Research on multimodal transport path optimisation with time windows under uncertainty conditions

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ABSTRACT

Considering the uncertainty of demand and transport time in the actual transport process, a fuzzy nonlinear planning model for multimodal transport considering hybrid time window constraints is established with the optimisation objective of the integrated operating cost of transport cost, transit cost, time penalty cost and carbon emission cost. The optimisation model containing uncertain variables is transformed into a mathematical model of deterministic form through the fuzzy opportunity constraint theory, and the hybrid simulated annealing algorithm combining genetic algorithm and simulated annealing algorithm is used for the solution, and the validity of the model and algorithm, as well as the effect of time window on the results, are verified by changing the time window constraints.

Keywords: Multimodal transport, carbon emission, uncertain demand, time window

1. INTRODUCTION

In today's context of globalisation, the logistics industry, as a key link connecting production and consumption, has a direct impact on the operational efficiency of smooth economic activities. As an important part of modern logistics, multimodal transport, through the integration of the advantages of different modes of transport, can achieve efficient, safe and low-cost transport of goods, to create greater competitive advantage for enterprises. However, in the actual operation process, the choice of multimodal transport paths is often challenged by many uncertainties, such as weather changes, traffic congestion, equipment failures, etc., which may lead to delays in transport time, increased costs and even loss of goods[1]. Therefore, how to optimise intermodal transport paths under uncertain conditions has become an important problem to be solved in the field of logistics[2].

Many domestic and international scholars have conducted a lot of research on multimodal transport problems[3]. Most of the established researches take the minimum carbon emission as one of the multi-objectives to be solved[4], and use the hard time window, soft time window or mixed time window as the constraints to select the transport scheme, in which the freight volume is used as a fixed value[5]. However, in the actual transport process, there are many uncertainties that make the cargo demand or cargo arrival time window cannot be determined in advance, such as seasonal replenishment, unexpected situations, etc. Therefore, this paper establishes a fuzzy nonlinear planning model with mixed time window constraints from the carrier's point of view, taking into account the uncertainty of cargo volume in the actual transport process, and de-fuzzification of the established fuzzy planning model using fuzzy opportunity constraints planning method[6]. Secondly, a hybrid simulated annealing algorithm was obtained to solve the model by combining the genetic algorithm with the simulated annealing algorithm.

2. PROBLEM DESCRIPTION AND MODELLING

2.1 Description of the problem

The multimodal transport path optimisation problem studied in this paper can be described as follows: a batch of goods with uncertain demand is transported from the transport origin to the destination according to a certain time window, passing through a number of urban nodes, there are two modes of transport to choose from between the two nodes that are connected: road and rail, and some nodes have a waterway between them, which allows them to perform transport

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switching, the distance between nodes varies according to the mode of transport, and the resulting transport costs, time, carbon emissions also vary, and goods can transit at any node except the origin and destination. Therefore, the aim of this paper is to obtain the transport path and mode choice that satisfies the lowest total cost[3], taking into account demand uncertainty and time window constraints[7].

2.2 Fuzzy requirements modelling

In this paper, we use the triangular fuzzy number in fuzzy mathematical chance-constrained planning to represent the uncertain demand, and the triangular fuzzy quantity is used $\tilde{q} = (q_a, q_b, q_c)$ to carry out the expression, where the q_b denotes the demand for goods with an affiliation of 1, q_a denotes the minimum quantity of goods demanded, q_c denotes the maximum cargo demand, and $q_a \le q_b \le q_c$ defines the affiliation function as in equation (1)[6].

$$u_q(p) = \begin{cases} \dfrac{(p - q_a)}{(q_b - q_a)}, q_a \le p \le q_b \\ 1, p = q_b \\ \dfrac{(q_c - p)}{(q_c - q_b)}, q_b \le p \le q_c \\ 0, \text{ else} \end{cases} \tag{1}$$

2.3 Parameter description

A is the set of transport nodes; K is the set of transport modes. $K = \{1, 2, 3\}$, 1, 2 and 3 in the set represent road, rail and waterway transport, respectively; C_{ij}^k is the unit transport cost of transporting goods from node *i* to node *j* by transport mode *k*, ¥/(t·km); l_{ij}^k is the transport distance between node *i* to node *j* using *k* modes of transport, km; C is the total cost, *$*; C_e is the carbon tax rate (¥/t); C_i^{kl} is the unit transit cost of converting goods from transport mode *k* to transport mode *l* at node *i*, ¥/*t*; x_{ij}^k is whether transport mode *k* is selected from point *i* to point *j*, taking the value 0 or 1; y_i^{kl} is whether to switch from transport mode *k* to *l* at point *i,* taking the value 0 or 1; C_s is the unit storage cost of goods arriving early, ¥/kg; C_p is the unit penalty cost of delayed arrival of goods, ¥/kg; E_{ij}^k is the unit carbon emission of the *k* mode of transport between node *i* and node *j*, kg/(t· km); E_i^{kl} is the carbon emission per unit of transport mode converted from *k* to *l* at point *i*, kg/t; v_k is the average travelling speed of transport mode *k*; t_{ij}^k is the transport time for transport nodes *i* and *j* by transport mode *k*, *h*; t_i^{kl} is the transit time for goods to be converted from transport mode *k* to *l* at node *i*, *h*/*t*; t_i is the time of arrival of the goods at location *i*; $[T_{Li}, T_{Ui}]$ is the soft time window for the arrival of goods acceptable to location *i*; $[T_{\min}, T_{\max}]$ is the hard time window for customer shipment orders to arrive.

2.4 Model objective function

The objective function can be expressed as:

$$\min C=\tilde{q}\sum_{i,l\in A}\sum_{k\in K}C_{ij}^{k}x_{ij}^{k}l_{ij}^{k}+\sum_{k,l\in K}y_{i}^{k,l}\leq 1,\forall i\in A\tilde{q}\sum_{i\in A}\sum_{k,l\in K}C_{i}^{kl}y_{i}^{kl}+\tilde{q}C_{s}\sum_{i=1}^{A}\max(T_{Li}-t_{i},0)$$
$$+\tilde{q}C_{p}\sum_{i=1}^{A}\max(t_{i}-T_{Ui},0)+\tilde{q}C_{e}\sum_{i,l\in A}\sum_{k\in K}E_{ij}^{k}x_{ij}^{k}l_{ij}^{k}+\tilde{q}C_{e}\sum_{i\in A}\sum_{k,l\in K}E_{i}^{kl}y_{i}^{kl} \tag{2}$$

2.5 Model constraint

Constraint (3) denotes that the arrival of goods at node *i* needs to satisfy the window constraint time; constraint (4) denotes the hard time window constraint; constraint (5) indicates that the cargo volume cannot exceed the capacity limit of the selected mode of transport between nodes; constraint (6) indicates that the amount of freight transported when transiting between the two nodes cannot exceed the transit capacity limit for both modes of transport; constraint (7) denotes that only one transport mode can be selected between two neighbouring nodes; and constraint (8) indicates that at most one transhipment occurs at a node.

$$T_{Li}\leq t_{i}\leq T_{Ui} \tag{3}$$

$$T_{\min}\leq T\leq T_{\max} \tag{4}$$

$$\tilde{q}x_{ij}^{k}\leq Q_{ij}^{k},\forall i,j\in A,k\in K \tag{5}$$

$$\tilde{q}y_{i}^{kl}\leq Q_{i}^{kl},\forall i\in A,k,l\in K \tag{6}$$

$$\sum_{i,j\in A}x_{ij}^{k}\leq 1,\forall k\in K \tag{7}$$

$$\sum_{k,l\in K}y_{i}^{k,l}\leq 1,\forall i\in A \tag{8}$$

3. MODEL DEFUZZIFICATION

The above model contains fuzzy variables that cannot be solved directly by substitution, and solving the model using heuristic algorithms requires the fuzzy variables to be treated with clarity so that the model is transformed into a deterministic mathematical expression. The core idea of opportunity constrained planning theory is to use confidence levels to solve uncertain variables, i.e., fuzzy opportunity constraints are transformed into deterministic forms, which need to satisfy the constraints at a given level of confidence. The model representation is as follows:

$$\min \overline{f} \tag{9}$$

$$s.t.\begin{cases}Pos\left\{f(x^{'},\xi)\leq\overline{f}\right\}\geq\alpha\\ Pos\left\{g_{i}(x^{'},\xi)\leq 0\right\}\geq\beta_{i}\end{cases} \tag{10}$$

In Equation: $\overline{f}$ is the model objective function; $x^{'}$ is fuzzy decision variables; ξ is a fuzzy vector; $f(x^{'},\xi)$ is the objective function; $g_{i}(x^{'},\xi)$ is the constraints of this fuzzy planning; $Pos\{\cdot\}$ is the probability that the event in $\{\cdot\}$ will occur; α is the confidence level of the objective function; β_{i} is the confidence level of the constraint, which is a pre-given value.

$\theta(0<\theta<1)$ is a given confidence level that holds when and only when $(1-\theta)q_{a}+\theta q_{b}\leq b$, $Pos\left\{\tilde{q}\leq b\right\}\geq\theta$. Therefore, the final explicit model constraint expressions are Equations (3), (4), (7), (8) and (9)-(14).

$$\begin{aligned}\overline{f} \geq & \left[(1-\alpha)q_a + \alpha q_b\right]\sum_{i,l\in A}\sum_{k\in K} C_{ij}^{k} x_{ij}^{k} l_{ij}^{k} + \left[(1-\alpha)q_a + \alpha q_b\right]\sum_{i\in A}\sum_{k,l\in K} C_{i}^{kl} y_{i}^{kl} \\ & + \left[(1-\alpha)q_a + \alpha q_b\right] C_s \sum_{i=1}^{A} \max(T_{Li} - t_i, 0) + \left[(1-\alpha)q_a + \alpha q_b\right] C_p \sum_{i=1}^{A} \max(t_i - T_{Ui}, 0) \\ & + \left[(1-\alpha)q_a + \alpha q_b\right] C_e \sum_{i,l\in A}\sum_{k\in K} E_{ij}^{k} x_{ij}^{k} l_{ij}^{k} + \left[(1-\alpha)q_a + \alpha q_b\right] C_e \sum_{i\in A}\sum_{k,l\in K} E_{i}^{kl} y_{i}^{kl}\end{aligned} \tag{11}$$

$$q_{ij}^{k} \geq x_{ij}^{k}(1-\beta_1)q_a + x_{ij}^{k}\beta_1 q_b \tag{12}$$

$$q_{i}^{kl} \geq y_{i}^{kl}(1-\beta_2)q_a + y_{i}^{kl}\beta_2 q_b \tag{13}$$

$$\alpha, \beta_1, \beta_2 \in (0,1) \tag{14}$$

In equation: α is the confidence level of the objective function, β_1, β_2 is the constraint confidence level.

4. CASE STUDIES

4.1 Case data

In this paper, a total of 10 regions from Changchun to Chengdu are taken as the object of multimodal transport research, assuming that a batch of goods needs to be transported from the starting point 1 Changchun to the end point Chengdu, and the middle passes through 8 intermediate regions. With nodes with node O, node D respectively, the transport starting point Changchun and the end point Chengdu, node 1 … node 8 respectively, Dalian, Tianjin, Nanjing, Wuhan, Jiujiang, Shanghai, Chongqing, Yichang 8 nodes. There are two modes of transport to choose between any two nodes connected in this there are roads and railways, and there are waterways between some nodes[8], which can be used for transport conversion. The multimodal transport routes are shown in Figure 1. The cargo demand is expressed in terms of triangular fuzzy numbers as $\tilde{q} = (100t, 160t, 200t)$. The penalty costs for early and late arrivals are ¥30/(t·h) and ¥45/(t·h), respectively, and the carbon tax rate is ¥150/t. The distances between city nodes and the maximum transport capacity are shown in Table 1.

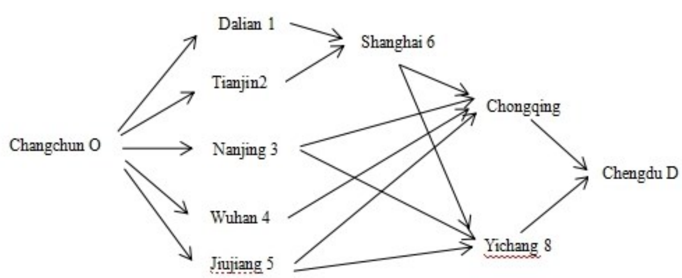

Figure 1. Multimodal transport route map.

The transport distances and maximum transport capacities of nodes using different transport modes between cities are shown in Table 1, where *i* represents the start node and *j* represents the end point. If there is no transport mode or transport route between two nodes, it is indicated by “--”.

Table 1. Distances between nodes and maximum transport capacity.

i	***j***	**Transport distance/km (maximum transport capacity/t)**			***i***	***j***	**Transport distance/km (maximum transport capacity/t)**		
		Roads	**Railway**	**Waterway**			**Roads**	**Railway**	**Waterway**
O	1	679(200)	710(210)	--	3	8	850(230)	808(210)	1359(220)
O	2	964(180)	1012(220)	--	4	7	867(150)	876(160)	1306(190)

i	*j*	Transport distance/km (maximum transport capacity/t)			*i*	*j*	Transport distance/km (maximum transport capacity/t)		
		Roads	Railway	Waterway			Roads	Railway	Waterway
O	3	1818(150)	2035(130)	--	5	7	1062(250)	1092(240)	1543(230)
O	4	2089(160)	2301(200)	--	5	8	504(180)	544(190)	895(190)
O	5	2176(170)	2339(220)	--	6	7	1654(130)	1672(120)	2399(170)
1	6	1113(215)	2430(205)	1043(150)	6	8	1100(180)	1119(160)	1751(200)
2	6	1136(220)	1325(160)	1346(170)	7	D	303(230)	319(210)	--
3	7	1387(190)	1361(200)	2007(220)	8	D	583(170)	857(165)	--

Based on the relevant research, a comprehensive comparison was made and assumptions were made on the parameters of each transport mode and the parameters of transport mode dressing, as shown in Tables 2 and 3.

Table 2. Mode of transport parameters.

Type of transport	Transport costs/(¥/t.km)	Transport speed/(km/h)	Carbon emissions per unit/(kg/t.km)
Roads	1.42	80	0.0320
Railway	0.41	70	0.0079
waterway	0.27	40	0.0176

Table 3. Mode of transport changeover parameters.

Mutual dressing method	Unit changeover cost/(¥/t)	Carbon emissions per unit change/(kg/t.km)	Changeover time/h
Roads-railway	5.13	0.27	7
Railway-waterway	7.45	0.31	10
Roads-waterway	6.37	0.31	8

The maximum transit capacity of each node is shown in Table 4.

In this paper, the hard time window is set to [0, 96] hours and the time window constraints for each node are shown in Table 5.

Table 4. Maximum transit capacity of nodes.

Nodal	Roads-railway	Railway-waterway	Roads-waterway	Nodal	Roads-railway	Rail-waterway	Roads-waterway
1	190	220	200	5	185	200	210
2	180	210	230	6	200	210	180
3	200	120	220	7	160	190	220
4	170	180	190	8	175	200	210

Table 5. Time windows for each node.

Nodal	Soft time window lower limit	Soft time window upper Limit	Nodal	Soft time window lower limit	Soft time window upper limit
0	0	96	5	24	30
1	10	16	6	60	71
2	10	18	7	75	88
3	15	29	8	80	86
4	23	32	D	82	90

4.2 Analysis of results

Setting the model parameter $\alpha = 0.2$, β_1=β_2=0.8 the population size of the genetic algorithm is 30, the number of iterations is 100, the probability of crossover and mutation is 0.9 and 0.1[1], respectively, and the annealing algorithm with a system temperature of 1000°C and an annealing rate of 0.98, and the evolution of the optimal solution of the objective function is shown in Figure 2.

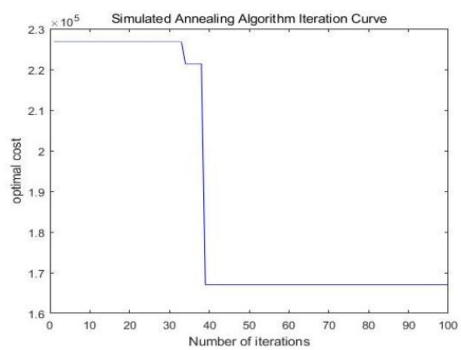

Figure 2. Iterative process for the optimal solution of the objective function.

The optimal solution of this paper’s example solved by hybrid simulated annealing algorithm is ¥167004.940, and the results of multimodal path optimisation are shown in Table 6.

Table 6. Optimisation results for intermodal routes.

Path selection	Type of transport	Transport cost/¥	Time cost/¥	Carbon emission cost/¥	Time/h	Total cost/¥
O-1-6-7-D	Railway-waterway-railway-railway	157239.04	46308.0	667.287	84.661	204224.327
O-4-8-D	Railway-waterway-roads	194892.32	4392.0	864.856	87.309	200149.176
O-4-7-D	Railway-waterway-railway	161472.64	4788.0	744.3	90.079	167004.940
O-1-6-8-D	Railway-waterway-railway-railway	156550.24	72504.0	675.296	84.446	229729.536

4.3 Analysis with and without time window constraints

If the time window constraints are not considered, the total cost of the model solution is ¥154171.275. The results of the study show that the consideration of time window constraints makes both transport and total costs increase significantly, which demonstrates the non-negligible impact of the time window effect on transport costs. Therefore, in multimodal transport path optimisation, carriers should reasonably set the node time window and arrival time window to reduce transport costs while ensuring the transport time frame[9].

5. CONCLUSION

In this paper, a fuzzy nonlinear planning model for intermodal transport considering hybrid time window constraints is developed under demand uncertainty with the optimisation objective of integrated operating costs of transport costs, transit costs, time penalty costs and carbon emission costs, which is analysed through a 10-node intermodal transport network case. The results of the case study show that the uncertainty factor significantly increases the integrated operating cost. Considering uncertainty factors can improve the reliability and accuracy of route planning results and provide more robust and effective solutions for multimodal transport. In future work, more uncertainty factors will be considered in the model to further improve the accuracy of route optimisation.

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