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Research of Optimizing Distribution Routing in Earthquake Rescue

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Abstract: In earthquake rescue, all kinds of secondary disasters may occur at any time, roads easily damaged. So we need pay more attention to the distance dynamic measurement. In this study directed distance is proposed and its assessment methods are discussed. Based on it, a new model of the route selection in earthquake rescue is established. An improved max-min ant colony algorithm is applied to solve the problem so that the emergency relief supplies will be sent to the disaster area more efficiently. Improved max-min ant system not only restricts the pheromone on paths, but also makes an improvement for update pheromone, which can avoid falling into local optimal path and can more easily found the global optimal path. Finally, a case shows that the algorithm is feasible.

Key words: Directed distance, route, selection, rescue

INTRODUCTION

Recently, natural disasters are frequency. Especially big earthquake disaster is not only sudden and unpredictable, but can lead to secondary disasters, which pose serious hazards for people's lives and property. How to find an effective rescue path for the rescue teams in the shortest possible time after the earthquake disaster becomes the focus of attention.

There are many different types of emergency response models to solve these natural disasters (Ibri *et al*., 2010; Zheng and Ling, 2013). VRP was much concerned in recent years and it is used to solve such problems but few considering the change of the roads (Chen and Ting, 2006; Li, 2013). In these studys, the straight line distances are widely used. In the earthquakes rescue, roads are easily damaged. Therefore, it is necessary to do more detailed studies on the route selection problem in earthquake rescue.

So we need renew the traditional model of the route selection problem in earthquake rescue, pay more attention to the role of distance in the model and to find the right method to measure and reflect its change , makes it more comply with the actual situation.

Ant colony algorithm is capable of intelligent search and global optimization; meanwhile, it has the characteristics of positive feedback, distributed computing, robust, easily combining with other algorithms and so on. Positive feedback can speed up the convergence rate, quickly find the best solution. Distributed computing can make the algorithm parallel and individuals can maintain continuous exchange of information and transmission, which is favorable to find better solutions (Zhu and Wang, 2007).

Ant Colony Optimization (ACO) was introduced in 1991 by Dorigo and it was successfully applied to symmetric TSP problems. Later it led to Max-min Ant System (MMAS) and the Ant Colony System (ACS) (Lee *et al*., 2010; Kazharov and Kureichik, 2010). These algorithms have been applied to routing problem, distribution problem, scheduling problem, subset problem and so on and all of which has received better results.

This study will discuss dynamic assessment method of directed distance and establish a new model of the route selection problem in earthquake rescue based on it, then propose an improved max-min ant colony algorithm to solve it, thus avoided falling into local optimal path and can ultimately found the global optimal path. At last the study will carry out a case of the model and algorithm.

Problem description: This is a problem of finding a shortest distance as our objective. There is only one rescue supply center which is the start point and also the end point. The supply center has K vehicles served for N accident points, each vehicle with capacity constraint Q. The vehicle returns to the supply center when the capacity constraint of the vehicle is met or when all customers are visited.

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Assumptions of the problem:

- Every vehicle must start with rescue supply center, return to it
- Each accident point is visited only once by one vehicle
- Total demand serviced by each vehicle cannot exceed the load weight of vehicle
- Because some parts of roads might be damaged, here distance from accident point i to accident point j not necessarily equal to the distance from accident point j to accident point i

Directed distance measurement: Let c_{ij} indicates the measurement value of the directed distance from accident point i to accident point j. Its value can be gained according to the following scale rules considering actual distance, road conditions and pass time.

- $0<c_{ij}=2$: Pass fast, road is slightly damaged
- $2<c_{ij}=3$: Pass faster, road is moderately damaged
- $3<c_{ij}=5$: Pass slower, roads is seriously damaged

c_{ij} $6\rightarrow\infty$: Can't pass, road is seriously damaged or no way

For this problem, we use the method of expert evaluation and can get the directed distance measurement value from one accident point to another accident point according to above scale rules.

Mathematical model: We present a mixed integer programming formulation for the VRP. Let us define variables:

c_{ij}: Directed distance measurement value from customer i to customer j
q_i: The shipment size of customer i
Q^k: The capacity of vehicle k

$$x_{ij}^k=\begin{cases}1 & \begin{array}{l}\text{if vehicle k travels directly}\\ \text{from customer i to customer j}\end{array}\\ 0 & \text{otherwise}\end{cases}$$

$$y_{ik}=\begin{cases}1 & \text{if vehicle k services customer i}\\ 0 & \text{otherwise}\end{cases}$$

s_i: the service order at customer i

The problem can be stated as follows:

$$\min C=\sum_{i=0}^{N}\sum_{j=0}^{N}\sum_{k=1}^{K}c_{ij}x_{ij}^k$$

subject to:

$$\sum_{i=0}^{N}q_i y_{ik}\le Q^k,\ k=1,2,\ldots,K \tag{2}$$

$$\sum_{k=1}^{K}y_{ik}=\begin{cases}1 & i=1,2,\ldots,N\\ K & i=0\end{cases} \tag{3}$$

$$\sum_{i=0}^{N}x_{ij}^k=y_{jk}\quad j=0,1,2,\ldots,N;k=1,2,\ldots,K \tag{4}$$

$$\sum_{j=0}^{K}x_{ij}^k=y_{ik}\quad i=0,1,2,\ldots,N;k=1,2,\ldots,K \tag{5}$$

$$x_{ij}^k=0\ \ \forall i=j;k=1,2,\ldots,K \tag{6}$$

$$\begin{array}{l}s_i-s_j+(N+1)\sum_{k}x_{ij}^k\le N\\ i\ne j,i=1,2,\ldots,N;j=1,2,\ldots,N\end{array} \tag{7}$$

$$x_{ij}^k\in\{0,1\};y_{ik}\in\{0,1\};s_i>0$$

The objective is to minimize the sum of all directed distance measurement values subject to vehicle capacity constraints. N is the number of customers, K is the number of vehicles.

Eq. 1 is the objective function of the problem. Equation 2 means the load of every vehicle cannot exceed the limit of capacity. Equation 3-6 state that all routes (tours) begin and end at the depot and that each customer i is serviced by one and only one vehicle and ensures every route starts and ends at the delivery depot , also specifies that there are maximum K routes going out of the delivery depot. Using Eq. 7 can avoid circuit.

ANT COLONY OPTIMIZATION

Many researchers also use ACO to obtain near optimal solutions or even global optimal solutions for VRP (Rizzoli *et al*., 2007). Bullnheimer et al. (1999) used a nearest neighbor heuristic for VRP in ant systems. Bell and McMullen (2004) applied ant colony optimization to an established set of vehicle routing problems.

Suppose $b_i(t)$ is the number of ants at point i at time t, m is total number of the ants, $\tau_{ij}(t)$ is pheromone amount at time t from point i to j.

Supposed ρ is the volatile coefficient of pheromone which shows the speed of pheromone's volatilization. When all the ants have traveled, the pheromone on each path is:

$$\tau_{ij}(t+1) = (1-\rho)\bullet\tau_{ij}(t) + \Delta\tau_{ij}(t,t+1) \quad (8)$$

$$\Delta\tau_{ij}(t,t+1) = \sum_{k=1}^{m}\Delta\tau_{ij}^{k}(t,t+1) \quad (9)$$

$\Delta\tau_{ij}(t,t+1)$ is incremental pheromone on path from i to j during traveling. At the beginning, $\Delta\tau_{ij}^{k}(t,t+1)$ is the pheromone that ant k release on the path from i to j during traveling, which is determined by ants' performance. The shorter the path is, the more pheromone is released:

$$\Delta\tau_{ij}^{k} = \begin{cases} \dfrac{C_1}{L_k} & \text{if ant k travels from i to j} \\ 0 & \text{otherwise} \end{cases} \quad (10)$$

where, C_1 is a constant and L_k is the length of the tour constructed by ant k. In the construction of a solution, ants select the following point to be visited through a stochastic mechanism. When ant k is in point i and has so far constructed the partial solution, the probability of going to point j is given by:

$$P_{ij}^{k} = \begin{cases} \dfrac{\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}}{\sum_{v\in allowed_k(t)}\tau_{ij}(t)^{\alpha}\eta_{ij}^{\beta}} & j \in allowed_k(t) \\ 0 & \text{otherwise} \end{cases} \quad (11)$$

where, $allowed_k(t) = (1,2,\ldots, N)-tabu_k$ is the set of points that ant k can choose currently. $tabu_k$ is the taboo list of ant k , recording the points that ant k has traveled through, to indicate ants' memo ability. η_{ij} is prior knowledge visibility, α is the importance of residual information on path i to j. â is the importance of elicitation information.

Ant colony system: The most interesting contribution of ACS is the introduction of a local pheromone update in addition to the pheromone update performed at the end of the construction process (called offline pheromone update).

The local pheromone update is performed by all the ants after each construction step. Each ant applies it only to the last edge traversed:

$$\tau_{ij} = (1-\sigma)\tau_{ij} + \sigma\tau_0 \quad (12)$$

where σ (0, 1] is the pheromone decay coefficient and τ_0 is the initial value of the pheromone. The main goal of the local update is to diversify the search performed by subsequent ants during iteration: by decreasing the pheromone concentration on the traversed edges, ants encourage subsequent ants to choose other edges and, hence, to produce different solutions. This makes it less likely that several ants produce identical solutions during one iteration.

The offline pheromone update is applied by only one ant, which can be either the iteration-best or the best-so-far. However, the update formula is slightly different:

$$\tau_{ij} \leftarrow \begin{cases} (1-\rho).\tau_{ij} + \rho.\Delta\tau_{ij} & \text{if (i, j) belongs to best tour} \\ \tau_{ij} & \text{otherwise} \end{cases} \quad (13)$$

Another important difference between ACO and ACS is in the decision rule used by the ants during the construction process. In ACS, the so-called pseudorandom proportional rule is used: the probability for an ant to move from point i to point j depends on a random variable q uniformly distributed over [0, 1] and a parameter q_0, that is:

$$j_{ij(k)} = \begin{cases} \arg\max\{\tau_{ij(k)}\eta_{ij(k)}^{\gamma}\}, & \text{if } q \le q_0 \\ J, & \text{othwise} \end{cases} \quad (14)$$

Otherwise Eq. 15 can be used.

IMPROVED MAX-MIN ANT SYSTEM

The max-min ant colony algorithm has been proved by simulation, possesses advantage on solving optimization problems (Yu and Wang, 2013; Liu *et al*., 2012).

The biggest difference between ACO and MMAS is that the pheromone on paths in MMAS is restricted to a certain extent to avoid into local stagnation as:

$$\tau_{ij}(t) = \begin{cases} \tau_{max} & \tau_{ij}(t) > \tau_{max} \\ \tau_{ij}(t) & \tau_{min} \le \tau_{ij}(t) \le \tau_{max} \\ \tau_{min} & \tau_{ij}(t) < \tau_{min} \end{cases} \quad (15)$$

In MMAS, introducing τ_{min} can effectively overcome stalled shortcomings of ACO. Introducing τ_{max} can overcome the shortcomings in local optimum of ACO.

Concerning the lower and upper bounds on the pheromone values, τ_{max} and τ_{min}, they are typically obtained empirically and tuned on the specific problem considered.

Here we may set initial value of τ_{max} and τ_{min} as constant, after first search update according to dynamic strategies as:

$$\tau_{max}(t) = \frac{1}{2(1-\rho)} \times \frac{1}{L^{best}} \quad (16)$$

$$\tau_{min}(t) = \frac{\tau_{max}}{C_2} \tag{17}$$

where C_2 is a constant. L^{best} is the length of the best path. In finding feasible solutions, ants perform the process of update pheromone. This process consists of both pheromone evaporation and new pheromone deposition which can guide ants to explore possible paths and avoid trapping in locally optimal solutions.

Improved max-min ant system not only restricts the pheromone on paths, but also makes proper improvement for update pheromone. Updating pheromone in ACO is for all ants, but in MMAS it is only for the ants that have found the best solution currently. Updating pheromone in MMAS is as follow:

$$\tau_{ij}(t+1) = (1-\rho).\tau_{ij}(t) + \Delta\tau_{ij}^{best} \tag{18}$$

$$\Delta\tau_{ij}^{best} = C_3 / f(L^{best}) \tag{19}$$

where, C_3 is a constant.

In the process of construct solutions, ants will utilize pheromone trail and heuristic information to build feasible solutions. Ant k at time t positioned on node r moves to the next node s with the rule governed by:

$$s = \begin{cases} \arg\{\max_{v=allowed_k(t)} [\tau_{rv}(t)\eta_{rv}^{\beta}]\} & when(q \le q_0) \\ S & otherwise \end{cases} \tag{20}$$

where $\tau_{rv}(t)$ is the pheromone trail at time t, η_{rv} is heuristic information, q is a random number uniformly distributed in [0,1], q_0 is a pre-specified parameter ($0 = q \mp 1$), $allowed_k(t)$ is the set of feasible nodes currently not assigned by ant k at time t and S is an index of node selected from $allowed_k(t)$ according to the probability distribution given by:

$$P_{rs}^{k}(t) = \begin{cases} \dfrac{\tau_{rs}(t)\eta_{rs}^{\beta}}{\sum_{v\in allowed_k(t)} \tau_{rv}(t)\eta_{rv}^{\beta}} & \text{if } s \in allowed_k(t) \\ 0 & otherwise \end{cases} \tag{21}$$

Here we set: $\eta_{rs} = 1/C_{rs}$, C_{rs} is the directed distance from point r to s.

ALGORITHM FLOW

- **Step 1:** NC = 0 (NC is iteration), load(k) = 0(that is the load of each vehicle), set initial value of τ_{max} and τ_{min} and other parameters initialization
- **Step 2:** Put m ants at the supply center
- **Step 3:** Calculate the transition probability of ant k based on Eq. 20 and 21. Choose and move to the next point s and add s to k $tabu_k$ at the same time
- **Step 4:** When solving the problems including more vehicles, algorithm is affected not only by probability transfer, but also by vehicles' maximum load capacity. Check whether the vehicle load reaches maximum load. If so, the vehicle returns to supply center directly
- **Step 5:** Check whether $tabu_k$ is full. If not, return to Step 3. Otherwise, go on Step 6
- **Step 6:** Calculate objective function and record the best solution currently
- **Step 7:** Update pheromone based on Eq. 18, 21
- **Step 8:** If $NC<NC_{max}$ then NC+1, empty $tabu_k$ and go back to Step2. If $NC<NC_{max}$, end

A case: Suppose that the coordinate of supply center is (0, 0). Supply center allocates 3 vehicles to 8 accident point to deliver relief supplies. The load weight of per vehicle is 100. Tab.1 indicates coordinate data and demand of each point.

First we need invite some experts for asymmetric directed distance assessment. Different from the straight line distance, here distance from point i to point j not necessarily equal to the distance from point j to point i. Under normal circumstances, matrix is asymmetric.

We use a large number M (For example, M=1000) represents that the road is impassable. Suppose after assessment all distance value from point i to j get as showed in Table 2.

We can use the method introduced above to solve asymmetric distance VRP in the earthquake rescue.

Table 1: Coordinates and demand

No.	1	2	3	4	5	6
	7	8	9			
x	0	8	13	15	5	9
	10	1	5			
y	0	5	6	2.5	5	3
	1	4	6			
Demand		0	30	25	33	3 0
	38	25	45	50		

Table 2: Distance assessment values

C_{ij}	1	2	3	4	5	6	7	8	9
1	-	4.82	3.71	4.94	3.83	4.75	3.99	4.89	3.95
2	4.82	-	4.56	4.63	4.92	4.66	4.75	4.79	3.44
3	4.56	4.56	-	4.87	2.56	4.65	2.58	2.83	3.39
4	1000	4.63	4.87	-	4.65	4.95	4.63	4.92	2.88
5	3.83	2.92	3.66	3.65	-	3.84	3.55	4.56	4.69
6	4.75	4.66	4.65	4.95	1000	-	4.49	2.68	4.97
7	3.49	2.75	3.58	2.63	4.55	4.49	-	4.95	4.29
8	4.39	3.79	4.83	3.92	3.56	3.68	4.95	-	4.86
9	2.95	4.44	4.39	4.88	4.69	4.97	3.29	3.86	-

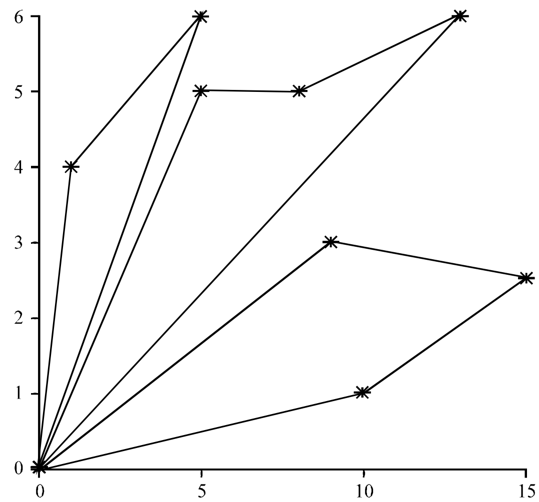

Fig. 1: Optimal path

In simulation, we need to identify a set of parameters. Experiments were conducted on PC with matlab7.0 for tools.

Let parameters as: $Nc_{max} = 1000$, $m = 50$, $\alpha = 1$, $\beta = 2$, $\rho = 0.25$, $C_1 = C_3 = 1$, $C_2 = 20$, $\tau_{min}^0 = 0.02$, $\tau_{max}^0 = 20$.

After many times experiments using different parameters we can find out that the results were same in the end. According to the computer simulation 3 routes found as Fig. 1. The optimal value is 42.89.

The first route is: supply center→point 5→point 2→point 3→supply center.

The second route is: supply center →point 6→point 4→point7→supply center.

The third route is: supply center →point 8→point 9→supply center.

CONCLUSION

In emergency rescue, emergency logistics environment is often uncertain. For all kinds of secondary disasters may occur at any time. Therefore, in the emergency rescue, we need consider vary conditions in order to better reflect the emergency route selection problem.

This study has made the beneficial attempt. The simulation results have verified the validity and practicability of the model and algorithm discussed above.

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