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Optimization of Multimodal Transport Routes Considering Carbon Emissions in Fuzzy Scenarios

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Abstract

In view of the optimization of multimodal transport path under the uncertainty of time window and demand, the multi-objective fuzzy opportunity constraint model is established by using keystone fuzzy number to represent fuzzy demand and fuzzy time window, considering carbon emission and transportation costs and customer satisfaction. The fixed crossover and mutation probability will directly affect the convergence of the algorithm. For this problem, the adaptability is combined with the NSGA-II algorithm, and the effectiveness of the proposed model and algorithm is verified by comparison with CPLEX. And based on the mandatory carbon emission model, the optimal paths of multiple orders are obtained through the adaptive NSGA-II algorithm.

Keywords

Multimodal Transportation; Path Optimization; Trapezoidal Fuzzy Number; Fuzzy Chance Constrained Model; Adaptive NSGA-II Algorithm.

1. Introduction

The rapid development of the global economy and the deepening of international trade have rapidly led to the development and improvement of multimodal transport, but at the same time, it has also led to increasingly serious problems of environmental pollution and energy shortages. Global warming caused by greenhouse gas emissions has become a common concern of the whole society. Right serious problem. In the global carbon emission statistics, transportation accounts for up to 14%, while road carbon emissions account for 70% of the carbon emissions of the entire transportation sector [1]. Under this situation, many countries have proposed to levy a carbon tax on carbon dioxide emissions for the purpose of protecting the environment.

In recent years, low-carbon and environmental protection topics in multimodal transport have emerged one after another. Figliozzi [2] pointed out that despite the increasing use and impact of commercial vehicles, few studies have made reducing emissions a primary goal of the routing problem. CarisA[3] believes that in addition to the consideration of terminal network design, multimodal transport service network design, and multimodal transport routes, environmental issues should also be added to the multimodal transport decision modeling. Therefore, carbon emissions are one of the essential factors in the model. Yuan Xumei[4] established an interval-based robust optimization model for the path optimization problem of fuzzy demand under different carbon emission policies. Fahimnia[5] proposes a strategic supply chain planning model that integrates economic and carbon emissions targets under a carbon tax policy program. Jiang Qiwei [6] explored the problem of route optimization of container multimodal transport with uncertain transportation time, and showed that the gradual increase in carbon tax value can effectively promote multimodal transport freighters to choose a lower-carbon transport scheme, which can be beneficial to the economy and the environment. favorable results. However, the research on the vehicle routing

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problem considering carbon emissions started late, and most of the research is only limited to the vehicle routing problem in a certain environment. Liao et al. [7] compared the CO2 emissions of truck-only transport with multimodal coastal transport and showed that replacing long-distance trucking with intermodal transport can significantly reduce CO2 emissions. Pizzol[8] has further verified that multimodal transportation is more energy-saving and emission-reducing than single transportation. Jiang Lingqian et al. [9] analyzed the influencing factors of carbon emissions and established a carbon emission calculation model for sea-land multimodal transport, and concluded that the "rail-sea-rail combined transport" model is the optimal solution.

With the accelerating pace of society, the operational efficiency of major industries is constantly improving, and consumers have put forward more personalized and refined service requirements. The related research on multimodal transportation has gradually shifted from deterministic problems to uncertain ones. Cheng and Gen [10] first proposed the vehicle routing problem with fuzzy appointment time, and studied the vehicle routing in the case of single-to-single cargo delivery and reception. problem. Li Jing and Shao Jing [11] modeled the VRP problem of multiple fuzzy time windows in pharmaceutical logistics, and introduced multiple fuzzy time windows to evaluate customer satisfaction. Based on the credibility theory, Goncalves et al.[12] used fuzzy simulation and intelligent algorithm to solve the path optimization problem with time window by establishing a fuzzy chance compensation model. Peng Yong, Xiao Yunpeng [13] etc. deal with the uncertainty in the multimodal transport network through the Monte Carlo method, and design a multi-objective ant colony algorithm based on non-dominated sorting to solve it. In addition, Geng Nana, He Yan et al. [14] took the multimodal transport route optimization of China-Europe trains under uncertain conditions as the research object, established a dual-objective optimization model, solved and verified the effectiveness of the model. Shi et al[15] considered the scheduling problem of family medical drugs with fuzzy demand, constructed a fuzzy chance constraint model, and proposed a solution method combining a hybrid genetic algorithm and a stochastic simulation method. Xie Jing, Lin Guolong et al. [16] introduced triangular fuzzy numbers to solve the problem of multimodal transport route selection in the case of fuzzy demand, and used the stepwise method to solve the model. However, triangular fuzzy numbers lack flexibility. Sun et al.[17] used trapezoidal fuzzy numbers to represent fuzzy demands, and took multiple transportation orders as optimization objects, established a fuzzy mixed integer nonlinear programming model, and used linearization technology to reconstruct the clear model. It is finally solved by standard mathematical programming software.

At present, stochastic programming and fuzzy programming are usually used to express uncertainty parameters, but in most cases, there is not enough data for decision makers to fit the probability distribution of demand, so the feasibility of stochastic programming is low. At the same time, triangular fuzzy numbers are commonly used in most fuzzy programming literature, but the maximum value of their membership degree can only correspond to one point, which is only suitable for a well-defined range. In contrast, trapezoidal fuzzy numbers are more flexible, and their membership degree is more The maximum value can correspond to an interval, allowing different decision makers to hold different opinions on the most likely value, which can better match the actual situation. Therefore, this paper uses a more flexible trapezoidal fuzzy number to represent the fuzzy demand and fuzzy time window, and studies the multimodal transport problem with multiple fuzzy parameters.

2. Problem Description and Model Building

2.1 Problem Description

As shown in Figure 1, the multimodal transport path optimization problem under the fuzzy scenario can be expressed as: in a transport network composed of several nodes, the nodes can be connected in two directions or one way, and there are at most three modes of transportation between any two nodes: road, water and railway. The transportation distance, transportation cost and carbon dioxide emissions corresponding to different transportation methods are different. A batch of goods with uncertain demand should be transported from the designated starting point to the corresponding

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destination. The transportation can pass through several intermediate nodes, and can be transferred several times or directly. The ever-changing market makes it difficult for customers to determine the exact demand and delivery time in advance, so the trapezoidal fuzzy number is introduced to represent the fuzzy demand and time window. In the whole transportation process, with the goal of minimizing transportation cost and carbon emission cost and maximizing customer satisfaction, the transportation route of the order is optimized, and a satisfactory transportation plan is obtained.

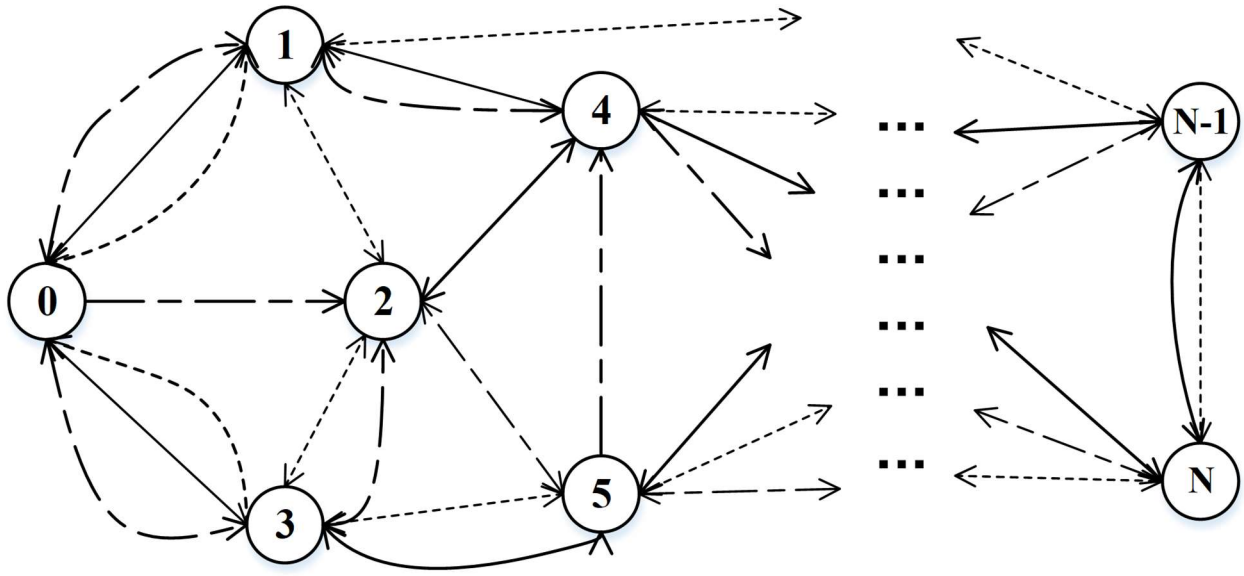

Figure 1. Multimodal transport network diagram

2.2 Model Assumptions

The thesis model is based on the following assumptions:

(1) Only one mode of transportation can be selected between two adjacent nodes;

(2) There is no transshipment capacity limit for each node, and cargo damage is not considered during transportation;

(3) The goods will be sent to the next destination after the transfer is completed at the node, regardless of storage costs;

(4) The order goods cannot be separated during transportation.

2.3 Symbol Description

For the convenience of modeling, the following notation definitions are introduced:

ISSN: 2414-1895 DOI: 10.6919/ICJE.202204_8(4).0035

Table 1. Decision variables and Parameter Description

Collections and Indexes			
N	A collection of transport network nodes (i, j ∈ N)		
L	Set of intermediate nodes		
M	The set of transport modes (m,l,k∈M), where m, l, k represent road, rail and water transport respectively		
parameter			
O	starting point for transport tasks	C^m	unit transportation cost of transportation mode m
D	The destination of the transport mission	d_{ij}^m	Using transport mode m, transport distance between transport arcs (i , j)
A_m	Fixed fee for shipping method m	co^{ml}	The unit carbon emission in the process of converting from m to l of transport mode
V_m	Average travel speed of transport mode m	h^{ml}	Transit cost to convert from m to l
U_a	The maximum value that total carbon emissions	T^{ml}	Transit time to convert the mode of transport from m to l
T_j	The time when the goods arrive at node j	EET	The earliest time the customer can tolerate the arrival of the goods
SA	Customer satisfaction with delivery time	LLT	The latest time the customer can tolerate the arrival of the goods
β	Minimum ustomer satisfaction	ET	The earliest time the customer expects the goods to arrive
e_m	Carbon emissions per unit of transport mode m	LT	The latest time when the customer most expects the goods to arrive
$\tilde{e}=(e_1,e_2,e_3,e_4)$	Client's Fuzzy Demand		
Decision variables			
x_{ijm}	Transportation decision variable, take 1 when the goods are transported from node i to j by transportation mode m, otherwise take 0		
y_{iml}	Transit decision variable, it takes 1 when the transportation mode of node i is converted from m to l, otherwise it takes 0		

2.4 Representation of Fuzzy Quantity

Fuzzy time window: The time when the customer can accept the arrival of the goods can be divided into different time periods, and the satisfaction is different in different time periods. As shown in Figure 2 [18], when the arrival time of the goods is within the range of [ET, LT], the corresponding customer satisfaction is 1, which is the time window when the customer most expects to receive the goods. When the arrival time of the customer's goods is within the range of [EET, ET) or (LT, LLT], the corresponding customer satisfaction increases and decreases linearly with time, respectively; when the arrival time of the goods exceeds the range of [EET, LLT] , beyond the upper and lower limits of the maximum tolerance time, the customer does not accept the service, and the customer satisfaction is 0. Therefore, the membership function of the time window is used to represent the customer satisfaction, as shown in formula (1).

ISSN: 2414-1895 DOI: 10.6919/ICJE.202204_8(4).0035

$$SA = \begin{cases} 0 & T_D \notin [EET, ELT] \\ \dfrac{T_D - EET}{ET - EET} & T_D \in [EET, ET] \\ 1 & T_D \in [ET, LT] \\ \dfrac{LLT - T_D}{LLT - LT} & T_D \in [LT, LLT] \end{cases} \tag{1}$$

In order to avoid the loss of customers due to low customer satisfaction, the minimum customer satisfaction is set to obtain the time window for cargo transportation. The calculation formula is as follows:

$$\begin{cases} Inf = ET \cdot \beta + ET \cdot (1-\beta) \\ Sup = LT \cdot \beta + LLT \cdot (1-\beta) \end{cases} \tag{2}$$

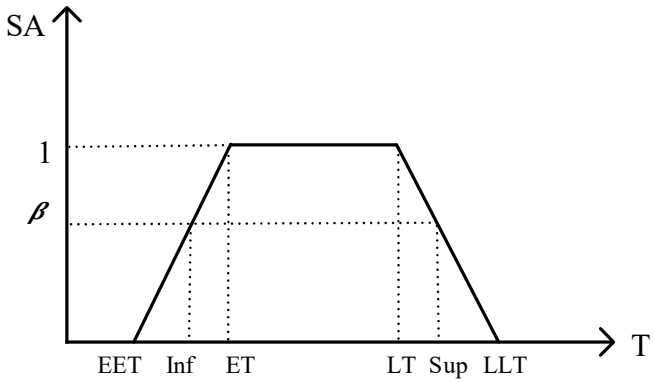

Figure 2. Customer satisfaction function diagram

Fuzzy demand: The needs of customers are gradually personalized, and the demand is no longer fixed. In this paper, the trapezoidal fuzzy number is used to represent the customer's fuzzy demand $\tilde{e}$.As shown in Figure 3, e_1 and e_4 are the most pessimistic and optimistic estimates, corresponding to very little and very large actual demand, respectively, and the probability of occurrence is extremely low. $[e_2, e_3]$corresponding to the most likely range of demand in reality, and most in line with the actual situation. Different decision makers can hold different views on the most probable interval of demand by changing the preference value of fuzzy demand θ. The trapezoidal fuzzy number $\tilde{e}$on the fuzzy demand preference value is $\tilde{e}_\theta = \{e | u_{\tilde{e}}(e) \geq \theta\}, \theta \in [0,1], [e_\theta^+, e_\theta^-]$ is the confidence interval of $\tilde{e}$ on the preference value of fuzzy demand, where $e_\theta^-$and e_θ^+ are the upper and lower bounds of the interval respectively [17], and formula (3) is the membership function of fuzzy demand.

$$u_{\tilde{e}}(e) = \begin{cases} 0 & e \notin [e_1, e_4] \\ \dfrac{e - e_1}{e_2 - e_1} & e \in [e_1, e_2] \\ 1 & e \in [e_2, e_3] \\ \dfrac{e_4 - e}{e_4 - e_3} & e \in [e_3, e_4] \end{cases} \tag{3}$$

ISSN: 2414-1895 DOI: 10.6919/ICJE.202204_8(4).0035

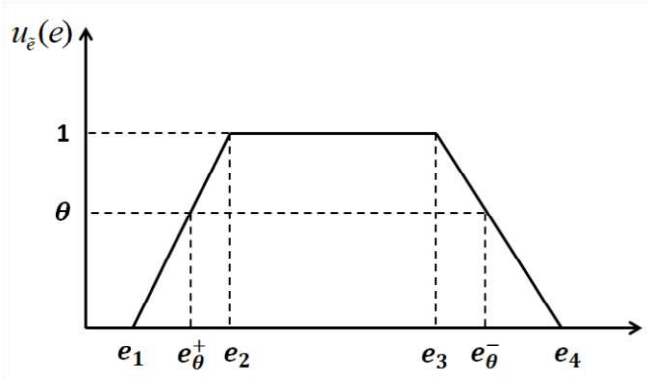

Figure 3. Fuzzy demand diagram

2.5 Objective Function

According to the above problem description, a multimodal transport route optimization model under the time window and demand fuzzy scenario and carbon mandatory emission policy is established. In the model, the minimum transportation cost and the maximum customer satisfaction are the goals, and the dual objective function is established as follows:

$$\begin{cases} min\ f_1 = Z_1 \\ max\ f_2 = Z_3 \end{cases} \tag{4}$$

Transportation costs: Transportation costs include fixed transportation costs, transportation distance costs and transit costs.

$$Z_1 = \sum_{i\in N}\sum_{j\in N}\sum_{m\in M} x_{ijm}A_m + \tilde{e}\left(\sum_{i\in N}\sum_{j\in N}\sum_{m\in M} x_{ijm}d_{ij}^m c^m + \sum_{i\in N}\sum_{m\in M}\sum_{l\in M} y_{iml}h^{ml}\right) \tag{5}$$

(2) Customer satisfaction: The customer satisfaction is expressed by the membership function of the customer time window, and different delivery times of the goods correspond to different satisfaction levels.

$$Z_2 = SA \tag{6}$$

There is no corresponding carbon emission cost under the carbon mandatory emission policy, but there are restrictions on the total carbon emission during transportation. The total carbon emission includes the carbon dioxide emitted during transportation and transit. The calculation formula is as follows:

$$S = \tilde{e}\left(\sum_{i\in N}\sum_{j\in N}\sum_{m\in M} e_m x_{ijm} d_{ij}^m + \sum_{i\in N}\sum_{l\in M}\sum_{m\in M} co^{ml} y_{iml}\right) \tag{7}$$

2.6 Constraints

$$\sum_{g\in N}\sum_{m\in M} x_{gO\mathrm{m}} - \sum_{j\in N}\sum_{m\in M} x_{\mathrm{Ojm}} = 1 \tag{8}$$

ISSN: 2414-1895 DOI: 10.6919/ICJE.202204_8(4).0035

$$\sum_{g\in N}\sum_{m\in M} x_{\mathrm{gim}} = \sum_{j\in N}\sum_{m\in M} x_{\mathrm{ijm}}, \forall i \in L \tag{9}$$

$$\sum_{g\in N}\sum_{m\in M} x_{g\mathrm{Dm}} - \sum_{j\in N}\sum_{m\in M} x_{\mathrm{Djm}} = -1 \tag{10}$$

$$x_{gim} + x_{ijl} \geq 2y_{iml}, \forall g, i, j \in N, m, l \in M \tag{11}$$

$$\sum_{m\in M}\sum_{l\in M} y_{iml} \leq 1, \forall i \in N \tag{12}$$

$$y_{Oml} = y_{Dml} = 0, \forall m, l \in M \tag{13}$$

$$T_j = T_i + \tilde{e}T^{ml} y_{iml} + x_{ijl} d_{ij}^{l} / v_l, \forall i, j \in N, m, l \in M \tag{14}$$

$$Inf \leq T_D \leq Sup \tag{15}$$

$$\sum_{m\in M} x_{ijm} \leq 1, \forall i, j \in N \tag{16}$$

$$S \leq U_a \tag{17}$$

$$x_{ijm}, y_{iml} \in \{0,1\}, \forall i, j \in N, m, l \in M \tag{18}$$

Equation (8) (9) (10) represents the node flow conservation; Equation (11) is the continuity constraint of the front and rear transportation modes, that is, when the node i is converted from the transportation mode m to l, it will reach i through m and leave i through l ; Equation (12) indicates that each batch of goods can only be transferred once at the same node; Equation (13) indicates that the start and end points of the order are not transferred; Equation (14) is the calculation formula for the time required for the goods to arrive at node j; Equation (15)) is the minimum customer satisfaction constraint; Equation (16) indicates that only one mode of transportation can be used between two adjacent nodes; Equation (17) indicates that the total amount of carbon dioxide emissions generated during transportation cannot exceed the specified upper limit; Equation (18)) is the value constraint for the decision variable.

Due to the fuzzy uncertainty of customer demand, constraint (14) is a fuzzy chance constraint, and the above model is a fuzzy chance constraint programming.

3. Model Solving

3.1 Fuzzy Chance Constraints based on Fuzzy Credibility

Fuzzy opportunistic constraint programming is a kind of uncertainty mathematical programming based on possibility theory and fuzzy set theory. The chance constraint is transformed into a deterministic form, that is, making the fuzzy clear [19], when given a certain number a and a trapezoidal fuzzy number, when the fuzzy confidence is adopted, they have the following relationship [20, 21]:

ISSN: 2414-1895 DOI: 10.6919/ICJE.202204_8(4).0035

$$Cr\left\{a \geq \tilde{b}\right\} = \begin{cases} 1 & a \geq b_4 \\ \dfrac{b_4 - 2b_3 + a}{2\left(b_4 - b_3\right)} & b_3 \leq a \leq b_4 \\ \dfrac{1}{2} & b_2 \leq a \leq b_3 \\ \dfrac{a - b_1}{2\left(b_2 - b_1\right)} & b_1 \leq a \leq b_2 \\ 0 & others \end{cases} \tag{19}$$

According to equation (19), the objective functions Z1, Z2 and the constraint (13) containing fuzzy numbers are clarified. From equation (19), it can be known that when θ∈ [0,0.5], the objective function Z1, Z2 can be transformed into equations (20) and (21), and constraints (13) can be transformed into equations (22).

$$Z_1 = \rho\left[2\theta e_2 + \left(1 - 2\theta\right)e_1\right]\left(\sum_{i\in N}\sum_{j\in N}\sum_{m\in M} e_m x_{ijm} d_{ij}^m + \sum_{i\in N}\sum_{l\in M}\sum_{m\in M} co^{ml} y_{iml}\right) \tag{20}$$

$$Z_2 = \left\{\sum_{i\in N}\sum_{j\in N}\sum_{m\in M} x_{ijm} A_m + \left[2\theta e_2 + \left(1 - 2\theta\right)e_1\right]\left(\sum_{i\in N}\sum_{j\in N}\sum_{m\in M} x_{ijm} d_{ij}^m c^m + \sum_{i\in N}\sum_{m\in M}\sum_{l\in M} y_{iml} h^{ml}\right)\right\} \tag{21}$$

$$T_j\text{-}T_i = T^{ml} y_{iml}\left[2\theta e_2 + \left(1 - 2\theta\right)e_1\right] + x_{ijl} d_{ij}^l / v_l, \forall i, j \in N, m, l \in M \tag{22}$$

When θ∈(0.5,1], the objective functions Z1, Z2 can be transformed into equations (23) and (24), and the constraints (13) can be transformed into equations (25).

$$Z_1 = \rho\left[2\theta\left(e_4 - e_3\right) - \left(e_4 - 2e_3\right)\right]\left(\sum_{i\in N}\sum_{j\in N}\sum_{m\in M} e_m x_{ijm} d_{ij}^m + \sum_{i\in N}\sum_{l\in M}\sum_{m\in M} co^{ml} y_{iml}\right) \tag{23}$$

$$Z_2 = \left\{\sum_{f\in F}\sum_{i\in N}\sum_{j\in N}\sum_{m\in M} x_{ijm}^f A_m + \left[2\theta_1\left(e_4 - e_3\right) - \left(\tilde{e}_4 - 2\tilde{e}_3\right)\right]\left(\sum_{i\in N}\sum_{j\in N}\sum_{m\in M} x_{ijm} d_{ij}^m c^m + \sum_{i\in N}\sum_{m\in M}\sum_{l\in M} y_{iml} h^{ml}\right)\right\} \tag{24}$$

$$T_j\text{-}T_i = T^{ml} y_{iml}\left[2\theta_2\left(\tilde{e}_4 - \tilde{e}_3\right) - \left(\tilde{e}_4 - 2\tilde{e}_3\right)\right] + x_{ijl} d_{ij}^l / v_l, \forall i, j \in N, m, l \in M \tag{25}$$

3.2 Linearization

Since customer satisfaction is a piecewise function, the DOCPLEX solver cannot be used directly to solve the model accurately, so this paper needs to introduce auxiliary variables to convert the customer satisfaction function into the following linear function:

$$\begin{cases} T_D = W_1 \cdot EET + W_2 \cdot ET + W_3 \cdot LT + W_4 \cdot LLT \\ SA = W_2 + W_3 \end{cases} \tag{26}$$

ISSN: 2414-1895 DOI: 10.6919/ICJE.202204_8(4).0035

Continuous variables and 0-1 variables satisfy the following relationship:

$$\begin{cases} W_1 + W_2 + W_3 + W_4 = 1 \\ R_1 + R_2 + R_3 = 1 \\ W_1 \le R_1, W_2 \le R_1 + R_2, W_3 \le R_2 + R_3, W_4 \le R_3 \\ 0 \le W_i \le 1, (i = 1,2,3,4) \\ R_j \in \{0,1\}, (j = 1,2,3) \end{cases} \tag{27}$$

4. Adaptive NSGA-II Algorithm

The traditional NSGA-II algorithm adopts a fixed probability of crossover and mutation, which will directly affect the convergence of the algorithm. The greater the crossover probability, the faster the new individuals will be generated, but the greater the probability of the genetic pattern being destroyed. If the crossover probability is too small, the search process will be slow or even stagnant. For the mutation probability, if it is too small, it is difficult to generate new individuals, and if it is too large, the algorithm will become a random search algorithm. Aiming at this defect, this paper improves the NSGA-II algorithm based on the adaptability, so that the crossover and mutation probability can be adjusted adaptively to avoid going to the local optimal solution.

4.1 Chromosome Encoding and Decoding

The multimodal transport route optimization problem involves the selection of nodes, the order of access, and the choice of transport mode, so this paper adopts three-stage coding. Assuming that the number of nodes in the transport network is N, the encoding length is 3N-1. As shown in Figure 4, taking a transport network with 6 nodes as an example, the first segment is the path sequence code, the first and last bits are the starting point and the ending point, and the middle is the rest of the nodes. The second segment is binary code, 1 means passing through this node, otherwise 0 means not passing through this node. The third paragraph is the mode of transportation code, with 1, 2, and 3 representing road, rail, and waterway transportation, respectively.

As shown in Figure 4, according to the first segment of the code, it can be known that the starting point and the end point are nodes 2 and 6 respectively, and the path node sequence is determined according to the position of the second segment of the code, which is 1, and the transport path is 2-1-6. Discard the last digit of the code in the second paragraph, and determine the mode of transportation according to the rest of the positions that take 1. In this figure, the mode of transportation is 3-2, so the meaning of the entire code is: 2-waterway-1-railway-6.

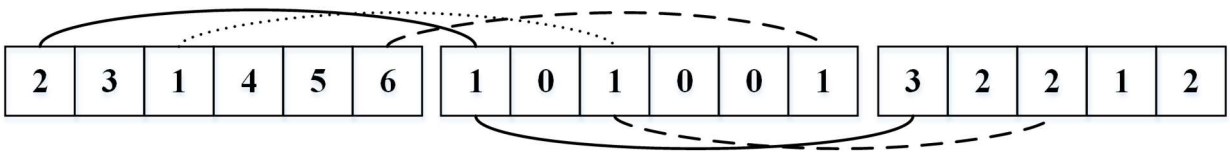

Figure 4. Chromosome coding

4.2 Initializing the Population

Based on the coding rules, this paper uses random generation to generate the initialization population. First, according to the starting point and ending point of the order, the first and last bits of the first segment of the code are determined respectively, and the rest of the nodes are randomly generated in the middle. The first and last digits of the second paragraph are all 1, and 0 or 1 are randomly generated in the middle, and the node is selected. The third segment of encoding randomly generates the transport mode supported by the corresponding path, and repeats N times to obtain an initial population with N individuals.

ISSN: 2414-1895 DOI: 10.6919/ICJE.202204_8(4).0035

4.3 Fast Non-dominated Sorting

Fast non-dominated sorting is a process of comparing all individuals in the population. For each individual i in the population, there are two parameters Ui and Ri, respectively, where Ui is the number of individuals that dominate individual i in the population, and Ri is the individual i in the population. Dominate the collection of individuals. If the transportation cost and carbon emission cost of individual i are less than that of individual j, and the customer satisfaction is greater than that of individual j, then individual i is said to dominate individual j, and all individuals i with Ui=0 are stored in the non-dominated set rank1, and then traverse rank1 For the dominant individual set Ri of all individuals i in Ri, reduce the Uj of all individuals j in Ri by 1, if Uj-1=0 is satisfied, save the individual j into the non-dominated set rank2, and so on, store all individuals in the into collections at different levels.

4.4 Genetic Process

(1) Select operation

The crowding degree in the niche technology can maintain the diversity of the population distribution. The crowding degree represents the density of the surrounding individuals at a given point in the population. Individuals in the same level after non-dominant sorting, those with higher crowding degree will be preferred. , the crowding degree calculation formula is as follows:

$$\begin{cases} d_i = \sum_{j=1}^{m} d_{i,j} \\ d_{i,j} = \dfrac{f_j^{(i+1)} - f_j^{(i-1)}}{f_j^{\max} - f_j^{\min}} \end{cases} \tag{28}$$

Among them, d_i is the crowding degree distance of the individual i of the population, $d_{i,j}$ represents the crowding degree distance of the individual i on the jth objective function, and d_i is equal to the sum of the crowding distances of the individual i on all objective functions. The objective function values of individuals with the same non-dominant level as individual i are arranged in ascending order, $f_j^{\max}$ and $f_j^{\min}$ are the maximum and minimum values of the target component j, respectively, $f_j^{(i+1)}$ and $f_j^{(i-1)}$ are the adjacent values of individual i on the objective function value j [22].

This paper chooses roulette selection, which is a replay-type random sampling method. The probability of each individual entering the next generation is equal to the ratio of its fitness value to the sum of the individual fitness values in the entire population. For the multi-objective model in this paper, the transportation cost, carbon emission cost and customer satisfaction will be calculated separately, and the sum of the three will be taken as the individual fitness. At the same time, combined with the elite retention strategy, the individuals with poor fitness in the new population are replaced by the Pareto non-dominated set.

(2) Adaptive crossover and mutation probability

Crossover and mutation probability (Pc, Pm) is the key to the performance of genetic algorithm. In this paper, the traditional crossover and mutation probability is improved according to the following formula, so that it can be adjusted adaptively and avoid going to the local optimal solution. where , $f_{\max i}$, f_{avgi} and $f_{\min i}$ are the maximum, average and minimum fitness of the ith objective function in the population, respectively. $f_i^{'}$ is the larger fitness value of the two individuals to be crossed, and f_i is the fitness value of the mutant individual. Pc and Pm are the average values of Pci and Pmi obtained by each objective function, respectively. The value ranges and magnitudes of other parameters are related as follows: $1 > P_{c1} > P_{c2} > P_{c3} > 0$,$1 > P_{m1} > P_{m2} > P_{m3} > 0$ [22].

ISSN: 2414-1895 DOI: 10.6919/ICJE.202204_8(4).0035

$$\begin{cases} p_c = mean(p_{ci}) \\ p_m = mean(p_{mi}) \\ p_{ci} = \begin{cases} \dfrac{p_{c1}\left(f_{avgi} - f_i^{'}\right) + p_{c2}\left(f_i^{'} - f_{\min i}\right)}{f_{avgi} - f_{\min i}}, & f_i^{'} < f_{avgi} \\ \dfrac{p_{c2}\left(f_{\max i} - f_i^{'}\right) + p_{c3}\left(f_i^{'} - f_{avgi}\right)}{f_{\max i} - f_{avgi}}, & f_i^{'} \geq f_{avgi} \end{cases} \\ p_{mi} = \begin{cases} \dfrac{p_{m1}\left(f_{avgi} - f_i\right) + p_{m2}\left(f_i - f_{\min i}\right)}{f_{avgi} - f_{\min i}}, & f_i < f_{avgi} \\ \dfrac{p_{m2}\left(f_{\max i} - f_i\right) + p_{m3}\left(f_i - f_{avgi}\right)}{f_{\max i} - f_{avgi}}, & f_i \geq f_{avgi} \end{cases} \end{cases} \tag{29}$$

(3) Cross operation

According to the coding rules, it can be seen that the first and last bits of the second segment of the code are all 1, and the crossover is meaningless. At the same time, to ensure the diversity of the population, the second segment of the middle segment and all the segments of the third segment of the code are crossed to change the path. The mode of transportation can be changed to ensure the diversity of the population.

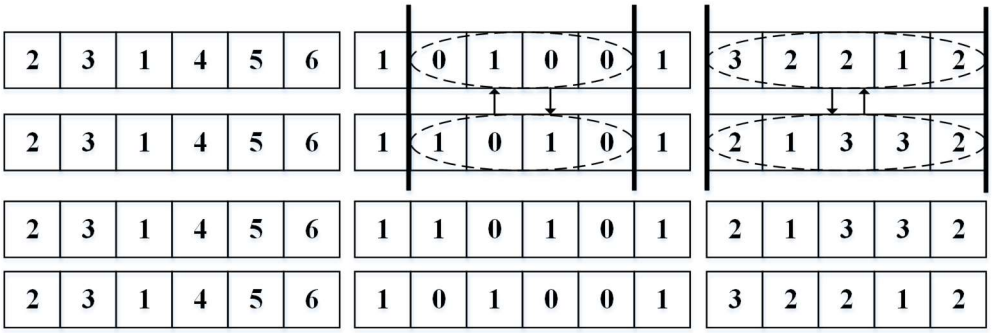

Figure 5. Fragment crossover

(4) Mutation operation

In this paper, two-point reciprocal variation of chromosomes is adopted. In the path coding, 0-1 is reciprocal, and in the mode of transportation coding, the 1-2-3 cycle is reciprocal. If the specified locus of the parent chromosome is 1, the corresponding locus of the offspring will be selected. 2. Similarly, if the parent is 2, the child is 3, the parent is 3, and the child is 1. As shown in Figure 6, the two sites in the middle of the second segment of the parent chromosome and the first two sites of the third segment are reversed and mutated. Since the first and last bits of the second segment must be 1, an intermediate site mutation is selected, and the third The first code of the third paragraph indicates the transportation mode from the starting point, which will definitely be included in the final result, so the first place of the third paragraph is the best mutation point.

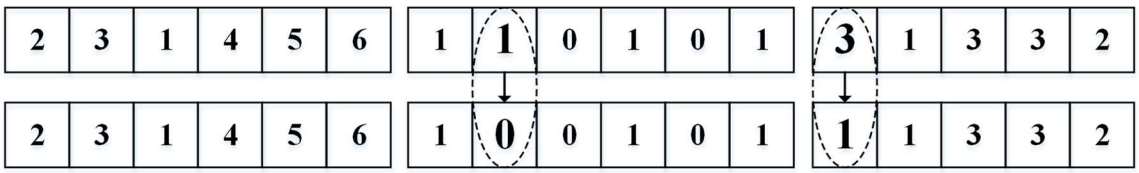

Figure 6. Take the contravariant difference

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4.5 Termination Conditions

The termination criterion is a condition for judging whether to stop running. In this paper, the maximum number of iterations M is set. When the evolutionary algebra reaches the maximum number of iterations, the algorithm ends. At this time, the solution with the lowest fitness value is output. Otherwise, the above process is repeated.

5. Example Data

In the context of the carbon tax policy, as of the beginning of 2018, 42 countries and 25 municipalities with local jurisdictions have priced carbon through the carbon emissions trading system or carbon tax. The carbon trading market in seven provinces and cities including Beijing, Tianjin, Shanghai, and Chongqing is very active, and the average transaction price ranges from 3.7 to 35.3 (yuan/ton) [23]. Therefore, the carbon tax value in this paper is 0.015 yuan/kg, which is vague. Demand preference value = 0.6, and parameters such as transportation mode and transportation task are shown in Tables 3 and 4 below. Use matlab2016b to implement the algorithm program. The parameters of the algorithm: the population size is 300, the number of iterations is 800, and the crossover mutation probability parameter: $P_{c1}=0.9, P_{c2}=0.7, P_{c3}=0.5$, $P_{m1}=0.1, P_{m2}=0.05, P_{m3}=0.01$.

Table 2. Transport mode parameters

parameter / Shipping method	Transit cost (¥/t); Transit time (h/1000t); Transit unit carbon emissions (kg/t)		
	highway	railway	waterway
highway	0,0, 0	8,1,0.128	9,2, 0.117
railway	8, 1, 0.128	0, 0, 0	10, 3, 0.113
waterway	9, 2, 0.117	10, 3,0.113	0, 0, 0

Table 3. Parameters of different modes of transportation

parameter / Shipping method	Average speed (km/h)	Unit cost (¥/(km·t))	Fixed cost (¥/time)	Unit carbon emission (kg/(km·t))
highway	80	0.162	80	0.0440
railway	60	0.491	160	0.0127
waterway	30	0.462	300	0.0091

6. Results Analysis

6.1 Algorithm Performance Analysis

The transportation network with 10-50 nodes is solved by DOCPLEX and self-adaptive NSGA-II algorithm, respectively. The starting point and end point of the order are 1-N (N is the maximum number of nodes). The transportation parameters such as fuzzy demand and time window are shown in the appendix Table 7. The objective function values solved by DOCPLEX , and represent the single-target lower bound value that only considers carbon emission cost and transportation cost, and the single-target upper bound value that only considers customer satisfaction. The result of the adaptive NSGA-II algorithm is the average value of 20 runs, and respectively represent the objective function value obtained based on the algorithm; gap1, gap2, and gap3 represent the difference between the algorithm and each objective function obtained by DOCPLEX. The comparison of the two results is shown in Table 4.

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The comparison results show that when the number of nodes is 10, the solution time of DOCPLEX is less than 1S, but with the continuous increase of the number of nodes, the solution time increases linearly. When the number of nodes reaches 50, the solution time is close to 2 minutes. However, the solution time of the adaptive NSGA-II algorithm only increases slightly. When the number of nodes is greater than 10, the solution speed is faster than that of DOCPLEX, and as the number of nodes increases, the difference between the solution speed of DOCPLEX and the algorithm is larger. It has great advantages to adapt to the NSGA-II algorithm to solve large-scale cases. At the same time, the difference between the target value obtained by the adaptive NSGA-II algorithm and the single target lower bound value obtained by DOCPLEX is not large. The maximum gap1 is 3.88%, and the maximum gap2 is 5.5%. The gap2 is relatively large but very close to the numerical value. within the normal range. The above analysis shows that the adaptive NSGA-II algorithm is effective for solving the case.

Table 4. Shipping order parameters

Order number	number of nodes	starting point-end point	Demand (t)	End time window (h)	Carbon Emission Cap (kg)
1	10	1—10	[65,70,78,88]	[1,2,4,6]	600
2	20	1—20		[1,3,4,6]	900
3	30	1—30		[1,4,6,10]	1300
4	40	1—40		[2,4,6,8]	1500
5	50	1—50		[3,5,7,10]	1900

Table 5. Comparison of solution results

number of nodes	DOCPLEX			Adaptive NSGA-II Algorithm			Gap percentage	
	$Z_{1\min}$	$Z_{2\max}$	run time(S)	Z_1	Z_2	run time(S)	gap1	gap2
10	5224.56	1	0.761	5364.2	1	1.342	2.67%	0
20	9854.88	1	5.949	10198.05	0.945	5.822	3.48%	5.5%
30	10737.7	1	20.832	11154.18	1	15.048	3.88%	0
40	5125.92	1	57.349	5308.02	0.961	21.742	3.55%	3.9%
50	7688.88	1	112.109	7905.36	1	38.849	2.82%	0

Table 6. Solve Path Results of DOCPLEX

number of nodes	path	Shipping method	Carbon Emission Cap (kg)
10	1-2-9-10	highway -water-rail	361.840
20	1-5-3-20	waterway-road-railway	785.272
30	1-5-26-30	waterway-railway- highway	1270.272
40	1-2-12-40	road-highway-highway	1327.04
50	1-2-25-40	highway -rail- highway	1399.576

7. Conclusion

In this paper, trapezoidal fuzzy numbers are used to represent the time window and demand, and the membership function of the time window is used to represent customer satisfaction, which improves the flexibility of time window and demand changes. A multi-objective fuzzy chance constraint model is established, and an example is established for a multimodal transport network with 10-50 nodes.

The adaptive NSGA-II algorithm and DOCPLEX are used to solve the results. By analyzing the specific results, the algorithm and model are verified effectiveness.

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