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A Dynamic Logistics Strategy for Dangerous Goods Based on Cloud Computing

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Aiming at the dynamic vehicle routing problem of dangerous goods under a dynamic environment, a mathematical model is established, which is to minimize the risk cost and distribution mileage in the road segment and to maximize the freight load factor. Here a cloud-based adaptive ant colony algorithm is proposed. There are crossover and mutation operations in ant colony algorithm that may lead to premature convergence and loss of late diversity. With the characteristics of dangerous goods logistics, cloud computing is introduced to design cloud crossover and mutation operators to operate this algorithm in response to the above gap. On this basis, the proposed algorithm can be improved in the context that the simulation schedule example will reduce premature probability and enhance the iterative search efficiency more than other algorithms.

1. Introduction

The Dynamic Vehicle Routing Problem (DVRP) (Dantzig and Ramser, 1959; Ahmed, 2018) was first proposed by Psaraftis in 1988. Later scholars made extensive studies on DVRP from two dimensions such as information updating and the demand impendency. The DVRP of hazardous goods refers to those occurred in remaining transportation schedules on the road segments other than those where the transportation of dangerous goods is not allowed in the government's existing transportation network system. Foreign scholars have carried out some exploratory works on the modeling of dangerous goods logistics transportation networks, etc., for example, Rico-Ramirez proposed a multi-type dangerous goods transportation based on a bilevel planning model. The goal of the model optimization is to minimize the risk of transport routes after dangerous goods are classified into several types (Rico-Ramirez, 2010). Ning T. built a dangerous goods transport network with a bilevel network model. The top model aims to minimize the weighted costs and risks, while the underlying model is to minimize the cost of the routes selected for logistics vehicles. On this basis, a heuristic algorithm that can improve the algorithm stability is also proposed (NING et al., 2016). Popp I. O presented a dangerous goods planning model that allows for risk balance of regional road network, which, from the perspective of low-level managers, aims to minimize the risk of road segments, and from the perspective of top-level managers, targets at minimizing the total risk of road network (Popp, 2016). Although China starts relatively late in the study of the dangerous goods logistics transportation network, there is still a definite phased achievement having gained up to now. Mohamed S., on the ground that a dangerous goods transport network model in Canada was explored, contemplated the practical operation of dangerous goods in China, corrected the key parameters therein, and built a time-constraint-based hazard goods logistics transport network model applicable to the specific situation of our country (Mohamed et al., 2017). Hari S. D. argued that the important factors for the sake of the safety in the dangerous goods logistics transportation are economy, and high weight avoidance. While an improved bilevel planning model for dangerous goods transportation is also investigated (Hari, 2017). The upper level of the model aims to minimize the risk of accidents to the level as the supervisor desires, and the underlying level minimizes the extra costs as expected by the transporter.
Based on the analysis of existing models, this paper proposes an improved cloud computing ant colony algorithm to solve the dynamic logistics schedule problem for dangerous goods. This algorithm firstly designs

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cloud crossover and mutation operators on the basis of cloud computing theory in an attempt to improve crossover and mutation operations in the ant colony algorithm, and further solve the problem of hazardous goods logistics. In section 1, the description o f dangerous goods logistics model is supplied; in section 2, the theory and process of adaptive ant colony optimization based on cloud computing is described; in order to verify the effectiveness of the proposed method, the experimental data is executed to verify the conclusion.

2. Dangerous Goods Logistics Model

2.1 Problem description

Dangerous goods logistics network is a special kind of transportation network system that requires extremely high safety and security. It features: (1) the multiplicity of network attributes (NING et al., 2016). Unlike the logistics of general goods, the transportation network of dangerous goods includes both attributes of general roads and the special attributes of dangerous goods since it must determine the collection of road segments that prohibit the access of dangerous goods vehicles. (2) the non-continuity of logistics transportation. The development of dangerous goods transportation is susceptible to the supply and demand of upstream and downstream firms, so that the dangerous goods logistics supply chain does not always have a transportation task. Its discontinuity mainly attributes to the logistics and the mission duration. (3) Traffic complexity. The redundant attributes of the dangerous goods transport network contribute to the complexity of its load flow. Dangerous goods transportation network must also undertake urban traffic and general goods transportation tasks in addition to the integrant tasks such as dangerous goods transportation, which leads to the variety of load flows on the dangerous goods transport network (Fattahi and Fallahi, 2010). (4) Traffic disturbance. During the dangerous goods logistics process, unforeseen and sudden events may disturb travelling vehicle, such as vehicle breakdowns and traffic jams, which exacerbates the normal transportation of dangerous goods transport networks.

2.2 Objective functions

When the dangerous goods logistics suffers from dynamic disturbances, the distribution vehicle may have accomplished part of its mission. As applicable to the vehicle load and the transportation segments, new distribution tasks can be added to the existing routes. If the current vehicle cannot cater for the new transportation of dangerous goods, new vehicles need to be added. If demands from original customer build up and exceeds the maximum vehicle load, the last distribution sites on this subroute is chosen as a new task until the distribution limit is satisfied. If this task is regarded as a dangerous goods warehouse, the distribution changes from original single route into multiple routes (NING, 2013). Assume that W is the aggregation of undistributed tasks in the static phase and the new added distribution tasks in the dynamic phase; M represents the number of tasks in a new dangerous goods warehouse, its number is N+1, N+2, ..., N+M, then the original warehouse number is changed to N+M+1; L represents the number of newly added vehicles. The vehicle that departs from the warehouse in the static phase is located at the customer *i*, which is numbered W+i; the remaining vehicle load in this phase is Q- q_{ik}.
Define the decision variable:

$$x_{ijk} = \begin{cases} 1, \text{Vehicle k in static phase has dynamic requirement from customers i to j} \\ 0, \text{ Others} \end{cases}$$

$$y_{ik} = \begin{cases} 1, \text{The demand of customer i is satisfied by vehicle k in static phase} \\ 0, \text{Others} \end{cases}$$

The mathematical model for the disturbed situation at time *t* is built as follows:

$$Z = \min(\sum_{k=1}^{K}\sum_{i=1}^{N+M+1}\sum_{j=1}^{N+M+1} c_{ij}x_{ijk} + \sum_{k=K+1}^{K+L}\sum_{i=1}^{N+M+1}\sum_{j=1}^{N+M+1} c_{ij}x_{ijk} + \sum_{k=K+1}^{K+L} F_k \sum_{j=1}^{N} x_{(N+M+1)jk}); \tag{1}$$

Formula (1) represents the objective function, including the unfinished distribution in static phase and the new added costs for transports and vehicles in the dynamic phase, and the departure cost of new dispatched vehicles in the dynamic phase.

s.t. $$\sum_{k=1}^{K+L} y_{ik} = 1, \forall i; \tag{2}$$

Formula (2) represents the constraints for each task that must be distributed.

$$\sum_{j=1}^{N+M+1} x_{ijk} = y_{ik}, \forall i,k; \tag{3}$$

$$\sum_{i=1}^{N+M+1} x_{ijk} = y_{jk}, \forall j,k; \tag{4}$$

Formulae (3) and (4) represent that each task can only be distributed by one vehicle.

$$\omega_{(N+M+1)jk} = x_{(N+M+1)jk} Q, \forall j,k; \tag{5}$$

Formula (5) represents that each vehicle departing from the warehouse is fully loaded.

$$\sum_{i=1}^{N+M+1} x_{ijk}(\omega_{ijk} - q_j) \geq 0, \forall j,k; \tag{6}$$

Formula (6) represents that the vehicle cannot be unloaded before distributing service to any customer.

3. Adaptive ant colony algorithm based on cloud computing theory

3.1 Cloud crossover operator

In the evolution process of the population, assume that the fitness of the two parent individuals is denoted as f_1 and f_2, the maximum fitness of the parent population is expressed as F_{max}, and the minimum fitness as F_{min}, then the real number p_{cr} is true for:

$$p_c = \begin{cases} t_1 e^{\frac{-(f-\bar{f})^2}{2y^2}} & , f \geq \overline{F} \\ t_2 & , f < \overline{F} \end{cases} \tag{7}$$

Call p_c a cloud crossover operator. In the formula (7), t_1, t_2 and $\bar{F}$ are all constants, and y is a normal random number about F_{max} and F_{min}. As the cloud crossover operator features adaptability and randomness (NING et al., 2018), this paper designs a crossover operator to optimize the crossover operation of general ant colony algorithm. The crossover operator is always subjected to change with the average adaptation of the parent individuals, but also with the normal random number y (Shi et al., 2018). The algorithm of the cloud crossover operator is given as follows:

Step 1: Calculate the average value of the fitness of the father individuals, expressed as $E_x=(f_1+f_2)/2$;

Step 2: Generate a normal random number E_n' with E_n as the expected value and H_e as the standard deviation;

Where $E_n=m_1(F_{max}-F_{min})$, $H_e=n_1E_n$, m_1 and $n_1$represent control coefficients.

Step 3: Calculate the cloud crossover operator according to formula (9) $p_c = \begin{cases} t_1 e^{\frac{-(f-E_x)^2}{2E_n'^2}}, f \geq \bar{F} \\ t_2 \quad\quad , f < \bar{F} \end{cases}$.

The constant $\bar{F}$ here represents the average fitness of the parent population, $f=max$ (f_1, f_2).

3.2 Cloud mutation operator

In the process of population evolution, assume that the fitness of a parent individual is expressed as f_1, there is real number p_{mt} that satisfies:

$$p_m = \begin{cases} s_1 e^{\frac{-(f-f_1)^2}{2y^2}} & , f \geq \overline{F} \\ s_2 & , f < \overline{F} \end{cases} \tag{8}$$

Call p_m as the cloud mutation operator. In the formula (8), s_1, s_2 and $\bar{F}$ are the constants. The concepts of F_{max}, F_{min} and y represent the same things as (7).

The stability tendency of the cloud mutation operator depends on three parameters f_1, F_{max} and F_{min} (Seyed et al., 2013).

The key to the cloud-based adaptive ant colony algorithm designed in this paper is to use cloud crossover operator, cloud mutation operator and cloud generator (Tamás and Illés, 2017) to improve the algorithm's

convergence speed and search effect.
Cloud adaptive crossover and mutation probabilities are shown in Figure 1:

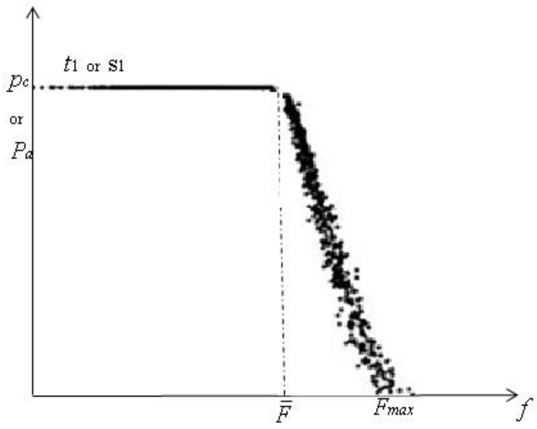

Figure 1: Cloud adaptive crossover probability p_c and mutation probability p_m

3.3 Design of cloud adaptive ant colony algorithm

Step 1: Perform the distribution scheme and update customer profiles in the initial schedule phase;
Step 2: If a new customer request appears, determine whether the number of new customer sites reaches the upper limit. If this is the case, go to step 3, otherwise, determine whether the next re-schedule time point is reached; if so, perform the steps 3, otherwise go to step 1;
Step 3: a fuzzy demand probability formula is referred to judge whether the customer site should be inserted into the current delivery route. If *S* is greater than the threshold of demands of the next customer site, the point is inserted into the current route to generate a new route by the quantum ant colony algorithm, otherwise go to step 4;
Step 4: Add vehicles to complete the distribution tasks for the new customer sites.

4. Experimental verification

Simulation experiment adopts Matlab7.0 to verify the feasibility and availability of the improved quantum ant colony algorithm (QACA). This paper assumes that there are coordinates (300,270), 14 static distribution points, 4 dynamic distribution points set in a dangerous goods warehouse, the distribution area is a square 450*450 (square kilometers), and the reschedule period is 1 hour. The experiment simulates the dynamic distribution of dangerous goods. The locations of different customers are shown in Table 1 and Table 2 below.

Table 1: Geographical coordinates of 14 static customers

Customer ID	X	Y	Customer ID	X	Y
1	260	115	8	110	150
2	175	345	9	35	242
3	220	88	10	363	131
4	92	305	11	95	205
5	124	31	12	417	224
6	108	405	13	371	69
7	105	380	14	48	153

Table 2: Geographical coordinates of 14 dynamic customers

Customer ID	X	Y
a	95	205
b	301	89
c	75	98
d	175	175

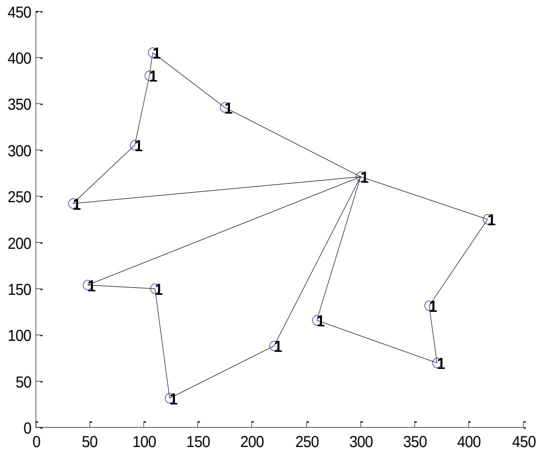

Figure 2: Result of vehicle routing optimization

Initiate each parameter, α_i, β_i takes $1/\sqrt{2}$,$\alpha=1$, $\beta=2$, $\gamma=1$, $\rho=0.9$, the iterations are 500 times, the number of ants is 40.
Within the time slice, 4 dynamic task points *a*, *b*, *c*, and *d* are added. According to the dynamic phase re-schedule strategy, new task points are inserted into the current distribution route, and an updated distribution route may be available, as shown in Figure 3.

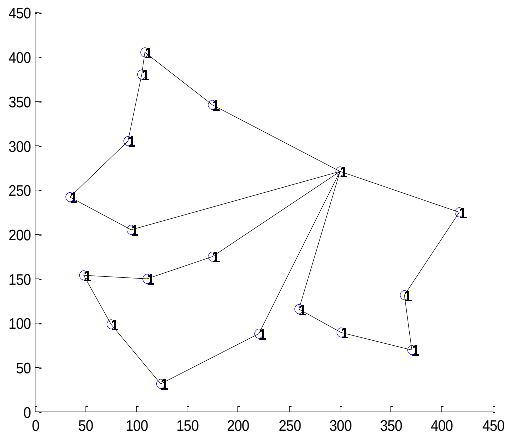

Figure 3: Distribution route in dynamic phase

5. Conclusion

Aiming at different constraints, we establish a dynamic logistics distribution model for dangerous goods with multi-targets and propose an ant colony encoding method based on dynamic strategy; the cloud crossover and mutation operators are designed to improve crossover and mutation operations of general ant colony algorithm. The simulation example is applied to the above algorithm to verify its availability. The results reveal that the proposed algorithm features fast convergence and high quality when solving dangerous goods schedule problems comparing with other optimization algorithms, t. Considering the disruption event will have an impact on user satisfaction and psychological perception, the research about how to make the dynamic evolutionary scenario into the model and improve the logistic distribution disruption management model is the focus of the next study.

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