International Journal for Housing Science and Its Applications
Publish August 3, 2025. Volume 46, Issue 3 Pages 1270-1282

https://doi.org/10.70517/ijhsa46398

Research on the Optimization and Safety of Road Transportation Route of Hazardous Chemicals Based on Improved PSO Algorithm

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Abstract How to reasonably plan the transportation path of hazardous chemical vehicles and reduce the risk and cost of hazardous chemical transportation is an urgent and very realistic problem. In this paper, a multi-objective planning model of multi-vehicle path considering the cost and risk of dangerous goods vehicle transportation is constructed. In the model solution, the multi-objective problem is firstly transformed into a single-objective problem using the $\varepsilon -$ constraint method. Then it is solved using the Adaptive Inertia Weights and Cauchy Variation Method Improved Particle Swarm Algorithm (ACMPSO). Finally, the simulation test is carried out according to the solution process of ACMPSO. The simulation results verify that the ACMPSO algorithm can effectively ensure transportation safety while taking into account the benefits of transportation enterprises. And the ACMPSO algorithm takes less time and has higher performance than the PSO algorithm in solving the optimal path. The results show that the ACMPSO algorithm can achieve the optimization of road transport paths for hazardous chemicals by taking the risk and cost as the main optimization objectives and ensuring that the risk is under control. In order to ensure the safety of road transportation of hazardous chemicals, improvements can be made in several aspects, including transportation companies, regulatory mechanisms, vehicle and personnel management, emergency management and accident rescue.

Index Terms Multi-objective planning model, Adaptive inertia weights, Cauchy variation, Particle swarm algorithm, Path optimization

I. Introduction

With the rapid development of the economy, the demand for the transportation of hazardous chemicals is increasing [1]. However, how to ensure the safety of hazardous chemicals transportation has become an urgent problem due to the traffic accidents and environmental pollution problems that may be caused during the transportation of hazardous chemicals [2]-[4]. For this reason, we propose a road transport path optimization method for hazardous chemicals based on the improved PSO algorithm to reduce the risks during the transportation of hazardous chemicals [5], [6].

The safety risks during the transportation of hazardous chemicals mainly come from traffic accidents, leakage and fire [7], [8]. In recent years, the losses caused by hazardous chemical transportation accidents have been growing gradually, and the pollution problem caused by hazardous materials leakage to the environment has become more and more serious, posing a great threat to people's life safety and ecological environment [9]-[11]. Therefore, how to optimize the transportation path of dangerous goods to ensure the transportation safety has become an urgent task [12]. Particle swarm algorithm (PSO) is a new type of evolutionary computation method based on iteration, and its basic idea is inspired by the results of their early research on the behavior of bird populations [13]-[15]. PSO algorithm has the advantages of concise concept, easy to implement, fewer parameter settings, and quicker convergence, which has been widely concerned and studied by scholars at home and abroad in recent years [16], [17]. And the improved PSO algorithm is currently a more advanced optimization algorithm, which is applicable to problems in many fields [18]. Its essence is to simulate the behavior of a flock of birds in group intelligence, slowly optimize through the optimization factors, and finally find the optimal solution [19], [20]. In the path optimization of hazardous chemicals road transport, the improved PSO algorithm can greatly improve the efficiency and path accuracy of hazardous chemicals road transport by determining the objectives and constraints, establishing a mathematical model, and solving the problem by using the improved PSO algorithm, which can provide a better guarantee and support for transport safety [21]-[24].

Literature [25] discussed the multi-objective transportation path optimization of hazardous chemicals based on geographic information system (GIS), considered the transportation cost, buildings, emergency facilities and other factors, and proposed a constrained multi-objective mixed-integer linear programming optimization model, which revealed that the building factors played an important role in the model, and the model had better performance. Literature [26] examined the transportation route optimization of hazardous chemicals under dynamic time-varying conditions and constructed a multi-objective nonlinear optimization model with the objective of minimizing transportation risk, cost and carbon emission, which verified the validity of the model, and that under time-varying conditions, the vehicles departing at different times would incur different transportation costs and risks. Literature [27] proposed a new dynamic route optimization method for the transportation of chemical hazardous materials and constructed a new linear minimum probability model, which was verified based on a case study, and its systematic transportation risk of the studied transportation task was significantly reduced when dealing with uncertainty. Literature [28] builds a hazardous chemical transportation risk evaluation model, proposes a hazardous chemical transportation risk cost optimization algorithm based on Dijkstra's algorithm, believes that the transportation risk can be reduced by setting the transportation risk cost of the enterprise unit, and proves the correctness of the model and the solution algorithm. Literature [29] explored the adipic acid transportation route optimization problem based on fuzzy compromise method and iterative algorithm, and proposed a multi-objective decision-making model of road transportation routes with the minimum transportation risk and the minimum cost, which showed that the model can well balance the risk and benefit of hazardous chemicals transportation. Literature [30] analyzed the multi-trip heterogeneous vehicle routing problem (MTHVRP-PCIC) aiming to find the route with the lowest cost, and designed a hybrid genetic algorithm, which was shown to be more advantageous by example analysis. Literature [31] proposed a multi-criteria route optimization method for multi-modal transportation networks for the hazardous materials transportation route optimization problem and introduced an improved multi-objective genetic algorithm DSNSGA3, which verified the effectiveness of the algorithm, and the proposed method was able to balance the various evaluation criteria and obtain a definite solution. Literature [32] addresses the characteristics of the dangerous goods transportation market and the development of carbon tax policy, and establishes a route optimization model for dangerous goods vehicles, by combining the Bacterial Foraging Algorithm (BFA) and Ant Colony Algorithm (ACO), which shows that the BFA-ACO algorithm optimizes the model better than a single algorithm optimization. Literature [33] analyzed the characteristics of dangerous goods road transport network planning, established a two-layer model of dangerous goods road transport network, and used genetic algorithm to calculate the model, revealing that genetic algorithm solving the two-layer planning model can achieve path optimization and find the optimal balance between risk and cost. Literature [34] in order to realize the dynamic risk assessment of hazardous chemicals road transport, established a risk assessment system based on the frequency of accident causes by collecting accident cases, and established a dynamic risk assessment model of hazardous chemicals road transport based on the back-propagation neural network algorithm, which is capable of realizing the evaluation of the risk dynamics of hazardous chemicals road transport. Literature [35] constructed a logistic regression scorecard model to evaluate the transportation risk of hazardous chemical transportation enterprises, taking China as an example, revealing that the more complex the type of hazardous goods transported, the higher its risk value, which can be achieved by safety training and rectification of drivers to reduce the occurrence of traffic accidents with hazardous materials. Literature [36] proposed a cost-risk optimization model for the hazardous goods transportation problem and compared the hazardous goods transportation routes in road, rail and pipeline transportation networks to prove the effectiveness of the method. Literature [37] based on the consideration of artificial intelligence, route optimization analysis of dangerous goods road transport using relevant algorithms, and through case study analysis, provides reference for other dangerous goods road transport, promoting the reduction of risk in the whole transport chain, improving safety and transport efficiency. The above study emphasizes the importance of route optimization for hazardous chemicals road transport, and proposes route optimization methods based on geographic information system, fuzzy compromise method, multi-criteria routes of multi-modal transportation network, etc. All these methods show good optimization effect, which not only improve the transportation efficiency, but also save costs and reduce the probability of accidents.

Regarding the transportation of hazardous chemicals, this paper takes the total transportation cost of hazardous chemical vehicles and the total risk of hazardous chemical vehicles as the objective function, establishes a path planning model for road transportation of hazardous chemicals, and solves the model based on the PSO algorithm. In order to make the algorithm converge quickly, by using the exponential form of inertia weights and the Cauchy variational step size adjustment strategy. In order to overcome the disadvantage that the elementary particle swarm tends to fall into local extremes at a later stage, the stochastic nature of the Cauchy variation is utilized to produce abrupt changes in the positions of the particles. The study also designed a model solution after transforming the multi-objective problem into a single-objective problem based on the $\varepsilon-$ constraint method. The validity of the above model and algorithm is finally verified by an arithmetic example analysis.

II. Multi-objective planning model for vehicle paths in hazardous material multi-vehicle yards

Since hazardous chemicals (referred to as dangerous chemicals) are a class of highly flammable or explosive, corrosive or radioactive chemicals, there are safety issues that cannot be ignored. People are more and more concerned about the safety of hazardous chemicals transportation, especially the safe transportation of hazardous chemicals vehicles. Hazardous chemical vehicles are different from ordinary vehicles, and once an accident occurs, it often brings huge environmental and personnel injuries and generates significant economic losses [38]. Therefore, how to reasonably plan the transportation path of hazardous materials vehicles and reduce the risk and cost of hazardous materials transportation is an urgent but very realistic problem. In order to save transportation costs and meet customer demand, multiple distribution centers must be set up, and the problem of how to reasonably allocate operations among multiple yards and the travel path of vehicles must be solved. In this context, the path planning problem for multiple vehicles is proposed.

II. A. Description of the problem

In a dangerous goods road transportation network, there are multiple yards, multiple customer demand points and multiple dangerous goods transport vehicles. Under the condition that there is no overload, the distribution center will distribute the needs of each customer according to the needs of each customer within a certain timeframe until the needs of all customers are met. Multiple dangerous goods carriers are delivered from the yards to each point of need and returned to the original yards at the end of the service. Assuming that there are three yards, 14 customers, and multiple vehicles respectively, assuming that the multi-yard dangerous goods transportation network is shown in Fig. 1, with A, B, and C as the yards, and the dots as the individual customer points.

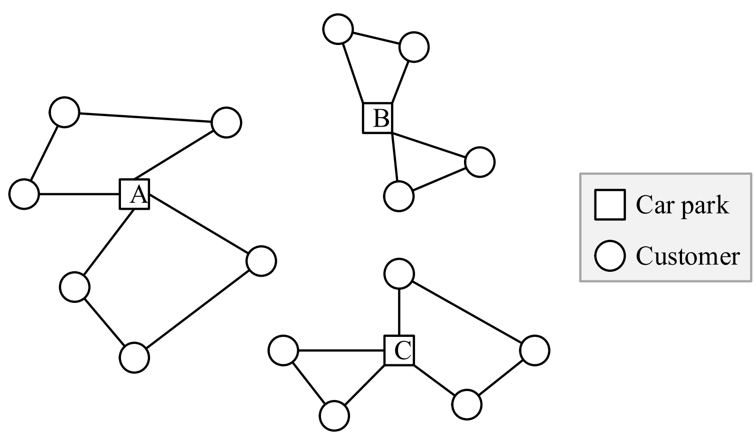


Figure 1: Transport network of hazardous chemicals in multi-yard

The basic assumptions of this study are as follows:
(1) There is sufficient capacity in the car parks to supply the various demand points in the region.
(2) Multiple customer points exist and will be assigned to different car parks.
(3) Each vehicle can serve multiple customer points and each customer can only be served once by a vehicle.
(4) The capacity of each transportation vehicle is the same.
(5) Vehicles cannot be overloaded.
The notation system used in this paper is shown below:
D - the set of nodes of the car park, $D = \{1, 2, ..., m\}, d \in D$.
Q_d - capacity of each car park.
q_c - demand per customer.
z_{dc} - indicates whether customer c belongs to yard d.
S_d - the set of car parks.
Q_d - total demand.
R_{ij} - R_{ij} is the transportation risk from node i to node j.
P_{ij} - P_{ij} is the probability of a vehicle accident on the arc $arc_{ij} \in L$.
h_{ij} - transportation distance between nodes $i, j \in N$.

pd_{ij} - Population density of the accident area.

AR_{ij} - Accident rate on arc $arc_{ij} \in L$.

Pr_{ij} - probability of hazardous chemical spillage accident on arc $arc_{ij} \in L$.

u_{ij}^{k} - the maximum acceptable level of node (i, j) for the kth number of hazardous materials vehicles.

a - the weight of the total risk of the transportation network set by the government in the overall multi-objective planning model, $a \in (0 \sim 1)$.

T^{lk} - the total number of vehicles in the l th flow for transportation of the kth type of hazardous materials.

II. B.Transportation risk assessment

The magnitude of the risk value depends on the probability of an accident and the impact of the consequences of the accident. In this paper, the safety of hazardous materials vehicle transportation is studied based on the value of risk. According to the framework of the "probability-consequence" theoretical framework, the transportation risk is defined as the product of the probability of an accident and the consequences of an accident [39], where the transportation risk between any two nodes is expressed as:

$$R_{ij} = P_{ij} \times Cs_{ij}, i, j \in N \tag{1}$$

In equation (1), R_{ij} is the transportation risk of a vehicle transporting hazardous materials from node i to node j, P_{ij} is the probability of a hazardous materials accident caused by a vehicle on the arc $arc_{ij} \in L$, and Cs_{ij} is the accident on the arc $arc_{ij} \in L$. The consequence, using the exposed population within the radius of the accident impact area is expressed as:

$$Cs_{ij} = pd_{ij} \times \pi r_{ij}^{2}, i, j \in N \tag{2}$$

In equation (2), pd_{ij} is the population density of the accident area, and r_{ij}^{2} is the radius of influence of the accident, which is usually set to 1 kilometer. The accident probability P_{ij} on the arc $arc_{ij} \in L$ is computed and expressed as:

$$P_{ij} = AR_{ij} \times Pr_{ij} \times d_{ij}, i, j \in N \tag{3}$$

In equation (3), AR_{ij} is the accident rate on the arc $arc_{ij} \in L$, and Pr_{ij} is the probability of hazardous chemical spillage accident on the arc $arc_{ij} \in L$.

II. C.Multi-objective planning model for vehicle paths

In this section, a multi-objective optimization model is constructed with the optimization objectives of minimizing transportation cost and transportation risk. The decision variable definitions are expressed as:

$$Y_{ij}^{d} = \begin{cases} 1 & \text{Vehicles in yard } d \text{ go from node } i \text{ to node } j \\ 0 & \text{other} \end{cases} \tag{4}$$

The model objective function is expressed as:

$$\begin{cases} Minimize(Z_1) = \sum_{d=1}^{m} \sum_{i=1}^{S_d} \sum_{j=1}^{S_d} Y_{ij}^{d} \times h_{ij} \\ Minimize(Z_2) = \sum_{d=1}^{m} \sum_{i=1}^{S_d} \sum_{j=1}^{S_d} Y_{ij}^{d} \times R_{ij} \end{cases} \tag{5}$$

In equation (5), z_1 is the objective function to minimize the transportation cost. z_2 is the objective function to minimize the transportation risk. h_{ij} is the transportation distance between nodes $i, j \in N$, and R_{ij} is the transportation risk of a vehicle transporting hazardous chemicals from node i to node j.

The model constraints are as in equations (6) to (10).

$$\sum_{c \in C_d} q_c \le Q_d \tag{6}$$

$$\sum_{d=1}^{m} Z_{dc} = 1, \forall c \in C \tag{7}$$

$$\sum_{i \in C_d} Y_{ij}^{d} = 1, \forall d \in D \tag{8}$$

$$\sum_{j \in C_d} Y_{ij}^{d} = 1, \forall d \in D \tag{9}$$

$$\sum_{i \in C_d} Y_{ic}^{d} - \sum_{j \in C_d} Y_{cj}^{d} = 0, \forall d \in D, \forall c \in C \tag{10}$$

In the above equation, equation (6) indicates that for the same yard, the sum of the total demand of each customer it needs to deliver is less than or equal to its yard capacity. Equation (7) indicates that each customer can only be served once by a depot. Equations (8) through (10) indicate that any one vehicle must start and end service from the same yard.

III. Optimize algorithm design

In this chapter, a road transportation path planning algorithm based on Adaptive Cauchy Mutated Particle Swarm (ACMPSO) is proposed.

III. A. Elementary Particle Swarm Algorithm

The basic idea of PSO algorithm solution is to seek the optimal solution with the help of information sharing and cross-reference between individuals [40]. Firstly, each particle represents a candidate solution in PSO, which can be initialized with a random solution due to the randomness of the elementary particles. Second, the particle state is evaluated with the help of the defined fitness function, and the individual optimal position P_{best} and the global optimal position p_{lest}^{G} can be obtained by comparison. Then every iteration, the particle updates its position and velocity with reference to P_{best} and p_{best}^{G}, and P_{best} and p_{best}^{G} are also dynamically updated. Through repeated iterations, the optimal solution will eventually be obtained.

In this paper, each particle represents a path. Considering the path planning for security, suppose the number of path nodes is n, and for the kth particle Eq. (11) and Eq. (12) represent its position vector and velocity vector, respectively:

$$P_k = [P^x, P^y, P^z)_{(k,1)}, \cdots, (P^x, P^y, P^z)_{(k,n)}]^T \tag{11}$$

$$V_k = [V^x, V^y, V^z)_{(k,1)}, \cdots, (V^x, V^y, V^z)_{(k,n)}]^T \tag{12}$$

If there are S particles in the particle swarm, then there must exist an individual optimal position for S particles, and for the whole particle swarm, there must also exist a global optimal position as in Eq. (13), where $k \in 1, \cdots, S$:

$$\begin{cases} P_{(k,best)} = [P_{(k,1,best)}, \cdots, P_{(k,n,best)}]^T \\ P_{best}^{G} \in [P_{(1,best)}, \cdots, P_{(S,best)}] \end{cases} \tag{13}$$

Substituting the position of the particle into the fitness function F, the path quality of the particle can be evaluated, and the higher the path quality, the smaller the value of the fitness function F of the corresponding particle. For particle k, if the value of F after the t th iteration is smaller than the value of the previous $t-1$ th iteration, it will be updated, otherwise, its historical best position is still used, as shown in equation (14). Finally, the one with the smallest F-value is the global optimal position selected among the historical optimal positions of S particles, as shown in Eq. (15):

$$P_{(k,best)}(t) = \begin{cases} P_{(k,best)}(t-1) & F(P_{(k,best)}(t-1)) \le F(P_k(t)) \\ P_{(k,best)}(t) & F(P_{(k,best)}(t-1)) > F(P_k(t)) \end{cases} \tag{14}$$

$$F(P_{best}^{G}(t)) = \min[F(P_{(1,best)}(t)), \cdots, F(P_{(s,best)}(t))] \tag{15}$$

At the next iteration, the velocity and position of each particle are updated according to Eq. (16) as follows:

$$\begin{cases} V_k(t+1) = w \cdot V_k(t) + c_1 \cdot r_1 \cdot (P_{(k,best)} - P_k(t)) + c_2 \cdot r_2 \cdot (P_{best}^{G}(t) - P_k(t)) \\ P_k(t+1) = P_k(t) + V_k(t+1) \end{cases} \tag{16}$$

Where: the inertia weight w is used to inherit the velocity of the particle, $c_1 \cdot c_2$ is the learning factor, which represents the ability to learn from its own historical best and the ability to learn from the optimal individual in the group, respectively, and r_1, r_2 are all arbitrary random numbers between 0 and 1.

III. B. Improvement Program for Particle Swarm Algorithm

III. B. 1) Adaptive inertia weights

The inertia weight w directly affects the search ability of the particle. The larger its value, the better the particle inherits the original velocity, thus obtaining a larger velocity and therefore a stronger global search capability. With the help of dynamically changing the value of inertia weight w, the global and local searching ability of the particle can be conveniently adjusted at different times [41]. In this paper, an exponential form of inertia weight adjustment method is used to improve the convergence speed:

$$\begin{gathered} w=(w_{\max}-w_{\min})\cdot\exp\left[(1-t)\cdot\alpha\right]+w_{\min} \\ t\in[2,T_{\max}] \end{gathered} \tag{17}$$

where: $w_{\max}$ is the maximum value of w, $w_{\min}$ is the minimum value of w, $t, T_{\max}$ is the current iteration number and the maximum iteration number, respectively, and α is a constant coefficient, which is used for controlling the rate of inertia weight decay.

III. B. 2) Kersey variation

The population diversity of traditional PSO algorithm is poor, and the introduction of evolutionary operators such as crossover and variation in its algorithm can effectively improve the diversity of the population, thus avoiding the generation of local optimal solutions. The commonly used variation operators are Gaussian variation operator (GM) and Cauchy variation operator (CM), due to the Cauchy distribution of the random number range is larger and the peak is lower, the introduction of Cauchy variation operator in PSO algorithm is more conducive to the particles to quickly jump out of the local extremes and increase the diversity of the population.

If x satisfies the condition given in equation (18), it will be a Cauchy distribution:

$$\begin{gathered} f(x;x_0,\gamma)=\frac{1}{\pi}\left[\frac{\gamma}{(x-x_0)^2+\gamma^2}\right] \\ x\in(-\infty,+\infty) \end{gathered} \tag{18}$$

where x_0 is the location of the maximum of the function and γ is the width associated with half of x_0. When γ and x_0 are 1 and 0, respectively, and x satisfies the conditions for the probability density function, equation (19) is its cumulative distribution function:

$$\begin{gathered} F(x;0,1)=\frac{1}{\pi}\arctan(x)+\frac{1}{2} \\ x\in(-\infty,+\infty) \end{gathered} \tag{19}$$

The inverse function can be derived by performing an inverse transformation on Eq. (19), and then the random numbers generated by the uniform distribution can be used to generate random numbers obeying the Cauchy distribution:

$$\begin{cases} \dfrac{1}{\pi}\arctan(CM)+\dfrac{1}{2}=Rand \\ CM=\tan[\pi(Rand-\dfrac{1}{2})] \end{cases} \tag{20}$$

where: CM is the Cauchy mutation operator, and Rand is any real number uniformly distributed in the range of (0, 1).

Similar to the inertia weights, the step size of the Cauchy variation needs to be dynamically adjusted in order to generate some perturbations in the early stage of the algorithm operation with a larger step size to make the particles jump out of the current position and avoid local optimization. The convergence is accelerated at a later stage with a smaller step size. The update rule for each particle in each iteration is:

$$\begin{gathered} P_k^{'}=P_k+P_k\cdot CM\cdot\exp[1-t)\cdot\beta] \\ t\in[1,2,\cdots,T_{\max}] \end{gathered} \tag{21}$$

where: P_k is the position of particle k, p_k is the position of particle k after it passes through the Cauchy mutation, β is a constant coefficient used to control the degree of fastness of the change of the mutation step, t is the number of the current iteration, and $T_{\max}$ is the maximum number of iterations.

IV. ACMPSO-based model solving

IV. A. Target model transformation

(1) $\varepsilon -$ constraint method

The basic idea of the $\varepsilon -$ constraint method is to convert two objective models into one objective model according to their priority, while the other objective becomes the constraint. By analyzing the interrelationships among the decision variables in the established mathematical model, the premise of using vehicles to transport hazardous chemicals is that the vehicles can run normally. Therefore, firstly, minimizing the transportation cost as the objective and minimizing the transportation risk as the constraint, for a specific application, the steps of the constraint method are as follows:

a) Transform the two objective models into a single-objective model, and at the same time take the other objective as a constraint, and the constructed single-objective model is:

$$\begin{aligned} \min \quad & Z_1 \\ s.t. \quad & Z_2 \leq \varepsilon_1 \end{aligned} \tag{22}$$

In equation (22), ε_1 is the upper limit of the risk function z_2.

b) The value of ε_1 is determined by $\frac{z_2^1 - z_2^N}{M}$. The value of $Z_2^1 - Z_2^N$ is divided into M equal parts according to M+1 equal points, where the initial value ε_1 is defined as:

$$\varepsilon_1 = Z_2^1 + \frac{Z_2^1 - Z_2^N}{M} * m, m = 0,1,...,M \tag{23}$$

In Eq. (23), the value of ε_1 varies with the value of m, z_2^1 denotes Problem 1, and z_2^N denotes Problem N.

c) Substitute the initial ε_1 into Eq. (23), based on which the solved optimization results are substituted into the bi-objective model to obtain the optimal values of risk and cost.

d) Substitute the obtained different ε_1 into Eq. (22) and calculate the |Pareto optimal solution.

(2) Model transformation

In the multi-objective planning model, the bi-objective problem is transformed into a single-objective problem by taking one of the objectives as the optimization objective while taking the other objective as a constraint. Specifically, the cost function is taken as the optimization objective and the risk function is taken as the constraint. In order to solve the constraints, a parameter ε is introduced so that the constraints are satisfied when the risk function is less than or equal to ε. In this way, a single-objective planning model can be obtained. Each individual path planning problem is solved using an improved particle swarm optimization algorithm to obtain a Pareto optimal solution for each problem. The specific steps of the algorithm are as follows:

a) Determine the range of (Z_2^1, Z_2^N).

b) Set an initial $\varepsilon_1 = Z_2^1 + \frac{z_2^1 - z_2^N}{M} * m, m = 0,1,...,M$.

c) The optimal solution x^* is obtained by the ACMPSO algorithm by computing equation (22).

d) Substitute x^* into the original objective function, and get the risk value and cost value by ACMPSO algorithm.

e) Substitute different values of ε_1 and repeat equation (22) by ACMPSO algorithm. If $\varepsilon_1 < Z_2^1$, return to step 3.

f) Repeat the computation to obtain the Pareto optimal solution.

IV. B. Case solving

In order to verify the applicability and effectiveness of the algorithm designed in this paper for solving the hazardous chemical transportation path selection problem, this paper designs case data for simulation experiments.

IV. B. 1) Case data

The transportation network solved in this paper is shown in Fig. 2, the whole network is divided into 4 regions, B, C, D and E. Different regions contain different road sections, i.e. $B=\{(1,2),(2,4)\}$, $C=\{(2,5),(3,4)\}$, $D=\{(1,3),(3,5)\}$, $E=\{(4,6),(5,6)\}$. Assuming that there are two types of dangerous goods in this network that need to be transported from origin 1 to destination 6, the number of vehicles required is $T^{11}=1$ and $T^{12}=2$ respectively. The attribute values for each road segment are shown in Tables 1 and 2. It is assumed here that the set of limit values for the maximum speed of hazardous materials vehicles is $I=\{60,70,80\}$. ACMPSO algorithm program is written using MATLAB software to implement the case study.

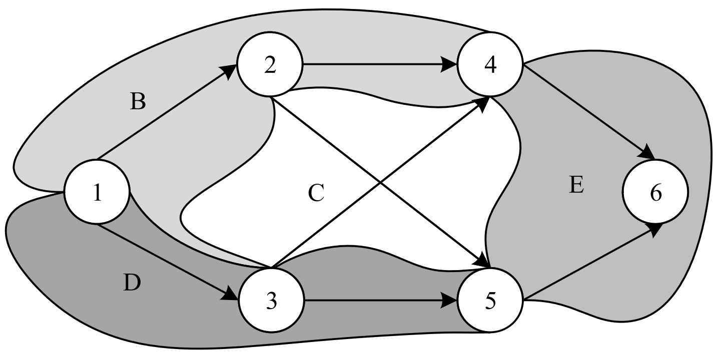


Figure 2: Transport network

Table 1: The length of the road and the population density of the districts

Region	Population density (people/km^2)	Road section	Road length (km)
B	900	1-2	45
		2-4	90
C	3200	2-5	55
		3-4	85
D	1000	1-3	70
		3-5	80
E	1500	4-6	55
		5-6	70

Table 2: The upper bound of different kinds of dangerous goods

Region	Road section	u_{ij}^1	u_{ij}^2
B	1-2	3	1
	2-4	2	1
C	2-5	1	1
	3-4	3	1
D	1-3	1	3
	3-5	2	3
E	4-6	3	1
	5-6	2	3

IV. B. 2)

IV. B. 3) Optimization results

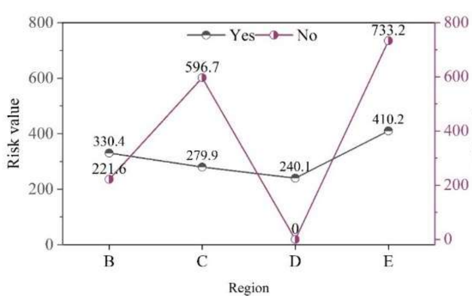
According to the vehicle path multi-objective planning model, the optimal dangerous goods transportation paths and the corresponding transportation cost and risk values on different road sections can be calculated when the weight a takes different values. The solution results when the weights are $a=0.7$, $a=0.6$ and $a=0.5$ are shown in Table 3. As the value of a decreases, the value of risk on some sections of the road increases and the transportation cost decreases. For example, when $a=0.7$, the total transportation cost and total network risk are 15,300 yuan and 1,782.3 yuan, respectively. When $a=0.5$, the total transportation cost and total network risk are 14600 and 2058.3, respectively. As the value of a decreases, the total risk rises by 276 and the total transportation cost decreases by 700yuan.

Table 3: Optimization of dangerous goods transportation network

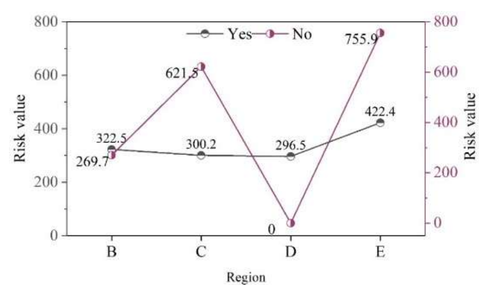
	T	Path	Risk	Cost
$a=0.7$	$T^{11}=2$	1→2→4→6	683.6	6200
	$T^{11}=1$	1→3→4→6	275.6	3600
	$T^{12}=1$	1→2→5→6	286.4	2400
	$T^{12}=1$	1→3→5→6	536.7	3100
$a=0.6$	$T^{11}=2$	1→2→4→6	683.6	6200
	$T^{11}=1$	1→3→4→6	301.6	3400
	$T^{12}=1$	1→2→5→6	286.4	2400
	$T^{12}=1$	1→3→5→6	603.7	3000
$a=0.5$	$T^{11}=2$	1→2→4→6	735.2	6000
	$T^{11}=1$	1→3→4→6	322.6	3400
	$T^{12}=1$	1→2→5→6	369.7	2200
	$T^{12}=1$	1→3→5→6	630.8	3000

IV. B. 4) Security analysis

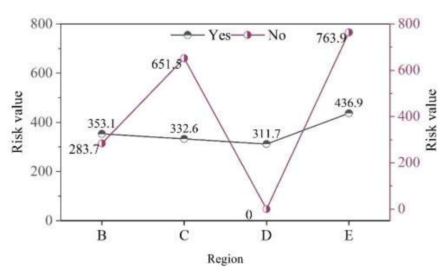
Transportation risk is assessed with (Yes) and without (No) the risk values of different regions are shown in Figure 3. (a)~(c) denote the results of the comparison of regional risk values when $a=0.7$, $a=0.6$ and $a=0.5$, respectively. The assessment of transportation risk can achieve an equal distribution of regional risk to some extent. When there is no transportation risk assessment, the transportation enterprises will not separate the transportation of the same kind of dangerous goods out of their own interests, which leads to the unequal distribution of risks in different regions. Take $a=0.7$ as an example, when there is no transportation risk assessment, the transportation enterprise will not choose the road sections $(4,5)$ and $(5,6)$ to transport dangerous goods, at this time, the risk value of region D is 0, while the risk value of region B and region C, E are 221.6, 596.7 and 733.2, respectively, with large differences, and there is a clear unequal distribution of risk in each region. After the assessment of transportation risk, the number of vehicles of different types of dangerous goods on different road sections is limited, which affects the deployment and route selection of transporters for vehicles of different types of dangerous goods, thus making the risk of each region as equally distributed as possible.



(a) $a=0.7$



(b) $a=0.6$



(c) $a=0.5$

Figure 3: Risk assessment of transport risks in different regions

IV. C. Comparative analysis of algorithms

In order to further validate the effectiveness of the algorithms, a performance comparison between the ACMPSO algorithm and the PSO algorithm is performed. Both algorithms were run on a computer configured with an AMD Ryzen 7 5800U CPU@ 3.20 GHzand 64.0 GB RAM, and the path-optimal solution in region D was used as an example for the runtime comparison.

The experiments were conducted by choosing 20, 30, 50, 100, and 200 according to the number of particles, and then solving the average and optimal solutions for different number of particles under each set of iterations.The comparison of the average path-optimal solutions of the two algorithms is shown in Fig. 4. When the number of iterations is 100, the average path optimal solution of ACMPSO algorithm is 67.07km, which is much smaller than that of PSO algorithm, which is 71.67km. It shows that ACMPSO algorithm is more capable of realizing the optimal path solution.

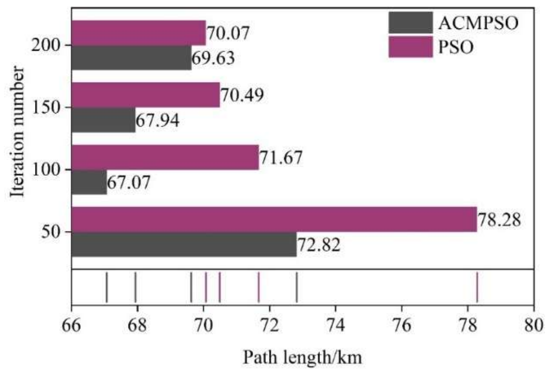


Figure 4: The average path is the optimal solution

The average time comparison of the solutions of the two algorithms is shown in Fig. 5. The ACMPSO algorithm performs path solving in the range of 3.21s to 9.29s, which is much shorter than the solution time of the PSO algorithm.

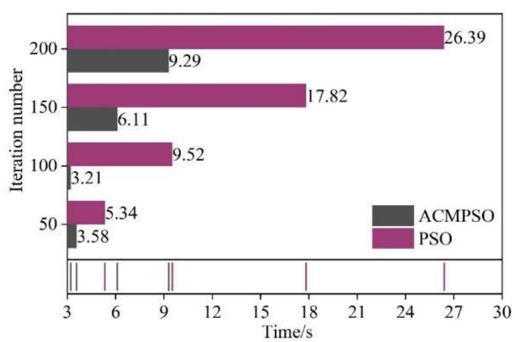


Figure 5: The average time of the two algorithms is compared

In order to better reflect the performance of ACMPSO algorithm, the acceleration ratio of the algorithm is counted and analyzed.

Acceleration ratio: it is one of the responses to the performance of the algorithm, through the improvement of the PSO algorithm makes the running time reduced. Its definition formula:

$$s = {}^{t_s}\!/_{t_p} \tag{24}$$

Where t_{PSO} represents the time required for the PSO algorithm to solve, and t_{ACMPSO} represents the time for the ACMPSO algorithm to solve.

Substituting the solution times of the two algorithms into Eq. (24), the average speedup ratio is found to be 2.554. The average algorithmic performance shows that the algorithms have better overall performance, and the performance tends to be in a steady state.

V. Hazardous chemical road transport safety guarantee strategy

V. A. Encouragement of specialized and large-scale transport companies

According to the survey, most of the dependent enterprises have problems such as small scale, few vehicles, full-time personnel and insufficient capital investment in safety production. Therefore, we can encourage large-scale professional dangerous goods transport enterprises or state-owned transport enterprises to reasonably merge with small dangerous goods transport enterprises, so that not only can better eliminate the transport vehicle dependence, but also better regulate the management of dangerous goods transport.

V. B. Promote the construction of a joint regulatory mechanism for road transport of hazardous chemicals

In view of the problems of information sharing, poor communication mechanisms, fragmented management and inefficient management among various departments, it is recommended to integrate the law enforcement and regulatory means and information sharing mechanisms of various departments, and to build a unified regulatory system platform. By grasping the source, management focus, control the key to form a regulatory synergy, realize the management data and information in the traffic control, transportation, safety supervision, real-time sharing between the four parties, to solve the problem of asymmetric safety supervision information, clarify the regulatory responsibility of the management department and the enterprise's own management responsibility.

V. C. Strengthening source management of key vehicles and drivers

The establishment of a regular public security, emergency response, transportation, market supervision, industry and information technology and other departments of the consultation mechanism, strict vehicle audit and driver access mechanism, the failure to obtain a certificate of conformity of the safety inspection of the vehicle, will not be issued inspection and conformity mark. The existence of vehicles “large tons and small standards”, illegal production, modification of dangerous goods transportation enterprises to carry out strict investigation and quick action. Strictly implement the requirements of “four look, three verification, two check”, carefully verify the application materials and qualification documents, and see the people, see the car, the transportation vehicles traveling routes, time and road surface to implement a full range of dynamic supervision, and regularly carry out supervision and inspection work. The establishment of a scientific assessment system, through the assessment to standardize enterprise management, to promote the implementation of the main responsibility of enterprises.

V. D. Establishment of a sound emergency management and incident response network

Organize and build professional emergency rescue teams for the safety of road transport of hazardous chemicals, formulate emergency rescue and disposal plans, and improve the efficiency of emergency disposal. It is recommended to take provincial or municipal administrative regions as a unit, comprehensively analyze the road conditions in the jurisdiction, and encourage local governments and enterprises to unify to establish one or several emergency rescue teams for hazardous chemicals in regions where the road density is large and the number of hazardous chemicals transportation vehicles pass through is high. Linkage of the relevant hazardous chemicals production, storage, operation and transportation units, improve the disposal program of road transport accidents of hazardous chemicals [42], to ensure that in the event of accidents or traffic accidents, the emergency rescue team can be the first time to know and rushed to the rescue.

VI. Conclusion

The study proposes an optimization model for hazardous materials transportation network considering transportation cost and safety, and designs an improved PSO algorithm for solving the model. The following conclusions are drawn through case solving:

(1) As the weight of the total risk of the transportation network in the whole multi-objective planning model decreases, the value of the transportation risk increases and the transportation cost decreases.

(2) The assessment of transportation risk can ensure that the risk of each region is equally distributed as far as possible, which ensures the safety of road transportation of hazardous chemicals.

(3) When model solving based on ACMPSO algorithm, the solving time is much shorter than PSO algorithm.

To further ensure the safety of hazardous chemicals road transport, the government should encourage specialized and large-scale transport companies, promote the construction of joint supervision mechanism for hazardous chemicals road transport, strengthen the source management of key vehicles and drivers, and establish and improve the emergency management and accident rescue network.

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