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Route Optimization for Hazardous Chemicals Transportation under Time-Varying Conditions

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Abstract: Since accidents of hazardous chemicals transportation will cause serious loss to the surrounding environment and lives and properties, this paper studies the transportation route optimization problem of hazardous chemicals under dynamic time-varying conditions. Combined with the goal of green sustainable development, a multiobjective nonlinear optimization model is constructed to minimize the transportation risk, transportation cost, and carbon emissions generated in the transportation. The model is solved by the improved Fast Non-Dominated Sorting Genetic Algorithm with Elite Strategy (NSGA-II) algorithm. The effectiveness of the model and the algorithm are tested on the Sioux Falls network. The experimental results show that under time-varying conditions, a vehicle's departure at different times will generate different transportation costs and risks. Therefore, enterprises need to rationally arrange the departure time of vehicles according to the time windows of customer nodes and road conditions. In additio, from the relationship between the optimization objectives, in order to achieve green, sustainable and low-risk transportation, enterprises should first reduce their transportation costs.

Keywords: time-varying conditions; hazardous chemicals transportation; vehicle routing problem; multiobjective optimization

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1. Introduction

Hazardous chemicals refer to highly toxic chemicals and other chemicals with the properties of poison, corrosion, explosion, combustion, and other hazards to human beings, facilities, and the environment. China is the world's largest producer of hazardous chemicals. As of the end of December 2021, there were as many as 26,947 chemical enterprises in China, with an annual total profit of CNY 1.16 trillion [1]. The chemicals industry is characterized by "high transportation demand, wide distribution of production capacity, and rapid growth in production". From the perspective of China's economic development and the demand of the petrochemicals industry, most of the chemicals processing enterprises are concentrated in the eastern coastal areas, while the production areas of chemical raw materials are relatively concentrated in the western areas. This phenomenon of uneven distribution of production and marketing increases the demand for the transportation of hazardous chemicals, with road transportation accounting for 70%.

Compared with developed countries which have established complete hazardous chemicals facilities and regulatory systems, China's hazardous chemicals transportation industry is in a stage of rapid development. The supporting facilities and infrastructure of the hazardous chemicals transportation industry are relatively weak, the professional skills of the practitioners need to be improved, and the relevant laws and regulations also need to be improved. These reasons are intertwined and result in accidents of hazardous chemicals road transportation. According to relevant statistics, a total of 344 safety accidents in the transportation of hazardous chemicals occurred from January to October in 2021 [2,3]. Once an accident occurs during the transportation of hazardous chemicals, it will cause serious damage to the surrounding population, environment, and economic property [4]. On 13

June 2020, an explosion of a liquefied petroleum gas tanker occurred on the G15 Shenhai Expressway near Liangshan Village, Daxi Town, Wenling City, Zhejiang Province. The explosion caused the extensive collapse of surrounding residential and factory buildings, resulting in a total of 20 deaths and 175 injuries, with a direct economic loss of CNY 94.77815 million [5].

The vehicle routing problem (VRP) was first proposed by Dantzig and Ramser in 1959 [6]. Afterwards, the vehicle routing problem with time windows (VRPTW), multidepot vehicle routing problem (MDVRP), vehicle scheduling problem with full load (VRPFL), and other derivatives of VRP have been proposed one after another. Desrochers et al. [7] solved the VRPTW with an unconstrained number of vehicles by utilizing the branch-and-bound and dynamic programming methods. Thangiah et al. [8] were the first to use genetic algorithms for solving the VRPTW. Wren and Holliday [9] proposed a scan-based algorithm and applied it to the multivehicle route problem. Golden et al. [10] proposed two heuristic algorithms for solving the MDVRP. The hazardous chemicals transportation route optimization problem belongs to a special branch of the VRP. The transportation of hazardous chemicals involves multiple subjects, including hazardous chemicals productions and transportation enterprises, governments, and the public. The objectives pursued by each subject in the process of hazardous chemicals transportation are different. Among them, the hazardous chemicals production and transportation enterprises usually prioritize minimizing the transportation costs from the perspective of economic interests; however, governments want to minimize the risk of hazardous chemicals transportation. So, the hazardous materials transportation route optimization problem is usually a multiobjective vehicle route optimization problem (MOVRP).

Transportation route optimization is an effective way to reduce the occurrence of accidents. Therefore, in order to reduce risk in the road transportation of hazardous chemicals and realize sustainable development, this paper optimizes the road transportation routes of hazardous chemicals by constructing a mathematical optimization model under time-varying conditions, solved by using the improved NSGA-II algorithm, which can expand the research scope of the optimization theory of hazardous chemicals road transportation. In addition, while minimizing transportation costs and transportation risks, the reduction of carbon emissions is incorporated into the optimization objective, which is important for the reduction of carbon emissions and the decision-making and operational management of hazardous chemicals transportation enterprises. The structure of this paper is arranged as follows: Section 2 gives a brief introduction to the MOVRP of hazardous materials transportation, and the optimization problem of hazardous chemicals transportation under time-varying conditions. Section 3 describes the multiobjective time-varying route optimization model for hazardous chemicals transportation. Section 4 proposes an improved NSGA-II algorithm and introduces the implementation process of the algorithm. Section 5 validates the effectiveness of the algorithm on the Sioux Falls network and analyzes the experimental results. Finally, Section 6 makes a conclusion and discusses the prospects for future research directions.

2. Literature Review

2.1. MOVRP for Hazardous Chemicals

Due to the high risk from hazardous chemicals during road transportation, the hazardous chemicals transportation route optimization problem usually needs to minimize the transportation risks and transportation costs. Konstantinos and Androutsopoulos [11] proposed a biobjective hazardous chemicals road transportation optimization model with a time window to minimize the transportation risk and time, and the biobjective optimization problem was transformed into a single-objective optimization problem, solved using the weighted summation method. Zou and Zhang [12] proposed five major hazardous chemicals transportation route selection indexes from the perspective of the transportation subject, and constructed a multiobjective hazardous chemicals transportation route optimization model with a hybrid time window, which was solved by using an improved genetic algorithm. Yuan et al. [13] established a biobjective optimization model considering both transportation cost and transportation risk, introduced a population hybridization strategy to improve the particle swarm algorithm, and tested it on a benchmark algorithm. Bula et al. [14] proposed a biobjective optimization model to minimize the transportation cost and the transportation risk from the point of view of different interested parties and solved it by using a neighborhood search algorithm. Jiang et al. [15] investigated the heterogeneous vehicle problem of hazardous materials transportation with time windows to minimize the transportation cost, transportation risk, and the average number of vehicle redundancies, and used a hybrid multiobjective algorithm to solve the problem. Chai [16] proposed a new driving risk during hazardous chemicals transportation taking into account the risk evaluation model, and constructed a biobjective optimization model for minimizing the transportation risk and transportation cost, which was solved by using a modified nondominated sequential genetic algorithm. Esmaeilidoukia et al. [17] proposed a fuzzy planning model for minimizing the time and risk, which was transformed into a deterministic model and then solved using an invasive weed algorithm.

The growth of carbon emissions and global climate change has become an important factor affecting the survival and development of mankind, and taking the path of green, low-carbon and sustainable development has become a global consensus. Along with the development of a global low-carbon economy, the green vehicle route transportation optimization problem (GVRP) has also attracted a lot of attention. Rahbari et al. [18] investigated the negative impacts of greenhouse gas emissions on the environment caused by hazardous materials and waste materials from transportation. They expressed the greenhouse gas emissions as a function related to the transportation distance, and established a location–inventory–routing problem, which minimizes the transportation cost, risk, and carbon emissions, and was solved using a multiobjective black widow optimization algorithm. Zhao and Cao [19] expressed carbon emissions as a function related to fuel consumption during transportation in the VRP problem, incorporated it into the transportation cost as the minimization objective, and constructed a biobjective optimization model to minimize the cost and risk. Wang et al. [20,21] investigated the effect of traffic flow uncertainty on transportation in the vicinity of an intra-city transportation route, expressed the carbon emissions as a function of vehicle travel speed, distance, and vehicle loading, and constructed a multiobjective optimization model minimizing the transportation risk, transportation cost, and carbon emissions, which was solved by using the improved NSGA-II algorithm. Lyu and He in [22] studied a multijourney heterogeneous vehicle route problem for hazardous chemicals, constructed a single-objective optimization model for minimizing the cost in two stages by adding the cost of carbon emissions to the transportation cost, and expressed it as a function of fuel consumption and vehicle loading. The model was solved using a two-stage mixing and summing metaheuristic algorithm. Sun et al. [23] investigated the multimodal transportation problem of hazardous materials by rail and public transport, considering the uncertainty of population exposure, constructed an uncertain optimization model to minimize the transportation risk and transportation cost, and used the carbon emissions related to the transportation distance and loading as the constraints of the optimization model to limit the maximum carbon emissions generated during transportation.

2.2. *The Application of Spatiotemporal Data and Information Technology in Transportation*

Vehicles will be affected by the combination of various factors such as time, weather and crowd flow in transportation. In the era of big data, with the development of information technology and the easier acquisition of dynamic time-varying data, many scholars use modern information technology to study dynamic spatiotemporal data in transportation. Meng et al. [24] studied the use of web-based real-time traffic data to estimate vehicle carbon emissions from the perspective of reducing urban carbon emissions. Experiments were performed in Chengdu, China, and results showed roadway-based emissions matched well spatio-temporally with traffic conditions. Xiao et al. [25] analyzed the relevant literature on spatiotemporal crowd flow prediction in Web of Science, from the perspectives of traffic control and public safety, using scientometric methods, social network analysis, and stochastic actor-oriented models (SAOMs), and proposed a knowledge evolution path construction process based on SAO structures. Zhang et al. [26] studied the application of dynamic data analysis in pedestrian movement risk and constructed a complete pedestrian movement risk identification process using video recognition technology and a support vector model (SVM). Li et al. [27] proposed a data-driven traffic shock wave detection technique, which combines machine learning techniques with traffic features, and conducted experiments on collecting vehicle trajectory data for highways in the United States, demonstrating the efficiency and accuracy of the proposed four-step method. Pourmoradnasseri et al. [28] studied the application of real-time traffic data flow on improving transportation systems to address the problems caused by traffic congestion in cities, and used road Internet of Things (IoT) data as the data source for a two-layer optimization model. The time dependence of traffic status was ensured by splitting the calculation process into a short-term framework during solving, and the efficiency of this method in processing real-time data flow was verified in a road network experiment in Tartu city. Chen et al. [29] proposed a framework that integrates a feature-enhanced scale aware descriptor, Kalman filter, Hungarian algorithm, and perspective projection theory to extract vehicle speeds from port surveillance videos for analyzing automated guided vehicle trajectories.

2.3. Hazardous Chemicals Dynamic and Time-Varying Route Optimization Problem

The road transportation of hazardous chemicals is a complex process related to time, and changes in the environment under different time conditions will have different effects on the transportation risk. Liu and Zhu [30] considered the effects of uncertain population density and terminal demand, expressed the accident rate during transportation as a time-dependent function, constructed a stochastic optimization model, and solved it using a hybrid heuristic algorithm combining particle swarm algorithms and genetic algorithms. Ke [31] explored the impacts caused by system disruptions in the hazardous material emergency logistics system, and proposed a risk metric model under discrete time-varying conditions. Ouertani et al. [32] investigated the dynamic route optimization problem of hazardous materials transportation with time windows, and considered that the customer's demand changes dynamically over time, so constructed a biobjective optimization model that minimizes both cost and risk, and solved it using a hybrid meta-heuristic algorithm. Xu et al. [33,34] studied the real-time route planning problem for hazardous chemicals transportation under the condition of changing road traffic service level. They first used the Dijkstra algorithm for initial route global planning, and then updated the local route in case of changes in traffic service level. He et al. [35] studied the hazardous chemicals transportation route optimization problem under discrete time-varying conditions and established an optimization model to minimize the conditional value-at-risk, and the results showed that the optimal route for transportation under different departure times would be different.

In summary, most of the current research on road transportation of hazardous chemicals focuses on the minimization of transportation risk and transportation cost under static conditions, and the carbon emissions during transportation are usually expressed as a function of transportation distance or transportation fuel consumption. During the road transportation of hazardous chemicals, spatiotemporal data has not been effectively utilized. The time factors of road transportation of hazardous chemicals are less frequently studied and are usually expressed as the time windows of the customers. However, the transportation cost, the incidence of transportation accidents, and the consequences of transportation accidents during the transportation of hazardous chemicals are all related to time. Therefore, this paper proposes a multiobjective optimization model for the transportation of hazardous chemicals under discrete time-varying conditions. The model considers the different accident rates and consequences of hazardous chemicals transportation under different time conditions. In addition to minimizing transportation risk and cost, the model also incorporates minimizing carbon emissions as an optimization objective.

3. Problem Formulation

In the multiobjective route optimization model under time-varying conditions for hazardous chemicals transportation, $G = (N, A)$ is an undirected road network, in which N represents the collection of nodes in the network, including the starting node O where the transportation enterprise is located, the collection of demand nodes N_C and the collection of the general nodes N_O. A represents the collection of road segments. Now, the transportation enterprise at O needs to deliver a certain kind of hazardous chemical to each customer node through the transportation network. The enterprise should be in the control of transportation cost, while minimizing the transportation risk. In addition, in order to achieve the goal of sustainable development, it is required to realize the minimization of carbon emissions. Under discrete time-varying conditions, the maximum speed, population density and accident rate of each road segment in the road network change dynamically over time, and the optimal transportation route of hazardous chemicals is planned according to the minimization objective.

3.1. Assumptions

(1) In the transportation network, there is only one type of hazardous chemicals transportation vehicle. The maximum loading of each vehicle is the same, and the interaction between vehicles is not considered.
(2) The vehicle leaves from the starting node and must return to it after providing services to different customer nodes.
(3) Each customer node is limited by a soft time window, and when a vehicle arrives outside the time window specified for that customer node it can be unloaded normally, but there will be a penalty cost.
(4) The demand of each customer node is indivisible and does not exceed the maximum loading of vehicle.
(5) In order to reduce the amount of traffic in the network, the vehicle serves each customer node in order from smallest to largest demand, and the actual loading of the vehicle is the sum of the customer demand it needs to serve.
(6) Each customer node has a fixed service time and can be converted to an ordinary node in the road network when the demand of customer is satisfied.
(7) The maximum speed limit for transportation vehicles is different at each time period. Considering the transportation cost of the enterprise, transport vehicles travel at a constant speed, at the maximum speed limit, during each time period.
(8) The population density around the road segment is divided into the population density on the road and the population density around the road, where the population density on the road changes dynamically over time.
(9) The accident rate in transportation of hazardous chemicals changes dynamically over time.
(10) The carbon emissions during transportation are related to the distance traveled and vehicle loading.

3.2. Symbols Definition

G: road network, $G = (N, A)$
N: node set, $N = \{0,\ 1,\ 2,\ \cdots, n\}$, node 0 is the starting node.
N_C: customer node set, $N_C \subset N$.
N_O: general node set, $N_O \subset N$.
A: road segment set among nodes, $A = \{(i,\ j) : i,\ j \in N\}$.
K: vehicle set, $K = \{0,\ 1,\ 2,\ \cdots, k\}$.
T: time period set, $T = \{[t_1, t_2], [t_2,\ t_3], [t_3,\ t_4],\ \cdots, [t_{n-1}, t_n]\}$.
V: speed set, $V = \left\{v_{(t_1,\ t_2)}, v_{(t_2,\ t_3)},\ v_{(t_3,\ t_4)},\ \cdots, v_{(t_{n-1},\ t_n)}\right\}$.

d_{ij}: the length of road segment $(i,\ j)$, $(i,\ j) \in A$.

$d_{(t_{n-1},\ t_n)}$: the distance that can be traveled in the time period $[t_{n-1},\ t_n]$.

fc: fixed cost per transport vehicle.

tc: cost per unit of distance traveled.

Q: maximum loading of the vehicle.

e: carbon emission factor per unit of distance during transportation.

q_c: demand at customer node c, $c \in N_C$.

η_{c1}: penalty factor when the vehicle at customer node c arrives earlier than the time window, $c \in N_C$.

η_{c2}: penalty factor when the vehicle at customer node c arrives later than the time window, $c \in N_C$.

bt_{ik}: departure time of vehicle k $(k \in K)$ from node j $(j \in N)$.

at_{jk}: time for vehicle k $(k \in K)$ to arrive at node i $(i \in N)$.

$[et_c, lt_c]$: time window at customer node c $(c \in N_C)$.

st_c: service time at customer node c $(c \in N_C)$.

l_{ij}^k: the loading of vehicle k $(k \in K)$ when traveling through the road segment $(i,\ j)$, $(i,\ j) \in A$.

$v_{ij(t_{n-1},\ t_n)}^k$: the speed of vehicle k $(k \in K)$ on the segment $(i,\ j)$ in the time period $[t_{n-1}, t_n]$, $(i,\ j) \in A$, $[t_{n-1}, t_n] \in T$.

$\rho_{ij(t_{n-1},\ t_n)}^l$: population density on the road segment $(i,\ j)$ in the time period $[t_{n-1}, t_n]$, $(i,\ j) \in A$, $[t_{n-1}, t_n] \in T$.

ρ_{ij}^o: population density around the road segment $(i,\ j)$, $(i,\ j) \in A$.

p_{ij}^k: accident rate of hazardous chemicals transportation when vehicle k $(k \in K)$ is traveling through the road segment $(i,\ j)$, $(i,\ j) \in A$.

AR_{ij}: the rate of traffic accidents on the road segment $(i,\ j)$, $(i,\ j) \in A$.

Pr_{ij}: conditional release probability of hazardous materials after a traffic accident on the road segment $(i,\ j)$, $(i,\ j) \in A$.

α: fixed parameters related to transport vehicle.

β: fixed parameters related to transport vehicle.

ε_m: fuel consumption per unit of distance when the transport vehicle is fully loaded.

ε_0: fuel consumption per unit of distance when the transport vehicle is empty.

r_{ij}^k: radius of impact after an accident when the vehicle k $(k \in K)$ is traveling through the road segment $(i,\ j)$, $(i,\ j) \in A$.

C_c^k: penalty cost of vehicle k $(k \in K)$ at customer node c $(c \in N_C)$

P_{ijc}^k: consequence of an accident after the vehicle k $(k \in K)$ passes through the road segment $(i,\ j)$ at risk while traveling to the customer node c $(c \in N_C)$, $(i,\ j) \in A$.

C_{ijc}^k: transportation cost of vehicle k $(k \in K)$ passing through the road segment $(i,\ j)$ on its way to customer node c $(c \in N_C)$, $(i,\ j) \in A$.

R_{ijc}^k: transportation risk of vehicle k $(k \in K)$ passing through the road segment $(i,\ j)$ on its way to customer node c $(c \in N_C)$, $(i,\ j) \in A$.

E_{ijc}^k: carbon emissions of vehicle k $(k \in K)$ passing through the road segment (i, j) on its way to customer node c $(c \in N_C)$, $(i,\ j) \in A$.

x_{ijc}^k: decision variable, $x_{ijc}^k = 1$ when vehicle k $(k \in K)$ passes through the road segment $(i,\ j)$ on its journey to customer c $(c \in N_C)$; else $x_{ijc}^k = 0$, $(i,\ j) \in A$.

y_c^k: decision variable, $y_c^k = 1$ when customer node c $(c \in N_C)$ is served by vehicle k $(k \in K)$; else $y_c^k = 0$.

3.3. Mathematical Optimization Model

3.3.1. Transportation Cost

The cost involved in the transportation of hazardous chemicals is the combination of the fixed cost per vehicle dispatched, the cost of the vehicle during transportation, and the penalty cost that may be incurred at each customer node. In a time-varying road network, the time taken by a vehicle to arrive at node j is related to the departure time from the previous node i as well as the vehicle speed. When transport vehicle k departs from node i at bt_{ik} through the road segment $(i,\ j)$ to arrive at node j, the arrival time at_{jk} is shown as below, where $(t_n - bt_{ik})v^k_{ij(t_{n-1},\ t_n)}$ represents the distance the vehicle traveled from bt_{ik} to t_n, and $\sum_{x=1}^{i-1} d_{(t_{n+\ x},\ t_{n+x+1})}$ represents the accumulation of the distance traveled by vehicles during the time period $[t_n,\ t_{n+i}]$, and so the numerator of the formula represents the total distance traveled by vehicles during the time period $[t_{n+i},\ t_{n+i\ +1}]$:

$$at_{jk} = t_{n+i} + \frac{\left\{d_{ij} - (t_n - bt_{ik})v^k_{ij(t_{n-1},\ t_n)} - \sum_{x=0}^{i-1} d_{(t_{n+\ x},\ t_{n+x+1})}\right\}}{v^k_{ij(t_{n+i},\ t_{n+i+1})}},\ bt_{ik} \in [t_{n-1}, t_n],\ at_{jk} \in [t_{n+i},\ t_{n+i\ +1}] \quad (1)$$

then the time for vehicle k to arrive at any demand node c from node m at bt_{mk} through the road segment $(m,\ c)$ is

$$at_{ck} = t_{n+i} + \frac{\left\{d_{mc} - (t_n - bt_{mk})v^k_{mc(t_{n-1},t_n)} - \sum_{x=0}^{i-1} d_{(t_{n+x},t_{n+x+1})}\right\}}{v^k_{mc(t_{n+i},t_{n+i+1})}},\ bt_{mk}\ \in [t_{n-1}, t_n],\ at_{ck}\ \in [t_{n+i}, t_{n+i+1}] \quad (2)$$

Each customer node c has a soft time window, and the vehicle can arrive at the customer node at any time and complete normal unloading. When the time of arrival at the customer node is not within the time window of the customer node, the penalty cost is incurred for arriving earlier or later than the time window. The penalty cost incurred by vehicle k at customer node c is

$$C^k_c = \eta_{c1}\max\{et_c - at_{ck}, 0\}\ +\ \eta_{c2}\max\{at_{ck} - lt_c, 0\} \quad (3)$$

and the total cost of vehicle k on the segment (i, j) can be composed of the fixed dispatch cost of the vehicle, the driving cost of the vehicle, and the penalty cost incurred at the customer nodes:

$$C^k_{ijc} = y^k_c fc + y^k_c x^k_{ijc} d_{ij} tc + \eta_{c1}\max\{et_c - at_{ck}, 0\} + \eta_{c2}\max\{at_{ck} - lt_c, 0\} \quad (4)$$

3.3.2. Transportation Risk

The risk of hazardous chemicals transportation is usually expressed as the product of the probability of the accident and the consequences of the accident [36]. The probability of hazardous chemicals road transportation accidents varies dynamically with the loading of the transport vehicle as well as with different road segments and times [15,37,38]. In Equation (5), α and β are constant values that depend on the type of hazardous chemicals [39]:

$$p^k_{ij} = AR_{ij} Pr_{ij} d_{ij} \alpha \left(l^k_{ij}\right)^\beta \quad (5)$$

The population exposure model is used to measure the consequences caused by the occurrence of transportation accidents [40]; the population density is divided into the population density on the road where the accident occurs and the population density around the road. Figure 1 shows the population exposure area after a traffic accident occurs. The circular area in the middle represents the road area directly affected by the accident, and the remaining area is the surrounding area. The population density of the road segment where the accident occurred varies dynamically with different time periods, and the consequences of road transportation accidents involving hazardous chemicals can be expressed as the number of people in the exposed area:

$$P^k_{ijc} = \rho^o_{ij}\left(\pi {r^k_{ij}}^2 + 2\pi r^k_{ij} d_{ij}\right) + \rho^l_{ij(t_{n-1},t_n)} \pi {r^k_{ij}}^2 \quad (6)$$

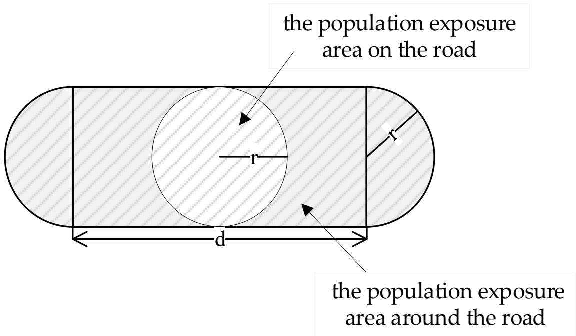


Figure 1. Population exposure area after the accident.

The transportation risk incurred by vehicle k $(k \in K)$ on road segment (i, j) can be expressed as the product of p_{ij}^k and P_{ijc}^k :

$$R_{ijc}^k = y_c^k x_{ijc}^k p_{ij}^k P_{ijc}^k = y_c^k x_{ijc}^k AR_{ij} Pr_{ij} d_{ij} \alpha \left(l_{ij}^k\right)^\beta \left[\rho_{ij}^o \left(\pi {r_{ij}^k}^2 + 2\pi r_{ij}^k d_{ij}\right) + \rho_{ij(t_{n-1},t_n)}^l \pi {r_{ij}^k}^2\right]. \quad (7)$$

3.3.3. Carbon Emissions

The carbon emissions of vehicle k $(k \in K)$ on road segment (i, j) are related to the transportation distance d_{ij} and the vehicle loading l_{ij}^k. According to [22,41], the calculation formula of carbon emissions is

$$E_{ijc}^k = x_{ijc}^k d_{ij} e \left(\frac{\varepsilon_m - \varepsilon_0}{Q} l_{ij}^k + \varepsilon_0\right) \quad (8)$$

3.3.4. Mathematical Model

In summary, the multiobjective road transportation route optimization model for hazardous chemicals under time-varying conditions is formulated as follows:

$$\min f_1 = \sum_{k \in K} \sum_{c \in N_c} \sum_{(i,j) \in A} \left\{ y_c^k fc + y_c^k x_{ijc}^k d_{ij} tc + \eta_{c1} \max\{et_c - at_{ck}, 0\} + \eta_{c2} \max\{at_{ck} - lt_c, 0\} \right\} \quad (9)$$

$$\min f_2 = \sum_{k \in K} \sum_{c \in N_c} \sum_{(i,j) \in A} y_c^k x_{ijc}^k AR_{ij} Pr_{ij} d_{ij} \alpha \left(l_{ij}^k\right)^\beta \left[\rho_{ij}^o \left(\pi {r_{ij}^k}^2 + 2\pi r_{ij}^k d_{ij}\right) + \rho_{ij(t_{n-1},t_n)}^l \pi {r_{ij}^k}^2\right] \quad (10)$$

$$\min f_3 = \sum_{k \in K} \sum_{c \in N_c} \sum_{(i,j) \in A} x_{ijc}^k d_{ij} e \left(\frac{\varepsilon_m - \varepsilon_0}{Q} l_{ij}^k + \varepsilon_0\right) \quad (11)$$

s.t.

$$\sum_{k \in K} \sum_{c \in N_c} \sum_{i \in N} x_{ijc}^k = 1, \forall j \in N_O \quad (12)$$

$$\sum_{k \in K} \sum_{c \in N_c} \sum_{j \in N} x_{ijc}^k = 1, \forall i \in N_O \quad (13)$$

$$\sum_{j \in N} x_{0jc}^k = \sum_{i \in N} x_{i0c}^k = 1, \forall k \in K, c \in N_C \quad (14)$$

$$\sum_{i \in N} \sum_{j \in N} x_{ijc}^k = \sum_{i \in N} \sum_{j \in N} x_{jic}^k, \forall k \in K, c \in N_C \quad (15)$$

$$\sum_{j \in N} l_{jc}^k - \sum_{j \in N} l_{cj}^k = q_c, \forall k \in K, c \in N_C \quad (16)$$

$$\sum_{i\,\in\,N} x_{ijc}^{k} \sum_{c\,\in N_c} q_c \leq l_{ic}^{k}, \forall\, k \,\in\, K,\, c\,\in N_C \tag{17}$$

$$\sum_{c\,\in N_c} y_c^k q_c \leq Q, \forall\, k \,\in\, K \tag{18}$$

$$x_{ijc}^{k} \in [0,\, 1], \forall\, k \,\in\, K,\, c\,\in N_C,\, (i,\, j) \in\, A \tag{19}$$

$$y_c^k \in [0,\, 1], \forall\, k \,\in\, K,\, c\,\in N_C \tag{20}$$

$$y_c^k = \begin{cases} 0, \sum_{i\,\in\,N} \sum_{j\,\in\,N} x_{ijc}^{k} = 0 \\ 1, \sum_{i\,\in\,N} \sum_{j\,\in\,N} x_{ijc}^{k} = 1 \end{cases}, \forall k \,\in\, K, c \in N_C \tag{21}$$

In this multiobjective nonlinear integer optimization model, Equations (9)–(11) are objective functions that represent the minimization of transportation costs of hazardous chemicals, the minimization of transportation risk, and the minimization of carbon emissions, respectively. Equations (12)–(20) are constraints of the model. Equations (12) and (13) indicate that each customer node must and can be served only once. Equation (14) indicates that each transport vehicle must depart from the starting node and return to the starting node after serving each customer node. Equation (15) provides the vehicle flow balance constraint for each node in the transportation network. Equation (17) indicates that the loading of the vehicle must meet the demand of the customer node to be served. Equation (18) indicates that the loading of each vehicle must not exceed the maximum loading of the transport vehicle. Equations (19) and (20) indicate that the decision variables are 0–1 variables. Equation (21) indicates the interrelation between the decision variables.

4. Solution Methodology

4.1. NSGA-II Algorithm

The multiobjective hazardous chemicals road transportation route optimization model under time-varying conditions belongs to the NP-Hard problem, which is not applicable to large-scale arithmetic cases using the exact algorithm. There may be conflicts between the optimization objectives, which make it impossible to find a deterministic optimal solution. The NSGA-II, as a heuristic algorithm, has been shown to have better results in solving multiobjective optimization problems [42,43], which utilizes the computation of nondominated ordering and congestion distance for population optimization and uses an elite strategy to select the optimal solution generated during the iteration process. In this paper, NSGA-II is improved to solve the multiobjective nonlinear optimization model.

4.2. Encoding

In the optimization model proposed in this paper, firstly the number of transport vehicles needs to be determined according to the demand of each customer node, and then the transportation route planning is carried out according to the customer nodes to be served by each transport vehicle. A chromosome needs to form multiple transportation routes based on the number of required transport vehicles, so the chromosome adopts priority integer coding. Each integer gene represents the priority of the corresponding node, and the length of the chromosome is determined by the number of nodes in the road network. The sequence of integers starting from 0 is randomly generated. Take the transportation road network shown in Figure 2 as an example; there are eight nodes in this road network, which contains the starting node A. Then the chromosome is an integer list from 0 to 7.

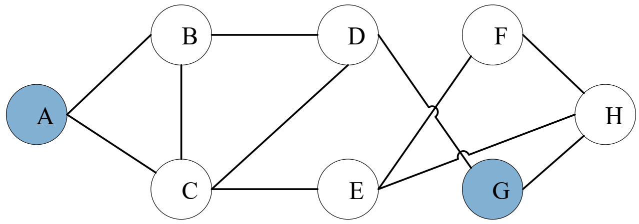


Figure 2. Example of a transportation network.

4.3. Decoding

Decoding is the process of mapping the generated integer chromosomes into multiple hazardous chemicals road transportation routes. In this paper, the decoding process is divided into two parts. The first part is the allocation of transport vehicles, which arranges transport vehicles for each customer node according to its demand and defines key nodes for each vehicle. The key nodes are some nodes that this transport vehicle must pass through during traveling, including the customer nodes it serves and the starting node to which it will eventually return. The second part is the generation of a transportation route, which consists of decoding the chromosome to generate a transportation route based on the key nodes. The specific decoding method is as follows:

Part 1—Transport vehicle allocation

Step 1.1: Obtain the demand of each customer node in the road network.

Step 1.2: Accumulate the demand of each customer node sequentially from the first customer node until it meets the demand of customer node that does not exceed the maximum loading of the transport vehicle. Allocate the same transport vehicle to these customer nodes and generate a list of key nodes for this vehicle.

Step 1.3: Repeat the above process until all the demand points can be served.

Part 2—Transportation route generation

Step 2.1: Mark the key nodes of the transport vehicle in the road network.

Step 2.2: Extract the adjacency node matrix of the node where the transport vehicle is currently located. Determine whether the next key node is in the adjacency matrix of the current node; if so, select the next key node to join the transportation route, update the node where it is currently located, and go to Step 2.4; otherwise, go to the Step 2.3.

Step 2.3: Find out the priority of each node in the adjacency node matrix of the current node according to the chromosome encoding and select the node with the highest priority. Determine whether it already exists in the current transportation route, and the node with the highest priority that is not in the current transportation route joins the transportation route; then update the node where it is currently located and go to the Step 2.4. If there is no node that meets the conditions, then determine that this route is an unfeasible route and the current chromosome is invalid.

Step 2.4: Judge whether the current node is the last key node. If so, end this route planning process and turn to Step 2.5; otherwise turn to Step 2.3.

Step 2.5: Judge whether all transportation vehicles have completed the route planning. If so, end the chromosome decoding process and output all transportation routes corresponding to this chromosome; otherwise turn to Step 2.1.

Using the road network in Figure 2 as an example, a chromosome is randomly generated: 8–3–4–7–6–1–2–5. If node G is a customer node, the list of key nodes during vehicle transportation is [A, G, A]. The adjacency node matrix of node A is [B, C], where node C has higher priority, so the next route node is chosen to be point C. The adjacency node matrix of node C is [A, B, D, E], because nodes A and B are already in the departure route, so the next route node selects point E. The adjacency node matrix of node E is [C, F, H], where node H has higher priority and is not in the current route, so node H is selected as the next node. The adjacency node matrix of node H is [F, E, G], which contains the customer node, so it goes directly to node G. After serving the customer node at node G, it needs to return to the starting node, and the adjacency node matrix of node G is [D, H], of which node D is of higher priority, so the next node of the route is D. Among the adjacent nodes of node D, node C has a higher priority, and the starting node A is in the adjacent nodes of node C. Therefore, the complete transportation route is A → C → E → H → G → D → C → A.

4.4. Crossover Operator

In this paper, the sequential crossover operator is used. As shown in Figure 3, taking the generation of subindividual C1 as an example. On two randomly selected individuals, two crossover points are randomly selected to form the gene fragments, and the gene fragments in P1 are copied to the corresponding positions in the subindividual C1. Scanning each gene fragment of the individual P2 from left to right, the gene fragments that are not in the subindividual C1 are filled into the empty positions in the individual C1 in order to generate the subindividual C1. The same steps are used to generate another subindividual C2.

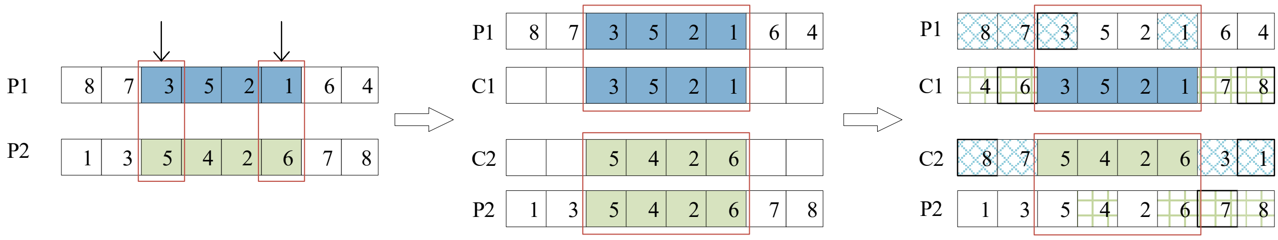


Figure 3. Example of crossover operator.

4.5. Mutation Operator

The two kinds of mutation operators used in this paper are two-point mutation and sequential mutation. As shown in Figure 4, two crossover points are randomly selected on individual P, and the gene fragments at the corresponding positions are exchanged to form a new individual P′.

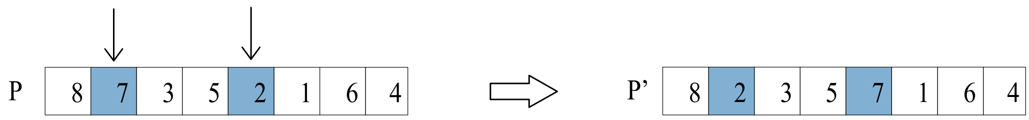


Figure 4. Example of two-point mutation.

As shown in Figure 5, a gene fragment on individual P is intercepted, and then the gene fragment is arranged in reverse order to form a new gene fragment, which is then placed in the corresponding position on the original chromosome to form a new individual P″.

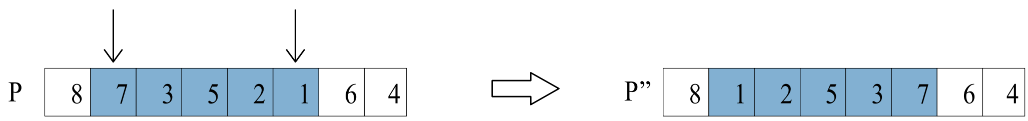


Figure 5. Example of sequential mutation.

4.6. Repair Operator

During the process of decoding, unfeasible routes are generated, resulting in invalid chromosomes. In order to reduce the number of invalid chromosomes, this paper introduces the repair operator. When a chromosome is judged as an invalid chromosome, firstly, a repair probability is randomly generated for each gene fragment on the chromosome and a repair threshold is set. Compare the repair probability of each gene fragment with the repair threshold from left to right, and if the repair probability is greater than the repair threshold, extract the node of the road network corresponding to the gene fragment as well as the adjacency matrix. Then, generate a new node priority by arranging the priorities of nodes in the node's adjacency matrix in inverse order. Replace the gene fragments in the existing chromosome with the new priorities, until all the gene fragments in the chromosome are traversed. A repair threshold of 0.5 is selected as shown in Figure 6.

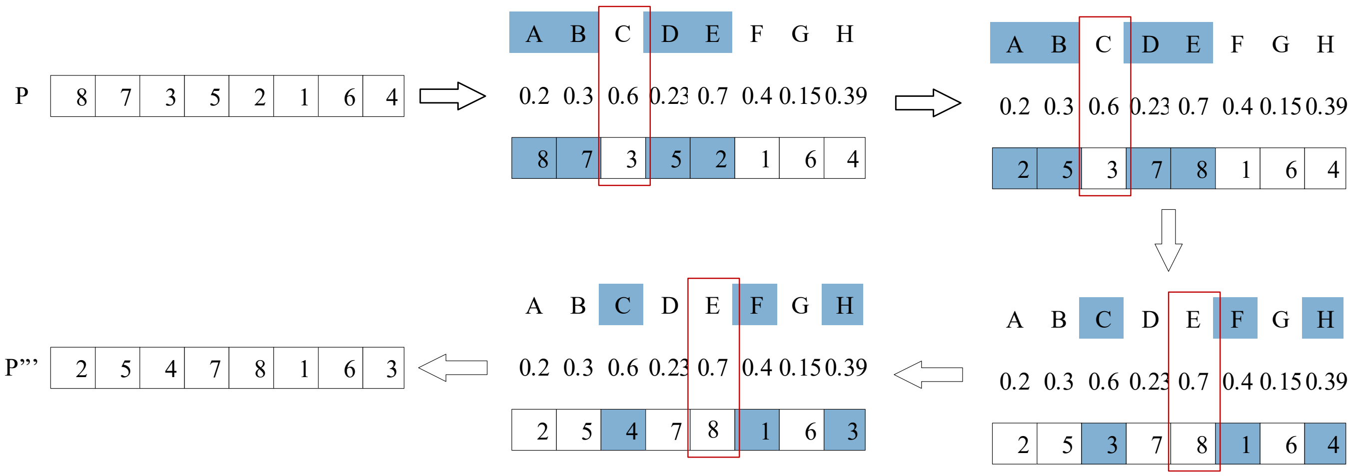


Figure 6. Example of repair operator.

4.7. Termination Condition

In this paper, the iteration of the algorithm is terminated by setting the maximum number of iterations. When the number of iterations of the algorithm reaches the preset iteration threshold, the algorithm is aborted and the Pareto optimal solution is outputted; otherwise, the algorithm is continued.

4.8. The Improved NSGA-II Algorithm Flow

The specific flow of the improved NSGA-II algorithm is as follows, and the flowchart is shown in Figure 7.

Step 1: Initialize the population and set the maximum number of iterations.

Step 2: Determine if it is an invalid chromosome. If it is, perform chromosome repair; otherwise, proceed to the next step.

Step 3: Determine whether the first subpopulation has been generated, and if so, proceed to the next step; otherwise, perform fast nondominated sorting on the initial population and generate offspring population through elite selection, crossover, and mutation operations.

Step 4: Update the number of iterations.

Step 5: Combine the parent population and the offspring population.

Step 6: Determine if a new parent population has been generated, and if so, proceed to the next step; otherwise, calculate the fitness function value of individuals in the population, perform fast nondominated sorting, calculate crowding distance, and obtain a new parent population through elite selection, crossover, and mutation operations.

Step 7: Determine if it is an invalid chromosome. If it is, perform chromosome repair; otherwise, proceed to the next step.

Step 8: Determine whether the preset number of termination iterations is reached, and end the algorithm operation; otherwise, return to Step 4.

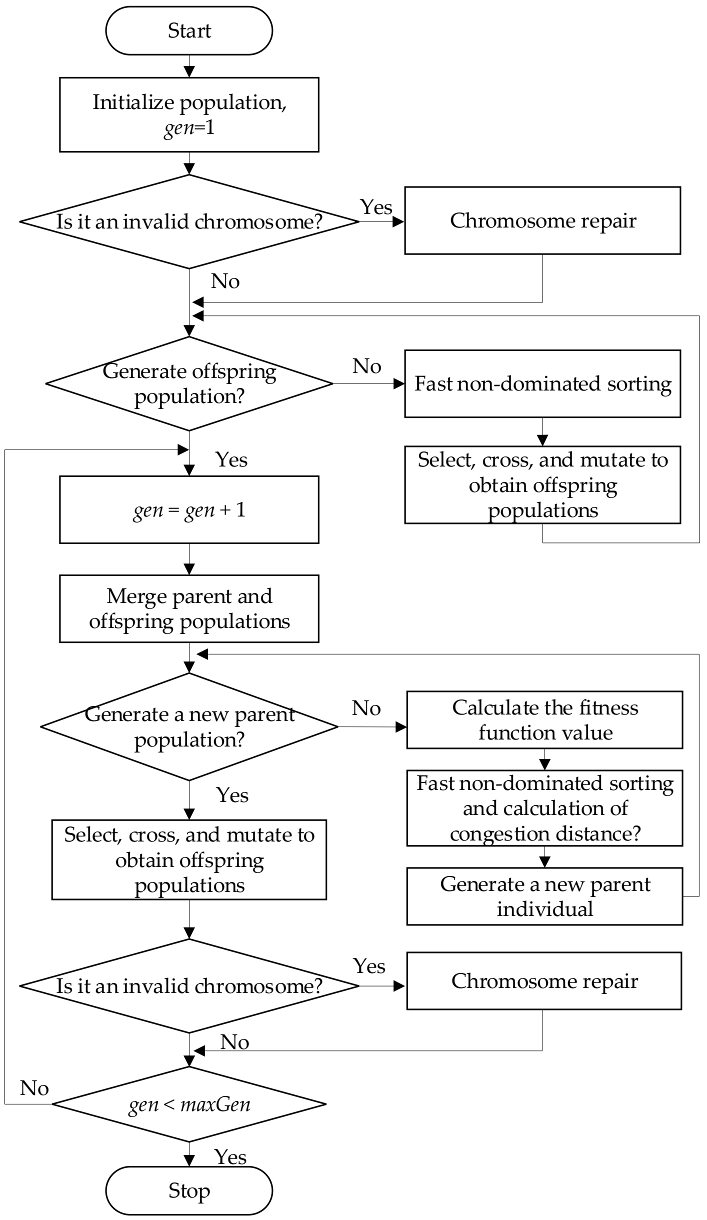


Figure 7. The flowchart of the improved NSGA-II algorithm.

5. Case Analysis

5.1. Road Network

In this section, Sioux Falls network [44] is used to verify the feasibility and effectiveness of the time-varying model and the improved NSGA-II algorithm. Sioux Falls network was derived from Sioux Falls, the largest city in South Dakota, USA, and this network has been widely used in route optimization problems. As shown in Figure 8, the network has 24 nodes and 38 road segments. Based on the optimization model of the hazardous chemicals transportation network under time-varying conditions proposed, the length of each road segment, the population density, hazardous chemicals leakage rate, and accident rate at different time periods are randomly generated, as shown in Table 1. Node 1 is the starting node of the hazardous chemicals transport vehicle, and the customer nodes, as well as the demands, time windows, and penalty cost, are randomly generated, as shown in Table 2. The day is divided into seven time periods based on light visibility as well as road traffic density, as shown in Table 3 [45]. The other parameters involved in this calculation example are set as shown in Table 4.

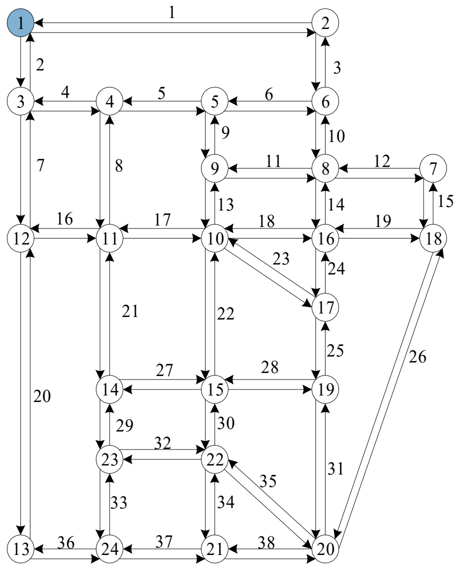


Figure 8. Sioux Falls network.

Table 1. Transportation road segment.

No.	Road Segment	Length/km	Conditional Release Probability	Accident Rate	Population Density/Person·km^{-2}							
					ρ^o_{ij}	ρ^l_{ij1}	ρ^l_{ij2}	ρ^l_{ij3}	ρ^l_{ij4}	ρ^l_{ij5}	ρ^l_{ij6}	ρ^l_{ij7}
1	[1, 2]	18.51	0.0057	0.0014	228	180	141	316	106	132	133	141
2	[1, 3]	15.19	0.0066	0.0046	129	311	289	51	445	254	438	387
3	[2, 6]	23.51	0.0037	0.0087	67	181	415	496	435	353	448	385
4	[3, 4]	23.91	0.0062	0.0045	396	203	90	198	342	107	278	474
5	[4, 5]	18.90	0.0076	0.0066	381	316	473	325	282	122	264	456
6	[5, 6]	14.02	0.0057	0.0041	361	172	387	303	122	242	276	61
7	[3, 12]	27.95	0.0046	0.0010	179	178	237	166	272	379	90	389
8	[4, 11]	13.29	0.0075	0.0039	484	436	310	67	206	161	131	113
9	[5, 9]	26.55	0.0069	0.0022	359	440	136	271	141	489	149	161
10	[6, 8]	27.19	0.0066	0.0066	270	113	449	84	248	271	121	192
11	[9, 8]	16.92	0.0074	0.0026	379	361	149	472	272	165	271	351
12	[8, 7]	26.42	0.0068	0.0022	169	111	469	130	497	329	197	442
13	[9, 10]	14.94	0.0038	0.0096	227	266	166	437	442	210	445	358
14	[8, 16]	16.25	0.0062	0.0035	442	79	232	371	483	411	158	412
15	[7, 18]	18.65	0.0051	0.0046	404	336	415	320	410	441	65	412
16	[12, 11]	12.57	0.0047	0.0090	296	219	192	496	227	166	293	56
17	[11, 10]	17.62	0.0050	0.0052	196	430	204	125	274	137	271	315
18	[10, 16]	17.26	0.0050	0.0025	75	260	75	297	493	370	339	177
19	[16, 18]	18.58	0.0060	0.0097	245	105	85	110	468	437	364	465
20	[12, 13]	16.31	0.0042	0.0065	209	378	107	446	383	439	253	302
21	[11, 14]	16.16	0.0044	0.0054	432	139	104	68	56	121	101	127
22	[10, 15]	25.68	0.0064	0.0082	357	294	434	252	469	403	469	61
23	[10, 17]	20.27	0.0049	0.0034	482	198	421	139	468	245	269	490
24	[16, 17]	15.81	0.0063	0.0073	60	388	163	357	262	141	50	106
25	[17, 19]	10.11	0.0074	0.0028	456	75	232	198	210	359	244	93
26	[18, 20]	28.35	0.0051	0.0089	194	495	296	138	329	347	241	98
27	[14, 15]	17.53	0.0055	0.0047	163	106	300	393	437	211	187	407
28	[15, 19]	29.07	0.0058	0.0013	315	450	314	156	495	156	394	442
29	[14, 23]	27.11	0.0043	0.0013	242	397	140	240	443	97	123	495
30	[15, 22]	16.37	0.0066	0.0056	218	350	179	295	176	251	236	472
31	[19, 20]	18.92	0.0062	0.0046	408	239	53	494	61	271	426	161
32	[23, 22]	22.06	0.0075	0.0082	246	163	56	140	86	375	425	386
33	[23, 24]	22.54	0.0066	0.0061	230	118	298	183	89	321	170	431
34	[22, 21]	15.67	0.0079	0.0023	386	343	313	226	299	372	462	155
35	[22, 20]	21.53	0.0042	0.0027	434	247	263	162	127	244	435	447
36	[13, 24]	12.87	0.0040	0.0045	387	235	335	442	104	330	469	264
37	[24, 21]	11.52	0.0075	0.0063	203	145	85	347	125	167	122	425
38	[21, 20]	14.63	0.0060	0.0092	403	417	125	477	245	477	371	345

In ρ^l_{ijn}, n represents the time periods.

Table 2. Customer nodes.

Customer Node	Demand/t	Time Window	Service Time/h	η_{c1}/CNY·h^{-1}	η_{c2}/CNY·h^{-1}
14	2	[8:30, 10:00]	0.6	9	11
17	5	[9:00, 10:00]	0.8	6	10
18	9	[13:00, 16:00]	0.9	5	14

Table 3. Time periods.

No.	Start	End	Speed/km·h^{-1}
1	0:00	6:00	60
2	6:00	7:00	70
3	8:00	11:00	80
4	11:00	13:00	70
5	13:00	18:00	80
6	18:00	20:00	70
7	20:00	0:00	60

Table 4. Other parameters.

Parameter	Value
Fix cost	180 CNY
Transportation cost	5 CNY/km
α	0.1
β	0.2
r	0.5 km
E	2.61 kg/L
ε_m	0.255 L/km
ε_0	0.165 L/km
Maximum loading	10 t

The experimental running environment consists of an Intel i5 processor, 3.20 GHz main frequency, 16 GB RAM, and the Windows 11 operating system, and the improved NSGA-II algorithm was tested using the Python 3.10.0 program on the VS Code platform. The parameter settings for the algorithm operation, according to the problem size and the analysis, are as follows: population of 200, maximum number of iterations of 100, crossover probability of 0.6 and variance probability of 0.8. For each experiment, run ten times and use the optimal results.

5.2. Experiment 1: Transportation Route Optimisation under Different Departure Times

In the time-varying model of this paper, the traveling speed of the vehicle and the population density around the road segment are affected by time and each customer node in the road network has a soft time window, so we firstly explore the time-varying characteristics of hazardous chemicals road transportation. On the basis of dividing a day into different discrete time periods, different vehicle departure times can change the time period of the entire transportation process. The experimental design randomly generates seven vehicle departure times in seven time periods and performs optimal route planning at each departure time. The Pareto solutions under each department time are shown in Figure 9, and the optimal routes responding to the Pareto solutions, as well as the objective function values, are shown in Table 5.

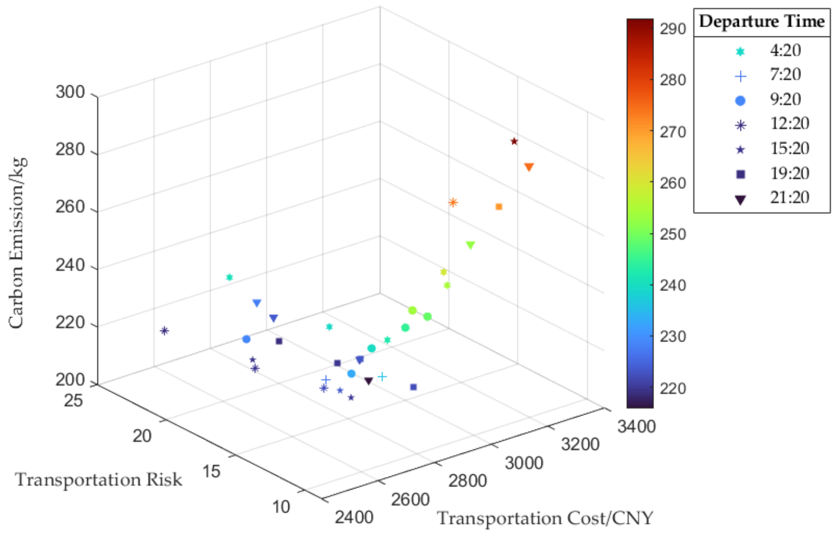


Figure 9. The Pareto fronts of Experiment 1.

As can be seen from Figure 9, running the improved NSGA-II algorithm proposed in this paper at different departure times can obtain the corresponding multiple Pareto solutions. And there may be overlap between multiple different Pareto optimal solutions, which suggests that the proposed algorithm can obtain the Pareto optimal solutions in many iterations, and the verification demonstrates the feasibility and validity of the improved NSGA-II algorithm in this paper.

Solving the multiobjective optimization model under each departure time obtains multiple sets of Pareto optimal solutions and randomly intercepts three optimal solutions in each group, as shown in Table 5. Three different customer nodes (14, 17, and 18) are set in the experiment and the sum of the overall demand of customer node 14 and customer node 17 does not exceed the maximum loading of the transport vehicle, so customer node 14 and customer node 17 are transported by one transport vehicle. Each Pareto optimal solution obtained by the optimization experiment when the customer node is the same at different departure times contains the optimization route of two different transport vehicles.

As can be seen from the experimental results in Table 5, vehicles also have different objective function values when transporting hazardous chemicals along the same transportation routes at different departure times. Taking the routes r_1^1 and r_2^2 as examples, at the different departure times of 4:20 and 7:20, the transportation routes are both [1, 3, 4, 11, 14, 15, 10, 17, 10, 11, 4, 3, 1] and [1, 3, 4, 11, 10, 16, 18, 16, 8, 6, 2, 1], but in terms of transportation cost, the transportation cost of r_1^1 is CNY 2646.93 higher than r_2^2 and the transportation cost of r_2^2 is CNY 2592.35. In terms of transportation risk, the transportation risk of r_1^1 is 20.47, which is higher than the transportation risk of r_2^2. The carbon emissions when departing at 7:20 are 226.63 kg, while the carbon emissions when departing at 7:20 were slightly lower at 240.55 kg. When the departure time of the vehicle at node 1 is 4:20, the time interval from the time window of each customer node is longer than that of the departure time of 7:20, resulting in an increase in the penalty cost at the earlier departure time and thus an increase in the total transportation cost. When the driving speed during transportation is low, the overall transportation time of the vehicle increases, resulting in an increase in carbon emissions. In addition, at different departure times, speed limits on different road segments and the surrounding population density will affect the transportation risk. When the speed is low, the travel time increases and the time it takes for the transporter to reach the customer node will vary, resulting in different penalty costs at each customer node.

Table 5. The results of Experiment 1.

Departure Time	Road No.	Vehicle No.	Route	Cost/CNY	Risk	Carbon Emission/kg
4:20	r_1^1	1 2	1, 3, 4, 11, $\underline{14}$, 15, 10, $\underline{17}$, 10, 11, 4, 3, 1 1, 3, 4, 11, 10, 16, 18, 16, 8, 6, 2, 1	2646.93	20.47	240.55
	r_2^1	1 2	1, 3, 12, 11, $\underline{14}$, 15, 19, $\underline{17}$, 16, 8, 6, 2, 1 1, 3, 12, 11, 10, 16, $\underline{18}$, 16, 8, 6, 2, 1	2700.91	10.15	242.34
	r_3^1	1 2	1, 3, 4, 11, $\underline{14}$, 15, 10, **17**, 10, 11, 14, 15, 22, 21, 20, 18, 7, 8, 6, 2, 1 1, 3, 4, 11, 10, 15, 22, 21, 20, $\underline{18}$, 7, 8, 6, 2, 1	2668.69	13.69	239.26
7:20	r_1^2	1 2	1, 3, 4, 11, $\underline{14}$, 15, 19, $\underline{17}$, 16, 8, 6, 2, 1 1, 3, 4, 11, 10, 16, $\underline{18}$, 16, 8, 6, 2, 1	2614.05	8.72	235.87
	r_2^2	1 2	1, 3, 4, 11, $\underline{14}$, 15, 10, $\underline{17}$, 10, 11, 4, 3, 1 1, 3, 4, 11, 10, 16, $\underline{18}$, 16, 8, 6, 2, 1	2592.35	12.37	226.63
9:20	r_1^3	1 2	1, 3, 4, 11, $\underline{14}$, 15, 10, $\underline{17}$, 10, 11, 4, 3, 1 1, 3, 4, 11, 10, 16, $\underline{18}$, 16, 10, 11, 4, 3, 1	2564.23	17.56	228.83
	r_2^3	1 2	1, 3, 12, 11, $\underline{14}$, 23, 22, 20, 19, $\underline{17}$, 10, 11, 12, 3, 1 1, 3, 12, 11, 10, 16, $\underline{18}$, 16, 10, 11, 12, 3, 1	2808.38	9.45	248.79
	r_3^3	1 2	1, 3, 4, 11, $\underline{14}$, 23, 22, 20, 19, $\underline{17}$, 10, 11, 4, 3, 1 1, 3, 4, 11, 10, 16, $\underline{18}$, 16, 10, 11, 4, 3, 1	2742.28	9.18	253.70
12:20	r_1^4	1 2	1, 3, 12, 11, $\underline{14}$, 15, 19, $\underline{17}$, 19, 20, 21, 24, 13, 12, 3, 1 1, 3, 12, 11, 10, 9, 8, 7, $\underline{18}$, 20, 21, 24, 13, 12, 3, 1	3048.23	12.51	273.31
	r_2^4	1 2	1, 3, 4, 11, $\underline{14}$, 15, 10, $\underline{17}$, 10, 11, 4, 3, 1 1, 3, 4, 11, 10, 16, $\underline{18}$, 16, 8, 6, 2, 1	2545.81	23.12	218.83
	r_3^4	1 2	1, 3, 12, 11, $\underline{14}$, 15, 19, $\underline{17}$, 16, 8, 6, 2, 1 1, 3, 12, 11, 10, 16, $\underline{18}$, 16, 8, 6, 2, 1	2600.55	12.72	222.32
15:20	r_1^5	1 2	1, 3, 4, 11, $\underline{14}$, 15, 10, $\underline{17}$, 10, 11, 4, 3, 1 1, 3, 4, 11, 10, 16, $\underline{18}$, 16, 10, 11, 4, 3, 1	2601.41	17.87	219.71
	r_2^5	1 2	1, 3, 12, 11, $\underline{14}$, 15, 19, $\underline{17}$, 19, 20, 21, 24, 13, 12, 3, 1 1, 3, 12, 11, 10, 9, 8, 7, $\underline{18}$, 7, 8, 9, 10, 11, 12, 3, 1	3214.37	11.48	291.88
	r_3^5	1 2	1, 3, 4, 11, $\underline{14}$, 15, 19, $\underline{17}$, 16, 8, 6, 2, 1 1, 3, 4, 11, 10, 16, $\underline{18}$, 16, 8, 6, 2, 1	2612.75	11.77	223.60
19:20	r_1^6	1 2	1, 3, 4, 11, $\underline{14}$, 15, 19, $\underline{17}$, 19, 20, 21, 24, 13, 12, 3, 1 1, 3, 4, 11, 10, 9, 8, 7, $\underline{18}$, 7, 8, 9, 10, 11, 4, 3, 1	3163.55	11.57	270.43
	r_2^6	1 2	1, 3, 4, 11, $\underline{14}$, 15, 10, $\underline{17}$, 10, 11, 4, 3, 1 1, 3, 4, 11, 10, 16, $\underline{18}$, 16, 8, 6, 2, 1	2748.17	18.94	218.83
	r_3^6	1 2	1, 3, 12, 11, $\underline{14}$, 15, 19, $\underline{17}$, 16, 8, 6, 2, 1 1, 3, 12, 11, 10, 16, $\underline{18}$, 16, 8, 6, 2, 1	2802.22	10.33	222.32
21:20	r_1^7	1 2	1, 3, 4, 11, $\underline{14}$, 15, 10, $\underline{17}$, 10, 11, 4, 3, 1 1, 3, 4, 11, 10, 16, $\underline{18}$, 16, 8, 6, 2, 1	2756.28	20.73	227.78
	r_2^7	1 2	1, 3, 12, 11, $\underline{14}$, 15, 19, $\underline{17}$, 19, 20, 22, 15, 10, 11, 12, 3, 1 1, 3, 12, 11, 10, 17, 19, 20, $\underline{18}$, 16, 8, 6, 2, 1	3354.55	13.27	274.43
	r_3^7	1 2	1, 3, 12, 11, $\underline{14}$, 15, 10, $\underline{17}$, 10, 11, 12, 3, 1 1, 3, 12, 11, 10, 16, $\underline{18}$, 16, 8, 6, 2, 1	2807.29	14.34	221.91

In Table 5, when the departure time is 7:20, there are two optimal transportation solutions r_1^2 and r_2^2. In these two transportation route plans, transport vehicle 2 has the same driving path, while transport vehicle 1 has different driving paths in the road network, resulting in differences in transportation cost, transportation risk, and carbon emissions between the two route schemes. Specifically, the vehicles in transportation path r_2^2 have a shorter travel distance, and the difference in travel distance between the two route schemes is mainly reflected in the transportation distance when returning to the starting node after serving the customer node. Therefore, the longer travel distance results in higher transportation cost and carbon emissions for route r_1^2. In terms of transportation risk, by comparing the probability of conditional leakage, accident occurrence rate, and population density of each road segment, it can be seen that the various indicators of transportation path r_2^2 are relatively high, so the transportation risk of transportation path r_2^2 is relatively high.

In conclusion, in the road transportation of hazardous chemicals, time factors affect the optimization of transportation route by affecting the driving speed and accident rate of transport vehicles. If transportation enterprises want to minimize cost during transportation, they need to choose a departure time closer to the customer's time window to minimize the penalty cost incurred at the customer node. If transportation enterprises want to minimize transportation risk, they should choose roads with lower accident rates among multiple transportation route schemes.

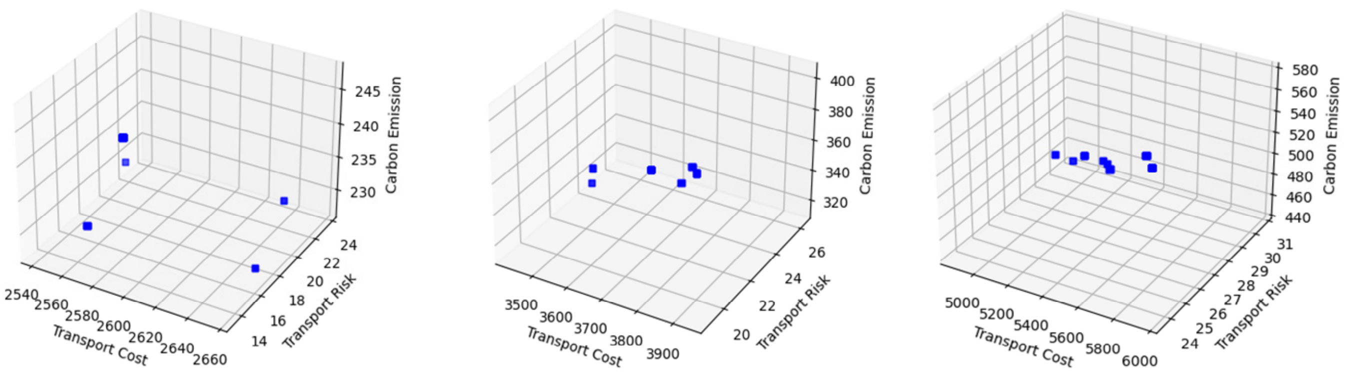
5.3. Experiment 2: Transportation Route Optimization with Customer Nodes Changing

In order to verify the scalability of the time-varying model constructed and explore the impact of changes in customer nodes on the optimization of hazardous chemical road transportation routes, on the basis of the existing customer nodes (14, 17, and 18), the customer node 10 and customer node 22 shown in the Table 6 were added, and the departure time was fixed at 10:30 to carry out the route optimization experiment.

Table 6. New customer nodes.

Customer Node	Demand/t	Time Window	Service Time/h	η_{c1}/CNY·h^{-1}	η_{c2}/CNY·h^{-1}
10	4	[10:00, 13:00]	0.6	4	9
22	8	[11:00, 14:00]	1	3	12

Figure 10 shows the Pareto optimal solution obtained by optimization experiments under the condition that the number of customer nodes in the road network increases at the same departure time, and Figure 10a–c are the Pareto optimal solutions at three customer nodes, four customer nodes and five customer nodes, respectively. As can be seen from the results in Figure 10, the number of Pareto optimal solutions gradually increases as the number of customer nodes increases. This indicates that the improved algorithm proposed in this paper has good scalability, which can obtain good solutions under the condition of changing numbers of customer nodes, and meet the requirements of the optimization experiment.



(**a**) (**b**) (**c**)

Figure 10. The Pareto optimal solution: (**a**) optimization results for three customer nodes; (**b**) optimization results for four customer nodes; and (**c**) optimization results for five customer nodes.

Table 7 shows each optimized route and the corresponding cost, risk and carbon emissions obtained by performing the optimization experiments at different customer nodes at the same departure time. As can be seen from the results in Table 7, transportation cost, transportation risk and carbon emissions rise as the number of customer nodes in the road network gradually increases. When the customer node is (14, 17, or 18) the transportation cost, transportation risk, and carbon emissions are between [2000, 3000], [10, 20] and [200, 300], respectively. When the customer node is (14, 10, 17, or 18), the transportation cost, transportation risk and carbon emissions are between [3000, 4000], and [300, 500], respectively. After adding node 22 into the network as the customer node, the objective function is increased to between [5000, 6000], [20, 35] and [400, 600], respectively. This is because the increase in customer nodes will first lead to an increase in the overall carrying capacity of transporters and an increase in the number of transport vehicles, which in turn leads to an increase in the transportation cost. Since the risk during transportation is directly related to the vehicle loading, when the number of customer nodes increases and the distance traveled by the vehicle increases, so the transportation risk also increases.

Table 7. The results of Experiment 2.

Customer Node	Road No.	Vehicle No.	Route	Cost /CNY	Risk	Carbon Emission/kg
14, 17, 18	r_1^8	1 2	1, 3, 4, 11, 14, 15, 10, 17, 10, 11, 4, 3, 1 1, 3, 4, 11, 10, 17, 16, 18, 16, 10, 11, 4, 3, 1	2642.98	23.67	230.23
	r_2^8	1 2	1, 3, 4, 11, 14, 15, 19, 17, 16, 8, 6, 2, 1 1, 3, 4, 11, 10, 17, 16, 18, 16, 8, 6, 2, 1	2655.75	16.70	228.29
	r_3^8	1 2	1, 3, 12, 11, 14, 15, 19, 17, 16, 8, 6, 2, 1 1, 3, 12, 11, 10, 16, 18, 16, 8, 6, 2, 1	2595.87	13.26	247.44
	r_4^8	1 2	1, 3, 4, 11, 14, 15, 10, 17, 10, 11, 4, 3, 1 1, 3, 4, 11, 10, 16, 18, 16, 10, 11, 4, 3, 1	2550.33	21.46	232.74
	r_5^8	1 2	1, 3, 4, 11, 14, 15, 19, 17, 16, 8, 6, 2, 1 1, 3, 4, 11, 10, 16, 18, 16, 8, 6, 2, 1	2563.09	14.49	230.81
14, 17, 10, 18	r_1^9	1 2 3	1, 3, 4, 11, 14, 15, 10, 11, 4, 3, 1 1, 3, 4, 11, 10, 17, 10, 11, 4, 3, 1 1, 3, 4, 11, 10, 17, 16, 18, 16, 8, 6, 2, 1	3521.06	26.28	314.08
	r_2^9	1 2 3	1, 3, 12, 11, 14, 23, 22, 20, 19, 17, 10, 11, 12, 3, 1 1, 3, 12, 11, 10, 17, 16, 8, 6, 2, 1 1, 3, 12, 11, 10, 16, 18, 16, 8, 6, 2, 1	3939.27	18.89	399.89
	r_3^9	1 2 3	1, 3, 12, 11, 14, 23, 22, 20, 19, 17, 10, 11, 12, 3, 1 1, 3, 12, 11, 10, 17, 10, 11, 12, 3, 1 1, 3, 12, 11, 10, 16, 18, 16, 10, 11, 12, 3, 1	3926.57	18.89	403.10
	r_4^9	1 2 3	1, 3, 4, 11, 14, 15, 10, 11, 4, 3, 1 1, 3, 4, 11, 10, 17, 10, 11, 4, 3, 1 1, 3, 4, 11, 10, 16, 18, 16, 8, 6, 2, 1	3428.40	24.07	316.60
	r_5^9	1 2 3	1, 3, 4, 11, 14, 23, 22, 20, 19, 17, 10, 11, 4, 3, 1 1, 3, 4, 11, 10, 17, 10, 11, 4, 3, 1 1, 3, 4, 11, 10, 16, 18, 16, 10, 11, 4, 3, 1	3826.82	20.75	371.16
	r_6^9	1 2 3	1, 3, 12, 11, 14, 15, 10, 11, 12, 3, 1 1, 3, 12, 11, 10, 17, 10, 11, 12, 3, 1 1, 3, 12, 11, 10, 16, 18, 16, 8, 6, 2, 1	3511.13	22.29	346.58
14, 17, 10, 18, 22	r_1^{10}	1 2 3 4	1, 3, 12, 13, 24, 21, 22, 20, 19, 17, 10, 11, 14, 15, 10, 11, 12, 3, 1 1, 3, 12, 13, 24, 21, 22, 20, 19, 17, 10, 11, 12, 3, 1 1, 3, 12, 13, 24, 21, 22, 21, 24, 13, 12, 3, 1 1, 3, 12, 13, 24, 21, 22, 20, 18, 20, 21, 24, 13, 12, 3, 1	5956.87	23.58	574.91
	r_2^{10}	1 2 3 4	1, 3, 4, 11, 14, 15, 10, 11, 4, 3, 1 1, 3, 4, 11, 10, 17, 10, 11, 4, 3, 1 1, 3, 4, 11, 10, 16, 17, 19, 20, 22, 21, 24, 13, 12, 3, 1 1, 3, 4, 11, 10, 16, 18, 16, 10, 11, 4, 3, 1	4882.80	30.69	446.20

Table 7. *Cont.*

Customer Node	Road No.	Vehicle No.	Route	Cost /CNY	Risk	Carbon Emission/kg
14, 17, 10, 18, 22	r_3^{10}	1	1, 3, 12, 11, 14, 15, 10, 11, 12, 3, 1	4998.83	28.29	486.45
		2	1, 3, 12, 11, 10, 17, 10, 11, 12, 3, 1			
		3	1, 3, 12, 11, 10, 16, 17, 19, 20, 22, 21, 24, 13, 12, 3, 1			
		4	1, 3, 12, 11, 10, 16, 18, 16, 10, 11, 12, 3, 1			
	r_4^{10}	1	1, 3, 12, 13, 24, 21, 20, 19, 15, 14, 11, 10, 11, 12, 3, 1	5481.99	26.28	523.81
		2	1, 3, 12, 13, 24, 21, 20, 19, 17, 10, 11, 12, 3, 1			
		3	1, 3, 12, 13, 24, 21, 22, 21, 24, 13, 12, 3, 1			
		4	1, 3, 12, 13, 24, 21, 20, 18, 20, 21, 24, 13, 12, 3, 1			
	r_5^{10}	1	1, 3, 4, 11, 14, 23, 22, 20, 19, 17, 10, 11, 4, 3, 1	5363.27	27.37	508.45
		2	1, 3, 4, 11, 10, 17, 10, 11, 4, 3, 1			
		3	1, 3, 4, 11, 10, 16, 17, 19, 20, 22, 23, 14, 11, 4, 3, 1			
		4	1, 3, 4, 11, 10, 16, 18, 16, 10, 11, 4, 3, 1			
	r_6^{10}	1	1, 3, 12, 11, 14, 23, 22, 20, 19, 17, 10, 11, 12, 3, 1	5475.62	24.90	548.23
		2	1, 3, 12, 11, 10, 17, 10, 11, 12, 3, 1			
		3	1, 3, 12, 11, 10, 16, 17, 19, 20, 22, 23, 24, 13, 12, 3, 1			
		4	1, 3, 12, 11, 10, 16, 18, 16, 10, 11, 12, 3, 1			
	r_7^{10}	1	1, 3, 12, 13, 24, 21, 20, 19, 17, 10, 11, 14, 15, 10, 11, 12, 3, 1	5618.47	24.89	542.24
		2	1, 3, 12, 13, 24, 21, 20, 19, 17, 10, 11, 12, 3, 1			
		3	1, 3, 12, 13, 24, 21, 22, 21, 24, 13, 12, 3, 1			
		4	1, 3, 12, 13, 24, 21, 20, 18, 20, 21, 24, 13, 12, 3, 1			
	r_8^{10}	1	1, 3, 12, 13, 24, 21, 22, 20, 19, 15, 14, 11, 10, 11, 12, 3, 1	5823.06	24.81	565.13
		2	1, 3, 12, 13, 24, 21, 22, 20, 19, 17, 10, 11, 12, 3, 1			
		3	1, 3, 12, 13, 24, 21, 22, 21, 24, 13, 12, 3, 1			
		4	1, 3, 12, 13, 24, 21, 22, 20, 18, 20, 21, 24, 13, 12, 3, 1			

5.4. Green Transportation

When the customer node in the network is (14, 10, 17, 18, or 22), excluding carbon emissions, the transportation cost of transportation route r_2^{10} is the lowest at CNY 4882.80, the transportation cost of transportation route r_8^{10} is CNY 5823.06, while the transportation risk of transportation route r_1^{10} is 23.58, and the transportation risk of transportation route r_2^{10} is 30.69. Figure 11 shows the relationship between transportation cost and carbon emissions. It can be seen that in the road transportation route optimization problem of hazardous chemicals, there is often a contradictory relationship between transportation cost and transportation risk, and the reduction of transportation cost often means the increase of transportation risk. Therefore, the hazardous chemical transportation enterprises need to weigh the relationship between the two in the actual path planning. In the case that the transportation cost and transportation risk cannot be optimal at the same time, the optimal road transportation route should be selected combined with enterprises' risk tolerance and economic benefits.

Figure 12 shows that carbon emissions will increase when transportation cost gradually increases, and there is a positive correlation between transportation cost and carbon emissions, indicating that when the transportation cost of vehicles gradually increase, it is often accompanied by an increase in carbon emissions. For example, the transportation cost of route r_2^8 in Table 7 is higher than r_4^8, but the carbon emissions are lower, indicating that the enterprise can indirectly reduce carbon dioxide emissions by reducing vehicle travel distance, setting reasonable departure times, and other means to reduce transportation cost, and promote the green development of hazardous chemicals transportation.

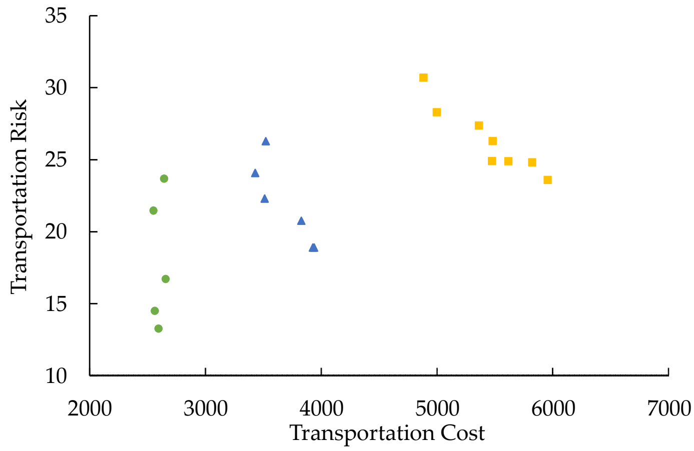


Figure 11. The relationship between transportation cost and transportation risk. The green circles represent the experimental results when the customer nodes are 14, 17, and 10, while the blue triangles represent the experimental results when the customer nodes are 14, 17, 10, and 18, and the yellow square represents the experimental results when the customer nodes are 14, 17, 10, 18, and 22.

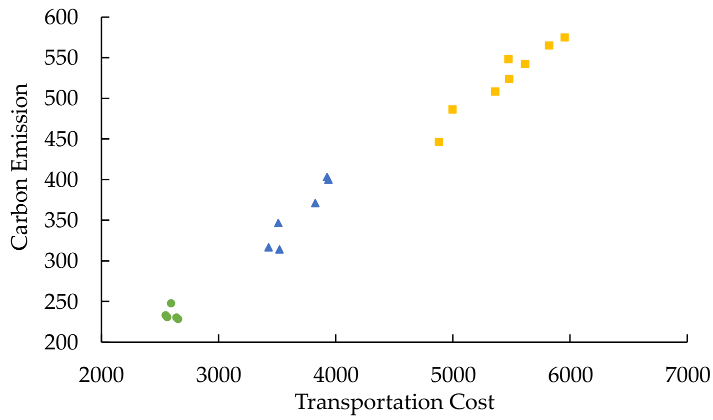


Figure 12. The relationship between transportation cost and carbon emissions. The green circles represent the experimental results when the customer nodes are 14, 17, and 10, while the blue triangles represent the experimental results when the customer nodes are 14, 17, 10, and 18, and the yellow square represents the experimental results when the customer nodes are 14, 17, 10, 18, and 22.

6. Conclusions and Future Work

Road transportation of hazardous chemicals is characterized by high risk, so the risk should be minimized during the transportation process. This paper innovatively proposes that from the perspective of transportation route schemes, enterprises should optimize transportation routes based on the time windows of customer nodes and dynamic road conditions by studying the time-varying factors in hazardous chemical road transportation. At the same time, by studying the interrelationships between optimization objectives, it is believed that the reduction of transportation cost should be the primary consideration during transportation. The specific research content of this paper is as follows:

(1) A multiobjective route optimization model is constructed to minimize transportation cost, transportation risk, and carbon emissions based on the risk of hazardous chemicals road transportation, the economy of transportation enterprises, and the "double carbon" goal. At the same time, the time factor is added into the model, and a soft time window is set for each customer node. The day is divided into different time periods. The speed limit of the road as well as the population density and accident rate are different during each time period.

(2) The NSGA-II algorithm is used for solving the problem, and the NSGA-II algorithm is improved to reduce the occurrence of a large number of invalid solutions during the optimization problem solving process. Based on the model proposed in this paper, road network optimization experiments in classical Sioux Falls networks are performed to verify the feasibility and effectiveness of the algorithm.
(3) The experimental results of route optimization show that the transportation routes obtained at different departure times are very different. When transport vehicles depart at different times, the same transportation route will generate different transportation costs, transportation risks, and carbon emissions. In addition, as the number of customer nodes increases, transportation cost, transportation risk, and carbon emissions during transportation will correspondingly increase.
(4) When optimizing the transportation route, enterprises need to reasonably plan the department time and transportation route according to the time-varying factors If enterprises want to minimize transportation cost, it needs to choose a departure time that is closer to the customer's time window and a transportation route that is shorter. If enterprises pay more attention to safety, they need to choose transportation routes with lower accident rates and population density based on road conditions.
(5) In the process of optimizing the road transportation route of hazardous chemicals, from the perspective of transportation enterprises, transportation cost is the primary factor to consider. Based on the negative correlation between cost and risk, as well as the positive correlation between cost and carbon emissions, multiple measures should be taken to reduce transportation cost, and then machine learning, artificial intelligence, and other technologies should be applied to construct a more reasonable and effective optimization model for minimizing transportation risk. Firstly, it is necessary to improve the construction of information infrastructure for road transportation of hazardous chemicals, construct a big data system for hazardous chemical transportation, achieve the circulation of transportation big data, and reduce the cost of data acquisition for transportation enterprises. Secondly, through the application of in-vehicle sensors, the IoT, and video recognition detection technology, intelligent supervision of transportation can be achieved, reducing the cost of supervision during transportation. Finally, the government can allocate financial subsidies to small and medium-sized transportation enterprises to reduce their cost burden.

Road transportation of hazardous chemicals is a process that is affected by time, weather, road conditions, and other factors, and the goals pursued by each participant in the transportation process are also in conflict. Firstly, this paper conducts route optimization experiments based on discrete time-varying conditions, and preliminarily concludes that the departure time of vehicles and the time window of customer nodes will have an impact on the cost and risk of the transportation. However, there are still shortcomings in specific time path planning, and more comprehensive experiments are needed to explore the impact mechanism of changes in time factors on transportation. Secondly, the time factor is included in the transportation route optimization model of hazardous chemicals, but the road information is known with certainty. In the future, the uncertain road transportation optimization problem based on time-varying factors can be considered to study the influence of uncertain external environmental conditions on the transportation route. Thirdly, the interaction between vehicles and the overall riskiness of the road network when multiple transport vehicles are traveling in the road network at the same time are not considered, and further research is needed on the interaction between vehicles and the overall risk and fairness of the transportation network. Meanwhile, the model and algorithm in the paper also require a larger network for testing.

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