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Low carbon logistics distribution route optimization research based on improved ant colony algorithm

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Because of global warming, the fog weather and other pollution problems, and the increasing deterioration of environment and energy, the low carbon issues become more and more popular in the whole world. Since most carbon pollutions are produced by logistics industry, low carbon is the inevitable trend for logistics industry. In this paper, starting from the actual requirements of low carbon logistics, microscopic quantitative analysis was used for low carbon logistics. The minimum cost of carbon emissions model with considering the cost of carbon emissions were established to find the reasonable distribution routes to achieve energy conservation and emissions reduction based on the solution of chaos ant colony algorithm. According to the simulation of MATLAB, chaos ant colony algorithm had a better effectiveness than the basic ant colony algorithm on the issue of low carbon logistics distribution route optimization.

Keywords: Low carbon logistics, distribution, route optimization, chaos, ant colony algorithm.

AIMS AND BACKGROUND

Because of global warming, the fog weather and other pollution problems, and the increasing deterioration of environment and energy, the low carbon issues become more and more popular in the whole world. Since most carbon pollutions are produced by logistics industry, low carbon is the inevitable trend for logistics industry. The so-called low carbon logistics focuses on the low energy consumption, low pollution and low emissions in logistics process with the utilization of the technologies of energy efficiency, reusable energy and greenhouse gas emissions reduction to reduce the carbon emissions in the logistics, cut down the pollution produced by logistics activities, and improve the efficiency of logistics resources utilization [1]. To achieve low carbon logistics, it should meet two requirements. On one hand, use a variety of low carbon technologies to reduce carbon emissions in the process of transportation. On the other hand, optimize the logistics system by planning reasonable logistics routes, improve logistics efficiency, reduce waste of resources, and make full use of logistics resources [2].

With development of low carbon logistics, more and more scholars become curious about this issue. It mainly includes: the connotation, characteristics and development of low carbon logistics mode and direction of analysis [3-5]; low carbon logistics development are faced with the problem and countermeasure research [6-8]; low carbon logistics system construction of research [9-10]; research of low carbon logistics distribution network optimization [11]. However, all the above researches are concentrated on the low carbon logistics macro qualitative studies, which lack microscopic quantitative researches.

In this paper, starting from the actual requirements of low carbon logistics, microscopic quantitative analysis was used for low carbon logistics. The minimum cost of carbon emissions model with considering the cost of carbon emissions were established to find the reasonable distribution routes to achieve energy conservation and emissions reduction based on the solution of chaos ant colony algorithm. According to the simulation of MATLAB, chaos ant colony algorithm had a better effectiveness than the basic ant colony algorithm on the issue of low carbon logistics distribution route optimization.

EXPERIMENTAL

DISTRIBUTION OPTIMIZATION MODEL OF MINIMUM COST OF CARBON EMISSIONS

Low carbon logistics is a kind of low energy cost and low pollution logistics whose goal is to achieve the highest efficiency of logistics with the lowest greenhouse gas emissions [12]. Relevant data shows that thermal power emission, vehicle exhaust emissions, and construction are the main sources of carbon dioxide emissions. Bearing the social goods transportation, storage, packaging, processing, distribution, loading, unloading and other services, logistics has become the big one for the carbon emissions. Looking for the reasonable distribution route to reduce carbon emissions is particularly important. The reduction in carbon

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emissions model reflects the reduction of carbon emissions cost. Therefore, this paper established low carbon logistics distribution route optimization model to achieve the minimizing carbon emissions.

As the vehicles pickup or delivery goods in the different order crossing all customers, the car load changes. With the increase of vehicle load, the unit distance fuel consumption rises, leading to the increase of carbon emissions cost [13]. With the increase of vehicle transport distance, carbon emissions cost will also increase. Thus, the cost of carbon emissions is not only has relationship with transport distance, but also related to the vehicles' load.

The unit distance fuel consumption $\varepsilon(q)$ has a linear relationship with the total weight of the vehicles q_{sum}, which is:

$$\varepsilon(q) = \delta q_{sum} + b = \delta(q + q_0) + b \tag{1}$$

Where, $\varepsilon(q)$ is the unit distance fuel consumption, δ is relationship factor between the unit distance fuel consumption and vehicles' weight, q_{sum} is the total weight of the vehicles including vehicle loading weight q and vehicle's weight q_0.
When vehicles are full, the unit distance fuel consumption is ε^*, which is:

$$\varepsilon^* = \delta(Q + q_0) + b \tag{2}$$

Where, ε^* is the unit distance fuel consumption when vehicles are full, Q is the vehicles' maximum load.

When vehicles are empty, the unit distance fuel consumption is ε_0, which is:

$$\varepsilon_0 = \delta q_0 + b \tag{3}$$

From formula (2) and formula (3), we can get:

$$\delta = \frac{\varepsilon^* - \varepsilon_0}{Q} \tag{4}$$

Bring formula (4) into formula (1), the unit distance fuel consumption $\varepsilon(q)$ is as:

$$\begin{aligned}\varepsilon(q) &= \delta q_{sum} + b = \delta(q + q_0) + b = \\ &= \delta q + (\delta q_0 + b) = \frac{\varepsilon^* - \varepsilon_0}{Q} q + \varepsilon_0\end{aligned} \tag{5}$$

Thus, the carbon emissions cost $CO_2(q_{ij})$ of the goods with the weight q_i from customer i to customer j is as:

$$CO_2(q_{ij}) = c_3\eta_0\varepsilon(q_i)d_{ij} = c_3\eta_0(\frac{\varepsilon^* - \varepsilon_0}{Q} q_i + \varepsilon_0)d_{ij} \tag{6}$$

Where, c_3 is the unit carbon emissions cost, η_0 is the carbon emissions factor, d_{ij} is the distance from customer i to customer j, $\eta_0\varepsilon(q_i)$ is the carbon emissions of the goods with the weight q_i from customer i to customer j.

For the convenience of model establishment, assume that there is only one distribution center whose location is known. All the vehicles starts from the distribution center, and return to distribution center after delivery. The vehicles' load is known. The location and the demand of customer are known. One vehicle is for one customer.

According to the above assumption, establish the minimizing carbon emissions cost model:

$$\begin{aligned}\min CO_2 &= \sum_{i=0}^{L}\sum_{j=0}^{L}\sum_{k=1}^{m'} co_2(q_{ij})x_{ijk} = \\ &= \sum_{i=0}^{L}\sum_{j=0}^{L}\sum_{k=1}^{m'} c_3\eta_0\varepsilon(q_i)d_{ij}x_{ijk} \\ &= \sum_{i=0}^{L}\sum_{j=0}^{L}\sum_{k=1}^{m'} c_3\eta_0(\frac{\varepsilon^* - \varepsilon_0}{Q} q_i + \varepsilon_0)d_{ij}x_{ijk} \\ &= \sum_{i=0}^{L}\sum_{j=0}^{L}\sum_{k=1}^{m'} c_3\eta_0\varepsilon_0 d_{ij}x_{ijk} + \\ &+ \sum_{i=0}^{L}\sum_{j=0}^{L}\sum_{k=1}^{m'} c_3\eta_0 \frac{\varepsilon^* - \varepsilon_0}{Q} q_i d_{ij}x_{ijk}\end{aligned} \tag{7}$$

Where, L is the number of customers, m' is the number of vehicles, q_i is the demand of the i customer, Q is the maximum load of the vehicles, k is the vehicle's number.

The number of distribution center is 0. The numbers of customers are 1, 2, 3 … L. Define variables x_{ijk} and y_{ki} as:

$$x_{ijk} = \begin{cases}1, vehicle \quad k \quad from \quad i \quad to \quad j \\ 0, \; others\end{cases} \tag{8}$$

$$y_{ki} = \begin{cases}1, i \, is \quad sevice \quad by \quad vehicle \quad k \\ 0, others\end{cases} \tag{9}$$

$$\sum_{i=0}^{L} q_i y_{ki} \le Q \qquad k \in [1, m'] \tag{10}$$

$$\sum_{k=1}^{m'} y_{ki} = 1 \qquad i \in [0, L], k \in [1, m'] \tag{11}$$

$$\sum_{i=0}^{L}\sum_{k=1}^{m'} x_{ijk} = 1 \qquad j \in [0, L], k \in [1, m'] \tag{12}$$

$$\sum_{j=0}^{L}\sum_{k=1}^{m'} x_{ijk} = 1 \qquad i \in [0, L], k \in [1, m'] \tag{13}$$

$$\sum_{i=0}^{L}\sum_{k=1}^{m'} x_{0ik} = \sum_{j=0}^{L}\sum_{k=1}^{m'} x_{j0k} \tag{14}$$

Formula (7) is the objective function. The first part is the carbon emissions cost caused by the vehicle's weight. The second part is the carbon emissions cost caused by the vehicle's load. Formula (10) shows the sum of customers' demand cannot be greater than the maximum load of vehicles. Formula (11), (12), (13) show one vehicles is for one customer. Formula (14) shows vehicles starts from distribution center, and then return to distribution center.

ANT COLONY ALGORITHM (ACA)

Assume that there are n cities. The distance between any two cities i and j is d_{ij} ($i, j = 1,2,\cdots,n$). $b_i(t)$ is the number of ants at time t at city i. $m = \sum_{i=1}^{n} b_i(t)$ is the total number of ants. $\tau_{ij}(t)$ is the pheromone at time t on the line ij. At time $t = 0$, every path has the same pheromone strength. $\Delta\tau_{ij}(t) = 0$.

With time passing by, the new pheromone is added, and old pheromones evaporate. ρ is the pheromone volatilization coefficient which indicates pheromones volatile speed. When all the ants accomplish one travel, pheromone on every path is:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij}(t) \tag{15}$$

$$\Delta\tau_{ij}(t) = \sum_{k=1}^{m} \Delta\tau_{ij}^{k}(t) \tag{16}$$

$\Delta\tau_{ij}(t)$ is the pheromone increment on the path ij. At the beginning, $\Delta\tau_{ij}(0) = 0$. $\Delta\tau_{ij}^{k}(t)$ is the pheromone released by ant k on the path ij, which is determined by the ants performance.

$$\Delta\tau_{ij}^{k}(t) = \begin{cases} Q/L_k & \text{section k of ants pass edge ij in the course of this tour} \\ 0 & else \end{cases} \tag{17}$$

Where, Q is constant, L_k is the path length of the ant k. The transition probability of ant k from city i to city j is:

$$P_{ij}^{\ k} = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}(t)]^{\beta}}{\sum_{s \in allowed_k} [\tau_{is}(t)]^{\alpha} \cdot [\eta_{is}(t)]^{\beta}} & j \in allowed_k \\ 0 & others \end{cases} \tag{18}$$

Where, $allowed_k = (1,2,.., n) - tabu_k$ indicates the city collection ant k can choose currently. $tabu_k$ $(k = 1,2,\cdots,m)$ is the taboo table of ant k, which indicates the cities ant k has passed by to show the memory of ants. $\eta_{ij}(t)$ is prior knowledge visibility. In the TSP problem, it is the heuristic information from one city moved to another city, which generally is $\eta_{ij}(t) = 1/d_{ij}$. α is the importance of the residual information on the path ij. β is the importance of the heuristic information.

The basic ant colony algorithm to achieving process is [14]: m ants start from one certain city at the same time to choose the next city based on formula (18), which indicates that ants prefer visit the path with higher intensity of pheromone. The passed cities will be put into $tabu_k$. After all ants finishing one travel, renew the pheromone on each path based on Formula (15) to Formula (17). Repeat the above processes until termination condition is established.

CHAOS ANT COLONY ALGORITHM (CACA)

Chaos is a kind of movement form of nonlinear dynamic system under certain conditions, which is a random behavior when the system is in a non-equilibrium process [15]. Chaos is produced by some fixed rules which is often nonlinear, simple and without any random factors. Chaos movements are seemingly random, but it consists of delicate internal structures with the characteristics of universality, randomness, etc, which can repeatedly traverse all state according to its own law within a certain range. Due to the periodicity of chaotic movement, chaos can be served as a local search method to improve other optimization algorithm's global convergence.

In ant colony algorithm, since the ant foraging behavior has the chaos characteristics, apply the periodicity and random characteristics into ant colony algorithm to improve the ant colony algorithm to have a wider search range and a faster search speed, therefore it forms a new search algorithm, chaos ant colony algorithm. Chaos ant colony algorithm is based on the basic ant colony algorithm introducing the chaos initialization and chaos disturbance to get a better optimization effect.

In the early stages of the basic ant colony algorithm, since ants leave the same pheromones on each path, the first ants process foraging behavior with the same probability. Such optimization is not only inefficient, but also difficult to find the global optimization. If the initial pheromone values in the basic ant colony algorithm are given according to the amount of chaos, the pheromone will be different on each path. Ants can select the optimal path based on the amount of pheromone to improve the efficiency of optimization. For chaos initialization, it generally chooses typical chaotic systems, Logistics mapping, as chaotic variables [16]:

$$Z_{ij}(t+1)=\mu Z_{ij}(t)[1-Z_{ij}(t)] \tag{19}$$

Where, μ is control parameter whose value is $[3.56,4]$ [17]. When the Logistics mapping is completely in chaos, $\mu=4$ and $0\le Z_{ij}(0)\le 1$. Use the permutation method in the literature [18] to process a whole arrangement to make each chaotic quantity correspond with an initial pheromone value.

Set a given cost in the basic ant colony algorithm, which can avoid unnecessary search by poor solution, therefore, to improve the search efficiency and convergence speed. When update the pheromone, introduce chaos disturbance to improve ants' periodicity to help ants get the better optimal solution and avoid falling into local optimum. The formulas with pheromone updating by chaos disturbance are as:

$$\tau_{ij}(t+1)=(1-\rho)\tau_{ij}(t)+\Delta\tau_{ij}(t)+q_1 Z_{ij}(t) \tag{20}$$

Where, $Z_{ij}(t)$ is chaotic variable from the iteration of formula (19), q_1 is its coefficient.

STEPS OF MODEL SOLUTION

(1) Regarding NC=0 (NC is iteration), the load of vehicles is 0, proceed parameters initialization and chaos initialization.

(2) Put m ants at the distribution center.

(3) Based on the transition probability from (18), choose and move the ants to the next city j, and add j to $tabu_k$ at the same time. Check whether the vehicles' load is larger than the maximum load. If so, return to distribution center.

(4) Check whether $tabu_k$ is full. If not, return to (3). Otherwise, go on (5).

(5) Calculate the target function (minimum carbon emissions cost or target evaluation function value). Record the best solution currently

(6) When the best solution is less than one certain value, update the chaotic pheromone based on formula (20).

(7) If $NC<NC_{\max}$, then $NC=NC+1$, empty $tabu_k$, and go back to Step2. If $NC=NC_{\max}$, end.

RESULTS AND DISCUSSION

Assume the distribution center has 18 customers whose coordinate is (42,50). Table 1 is the demand of each customer. Table 2 is the coordinate of each customer. The maximum load of each vehicle is 5 tons. In the simulation, set $c_0=0, c_1=1, c_2=\infty$. The unit distance fuel cost of empty car and full car are $\varepsilon_0=1$ and $\varepsilon^*=2$. The unit carbon emissions cost is $c_3=0.3$. The emission factor is $\eta=2.61$ [19]. The distances between each customer and distribution center can be calculated by formula (21). The delivery car can be calculated by formula (22).

$$d_{ij}=\sqrt{(x_i-x_j)^2+(y_i-y_j)^2} \tag{21}$$

$$m'=\left[\frac{\sum_{i=1}^{L} g_i}{\lambda q}\right]+1 \tag{22}$$

Since the total demand of each customer is 16.2 tons. According to formula (22), if $\lambda=0.98$, the number of vehicles is:

$$m'=\left[\frac{16.2}{0.98\times 5}\right]+1=4 \tag{23}$$

Where, $[\cdot]$ indicate get the integer. $\lambda\in(0,1)$, which can be adjusted by the complexity of loading and constraint. Generally, the more complex the loading is, the less λ is. Otherwise, the λ is bigger [20].

Table 1. Demand of Customer.

Customer	1	2	3	4	5	6	7	8	9
Demand	0.3	0.5	1.0	1.3	0.9	1.2	1.5	0.4	1.5
Customer	10	11	12	13	14	15	16	17	18
Demand	0.2	0.4	1.0	1.1	1.3	1.5	1.0	0.5	0.6

Table 2. Coordinate of Customer.

Customer	1	2	3	4	5	6	7	8	9
X	16	25	10	60	33	18	20	50	58
Y	32	50	40	65	63	22	60	25	20
Customer	10	11	12	13	14	15	16	17	18
X	70	48	25	38	12	20	15	22	52
Y	23	30	42	62	12	18	65	27	52

Table 3. The results basic ant colony algorithm (minimum carbon emissions cost)

NO.	1	2	3	4	5	6	7	8	9	10	Ave
Carbon emissions cost	483.7	536.7	564.1	564.1	465.6	545.6	485.5	487	492	479.1	500.49
Vehicles	4	4	4	4	4	4	4	4	4	4	4
End iteration	96	67	56	63	79	62	151	71	51	47	74.3
Deviations	18.1	71.7	98.5	98.5	0	80	19.9	21.4	26.4	13.5	44.8

Table 4. The results chaos ant colony algorithm (minimum carbon emissions cost)

NO.	1	2	3	4	5	6	7	8	9	10	Ave
Carbon emissions cost	439.5	497	474.5	456.5	415.8	490.5	455.1	456.5	455.4	448.9	458.97
Vehicles	4	4	4	4	4	4	4	4	4	4	4
End iteration	20	85	32	14	56	36	54	16	76	20	40.9
Deviations	23.7	81.2	58.7	40.7	0	74.7	39.3	40.7	39.6	33.1	43.17

Table 3 is the 10 results by using the basic ant colony algorithm to solve the minimum carbon emissions cost model. Table 4 is the 10 results by using the chaos ant colony algorithm to solve the minimum carbon emissions cost model. Comparing Table 3 with Table 4 we can find:

(1) Carbon emissions cost: the minimum carbon emissions cost of basic ant colony algorithm is 465.6, the cost of chaos ant colony algorithm is 415.8. The chaos ant colony algorithm saves 10.6% of minimum carbon emissions cost comparing with basic ant colony algorithm. The average carbon emissions cost of basic ant colony algorithm is 500.49. The average cost of chaos ant colony algorithm is 458.97. For the average distribution cost, the chaos ant colony algorithm saves 8.2% comparing with basic ant colony algorithm. Thus, for the solution of minimum carbon emissions cost distribution model, chaos ant colony algorithm can find the path with less carbon emissions cost, which is better for environmental protection.

(2) The number of final generation: the average number of final generation of basic ant colony algorithm is 74.3. The average number of final generation of chaos ant colony algorithm is 40.9. From the average number of final generation, we can find the chaos ant colony algorithm has a better convergence.

(3) The difference with minimum carbon emissions cost. The average difference between basic ant colony algorithm and minimum carbon emissions cost is 44.8. The average difference between chaos ant colony algorithm and minimum carbon emissions cost is 43.17. From the difference with minimum carbon emissions cost, we can find

the chaos ant colony algorithm is more stable in the process of search minimum carbon emissions.

Figure 1 is the optimization curves of minimum carbon emissions cost. From the figure, we can find chaos ant colony algorithm has a better effectiveness in the process of searching minimum carbon emissions cost. Comparing with basic ant colony algorithm, it can find the lower carbon emissions cost with a faster convergence speed. Figure 2 is distribution path of basic ant colony based on the minimum carbon emissions cost model. Figure 3 is distribution path of chaos ant colony based on the minimum carbon emissions cost model.

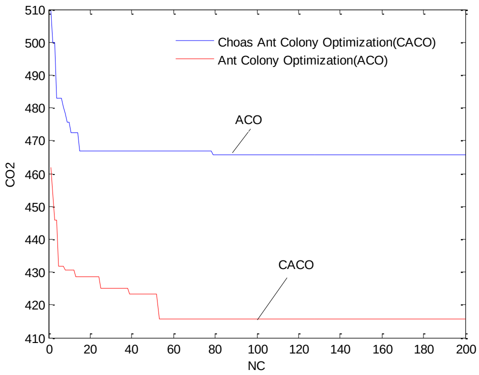

Fig. 1. Optimization curve

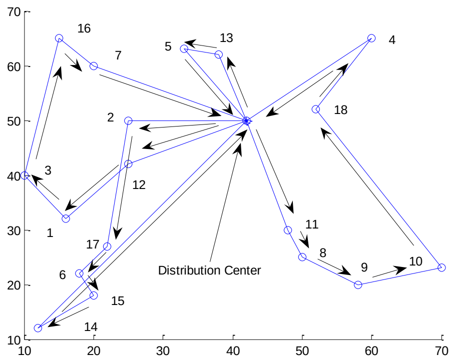

Fig.2. Distribution Path of ACA

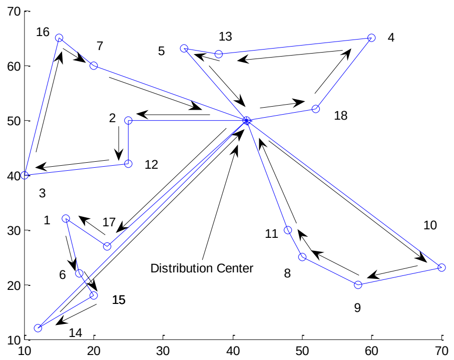

Fig. 3. Distribution Path of CACA

CONCLUSIONS

This paper introduced the low carbon logistics distribution path optimization models, including minimum carbon emissions cost model. Use chaos ant colony algorithm, the new mixed algorithm, to solve the two models to prove its effectiveness through simulation. But this is the preliminary research on the low carbon logistics distribution route optimization problem. It is the exploration stage for low carbon logistics distribution route optimization model. The models are established based on the ideal situation without consideration of many complex factors and real situations in the constraints of the models. In future study, it still needs to optimize the model to make the model more accord with the actual needs. Although there have been some algorithm researches, they are limited to chaos ant colony algorithm, the certain kind of algorithm to solve the optimization model. In the future research, it needs to develop solutions of different intelligent algorithm models to find the more suitable intelligent algorithm for models' solutions.

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