IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 10 July 2023, accepted 20 July 2023, date of publication 31 July 2023, date of current version 10 August 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3300041

RESEARCH ARTICLE

Multi-Depot Heterogeneous Vehicle Routing Optimization for Hazardous Materials Transportation

JUANMEI ZHANG[1], GUOYONG WANG[1], QIAN SHENG[2], XINYU JIA[3], AND PING XIE[3]
[1]Luoyang Institute of Science and Technology, Luoyang 471023, China
[2]Googol Technology Company Ltd., Shenzhen 518057, China
[3]Henan University of Science and Technology, Luoyang 471023, China

Corresponding author: Qian Sheng (sheng.qian@googoltech.com)

This work was supported by the National Natural Science Foundation (NSFC) under Grant 62176113.

ABSTRACT This paper considers a multi-depot heterogeneous vehicle routing problem (MDHVRP) with time windows, which is very crucial for hazardous materials transportation. For this reason, we formalize this problem as a multi-objective MDHVRP optimization model, where the actual load dependent risk of hazardous materials transportation is considered. To solve the optimization problem, we propose a hybrid multi-objective evolutionary algorithm (HMOEA) and a two-stage algorithm (TSA). In addition, we verify the performance of the proposed algorithms by experiments on the modified Solomon's VRPTW examples. In the experiment, it can be seen from the distribution of Pareto solution sets and the convergence distribution of IGD values that HMOEA is significantly superior to the other three algorithms in searching for Pareto solutions, as well as in the convergence and diversity of the algorithm. HMOEA and TSA were compared, and the minimum cost obtained by TSA was 13.38% lower than HMOEA, while the minimum risk was 81.69% higher than HMOEA. The advantages of each algorithm in finding solutions in reality were analyzed. A comparison was made between multi-depots heterogeneous VRP and multi-depots homogeneous VRP in the C101 instance, and the results showed that scheduling heterogeneous vehicles would reduce risk and cost.

INDEX TERMS Hazardous materials transportation, actual load, robust multi-depot heterogeneous vehicle routing problem, hybrid multi-objective evolutionary optimization algorithm, two-stage algorithm.

I. INTRODUCTION

With the rapid economic development, industrial production activities are increasing, and a large number of hazardous materials are transported through road transportation networks. By the end of 2018, there existed a total of 373 thousand vehicles and 1.6 million relevant practitioners for hazardous materials transport in China. Among them, road transport accounted for 70% of the total hazardous materials. Different from general goods, hazardous materials are prone to rollover, collision, leakage, burning, explosion, poisoning, etc. During transportation, and once an accident occurs, it may cause serious consequences such as personal injury and death, property damages, and traffic interruptions [1]. For example, on 13 June 2020, in the middle section of the Wenling exit interchange ramp of Shenhai Expressway, a liquefied gas tanker exploded caused 20 deaths and more than 175 were hospitalized [42]. Because dangerous goods transport is essential in the national economic development, it is very necessary to avoid all potential risks as far as possible during the hazardous materials transportation [3].

With the aid of vehicle network communication technology, vehicles can know the location of other things on the road in real time [4], [5], [6]. In particular, dynamic navigation of vehicle network can help dangerous goods transport vehicles avoid crowded areas or places with high accident rate.

The associate editor coordinating the review of this manuscript and approving it for publication was Wei Quan.

Therefore, vehicle routing problem (VRP) has been widely concerned in hazardous materials transportation [7], [8] received extensive attention in hazardous materials, however, most researches focus on uniform vehicle routing in single repository, which is inconsistent with the actual situation. In practice, different types of vehicles are transported between multiple depots and customers, therefore, it has more practical significance to study the multi-depot heterogeneous vehicle routing problem (MDHVRP) for hazardous materials transportation [9], [10]. The transportation risk must be considered firstly. Usually, the traditional risk model [12], [13] is used to evaluate the safety of transportation, which defines the risk as inner product of accident probability and accident consequence. The accident probability is usually represented by a random distribution, and the accident consequences are represented by the number of affected residents within a certain distance from the accident site [14]. Nonetheless, it does not make sense to view the traditional risk as merely transport risk within a road segment. The range of areas affected by hazardous materials vehicles with different loads during accidents is also significantly. Therefore, it is very necessary to consider the actual load dependent risk of vehicles on the road segment when building the risk assessment model of MDHVRP.

Because of the above-mentioned reasons, the transportation of hazardous materials has been taken as a MDHVRP model in this manuscript at first. A multi-objective vehicle routing optimization model that simultaneously considers uncertain transportation risks and costs has been proposed in this article. According to literature research, although there are many researches on the optimization of IoV resources [15], [16], there are few researches the MDHVRP with time windows for uncertain hazardous materials transport. In this work, the actual load dependent risk of vehicles at different times along each route is regarded as the main uncertain transportation risk. The transportation risks and costs of planing routs are used to determine the goals and form a dual objective problem. A hybrid multi-objective evolutionary method (HMOEM) based on the Nsga-ii framework and a two-stage algorithm (TSA) has been proposed in this work to solve the MDHVRP, which integrates a sequence-based crossover operator, a route elimination mutation operator and variable neighborhood descent algorithm to generate better offspring. TSA decomposes MDHVRP into multiple single-depot vehicle routing problems in the first stage. Push-forward insertion heuristic (PFIH) is used to construct part of the initial population and a HMOEM is used to solve the routing optimization problem in the second stage.

The rest of this paper is organized as follows. The existing relevant studies are introduced briefly in Section II. The description and formula of MDHVRP are provided in Section III. The hybrid multi-objective evolutionary method (HMOEM) is presented in Section IV. Afterwards, the experimental settings and results are reported in Section V. Finally, conclusions are given in Section VI.

II. RELATED WORK

As a major issue in the field of transport safety, the VRP for hazardous materials transportation has been widely concerned in recent years. Most studies in this area assume that there is only a single depot and homogeneous vehicles.

However, in reality, there may be multiple depot and multiple types of vehicles involved in the transportation. Reference [21] formulated a multi-level programming model for urban hazardous materials transportation based on the VRP with multi-depot capacity constraints, which took into account multiple factors in practical applications. Reference [22] converted MDVRP into multiple VRPs with a single depot according to the distance between each depot and each customer, and then use genetic algorithms to solve each VRP. Reference [23] proposed a bi-objective optimization model to minimize the total energy consumption and risk for MDVRP of hazardous materials transportation, focusing on energy consumption. Reference [11] proposed a half open MDHVRP model for hazardous materials transportation, which mainly considers that vehicles at multiple depots can stop at any depot after serving the last customer. Reference [18] established a low-carbon multi-objective hazardous materials transportation model and took road traffic elasticity as one of the weighting factors for hazardous materials transportation risk calculation. In addition, some studies have also focused on the transportation of hazardous materials with different vehicle types, in stochastic transportation networks [19], and with traffic restriction constraint in inter-city roads [20], where vehicles have different capacities, transportation costs, and accident probabilities, etc. [24] focused on building a heterogeneous VRP (HVRP) model for the transportation of hazardous materials, and used a variable neighborhood search algorithm to find the route set with the least total transportation risk. After that, [25] proposed a bi-objective model for minimizing the total transportation risk and cost of HVRP for hazardous materials.

For the modeling of hazardous materials transportation VRP, risk assessment method is an important content. Reference [26] studied with the dual objectives of minimizing the individual risk and transportation cost of vehicles, so as to avoid the adverse situation that the total risk is not high but the risk of a vehicle is particularly high. Reference [27] gave the risk definition based on the real-time loading capacity of vehicles, and established the vehicle route optimization model with the objective of minimizing the individual risk of vehicles and cost. Reference [28] proposed a risk assessment model for hazardous materials transportation that considers waiting time and heterogeneous vehicle types. Taking into account the uncertainty of dangerous goods transportation, [29] constructed an uncertainty set containing multiple potential accident situations, and establishes a robust model for the uncertain parameters. Reference [42] used Causal Bayesian Network (CBN) to describe the relationship between risk factors in view of time-varying conditions of hazardous materials transportation location and environment.

TABLE 1. Main notations.

Notation	Description
D	Set of depots nodes
d	Index of depot
C	Set of customers nodes
c	Index of customer
N	Set of all nodes, $N = D \cup C$
A	Set of all arcs, $A = \{(i,j) \mid i,j \in N \setminus i,j \in D\}$
V	Set of vehicle types
K_d	Set of vehicle types in depot d, $K_d \subseteq V$
v	Index of vehicle type
v_d	Set of vehicles of type v in depot d
k	Index of vehicle

TABLE 2. Main parameters.

Parameter	Description
p_v	Accident probability of a vehicle of type v
Pop_{ij}	Population density along arc (i,j)
l_{ij}	Distance between node i and node j
f^v	Fixed cost of a vehicle of type v
δ_c	Demand of customer c
s_c	Service time required by customer c
$[ET_c, LT_c]$	Time window at customer c
q^v	Maximum capacity of vehicle of type v
y_{ijk}^{dv}	Loading of vehicle k of type v of depot d travels from node i to node j
tc_{ij}^v	Unit distance transportation cost of a vehicle of type v on arc (i,j)
t_{ij}	Travel time of a vehicle travels from i to node j
Cap_d	The existing quantity of hazardous materials of depot d
w_c	Waiting time of a vehicle at customer c, w_c =max$(0, ET_c - AT_c)$
AT_j	The time for a vehicle from node i to arrive at node j, $AT_j = \tau_i + t_{ij}$
ρ_{ij}	Conditional release probability given an accident on arc (i,j)
τ_c	The time when vehicle departs from customer c, $\tau_c = AT_c + w_c + s_c$
R_{ij}	The transportation risk on arc (i,j)

TABLE 3. Variable.

Decision variable	Description
x_{ijk}^{dv}	Binary decision variable. 1, if the rout of vehicle k of type v from depot d contains the road segment from node i to j; otherwise, 0

In summary, it can be seen that in previous related work, when considering the transportation of hazardous materials, most of them only focused on a certain aspect of factors. For example, [11], [26], and [27] did not consider time windows, [29] did not consider multiple vehicle types, and [28] did not consider multiple depots. In this paper, we define a risk assessment model for hazardous materials transportation considering heterogeneous fleet, actual load dependent risk of vehicles, and stochastic time-dependent population density of road segments. A multi-objective vehicle routing model that minimizes transportation cost and risk is established by integrating factors such as multiple depots, heterogeneous fleet, time windows, and depot distribution capabilities. A hybrid multi-objective evolutionary algorithm and a two-stage algorithm are proposed to solve it. The next section will provide a problem description and model.

III. PROBLEM DESCRIPTION AND FORMULATION

In this section, we define the MDHVRP and then formulate the mixed integer programming (MIP) model. For simplicity, we define the related notations in Table 1, Table2 and Table3.

A. PROBLEM DESCRIPTION

We consider that MDHVRP consists of multiple depots, customers, and different types of vehicles. Each depot has the number of different types of vehicles and hazardous materials capacity which means that all depots cannot provide unlimited vehicles and hazardous materials. An illustrative example with 2 depots, 13 customers and 2 types of vehicles is given in Figure 1. Among them, depot d_1 has 150 existing hazardous materials, and has two a-type vehicles with a maximum load of 50 and one b-type vehicle with a maximum load of 70. Similarly, depot d_2 has 130 existing hazardous materials and has two b-type vehicles. Each customer's demand is 20. As shown in Figure 1, each depot will deliver to customers based on existing hazardous materials and vehicles and plan the driving path of the vehicles.

We formulate the above problem as a bi-objective MIP model that minimizes transportation risks and transportation costs. The goal is to determine the distribution of customers in the depot and the optimal driving route of the vehicles with the constraints of the existing hazardous materials and the number of vehicles in the depot, customer's demands and service time windows, and the maximum load of various types of vehicles. Before formulating the model, several assumptions are listed as follows:

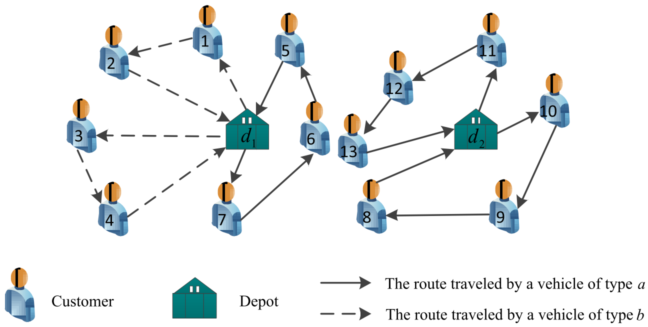


FIGURE 1. **Multi-depot heterogeneous vehicle routing problem.**

1) The amount of hazardous materials owned by each depot and the number of various types of vehicles are known.
2) The total number of vehicles and the total volume of hazardous materials in all depot meet the distribution requirements.
3) Each vehicle must return to the depot at the time of departure after completing its transportation task.
4) The demand and time window of each demand point can be known in advance and the demand cannot be split.
5) The vehicle must arrive and serve within the predefined time window of the demand point, and wait if it arrives early.
6) The maximum load of all types of vehicles is known, and all vehicles must not be overloaded.
7) The depot must deliver to the demand points according to the number of existing vehicles and the volume of hazardous materials.

B. DETERMINISTIC MDHVRP

According to the hazardous materials transportation guidelines [30], the formulation of the transportation risk on arc(i, j) can be expressed as:

$$R_{ij} = P_{ij}C_{ij}, \tag{1}$$

where P_{ij} and C_{ij} are the accident probability and the accident consequence on arc (i, j), respectively. Moreover, the accident probability includes the probability of the accident and the conditional release probability for the given accident. The probabilities can generally be obtained through historical data [31]. In related studies, the consequences of accidents are usually expressed in terms of population coverage, which is measured by the population density and affected area. However, the areas affected by vehicles with different loads are obviously different in the event of an accident. The area affected by a hazardous materials vehicle can be shown in Figure 2.

The area is regarded as a circle with a center point of vehicle k and a radius of r. When the vehicle k has served the demand point i, its carrying capacity when traversing the arc (h, i) is less than the carrying capacity when traversing the

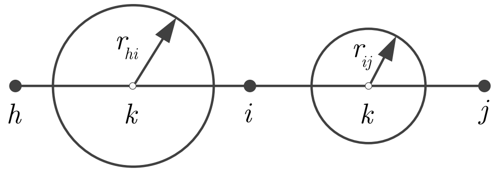


FIGURE 2. **Multi-depot heterogeneous vehicle routing problem.**

arc (i, j) [17]. Therefore, the affected area of transport vehicles is dynamic, and the smaller the cargo load, the smaller the radius of the affected area. For example, r_{ij} is less than r_{hi}. Similar to the works [24], [25], this study defines the transportation risk as on arc (i, j), i.e.,

$$R_{ij} = p^v_{ij}\rho_{ij}Pop_{ij}\pi(\alpha(y^{dv}_{ijk})^{\beta})^2, \tag{2}$$

where α and β are based on the constant value of the vehicle type and hazardous materials category, the p^v_{ij} can be obtained from historical traffic data.

This paper defines a bi-objective deterministic MDHVRP model for the transportation of hazardous materials. Aiming at the safety and economic factors optimized for this problem, the established objective functions are Eqs. (3) and (4). Eq. (3) is to minimize the total risk, and Eq. (4) is to minimize the total transportation cost. In Eq. (4), the first item is the routing cost, the second item is the fixed cost for all types of vehicles.

$$\min f_1 = \sum_{d\in D}\sum_{v\in K_d}\sum_{k\in v_d}\sum_{i\in N}\sum_{j\in N} R_{ij}x^{dv}_{ijk}, \tag{3}$$

$$\min f_2 = \sum_{d\in D}\sum_{v\in K_d}\sum_{k\in v_d}(\sum_{i\in N}\sum_{j\in N} tc^v_{ij}l_{ij}x^{dv}_{ijk} + \sum_{i\in D}\sum_{j\in C} f^v x^{dv}_{ijk}), \tag{4}$$

subject to

$$\sum_{i\in N}\sum_{d\in D}\sum_{v\in K_d}\sum_{k\in v_d} x^{dv}_{ijk} = 1,\ \forall j \in C, \tag{5}$$

$$\sum_{j\in N}\sum_{d\in D}\sum_{v\in K_d}\sum_{k\in v_d} x^{dv}_{ijk} = 1,\ \forall i \in C, \tag{6}$$

$$\sum_{i\in N}\sum_{j\in C} \delta_j x^{dv}_{ijk} \le q^v,\ \forall d \in D, v \in K_d, k \in v_d, \tag{7}$$

$$\sum_{j\in C}\sum_{k\in v_d} x^{dv}_{ijk} \le |v_d|,\ \forall i \in D, d \in D, v \in K_d, \tag{8}$$

$$\sum_{i\in N}\sum_{j\in C}\sum_{v\in K_d}\sum_{k\in v_d} \delta_j x^{dv}_{ijk} \le Cap_d,\ \forall d \in D, \tag{9}$$

$$\sum_{i\in N} y^{dv}_{ijk} - \sum_{i\in N} y^{dv}_{jik} = \delta_j,$$
$$\forall j \in C, d \in D, v \in K_d, k \in v_d, \tag{10}$$

$$\sum_{j\in C} x^{dv}_{ijk} - \sum_{j\in C} x^{dv}_{jik} = 0,$$
$$\forall i \in D, d \in D, v \in K_d, k \in v_d, \tag{11}$$

$$\sum_{j\in D} x_{ijk}^{dv} = \sum_{j\in D} x_{jik}^{dv} = 0,$$
$$\forall i \in D, d \in D, v \in K_d, k \in v_d, \tag{12}$$
$$ET_i \leq AT_i + w_i \leq LT_i, \ \forall i \in C, \tag{13}$$

where Eqs. (5) and (6) ensure that each demand point has and can only be served by a transport vehicle sent by any depot. Eq.(7) means that any type of vehicle in all depots should meet the corresponding load constraint, that is, it cannot be overloaded. Eq. (8) indicates that the number of vehicles used to transport hazardous materials in any depot cannot exceed the number of vehicles owned by it. Eq. (9) indicates that the quantity of hazardous materials in the depots is limited, and the total quantity of hazardous materials delivered by any depot to the demand point cannot exceed its existing quantity of hazardous materials. Eq. (10) ensures that the needs of all demand points are met. Eq. (11) ensures the formation of a vehicle loop, that is to say, each vehicle starts from the depot and completes its task before returning to the same depot. Eq. (12) restricts transportation vehicles from being able to drive from one depot to another. Eq. (13) represents the hard time window constraint. Although the vehicle must start delivery within the customers time window, vehicles that arrive earlier are allowed to wait for the beginning of the customers time window.

IV. SOLUTION METHODS

This section proposes an efficient hybrid multi-objective optimization evolutionary algorithm (HMOEA) and a two-stage algorithm (TSA) for solving the multi-objective MDHVRP in the transportation of hazardous materials.

A. HYBRID MULTI-OBJECTIVE OPTIMIZATION EVOLUTIONARY ALGORITHM

In this section, we propose a hybrid multi-objective evolutionary algorithm to solve MDHVRP, which comprehensively considers the customer points to be served by each depot and the service order in the solution process. Algorithm 1 gives the main framework of HMOEA. The specific operations are as follows:

1) REPRESENTATION STRUCTURE

The optimal solution of the MDHVRP problem includes determining the optimal routes, vehicle types and service order of each depot. In addition, there are still some problems to be determined in the transportation of hazardous materials in the MDHVRP: (1) each depot should serve which customers. (2) which type of vehicle should each customer be served. (3) routes of vehicles serving customers. (4) whether to meet customer demands, customer time windows and vehicles capacities. (5) whether it meets the existing hazardous materials volume and the number of vehicles in the depot. It is worth noting that a feasible solution represents a chromosome. A feasible solution consists of a set of routes $x = \{\gamma_1, \gamma_2, \cdots, \gamma_{|x|}\}$, where $|x| \leq \sum_{d\in D}\sum_{v\in K_d} |V_d|$. A route $\gamma_i = \{d, v, \gamma_1^i, \gamma_2^i, \cdots, \gamma_{|\gamma_i|-2}^i\}$, where d and v represent the depot and vehicle type, $\forall \gamma_j^i \in C$ and $|\gamma_i| - 2$ represent the customer sequence and the number of customers to be served in the i-th route, respectively.

Algorithm 1 The Main Framework of the Proposed HMOEA

Input: Instance data
Output: The non-dominated solution set in *Population*
Initialization:*Population* of size $|C|$ for the RMDHVRP

```
while stopping criterion not met do
    Parent ← Tournament Selection(Population)
    Off ← Sequence-Based Crossover (Parent)
    Off ← Route Eliminate Mutation (Off)
    for all solutions do
        x' ← VND (x), Update Off
    end for
    Population ← Parent ⋃ Off
    NDSet ← Fast non-dominated sort (Population)
    Population ← Elite strategy select (NDSet)
end while
```

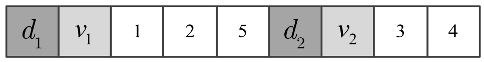


FIGURE 3. Chromosome structure of HMOEA.

As shown in Figure 3, the chromosome can be expressed as $(d_1, v_1, 1, 2, 5, ; d_2, v_2, 3, 4)$, in which dark grey squares indicate depots, light grey squares indicate vehicle types and white squares indicate customers. For example, depot d_1 and depot d_2 respectively dispatch one v_1-type vehicle and one v_2-type vehicle to serve customers 1, 2, 5 and customers 3, 4 in order. After that, each vehicle returns to its depot after completing the delivery task.

It is worth noting that the constructed solution cannot violate all constraints. Similarly, in the process of crossover, mutation, local search and selection, the direct elimination method is used to eliminate infeasible solutions. The constraints mainly include: vehicle load constraints, see Eq. (7); vehicle quantity constraints, see Eq. (8), depot inventory constraints, see Eq. (9), and customer time window constraints, see Eq. (13).

2) POPULATION INITIALIZATION

The initial population are constructed randomly. Specifically, it is to randomly select a node g from $C = (1, 2, \cdots, n)$ to reorganize C into $RC = (g, \cdots, n, 1, \cdots, g-1)$, and then sequentially insert the customers in RC into the empty route when the all constraints are met.

3) EVOLUTIONARY OPERATORS

The proposed HMOEA uses crossover and mutation methods in genetic algorithms (GA) to generate offspring populations. According to the characteristics of the problem, we use sequence-based crossover and route eliminate mutation to generate offspring.

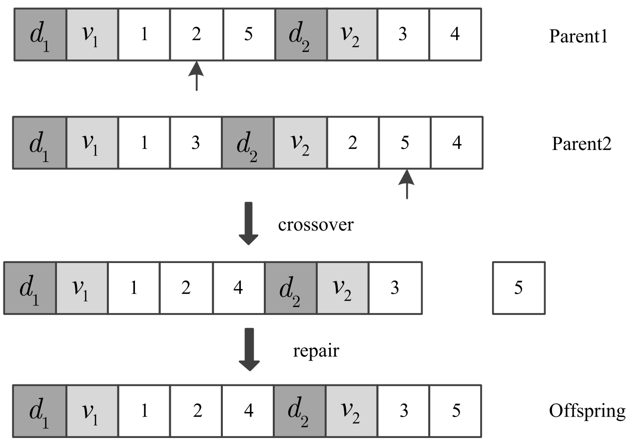


FIGURE 4. Sequence-based crossover.

a: SEQUENCE-BASED CROSSOVER

This paper uses a sequence-based crossover method to generate offspring. The main idea is to use the combination of the first half of a route of *parent*1 and the second half of a route of *parent*2 [32]. As is well known, time windows constraint greatly increase the difficulty of generating new route sequences in VRP. Based on sequence crossing, a feasible route plan will strictly arrange vehicle delivery according to the customer's time windows requirements. Therefore, connecting customers at the front of one route with customers at the back of another route is likely to form a new route that meets the time windows constraint. As shown in Figure 4, randomly select a route from *parent*1 and *parent*2, namely $\gamma_1 = (d_1, a, 1, 2, 5, d_1)$ and $\gamma_2 = (d_2, b, 2, 5, 4, d_2)$. And randomly select a breakpoint from the customer sequence of γ_1 and γ_2, and divide each customer sequence into two sequences. Then replace the second half sequence (5) of γ_1 of *parent*1 with the second half sequence (4) of γ_2 to generate a new route $(d_1, a, 1, 2, 4, d_1)$. If there are duplicate customers, delete the customers in the old route, such as customer 4. If there are unrouted customers, it is repaired by randomly inserting a feasible position of *parent*1, such as customer 5. In the same way, *parent*2 can be used as the mainstay to create a second offspring. The specific process is described in Algorithm 2.

b: ROUTE ELIMINATE MUTATION

Due to the time windows constraint of MDHVRP, it may be difficult for vehicles to select customer delivery routes, resulting in a vehicle that only delivers a small number of customers. This will make the utilization rate of a certain vehicle too low, increase the number of vehicles and transportation distance that could have been avoided, thus increasing the degree of difficulty of bi-objective optimization. Therefore, we use the route elimination method proposed by [33] to eliminate the route with the fewest customers to improve the above problems.

Algorithm 2 Sequence-Based Crossover

Input: Two solutions, x_1 and x_2
Output: The offspring solution x_1'
Initialization: Randomly select two routes γ_1 and γ_2 from x_1 and x_2 respectively, *feasible* $= 0$, *times* $= 1$

$m_1 = (length(\gamma_1) - 3) * (length(\gamma_2) - 3)$
while $(feasible = 0) \; || \; (times \leq m_1)$ **do**
  Randomly select two breakpoints bp_1 and bp_2 from γ_1 and γ_2 respectively
  $(\gamma_1^f, \gamma_1^b) = segmentation(\gamma_1, bp_1)$
  $(\gamma_2^f, \gamma_2^b) = segmentation(\gamma_2, bp_2)$
  $\gamma_1' = combine(\gamma_1^f, \gamma_2^b)$
  Clear duplicate customers in γ_1'
  if γ_1' satisfies time windows constraint and load constraint **then**
    $feasible = 1$
    $x_1' \leftarrow replace(x_1, \gamma_1, \gamma_1')$
    Clear duplicate customers in x_1'
    if x_1' does not meet depot distribution capabilities constraint **then**
      $feasible = 0$
    end if
  end if
  $times = times + 1$
end while
if $feasible = 1$ **then**
  Clear duplicate customers in γ_1^b
  Customers in γ_1^b insert in x_1'
else
  $x_1' = x_1$
end if

4) LOCAL SEARCH EXPLOITATION

In this paper, in order to enhance the performance of HMOEA in solving MDHVRP, a VND procedure [34] is used for local search. The optimal solution of a neighbor structure does not mean that the structure in another neighborhood is locally optimal. For the local optimal solution with only one neighborhood structure, the local optimal solution generated by the multiple, changeable neighborhood structure of the VND is more likely to converge [36].

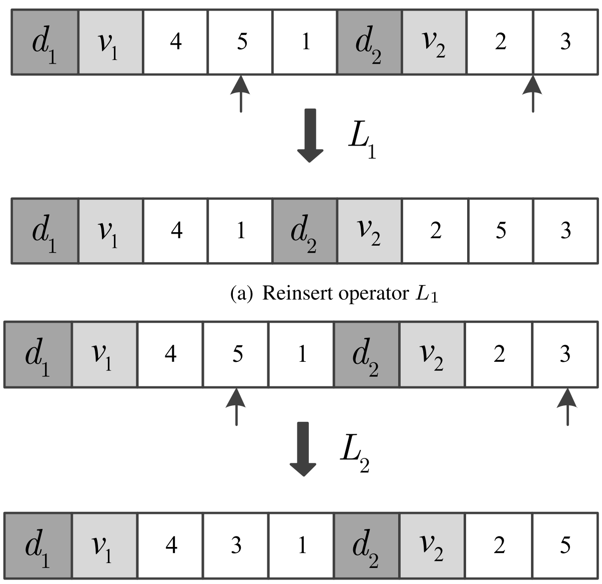
The specific process is described in Algorithm 3, where x is the solution that meets the local search conditions, and L_λ is the λth neighborhood structure developed by the solution. If the current solution x in the λth neighborhood structure searched for the solution x^* dominates $x(x^* \succ x)$, then x is replaced by x^*. Our neighborhood search strategy is to search for $\lceil 0.1|C| \rceil$ feasible solutions in each neighborhood structure, and then select the best solution from these solutions as the new current solution. As used herein, the neighborhood structures are as follows:

a) L_1 Operator : L_1 randomly selects a customer on a route and reinserts it to another feasible position. As shown in

Algorithm 3 Variable Neighborhood Descent (VND)

Input: A solution x, a set of neighborhood structures L_λ, $\lambda = 1, 2, \ldots, \lambda_{\max}$
Output: The improved solution x
Initialization: $\lambda = 1$, $random_{rate}$: random value in [0, 1]

if x is non-domination **then**
  $LS_{rate} = 1\%$
else
  $LS_{rate} = 0.1\%$
end if
if $random_{rate} \leq LS_{rate}$ **then**
  while $\lambda \leq \lambda_{\max}$ **do**
    $x^* \leftarrow Best\,(L_\lambda(x))$
    if $x^* \succ x$ **then**
      $x \leftarrow x^*$
      $\lambda = 1$
    end if
    $\lambda = \lambda + 1$
  end while
end if



(a) Reinsert operator L_1

(b) Swap operator L_2

FIGURE 5. Procedure of the local search.

Figure 5(a), L_1 selects customer 5 from the current solution $((d_1, a, 4, 5, 1, d_1), (d_2, b, 2, 3, d_2))$ and reinserts it into the feasible position after customer 2 to obtain a new solution $((d_1, a, 4, 1, d_1), (d_2, b, 2, 5, 3, d_2))$.

b) L_2 Operator : L_2 randomly selects two customers in the two routes and exchanges their positions. As shown in Figure 5(b), L_2 selects customer 5 and customer 3 from route $(d_1, a, 4, 5, 1, d_1)$ and route $(d_2, b, 2, 3, d_2)$ respectively, and exchanges their positions to generate a new feasible solution $((d_1, a, 4, 3, 1, d_1), (d_2, b, 2, 5, d_2))$.

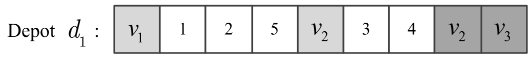


FIGURE 6. Chromosome structure of TSA.

B. TWO-STAGE ALGORITHM

Meanwhile, we propose a two-stage algorithm to solve MDHVRP. In the first stage, the multi-depot VRP is transformed into a multiple single-depot VRPs by assigning customers to the nearest depot according to the distance between each customer and all depots. Then in the second stage, we adopt the hybrid multi-objective evolutionary algorithm to solve the VRP of each single depot transformed in the first stage separately. Therefore, the algorithm is different from HMOEA mainly in representation structure and population initialization. The specific operations are as follows:

1) REPRESENTATION STRUCTURE

Since each single depot problem is solved separately, the chromosome does not need to represent depots. As shown in Figure 6, the chromosome of depot d_1 can be expressed as $(v_1, 1, 2, 5; v_2, 3, 4; v_2; v_3)$, in which one type v_2 vehicle and one type v_3 vehicle are idle.

2) POPULATION INITIALIZATION

Before initializing the population, according to the distance between each customer and all depots, customers are assigned to the nearest depot under the constraints (8)-(9). The specific allocation method is as follows:

If $l_{c_1 d_1} \leq l_{c_1 d_2}$, and $\delta_{c_1} \leq \min(\sum_{v \in K_{d_1}} |v_{d_1}| \, q^v, Cap_{d_1}) - \sum_{c \in C} \xi_c^{d_1} \delta_c$, customer c_1 is assigned to depot d_1.

Here $\sum_{c \in C} \xi_c^{d_1} \delta_c$ is the total demand of all customers who have been assigned to depot d_1. $\xi_c^{d_1}$ is a binary variable,which is 1 when depot d_1 serves customer c and 0 in other cases.

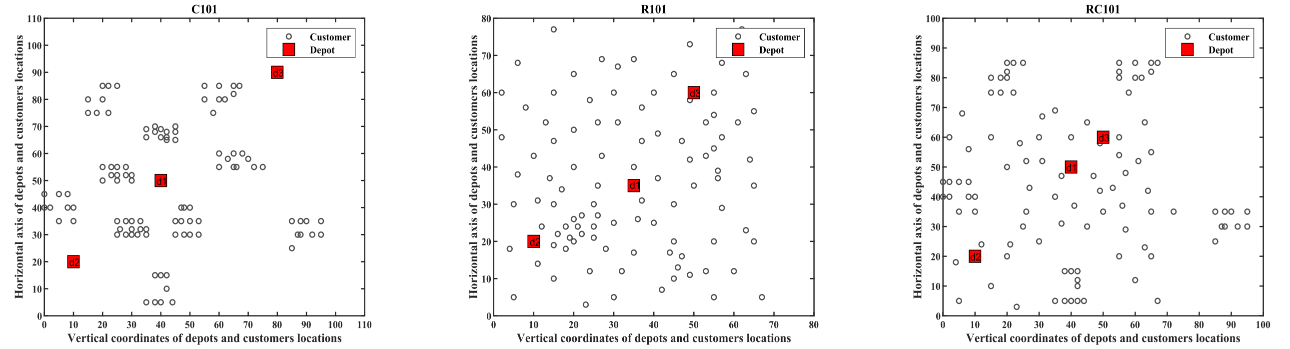
If a fast and simple heuristic method is used to obtain a part of the initial population, the evolution time within a reasonable local minimum can be significantly reduced [36]. In the population initialization stage, this paper uses the PFIH of [29] to construct a feasible individual, and then selects some individuals in its neighborhood. These individuals are accounted for one-tenth of the initial population, and the remaining viable individuals are constructed randomly.

V. COMPUTATIONAL RESULTS

In this section, the model and algorithm are evaluated by experiments. The proposed methods are coded with on MatlabR2019a software platform. All experiments and algorithms are based on a PC (Core 3.60GHz with 8.0GB of RAM) under Windows 10.

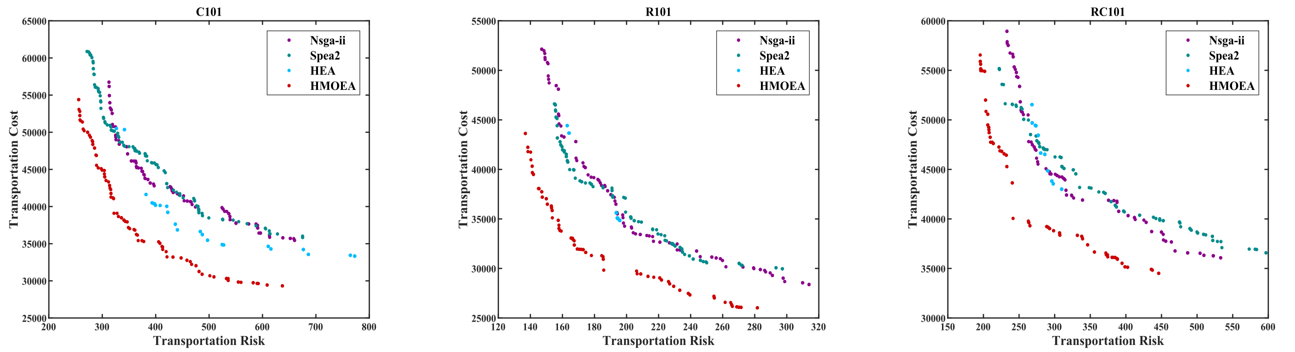
A. PROBLEM INSTANCES AND EXPERIMENT SETUP

The applicability and effectiveness of HMOEA to the MDHVRP solution are verified by testing on the modified



(a) (b) (c)

FIGURE 7. Locations of depots and customers.



(a) (b) (c)

FIGURE 8. Distribution of pareto solutions at 1000 generations.

Solomon's VRPTW standard problem set [37]. Its problem scale is divided into 25 customers, 50 customers and 100 customers according to the number of delivery customers. Here we choose the larger problem scale, i.e., an instance of 100 customers for experimentation. In each data set, it includes the coordinate information, demand, service time and time window of a depot and multiple customers, and the maximum load of the vehicle. The Euclidean distances between the customers and the distribution center are used to express the distances. The travel time is equal to the corresponding distance.

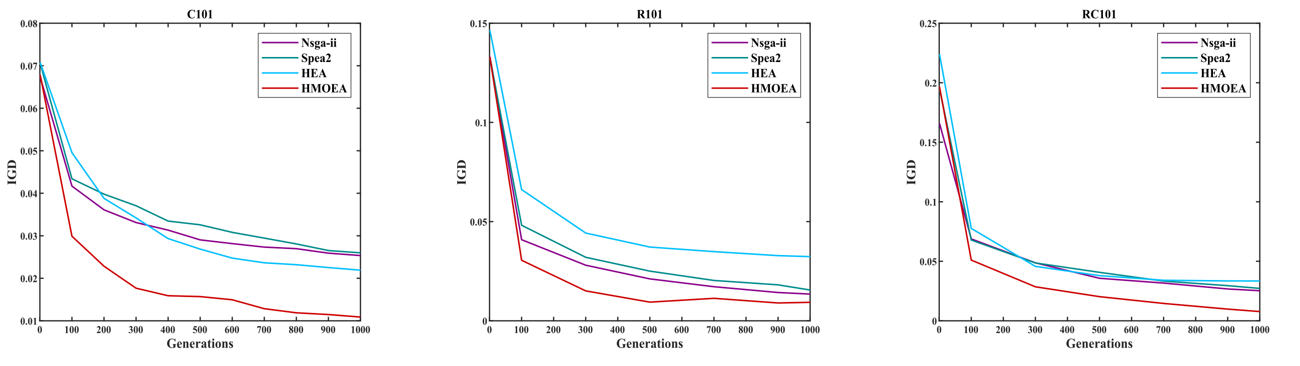
In this paper, we establish three test examples based on the customer data of the C101, R101 and RC101 instances in the Solomon standard dataset. Where the geographic data are randomly generated in instance R101, clustered in instance C101 and and a mix of random and clustered structures in instance RC101. The depot coordinates of the modified instance C101 are (40, 50), (10, 20) and (80, 90), respectively. The depot coordinates of the modified instance R101 are (35, 35), (10, 20) and (50, 60), respectively. The depot coordinates of the modified instance RC101 are (40, 50), (10, 20) and (50, 60), respectively. Table 4 and Table 5 give the vehicle attributes and depot attributes, respectively. The red squares and black circles in Figure 7 represent the locations of depots and customers, respectively. Population density is randomly generated, ranging from 0 to 50. Besides, ρ_{ij} is set to 1. We divide it into four equal periods according to

TABLE 4. Vehicles attributes.

V	q	f	c	$p_{ij} \times 10^{-5}$	α	β
v_1	200	500	25	7	0.25	1.05
v_2	120	250	14	6	0.25	1.05
v_3	80	140	8	5	0.25	1.05
v_4	50	80	5	4	0.25	1.05

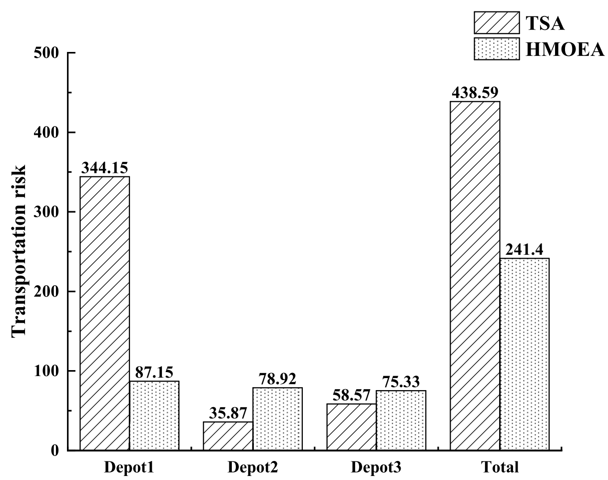
TABLE 5. Depots attributes.

D	Cap	Time window	Number of vehicles			
			v_1	v_2	v_3	v_4
d_1	900	[0, 1236]	3	2	2	2
d_2	700	[0, 1236]	1	2	3	2
d_3	600	[0, 1236]	2	2	3	1

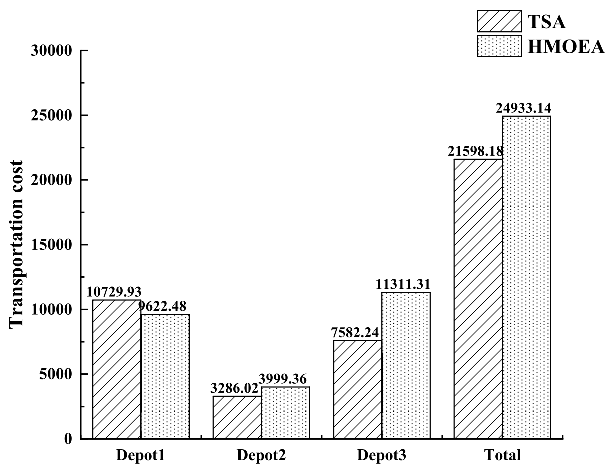


(a) (b) (c)

FIGURE 9. Values of IGD metric.



(a) The minimum risk



(b) The minimum cost

FIGURE 10. The minimum risk and cost of HMOEA and TSA.

the depot's time window. For the population density of some road sections in periods 1 and 4, increase the fluctuation range by ±20. For the population density of some road sections in periods 2 and 3, increase the fluctuation range by ±10.

The parameters are set as follows: population size is 100; max generation is 1000; crossover rate is 0.9; mutate rate is 0.1; repeat the experiment 5 times.

B. ALGORITHM EXPERIMENT

This section compares the results of HMOEA with Nsga-ii [38], Spea2 [39] and HEA [29]. HEA is proposed to solve the robust multi-objective VRP with time windows for hazardous materials. Both Nsga-ii and Spea2 are currently popular high-efficiency multi-objective genetic algorithms, which have the advantages of fast running speed, good convergence and distribution of the solution set, and are the benchmarks for the performance of other multi-objective algorithms. Since Nsga-ii and Spea2 are not tailor-made for MDHVRP, they all use the population initialization method and evolutionary operators of this paper.

Due to MDHVRP is a bi-objective problem, the performance of the algorithms can be intuitively demonstrated through the distribution of the pareto solution set. Figure 8 shows the approximation of each of the four algorithms for the Pareto-optimal front. It can be seen from the figure that the pareto solutions obtained by Nsga-ii, Spea2 and HEA are similar, and the pareto solutions obtained by HMOEA are far superior to the first two in terms of risk value and cost value in all three instances. Inverted generational distance (IGD) [40] is a commonly used index that can simultaneously evaluate the convergence and diversity of algorithms. In this section, we use IGD to evaluate the overall performance of the algorithms. It mainly calculates the average distance from each point (individual) on the true POF to the nearest solution in the non-dominated solution set obtained by the algorithm. The smaller its value, the better the overall performance of the algorithm. Since the true POF of MDHVRP is unknown, the non-dominated solutions among all the solutions obtained after 3000 iterations by the four algorithms compared is regarded as the true POF. From the convergence distribution of IGD values in Figure 9, it can be seen that HMOEA significantly outperforms the other three algorithms in all three instances.

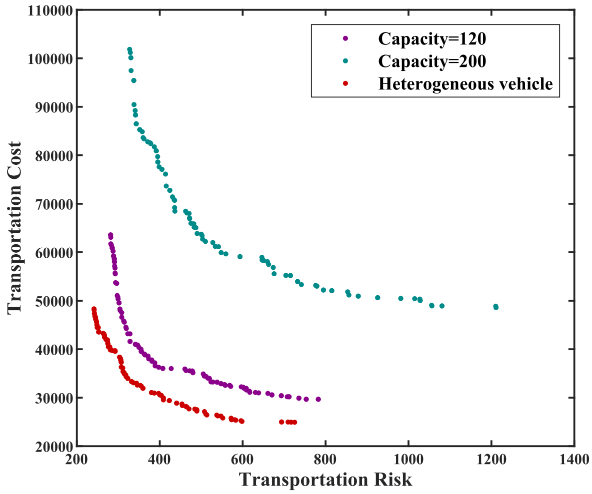


FIGURE 11. Final non-dominated solutions found by HMOEA.

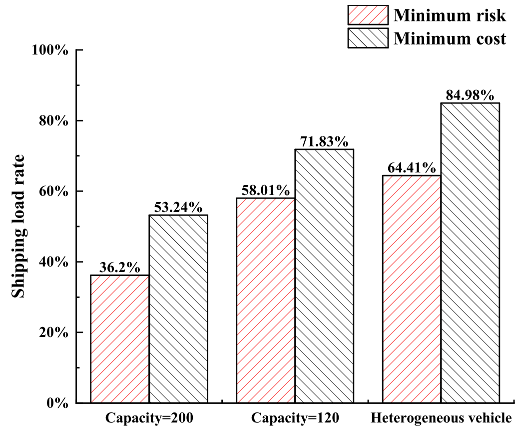


FIGURE 12. Shipping load rates for homogeneous VRP and heterogeneous VRP.

C. EXPERIMENTAL RESULTS OF THE HMOEA AND THE TSA

In real life, most depots prefer to deliver goods to customers around them. Therefore, we propose a two-stage algorithm and compare the experimental results with HMOEA in instance C101. Figure 10 shows the minimum risk value and cost value obtained by the two algorithms, respectively. It can be seen that although the minimum cost obtained by TSA is 13.38% lower than that of HMOEA, the minimum risk is 81.69% higher than that of HMOEA. For the transportation cost, it is closely related to travel distance. TSA is committed to the least distance, that is, each depot chooses customers gathered around it for distribution. For risk, it is closely related to vehicle accident rate, population density and real-time load. HMOEA has more options than TSA when it comes to deciding which vehicle in which depot will deliver to which customer. Moreover, it can be seen from Figure 10(a) that in the optimal risk solution obtained by HMOEA, the risks borne by each depot are relatively balanced. Hence, when solving the MDHVRP of hazardous materials transportation, TSA is more suitable for enterprises pursuing cost, and HMOEA is more suitable for the government considering social risk.

D. MODEL EXPERIMENT

We compare multi-depots heterogeneous VRP with multi-depots homogeneous VRP to demonstrate the benefit of adopting heterogeneous vehicles in instance C101. Among them, multi-depot heterogeneous VRP adopts four vehicle types, with capacities of 200, 120, 80 and 50 respectively. Figure 11 shows the distribution of the final non-dominated solutions found by HMOEA. Figure 12 shows the shipping loading rates of different types of vehicles when the risk is optimal and the cost is optimal. The computational results obtained using heterogeneous vehicles are better in terms of risk and cost. This is because the use of heterogeneous vehicles enables different types of vehicles to be assigned suitable customers for delivery due to all constraints. As shown in Figure 12, regardless of the type of vehicle, the lowest-cost solution will have a higher shipping load rate than the lowest-risk solution. This is because the transportation cost is closely related to the fixed cost of the vehicle. When vehicles choose to deliver more customers, the number of vehicles decreases, load rate increase, and transportation cost decrease. But vehicles may therefore travel riskier routes.

VI. CONCLUSION

This paper has considered the vehicle routing optimization problem of road transport for hazardous materials in practice. For this reason, more factors such as multiple depots, heterogeneous fleets, time windows, vehicle quantity, vehicle actual load, and depot stock have been considered simultaneously. Given the actual load dependent risk of vehicles on the road segment during hazardous materials transport, a multi-objective MDHVRP model has been proposed to minimize total travel cost and transport risk. In this model, the risk of road sections is measured by the actual load of vehicles and the number of people who could be affected.

To solve MDHVRP, we have devised two algorithms called HMOEA and TSA. In the algorithm design of HMOEA, the customer points to be served by the depot and travel route are optimized at the same time. In the TSA, the first stage is to assign customers to be served to each depot according to the distance between the customer and the depot and the distribution ability of each depot. In the second stage, the vehicle routing problem for each single depot is solved separately. Tested on the modified Solomon's VRPTW examples. The results have shown that compared with Nsga-ii, Spea2 and HEA, HMOEA has certain competitiveness in terms of convergence and diversity. The solutions found by TSA and HMOEA have their own advantages. The numerical experiments of RMDHVRP are compared with MDHVRP, demonstrating the validity of the model.

The future work will consider the impact of uncertain factors such as customer needs, road conditions and environment on transportation, and design a dynamic transportation planning.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interests regarding the publication of this paper.

DATA AVAILABILITY STATEMENTS

No additional data are available.

REFERENCES

[1] T. Vincenzo, "Transportation of dangerous substances: A decisional support system for risk analysis," *Chem., Biol. Environ. Eng.*, vol. 78, pp. 310–314, Dec. 2010.

[2] Emergency Management Department of Zhejiang Province. (Dec. 2020). *The Investigation Report on the '6.13' Liquefied Petroleum Gas Transportation Tanker Major Explosion Accident in the Wenling Section of Shenhai Expressway*. [Online]. Available: https://yjt.zj.gov.cn/art/2020/12/31/art_1228978417_59031875.html

[3] E. Erkut, S. A. Tjandra, and V. Vedat, "Hazardous materials transportation," in *Handbooks Operations Research Managing Sciences*, vol. 14. Cham, Switzerland: Springer, Dec. 2007, pp. 539–621.

[4] W. Quan, N. Cheng, M. Qin, H. Zhang, H. A. Chan, and X. Shen, "Adaptive transmission control for software defined vehicular networks," *IEEE Wireless Commun. Lett.*, vol. 8, no. 3, pp. 653–656, Jun. 2019.

[5] W. Quan, M. Liu, N. Cheng, X. Zhang, D. Gao, and H. Zhang, "Cybertwin-driven DRL-based adaptive transmission scheduling for software defined vehicular networks," *IEEE Trans. Veh. Technol.*, vol. 71, no. 5, pp. 4607–4619, May 2022.

[6] K. Liu, W. Quan, N. Cheng, W. Wu, Z. Xu, L. Guo, D. Gao, and H. Zhang, "Reliable PPO-based concurrent multipath transfer for time-sensitive applications," *IEEE Trans. Veh. Technol.*, early access, May 23, 2023, doi: 10.1109/TVT.2023.3277712.

[7] K. N. Androutsopoulos and K. G. Zografos, "A bi-objective time-dependent vehicle routing and scheduling problem for hazardous materials distribution," *EURO J. Transp. Logistics*, vol. 1, nos. 1–2, pp. 157–183, Jun. 2012.

[8] R. Pradhananga, E. Taniguchi, T. Yamada, and A. G. Qureshi, "Environmental analysis of Pareto optimal routes in hazardous material transportation," *Proc. Social Behav. Sci.*, vol. 125, pp. 506–517, Mar. 2014.

[9] R. Dondo and J. Cerdá, "A cluster-based optimization approach for the multi-depot heterogeneous fleet vehicle routing problem with time windows," *Eur. J. Oper. Res.*, vol. 176, no. 3, pp. 1478–1507, Feb. 2007.

[10] S. Salhi, A. Imran, and N. A. Wassan, "The multi-depot vehicle routing problem with heterogeneous vehicle fleet: Formulation and a variable neighborhood search implementation," *Comput. Oper. Res.*, vol. 52, pp. 315–325, Dec. 2014.

[11] Z. Zhou, M. Ha, H. Hu, and H. Ma, "Half open multi-depot heterogeneous vehicle routing problem for hazardous materials transportation," *Sustainability*, vol. 13, no. 3, p. 1262, Jan. 2021.

[12] E. Erkut and A. Ingolfsson, "Transport risk models for hazardous materials: Revisited," *Oper. Res. Lett.*, vol. 33, no. 1, pp. 81–89, Jan. 2005.

[13] B. Wang, Q. Qian, Z. Tan, P. Zhang, A. Wu, and Y. Zhou, "Multidepot heterogeneous vehicle routing problem for a variety of hazardous materials with risk analysis," *Sci. Program.*, vol. 1, Dec. 2020, Art. no. 8839628.

[14] V. Torretta, E. C. Rada, M. Schiavon, and P. Viotti, "Decision support systems for assessing risks involved in transporting hazardous materials: A review," *Saf. Sci.*, vol. 92, pp. 1–9, Feb. 2017.

[15] M. Zhang, B. Hao, Q. Ge, J. Zhu, R. Zheng, and Q. Wu, "Distributed adaptive subgradient algorithms for online learning over time-varying networks," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 52, no. 7, pp. 4518–4529, Jul. 2022.

[16] M. Zhang, Y. Zhou, Q. Ge, R. Zheng, and Q. Wu, "Decentralized randomized block-coordinate Frank–Wolfe algorithms for submodular maximization over networks," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 52, no. 8, pp. 5081–5091, Aug. 2022.

[17] L. Zhao and N. Cao, "Fuzzy random chance-constrained programming model for the vehicle routing problem of hazardous materials transportation," *Symmetry*, vol. 12, no. 8, p. 1208, Jul. 2020.

[18] Z. Wang, Y. Wang, and Y. Jiao, "Uncertain multi-objective hazardous materials transport route planning considering resilience and low–carbon," *IEEE Access*, vol. 11, pp. 26921–26931, 2023.

[19] M. Owais and A. Alshehri, "Pareto optimal path generation algorithm in stochastic transportation networks," *IEEE Access*, vol. 8, pp. 58970–58981, 2020.

[20] H. Hu, X. Li, Y. Zhang, C. Shang, and S. Zhang, "Multi-objective location-routing model for hazardous material logistics with traffic restriction constraint in inter-city roads," *Comput. Ind. Eng.*, vol. 128, pp. 861–876, Feb. 2019.

[21] J. Du, X. Li, L. Li, and C. Shang, "Urban hazmat transportation with multi-factor," *Soft Comput.*, vol. 24, no. 9, pp. 6307–6328, May 2020.

[22] J. Qin, Y. Ye, B.-R. Cheng, X. Zhao, and L. Ni, "The emergency vehicle routing problem with uncertain demand under sustainability environments," *Sustainability*, vol. 9, no. 2, p. 288, Feb. 2017.

[23] C. Ma, B. Mao, Q. Xu, G. Hua, S. Zhang, and T. Zhang, "Multi-depot vehicle routing optimization considering energy consumption for hazardous materials transportation," *Sustainability*, vol. 10, no. 10, p. 3519, Sep. 2018.

[24] G. A. Bula, C. Prodhon, F. A. González, H. M. Afsar, and N. Velasco, "Variable neighborhood search to solve the vehicle routing problem for hazardous materials transportation," *J. Hazardous Mater.*, vol. 324, pp. 472–480, Feb. 2017.

[25] G. A. Bula, H. Murat Afsar, F. A. González, C. Prodhon, and N. Velasco, "Bi-objective vehicle routing problem for hazardous materials transportation," *J. Cleaner Prod.*, vol. 206, pp. 976–986, Jan. 2019.

[26] N. Wang, M. Zhang, A. Che, and B. Jiang, "Bi-objective vehicle routing for hazardous materials transportation with no vehicles travelling in Echelon," *IEEE Trans. Intell. Transp. Syst.*, vol. 19, no. 6, pp. 1867–1879, Jun. 2018.

[27] M. Zhang, N. Wang, Z. He, Z. Yang, and Y. Guan, "Bi-objective vehicle routing for hazardous materials transportation with actual load dependent risks and considering the risk of each vehicle," *IEEE Trans. Eng. Manag.*, vol. 66, no. 3, pp. 429–442, Aug. 2019.

[28] P. Jiang, J. Men, H. Xu, S. Zheng, Y. Kong, and L. Zhang, "A variable neighborhood search-based hybrid multiobjective evolutionary algorithm for HazMat heterogeneous vehicle routing problem with time windows," *IEEE Syst. J.*, vol. 14, no. 3, pp. 4344–4355, Sep. 2020.

[29] J. Men, P. Jiang, H. Xu, S. Zheng, Y. Kong, P. Hou, and F. Wu, "Robust multi-objective vehicle routing problem with time windows for hazardous materials transportation," *IET Intell. Transp. Syst.*, vol. 14, no. 3, pp. 154–163, Mar. 2020.

[30] N. Holeczek, "Hazardous materials truck transportation problems: A classification and state of the art literature review," *Transp. Res. D, Transp. Environ.*, vol. 69, pp. 305–328, Apr. 2019.

[31] V. Kazantzi, N. Kazantzis, and V. C. Gerogiannis, "Risk informed optimization of a hazardous material multi-periodic transportation model," *J. Loss Prevention Process Industries*, vol. 24, no. 6, pp. 767–773, Nov. 2011.

[32] J.-Y. Potvin and S. Bengio, "The vehicle routing problem with time windows Part II: Genetic search," *Informs J. Comput.*, vol. 8, no. 2, pp. 165–172, May 1996.

[33] D. C. Paraskevopoulos, P. P. Repoussis, C. D. Tarantilis, G. Ioannou, and G. P. Prastacos, "A reactive variable neighborhood Tabu search for the heterogeneous fleet vehicle routing problem with time windows," *J. Heuristics*, vol. 14, no. 5, pp. 425–455, Oct. 2008.

[34] Y.-L. Lan, F. Liu, W. W. Y. Ng, J. Zhang, and M. Gui, "Decomposition based multi-objective variable neighborhood descent algorithm for logistics dispatching," *IEEE Trans. Emerg. Topics Comput. Intell.*, vol. 5, no. 5, pp. 826–839, Oct. 2021.

[35] P. Hansen, N. Mladenovi, R. Todosijevi, and S. Hanafi, "Variable neighborhood search: Basics and variants," *EURO J. Comput. Optim.*, vol. 5, no. 3, pp. 423–454, Sep. 2017.

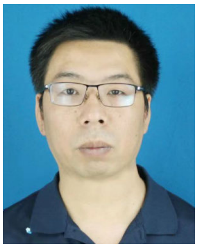
[36] K. C. Tan, Y. H. Chew, and L. H. Lee, "A hybrid multiobjective evolutionary algorithm for solving vehicle routing problem with time windows," *Comput. Optim. Appl.*, vol. 34, no. 1, pp. 115–151, May 2006.

[37] M. M. Solomon, "Algorithms for the vehicle routing and scheduling problems with time window constraints," *Oper. Res.*, vol. 35, no. 2, pp. 254–265, Apr. 1987.

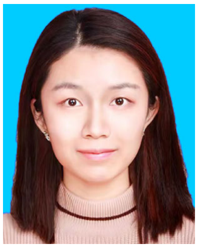
[38] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE Trans. Evol. Comput.*, vol. 6, no. 2, pp. 182–197, Apr. 2002.

[39] E. Zitzler, M. Laumanns, and L. Thiele, "SPEA2: Improving the strength Pareto evolutionary algorithm," Comput. Eng. Netw. Lab., ETH Zurich, Zürich Switzerland, TIK-Rep. 103, 2001.
[40] C. A. C. Coello and N. C. Cortïs, "Solving multiobjective optimization problems using an artificial immune system," *Genetic Program. Evolvable Mach.*, vol. 6, no. 2, pp. 163–190, Jun. 2005.
[41] Ministry of Transport of the People's Republic of China. (Nov. 2019). *Administrative Measures for the Safety of Road Transport of Dangerous Goods*. [Online]. Available: https://xxgk.mot.gov.cn/2020/jigou/fgs/202006/t20200623_3308239.html
[42] M. Liu, Y. Ding, F. Chu, and C. Chu, "Robust optimization for the risk mitigation of hazardous material road transportation system," in *Proc. IEEE 25th Int. Conf. Intell. Transp. Syst. (ITSC)*, Oct. 2022, pp. 773–778.

JUANMEI ZHANG received the master's degree in control theory and control engineering from the Henan University of Science and Technology, China, in 2005. Then, she joined the Luoyang Institute of Science and Technology, where she is currently an Associate Professor with the School of Electrical Engineering and Automation. Her research interests include automatic control theory, machine learning, and data mining.



GUOYONG WANG received the master's degree in software engineering from the Huazhong University of Science and Technology, China, in 2008. Then, he joined the Luoyang Institute of Science and Technology, where he is currently an Associate Professor with the School of Computer and Information Engineering. His research interests include information fusion, artificial intelligence, and data mining.



QIAN SHENG received the master's degree in industrial engineering and management from the Polytechnic University of Turin, Italy, in 2017. Then, she joined the Training Department of Googol Technology Company Ltd., in Shenzhen of China, where She is currently an Engineer. Her research interests include motion control, industrial robots, industrial internet, and data analysis.

XINYU JIA received the master's degree in computer science and technology from the Henan University of Science and Technology, Luoyang, China, in July 2022. Then he joined Huaibin County Party Committee office in Xinyang City of China, where he is currently a computer technician. His current research interests include hazardous materials transportation, vehicle routing optimization, and machine learning.

PING XIE received the Ph.D. degree from the Beijing University of Posts and Telecommunications, China, in 2014. Then, she joined the Henan University of Science and Technology, where she is currently an Associate Professor with the School of Information Engineering. Her research interests include cognitive radio networks, wireless network security, and resource allocation for fading channels.