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A MULTI-OBJECTIVE MULTIMODAL TRANSPORTATION ROUTE PLANNING MODEL CONSIDERING FUZZY NODE LOADS

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Abstract. *With the advancement of economic globalization, multimodal transportation is gradually gaining importance in the field of logistics. This paper addresses the multimodal transportation route planning problem with uncertain node loads and proposes a chance-constrained model based on fuzzy sets to balance the costs, carbon emissions, and customer satisfaction. Additionally, an improved cooperative coevolution algorithm is introduced to solve the problem. The proposed model is applied to a real-world case to validate its effectiveness, and through algorithm comparison, the performance of the improved algorithm is demonstrated. The findings indicate that node loads at varying confidence levels exert a noteworthy impact on both delivery time and waiting time for shipments. Furthermore, a more intricate transportation network results in extended waiting times, highlighting the heightened importance of accounting for uncertain node loads and transportation schedules.*

Keywords: Multimodal transportation, Route planning, Node loads, Fuzzy uncertainty, Chance constrained planning

1. Introduction.

In recent years, with the escalating challenges of environmental pollution and energy shortages, global attention has gradually shifted to adopting a "low-carbon" development model, which places new requirements on socio-economic construction [1]. The International Transport Forum (ITF) estimates that over 7% of global greenhouse gas emissions come from the shipment sector, with about 50% from shipping and 40% from road transport [2]. As a result, low-carbon logistics, which is characterized by its environmentally friendly and energy-efficient features, has attracted widespread international interest, advocating the use of low-carbon energy through technological innovation and management practices that achieve low energy consumption and high efficiency to meet the goal of reducing environmental pollution [3].

As a modern comprehensive transport mode, multimodal transportation has characteristics such as speed, safety, low-cost efficiency, and environmental sustainability [4]. This type of transportation is well suited to meeting diverse customer demands, realizing cost

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savings in shipment transportation, and reducing energy consumption and gas emissions during transportation processes [5]. Therefore, multimodal transportation will be a crucial direction for the future development of the logistics industry, especially intercontinental logistics transportation.

However, when planning multimodal transportation routes, decision-makers need to consider different perspectives, including those of carriers, shippers, and the environment [6], to reduce operating costs, improve service quality, and minimize negative environmental impacts [7]. They must strategically choose the optimal transport route from origin to destination, including the choice of intermediate nodes and the transport modes between these nodes which is a critical tactical decision-making challenge [7]. Many countries have developed considerable scale in highway, railway, and waterway transport, but the imbalance in the share of traffic between the different modes leads to poor coordination [8]. Therefore, there is a need to pay considerable attention to route planning problems in the field of multimodal transport. On the one hand, it facilitates the enhancement of goods transportation efficiency, reduces logistics costs, and promotes the circulation of commodities; on the other hand, it provides a scientific and rational basis for decision-making for relevant operators, and promotes the development and improvement of China's integrated transportation system.

This paper is organized as follows. Section 2 provides a review of the literature related to the key themes within multimodal transportation route planning. Section 3 delves into the problem description and modeling methodology for Node Load Uncertainty in Multimodal Transportation Route Planning (NLU-MTRP). Section 4 presents the mathematical model developed for NLU-MTRP. In Section 5, we introduce an improved Cooperative Coevolutionary Genetic Algorithm (CCGA) tailored for solving the NLU-MTRP problem, including its encoding strategy and search strategies. Section 6 presents a detailed example analysis to illustrate the practical application of the proposed model, and offers a sensitivity analysis and compares the proposed algorithm with existing approaches to highlight its efficacy. Finally, Section 7 concludes the paper by summarizing the key findings and discussing potential directions for future research.

2. **Literature Review.** Works of literature on multimodal transport route planning focused on analyzing the problem from several perspectives: 1) optimization of transport costs, 2) optimization of carbon emissions, and 3) optimization of time-related customer satisfaction.

In the literature on optimizing costs in the context of multimodal transportation, researchers have developed a series of comprehensive cost models by considering costs at different stages of multimodal transportation. For example, the multi-criteria decision-making and multi-objective planning methods for weighing unit transportation costs and mode switching costs in multimodal route decision-making have shown that unit transportation and mode switching costs are the main components of the multimodal transportation cost framework, which are influenced by factors such as shipment volumes, modes, and distances [9,10]. Another study discusses the cost advantages of containerized transportation and considers route and mode matching in multimodal route planning [11].

In the literature on optimizing carbon emissions in the context of multimodal transportation, some studies discuss the relationship between carbon emissions and transportation distance for different modes [12,13], while others discuss carbon emissions during transportation and loading or unloading of shipments [14], and still, others discuss the impact of different carbon emission policies on route selection [15].

In the literature related to service quality in the context of multimodal transportation, customer satisfaction as affected by delivery time is mainly discussed. Delivery time minimization [12,13,16] and time windows [17,18] are two common approaches to modeling customer satisfaction. An alternative approach is to use soft time window constraints [19,20], as customers may be willing to accept, to some extent, the additional inventory and administrative costs incurred by shipments arriving outside the specified time.

The above-mentioned studies cover key aspects of multimodal transportation, modeling various optimization objectives and factors to achieve optimization of logistics costs, carbon emissions, and time-related customer satisfaction in different scenarios. However, in reality, the demand for transportation and the processes in transportation are often uncertain, as the actual situation may be affected by many factors such as the external environment and human subjectivity. Therefore, many scholars developed the route planning model by considering uncertain factors based on the deterministic model with expectation value or opportunity constraint planning. Table 1 shows the application of uncertainty planning in the multimodal transportation route optimization model.

Table 1. Application of multimodal route planning models based on uncertainty methods and parameters

Ref	Mode	Uncertainty method	Uncertain parameters	Solution method
[4]	H-R-S	Chance constraints	Demand/ Delivery time	Sparrow search algorithm
[10]	H-R	Chance constraints	Capacity/ Delivery time	Linear exact solution method
[12]	H-R	Fuzzy set	Accident/ Emission cost	Bounded objective function method
[21]	H-R	Chance constraints	Risks	Linear exact solution method
[22]	H-R-S	Interval number	Network weights	GA
[23]	H-R-S	Interval number	Duration	NSGA-II

H: Highway transportation network R: Railway transportation network

S: Shipping transportation network GA: Genetic Algorithm

NSGA-II: Non-dominated Sorting Genetic Algorithms II

Uncertainty planning helps to improve the reliability of multimodal transportation route planning models and has great practical and engineering significance. However, the uncertainty-based multimodal transportation route planning model in the table ignores the load conditions within the mode-switching nodes, such as the hoarding of shipments at terminals and stations, as well as the shipment throughput efficiencies and schedules of the transport modes in different cities. This oversight can lead to sub-optimal planning outcomes, as the unpredictability of node loads directly affects queuing and waiting times, which are crucial for timely and cost-effective transportation.

This study addresses this gap by integrating a sophisticated uncertainty handling mechanism into the route planning model, enhancing both the realism and applicability of the model. Unlike previous models that predominantly rely on deterministic or simple probabilistic approaches, this study employs a comprehensive uncertainty planning framework that incorporates real-world complexities such as the stochastic nature of load conditions at terminals and the dynamic schedules of transport modes. By doing so, this research not only advances the theoretical modeling of multimodal transportation systems but also significantly boosts the practical relevance and reliability of the route optimization outcomes, facilitating more robust decision-making in the face of uncertainty. Thus, the proposed model offers a substantial improvement over existing methodologies by ensuring that transportation plans are both resilient and adaptable to unpredictable changes in the transportation environment.

3. Problem Description and Modeling Methodology.

3.1. Problem description.

As shown in Figure 1, assuming there are M cities in the network, a logistics company plans to transport a batch of shipments from the origin point O to the destination point D within the network whilst there are R_{ij} options of transport modes between each city. The above multimodal transportation route planning problem not only requires consideration of the environmental and transportation costs associated with different modes and routes but also requires ensuring transportation timeliness to improve customer satisfaction. Moreover, to model delivery time more comprehensively, we consider the impact of waiting time resulting from the schedule of transport modes and the uncertain node loads on transport efficiency. The waiting of shipments within nodes not only affects customer satisfaction but also influences carrier route decisions due to the additional costs incurred.

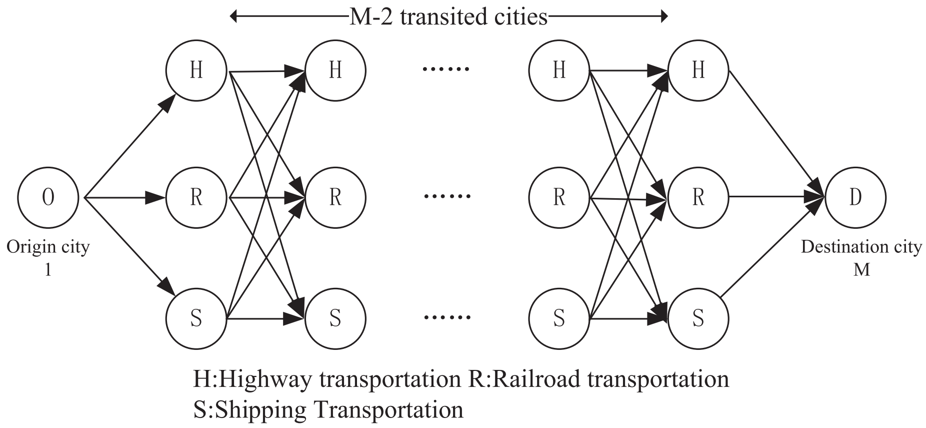

FIGURE 1. Multimodal transportation network

To address this uncertain problem, this paper establishes a chance-constrained multimodal transportation route planning model considering node load uncertainty (NLU-MTRP), which optimizes transportation costs, customer satisfaction and carbon emissions, all while ensuring that the dwell time of shipments within nodes does not exceed carriers' acceptable levels.

For the purpose of our research, the following assumptions are made when addressing this problem. 1) No consideration is given to the impact of freight volume on transportation prices and times. 2) All modes of transportation are assumed to move at a uniform speed. 3) Only the transport and transit of shipments are taken into account, without considering processing and storage costs. 4) External factors such as weather, unforeseen accidents, and transportation equipment failures are not taken into consideration.

3.2. Modeling methodology for NLU-MTRP.

3.2.1. *Formula for transportation costs.* The proposed model focuses on two parts of costs in multimodal transportation. 1) The transport cost, denoted as C_1, signifies the expenditure involved in transporting shipments between nodes. This cost is influenced by the length of the paths and the modes of transportation. 2) The mode-switching cost, denoted as C_2, represents the expense associated with shipments transitioning between modes of transportation at transited nodes, which is contingent upon the specific mode-switching scenario. In summary, the transportation costs in this paper are computed according to Equations (1)-(4).

$$C_1 = \sum_{i\in M}\sum_{j\in M}\sum_{k\in N} u^k g_{ij}^k d_{ij}^k x_{ij}^k \tag{1}$$

$$x_{ij}^k = \begin{cases} 1, & \text{Transported from } i \text{ to } j \text{ with } k \\ 0, & \text{else} \end{cases} \tag{2}$$

$$C_2 = \sum_{i\in M}\sum_{j\in M}\sum_{k\in N}\sum_{l\in N} h_i^{kl} g_{ij}^k y_i^{kl} \tag{3}$$

$$y_i^{kl} = \begin{cases} 1, & \text{Mode switched from } k \text{ to } l \text{ at } i \\ 0, & \text{else} \end{cases} \tag{4}$$

Equation (1) denotes the transport cost accrued during the transportation process, correlating with unit transport cost, distance, shipment volume, and transport modes. Here, u^k denotes the unit transport cost for mode k, and g_{ij}^k, d_{ij}^k represent the shipment volume and distance between nodes i and j using mode k, respectively. M and N represent the sets of nodes and available transport modes, respectively. x_{ij}^k in Equation (2) is a binary variable.

Equation (3) delineates the cost associated with transport mode switching, contingent on shipment volume and the specific transport mode types before and after the switch. Here, h_i^{kl} represents the unit cost of switching from mode k to l at node i. y_i^{kl} in Equation (4) is a binary variable.

3.2.2. *Formula for customer satisfaction.* According to the problem description, our main focus is on customer satisfaction related to transportation timeliness. As shown in Figure 2, we describe customer expectations for timeliness as a soft time window comprising an acceptable and optimal time range to better reflect reality.

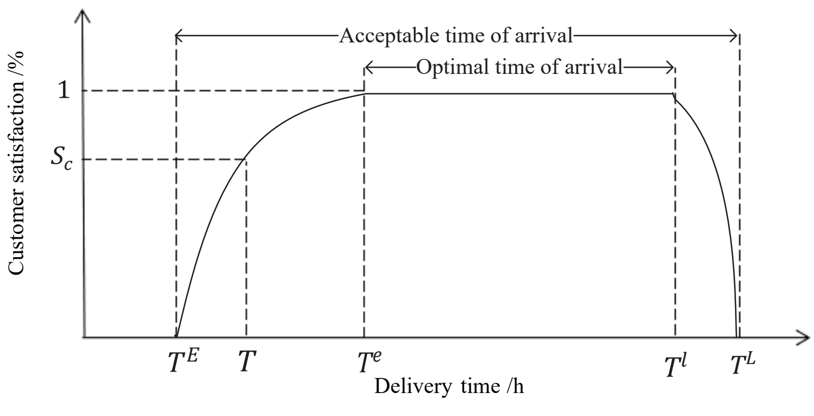

FIGURE 2. The soft time window of customers

Figure 2 can be formalized as a piecewise function of satisfaction related to delivery time, i.e., Equation (5).

$$S_c = \begin{cases} \dfrac{T - T^E}{T^e - T^E}, & \text{if } T^E \le T < T^e \\ 1, & \text{if } T^e \le T < T^l \\ \dfrac{T^L - T}{T^L - T^l}, & \text{if } T^l \le T < T^L \\ 0, & \text{if } T < T^E,\ T > T^L \end{cases} \tag{5}$$

In Equation (5), T represents the delivery time of shipments, T^E and T^L denote acceptable arrival time ranges, and T^e and T^l denote optimal arrival time ranges. Regarding transportation time, we considered the time consumption of three transportation activities, namely, transport time T_1, mode switching time T_2, and waiting time T_3, with Equations (6)-(8).

$$T_1 = \sum_{i \in M} \sum_{j \in M} \sum_{k \in N} T_{ij}^k x_{ij}^k \tag{6}$$

$$T_2 = \sum_{i \in M} \sum_{j \in M} \sum_{k \in N} \sum_{l \in N} T_i^{kl} y_i^{kl} \tag{7}$$

$$T_3 = \sum_{i \in M} T_i^s \tag{8}$$

$$T = T_1 + T_2 + T_3 \tag{9}$$

Equation (6) represents the calculation of the total transport time T_1, where T_{ij}^k refers to the time consumed by the shipment transport between nodes i and j. Equation (7) represents the calculation of the total mode switching time T_2, where T_i^{kl} refers to the time consumed by the switching from mode k to l at node i. Equation (8) represents the calculation of the total waiting time T_3, where T_i^s refers to the waiting time of the shipment within node i. The waiting time for the shipment is the time spent in a queue during the mode-switching process, which is related to the loads and schedules of the modes within the node. Thus, the total delivery time T is the sum of T_1, T_2, and T_3, as shown in Equation (9).

3.2.3. *Formula for carbon emissions.* From the perspective of transportation and mode-switching activities, we optimize carbon emissions in multimodal transportation. E_1 denotes the carbon emissions generated by the vehicles during the movement of shipments between nodes, calculated by Equation (10). E_2 represents the carbon emissions generated by the loading and unloading equipment during the mode-switching of shipments within nodes, calculated by Equation (11).

$$E_1 = \sum_{i \in M} \sum_{j \in M} \sum_{k \in N} e^k g_{ij}^k d_{ij}^k x_{ij}^k \tag{10}$$

$$E_2 = \sum_{i \in M} \sum_{j \in M} \sum_{k \in N} \sum_{l \in N} e^{kl} g_{ij}^k y_i^{kl} \tag{11}$$

In Equations (10) and (11), e^k and e^{kl} denote the unit emission factors during transportation and mode switching.

4. **Mathematical Model for NLU-MTRP.** The framework of NLU-MTRP is shown in Figure 3. Combined with Equations (1)-(11) introduced in the previous section, in this section, we first present a mathematical model that incorporates fuzzy parameters and represents the objective function and constraints of the model. Then, we introduce a linearization strategy for fuzzy parameters to facilitate the solution using mathematical programming.

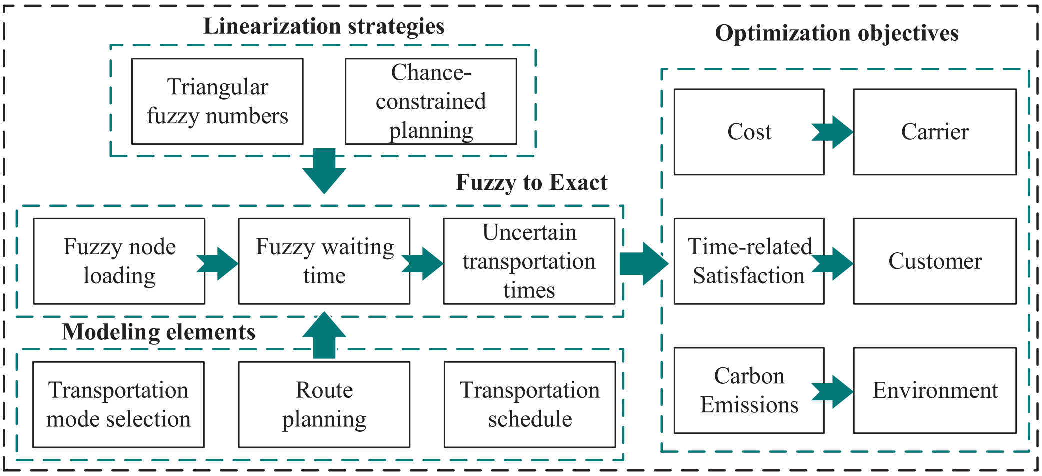

FIGURE 3. Framework of NLU-MTRP

4.1. A fuzzy chance-constrained NLU-MTRP model.

4.1.1. *Objective function.*

$$
\begin{aligned}
Z_1 &= \min(C_1 + C_2) && (12)\\
&= \min\left(\sum_{i\in M}\sum_{j\in M}\sum_{k\in N} u^k g_{ij}^k d_{ij}^k x_{ij}^k + \sum_{i\in M}\sum_{j\in M}\sum_{k\in N}\sum_{l\in N} h_i^{kl} g_{ij}^k y_i^{kl}\right) && (13)
\end{aligned}
$$

From the perspective of the logistics company (carrier), the multimodal transportation route planning should save the delivery cost as much as possible. Therefore, in this paper, the minimum transport and mode switching costs are taken as the optimization objective in Equations (12) and (13).

$$
\begin{aligned}
Z_2 &= \max S_c \\
&= \min(1 - S_c)
\end{aligned} \tag{14}
$$

$$
S_c = \begin{cases} \dfrac{T - T^E}{T^e - T^E}, & \text{if } T^E \le T < T^e \\ 1, & \text{if } T^e \le T < T^l \\ \dfrac{T^L - T}{T^l - T^L}, & \text{if } T^l \le T < T^L \\ 0, & \text{if } T < T^E,\ T > T^L \end{cases} \tag{15}
$$

$$
T = \sum_{i\in M}\sum_{j\in M}\sum_{k\in N} T_{ij}^k x_{ij}^k + \sum_{i\in M}\sum_{j\in M}\sum_{k\in N}\sum_{l\in N} T_i^{kl} y_i^{kl} + \sum_{i\in M} \tilde{T_i^s} y_i^{kl} \tag{16}
$$

From the perspective of the customer (shipper), the multimodal transportation route planning should improve satisfaction as much as possible. Therefore, in this paper, the customer satisfaction is taken as the optimization objective in Equations (14)-(16). Note that the delivery time T in Equation (16) is uncertain because it contains a fuzzy variable $\tilde{T_i^s}$, which is affected by uncertain loads and the schedule of different transport modes, calculated in Equation (17).

$$
\tilde{T_i^s} = \begin{cases} \left\lfloor \left(T_i + t_i^k\right)/t_i^k \right\rfloor \times t_i^k - T_i, & \tilde{T_i^q} \le \left\lfloor \left(T_i + t_i^k\right)/t_i^k \right\rfloor \times t_i^k - T_i \\ \left\lceil \left(\tilde{T_i^q} + T_i\right)/t_i^k \right\rceil \times t_i^k - T_i, & \tilde{T_i^q} > \left\lfloor \left(T_i + t_i^k\right)/t_i^k \right\rfloor \times t_i^k - T_i \end{cases} \tag{17}
$$

where $\tilde{T_i^q} = \left(\tilde{L_i^k} + g_{ij}^k\right) \Big/ V_i^k$

In Equation (17), T_i and t_i^k denote the arrival time of shipments at node i and the scheduled time interval of transport mode k at node i, respectively. $\tilde{T_i^q}$ denotes the fuzzy queuing time of shipments at node i, which can be computed from g_{ij}^k, the fuzzy shipment load at node i, and the unit shipment throughput V_i^k with transport mode k at node i.

$$\begin{aligned} Z_3 &= \min(E_1 + E_2) \\ &= \min\left(\sum_{i\in M}\sum_{j\in M}\sum_{k\in N} e^k g_{ij}^k d_{ij}^k x_{ij}^k + \sum_{i\in M}\sum_{j\in M}\sum_{k\in N}\sum_{l\in N} e^{kl} g_{ij}^k y_i^{kl}\right) \end{aligned} \tag{18}$$

From the perspective of environmental protection, multimodal transportation route planning should minimize carbon emissions. Therefore, this paper takes the carbon emission in the delivery process as the optimization objective in Equation (18).

4.1.2. *Constraint condition.* The following constraints are given to ensure that the model has practical significance.

1) Choice of transport modes

$$\sum_{i\in M}\sum_{j\in M}\sum_{k\in N_{i,j}} x_{ij}^k = 1 \tag{19}$$

where x_{ij}^k denotes the transport mode k chosen between i and j, $x_{ij}^k \in \{0,1\}$. Equation (19) indicates that only one transport mode can be chosen between any i to any j. $N_{i,j}$ represents the set of transport modes available for selection between nodes i and j in the optimization context.

2) Number of transport mode switching

$$\sum_{k,l\in N} y_i^{kl} \le 1,\ \forall i \in M \setminus \{O, D\} \tag{20}$$

where y_i^{kl} denotes the switching of the transport mode at point i, $y_i^{kl} \in 0, 1$. $M \setminus \{O, D\}$ denotes the complement of $\{O, D\}$ in M. Equation (20) indicates that the shipments are switched up to once in the transport mode at any node i.

3) Flow conservation constraint

$$\sum_{l\in N_{i,j'}} g_{ij'}^l - \sum_{k\in N_{j'',i}} g_{j''i}^k = 0,\ \forall i \in M \setminus \{O, D\};\ j' \in M_{(i)}^+;\ j'' \in M_{(i)}^- \tag{21}$$

where $M_{(i)}^-$ and $M_{(i)}^+$ are the sets of nodes forward and backward of node i on the route, respectively. Equation (21) is a flow-holding constraint that ensures that the quantity of shipments remains constant as transported between the previous and subsequent nodes.

4) Continuity of transport modes

$$\begin{aligned} &\sum_{k\in N_{j'',i}} x_{j''i}^k - \sum_{k,l\in N} y_i^{kl} \ge 0,\ \forall i \in M \setminus \{O, D\};\ j'' \in M_{(i)}^- \\ &\sum_{k,l\in N} y_i^{kl} - \sum_{l\in N_{i,j'}} x_{ij'}^l = 0,\ \forall i \in M \setminus \{O, D\};\ j' \in M_{(i)}^+ \end{aligned} \tag{22}$$

Equation (22) indicates that if shipments reach node i through transport mode k, then at node i, the shipment can only switch from mode k to another transport mode. Since the multimodal transport process finishes when the shipment arrives at the destination, $i \ne D$. Similarly, the origin is the first node of the route, which makes no sense to impose a constraint on the continuity of the transport mode, so $i \ne O$.

5) Detention time constraints for shipments

$$Cr\left\{\sum_{i\in M\backslash\{D\}} \tilde{T}_i^s y_i^{kl} \leq T_a\right\} \geq \theta \tag{23}$$

During transportation, additional inventory management and labor costs are incurred when shipments switch modes in nodes due to waiting for scheduling and queuing. If the waiting time exceeds the carrier's acceptance level, they may opt not to switch modes or choose an alternative route. Therefore, we impose constraints on the total waiting time of shipments within nodes during transportation to ensure the feasibility of route planning.

In Equation (23), T_a denotes the carrier's maximum acceptance of waiting time. $Cr\{\cdot\}$ denotes the confidence level associated with the event that the uncertain waiting time $\tilde{T}_i^s$ does not surpass the carrier's maximum acceptance level. This confidence level should adhere to the predetermined threshold $\theta \in [0, 1]$, which can be determined based on the preferences of the decision maker.

6) 0-1 variables

$$x_{ij}^k = \{0, 1\},\ \forall i, j \in M,\ i \neq D,\ j \neq O;\ \forall k \in N_{i,j} \tag{24}$$

$$y_i^{kl} = \{0, 1\},\ \forall i \in M;\ \forall k, l \in N \tag{25}$$

x_{ij}^k and y_i^{kl} are 0-1 variables used in the mathematical modeling of the system to determine the selection of transport modes and mode switching.

4.2. **An exact solution strategy based on chance-constrained planning.** The NLU-MTRP fuzzy model is grounded in a specific multimodal transportation route planning problem and includes non-linear components, such as the load inside each node, which determines the waiting time of shipments and complicates problem-solving. Due to this non-linearity, solutions often converge to local optima, extending the optimization search process. To address this, the chapter proposes performing an equivalent linear reconstruction of the non-linear equations, enhancing the model's tractability and making it amenable to mathematical programming techniques.

Building on the linear reconstruction approach discussed earlier, this paper employs chance-constrained planning as a strategic method to address the non-linearity introduced by node load uncertainties. Grounded in credibility theory, this planning method enables more flexible decision-making by allowing constraints to be satisfied in a probabilistic manner, rather than absolutely.

Triangular fuzzy variables are frequently utilized in route optimization problems to handle uncertainty. Uncertain parameters are transformed into a degree of membership function by providing upper and lower bounds and maximum possible values, which can be obtained empirically or from previous data. In this paper, we denote the uncertain node loads as $\tilde{L}_i^k = (L_1, L_2, L_3)$ with triangular fuzzy variables, where $L_1 < L_2 < L_3$. L_1, L_3 denote the upper and lower bounds of the node loads, and L_2 denotes the most probable node loads. From this, the confidence level can be expressed as Equation (26), where L_i^k denotes the actual load at node i in mode k.

$$Cr\left\{L_i^k \leq \tilde{L}_i^k\right\} = \begin{cases} 1, & \text{if } L_i^k < L_1 \\ \dfrac{2L_2 - L_1 - L_i^k}{2(L_2 - L_1)}, & \text{if } L_1 \leq L_i^k < L_2 \\ \dfrac{L_3 - L_i^k}{2(L_3 - L_2)}, & \text{if } L_2 \leq L_i^k < L_3 \\ 0, & \text{if } L_i^k \geq L_3 \end{cases} \tag{26}$$

The piecewise function and constraints can be linearized based on the confidence levels shown in Equation (26) and the uncertain node loads in the fuzzy model can be converted into quantification at different confidence levels, given in Equation (27).

$$\tilde{L_i^k} = \begin{cases} 2\theta L_2 + (1-2\theta)L_1, & \text{if } 0 \le \theta \le 0.5 \\ (2\theta-1)L_2 + 2(1-\theta)L_3, & \text{if } 0.5 < \theta \le 1 \end{cases} \tag{27}$$

Then Equations (16), (17), and (23) which contain the fuzzy variable can be transformed into Equations (28)-(30).

$$T = \sum_{i\in M}\sum_{j\in M}\sum_{k\in N} T_{ij}^k x_{ij}^k + \sum_{i\in M}\sum_{j\in M}\sum_{k\in N}\sum_{l\in N} T_i^{kl} y_i^{kl} + \sum_{i\in M} T_i^s y_i^{kl} \tag{28}$$

$$\sum_{i\in M\backslash\{D\}} T_i^s y_i^{kl} \le T_a \tag{29}$$

$$\begin{gathered} T_i^s = \begin{cases} \left\lfloor \left(T_i + t_i^k\right)/t_i^k \right\rfloor \times t_i^k - T_i, & T_i^q \le \left\lfloor \left(T_i + t_i^k\right)/t_i^k \right\rfloor \times t_i^k - T_i \\ \left\lceil \left(T_i^q + T_i\right)/t_i^k \right\rceil \times t_i^k - T_i, & T_i^q > \left\lfloor \left(T_i + t_i^k\right)/t_i^k \right\rfloor \times t_i^k - T_i \end{cases} \\ \text{where } T_i^q = \begin{cases} \left(2\theta L_2 + (1-2\theta)L_1 + g_{ij}^k\right)/V_i^k, & \text{if } 0 \le \theta \le 0.5 \\ \left((2\theta-1)L_2 + 2(1-\theta)L_3 + g_{ij}^k\right)/V_i^k, & \text{if } 0.5 < \theta \le 1 \end{cases} \end{gathered} \tag{30}$$

5. An Improved Cooperative Coevolutionary Genetic Algorithm for Solving NLU-MTRP.

This study requires a nuanced optimization strategy due to the complex interplay between customer satisfaction, transportation costs, and carbon emissions. However, the traditional single-objective genetic algorithm faces inherent challenges in solving this multifaceted problem. To address these complexities, the Cooperative Coevolutionary Genetic Algorithm (CCGA) is employed to provide a tailored solution to the multi-objective nature of the problem at hand.

5.1. Introduction of improved CCGA.

CCGA is a variant of the genetic algorithm. Its basic idea involves decomposing the entire problem into relatively independent subproblems. Independent sub-populations are assigned to each sub-problem. These subpopulations collaborate through independent evolution and information exchange to achieve multi-objective optimization.

CCGA has the advantage of optimizing multiple subproblems in parallel, which balances the independence of each subproblem with global co-evolution, resulting in improved overall search efficiency. However, the algorithm cannot be directly used to solve route planning and transport mode combination optimization, because random crossover and mutation cannot guarantee the quality of the solution in the search. Therefore, we introduce a deep search algorithm to improve the crossover and mutation strategy according to the problem characteristics. The improved algorithm is made available for solving NLU-MTRP while retaining the advantages of parallel optimization.

5.2. Encoding strategy of improved CCGA.

The problem of multimodal transport planning involves the selection of transit nodes and transport modes. In this paper, we utilize the position-value coding depicted in Figure 4. Each individual's length is denoted by n.

Figure 4 shows how an individual can be broken down into two parts of encodings that contain routes and transport modes based on the location and value of non-zero values. The individual's path can be determined by locating the position of '1' in the path encoding sequence: 1-3-5-6-8. The non-zero values on the 2nd to nth positions of the individual indicate the mode of transportation used between the nodes. In the transport

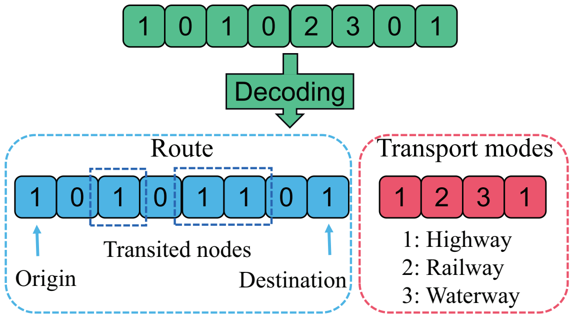

FIGURE 4. Principle of individual coding

encoding, '1' denotes highway, '2' denotes railway, and '3' denotes waterway. Finally, the individual can be decoded as follows: 1 for highway, 3 for railway, 5 for waterway, 6 for highway, and 8 for an unknown type of transportation.

5.3. **Search strategies for improved CCGA.**

5.3.1. *Depth-first search algorithm.* The Depth-First Search algorithm (DFS) is a classical graph search algorithm that systematically traverses the nodes in a graph and explores the branching structure of the graph in a depth-first manner. DFS is used for solution repair to ensure the validity of the routes obtained from the search, as the route of individuals may have a probability of failure during the search process, meaning that the produced route may not reach the destination.

5.3.2. *DFS-based crossover operator.* The improved crossover operator comprises two parts: crossover and repair. 1) Crossover: Two individuals in the parent population are randomly selected for crossover. As depicted in Figure 5(a), two points are randomly chosen from the genes of the two individuals, I_1 and I_2 (excluding the origin and destination points), and the gene segments between the two points are crossed. 2) Repair: If the route coding of an individual fails at the crossover, the DFS and roulette strategy are used to repair the individual. To avoid greedy solving, we will first apply the roulette selection to the set of routes derived from the DFS based on the number of nodes constituting the route. Then, we will update the individuals by randomly selecting transport modes for the newly generated routes according to the limit of available transport modes. The repair strategy is repeated until the route given by the individual is valid.

In Figure 5(b), if the decoding results in an invalid route of 1-3-4-8, the repair strategy is applied to the breakpoints between nodes 4 and 8 on the route. Assuming the repair

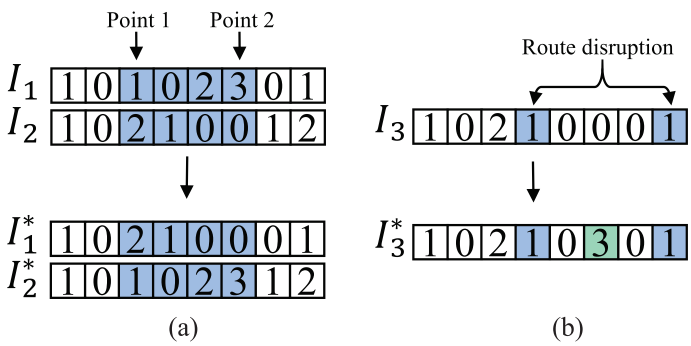

FIGURE 5. Improved crossover operator

strategy generates the route 4-6-8 and the randomly generated mode is the waterway, the individual I_3 can be adjusted to I_3^*, which represents the multimodal transportation route planning as follows: 1-railway-3-roadway-4-waterway-6-roadway-8.

5.3.3. *DFS-based mutation operator.* During iterative optimization search, individuals may undergo mutations in their routes and transport modes. This involves randomly selecting a position from an individual that is not 0 and changing the transport mode or route in conjunction with the transport mode constraints.

Figure 6 illustrates two possible ways of mutation. If an individual is mutated, a non-zero position on the individual is randomly selected as a mutation point, and the number on the mutation point is randomly mutated to an integer between 0 and 3, depending on the constraints. In Figure 6(a), when the mutation is set to 0, the route is repaired using DFS, during which both the route and the transport mode undergo mutation. In contrast, Figure 6(b) illustrates that only the transport modes between nodes are mutated, leaving the individual routes unchanged.

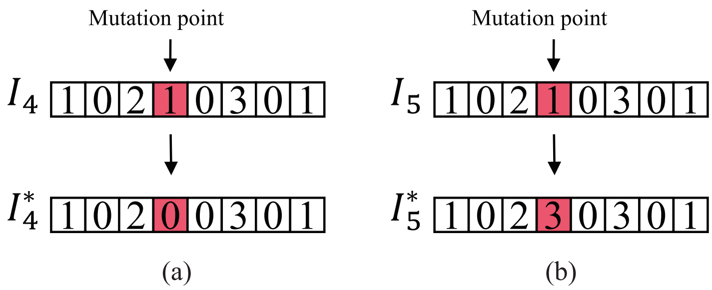

FIGURE 6. Improved mutation operator

Building upon the descriptions in Sections 5.1 to 5.3, this paper decomposes multimodal route planning into three distinct subproblems: cost minimization, customer satisfaction maximization, and carbon emission minimization. Each of these subproblems is then optimized using the CCGA framework as outlined in Table 2.

6. **Example Analysis.**

This paper presents a case study of a multimodal transportation network that includes 15 cities in China. Figure 7 illustrates the network, and Table 3 displays the available transport modes between nodes and the corresponding distances.

6.1. **Parameter setting.** To validate the model, we utilized the proposed NLU-MTRP to plan the multimodal transportation route from Nanning to Harbin. Table 4 displays the unit transportation prices, carbon emission factors, costs, and carbon emissions during mode switching for different transportation modes in the multi-objective multimodal route planning model. All experiments were conducted in the MATLAB 2021a environment on a personal laptop with a 12th Gen Intel(R) Core(TM) i7-12700H 2.70 GHz processor running Windows 11.

6.2. **Results analysis.** In the case study, the shipment volume was assumed to be twenty tons, and the confidence level was 0.9. The customer's preference for delivery time T^E, T^e, T^l, and T^L are set to 50, 80, 110, and 140 hours, respectively. The carrier's acceptance of waiting time T_a is set to 15 hours. The multimodal transportation route from Nanning to Harbin was solved using the ICCGA algorithm in the given example. Table 5 displays the delivery cost (in CNY), total carbon emissions (in kg), customer satisfaction (in %), and corresponding multimodal transport routes for each solution. The transportation modes are denoted by H for highway, R for railway, and S for waterway.

Table 2. Framework of ICCGA

Initialization:
  Set sub-population size X
  Set number of sub-populations Y
  Set maximum number of iterations Z
  Randomly generate Y initial sub-populations, each with X individuals
  Calculate the fitness of each sub-population
  iter = 0
While iter $< Z$ **do:**
  Parallel evolution of sub-populations:
    Parfor i to Y **do:**
      Execute elite retention strategy to select parent from remaining individuals
      Perform crossover and mutation operations
      If individual routes fail **then:**
        Perform repair strategy
      End if
      Calculate individual fitness, sort
    End Parfor
  iter = iter + 1
Cooperative evolution:
  Select the most dominant individual from each sub-population
  Replace the most dominant individuals in each sub-population
  Recalculate and rank the fitness of the sub-populations
  Adjust the size of the sub-populations, update
End While
Calculation of non-domination:
  Merging sub-populations
  Calculate individual fitness
  Calculate the non-dominated sorting and crowding of individuals
Output:
  Output the set of non-dominated solutions I
End

Based on the analysis results, increasing delivery costs can effectively reduce carbon emissions during transportation. The scenarios demonstrate a 100% customer satisfaction rate due to the implementation of a soft time window, making it easier for logistics companies to choose trade-off solutions that align with their cost or carbon emission preferences.

After comparing trade-off solutions 1-6, it is clear that highway transportation has the lowest unit costs, making it the preferred choice for logistics companies in practical scenarios. However, it is important to note that the solution that relies heavily on highway transport results in higher carbon emissions. For instance, many domestic logistics companies in China often use traditional single-mode transportation to minimize handling and reduce costs, but this may not always be the most cost-effective option. Table 6 displays the minimum transportation costs and carbon emissions for highway and railway transportation.

Logistics firms often prioritize minimizing transportation time, which makes the soft time window less suitable for assessing customer satisfaction in traditional transportation

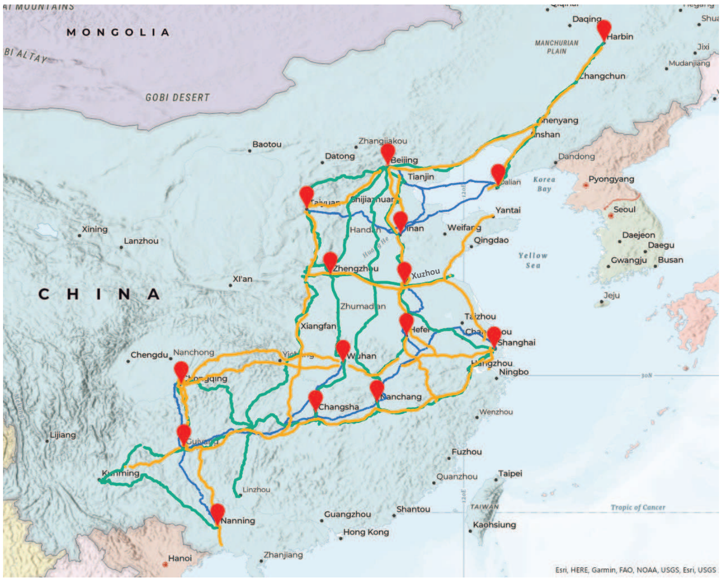

FIGURE 7. Example network

TABLE 3. Distance in transport modes

Link	Distance			Link	Distance		
	H	R	S		H	R	S
Nanning—Guiyang	604	875	105	Hefei—Jinan	675	614	–
Nanning—Chongqing	986	1338	422	Shanghai—Zhengzhou	942	998	–
Guiyang—Nanchang	1156	1264	337	Shanghai—Taiyuan	1356	1497	–
Guiyang—Changsha	793	949	–	Shanghai—Beijing	1206	1328	–
Chongqing—Wuhan	932	1159	658	Xuzhou—Zhengzhou	366	349	–
Chongqing—Hefei	1285	1492	1322	Xuzhou—Taiyuan	775	926	–
Nanchang—Shanghai	728	807	–	Xuzhou—Beijing	695	814	–
Nanchang—Xuzhou	743	817	–	Jinan—Zhengzhou	446	668	–
Nanchang—Jinan	1056	1162	–	Jinan—Taiyuan	526	529	497
Changsha—Shanghai	1066	1173	398	Jinan—Beijing	410	495	1026
Changsha—Xuzhou	993	1247	–	Zhengzhou—Harbin	1976	2139	–
Changsha—Jinan	1181	1291	–	Taiyuan—Beijing	491	568	612
Wuhan—Shanghai	821	811	–	Taiyuan—Dalian	1304	1452	1168
Wuhan—Xuzhou	641	595	572	Taiyuan—Harbin	1774	1846	–
Wuhan—Jinan	846	976	–	Beijing—Dalian	840	938	697
Hefei—Shanghai	437	457	–	Beijing—Harbin	1288	1278	–
Hefei—Xuzhou	318	295	–	Dalian—Harbin	1032	946	–

TABLE 4. Parameters in the example

Mode	u^k	h_i^{kl}			e^k	e^{kl}			Schedule intervals	Throughput speed	Fuzzy loads
		H	R	S		H	R	S			
H	0.162	0	8	9	0.0440	0	0.128	0.117	0.5h	60t/h	(120t, 150t, 180t)
R	0.491	8	0	10	0.0127	0.128	0	0.113	4h	120t/h	(800t, 1000t, 1200t)
S	0.462	9	10	0	0.0091	0.117	0.113	0	12h	400t/h	(2000t, 3000t, 4000t)

Table 5. Trade-off solutions

Solutions	Cost	Carbon emissions	Customer satisfaction	Transportation routes
1	13096.32	5121.876	100	Nanning—S—Guiyang—S—Nanchang—H—Xuzhou—H—Beijing—H—Harbin
2	18891.94	4335.471	100	Nanning—S—Guiyang—S—Nanchang—R—Xuzhou—H—Beijing—H—Harbin
3	21356.44	4052.946	100	Nanning—S—Guiyang—S—Nanchang—R—Jinan—H—Beijing—H—Harbin
4	21723.88	3718.366	100	Nanning—S—Guiyang—S—Nanchang—H—Jinan—H—Beijing—R—Harbin
5	29893.28	2600.156	100	Nanning—S—Guiyang—S—Nanchang—R—Jinan—H—Beijing—R—Harbin
6	33105.78	2187.761	100	Nanning—S—Guiyang—S—Nanchang—R—Jinan—R—Beijing—R—Harbin

Table 6. Traditional modes of transportation

Mode	Cost	Carbon emissions	Transportation routes
Highway	13854.24	7525.76	Nanning—Guiyang—Changsha—Jinan—Beijing—Harbin
Railway	48000.16	3103.88	Nanning—Guiyang—Changsha—Jinan—Beijing—Harbin

schemes. To provide a comprehensive comparison, we will focus on contrasting transportation costs and carbon emissions between single-mode and multimodal transportation solutions while setting aside customer satisfaction.

Compared to water-highway Combined Transportation (Solution 1), single-mode highway transportation lacks advantages in both cost and carbon emissions. This not only increases logistics expenditures but also poses a significant challenge to environmental conservation.

Similarly, when compared to rail-waterway Combined Transportation (Solution 4), single-mode railway transportation is not cost-effective and environmentally friendly. This highlights the advantages and necessity of multimodal transportation.

Furthermore, all solutions in Table 5 use water transport for the Nanning—Guiyang—Nanchang transport segment, ensuring that shipments reach customers within the most satisfactory time frames. This suggests that sacrificing transport time to save costs may be economically viable in some network segments.

The NLU-MTRP model is a valuable tool for reducing logistics costs, improving logistics service quality, and promoting environmentally friendly logistics development. By adhering to green logistics requirements, this model helps mitigate the negative environmental impacts of logistics and transportation processes. It aids decision-makers in logistics companies with multimodal route planning based on cost and carbon emission preferences.

6.3. **Sensitivity analysis and comparison of algorithms.** Due to variations in estimated values of fuzzy node loads under different confidence levels, corresponding transportation times are also expected to vary. This section aims to discuss the changes in estimated transportation times for shipments under different confidence levels, in order to offer decision-makers clearer insights for making decisions. This will assist decision-makers in better meeting the diverse needs of various customers.

6.3.1. *Analysis of transportation time with fuzzy loads.* In the previous section, we conducted a case analysis under the given confidence level condition ($\theta = 0.9$), where confidence level affects both the delivery time and waiting time of shipments. To reveal the impact of estimated node loads on carrier route decisions under different confidence levels, we analyzed the variations in shipment waiting time as the traffic mode load level increased. Taking solutions 1, 2, and 5 from Table 5 as examples, Figure 8 illustrates the effects of increasing node loads in three multimodal transportation modes (H-S, H-R-S, H-R) on waiting time.

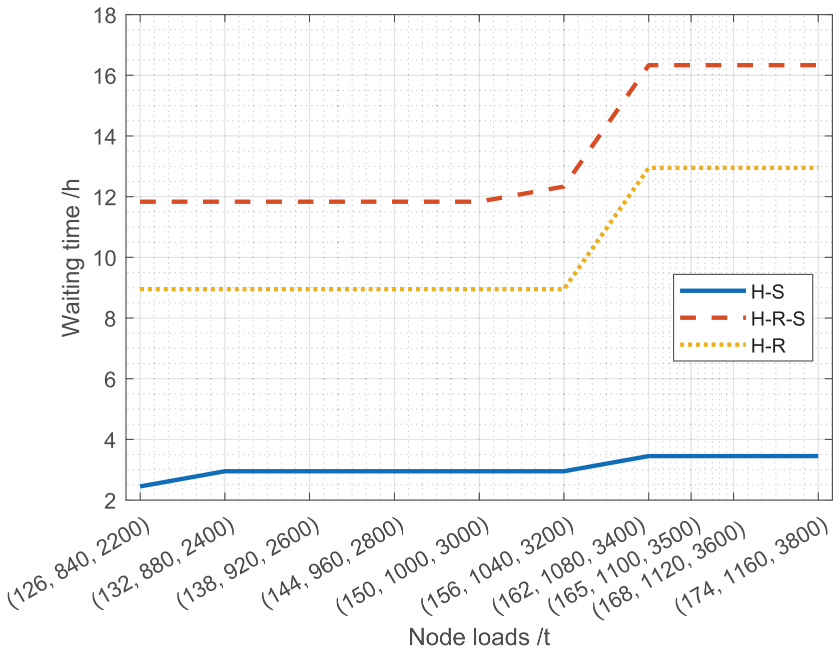

FIGURE 8. Estimation of waiting time at different node loads

In Figure 8, the x-axis scale in parentheses represents the estimated values of the three transportation modes under confidence levels. Among the three solutions, Solution 1 (H-S) involves one transition from water transportation to road transportation, Solution 2 (H-R-S) involves one transition from water to rail and one transition from rail to road, and Solution 5 (H-R) involves one transition from water to rail. As waiting for shipments occurs only during mode transitions, solutions with more mode transitions are more significantly affected by node loads. Therefore, the waiting time corresponding to Solution 2 (H-R-S) is the highest among the solutions.

The numerical changes in the curves indicate that when node loads increase, waiting time may not necessarily increase. This is because the waiting time for shipments is not only influenced by queuing time but also constrained by the transportation schedule. Even if shipments do not need to wait in a queue, they still need to wait for the arrival of vehicles. Comparing the three solutions, in H-S and H-R solutions, the waiting time for shipments increases by 0.5 and 4 hours, respectively, corresponding to road and rail schedules. In the H-R-S solution, the waiting time increases by 0.5 and 4 hours, which reflects the impact of differences in the capacity to handle shipments by highway and railway on waiting times.

The above analysis indicates that both schedule and node loads significantly impact the waiting time for shipments, and considering both schedule and node load becomes more necessary as the number of mode switching increases.

6.3.2. *Algorithm comparison.* To validate the effectiveness of the proposed algorithm, this section compares the ICCGA algorithm proposed in this paper with the commonly used Non-dominated Sorting Genetic Algorithm II (NSGA-II) for solving multimodal transportation problems in terms of solution quality and computational speed. In Figure 9, we adjusted the y-axis direction to provide a clearer representation with points located towards the left side of the graph indicating more favorable solutions. Based on the distribution of points, it appears that the ICCGA algorithm is more effective than NSGA-II. The solutions generated by ICCGA are located further to the left. The processing times for both algorithms were measured under identical parameter conditions, with NSGA-II taking 1.475225 seconds and ICCGA taking 0.859640 seconds to process the given example. ICCGA's parallel optimization capabilities improve solution efficiency, resulting in faster and higher quality solutions for multimodal transportation path planning problems.

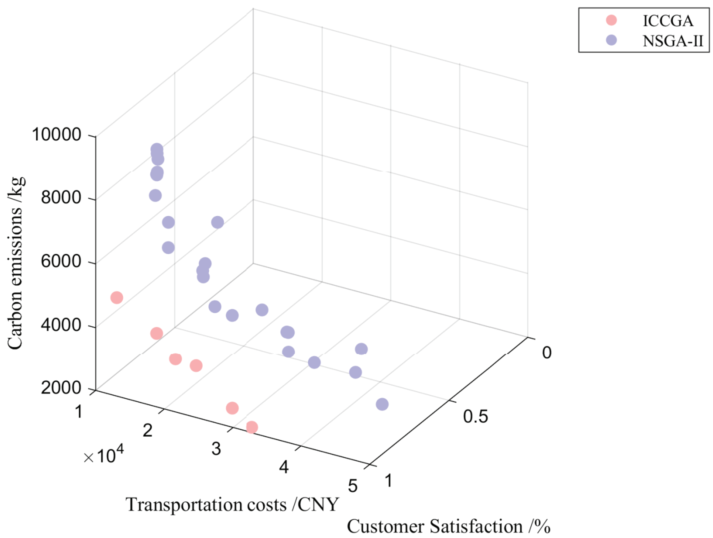

Figure 9. Comparison of ICCGA and NSGA-II algorithms

7. **Conclusions.** This study proposes a chance-constraints multimodal transportation route planning model that considers fuzzy node loads, where the waiting time for shipments, influenced by queuing and transport schedules, is taken into account in customer satisfaction modeling. The objective of this model is to optimize delivery costs, customer satisfaction, and carbon emissions in multimodal transportation.

Through case studies, we have confirmed the efficacy of the proposed model. In contrast to single-mode transportation, the multimodal solutions obtained demonstrate greater cost efficiency and reduced carbon emissions, all the while ensuring customer satisfaction. Our research underscores the imperative of accounting for uncertain node loads and real-world transportation schedules in multimodal transportation route planning. In the case solution, the estimated node loads at different confidence levels resulted in wait times ranging from 2.5 to 16 hours, which not only significantly impacted customer satisfaction with delivery times, but also played a key role in the carrier's routing decisions. Additionally, a performance comparison with the NSGA-II algorithm highlights the efficiency and effectiveness of the proposed improved cooperative coevolutionary genetic algorithm.

However, this work still has limitations. For instance, different types of shipments in transportation may have different queue waiting time requirements, and there may be a priority order for processing shipments at nodes. Future research can expand on this work by considering multimodal transportation with mixed types of shipments, which would advance the development of multimodal transportation.

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