A Study on Emergency Logistics Vehicle Routing Problem Based on Improved Ant Colony Algorithm

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Abstract

Taking the emergency materials distribution after natural disasters as background, a mathematical model with the shortest distribution path as the goal is set up. The model is solved by ant colony algorithm and the ant path transfer and pheromone evaporation factor is optimized, at the same time using C - W algorithm and 2 - opt method to optimize the algorithm.The case study shows that the improved ant colony algorithm is effective in the emergency logistics vehicle routing problem.

Keyword — *Emergency logistics;Vehicle routing problem;Ant colony algorithm*

I. INTRODUCTION

When natural disasters occur in the real world, it can be predicted and can not prevent it from happening, so we should respond quickly after the natural disasters and carry out the related rescue work as soon as possible in order to reduce the casualties and economic losses.From the 2008 Wenchuan earthquake in the Japanese earthquake in June 2018, these natural disasters have warned people that rescue after disasters plays a key role in reducing casualties and economic losses.Among them, emergency material distribution plays an important role in emergency rescue. Therefore, the study of emergency logistics vehicle routing problem has important theoretical and practical significance.

Some scholars have studied the emergency logistics vehicle routing problem from the perspective of model: Zhang Wei et al. established a multi-objective mixed integer nonlinear optimization model with the objective of the shortest transportation time, the minimum transportation distance and the minimum path complexity [1]. Liu Yang takes full account of the possibility of vehicle congestion and road damage, and establishes a model for the time expected and a minimum of the last called car called the rescue center to reach the disaster point [2]. Xu Zhiyu et al. set up a SplitDelivery Vehicle Routing Problem model (SDVRP) with the shortest total delivery time and the lowest degree of imbalances [3].

Some scholars have made relevant researches on the vehicle path problem of emergency logistics from the perspective of solving model algorithm: Tang Chong applies the simulated annealing algorithm to the VRP problem of single time windows and proves the effectiveness of the algorithm [4]. Gong Yawei focused on the classic shortest path algorithm Dijkstra algorithm in path optimization [5].Zhang Bin used the saving algorithm and immune algorithm to study the optimization of emergency logistics vehicle scheduling, and proved that the immune algorithm was greater than to the genetic algorithm [6]. Xu Haoqin studied vehicle scheduling using a hybrid optimization strategy combining genetic algorithms and tabu search [7].Zhang Yuhua et al. used ant colony algorithm to solve the vehicle delivery path model with time window and was an improvement analysis[8].

In this paper, a mathematical model aiming at the shortest vehicle path is established and the model is solved by ant colony algorithm. The correlation optimization was carried out based on the ant colony algorithm and compared with the unfertilized algorithm, so as to prove the effectiveness of the algorithm optimization.

II. PROBLEMDESCRIPTION

In order to carry out rescue and reduce the loss as soon as possible, it is necessary to transport relief materials from the emergency logistics center to each disaster point in the shortest time. The vehicle starts from the emergency logistics center and delivers materials to multiple disaster points in turn, requiring each vehicle to be responsible for distribution. The location and coverage of emergency logistics centers are known. Each emergency logistics center has a certain number of vehicles of the same type, and the demand for materials at each disaster point is known. The problem to be solved in this article: How to arrange the distribution route reasonably so that each disaster site can receive materials as soon as possible.

III. ESTABLISHMENT of MODEL

A. Assumptions

1) Emergency logistics center to respond to the material needs of all disaster points.

2) From each vehicle emergency logistics center, each vehicle only serves a distribution path.

3) Each vehicle can be dispatched for multiple disaster points, but each affected site has only one vehicle service.

4) Road conditions from the logistics center to each demand point and each demand point are the same ones.

B. symbol description

N:The set of nodes, N = {$i, j \mid i, j$ = 1, ⋯, n}, set the emergency logistics center to 1;

K:Material transport vehicles, K = {k|1, 2, ⋯, m}, k is a material transport vehicle;

n: The number of disaster points;

m: Number of material transportation vehicles;

W: Material transport vehicle capacity;

w_i: The demand for materials at the disaster point$i$;

d_{ij}: The distance from point i to point j;

$$\varphi_{ik} = \begin{cases} 1 & point\ i\ is\ delivered\ by\ vehicle\ k \\ 0 & otherwise \end{cases}$$

$i \in N, k \in K$;

$$\varphi_{jk} = \begin{cases} 1 & point\ j\ is\ delivered\ by\ vehicle\ k \\ 0 & otherwise \end{cases}$$

$j \in N, k \in K$;

$$w_{ijk} = \begin{cases} 1 & Vehicle\ k\ from\ point\ i\ to\ point\ j \\ 0 & otherwise \end{cases}$$

$i, j \in N, k \in N$.

C. Model

Objective function

$$\min d = \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{m} d_{ij} w_{ijk} \qquad (3\text{-}1)$$

Constraints

$$\sum_{i=1}^{n} q_i \varphi_{ik} \le Q, k \in K \qquad (3\text{-}2)$$

$$\sum_{k=1}^{m} \varphi_{ik} = 1, i \in N \qquad (3\text{-}3)$$

$$\sum_{i=1}^{n} w_{ijk} = \varphi_{jk}, j \in N, k \in K \qquad (3\text{-}4)$$

$$\sum_{j=1}^{n} w_{ijk} = \varphi_{ik}, i \in N, k \in K \qquad (3\text{-}5)$$

The description of the constraint is this: Equation (3-1) represents the shortest delivery path under the constraint condition.Equation (3-2) means that the total demand of the delivery points for each vehicle cannot exceed the capacity of the vehicle.Equation (3-3) means that point i is responsible for the vehicle k, and each point has a vehicle responsible for the transportation of the material.Equation (3-4) shows that when the vehicle k is responsible for the transportation of the goods from point i to point j, the point j is carried by the vehicle k in charge of the goods.Equation (3-5) shows that whena vehicle$k$ is responsible for material transportation from point$i$ to point j, point$i$is responsible for material transportation of vehicle k.

IV. MODEL SOLUTION

The Ant Colony Algorithm (ACA) is used to solve the basic idea of the path optimization problem: the ant's walking path is used to represent the feasible solution of the problem to be optimized, and all the paths of the entire ant group constitute the solution space of the problem to be optimized. Ants with shorter paths have more pheromones released. As time progresses, the concentration of pheromone accumulating on shorter paths gradually increases, and the number of ants that choose the route will increase. In the end, the whole ant will concentrate on the best path under the action of positive feedback, and the corresponding solution is the optimal solution to be optimized.

Firstly, this paper adds a C-W algorithm in the ant colony algorithm, and improves the transition probability based on the C-W algorithm. Secondly, pheromone evaporation factor scaling was adjusted in different stages. Finally, the optimal solution is optimized by the 2-opt algorithm.

A. C-W algorithm

The Clarke-Wright algorithm(C-W algorithm) is a simple and feasible heuristic algorithm proposed by Clarke and Wright in 1964, according to the distribution center's distribution capacity and distribution center to each distribution demand point and the distance between each demand point, and the scheme to make the total number of kilometers (or time or cost) for total vehicle transportation[9].

The basic process of saving algorithm: the distribution center delivers materials to two demand points, the distance from the distribution center to the demand point i and the demand point j are di0 and dj0, respectively, and the distance between the demand point i and the demand point j is dij , the savings are:

$$s(i,j)=d_{i0}+d_{j0}-d_{ij}$$

B. Transition Probability Improvement

According to the C-W algorithm, the savings factor is obtained. The larger the savings factor, the smaller the total path length, and the greater the probability of (i, j) selection, which is more conducive to global optimization. According to formula s(i,j) to optimize the transition probability [11]:

$$P_{ij}^{k}=\begin{cases}\dfrac{\left[\tau_{ij}(t)\right]^{\alpha}\left[\eta_{ij}(t)\right]^{\beta}\left[s_{ij}\right]^{\gamma}}{\sum\limits_{s\notin tabu_k}\left[\tau_{is}(t)\right]^{\alpha}\left[\eta_{is}(t)\right]^{\beta}\left[s_{ij}\right]^{\gamma}}, & s\notin tabu_k\\ 0, & otherwise\end{cases}$$

Among them, $\tau_{ij}(t)$ is the information amount on the path (i, j) at the time$t$; $\eta_{ij}(t)$ is the heuristic function, and its expression is $\eta_{ij}(t)=1/d_{ij}$;$\alpha$is the information heuristic factor, representing the relative importance of the path; $\beta$is the heuristic factor, representing therelative importance of the visibility; tabu$_k$is the taboo collection.

C. Pheromone Evaporation Factor Scaling

The pheromone evaporation factor $\rho(0<\rho<1)$ is an important parameter in the ant colony algorithm, and its size has a direct influence on the search ability and convergence speed of the algorithm[12]. Therefore, the specific value of ρ needs to be considered carefully. If ρ is too large, the disadvantage is that it is easy to make certain pheromone on the path that has not been searched or ants evaporate rapidly. In the initial stage of optimization, the diversity of the solution remains unfavorable, and the algorithm is easily trapped into local optimum. The advantage is that the algorithm converges fast.If ρ is too small, the advantage is that the pheromone evaporation slowly, which is beneficial to the improvement of the global search ability and the generation of multiple solutions, and the problem of local convergence can be avoided. The disadvantage is that the convergence speed is slow.

Therefore, this paper adopts the method of segmentally adjusting ρ, and uses the size of ρ to adjust the algorithm in combination with the situation in different periods. In the early stage, ρ is set to a smaller value. Although the convergence speed of the algorithm is slower, the global search ability of the algorithm is improved, which is beneficial for the search of the optimal solution. In the later stage, as the number of iterations increases, the probability that the optimal solution is searched increases, and ρ is set to a larger value, thereby increasing the convergence speed.As follows:

$$\rho = \begin{cases} 0.1, NC \in \left(0, 0.8NC\_\max\right] \\ 0.95, NC \in \left(0.8NC\_\max, NC\_\max\right] \end{cases}$$

The NC is the number of iterations of the ant colony algorithm, and NC_max represents the maximum number of iterations. First, in the first 80% of the whole iterative process, setting ρ to 0.1 can improve the global search ability of the algorithm in the early stage; secondly, in the last 20% of the iteration, ρ is set to 0.95, and the search result is basically determined, thus speeding up the convergence speed of the algorithm.

D. 2-opt algorithm

The 2-opt algorithm was first proposed by Croes and is a local search algorithm[10]. When solving path optimization problems, the 2-opt algorithm can be combined with other algorithms to further optimize the original solution, which is beneficial to improve the efficiency of the algorithm.

The basic principle of the 2-opt algorithm:firstly, find an original solution, randomly select two demand points, flip the path between the two points, and the other demand points are unchanged; secondly, the new one will be obtained. The solution is compared with the original solution, and if the new solution is good, it is retained, otherwise it is abandoned.

V. CASE ANALYSIS

In order to test the performance of the algorithm, this paper uses two examples of eil22 and eil30 in Wang Shuqin [13], and uses the ant colony algorithm before optimization and optimization to solve the example, from three Aspects of the performance analysis of the algorithm. The emergency logistics centerand demand pointinformation statistics are shown in Table 1 and Table 2. It Data processing was carried out byMatlab2016 software.

According to the research on the parameters of ant colony algorithm by Li Yan [14] and Yang Changwei [15], the basic ant colony algorithm sets: the number of ants is 3/5 of the number of cities, the NC_max=50 of eil22, and the NC_max =500of eil30, α=1, β=5, ρ=0.5, Q=1, q_0=0.1; segmentation setting in the algorithm after optimization: NC<=0.8 NC_max, α=1, β=5, ρ=0.1, Q =1, q_0=0.1; when NC>0.8 NC_max, α=1, β=5, ρ=0.95, Q=1, q_0=0.1.

Table 1

Demand point coordinates and demand of eil22

number	x	y	w_i(kg)
1	145	215	0
2	151	264	1100
3	159	261	700
4	130	254	800
5	128	252	1400
6	163	247	2100
7	146	246	400
8	161	242	800
9	142	239	100
10	163	236	500
11	148	232	600
12	128	231	1200
13	156	217	1300
14	129	214	1300
15	146	208	300
16	164	208	900
17	141	206	2100
18	147	193	1000

19	164	193	900
20	129	189	2500
21	155	185	1800
22	139	182	700

eil22: 1 emergency logistics center, 21 demand points, and the vehicle load is 6000kg.

Table 2

Demand point coordinates and demand of eil30

number	*x*	*y*	w_i(kg)
1	162	354	0
2	218	382	300
3	218	358	3100
4	201	370	125
5	214	371	100
6	224	370	200
7	210	382	150
8	104	354	150
9	126	338	450
10	119	340	300
11	129	349	100
12	126	347	950
13	125	346	125
14	116	355	150
15	126	335	150
16	125	355	550
17	179	357	150
18	115	341	100
19	153	351	150
20	175	363	400
21	180	360	300
22	159	331	1500
23	188	357	100
24	152	349	300
25	215	389	500
26	212	394	800
27	188	393	300
28	207	406	100
29	184	410	150
30	207	392	1000

eil22: 1 emergency logistics center, 29 demand points, and the vehicle load is 4500kg.

A.Effectiveness Analysis

The optimal distance from the improved ACA to the eil22 operation is 375.2798km, as showed in Fig. 1. The optimal path is:

1) 1-10-8-6-3-2-7-1, driving distance 112.1702km, load: 5600kg, full load rate: 93.3%;

2) 1-18-21-19-16-13-1, driving distance 83.6680km, load: 5900kg, full load rate: 98.3%;

3) 1-11-9-4-5-12-14-1, driving distance 102.5806km, load: 5400kg, full load rate: 90.0%;

4) 1-15-22-20-17-1, driving distance 76.8610km, load: 5600kg, full load rate: 93.3%.

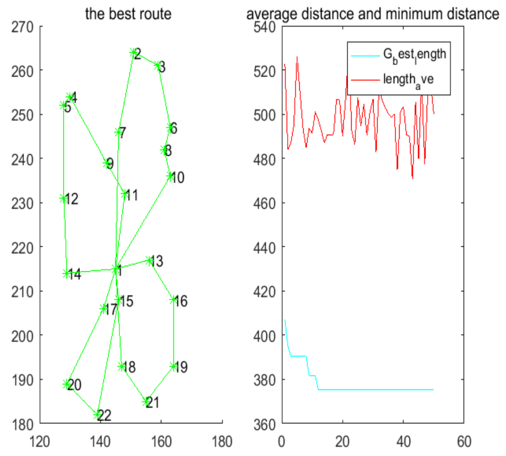

Fig.1:eil22 Eil22 optimal results

The optimal distance from the improved ACA operation to eil30 is 504.1711km, as showed in Fig. 2. The optimal path is:

1) 1-10-8-6-3-2-7-1, driving distance 112.1702km, load: 5600kg, full load rate: 93.3%;

2) 1-18-21-19-16-13-1, driving distance 83.6680km, load: 5900kg, full load rate: 98.3%;

3) 1-11-9-4-5-12-14-1, driving distance 102.5806km, load: 5400kg, full load rate: 90.0%;

4) 1-15-22-20-17-1, driving distance 76.8610km, load: 5600kg, full load rate: 93.3%.

It can be seen from Table 3 that the optimal path length of the improved ACA solution is smaller than that of ACA and Wang Shuqin [13]. Therefore, the optimization of the algorithm is effective.

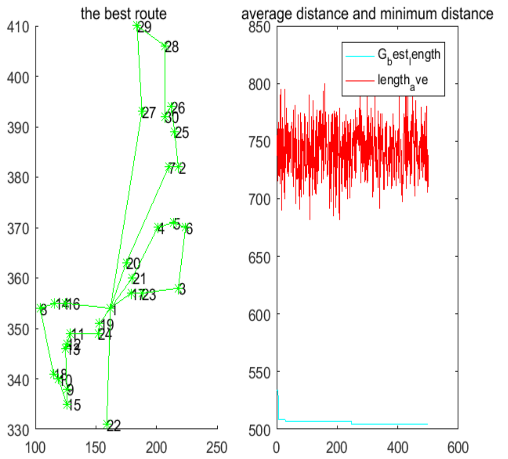

Fig.2:eil30 optimal results

Table 3

Comparison table of optimal solution

		optimal length (km)	Difference (km)
eil22	Improved ACA	375.2798	
	ACA	393.716	18.4362
	Wang Shuqin	381.6895	6.4097
eil30	Improved ACA	504.1711	
	ACA	548.2241	44.053
	Wang Shuqin	505.0111	0.84

B. Analysis of Convergence Properties

Two cases were run ten times through ACA and improved ACA respectively, and the optimal length was recorded, the number of iterations to obtain the optimal solution, and the running time was calculated according to equation [16]:

$$E_T = \frac{I_a T_0}{I_{\max}} \times 100\%$$

Among them, Ia: algorithm is run multiple times, the average number of iterations of the optimal solution is obtained, I_{max}: the maximum number of iterations given, and T_0: the average time of one iteration of the algorithm. E_T is used to measure how fast the ant colony algorithm searches for the problem. Under the premise of the maximum number of iterations, the smaller the $E_T$is, the faster the convergences speed is.

1）In eil22,according to Table4,I_a = 17.7, T_0 = 0.135, I_{max} = 50

$$E_T = \frac{I_a T_0}{I_{\max}} \times 100\% = \frac{17.7 \times 0.135}{50} \times 100\% = 4.8\%$$

2) In eil30, according to Table 4, I_a=189.9,T_0=0.176, I_{max}=500

$$E_T = \frac{I_a T_0}{I_{\max}} \times 100\% = \frac{189.9 \times 0.176}{500} \times 100\% = 6.7\%$$

The $E_T$values of eil22 and eil30 are both small, so the convergence performance of the algorithm is good and the convergence speed is fast.

Table 4

runs ten records

	eil22			eil30		
number	Optimal length (km)	Optimal solution iterations	operation hours（s)	Optimal length (km)	Optimal solution iterations	operation hours（s)
1	375.2798	16	5.75	506.7736	426	102.22
2	375.2798	33	8.47	506.2671	40	101.48
3	375.2798	5	9.41	504.1711	113	95.88
4	375.2798	36	4.44	506.7736	105	91.65
5	375.2798	13	6.47	505.2151	97	75.95
6	375.2798	16	6.08	504.1711	335	75.7
7	385.2854	18	11.12	504.1711	276	74.49
8	376.5091	9	4.43	505.7097	163	74.42

9	375.2798	5	5.6	504.1711	116	86.22
10	375.2798	26	5. 7	506.7736	228	103.91

C. Stability Analysis

The error ε , robustness r is given by formula [11]:

$$\varepsilon = |\frac{best - ave}{best}| \times 100\%$$

$$r = \frac{m}{n} \times 100\%$$

Among them, best: the optimal solution obtained by each run, ave: average length, n: maximum number of iterations, m: number of times to find the optimal solution.

Table5
Stability Analysis

Case	Optimal Length (km)	Average Length (km)	ε (%)	r (%)	t (s)
eil22	375.2798	376.4033	0.3	1	5.4
eil30	504.1711	505.4197	0.2	1	88.13

From Table 5, the errors of eil22 and eil30 are 0.003 and 0.002, respectively, and the stability is 1, so the algorithm has stability.

VI. CONCLUSION

In this paper, the improved ant colony algorithm is used to solve the problem of emergency logistics vehicle routing, and the better results are obtained, which proves that the improvement of the algorithm is effective. In the next study, the model with time constraints and road incomplete connectivity and the choice of parameters in the ant colony algorithm should be considered. Therefore, the research and conclusions in this paper provide some ideas and values for the study of emergency logistics distribution routes.

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REFERENCES

[1] Zhang wei, Yang bin,Zhu xiaolin. Research on multi-objective emergency logistics path selection [J]. Journal of jiangsu university of science and technology (nature science edition),2017,31(02):219-224.

[2] Liu Yang. A study on the scheduling of humanitarian aid in uncertain time [D]. Shandong university,2017.

[3] Xu zhiyu, Peng jiacheng, Xu weisheng. Batch distribution planning of emergency logistics and ant colony optimization solution [J]. Computer engineering and application,2011,47(24):1-3+8.

[4] Tang chong. Emergency logistics vehicle scheduling based on simulated annealing algorithm [J]. Logistics technology,2017,36(01):114-116.

[5] Gong yawei. Research and implementation of optimal path selection for emergency relief vehicles [D]. Wuhan university of technology,2008.

[6] Zhang bin. Research on the optimal scheduling of emergency logistics vehicles [D]. Dalian maritime university,2007.

[7] Xu haoqin. Emergency resource scheduling research based on hybrid optimization strategy [D]. Henan university,2009.

[8] Zhang yuhua, Pan yu. Research on emergency logistics delivery vehicle scheduling based on ant colony algorithm [J]. Modern logistics,2009, (5):47-50.

[9] G.Clarke,J. W. Wright. Scheduling of Vehicles from a Central Depot to a Number of Delivery Points[J]. Operations Research,1964,12(4).

[10] M.G.A. Verhoeven,E.H.L. Aarts,P.C.J. Swinkels. A parallel 2-opt algorithm for the Traveling Salesman Problem[J]. Future Generation Computer Systems, 1995,11(2).

[11] Zhai lulu. Optimization research on ship waste collection and transportation route based on hybrid ant colony algorithm [D]. Donghua university, 2017.

[12] Zhang jun, Zhang jing, Song xuechao. Simulated annealing ant colony algorithm in the application of VRP problems [J]. Journal of xihua university (natural science edition), 2017, 4 (6) : 6 - 12.

[13] Wang shuqin. Research on ant colony algorithm for vehicle path problem [D]. Chongqing university, 2008.

[14] Li yanv, Pan guangzhen. Study on the relationship between volatility and iteration number and optimal path length in ant colony algorithm [J]. Science, technology and engineering,2013,13(23):6734-6738.

[15] Yang changhao, zhang zhuo. Study on parameter selection of basic ant colony algorithm in solving TSP problem [J]. Network security technology and application, 2018(05):26-28.

[16] Wu jun. Research on logistics distribution path optimization based on improved ant colony algorithm [D]. Wuhan University oftechnology, 2000.