Bi-level programming model for post-disaster emergency supplies scheduling with time windows and its algorithm

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Abstract: Aiming at the emergency supplies scheduling problem in disaster situations, a bi-level programming model with time window constraints is built by considering the actual characteristics and demand of emergency material dispatching, with the minimum system response time as the upper objective and the minimum total system cost as the lower objective. According to the characteristics of mutual correlation and restriction between the upper and lower levels of the emergency supplies scheduling model, a two-stage heuristic algorithm is designed. At the first stage, the algorithm uses the clustering method for location-allocation and at the second stage uses the improved glowworm swarm optimisation algorithm for transportation route arrangement. Then, the simulation experiment is performed, which shows that the model and algorithm can effectively solve the post-disaster emergency supplies scheduling problem, and the designed algorithm has good performance and high computational efficiency.

Keywords: time windows; bi-level programming; heuristic algorithm; emergency supplies scheduling.

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1 Introduction

China is one of the countries' most seriously affected by natural disasters because of its vast territory and complex natural environment. Snow disasters, earthquakes, floods and other sudden natural disasters occur from time to time, bringing huge property losses and casualties to the people. At the same time, natural disaster incidents have the characteristics of sudden, uncertain and high social hazards, so the demand for emergency rescue after disasters is more urgent. Therefore, when faced with this type of sudden disaster, how to precede from the disaster relief characteristics, carry out emergency rescue activities efficiently under limited time, space and resource conditions, rationally deploy emergency dispatch centres, and timely optimise the dispatching materials rescue vehicles. And it is of great significance to transport emergency relief supplies to demand points under the constraints of time windows (Wang et al., 2018; Wang and Li, 2019).

In order to solve the problem of emergency material dispatching under different disaster situations, scholars at home and abroad have carried out a series of studies, and mainly focused on the construction of dispatching model and algorithm design. At present, there are mainly three types of emergency material scheduling models: single-objective models with minimum system time, single-objective models with minimum system cost, and multi-objective models with minimum system time and cost. For example, Guo et al. (2015) combined fuzzy chance-constrained planning with emergency material dispatching, and based on triangular fuzzy information, constructed an emergency material dispatching model with minimum time as the objective. Chi et al. (2016) combined time and material satisfaction as a timeliness function to solve the multi-objective optimisation problem of emergency material dispatching, aim to construct a nonlinear time evaluation model for emergency resource scheduling. Liu et al. (2016) constructed a multi-period fuzzy optimisation model aiming at the shortest total supply time of emergency materials, taking into account the uncertainties of emergency materials, time window limitation and some road network damage after the earthquake. Wu et al. (2018) constructed a multi-source emergency resource dispatching model for the sudden river pollution incident with the shortest emergency response time as the target and combined with the path optimisation algorithm. Chen and Shuai (2015) considering the damage of road network after the earthquake, the emergency material dispatching model is constructed with cost as the objective and solved by heuristic algorithm. He et al. (2018) considered the risk variables according to the situation of multiple disaster points and multiple emergency materials. By analysing the impact of risk factors on the risk values, the emergency dispatching model was constructed with the minimum total dispatching cost as the target. Li et al. (2011) established a multi-objective model of emergency material location-allocation, aiming at the shortest total transportation time and the smallest system loss. Widener and Horner (2011) established a multi-objective emergency material dispatching model aiming at the lowest total cost, the shortest response time and the greatest satisfaction of the victims. Hu et al. (2016) established a model with the least time-consuming and the lowest cost to deal with the emergency material dispatching problem, and proposed a genetic algorithm to solve the model. Song et al. (2017) starting from the objective fact of nonlinear continuous supply and consumption, by judging the relationship between the inventory of distribution centre and its critical inventory, established a two-tier emergency material scheduling model with the objective of minimum total cost and earliest system response time. Chen and Ma (2017) discussed the two-tier distribution network of emergency material dispatching in series demand system for system repair, aiming at the shortest time and the lowest cost, the scheduling model of vertical and horizontal distribution is established, and the genetic algorithm is used to optimise the model.

In other aspects of emergency material dispatching and corresponding algorithm solving, Zhang et al. (2011) designed an adaptive mutation genetic algorithm to solve the emergency material scheduling model, and compared the experimental results of the standard genetic algorithm and the improved genetic algorithm, and proved the superiority of the improved genetic algorithm. Chang et al. (2014) designed a multi-objective genetic algorithm based on greedy search to solve the emergency logistics scheduling problem, the algorithm was validated by the Taiwan earthquake as an example, the results show that the algorithm has superiority under the conditions of vehicle constraints and no vehicle constraints. Zheng et al. (2017) aiming at the optimisation of post-earthquake emergency logistics, a bi-level programming model with the objective of minimising material delivery time at the upper-level and maximising the fairness of material distribution at the lower-level was established, and a hybrid genetic algorithm was designed to solve the model. Song et al. (2015) analysed the advantages and disadvantages of particle swarm optimisation (PSO) and non-gradient side-step climbing algorithm, and designed a hybrid multi-objective PSO algorithm to solve the emergency material scheduling problem. Mohamed et al. (2018) proposed an optimal path planning algorithm for autonomous vehicle with two trailers in autonomous navigation. Zhu et al. (2018) considering the dynamic variability of emergency materials demand, a two-stage (pre-disaster selection model and post-disaster emergency rescue scheduling-rescheduling model) emergency material scheduling model was constructed. Chen and Fu (2018) established an emergency material allocation model with the objective of minimising the total weighted jealousy value and total logistics cost, and designed an improved genetic algorithm model for solving the problem. Li and Zheng (2019) comprehensively considered the post-earthquake road network repair and emergency material distribution, established a bi-level programming optimisation model, and designed a stable hybrid genetic algorithm to solve the model.

In summary, scholars have studied the emergency material dispatching problem from different angles, which has made the research results in this field increasingly rich. In the related research on emergency material dispatch after disaster, single-level programming is the main method. Documents mostly use the shortest total rescue time and the lowest total cost of the system as a single-objective model, or combine the response time, cost and satisfaction of the victims to build a multi-objective model. In the actual decision-making of emergency rescue after disaster, there are different participants, and the objectives of different participants are inconsistent, or even contradictory. Through analysis, it can be found that as a manager of emergency rescue, the objective is to minimise the response time of the system in order to reduce casualties and property losses; while as an emergency rescue department, not only the time factor but also the cost factor in the process of dispatching should be taken into account in the specific operation. Therefore, this paper considers that in the limited time after the occurrence of sudden disasters, by choosing a number of appropriate emergency distribution centres to complete the material transfer, the emergency relief materials can be quickly transported to various demand points. On the premise of meeting the demand of emergency materials at demand point, a model of emergency materials dispatching after disaster with time window is constructed by using network flow theory and bi-level programming modelling method, taking the shortest response time of the system as the upper objective and the lowest cost of material distribution as the lower objective. According to the characteristics of the model, a two-stage heuristic algorithm is proposed. In the first stage, the clustering method is used to locate-assign, and in the second stage, the improved glowworm optimisation algorithm is used to arrange the transportation route. Finally, the numerical results show the validity of the model and the feasibility of the algorithm.

2 Construction of emergency supplies scheduling model after disaster

2.1 Problem description

After the occurrence of sudden disasters, it is necessary to quickly transport emergency relief materials to various demand points in limited time, space and resources. In this process, it is necessary to select a number of appropriate emergency distribution centres to complete the material transportation, that is, the relief materials should first arrive at the distribution centre and then be distributed.

The assumptions of this paper are as follows:

1. Consider the small size, urgent demand, can be mixed goods itinerant distribution.
2. There are viable paths between the emergency distribution centre and the demand point and between the demand point and the demand point.
3. On each delivery route, the demand for emergency relief supplies at the demand point can be completed by one shipment.
4. The loading and unloading time and cost of emergency materials are not considered.
5. After the vehicle service is completed, return to its departure emergency distribution centre.

2.2 Model variable symbol description

The parameters of this paper are as follows:

$M = \{f \mid f = 1, 2, \cdots, F\}$ indicates the collection of candidate emergency distribution centre

$R = \{r \mid r = 1, 2, \cdots, R\}$	indicates the collection of emergency supplies demand points
$N = M \cup R$	represents the set of all nodes
$V = \{l \mid l = 1, 2, \cdots, L\}$	represents the collection of emergency rescue vehicles
q_r	represents the demand for disaster site r
MQ_f	represents the maximum throughput of emergency distribution centre f
TM_f	represents the preparation time for emergency distribution centre f to be put into use
VQ_l	represents the capacity of the delivery vehicle l
TV_l	represents the average travel time per unit distance of emergency rescue vehicle l
d_{ij}	represents the road distance from node i to node j
CM_f	represents the preparation cost of the emergency distribution centre f
CV_l	represents the dispatch cost of the emergency rescue vehicle l
C_r	represents the penalty cost of the demand point being delivered between $\{ET_r, LT_r]$
g	represents the unit cost of punishment
h	represents the proportional coefficient of penalty cost and time in the time window
D	represents the unit distance transportation cost of emergency rescue vehicles
T_r	represents the time when emergency supplies arrive at demand point r
ET_r	represents the time at which the demand point r expects emergency supplies to arrive
LT_r	represents the latest arrival time of emergency supplies required by demand point r.

The decision variables of this paper are as follows:

$$x_f = \begin{cases} 1, \text{if the candidate emergency distribution centre } f \text{ is selected} \\ 0, \text{else, } f \in M \end{cases}$$

$$z_l = \begin{cases} 1, \text{if the vehicle } l \text{ is put into use} \\ 0, \text{else, } l \in V \end{cases}$$

$$y_{ijl} = \begin{cases} 1, \text{if vehicle } l \text{ goes from node } i \text{ to node } j \\ 0, \text{else, } i, j \in N, l \in V \end{cases}$$

$$\mu_{fr} = \begin{cases} 1, \text{if the demand point } r \text{ is allocated to the emergency distribution} \\ \text{centre} f \text{ in use} \\ 0, \text{else}, f \in M, r \in R \end{cases}$$

2.3 Model establishment

$$\text{Min } Z_1 = \sum_{f \in M} TM_f x_f + \sum_{l \in V} \sum_{i \in N} \sum_{j \in N} TV_l d_{ij} y_{ijl} \tag{1}$$

s.t.

$$\sum_{r \in R} q_r \mu_{fr} \leq MQ_f, \forall f \in M \tag{2}$$

$$\sum_{r \in R} q_r \sum_{i \in N} y_{irl} \leq VQ_l, \forall l \in V \tag{3}$$

$$\sum_{i \in N} y_{ijl} - \sum_{i \in N} y_{jil} = 0, \forall j \in N, l \in V \tag{4}$$

$$\sum_{i \in M} \sum_{j \in R} y_{ijl} \leq 1, \forall l \in V \tag{5}$$

$$\sum_{l \in V} y_{ijl} = 0, \forall i, j \in M \tag{6}$$

$$\sum_{r \in R} \sum_{l \in V} y_{frl} \geq x_f, \forall f \in M \tag{7}$$

$$y_{frl} \leq x_f, \forall f \in M, r \in R, l \in V \tag{8}$$

$$\sum_{i \in N} \sum_{l \in V} y_{irl} = 1, \forall r \in R \tag{9}$$

$$\sum_{r \in R} y_{irl} + \sum_{r \in R} y_{rjl} \leq 1, \forall i, j \in M, l \in V \tag{10}$$

$$\mu_{fr} \in \{0, 1\}, x_f \in \{0, 1\}, y_{ijl} \in \{0, 1\} \tag{11}$$

In the upper model, the objective function (1) represents the minimum response time of the system, which consists of two parts: the first one represents the preparation time of the emergency distribution centre, and the second one represents the transportation time of the vehicle. Constraint (2) represents the maximum processing capacity limit of the emergency distribution centre. Constraint (3) represents the maximum processing capacity limit of emergency rescue vehicles. Constraint (4) denotes the continuity restriction of distribution routes, that is, vehicles must leave the node after entering it. Constraint (5) means that each emergency rescue vehicle can only be allocated to one emergency distribution centre at most. Constraint (6) indicates that there is no connection between two emergency distribution centres. Constraint (7) means that as long as the emergency distribution centre is selected, emergency rescue vehicles will be allocated to it. Constraint (8) means that only when the candidate emergency distribution centre is selected, can the distribution service be provided for the demand point. Constraint (9) indicates that each requirement point is served only once. Constraint (10) means that the emergency vehicle must return to its departure emergency distribution centre after completing the distribution task. Constraint formula (11) is 0-1 variable constraints.

$$\text{Min } Z_2 = \sum_{f \in M} CM_f x_f + \sum_{l \in V} CV_l Z_l + \sum_{l \in V} \sum_{i \in N} \sum_{j \in N} Dd_{ij} y_{ijl} + \sum_{r \in R} C_r \tag{12}$$

s.t.

$$y_{ijl} \le z_l, \forall i, j \in N \tag{13}$$

$$\sum_{f \in M} \mu_{fr} = 1, \forall r \in R \tag{14}$$

$$T_i + TV_l d_{ij} = T_j, \forall i, j \in R, l \in V \tag{15}$$

$$T_i + TV_l d_{ij} \le LT_j, \forall i, j \in R, l \in V \tag{16}$$

$$TV_l d_{fr} \le LT_r, \forall f \in M, r \in R, l \in V \tag{17}$$

$$C_r = \begin{cases} 0, & T_r \le ET_r \\ ghq_r \left(T_r - ET_r\right), & ET_r \le T_r \le LT_r \end{cases} \tag{18}$$

$$z_l \in \{0, 1\} \tag{19}$$

In the lower model, the constraints of the upper model are also the constraints of the lower model. The objective function (12) represents the total cost of all the minimisation systems and consists of four parts: the first represents the preparation cost of the emergency distribution centre; the second represents the dispatch cost of vehicles; the third represents the transportation cost of vehicles; and the fourth represents the time penalty cost. Constraint (13) indicates that the distribution of vehicle l exists only when vehicle l is put into use. Constraint (14) means that each emergency material demand point can only be served by a candidate emergency distribution centre. Constraint (15) represents the calculation method of the time when the vehicle arrives at the demand point. Constraint (16) represents the time window constraints of demand points in the process of vehicle itinerant distribution. Constraint (17) denotes the time window constraints at the point of demand when a vehicle departs from an emergency distribution centre. Constraint (18) represents penalty cost function, which is related to the demand of the disaster site and the length of time beyond the expected arrival time. When $T_r \le ET_r$, the penalty cost is 0; when $ET_r \le T_r \le LT_r$, the penalty cost is $ghq_r(T_r - ET_r)$. Constraint (19) represents constraints of 0-1 variables.

3 Model solving

3.1 Standard glowworm swarm optimisation

Glowworm swarm optimisation is a new bionic swarm intelligence optimisation algorithm proposed by Kaipa and Ghose (2017), two Indian scholars. The principle of the glowworm swarm optimisation is that the individual glowworm is regarded as a feasible solution, and the process of attracting each other by utilising the luminescence characteristics of glowworms is regarded as the process of searching and optimising. The glowworm with weak illuminating ability is attracted by the glowworm with strong illuminating ability as a mathematical problem model optimisation solution. The glowworm in the best position has the most fluorescein, representing the minimum or maximum objective function we seek.

Step 1 Renewal of fluorescein

The fluorescence intensity of the glowworm determines its position. The updating of fluorescein is based on the change of current fitness. The updating rule is shown in formula (20):

$$l_i(t) = (1-\rho) * l_i(t-1) + \gamma * J\left(x_i(t)\right) \tag{20}$$

Among them: $l_i(t)$ denotes the fluorescein value of individual i in iteration t; $l_i(t-1)$ denotes the fluorescein value of individual i in iteration $t-1$; ρ denotes the fluorescein volatile factor, and the fluorescein value decreases with each iteration, γ denotes a fluorescein-enhancing factor, $\rho, \gamma \in (0, 1)$; $J(x_i(t))$ denotes the objective function value of the location of glowworm i in iteration t, that is, the fitness function.

Step 2 Constituting neighbourhood sets

Each glowworm finds its neighbour set in the radius of its dynamic decision domain, and the neighbourhood set is as shown in equation (21):

$$Ni(t) = \left\{ j : d_{ij}(t) < r_d^i(t); l_i(t) < l_j(t) \right\} \tag{21}$$

Among them: $Ni(t)$ represents the set of neighbourhoods of glowworm i in iteration t; $d_{ij}(t)$ denotes the distance between i and j in iteration t; $r_d^i(t)$ denotes the neighbourhood radius of i in iteration t.

Step 3 Calculating the probability of movement

In the neighbourhood, individuals with low fluorescein values are attracted by those with high fluorescein values and move toward them. The rule of mobility probability is shown in equation (22):

$$P_{ij}(t) = \frac{l_j(t) - l_i(t)}{\sum_{k \in N_i(t)} l_k(t) - l_i(t)} \tag{22}$$

Among them: $P_{ij}(t)$ denotes the moving probability of glowworm i to glowworm j in the neighbourhood set.

Step 4 Position updating

Update the position of the glowworm i after the move, and the update rule is as shown in equation (23):

$$x_i(t+1) = x_i(t) + s * \left(\frac{x_j(t) - x_i(t)}{\left\| x_j(t) - x_i(t) \right\|} \right) \tag{23}$$

Among them: s represents the moving step size.

Step 5 Neighbourhood radius updating

Update the neighbourhood radius of the glowworm i after the move, and the update rule is as shown in equation (24):

$$r_d^i(t+1) = \min\left\{r_s, \max\left\{0, r_d^i(t) + \beta\left(n_t - |N_i(t)|\right)\right\}\right\} \tag{24}$$

Among them: r_s denotes the maximum perception radius of the individual glowworm; β denotes the rate of neighbourhood change; n_t represents the limit value of the number of glowworms in the glowworm neighbourhood collection, i.e., the domain threshold.

3.2 *Improved glowworm swarm optimisation algorithm*

Although the glowworm swarm optimisation algorithm has the characteristics of simple steps, easy implementation and high efficiency in solving problems, it has been successfully applied in path planning (Marinaki and Marinakis, 2016), situation prediction (Pistolesi et al., 2017), combinatorial optimisation (Fan et al., 2015) and other fields, and shows good optimisation performance. At present, glowworm swarm optimisation algorithm is mainly used to solve continuous problems. However, emergency material dispatch after disasters belongs to discrete problems. Therefore, it is necessary to improve the glowworm swarm optimisation algorithm in order to solve these problems effectively. In addition, the glowworm swarm optimisation algorithm is that multiple glowworms participate in the search for the optimal solution at the same time, which makes the global search ability of the algorithm strong. However, in the process of solving some problems, there will be multiple peaks and poles. In the later stage of operation, the glowworm swarm optimisation algorithm is prone to premature convergence and fall into local optimum. Therefore, this paper improves the standard glowworm swarm optimisation algorithm through discretisation, Gauss mutation and multi-population learning mechanism.

3.2.1 *Discrete processing*

Because the standard glowworm swarm optimisation algorithm has limitations in solving such discrete problems as emergency material dispatch after disaster, it is necessary to discretise the glowworm swarm optimisation algorithm.

In the solution space of the glowworm swarm optimisation algorithm, assuming that the location of a glowworm is represented by a vector $x_i = \{x_{i1}, x_{i2}, \cdots, x_{in}\}$, and each component is a random number between (0, 1), each component represents a disaster point, and the components are rearranged by ascending order coding. After rearrangement, the location of the components corresponds to the rescue order of the disaster points represented by the components one by one. The discretisation process of the glowworm swarm optimisation algorithm is as follows: the vector x_i = {0.63, 0.81, 0.22, 0.55, 0.03} is generated randomly and the components are arranged in ascending order to x_i = {0.03, 0.22, 0.55, 0.63, 0.81}. Component 0.03 ranks 5 in the original vector, component 0.22 ranks 3 in the original vector, component 0.55 ranks 4 in the original vector, component 0.63 ranks 1 in the original vector, and component 0.81 ranks 2 in the original vector. Therefore, the sequence of rescue after coding is 5 → 3 → 4 → 1 → 2.

3.2.2 Gauss mutation

Gauss mutation is to add a random vector which obeys the Gauss distribution on the basis of the original individual state (Mo et al., 2013). The definition is shown in expression (25):

$$X_i = X_i * [1 + k * N(0, 1)] \tag{25}$$

Among them: X_i is the state of the individual *i*; *k* is the decreasing variable between 0 and 1; *N*(0, 1) is the random vector of Gaussian distribution with mean value of 0 and variance of 1.

Gauss mutation is to add a decreasing random perturbation term $X_i * k * N(0, 1)$ to the original individual state X_i. By perturbing the current state, the diversity of population states is increased, the search speed is increased, the search scope is expanded, and the local optimum is avoided.

3.2.3 Multi-population learning mechanism

Combining the idea of multi-population evolution with the standard glowworm swarm optimisation algorithm, based on this mechanism, the glowworm swarm optimisation algorithm is divided into two stages:

Stage 1 Divide glowworms into several populations and the number of glowworms in each population are the same. Set parameters for each population and form differences among populations, so that each population achieves different optimisation effects and forms a contrast in the optimisation process.

Stage 2 Find the best and worst values for each population, share information among populations, define the best value individual of the previous population as immigration operator, replace the worst value of the next population with immigration operator, then update the location of glowworms of each population again, iterate over and over again, compare the optimal solutions of each population, and get the final satisfactory solution.

The steps of solving the improved glowworm swarm optimisation algorithm can be described as follows:

Step 1 Initialisation parameters: The number of glowworm population *mp*, the maximum number of iterations *N*, the maximum perceived radius *rs*, fluorescein volatile factor *ρ*, fluorescein enhancement factor *γ* and so on.

Step 2 Random coding to generate initial solutions.

Step 3 Calculate the fitness of glowworm and update the concentration of fluorescein.

Step 4 Determine the moving object. Firstly, the neighbourhood set within the dynamic decision radius is determined, and then the moving probability is calculated. Finally, the next moving object is selected by roulette method.

Step 5 Update the individual position, neighbourhood radius and fluorescein value of the mobile glowworm.

Step 6 Judging whether the optimal state is invariant for three consecutive times or has little change ($|Amount\ of\ change| < \mu$), if it is, it is regarded as falling into the local optimum. The seventh step is carried out, and the eighth step is carried out on the contrary, μ is a parameter of Gauss mutation. With the larger the value of μ, the higher the probability of Gauss mutation, the faster the convergence rate, the calculation amount of each variation will be increased. Therefore, it is not appropriate to take too large or too small a value. Generally, the number between 10^{-6} and 10^{-4} is chosen.

Step 7 Gauss mutation. The current worst-case individual position is replaced by the historically optimal individual position to form an intermediate population, and Gauss mutation is performed on the glowworm in the middle population.

Step 8 Inter-population learning.

Step 9 Determine whether the termination condition is satisfied, if so, output the result, and return to the third step.

The flowchart of the improved glowworm swarm optimisation algorithm is shown in Figure 1.

3.3 Coordinate area setting

Before designing the algorithm in this paper, we need to understand the relevant coordinate region settings. In combination with Figure 2, we are familiar with the following relevant definitions:

Definition 1: In the plane coordinate graph, select a point, make two straight lines parallel to the coordinate axis through the point, and divide the plane into four regions by the two straight lines: the upper left domain, the lower left domain, the lower right domain and the upper right domain.

Definition 2: In the plane coordinate graph, according to the counterclockwise direction, the latter is called the right neighbourhood of the former, for example, the lower right neighbourhood is the right neighbourhood of the lower left neighbourhood, and the upper right neighbourhood is the right neighbourhood of the lower right neighbourhood.

Figure 1 Flowchart of improved glowworm swarm optimisation algorithm (see online version for colours)

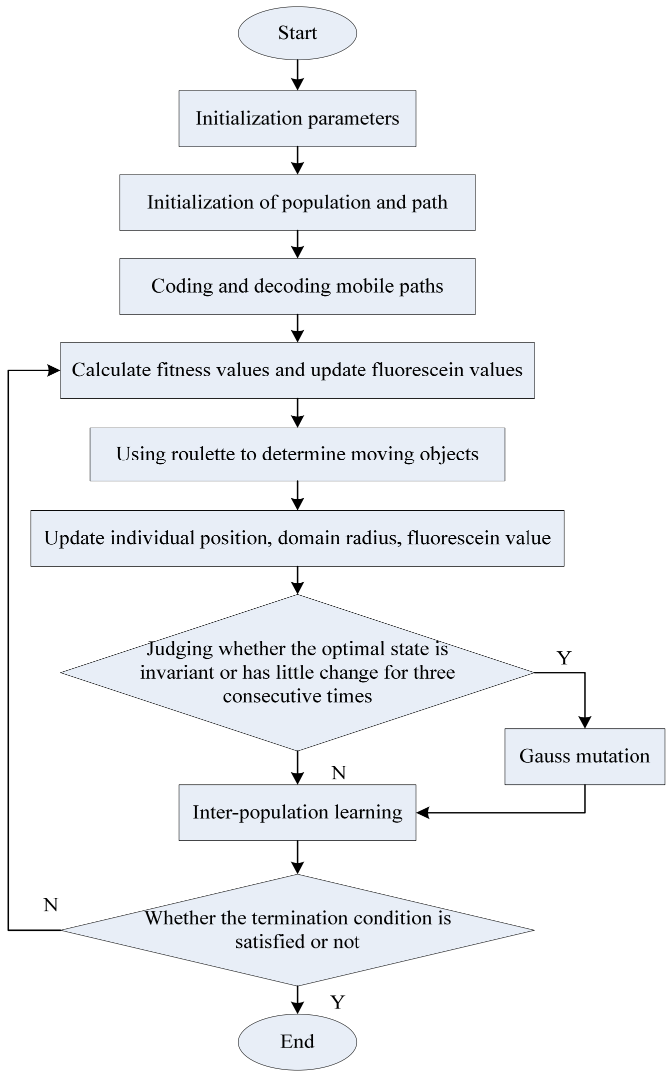
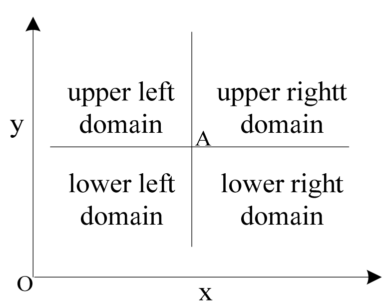


Figure 2 Planar coordinate map



3.4 Solving process

The emergency material scheduling model in this paper is a typical mixed integer nonlinear bi-level programming model, which belongs to NP-hard problem. When the scale of the problem is large, it is difficult to solve it with an accurate algorithm. Therefore, the intelligent optimisation algorithm is usually used to solve the emergency material scheduling problem. At present, most of these problems are solved by two-stage heuristic method, which mainly includes: first locating-allocating, then arranging transportation routes; first arranging transportation routes, then locating-allocating. According to the characteristics of the established model, this paper chooses to perform positioning-allocation first, and arranges the transportation path. As far as the whole emergency logistics system is concerned, the significance of the emergency distribution centre is to centralise the transit distribution of materials, so the number of candidate emergency distribution centres and selected emergency distribution centres will not be too large. When the capacity of the selected emergency distribution centre can meet the requirements of the demand point, the remaining emergency distribution centre will not be put into use. Otherwise, it will not only prolong the preparation time for the emergency distribution centre to be put into use in the upper-level planning, but also increase the preparation cost for the emergency distribution centre to be put into use in the lower-level planning.

According to the characteristics and significance of the model, in the location-allocation stage, the distribution centres are selected by clustering method and the demand points are divided into corresponding distribution centres, so that the multi-distribution centres and multi-demand points are transformed into single distribution centre and multi-demand points. In the stage of transportation route arrangement, the improved glowworm swarm optimisation algorithm is used to solve the bi-level programming model, find out the time and cost, and determine the transportation route. The flowchart of the two-stage algorithm is shown in Figure 3.

Stage 1 Location-allocation

- Step 1 Number each candidate emergency distribution centre and emergency material demand point, and calculates the sum of the distances from all the demand points to any distribution centre, and selects the minimum sum of distances corresponding to the distribution centre f_1.
- Step 2 Take f_1 as a designated point, find out its upper left domain, lower left domain, lower right domain and upper right domain, sort the demand points in the order of upper left domain, lower left domain, lower right domain and upper right domain, and sort them in the same region in the order of left to right, and get the set of demand points R_0 after ranking.
- Step 3 According to the order from left to right, the sum of demand points in R_0 is calculated, and the demand points j whose sum of demand points is not greater than the capacity of emergency distribution centre f_1 are found. The subset R_{01} is composed of demand point 1 to demand point j in R_0, a set of demand points R_{01} assigned to f_1 is obtained. If there are remaining demand points, go to Step 4, otherwise go to Step 5.

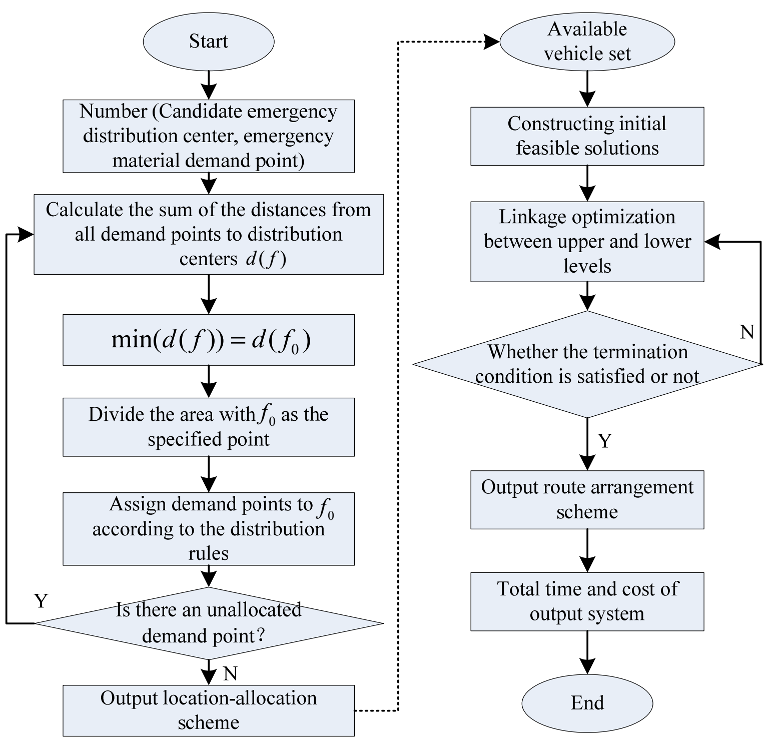
Step 4 Unselected candidate emergency distribution centres form a set $\bar{M}$, unallocated demand points constitute a set $\bar{R}$. Repeat Steps 2 and 3 to get subset R_{02} and assign it to emergency distribution centre f_2. If there are remaining demand points, repeat Step 4, otherwise go to Step 5.

Step 5 The location-allocation scheme of emergency distribution centres and the open set of emergency distribution centres M_0 are obtained, ($M_0 = \{f_1, f_2, \cdots, f_n\}$).

Stage 2 Transportation route arrangement

According to the location-distribution scheme of emergency distribution centre given in Stage 1, the improved glowworm swarm optimisation algorithm is used in Stage 2 to determine the transportation path of emergency supplies. Firstly, the initial feasible solution is generated randomly to verify its feasibility, and the solution of lower-level programming is substituted into the upper-level programming model; secondly, the solution of lower-level programming is obtained by operating glowworm swarm optimisation individuals; finally, the solution is substituted into the upper-level programming, and the optimal solution in the process is retained until the specified termination conditions are met.

Figure 3 Two-stage algorithm flowchart (see online version for colours)



4 Example analysis

Construct an example: assume that there are four candidate emergency distribution centres (numbers A–D) and 20 emergency material demand points (number 1–20). The specific data in this paper are as follows:

1. Firstly, the candidate emergency distribution centre data (Table 1) and emergency material demand point information (Table 2) are generated randomly at 300 km × 300 km.
2. Assuming that the number of vehicles is sufficient, the capacity of vehicles VQ_l is 800 pieces per vehicle, all of TV_l are 0.67 min/km, the dispatch cost is CV_l 600 yuan per vehicle, the transportation cost per unit distance of vehicles D is 1 yuan/km, the time penalty cost is 1 yuan per piece per hour.

Table 1 Candidate emergency distribution centre information

Number	*A*	*B*	*C*	*D*
Coordinate	(25, 250)	(80, 80)	(300, 100)	(200, 250)
Capacity / piece	2,500	1,600	2,000	1,500
Preparation cost / yuan	25,000	16,000	20,000	15,000
Preparation time / h	2	2	2	2

Table 2 Emergency supplies demand point information

Number	*1*	*2*	*3*	*4*	*5*	*6*	*7*
Coordinate	(20, 100)	(16, 50)	(72, 36)	(212, 108)	(156, 36)	(165, 158)	(62, 58)
Demand / piece	120	180	100	180	160	120	150
Time window / h	[6, 8]	[7, 9]	[7, 9]	[8, 10]	[7, 9]	[6, 8]	[9, 11]
Number	*8*	*9*	*10*	*11*	*12*	*13*	*14*
Coordinate	(89, 52)	(185, 92)	(36, 163)	(139, 68)	(226, 98)	(125, 139)	(58, 158)
Demand / piece	160	200	160	180	160	200	120
Time window / h	[10, 12]	[7, 9]	[8, 10]	[6, 8]	[10, 12]	[6, 8]	[7, 9]
Number	*15*	*16*	*17*	*18*	*19*	*20*	
Coordinate	(258, 28)	(109, 47)	(112, 129)	(38, 96)	(135, 238)	(146, 78)	
Demand / piece	180	160	200	180	140	160	
Time window / h	[7, 9]	[8, 10]	[8, 10]	[7, 9]	[9, 11]	[9, 11]	

Using the algorithm designed in Stage 1, the location-allocation scheme is obtained as shown in Table 3. The improved glowworm swarm optimisation algorithm in Stage 2 is used to determine the transportation route. The parameters of the improved glowworm swarm optimisation algorithm are set as follows: population number $mp = 5$, individual number of glowworm population $n = 50$, maximum iteration number of algorithms $N = 200$, fluorescein volatile factor $\rho = 0.4$, fluorescein enhancer $\gamma = 0.6$, neighbourhood change rate $\beta = 0.1$, neighbourhood threshold $n_t = 5$, step length factor $s = 0.5$, initial decision radius $r_s(0) = 10$, maximum perception radius $r_s = 20$, initial fluorescein value $l_i(0) = 5$, Gauss variation parameter $\mu = 10^{-4}$, update parameters $p_1 = 0.8$, $p_2 = 0.9$.

Programming with MATLAB R2016a, it runs on a computer with Windows 8 operating system, 2.4 GHZ processor main frequency and 4 GB physical memory. The transportation route of emergency materials after disaster is shown in Figure 4 and the convergence chart is shown in Figure 5.

Table 3 Location-allocation scheme

Distribution centre	*Demand point set*	*Aggregate demand*
B	1, 2, 3, 7, 8, 10, 14, 16, 17, 18	1,530
C	4, 5, 6, 9, 11, 12, 13, 15, 19, 20	1,680

Figure 4 Emergency transportation route map (see online version for colours)

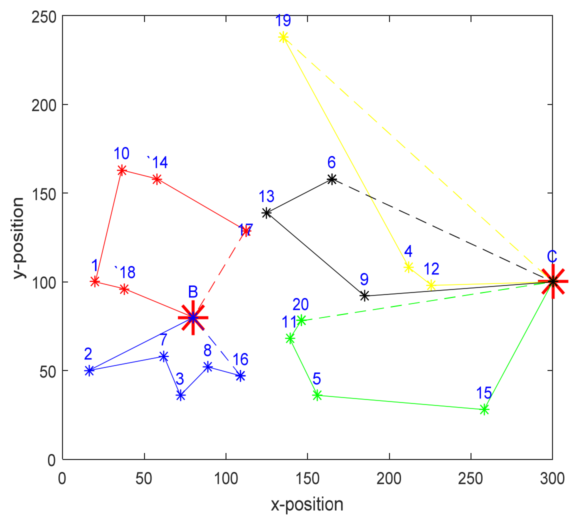
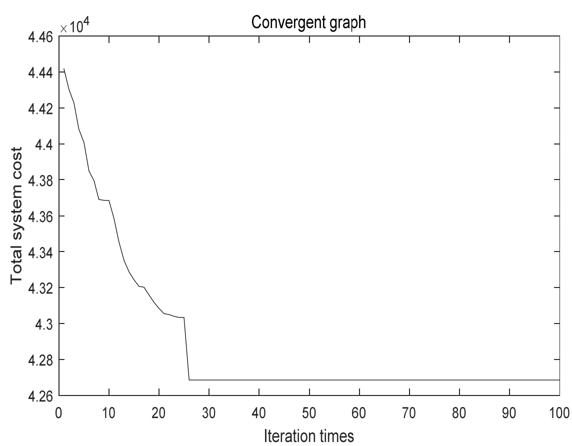


Figure 5 Algorithmic convergence graph

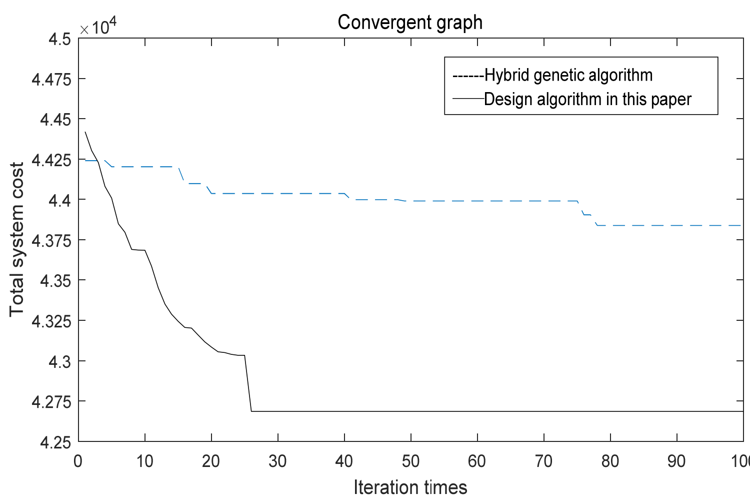


In addition, the hybrid genetic algorithm designed by Zheng et al. (2017) is compared with the algorithm designed in this paper. The emergency material scheduling schemes of the two algorithms are shown in Table 4, and the convergence comparison of the two algorithms is shown in Figure 6.

Table 4 Post-disaster emergency material dispatching scheme of two algorithms

Two-stage heuristic algorithm		*Genetic algorithm*	
Distribution centre	*Distribution route*	*Distribution centre*	*Distribution route*
B	B → 18 → 1 → 10 → 14 → 17 → B	A	A → 2 → 1 → A
	B → 2 → 7 → 3 → 8 → 16 → B		A → 10 → 18 → 14 → 3 → 7 → A
C	C → 15 → 5 → 11 → 20 → C		A → 8 → 17 → 13 → 16 → 7 → A
	C → 9 → 13 → 6 → C	D	D → 6 → 5 → 19 → 11 → 20 → D
	C → 12 → 4 → 19 → C		D → 9 → 12 → 15 → 4 → D
System response time / h	22.60		23.42
Total system cost / yuan	42,686		43,838

Figure 6 Convergence contrast diagram of algorithms (see online version for colours)



By analysing and comparing the results of the two-stage heuristic algorithm and the hybrid genetic algorithm, we can see from Table 4 that the response time of the two-stage heuristic algorithm is 0.82 hours less than that of the hybrid genetic algorithm, which is 3.5% lower than that of the hybrid genetic algorithm, and the cost is 1,152 yuan less than that of the hybrid genetic algorithm, which is 2.6% lower than that of the hybrid genetic algorithm. From the comparison chart of convergence, it can be seen that the algorithm designed in this paper is superior to the hybrid genetic algorithm in terms of convergence speed and the ability to find the optimal solution. In summary, the results show that the proposed algorithm is superior to the hybrid genetic algorithm in total cost and total response time of emergency material dispatching system after disaster, which fully proves the effectiveness of the proposed algorithm in solving the bi-level programming model of emergency material dispatching after disaster.

5 Conclusions

Aiming at the problem of emergency material dispatching with time windows in the process of emergency rescue after disaster, this paper studies the linkage between location selection of emergency distribution centre and emergency material transportation, and establishes a bi-level programming model. The upper-level of the model aims at the shortest response time of the system, while the lower-level aims at the minimum total cost of the system. Then, a two-stage heuristic algorithm is designed according to the characteristics of independence and interaction between the upper and lower layers of the bi-level programming model. The first stage uses clustering method to locate-distribute, and the second stage uses the improved glowworm swarm optimisation algorithm with Gauss mutation and multi-population learning mechanism to arrange the transportation route. Finally, an example is constructed to prove the feasibility and validity of the model and the algorithm.

This paper only studies the problem of emergency material dispatch under deterministic demand, but a lot of information in practical problems is uncertain, so uncertain information, multi-modal transportation and multi-stage emergency material dispatch need to be further studied. In addition, considering the satisfaction of the victims and combining the return of empty vehicles and the evacuation of the wounded are also the future research directions.

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