Research on Modeling of Multi — vehicle Supply Chain Logistics Transportation Scheduling Based on Improved Ant Colony Algorithm

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Abstract. A multi-vehicle supply chain logistics transportation scheduling model based on improved ant colony algorithm is studied to realize high speed and high quality path optimization and reduce transportation cost and time.Based on basic ant colony algorithm of heuristic information function and pheromone update model to implement improvements,improved ant colony algorithm,on this basis,set by the transportation cost and shipping time,vehicle fuel consumption,distribution range and highest capacity into the algorithm,the constraint factors such as building contains multiple constraint factor of the scheduling model,realize the model of supply chain logistics transportation scheduling,Results show that the model has high convergence speed and the path optimization performance,the search for the path to the high quality,can according to different retailers distribution network to search for the optimal path,and to seek different path scheduling models of vehicles,scheduling results can meet the highest distribution of each vehicle distance and capacity constraints,realize the model of supply chain logistics optimization scheduling,Achieve the goal of reducing transportation cost and transportation time.

Keywords: Improved ant colony algorithm; Many models; Supply chain; Logistics transportation; Scheduling model;The constraint factors

1 Introduction

The supply chain mainly includes manufacturers, suppliers and retailers, etc. With an enterprise as its core, through controlling logistics and information flow, the whole process from purchasing raw materials to producing products and then selling to users[1]. In the process of the sustainable development of network marketing economy, the market competition is gradually strengthened, and the market competition mode has changed from the competition mode among enterprises to the competition mode among each supply chain[2][3]. Therefore, the reasonable and effective management of the supply chain has become a key problem to be solved at present. Because the cost of goods is basically fixed, the cost of logistics and transportation scheduling has become the key to reduce the cost of the whole supply chain and improve the overall competitiveness[4]. The high-quality transportation path can guarantee the realization of the low cost and high efficiency of the supply chain logistics transportation, and improve the overall competitiveness of the supply chain system[5][6].

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In the context of supply chain management, artificial intelligence is very widely used. For example, multi-modal emotion recognition model[7] and session emotion recognition model[8] can better process employee information, convolutional neural network[9] can process a large amount of redundant data, and improve the efficiency of supply chain management. Algorithms are gradually changing the traditional supply chain management mode. At present, the genetic algorithm and ant colony algorithm are the most widely used in the supply chain vehicle scheduling problem. However, the ant colony algorithm can reach the global minimum point faster than the genetic algorithm. The ant colony algorithm is simple, but it is easy to appear local optimal solution, and it is prone to stagnation and poor convergence performance. The improved ant colony algorithm can be obtained by combining other algorithms or implementing corresponding improvements to the basic ant colony algorithm, which can avoid the defects of the ant colony algorithm and improve the application performance[10].

2 Improve the multi-model supply chain logistics and transportation scheduling model of the ant colony algorithm

2.1 Basic ant colony algorithm

The random advance probability of the search for food ants from the starting point to the target point is calculated as follows:

$$q_{ij}^{l}(t) = \begin{cases} \frac{\tau_{ij}^{\varphi}(t)\mu_{ij}^{\phi}(t)}{\sum \tau_{is}^{\varphi}(t)\mu_{is}^{\phi}(t)}, j \in allowed_l \\ 0, otherwise \end{cases} \tag{1}$$

In the equation (1), The origin point where the ants search for food is indicated in i, The target point is represented as j; individual ants searching for food are represented as l, The time of the food search is expressed in t, The walking transition probability of ant l from i to j is expressed as $q_{ij}^{l}(t)$; the expectation and pheromone inspired factors are expressed as Φ and φ, respectively; the concentration of pheromone on the section from i to j is expressed as $\tau_{ij}(t)$; ant l can search food in the future; the set of path nodes is expressed as $allowed_l$, And $allowed_l = \{1, 2, \ldots, m-1\} - tab_l$, among, The tab_l represents the set of nodes that the ant l has already passed; the inspired information function corresponding to the ij section is represented as $\mu_{ij}(t)$.

After all ants experience a search food traversal cycle, update the pheromone change operation on all paths involved in the m target nodes as follows:

$$\tau_{ij}(t+1) = (1-\delta) \times \tau_{ij}(t) + \Delta\tau_{ij}(t) \tag{2}$$

In equation (2), the volatile variable of pheromone changed over time is expressed as δ and $\delta \in [0,1)$; the variation of pheromone at time t is expressed by $\Delta\tau_{ij}(t)$, and its operation formula is:

$$\Delta\tau_{ij}(t) = \sum_{l=1}^{n} \tau_{ij}^{l}(t) \tag{3}$$

In equation (3), the amount of information released into the ij path in the loop is shown in $\Delta\tau_{ij}^{l}(t)$; the total number of ants is expressed in n.

2.2 Logistics and transportation scheduling model of Ant Group Algorithm

1. Set the average smooth flow factor of vehicle transportation path in supply chain logistics transportation scheduling as:

$$X_1(j) = \begin{cases} DK_j/DK_{jmax}, DK_j \leq DK_{jmax} \\ 0, otherwise \end{cases} \tag{4}$$

In formula (4), the tolerance limit value of the road of the transport vehicle is expressed by DK_{jmax}; the smoothness of the route where the transport vehicle travels to node j is expressed by DK_j.

2. Set the transportation cost factor in the supply chain logistics transportation scheduling as follows:

$$X_2(j) = \begin{cases} e_j/e_{jmax}, e_j \leq e_{jmax} \\ 0, otherwise \end{cases} \tag{5}$$

In equation (5), the real transportation cost and the estimated highest transportation cost are expressed in e_j and e_{jmax} respectively. Real transportation cost e_j can be expressed as:

$$\begin{cases} e_j = Ab_j + To_j + Fu_j \\ e_j \leq e_{jmax} \end{cases} \tag{6}$$

In formula (6), the oil consumption and toll generated in logistics transportation are expressed by Fu_j and To_j respectively, and the wear cost generated is expressed by Ab_j.

3. Set the transportation time factor in the logistics transportation scheduling as:

$$X_3(j) = \begin{cases} T_j/T_{jmax}, T_j \leq T_{jmax} \\ 0, otherwise \end{cases} \tag{7}$$

In formula (7), the time of logistics transport vehicle is expressed in T_j; the maximum estimated time is expressed in T_{jmax}.

4. The fuel consumption constraint factor per unit distance should be set, which can be expressed as:

$$minz = \left\{\sum_{\alpha\in A}\sum_{i\in I}\sum_{j\in J} b_{ij}x_{ij\alpha}FC_\alpha, \sum_{\alpha\in A}\sum_{i\in I}\sum_{j\in J} b_{ij}x_{ij\alpha}\right\} \tag{8}$$

In equation (8), the fuel consumption per unit distance of vehicle a is expressed as FC_α, the decision scalar of $\alpha \in A$; $0 \sim 1$ is expressed by $x_{ij\alpha}$, and $x_{ij\alpha} \in \{0,1\}$.

5. Setting of vehicle load and maximum distribution distance. The load weight and the maximum distribution distance are different. The constraint factor of the two is set as:

$$\begin{cases} \sum_{j\in J} y_{j\alpha}d_j \leq VL_\alpha, \forall\alpha \in A \\ \sum_{i\in I}\sum_{j\in J} x_{ij\alpha}b_{ij} \leq MD_\alpha, \forall\alpha \in A \end{cases} \tag{9}$$

In formula (9), the load weight of vehicle a a and the highest distribution distance are expressed by VL_{α} and MD_{α} respectively; the cargo demand at the target distribution point j is expressed by d_j; the decision scalar of $0 \sim 1$ is expressed by $y_{j\alpha}$, and $y_{j\alpha} \in \{0,1\}$.

Based on the above analysis, the mathematical model $X(j)$ of logistics and transportation scheduling created by the various constraint factors can be expressed as follows:

$$X(j) = \omega_1 X_1(j) + \omega_2 X_2(j) + \omega_3 X_3(j) + \omega_4 FC_{\alpha} + \omega_5 VL_{\alpha} + \omega_6 MD_{\alpha} \tag{10}$$

In formula (10), in the process of the logistics transport vehicle to node j, the average patency weights of the passing path are shown as ω_1, the weight of the required transportation cost is ω_2, the weight of the time consumed is ω_3; the weight of the fuel consumption of the vehicle a is ω_4, the load weight is ω_5, and the weight of the highest distribution distance is ω_6.

In the basic ant colony algorithm, the inspired information function only takes into account the reciprocal of the spacing between the two nodes before and after. To solve such problems, by integrating the spacing of the next node j and the termination point h into the inspired information function, then the inspired information function can be improved by:

$$\mu_{ij} = 1/(b_{ij} + b_{jh}) \tag{11}$$

In equation (11), the spacing between the next node j and the termination point h is represented by b_{jh}; the spacing of the current node i from the next node j is represented by b_{ij}. Integrating b_{jh} into the enlightening information function can make the goal of ant colony search clear and improve the convergence speed of the improved ant colony algorithm. When $b_{jh} > b_{ij}$, the node j is set to a close node, instead, this node to a distant node. In the process of ant colony search, operations can be performed on each node adjacent to node i, without searching for remote nodes. In this way, the operation amount of the algorithm can be effectively reduced and the convergence performance can be improved. Therefore, the basic colony algorithm can be improved by equation (11):

$$q_{ij}^{l}(t) = \begin{cases} \dfrac{\tau_{ij}^{\varphi}(t) \times \left\{ [1/(b_{ij}+b_{jh})]^{\phi}(t) \right\}}{\sum_{s \in allowed_l} \tau_{is}^{\varphi}(t) \times \left\{ [1/(b_{ij}+b_{jh})]^{\phi}(t) \right\}}, j \in allowed_l \\ 0, otherwise \end{cases} \tag{12}$$

The created mathematical model $X(j)$ is used as the constraint function to improve the pheromone update mode in the basic ant colony algorithm. The pheromone update operation within the improved base ant colony algorithm can be expressed as:

$$\tau_{ij}(t+1) = \begin{cases} \dfrac{(1-\delta) \times \tau_{ij}(t)}{X(j)} + \eta(|B_{wrost}| - |B_{best}|), (i,j \in B_{best}) \\ \dfrac{(1-\delta) \times \tau_{ij}(t)}{X(j)} - \eta(|B_{wrost}| - |B_{best}|), (i,j \in B_{wrost}) \\ 0, otherwise \end{cases} \tag{13}$$

In equation (13), the worst quality path and the highest quality path are expressed as B_{wrost} and B_{best} respectively, and the length is expressed by $|B_{wrost}|$ and $|B_{best}|$ respectively; the pheromone enhancement factor in the improved ant colony algorithm is expressed as η, and $\eta \in [0,1]$. By enhancing the pheromone of the highest quality path searched, the pheromone concentration of this path is increased, whereas the worst quality path searched is punished. Therefore, the pheromone constraint formula for improving the ant colony algorithm should be set as follows:

$$\tau_{ij} = \begin{cases} \tau_{max}, \tau_{ij} \geq \tau_{max} \\ \tau_{ij}, \tau_{min} < \tau_{ij} < \tau_{max} \\ \tau_{min}, \tau_{ij} \leq \tau_{min} \end{cases} \quad (14)$$

3 Analysis of the experimental results

Taking a logistics company as an example, two supplier outlets (A and B) are randomly selected as the two starting points from the numerous supplier outlets of the logistics company, in which supplier outlet A belongs to the close-distance distribution outlet, while supplier outlet B belongs to the long-distance distribution outlet. We first test the optimal performance of the improved ant colony algorithm applied in the model in this paper. Supplier outlets, for example, by its many retailers randomly selected 55 retailers outlets, and divided into A1 and A2 groups, including A1 retailers outlets number of 26, A2 retailers outlets number of 29, respectively using the optimal carrier algorithm and the two groups of retailers outlets, on the basis of the final search path effect and required, generation times, analysis of the two in the transportation path for optimal actual application performance. In this paper, the improved ant carrier algorithm and the optimal carrier algorithm of A1 and A2 are shown in**Fig.1.** The optimal path search effect of the two groups of retailer outlets of the two algorithms.

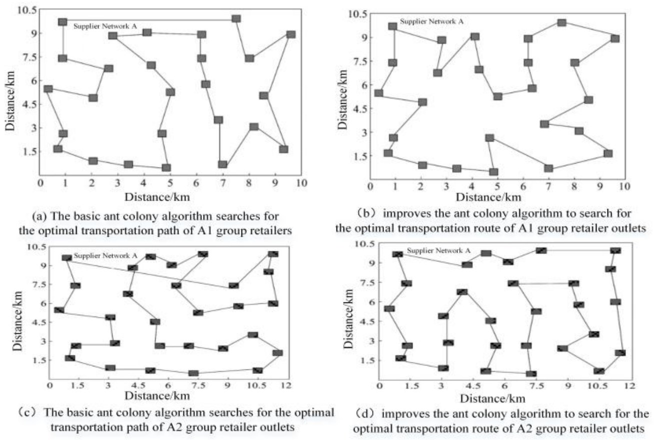

Fig.1. The optimal path search effect of the two groups of retailer outlets of the two algorithms.

It can be seen from Figure 1 that the two sets of optimal paths searched by the improved ant colony algorithm are significantly better than the basic ant colony algorithm.This paper improves the scheduling model of multi-model supply chain logistics transportation, dispatches the logistics transportation model of different models of experimental supplier network B, and verifies the scheduling performance of this model through the actual scheduling results. 16 retailer outlets (1 ~ 16) are randomly selected from many retailer outlets of outlet B, 0 represents supplier outlet B, and this model is used to implement logistics and transportation scheduling. The distribution of 16 retailer outlets and the four optimal paths obtained in the model scheduling are shown in **Fig.2.** Distribution and 4 optimal paths., and the retailer outlet information, transportation vehicle information and the final scheduling results of the model are shown in **Table 1.**Statistics of retailer outlet information, transport vehicle information and scheduling results..

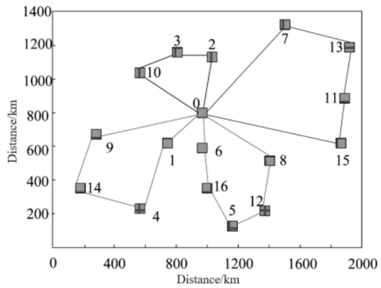

Fig.2. Distribution and 4 optimal paths.

Table 1. Statistics of retailer outlet information, transport vehicle information and scheduling results.

Transport vehicle information	Model number	Maximum distribution distance / km	Maximum carrying capacity / kg	Fuel consumption per unit distance / L·km^{-1}	
	a	1800	2400	0.35	
	b	890	3100	0.07	
	c	1640	3900	0.11	
	d	2000	3500	0.24	
Retailer outlet information	Retailers' outlet number	Required cargo weight / kg	Retailers' outlet number	Required cargo weight / kg	
	1	395	9	396	
	2	800	10	980	
	3	1050	11	1026	
	4	895	12	570	
	5	830	13	895	
	6	1010	14	586	
	7	463	15	986	
	8	510	16	940	
Dispatch results	Model number	Actual distribution distance / km	Actual carrying capacity / kg	Actual fuel consumption/L	Transportation path
	a	1708	1480	597.8	0→1→4→14→9→0
	b	869	2830	60.83	0→2→3→10→0
	c	1619	3860	178.09	0→6→16→5→12→8→0
	d	1890	3370	453.6	0→15→11→13→7→0
	total	6086	11540	1290.3	——

Combined with figure 2 and table 1, this model can realize the model of supply chain logistics optimization scheduling, scheduling results can satisfy the pre-set constraints.

4 Conclusions

In this paper, we study a multi-vehicle supply chain logistics transportation scheduling model based on the improved ant colony algorithm. The experimental results show that the improved

ACO algorithm used in this model has high performance in searching for the optimum, can achieve faster convergence, and the optimal path searched for is of high quality, the application of this algorithm can realize the optimal scheduling of multi-vehicle supply chain logistics transportation, and the result can meet the constraints such as the maximum distribution distance and the carrying capacity of the vehicle to achieve the goals of low transportation cost and transportation time, and effectively improve the transportation efficiency. The result can meet the constraints of maximum distribution distance and carrying capacity of vehicles.

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