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The Location-Routing Problem of Urban Disaster Emergency Based on an Improved Ant Colony Algorithm

Renhui LIU, Yang YANG

School of Management, Harbin Institute of Technology,
13 Fayuan St, Nangang Dist, Heilongjiang, Harbin, 150001, China
Tel.: 86 18604502333, fax: 860451-86402181
E-mail: lrh@hit.edu.cn

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Abstract: The optimization of urban emergency supplies transportation can effectively improve disaster relief efficiency and reduce disaster losses. In this study, a multi-objective location-routing problem (LRP) model is established aiming at minimizing the time, route length, and cost in urban emergency rescue. Moreover, an improved ant colony algorithm is designed to solve this model. In this algorithm, the pheromone updating strategy and heuristic factor are enhanced considering the disadvantages of ant colony algorithm. Finally, combining with the risk slope control works in Shenzhen, China, empirical studies are conducted in 30 dangerous slopes in Baoan District, Shenzhen to verify the feasibility and effectiveness of the improved ant colony algorithm. *Copyright © 2013 IFSA.*

Keywords: Urban emergency, Emergency management, Ant colony algorithm, Emergency Logistics, LRP.

1. Introduction

In recent years, China faces with a grim natural disaster situation. The number of natural disasters and the cost caused by these disasters present a constant growing trend. Especially since the reform and openness, China's urbanization process has been significantly accelerated. The related reports released by the National Bureau of Statistics of China indicate that China's urbanization rate has reached to 51.27 % in 2011. In urbanization process, population and wealth are more concentrated. Furthermore, in 21st century, disasters leaded by artificial terrorist accidents, such as bombings and terrorist attacks etc. present a severe test to urban safety. Due to the particularity of China's natural conditions, the urban disaster emergency in China is more challenging. Statistics suggest that, 70 % more of big towns, half more of China's population, and 75 % more of industrial and agricultural output value are distributed in the regions with serious meteorology, marine, flood, earthquake etc. disasters. China is one of the countries with the most serious natural disasters in the world. Its disasters are characterized by wide range, high frequency, and strong regional properties. The economic losses caused by natural disasters have been in a rising trend since 1990s especially. Natural disasters have become an important factor affecting economic development and social stability of China. In urban disasters, geological disasters, especially the emergency disasters such as volcano and earthquake etc., occupy an important position. Tangshan Earthquake in magnitude of 7.8 in July 28, 1976 and Wenchuan Earthquake in magnitude of 8 in May 12, 2008 result in extremely large casualties and economic property losses.

2. Review

Urban emergency rescue is an important part of urban emergency system. It can effectively reduce the loss in life and property. Urban rescue is complicate system engineering, in which, ensuring the timely arrival of rescue force is the core issue of rescue works. Therefore, it is required to establish scientific and efficient emergency rescue systems to guarantee emergency disaster relief supplies arriving in the shortest time and minimizing the losses caused by disasters. Emergency rescue generally aims at maximizing time efficiency and minimizing disaster loss. It includes two core issues, namely, the optimizations of distribution center location-allocation and disaster relief supplies transportation route [1-3]. Through investigating the LRP in corresponding emergency rescue system, emergency rescue route can be effectively determined and loss can be reduced.

LRP is derived from the optimization solution in logistics system. Currently, the LRP study in business logistics is widely developed around the world, while that on emergency rescue is less found. Due to the differences on characters, emergency rescue LRP and business logistics LRP present different targets and beneficiaries. Business logistics tends to pursue benefit maximization or total cost minimization etc., while emergency rescue emphasizes on rescue timeliness and loss minimization etc. In China, Zheng Bin and Ma Zujun et al. set up a fuzzy multi-objective LRP optimization model of emergency supplies demand by comprehensively considering the differences in emergency rescue LRP and business logistics LRP. This model was designed to minimize the emergency supplies' total transportation time and system's total cost. Moreover, they presented a multi-objective genetic algorithm to solve this model [4]; Dai Ying and Ma Zujun et al. studied the joint decision of the location of post-earthquake emergency supplies distribution center and distribution vehicle routing arrangement in aspect of system integration optimization. Then, attempting to minimize the sum of the arrival time of the emergency supplies from each supplies-demand site, they established a fuzzy dynamic location route optimization model using chance constrained programming method. Furthermore, they developed a two-stage heuristics algorithm to solve this model [5]. Ceng Mingang et al. divided emergency rescue issue into two sub-issues, namely, the location of emergency service facilities and the arrangement of emergency supplies transportation route. Focusing on these two sub-issues, they built a LRP model with the minimum total cost as target and employed a two-stage heuristic algorithm to solve this model [6].

The effectiveness and timeliness of solution method plays a vital role in realizing the emergency rescue LRP optimization model. At present, researchers around the world consider that traditional operations research algorithms are difficult to adapt to the solution of large-scale and complex models. For practical problems, heuristic algorithms are usually employed. Ant colony algorithm is a novel simulated evolutionary algorithm. Since this algorithm is high in computational efficiency and easy to combine with other heuristic algorithms, it is widely used in solving logistics LRP problems. However, it is less used in the model optimization of emergency rescue LRP. Ant colony algorithm was first proposed by M. Dorigo et al. (Italian researchers) in 1991 [7-9]. In 1996, M. Dorigo and Gambardella published an article named "Ant system: optimization by a colony of cooperating agents" [10] and proposed a modified ant colony algorithm. They called this modified ant colony algorithm as ant colony system. Thereafter, M. Dorigo et al. continued to improve ant colony algorithm and more systematically elaborated the basic principle and mathematical model of ant colony algorithm. They further compared ant colony algorithm with genetic algorithm, tabu search algorithm, simulated annealing algorithm, and hill climbing method by simulation experiments. Moreover, they applied this algorithm to traveling salesman problem (TSP) [9], assignment problem [11], job-shop scheduling problem [9] and achieved a series of good test results.

Since 1996, ant colony algorithm has attracted the attention of a lot of researchers in all fields in the world. Its application is greatly extended thereby. German researcher Thomas Stutzle and Holger Hoos proposed another improved ant colony algorithm, namely, "max-min ant system" (MMAS) [12]. The basic idea of MMAS is accelerating convergence rate by merely adjusting the information quantity on the route that the best individual in each generation traveled. Although stagnation behavior is easy to be induced, MMAS is still one of the most proper models to solve optimization problems in discrete domain until today.

The study of ant colony algorithm starts relatively late in China. Zhang Jihui and Xu Xinhe from Northeastern University Control Simulation Research Center [13] firstly investigated ant colony algorithm. They minutely explained the principle, system model and implementation of ant colony algorithm and summarized the advantages and disadvantages of ant colony algorithm in their paper published in 1999. At present, ant colony algorithm is studied and applied more and more widely in China. Zhang Zhaojun and Feng Zuren et al. studied the disadvantages of MMAS system, i.e. pheromone lower bound is difficult to be determined, and algorithm performance is easily affected by isomorphism problem. Aiming at solving these problems, they pointed out that the upper and lower boundaries of pheromone did not change with the update of objective function value, namely, the update amount of pheromone is an irrelevant constant of objective function value [14]. Chen Yingxin employed an improved ant colony algorithm to solve the vehicle routing optimization problem [15]. The improvement in their algorithms was mainly reflected in the following aspects. Firstly,

the improvements on pheromone update strategy. Chen proposed a mixed update strategy first using real-time update then using global update strategy by summarizing the advantages and disadvantages of pheromone real-time update and global update; secondly, the improvement on heuristic factor; thirdly, introduction of search hot-area. The transfer probability of route selection in the next step is determined according to whether the route is in search hot-area or not. Wu Bin, Shi Zhongzhi carried out a meeting ant colony algorithm on the basis of ant colony algorithm [16]. The basic idea of this algorithm was allocating one tour of an ant into two ants separately. Thereby, the quality of one tour of ant was improved. Then by incorporating meeting algorithm with the segmentation algorithm of parallel strategy, they further proposed an ant colony algorithm-based TSP segmented solution algorithm.

In reference with existing research results, a LRP optimization model, aiming at minimizing emergency rescue time and rescue route length, is built in this study. It is then solved by the ant colony algorithm with better solving performance. Moreover, ant colony algorithm is enhanced in this paper considering the characteristics of emergency rescue. Finally, the feasibility and effectiveness of the improved ant colony algorithm is verified by the empirical studies conducted to 30 dangerous slopes in Baoan District, Shenzhen.

2. Establishment of Emergency Rescue Model

After disasters take place, urban emergency center is required to transfer the demanded human forces and supplies to disaster sites in limited time to minimize loss.

Assume that existing urban emergency rescue site is u (recorded as 0 points); the disaster site set can be rescued by this site is $V = \{v_1, v_2, ..., v_n\}$; there is only one emergency rescue vehicle on rescue site u; the total traveling route of this vehicle is D; total rescue time is T; total transportation cost is C; In the model, the cost of vehicle traveling from site i to site j is c_{ij}; the travelling time from site i to site j is t_{ij}; emergency supplies demand amount is $E_j (j = 1,2,....., n)$; the supply quantity provided by emergency rescue site is E_0.

d_{ij} is the distance from disaster site i to disaster site $j(i, j = 1,2,....., n)$. Its Euclidean distance is recorded as:

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{1}$$

In emergency rescue, the minimum distance of vehicle to emergency site is linear distance. Considering that vehicle will definitely encounter some detour route in rescue in actual situation, detour factor A is added in, namely:

$$A\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{2}$$

Decision variable is defined in the following:

$$\begin{cases} 1, \text{The routes between i and j travelled by vehicle} \\ 0, \text{Otherwise} \end{cases} \tag{3}$$

The mathematical models of objective functions can be established:

$$D = \min \sum_{i=0}^{n} \sum_{j=0}^{n} d_{ij} x_{ij} \tag{4}$$

$$T = \min \sum_{i=0}^{n} \sum_{j=0}^{n} t_{ij} x_{ij} \tag{5}$$

$$C = \min \sum_{i=0}^{n} \sum_{j=0}^{n} c_{ij} x_{ij} \tag{6}$$

By introducing in the weights of each objective, total objective function is defined as:

$$f = \omega_1 D + \omega_2 T + \omega_3 C \tag{7}$$

Related constraints are shown as below:

$$\sum_{i=0}^{n} x_{ij} = 1, (j = 1,2,....., n) \tag{8}$$

$$\sum_{i=0}^{n} x_{iq} = \sum_{j=0}^{n} x_{qj}, (q = 1,2,....., n) \tag{9}$$

$$\sum_{i=0}^{n} \sum_{j=0}^{n} x_{ij} \leq n + 1 \tag{10}$$

$$\sum_{i=0}^{n} \sum_{j=0}^{n} E_j x_{ij} \leq E_0 \tag{11}$$

Formula (8) constrains that vehicle only arrives at slope j for one time; formula (9) constraints that when vehicle arrives at slope q from slope i, this vehicle must leave slope q to slope j; formula (10) restricts that vehicle only starts or ends at distribution center point u; formula (11) limits the number of the most disaster sites that can be rescued by emergency site.

3. The Improved Ant Colony Algorithm

In reference with existing research results, ant colony algorithm is improved in this study according to the specific situations of emergency rescue to solve the LRP model built.

3.1 Setting of Heuristic Information

In ant colony algorithm, p_{ij}^{l} (t) is set as the possibility of ant l moving from site i to site j at time t. It value is as below.

$$p_{ij}^{l}(t)=\begin{cases}\dfrac{[\tau(t)]_{ij}^{\alpha}[\eta(t)]_{ij}^{\beta}}{\sum_{s\in allowed}[\tau(t)]_{ij}^{\alpha}[\eta(t)]_{ij}^{\beta}}, j\in allowed\\ 0, j\notin allowed\end{cases} \quad (12)$$

In formula (12), $allowed=\{0,1,2,.....,n-1\}-tabu_l$, it refers to the disaster sites allowing ant to select. α,β denote the accumulated information of ant in motion and the effects of heuristic factor in route selection of ant respectively. η_{ij} represents the expectation degree of transferring from site i to site j. Here, it is set as:

$$\eta_{ij}^{l}=\omega_1\times\frac{1}{d_{oj}}+\omega_2\times\frac{1}{t_{ij}}+\omega_3\times\frac{1}{c_{ij}} \quad (13)$$

In formula (13), d_{oj} is the distance from emergency site u to the emergency site j that vehicle arrive at. The improvement above can indicate direction for ant colony searching the global optimum by focusing on global situation and find the relations between the various nodes and the origin. The accuracy and search efficiency are thereby effectively improved.

3.2. Update of Pheromone

Previous information left in ant colony algorithm gradually fades away with the passage of time. Parameter $1-\rho$ is used to express the fading degree of information. Where, ρ is exerting coefficient. Assume that ant can complete one cycle by y time periods. The information amount on each route is correspondingly adjusted according to the following formula.

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

$$\Delta\tau_{ij}=\sum_{l=1}^{M}\Delta\tau_{ij}^{l} \quad (15)$$

$\Delta\tau_{ij}^{l}$ refers to the information amount of ant l left on route $i--j$ in this cycle. $\Delta\tau_{ij}$ is the increment of the information amount on route $i--j$ in this cycle. The update method above is given by M. Dorigo. M. Dorigo has presented three different models, including ant-cycle system, ant-quantity and ant-density system. The latter two utilize local information. The expression formula of $\Delta\tau_{ij}^{l}$ of global pheromone is as follows:

$$\Delta\tau_{ij}^{l}=\begin{cases}Q/L_l, & \text{If ant } l \text{ travels through route ij in this cycle.}\\ 0, & \text{Otherwise.}\end{cases} \quad (16)$$

where Q is a constant, L_l is the route length of ant l traveled in this cycle.

The expression formula of $\Delta\tau_{ij}^{l}$ of local pheromone is as follows

$$\Delta\tau_{ij}^{l}=\begin{cases}Q/d_{ij}, & \text{If ant } l \text{ travels through route ij in this cycle}\\ 0, & \text{Otherwise}\end{cases} \quad (17)$$

However, the value of the evaporation factor of this pheromone is the same in each route. Moreover, practical factor are not involved in. Combined with existing research results [17], the product of $\omega\rho$ is used to represent the evaporation factor of pheromone. This improvement can enable faster convergence of model solution. Specific classification rules are as follows:

$$\omega=\begin{cases}1/3, \text{in other conditions}\\ 2/3, 1.2d\le d<1.6d\\ 1/9, 1d<d<1.2d\end{cases}, \quad (18)$$

where d refers to the routes in $i--j$. That is, when the route length in $i--j$ is in $[1.2d,1.6d)$, $\omega=2/3$. When the route length is in $[1d,1.2d)$, $\omega=1/9$. In other conditions, $\omega=1/3$. Thus the update formula of pheromone is as follows:

$$\tau_{ij}(t+y)=(1-\omega\rho)\bullet\tau_{ij}(t)+\Delta\tau_{ij} \quad (19)$$

It can be seen from formula (19) that when route length tends to d from infinite, ω is reduced. Thus the value of $(1-\omega\rho)$ is increased and the evaporation amount in route is decreased. Thus the pheromone on route grows and model solution more rapidly converges on the route.

3.3. The Realization of the Improved Ant Colony Algorithm

In view of the above improvements on ant colony algorithm, the realization steps of the improved ant colony algorithm is as follows:

1) Initialize parameter. Set cycle number $N_c = 0$, time $t = 0$; the maximum cycle number is set as $N_{c\max}$; m ants are placed on the nodes of distribution center; initial pheromone $\tau_{ij}(0) = c$.

2) Update cycle number N_c, namely, $N_c = N_c + 1$;

3) Set ant tabu list, quote is l;

4) Ant individuals select disaster site j according to the probability calculated by state transfer probability formula (12) and move forward. Meanwhile, the pheromone on the route they travelled is updated and new disaster site j is added to the tabu list;

5) Update global pheromone using formula (16), and record the current optimal solution;

6) Repeat step 2-5 until ants find the route containing all nodes;

7) Select the shortest route from the feasible solutions generated, and take this route as the optimal route of this cycle;

8) All the routes that have been travelled by ants are conducted with global pheromone update according to formula (15), (18), (19);

9) Repeat step 2-8 until iteration no longer shows the optimal solution or reach cycle number $N_{c\max}$. Suspend the calculation and output of the optimal solution.

4. Empirical Studies

Combined with existing urban emergency plan of Shenzhen, the LRP model above is applied to the dangerous slope control works of Shenzhen. Dangerous slopes, especially the slopes formed by the excavation, cut, and backfilling on the foot of slope in house building process, and the building slopes formed by transportation engineering construction and quarrying, are the main areas of slope geological disasters, such as landslide, collapse etc. Slope geological disasters are concentrated in flood season. They show strong abruptness and cannot be easily avoid. Although the scale of single site is small, slope geological disasters can easily induce casualties and property losses due to the developed economy and dense population in Shenzhen. In 2011, Shenzhen saw a total of 6 geological disasters, whose specific accidents were shown in Table 1. In the 6 disasters, the most serious one was the collapse accident occurred in the west side of Yinuofei Health Sports Equipment Factory in Dashuikeng Community on Guanlan Street of Baoan District in June 17, 2011. This accident caused property losses of about 850,000 Yuan, but no casualties. Losses can be effectively reduced by establishing effective slope emergency control measures. In 2011, Shenzhen allocated a total of 540 million Yuan for the control of geological disasters and dangerous slope. More than 6,000 people are prevented from the threat of geological disasters and dangerous slope and about 2.6 billion yuan economic loss is avoided.

In reference with Shenzhen's existing research achievements, thirty hidden slopes in Baoan District are calculated in this study. The basic data of these slopes are shown in Table 1.

Table 1. The basic data of the dangerous slops in Baoan District.

No.	Slope No.	Coordinate		No.	Slope No.	Coordinate	
		X	Y			X	Y
1	W/BAXA0131	24372	98590	16	W/BASY0302	35491	105191
2	W/BAXA0296	22657	99362	17	in process	36503	105023
3	S/BASG0287	45888	90918	18	in process	34640	100375
4	W/BASG0112	45761	93752	19	W/BASY0021	35384	102096
5	W/BASG0155	45426	93050	20	S/BASY0344	34952	104546
6	S/BAXX0789 S/BAXX0788	30424	93208	21	In process	35941	103304
7	S/BAXX1595	26034	93889	22	W/BASY0651	35194	103731
8	In process	32450	91308	23	In process	34419	103147
9	S/BASY0293	35850	105653	24	W/BASY0058	34366	103266
10	In process	36861	104858	25	S/BASY1094	34491	102473
11	In process	36432	105360	26	W/BASY0706	36275	103029
12	In process	36502	101558	27	S/BASY0813	37178	102781
13	S/BASY0794	35940	101887	28	S/BASY0247	37088	106283
14	In process	36838	105220	29	RS/BASY0248	37157	106355
15	In process	34971	105850	30	S/BASY0256	37780	106268

The improved ant colony algorithm above is employed for calculation. The basic parameters are set as: the number of ants $m = 50$; initial pheromone $\tau_{ij}(0) = 10$; pheromone evaporation factor $\rho = 0.6$; the influence coefficient of pheromone to selection probability $\alpha = 1$; the influence coefficient of heuristic information to selection probability $\beta = 5$; the weight in heuristic information $\omega_1 = \omega_2 = \omega_3 = 1/3$; the pheromone quantity updated by ants is 1; the maximum cycle number $N_{c\max} = 100$. According to the results obtained from the improved ant colony algorithm above, MATLAB (MATLAB version MATLAB 2012B) is used to simulate emergency route. The simulation results are shown in Fig. 1 and Fig. 2.

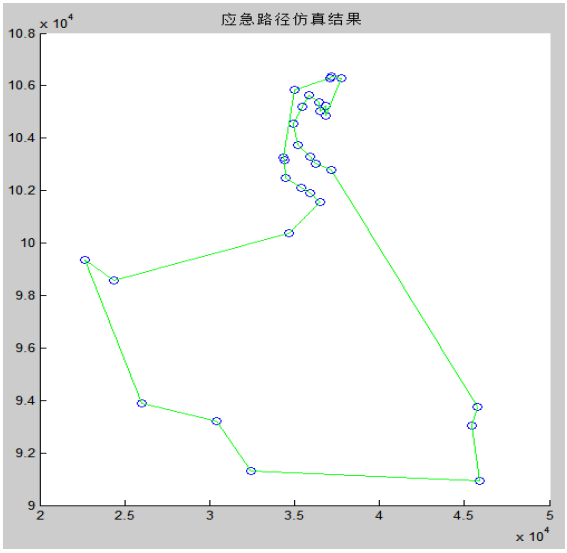

Fig. 1. MATLAB simulation results 1.

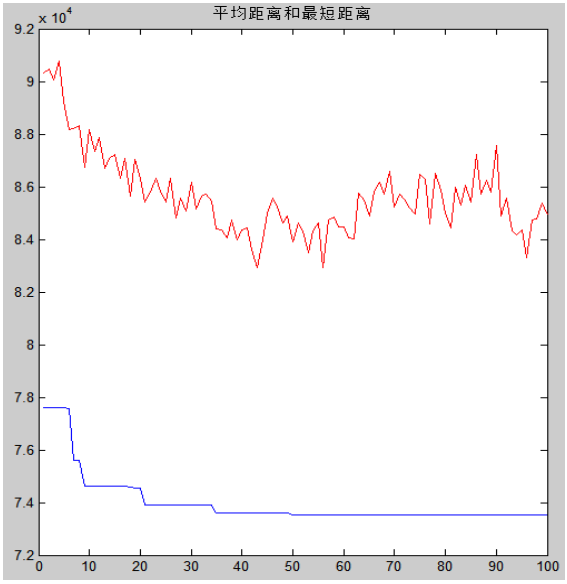

Fig. 2. MATLAB simulation results 2.

5. Conclusions

A multi-objective LRP model is established in this study aiming at minimizing the time, route length, and cost in urban emergency rescue. An improved ant colony algorithm is also designed to solve this model. In this algorithm, the update strategies of heuristic information and pheromone are mainly improved. This algorithm is verified by the empirical studies on the dangerous slope control work in Shenzhen. The emergency routes obtained are simulated by MATALB. Simulation results show that the algorithm has good computational efficiency and solution properties. In the next step, we will study multi-vehicle distribution and the information dynamic updating problem in vehicle distribution process.

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