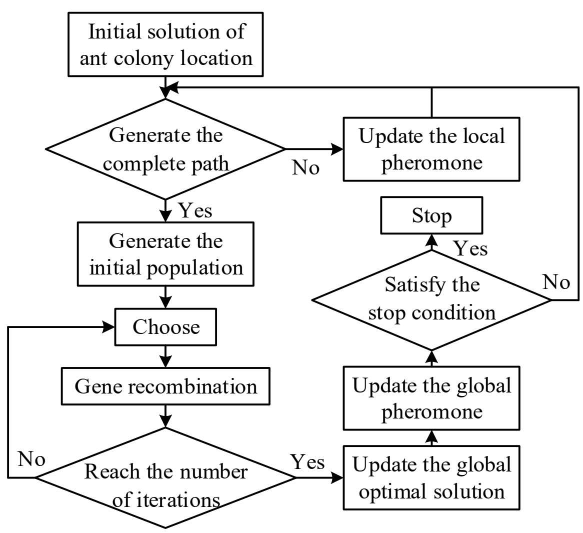


Figure 2: Ant colony - Single-parent genetic algorithm

(1) Based on the initial solution of the optimal path generated above S, $P_1, P_2, P_3, ..., P_d$ and T, set the free links of the nodes as $L_i(i=1,2,....,d)$, and the starting point of the link L_i is $P_i^{(0)}$ and the end point is $P_i^{(1)}$. The other points can be represented as:

$$p_i(h_i) = p_i^{(0)} + (P_l^{(l)} - P_1^{(0)})h_i \tag{15}$$

where the scale parameter h_ið$[0,1], i=1,2,...,d$, d is the number of nodes in the path.

(2) The ant colony algorithm derives the shortest path in discrete space by optimizing the path parameters $\{h_i \mid i=1,2,\cdots,d\}$. There exist m ant operators on the path from the starting point S to the ending point T, and the path cycle is $S \to n_{1j} \to n_{2j} \to ... \to n_{dj} \to T$. where n_{ij} denotes the intersection that exists between the $S \to T$ path and the d th connected j th contour.

(3) The ant operator that is in the L_i path selects the next node based on equation (16):

$$l = \begin{cases} arg\max(|\tau_{ik}|\eta_{ik}^{B}|), l \geq l_0 \\ J, \text{other} \end{cases} \tag{16}$$

where i is the set of all nodes. l is a random number within [0, 1]. l_0 is a variable parameter within [0, 1]. τ_{ik} is a pheromone. n_{ij} is the heuristic value.

(4) Compute j. Calculate the link probability P_{ij} between all nodes i and j as shown in equation (17). Select the next node j based on the probability P_{ij}:

$$P_{ij} = \frac{\tau_{ij}\eta_{ij}^{B}}{\sum_{w \in I}\tau_{iw}\eta_{iw}^{\beta}} \tag{17}$$

where $\tau_{ij} = (1-\rho)\tau_{ij} + \rho\tau_0$. τ_0 is the initial pheromone value.

IV. Model testing and case studies

IV. A. Model testing

In order to test the performance of the monophilic genetic hybrid ACO algorithm for solving the path optimization problem, five classical datasets (Berlin52, Eli51, Eli76) from the path optimization LIB standard library were analyzed by Matlab 2016b using the basic ant colony algorithm (ACO), the chaotic ACO algorithm (CACO) [22], and the monophilic genetic hybrid ACO algorithm (PGHACA), respectively, St70 and Rat99) were analyzed.

In the test, set the number of ant colonies $m = 1-5n$, n is the number of nodes, the number of RNA population update generations $G = 10$, the size of RNA population $NUM = 30$, the probability of permutation operation $P_h = 0.3$, the probability of recombination operation $P_c = 0.2$, the probability of initial stage substitution $P_\alpha = 0.1$, replacement probability variation range $b = 0.1$, total pheromone release $Q = 100$, pheromone importance factor $\alpha \in [1,2]$, heuristic function importance factor $\beta \in [2,5]$, pheromone global volatilization factor $\rho \in [0,1]$.

IV. A. 1) Algorithm optimization capability

The results obtained by ACO, CACO and PGHACA for 20 consecutive solutions for Berlin52, Eli51, Eli76, St70 and Rat99 are shown in Table 1. The optimal solutions are the known optimal values provided in the path optimization LIB standard database. It can be seen that, under the same basic parameter settings, the average values obtained by the uniparental genetic hybrid ant colony algorithm for the five algorithms are smaller than those obtained by the basic ant colony algorithm by 2.01%, 1.8%, 2.25%, 2.19%, 2.85% and smaller than those obtained by the chaotic ant colony algorithm, respectively. The optimal values are 1.5%, 1.36%, 1.92%, 0.85% and 2.23% smaller than the basic ant colony algorithm, which are also smaller than the optimal values obtained by the chaotic ant colony algorithm, indicating that the uniparental genetic hybrid ant colony algorithm's ability of searching for the optimal value is better than the basic ant colony algorithm and the chaotic ant colony algorithm.

Table 1: Experimental results obtained by ACO, CACO and PGHACA

Data set	Optimal solution	Test optimal value			Test mean		
		ACO	CACO	PGHACA	ACO	CACO	PGHACA
Berlin52	7553	7663.584	7596.363	7549.004	7707.752	7619.451	7552.684
Eli51	424	446.168	443.267	440.097	449.707	445.261	441.618
Eli76	529	568.63	567.308	557.733	571.926	569.292	559.058
St70	671	699.557	694.323	693.62	712.318	702.688	696.711
Rat99	1236	1300.905	1296.477	1271.893	1316.714	1308.348	1279.127

The parameters corresponding to the test optimal values obtained by the PGHACA solution are shown in Table 2. For different examples, the parameter combinations that make the algorithm produce optimal solutions are different, indicating that for the basic ACO algorithm, there is no uniform parameter combination that can make it solve all kinds of path optimization problems to obtain the optimal solution.

Table 2: Corresponding parameters of optimum value obtained by PGHACA

Data set	α	β	ρ
Berlin52	1.7	4.58	0.73
Eli51	1.95	4.29	0.44
Eli76	1.1	2.37	0.4
St70	1.08	3.47	0.65
Rat99	1.21	3.85	0.58

IV. A. 2) Algorithm reliability and speed of convergence

The reliability and convergence speed statistics of the results obtained by ACO, CACO and PGHACA for 20 consecutive solvers for Berlin52, Eli51, Eli76, St70 and Rat99, respectively, are shown in Table 3. In terms of reliability, the success rate of PGHACA solving the five algorithms is 100%, which is significantly higher than that of ACO and CACO. In terms of convergence speed, the average number of convergence generations of the five algorithms solved by PGHACA is smaller than that of ACO and CACO, indicating that the reliability and convergence speed of the uniparental genetic hybrid ACO algorithm are better than those of the basic ACO and chaotic ACO algorithms.

Table 3: Statistics of reliability and convergence rate

Data set	Critical value	Success rate			Mean convergence algebra		
		ACO	CACO	PGHACA	ACO	CACO	PGHACA
Berlin52	7641	47%	89%	100%	96.9	70.8	68.3
Eli51	420	41%	69%	100%	95.6	74.9	27.1
Eli76	540	42%	58%	100%	105.6	39.1	32.2
St70	675	22%	46%	100%	124.3	77.4	50.3
Rat99	1280	18%	66%	100%	105.1	105	53.7

IV. A. 3) Algorithm stability and robustness

The stability and robustness statistics of the results obtained by ACO, CACO and PGHACA for 20 consecutive solving of five algorithms respectively are shown in Table 4.The standard deviation and robustness performance ratio of the solving results of PGHACA are smaller than those of ACO and CACO, which indicate that the uniparental genetic hybrid ACO algorithm has better stability and robustness.

Table 4: Statistics of stability and robustness

Data set	Success rate			Mean convergence algebra		
	ACO	CACO	PGHACA	ACO	CACO	PGHACA
Berlin52	51.43	31.22	7.41	0.022	0.011	0.002
Eli51	3.82	3.12	0.45	0.055	0.046	0.034
Eli76	2.03	1.1	1.03	0.064	0.059	0.041
St70	4.24	3.52	2.19	0.055	0.04	0.031
Rat99	7.95	6.8	6.15	0.086	0.081	0.058

Then we take Eli76 as an example, and compare and analyze the specific example from the optimal path obtained by solving the algorithm and the convergence process.

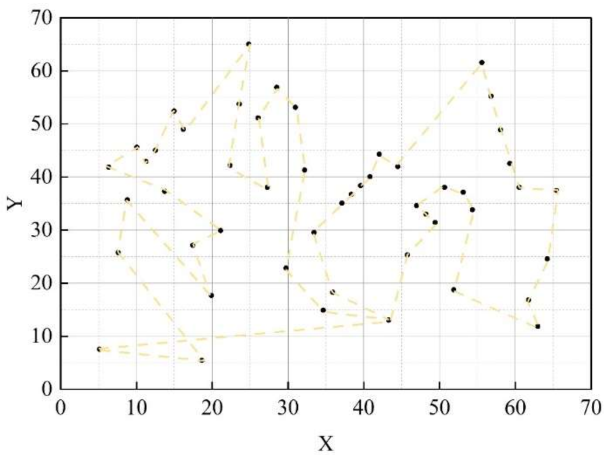
The optimal path obtained by the algorithm solving Eli76 is shown in Fig. 3. (a)~(c) represent the optimal paths solved by ACO, CACO and PGHACA algorithms, respectively. The comparison reveals that the PGHACA algorithm reduces unnecessary crossings and loops and solves a shorter total path.

The convergence process of PGHACA algorithm for solving Eli76 is shown in Fig. 4.The convergence speed and optimization searching ability of PGHACA algorithm are better than that of basic ant colony algorithm and chaotic ant colony algorithm.

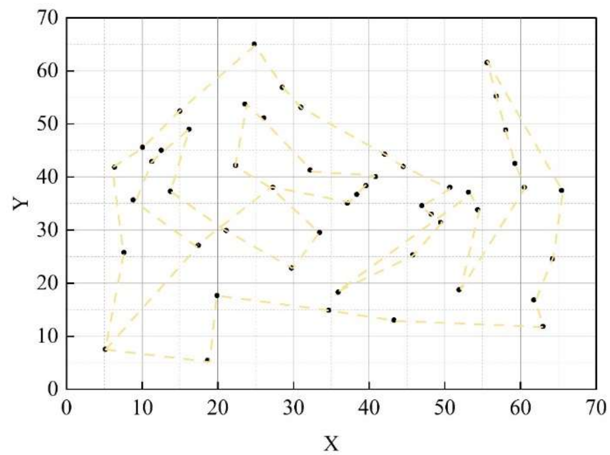
IV. B. Case Studies

IV. B. 1) Case background

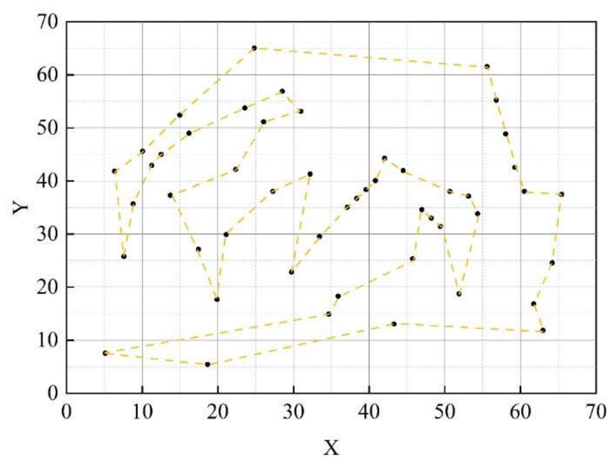
This study selects a representative residential construction enterprise in Province X as the project research object. The building project is a residential building with 33 floors above ground and 1 floor below ground, with a total floor area of 24596.13m2 and a structural system of reinforced concrete shear wall structure. The project adopts prefabrication technology above the 2nd floor, and the prefabricated components are prefabricated beams, prefabricated walls, prefabricated laminated panels, etc. There exists an assembly building supply chain for the building project, and the supply chain service object is the production of components for assembly building, and the main body involves the material supplier, the component producer and the construction site. In order to help the assembly building supply chain choose a better production decision, this paper establishes a multi-objective optimization model of total cost-carbon emission in the assembly building supply chain considering the production capacity constraint, and uses the uniparental genetic hybrid ant colony algorithm to find a satisfactory solution to make the multi-objective optimization problem optimal.



(a) The optimal path for ACO solution



(b) The optimal path for CACO solution



(c) The optimal path for PGHACA solution

Figure 3: The algorithm is solved by solving the optimal path of Eli76

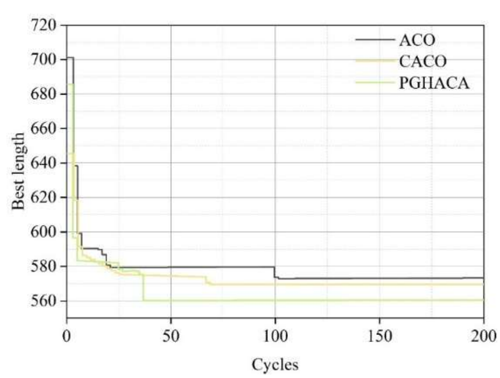


Figure 4: Comparison of convergence process (Eli76)

The component cost of the assembly building project is calculated according to the known data, the depreciation cost, technology cost, labor cost, and management cost used in the molds have been discounted into the unit price of the components, and the total amount of components and raw materials required for the construction project is shown in Table 5.

Table 5: The total amount of components and raw materials required for the project

The main body of the assembly building supply chain	Resource type	Quantity	Unit price
Component manufacturer	Precast column	120	3652 yuan/item
	Precast wall	70	6496 yuan/item
	Precast beam	120	1365 yuan/item
Material supplier	Cement	123652.36kg	463 yuan/t
	Sand	136352kg	45.3 yuan/t
	Pebbles	345625kg	50 yuan/t
	Reinforcement bar	65241kg	43652 yuan/t

The main energy consumption for the production of the assembly building supply chain is shown in Table 6.

Table 6: The assembly building supply chain produces the main energy consumption

The main body of the assembly building supply chain	Resource type	Quantity	Unit price	Carbon factor
Material supplier	Diesel oil	0.13L/m³	6.21 yuan/L	2.61 $kgCO_2/t$
	Electricity	5.52KWh/m³	0.51 yuan/KWh	0.94 $kgCO_2/t$
Component manufacturer	Diesel oil	0.13L/m³	6.21 yuan/L	2.61 $kgCO_2/t$
	Electricity	5.52KWh/m³	0.51 yuan/KWh	0.94 $kgCO_2/t$
Construction site	Diesel oil	0.13L/m³	6.21 yuan/L	2.61 $kgCO_2/t$
	Electricity	5.52KWh/m³	0.51 yuan/KWh	0.94 $kgCO_2/t$

Data on the raw materials required for the production of the components are shown in Table 7.

Table 7: Raw material data for component production

Member	Volume	Required raw material	Number (kg)	Unit price (yuan/kg)	Carbon factor (kg CO2/t)
Precast column	1.06m³	Cement	493.4	0.446	737
		Sand	547.75	0.04225	2.53
		Pebbles	1341.94	0.01263	2.16
		Reinforcement bar	230.51	3.4	2323
Precast wall	1.73m³	Cement	794.88	0.446	737
		Sand	882.18	0.04225	2.53
		Pebbles	2162.05	0.01263	2.16
		Reinforcement bar	260.42	3.4	2323
Precast beam	0.52m³	Cement	224.57	0.446	737
		Sand	249.32	0.04225	2.53
		Pebbles	610.83	0.01263	2.16
		Reinforcement bar	218.16	3.4	2323

Data related to transportation at each stage of the assembly building supply chain is shown in Table 8.

Table 8: Supply chain data

Mode of transport	Load	Carbon factor	Freight
Light gasoline truck	2t	0.325kgCO2/t	2.1 yuan /t/km
Light diesel truck	2t	0.325kgCO2/t	1.6 yuan /t/km
Medium diesel truck	8t	0.163kgCO2/t	3.2 yuan /t/km
Medium power truck	8t	0.013kgCO2/t	3.2 yuan /t/km
Heavy gas truck	18t	0.131kgCO2/t	4.1 yuan /t/km
Heavy diesel truck	30t	0.075kgCO2/t	6.2 yuan /t/km
New energy heavy card	20t	0.01kgCO2/t	11.3 yuan /t/km

IV. B. 2) Case Solving and Analysis

In order to prove that the uniparental genetic hybrid ant colony algorithm has effectiveness in solving the multi-objective optimization model of this paper, this section uses the CPLEX commercial solver and the two algorithms of CACO and PGHACA to solve the established mathematical model on the basis of the acquired case data, and proves that the uniparental genetic hybrid ant colony algorithm has applicability in solving this kind of optimization problem by deriving the solution results of the commercial solver and algorithms.

The relevant data and the optimization objectives and constraints of the established mathematical model are inputted into the MATLAB R2016a software, and the total cost and carbon emissions of each scenario are shown in Table 9.The optimal results of the CACO algorithm and the PGHACA algorithm for solving the supply chain total cost-carbon emission multi-objective optimization model are Scenario 3 and Scenario 6.The optimal supply chain total cost and carbon emission of the PGHACA algorithm are are 1196101 yuan and 252721 $kgCO_2$ respectively, which are 498 yuan and 128 $kgCO_2$ less than Scheme 3 respectively.

Table 9: Assembly building cost - carbon emission optimization solution set

Algorithm	Scheme	Cost (yuan)	Carbon emissions ($kgCO_2$)	Optimized target
CACO	Scheme 1	1189501	253399	Cost optimal
	Scheme 2	1189899	253121	Carbon emissions are optimal
	Scheme 3	1196599	252849	Compromise
PGHACA	Scheme 4	1198900	253430	Cost optimal
	Scheme 5	1189502	253360	Carbon emissions are optimal
	Scheme 6	1196101	252721	Compromise
CPLEX	Scheme 7	1192302	252931	

IV. B. 3) Optimization results

The PGHACA algorithm was used above to solve that Scenario 6 can effectively save the cost of enterprise supply chain and reduce carbon emissions. The number of component producer-construction site components under this scheme is shown in Table 10.

Table 10: Member manufacturer - Number of site components in construction

	Member type	Field (quantity/number)
Member manufacturer 1	Precast column	53
	Precast wall	7
	Precast beam	60
Member manufacturer 2	Precast column	45
	Precast wall	43
	Precast beam	82

The number of material supplier-component producer components is shown in Table 11.

Table 11: Material supplier - Member number of member manufacturer

	Material type	Member manufacturer 1 (quantity/t)	Member manufacturer 1 (quantity/t)
Material supplier 1	Cement	0	0
	Sand	0	81.63
	Pebbles	0	0
	Reinforcement bar	26.5	36.5
Material supplier 2	Cement	0	76.32
	Sand	0	0
	Pebbles	136.52	210
	Reinforcement bar	0	0
Material supplier 3	Cement	52	0
	Sand	53.63	0
	Pebbles	0	0
	Reinforcement bar	0	0

Based on Scenario 6 a two-stage production scenario is derived for this residential building project material supplier-component manufacturer and component manufacturer-construction site. The model optimization results are presented more clearly to the decision makers of the assembly building supply chain.

V. Conclusion

In this paper, we use a uniparental genetic hybrid ACO algorithm to solve a multi-objective model of total supply chain costs and carbon emissions. The algorithm is tested on Berlin52, Eli51, Eli76, St70 and Rat99, and the optimal and average values obtained by solving using the uniparental genetic hybrid ant colony algorithm are smaller than those of the basic ant colony algorithm. A representative residential construction enterprise project in Province X is taken as the research object, and the constructed supply chain cost-carbon emission multi-objective optimization model is solved using the uniparental genetic hybrid ACO algorithm. Through simulation, the cost and carbon emission optimization solution set of the assembly building supply chain is obtained, and at the same time, the two-phase production schemes of material supplier-component manufacturer and component manufacturer-construction site are obtained based on the optimization results. The method in this paper can show the cost-carbon emission optimization results of the assembly supply chain under production capacity constraints more clearly to the decision makers of the assembly building supply chain, and help them to make decisions. Comparing the solutions obtained by CPLEX commercial solver and CACO algorithm, the results all show that the model constructed in this study is effective and feasible, and the uniparental genetic hybrid ant colony algorithm is reliable.

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