Logistics Support Path Planning Model of Forest Fire Based on Ant Colony Algorithm

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Abstract. The problem of the network node and the complex constrain in the path planning has become a difficulty in forest fire logistics support. The traditional ant colony algorithm is improved. We establish two objective functions for the distance between nodes and the time required to finish task. We optimize the two objective functions. We redesigned the calculation method of heuristic information and the update function of pheromone. We set a time window to limit the time to complete urgent tasks. Finally, an example is given for verification. The results show that the improved algorithm can solve the problem of logistics support path planning model of forest fire. The results are more close to the actual situation.

1. Introduction

Logistics support is an important guarantee for forest fire disaster relief. Support path optimization is an important means to improve the efficiency of logistics support [1]. How to select support path and determine task order based on quickly and scientifically? It has become an important means to improve the efficiency of forest fire logistics support. It completes the dynamic screening of the optimal solution by simulating the social behavior of ant colony [2]. Ant colony algorithm adopts "elite ant" strategy and introduces "best-worst ant" in the literature [3]. It can make the algorithm convergence faster, search more efficient and get better path. It introduce the concept of fuzzy membership and information entropy in the literature [4], which balanced the relationship between the population diversity of algorithm and convergence rate. In view of the selection of the wounded transportation path. It expresses the different injury degree by restricting different time windows in the literature [5-7]. It focus different disaster area impacts and discuss the cross-regional emergency vehicle routing problem in the literature [8]. A vehicle routing optimization model with minimizing the traveling time is developed. This paper improves the traditional ant colony algorithm and the search efficiency.

2. Basic Ant Colony Algorithm

Take travelling salesman problem for example. Suppose the number of ants in the ant colony is M, the number of cities is n. There are many different paths between cities. At time t, the transfer probability of the K ant from city i to j is:

\[ P_{ij}^k(t) = \begin{cases} \frac{\tau_{ij}^\alpha(t)\eta_{ij}^\beta(t)}{\sum_{j \text{ allowed}} \tau_{ij}^\alpha(t)\eta_{ij}^\beta(t)} & j \in \text{allowed}, \\
0 & j \notin \text{allowed} \end{cases} \]

(1)
In the formula, \( k=1,2,\ldots,N; \) \( \tau_{ij}(t) \) is the pheromone of the path between city \( i \) and city \( j; \) \( \eta(t) \) is the heuristic information, which is generally taken as \( \eta(t) = 1/d_{ij} \) ( \( d \) is the distance between city \( i \) and city \( j; \) \( \alpha \) and \( \beta \) are heuristic factors; \( \text{allowed}_i \) is the set of cities where ant \( K \) does not pass at time \( t. \)

Ants leave pheromones on each path. We introduce the pheromone volatilization mechanism to avoid the algorithm falling into local optimum. So, the pheromone is updated in the following way:

\[
\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \Delta \tau_{ij}(t)
\]

\[
\Delta \tau_{ij}(t) = \sum_{k=1}^{M} \Delta \tau_{ij}^k(t)
\]

Among: \( \rho \) is the coefficient of volatilization \( (\rho \in [0,1]) \); \( \Delta \tau_{ij}^k(t) \) is the pheromone left by the \( k \)-th ant in the path.

3. Analysis on the Logistics Support Path Planning of Forest Fire

3.1. Principle Description

The general path optimization problem can be simply described as selecting the shortest path problem. But first of all, we should consider the issue of execution order from the urgency of the task in the logistics support path planning of forest fire. Secondly, transportation benefits can be considered[9]. The logistics support path planning of forest fire has its own characteristics except the characteristics of general path planning.

First, the path network is complex. Secondly, the primary and secondary tasks of emergency rescue are clear. We must give priority to the tasks of ensuring life safety and time limit. Finally, if we make a decision, we should consider the situation of the fire scene and the operation of the security system when selecting a path.

3.2. Mathematical Description

According to the characteristics of logistics support path planning problem, set: A logistics support group completes \( n \) support tasks according to the requirements of the logistics command office. These \( n \) tasks are in \( n \) different locations \( p_1, p_2, \ldots, p_n \); \( d_{ij} \) is the distance between \( p_i \) and \( p_j; p_0 \) as the starting point of the support group, which has no support mission. Any support group \( k \) \( (k=1,2,\ldots,K) \), the set of nodes it experiences and completes is \( n_k; \) Set \( R_k \) is the route of Group \( K \), and \( n_k \) represents the \( i \)-th task point of route \( R_k \), that is \( R_k = \{r_k, r_{k1}, L, r_k, r_k, r_{km}, r_k, r_{km+1}, L, r_k, r_k, r_{k+1}\} \). \( r_k \) and \( r_{k+1} \) represent departure and return, respectively. Set: the road condition between any two points is the same, the average speed of the support group is \( v. \) The time required by the support team from point \( p_i \) to point \( p_j \) is \( \tau_{ij} = d_{ij}/v \). The time window \([0, t_i]\) express that the support team needs to reach the disaster site \( i \) within \( t_i \) time.

The completion time of support task \( i \) is limited to \( T_{iLimit} \). There are two objectives to be optimized: at first, the waiting time for the recovery ability of the fire fighting element is the shortest, and second, the total distance of the support team is the shortest. Obviously, this is a multi-objective optimization problem.

3.3. Model Establishment

We establish the following multi-objective optimization model:
\[ \text{Min} Z_i = \sum_{i=1}^{n} d_{ij} x_{ij} \]

\[ \Delta t_{ij}^t = \begin{cases} Q / L_k \times T_k & \text{if } \Delta t_{ij}^t > 0 \\ 0 & \text{otherwise} \end{cases} \]

\[ s.t. \begin{cases} t_i + T_{i|\text{pair}} \leq T_{i|\text{Limit}} \\ t_0 = 0 \end{cases} \]

\[ R_k = \{ r_{ij} | r_{ij} \in \{1, 2, \cdots N\} \} \]

\[ s_{t_i} \leq b_i \]

\[ x_{ij} = \begin{cases} 1 & \text{Select task J after the support group completes task I} \\ 0 & \text{otherwise} \end{cases} \]

\( t_i \) is the time of that the forward support team arrives at the ith support task site. (6) is the limit time of complete support task \( i \). (7) is the path of the team \( k \) arrives at mission point. (8) is the constraint of different time windows for the support team to reach each task point.

4. Improvement of Ant Colony Algorithm and its Solution Flow

4.1. Improvement of the Ant Colony Algorithm

4.1.1. Improvement measures for algorithm design
- The improvement of sub path construction process. Every ant must pass through all nodes in the basic ant colony algorithm. However, in the improved ant colony algorithm, each ant does not need to traverse all nodes.
- In the improved ant colony algorithm, we should not only consider the distance between each task point, but also to consider the limit time requirements of each task point.
- In the improved ant colony algorithm, the loop constructed by each ant may or may not get some feasible solutions.

4.1.2. The improvement of pheromone updating and path node selection
The optimization of the two objective functions established in this paper, we need to redesigned the calculation method of heuristic information and the update function of pheromone. They are binary functions of path length and recovery time of fire fighting element[10].

In the multi-objective optimization ant colony algorithm, the calculation method of heuristic information is as follows:

\[ \eta_{ij} = \frac{1}{d_{ij} \times |T_j + T_{i|\text{pair}} - t_j - T_{j|\text{pair}}|} \]

The total number of pheromone released is a constant \( Q \) when a ant cycle for a week. In order to adjust the relationship between them, this paper introduces the adaptive inertia weight value of particle swarm optimization algorithm to adjust the \( Q \) value. In this way, it can adapt change in the process of search, so as to take into account the relationship between global and local search [11]. The formula is as follows:
Among them, $\omega_{\text{max}}$ is the maximum value of particle inertia weight. $\omega_{\text{min}}$ is the minimum value of particle inertia weight. $k$ represents the current number of iterations. $K_{\text{max}}$ is the maximum number of iterations. Therefore, when all ants have completed the path search, the pheromone update method on the path is as follows:

$$Q^* = (\omega_{\text{max}} - \frac{k(\omega_{\text{max}} - \omega_{\text{min}})}{K_{\text{max}}}) \cdot Q$$

(11)

$$\Delta \tau_{ij} = \sum_{s=1}^{m} \Delta \tau_{ij}^s$$

(12)

$$\Delta \tau_{ij}^s = \begin{cases} 
Q^* & \text{The } K \text{ ant passes through } ij \text{ in this cycle} \\
\frac{Q^*}{L_i \times T_k} & \text{The } K \text{ ant does not pass } ij \text{ in this cycle} \\
0 & \text{ otherwise}
\end{cases}$$

(13)

$L_i$ is the route length of the $k$-th ant in this cycle. $T^k$ is the total recovery time of fire fighting ability of all fire fighting element of the $K$ ant in this cycle. Description of path selection method: first, take a random number $q_0$ to determine whether it meets the requirements of $q \leq q_0$, $q_0$ is a pre-determined parameter, and If it is satisfied, select the next path node according to equation (14). If not, the next path node is randomly selected according to the probability obtained by equation (15).

$$j = \begin{cases} 
\arg \max_{j \text{ allowed}} \left\{ \tau_{ij}^a(t) \times \eta_{ij}^\beta(t) \right\} & q \leq q_0 \\
\text{other} & \text{otherwise}
\end{cases}$$

(14)

$$P_{ij}^k(t) = \begin{cases} 
\sum_{s \text{ allowed}} \tau_{ij}^a(t) \times \eta_{ij}^\beta(t) & s \in \text{ allowed} \\
0 & s \notin \text{ allowed}
\end{cases}$$

(15)

4.2 Solving Process

Step 1: Select any feasible path as the initial path, calculate the shortest path $L_0$ and the minimum recovery time $T_0$. And they are added to Pareto optimal solution set; Add them to the optimal solution set Pareto.

Step 2: Initializes the pheromone, giving each edge the same pheromone. Set the initial taboo list to null. Set the volatility of pheromone to $\rho$.

Step 3: while(iteration steps $<$ scheduled iterations)

Step 3.1: Initialize ants, put m ants into the nodes randomly of represent the front office support team.

Step 3.2: Take any ant starts searching the path, Cycle 1: for $k=1$ to $m$, the step length is 1.

Step 3.2.1: Ants start searching the path, Cycle 2: for $k=1$ to $n$, the step length 1;

Step 3.2.2: According to the formula 10, computational heuristic information $\eta_{ij}$ of each task point not in the taboo list.

Step 3.2.3: Produce a random number $q$. It selects the largest emergency repair task point $p_j$ according to equation (14). Otherwise, it selects the randomly emergency repair task point $p_j$ according to the probability determined by equation (15).
Step 3.2.4: Judge whether \( t_j + T_{j_{pair}} \leq T_{j_{limit}} \) is satisfied, if not, go to step 3.2.1.

Step 3.2.5: Judge whether \( L_k + \nu \leq t_k \) is satisfied, if not, go to step 3.2.1.

Step 3.2.6: Put support task point \( p_j \) into the taboo list.

Step 3.2.7: If all support task points are in the taboo list, cycle 2: end for.

Step 3.3: Using the route \( r \) obtained by the ant to calculate \( Z_1 \) and \( Z_2 \). Compare them with the solutions in each optimal solution set Pareto. If \( r \) is the non dominated solution of the solution set, then this solution is added to the optimal solution set Pareto.

Step 3.4: If all ants are searched, cycle 1: end for.

Step 4: Arrange the optimal solution set Pareto and start the next cycle.

Step 5: end while.

After getting the optimal solution set Pareto, the decision-maker can balance the path length and support time according to the actual situation of the fire scene\(^{12}\). Then, the decision chooses a path from the optimal solution set Pareto.

5. Example Experiment and Result Analysis

This paper adopts a support path planning problem of forest fire logistics support scenario. We use it for a testing. The specific location of 9 access nodes is shown in Figure 1.

![Figure 1. The location map of support task points.](image)

The distance between support task points is shown in Table 1. The paths that are not directly connected between two mission sites are represented by \( \infty \).

| Node/d_{ij} | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|-------------|---|---|---|---|---|---|---|---|---|---|
| 0           | 0 | 3 | \( \infty \) | 5.7 | \( \infty \) | \( \infty \) | \( \infty \) | 5.8 | 4 |
| 1           | 3 | 0 | 3.4 | 4.1 | \( \infty \) | \( \infty \) | \( \infty \) | 5.1 | \( \infty \) | 8.2 |
| 2           | \( \infty \) | 3.4 | 0 | 5.1 | 9.7 | \( \infty \) | \( \infty \) | \( \infty \) | \( \infty \) | \( \infty \) |
| 3           | 5.7 | 4.1 | 5.1 | 0 | 4.2 | 7.3 | \( \infty \) | \( \infty \) | \( \infty \) | \( \infty \) |
| 4           | \( \infty \) | \( \infty \) | 9.7 | 4.2 | 0 | 4.3 | \( \infty \) | \( \infty \) | \( \infty \) | \( \infty \) |
| 5           | \( \infty \) | \( \infty \) | \( \infty \) | 7.3 | 4.3 | 0 | 5.9 | 6.3 | \( \infty \) | \( \infty \) |
| 6           | \( \infty \) | \( \infty \) | \( \infty \) | \( \infty \) | \( \infty \) | 5.9 | 0 | 3.2 | 3.4 | \( \infty \) |
| 7           | \( \infty \) | 5.1 | \( \infty \) | \( \infty \) | \( \infty \) | \( \infty \) | 6.3 | 3.2 | 0 | 3.5 | \( \infty \) |
| 8           | 5.8 | \( \infty \) | \( \infty \) | \( \infty \) | \( \infty \) | \( \infty \) | 3.4 | 3.5 | 0 | 3.7 | \( \infty \) |
| 9           | 4 | 8.2 | \( \infty \) | \( \infty \) | \( \infty \) | \( \infty \) | \( \infty \) | 3.7 | \( \infty \) | 0 | \( \infty \) |

The time requirements, completion time limits and time window limits for each task point to complete support tasks are shown in Table 2:
Table 2. The time requirements, completion time limits and time window for each task point to complete support tasks.

| Node | $T_{\text{repair}}$ | $T_{\text{limit}}$ | $t_i$ |
|------|------------------|--------------------|--------|
| 0    | -                | -                  | -      |
| 1    | 0.5              | -                  | -      |
| 2    | 1.6              | -                  | -      |
| 3    | 0.4              | -                  | -      |
| 4    | 0.8              | -                  | -      |
| 5    | 0.6              | -                  | -      |
| 6    | 1.0              | -                  | -      |
| 7    | 2.3              | -                  | -      |
| 8    | 1.2              | -                  | -      |
| 9    | 1.2              | -                  | -      |

Using the basic ant colony algorithm, according to equation (1) (2) (3), the optimal path is:

$$0 \rightarrow 1 \rightarrow 2 \rightarrow 3 \rightarrow 4 \rightarrow 5 \rightarrow 6 \rightarrow 7 \rightarrow 8 \rightarrow 9$$

The heuristic information of the ant colony algorithm for multi-objective optimization by formula (12) and formula (13). Search from task point 0. The path selection method is: Judge whether it meets $q \leq q_0$. If it does, select the next path node according to equation (14). If not, the next path node is randomly selected according to the probability obtained by equation (15). After the improved algorithm is solved, the final optimal path is:

$$0 \rightarrow 3 \rightarrow 5 \rightarrow 4 \rightarrow 2 \rightarrow 1 \rightarrow 7 \rightarrow 6 \rightarrow 8 \rightarrow 9$$

6. Concluding Remarks

This paper improves the traditional ant colony algorithm. The improved algorithm can find some optimal solutions quickly, and the results are closer to reality. It also proves that this method has certain theoretical reference value and practical significance.

7. References

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