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THE ROUTE PROBLEM OF MULTIMODAL TRANSPORTATION WITH TIMETABLE UNDER UNCERTAINTY: MULTI-OBJECTIVE ROBUST OPTIMIZATION MODEL AND HEURISTIC APPROACH

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Abstract. The uncertainty of transportation duration between nodes is an inherent characteristic and should be concerned in the routing optimization of the multimodal transportation network to guarantee the reliability of delivery time. The interval number is used to deal with the uncertainty of transportation duration, and the multi-objective robust optimization model is established which covers the transportation duration and the cost. To solve the combinatorial optimization problem of this study, Non-Dominated Sorting Genetic Algorithm-II (NSGA-II) is designed, which integrates the $(\mu + \lambda)$ selection method elite retention and the external filing elite retention. Our findings verify the efficiency of the proposed approach by analyzing the diversity, distribution and convergence of the frontier solutions. Finally, near-optimal solutions are obtained with the proposed algorithm in the numerical example. The present study can provide decision reference for multimodal transportation carriers in making transportation plan under uncertainty.

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1. Introduction & literature review

The advanced stage of transportation development is multimodal transportation [18,27]. Routing optimization is one of the important research directions of multimodal transportation [5,12,32], which is also the extension and expansion of the classic shortest path problem [3, 25, 29]. Combining the real transportation environment with an innovative approach to improve transportation efficiency, reduce transportation cost and satisfy customer requirements is the core of the path optimization problem.

In the previous literature, multimodal transportation route optimization has been extensively studied [26]. Most multimodal transportation route optimization problems were developed with a single objective under certain conditions [28,34,37]. However, the requirements of customers and transportation enterprises were often diverse and even conflicting. For example, some customers preferred the lowest freight rates while some others would rather pay more for faster delivery or a certain person expected to cut transportation cost and duration simultaneously [23, 38]. This means that it cannot depend on a single objective and should be considered as a multi-objective optimization problem [4, 13, 15, 31]. In general, there were two conventional methods for

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addressing multi-objective optimization problems, which are the ϵ-constraint method and the weighted sum method [6, 20, 39].

In the complex transportation environment, it is more significant to take the uncertainty factors of multimodal transportation into account. Resat and Turkay [23] proposed a mixed-integer optimization model that considered traffic congestion of the routes among nodes that account for the transportation duration uncertainty. Assadipour *et al.* [2] considered the uncertainty of transportation duration caused by the congestion of the intermodal yards in the railtruck intermodal transportation of hazardous materials. In this regard, the risk uncertainty related to the placement of transfer yards as well as the possibility of disruptions at those facilities was concerned with the intermodal transportation of hazardous materials by Ghaderi *et al.* [11]. Meanwhile, information uncertainties were discussed in the modeling and optimization of railtruck system intermodal transportation by Wang *et al.* [30]. In addition to considering the uncertainties of using cost, the capacities of terminals and transportation cost also were observed in the works of Abbassi *et al.* [1].

There are various researches for the uncertainty of multi-objective multimodal transportation route optimization. Demir *et al.* [8] studied the design of green intermodal transportation service network problems with transportation duration as well as demands uncertainties for combined offline intermodal routing decisions. According to their formulation, a stochastic approach of the sample average approximation method was adopted to generate robust transportation plans. Hrusovsky *et al.* [14] further extended the study by improving the algorithm. The paper innovated a novel solution framework to support the operational-level decisions by using a simulation model that includes stochastic elements. It should be noted that the approach of fuzzy logic was also frequently employed to deal with uncertainty problems. Yang *et al.* [35] considered the uncertainty of transportation duration and cost as well as developed a comprehensive hybrid methodology of combining the Fuzzy Random Simulation (FRS) technique and Multi-start Simulated Annealing (MSA) algorithm to achieve near-optimal solutions in a reasonable time for the proposed problem. Fazayeli *et al.* [9] studied the location routing decision-making issue in the multimodal transportation network and established a mixed-integer mathematical fuzzy model. Time window constraints and fuzzy numbers were imposed upon the formulation to represent the uncertainty of transportation duration and demand respectively. Additionally, metaheuristic approaches have gained attention in dealing with NP-hard Problem in the context of multimodal transportation network route optimization with uncertainty elements. A new method of handling multi-objective based on Fire-Works Algorithm (FWA) was introduced by Mnif *et al.* [21], which aimed to determine the shortest and efficient itinerary of satisfying a certain set of demands and operational constraints. Wang *et al.* [30] adopted a Memetic Algorithm (MA) to solve the problem of the hub-and-spoke based road-rail intermodal transportation network design and obtained high-quality solutions. Abbassi *et al.* [1] developed an effective hybrid solution approach combining the Population-Based Simulated Annealing (PBSA) with an exact method to achieve near-optimal solutions in a reasonable time for a real network case study.

Rail and water transportation usually have a fixed departure timetable [16], When the goods arrived at the transfer nodes and completed the loading and unloading, it might not be transported immediately due to the timetable limitation of the next mode of transportation [33]. Liu *et al.* [17] indicated that timetable would affect the choice of transportation routes and modes. So it makes more sense to consider timetable in multimodal transportation.

Table 1 outlines a taxonomy of relevant research on multimodal transportation route optimization in recent years and the taxonomy contains five major categories in terms of models and algorithms that further explain the studies differences. As can be found from Table 1, multi-objective optimization is often considered in the previous studies, but there are few attention about the some more realistic aspects that could be expressed as follows: Frist, there few formulations integrated the time uncertainty of transportation and the influence of timetable for trains and barges in the route optimization of multimodal transportation simultaneously. Second, in most literature, the method of dealing with uncertainty is to use an accurate probability distribution or fuzzy membership function with more reliable prior data. However, the reliable prior data are often difficult to obtain and irregular [36]. Third, in the problem solving, there is less literature applied heuristic algorithms combined with non-dominance theory to deal with multi-objective optimization, Furthermore, NSGA-II is

TABLE 1. Some related papers.

Paper	Uncertainty type	Uncertain para. exp.	TB	Obj.	Treatment method	
					For obj.	For alg.
[32]	–	–	–	C,T	SW	Exact
[28]	–	–	–	C	–	B&B
[34]	–	–	–	C	–	Goal program
[23]	T	–	✓	C,T	A_ϵ	Exact
[13]	–	–	–	C	–	DP
[15]	–	–	–	C,T	ND	Cplex
[6]	–	–	–	C,T	SW	DP
[39]	C,T	RN	–	C,T	C_c	Exact
[2]	T	–	–	C,R	ND	NSGA-II
[30]	Demand,C,T	TFN	–	C,T	SW	MA
[1]	Capacity,C	IN	–	C	–	PBSA & Exact
[8]	Demand,T	RN	–	C,T,E	SW	SAA
[14]	T	RN	–	C,T,E	SW	HS
[35]	C,T	TFN	–	C,T	SW	MSA
[9]	Demand,T	TFN	–	C	–	Two-part GA
[21]	–	–	–	C,T	ND	FWA
[33]	–	–	✓	C,R	SW	B&B
[17]	T	IN	✓	C	–	GA
This paper	T	IN	✓	C,T	ND	NSGA-II & EFER

Notes. T: time, C: cost, exp.: expression, RN: random number, TFN: Triangular fuzzy number, IN: Interval number, TB: Timetable, R: risk, E: environment, SW: Sum weighting, A_ ϵ: Augmented ϵ-constraint, C_c: chance constraint, ND: Non-dominance theory, B&B: Branch&Bound, DP: Dynamic program, SAA: Sample average approximation, HS: Hybrid simulation-optimization, GA: Genetic algorithm, EFER: External filing elite retention.

a common multi-objective optimization evolutionary algorithm, while the merits and demerits of elite retention strategies in NSGA-II has not been discussed in any of the previous studies of multimodal transportation route optimization. This study is an effort to bridge the stated gaps with contributions in both model formulation and solution methodology.

– The impact of timetable on transportation mode is analyzed and making a detailed description in the mathematical model;
– Interval numbers are used to indicate uncertain transportation time, and introduced robust control parameters to analyze the uncertainty characteristics;
– Designing a non-dominated genetic algorithm with external archiving strategy to solve the proposed problem and the performance of the algorithm and the quality of the solution are evaluated.

The rest of this paper is organized as follows. Following the introduction & literature review, a description of the problem and its formulation are presented in Section 2. The solution methodology is presented in Section 3. Algorithms analysis and numerical results for proposal problem instances are reported in Section 4. Finally, Section 5 concludes the paper.

2. Problem description

In this paper, we consider a multimodal transportation network including three modes of the highway, railway and waterway, and more than two available modes could be selected between origin node and destination. However, road transportation duration is often influenced by congestion and unexpected accidents. Extreme weather and port congestion are important reasons for the uncertainty of shipping duration. Besides, waterway and railway transportation timetable limitations also affect the goods departure time to the next node after reload. The routing decision of our model which aims to simultaneously minimize the total transportation cost and duration between the origin node and destination is based on some assumptions given as follows:

(1) Only a batch of goods and not allow to spill in transportation;
(2) The transfer duration and cost between different modes of transportation are known;
(3) The arrival time of goods is the start time of transferring;
(4) The time of goods leave for the next node is the latest departure time from the timetable of the selected transportation mode after finished loading and unloading;
(5) Sufficient capacity of transportation and transshipment facilities.

2.1. Index set

In this study, we assume a multimodal transportation network $G = (N, E, M)$ where N is the set of nodes (o is the origin node, d is the destination, $o, d \in N$), $E = \left\{e^a_{i,j} | i, j \in N, a \in M\right\}$ is the set of arcs, $e^a_{i,j} = \left\{t^a_{i,j}, c^a_{i,j}\right\}$, M is the set of transportation modes.

Parameters

C	The total cost of transportation;
T	The total duration of transportation;
δ_i	The time that the goods finished transshipment at the node i;
$c^a_{i,j}$	The transportation cost of one unit of good from node i to j with a transportation mode selected;
$t^a_{i,j}$	The transportation duration from node i to j with a transportation mode selected;
T^G_i	The goods depart time from the node i, and the goods departure time of node o is known;
T^R_i	The time that the goods arrive at the node i;
$\widetilde{t}^a_{i,j}$	The Interval Number of transportation duration from node i to j with a transportation mode selected;
$\Gamma^a_{i,j}$	The timetable corresponding to transportation mode a from node i to j, it has been known in advance and can be defined as $\Gamma^a_{i,j} = (\ldots, \Phi_{n-1}, \Phi_n, \ldots)$, and Φ_n represents the departure time of n shift.
$\theta^{a,b}_i$	The cost on the changing of transportation mode from a to b at the node i;
$\tau^{a,b}_i$	The transshipment duration of transportation mode from a to b at the node i;
$\hbar^a_{i,j}$	The interval robust control parameter from node i to j with a transportation mode selected.

Decision variable

$$x^a_{i,j} = \begin{cases} 1, & \text{if the transportation mode a is selected from node } i \text{ to } j \\ 0, & \text{otherwise.} \end{cases}$$

Set $U = \left\{(i, j, a) | x^a_{i,j} = 1\right\}$, $W = \left\{(j, a, b) | x^a_{i,j} = 1 \& x^b_{j,k} = 1\right\}$. Equation (2.1) indicates how to obtain the departure time of node i according to the time δ_i and the timetable $\Gamma^a_{i,j}$.

$$\varphi\left(\delta_i, \Gamma^a_{i,j}\right) = \Phi_n, \Phi_{n-1} < \delta_i \leq \Phi_n. \tag{2.1}$$

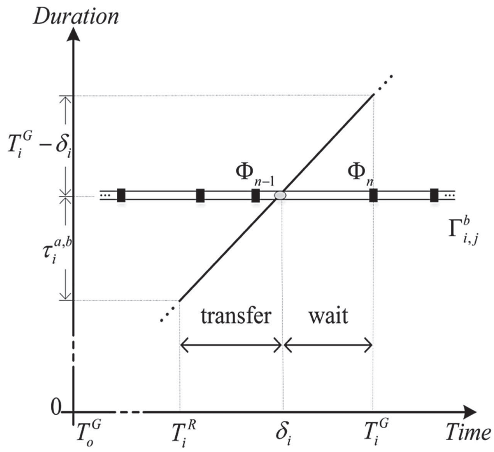

FIGURE 1. The transshipment duration in the node i.

2.2. Interval uncertainty and robust control

The Interval Number represents a kind of uncertainty, which is composed of a pair of ordered real numbers, with the dual characteristics of set and number value [22]. This $\widetilde{t}_{i,j}^a = [t_{i,j}^{a-}, t_{i,j}^{a+}] = \left\{t_{i,j}^a | t_{i,j}^{a-} \le t_{i,j}^a \le t_{i,j}^{a+}\right\}$ represents the uncertainty of the transportation duration from node i to j with a transportation mode selected. "−" and "+" represents the lower bound of interval and the upper bound of interval respectively. Equation (2.2) indicates the uncertainty relationship between the control parameter $\hbar_{i,j}^a$ and the transportation time $t_{i,j}^a$ in the interval.

$$\hbar_{i,j}^a = \frac{t_{i,j}^a - t_{i,j}^{a-}}{t_{i,j}^{a+} - t_{i,j}^{a-}}, \quad \forall i,j \in N,\ \forall a \in M. \tag{2.2}$$

2.3. Multi-objective multimodal transportation robust optimization model

As shown in Figure 1, the transshipment duration in the node i under the timetable limitation includes the transferring duration and the waiting duration considering the timetable. The δ_i can be formulated as follow:

$$\delta_i = T_i^R + \tau_i^{a,b}, \quad \forall (i,a,b) \in W. \tag{2.3}$$

The T_i^G can be formulated as follow:

$$T_i^G = \varphi\left(\delta_i, \Gamma_{i,j}^b\right), \quad \forall (i,j,b) \in U. \tag{2.4}$$

The T_j^R can be formulated as follow:

$$T_j^R = T_i^G + \hbar_{i,j}^a (t_{i,j}^{a+} - t_{i,j}^{a-}) + t_{i,j}^{a-}, \quad \forall (i,j,b) \in U. \tag{2.5}$$

In this paper, we propose a bi-objective optimization model. The first objective seeks to minimize the total cost of multimodal transportation, including the itinerary and transshipment cost. The second objective seeks to minimize the total duration of multimodal transportation. A robust optimization method based on control parameters $\hbar_{i,j}^a$ is employed to solve the problem. (The constraints given above are not repeated in the following models.)

$$\min\ T = T_d^R - T_o^G \tag{2.6}$$

$$\min\ C = \sum_{i\in N} \sum_{j\in N\setminus\{i\}} \sum_{a\in M} c_{i,j}^a x_{i,j}^a + \sum_{(i,a,b)\in W} \theta_i^{a,b} \tag{2.7}$$

s.t.

$$\sum_{j\in N\setminus\{i\}}\sum_{a\in M} x_{i,j}^{a} \leq 1, \quad \forall i \in N \tag{2.8}$$

$$\sum_{i\in N\setminus\{o\}}\sum_{a\in M} x_{o,i}^{a} = \sum_{i\in N\setminus\{d\}}\sum_{a\in M} x_{i,d}^{a} = 1 \tag{2.9}$$

$$\sum_{i\in N\setminus\{o\}}\sum_{a\in M} x_{i,o}^{a} = \sum_{i\in N\setminus\{d\}}\sum_{a\in M} x_{d,i}^{a} = 0 \tag{2.10}$$

$$\sum_{i\in N\setminus\{j\}}\sum_{a\in M} x_{i,j}^{a} = \sum_{i\in N\setminus\{j\}}\sum_{a\in M} x_{j,i}^{a}, \quad \forall j \in N\setminus\{o,d\}. \tag{2.11}$$

Equation (2.8) means the selection of mode, that one mode (transportation route) can be selected between two nodes. If it is zero, it means that this node i is not included in the transportation. Equations (2.9) and (2.10) ensure that the goods depart from the origin node o to the destination d; Equation (2.11) represents that the conservation of flow at the node j that requires the flow originating at the node j to equal the flow entering the node j.

3. The NSGA-II solution methodology

The solution space of our proposed problem is discontinuous, and GA can directly deal with the discrete property of the problem [19]. The NSGA-II, as the variant of genetic algorithm, is one of the most popular multi-objective evolution algorithms with fast running speed and good convergence advantages [7]. For these reasons, NSGA-II is used to solve this problem.

3.1. Coding and evolution operations

In this study, the adopted method of chromosome coding, the crossover operator and the mutation operator were referred to the literature of Liu *et al.* [17].

3.2. Fast non-dominant sort

The core of solving multi-objective optimization problem is to find Pareto optimal solution sets [7]. Performing the fast non-dominated sorting refers to hierarchically ranking based on the advantages and disadvantages of all individuals in the population. If the individuals are in the same layer, the individuals are dominated by no others, while in different layers, the individuals are either dominated by others or dominate others. The specific operations are as follows.

We assume a variable n_i and set S_i for each individual i of the population Z, where n_i is the number of individuals dominating the individual i and S_i is the set of individuals dominated by the individual i in the population. Let $l = 1$, $Z' = Z$;

(1) To calculate the n_i and S_i of each individual i in the population Z;
(2) To find out the individuals of $n_i = 0$ in the population Z', and put them into the current set P_l (P_l represents the l layer of the set), and execute $Z' = Z' \setminus P_l$;
(3) To perform $n_j = n_j - 1$ on each individual j in the set S_i which corresponds to each individual i in the current set P_l;
(4) If the set Z' is not empty, $l = l + 1$, and turn to step (2). Otherwise, terminate the algorithm.

Finally, the individuals of the population Z are divided into l layers.

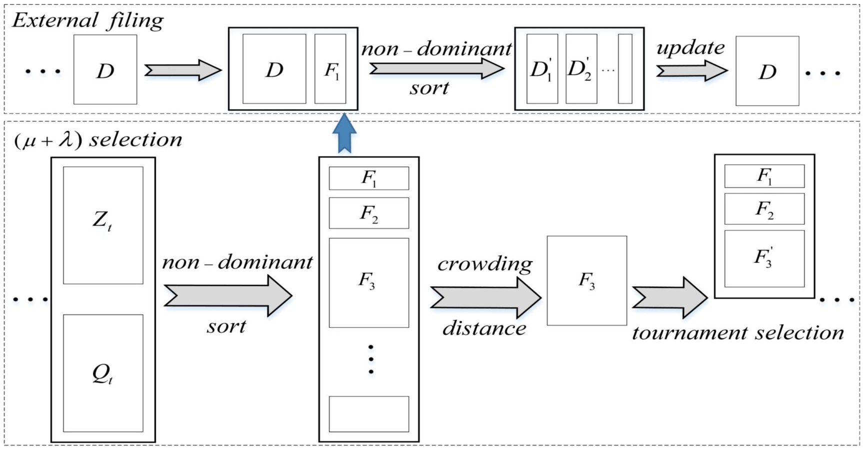

FIGURE 2. Integrating the $(\mu + \lambda)$ selection method elite retention and the external filing elite retention.

3.3. Crowding distance

The crowding distance is applied to measure the degree of similarity between individuals in the population. The closer the crowding distance of the individuals, the more similar to each other. Assume the number of the objective function is m in the constructed model. Individuals are ranked in ascending order based on the kth objective value of all individuals in the population. Besides, f_k^{i+1} and f_k^{i-1} represent the function values of two individuals adjacent to the individual i on the kth objective.The $f_k^{\max}$ and $f_k^{\min}$ are the maximum and minimum values. The crowding distance d_i of an individual i is calculated as follows:

$$d_i = \begin{cases} \infty, & \text{ranked in the first and last individuals} \\ \sum_{k=1}^{m} \frac{f_k^{i+1} - f_k^{i-1}}{f_k^{\max} - f_k^{\min}}, & \text{otherwise.} \end{cases} \tag{3.1}$$

3.4. Tournament selection

Tournament selection is random sampling with replacement used to select parents in producing offspring. Firstly, several individuals are randomly taken out of the population, and then the individuals with larger crowding distance are selected and retained to the next generation population set. Secondly, repeat the operation until as many individuals as the next generation of the population need to be saved. The purpose of this operation is to maintain population diversity.

3.5. Elitism strategy

In the multi-objective optimization algorithm, the elitism strategy can effectively prevent the loss of excellent individuals in the evolutionary process. The $(\mu + \lambda)$ selection [10] method (strategy I) can preserve excellent genes and make the population evolve in a better direction. However, with the operation of crossover and mutation, it may lead to the failure of excellent individuals to continue to the last generation of the population. The external filing method can effectively avoid this problem and make the elite individuals preserved in the evolution process. Therefore, the second strategy (strategy II) of this study combines the $(\mu + \lambda)$ selection method with the external filing method to achieve elite retention. The following is a schematic diagram of the NSGA-II elite retention process, as shown in the Figure 2.

The specific flow expression of NSGA-II is as follows:

Step 1. To generate an initial population Z_t with size μ and let iterations times as Υ, crossover probability as P_c and mutation probability as P_m;

Step 2. To perform the crossover and mutation operation on the population Z_t to generate a new offspring population Q_t, and then combine Z_t with Q_t to form a population R_t with size $(\mu + \lambda)$;
Step 3. To evaluate the bi-objective fitness for each individual in the population R_t, and perform fast non-dominated sorting;
Step 4. To adopt the external filing method to update the external archive sets;
Step 5. To apply the crowding distance and tournament selection methods to generate an offspring population Z_{t+1};
Step 6. If the iteration termination condition is not satisfied, turn to step (2). Otherwise, terminate the algorithm.

4. Results and discussion

4.1. Analysis of algorithms

To compare the performance of the strategy I and strategy II, we employ three evaluation metrics, including the diversity, the convergence and the distribution degree of the Pareto Frontier solution sets. Set A and B as two different Pareto Frontier solution sets. The evaluation index of diversity depends on the number of solutions in solution Pareto Frontier set. Assuming u and v are two solutions in the Pareto Frontier solution set. Equation (4.1) means the dominance between u and v. Equation (4.2) represents the relative convergence rate of solution set A to B [40]. $r(A, B) > r(B, A)$ indicates that A has better convergence.

$$s_{(u,v)} = \begin{cases} 1, & \text{if } u \text{ dominates } v \\ 0, & \text{if } v \text{ dominates } u \end{cases} \tag{4.1}$$

$$r(A, B) = \frac{\sum_{u\in A}\sum_{\in B} s_{(u,v)}}{\sum_{u\in A}\sum_{v\in B} s_{(u,v)} + \sum_{u\in B}\sum_{v\in A} s_{(u,v)}}. \tag{4.2}$$

Equation (4.3) represents that the function of $F(A)$ is to evaluate the distribution degree of solutions in the Pareto Frontier solution set A [24], where $d_i^* = \min_{j\in A\setminus\{j\neq i\}} \sum_{k=1}^{m} \mid f_k^i - f_k^j \mid$, $\bar{d} = (\sum_{i=1}^{\|A\|} d_i^*)/ \parallel A \parallel$, $i, j \in A$, α is a constant and the number of the objective functions is m. The more uniform the solution distribution in the solution set A, the value of the $F(A)$ is bigger.

$$F(A) = \alpha \left[\sqrt{\frac{1}{\parallel A \parallel -1} \sum_{i=1}^{\|A\|} (d_i^* - \bar{d})^2} \right]^{-1}. \tag{4.3}$$

In Solomon C101 case, we randomly select 20 nodes, 40 nodes and 60 nodes to construct three multimodal transport networks respectively. In the three networks, transportation duration, cost and modes are generated randomly. The data of transfer are shown in Table 3. The transfer nodes have a fixed timetable for each mode of transportation. The timetable of railway transportation is 3:00; 6:00; 9:00; 12:00; 15:00; 18:00; 21:00. The timetable of waterway transportation is 11:00; 18:00. Highway transportation has no timetable. The interval robust control parameter corresponding to all edges in transportation network is set to 1. It is worth noting that algorithm program is conducted using MATLAB2014b software on an Intel Corei5 PC with 4 gigabytes of RAM and over 2.5 GHz CPU.

Taking the 40 nodes network as an example, Figure 3 depicts the average total duration and cost of all individuals in each generation of the population during the evolution of NSGA-II. Meanwhile, it shows that the objectives of total duration and cost are searched towards the smallest direction by NSGA-II and verifies the reasonableness of the designed algorithm. Figure 4 illustrates the trend of changes in the obtained minimum total duration and cost through both strategy I and strategy II, respectively, as the population evolves. According to

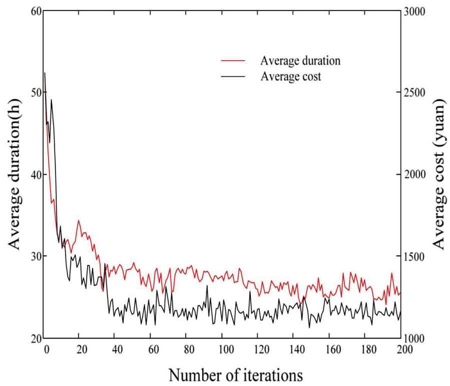

FIGURE 3. The variation of average cost and duration.

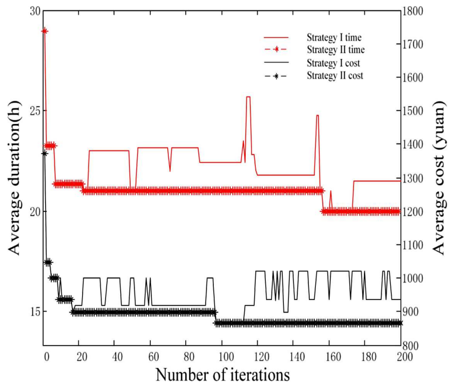

FIGURE 4. The variation of the minimum duration and cost under comparison strategies.

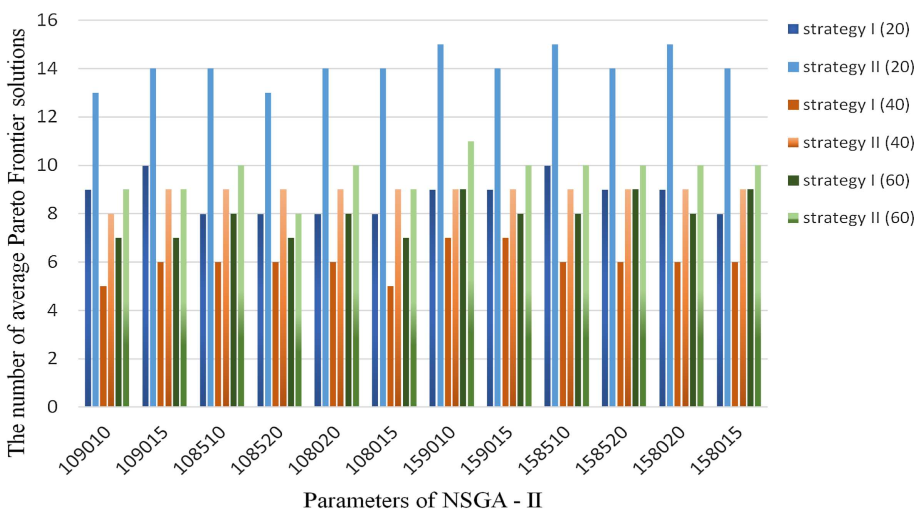

FIGURE 5. Average number of Pareto Frontier solutions under different strategies and networks.

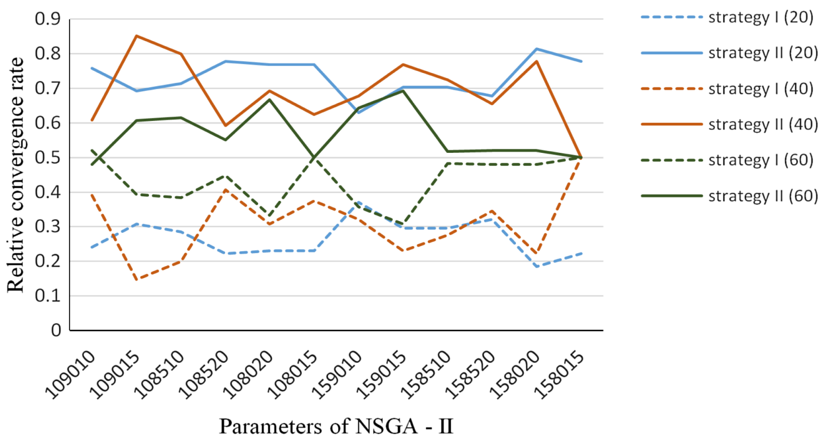

FIGURE 6. Relative convergence rate under different solution strategies and networks.

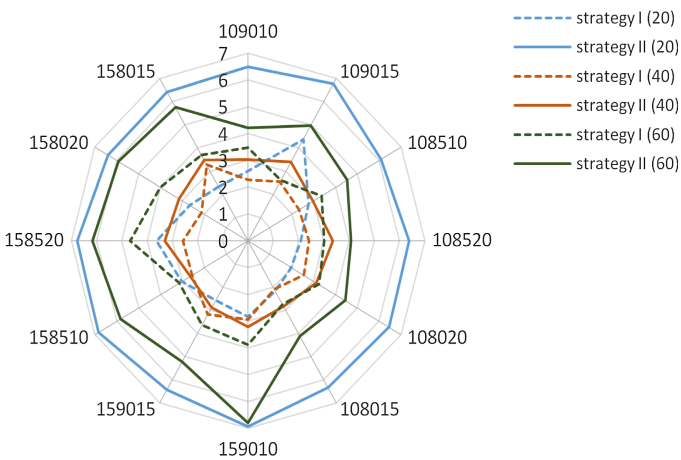

FIGURE 7. The distribution of the solutions under different solution strategies and networks.

Figure 4, the minimum value of each objective obtained through Strategy I will fluctuate, leading to the loss of the elite. By contrast, strategy II can better achieve elite retention.

Different NSGA-II parameters are set (In the "109010", the first and second digits represent a population size of $100(10 * 10)$, the third and fourth digits represent a crossover probability of $0.90(90/100)$ and the fifth and sixth digits represent a mutation probability of $0.10(10/100)$) and iterations are performed 200 times. In Figures 5–7 we graphically describe the diversity, the convergence and the distribution degree of the Pareto Frontier solution sets obtained by adopting strategy I and strategy II under different network scales after the algorithm runs 30 times. In Figure 7, the axis index represents the distribution degree of Pareto optimal solution set, and the strategy II has more desirable ability to make the dispersion of solution more uniform under different genetic parameter combinations. The results of the three algorithm evaluation indicators can be significantly verify that Strategy II is superior to strategy I.

Different parameters are set (The "2109010" is composed of "2" and "109010", the "2" represents that the number of network nodes is $2 * 10$ and the "109010" as explained above) and iterations are performed 200 times. Considered different parameters and strategies, Table 2 states the mean deviation of the minimum and

TABLE 2. The evaluation metric data of the two solution strategies.

Param	Strategy I					Strategy II				
	Obj.1		Obj.2		CPU(s)	Obj.1		Obj.2		CPU(s)
	Ave. min%	Ave. max%	Ave. min%	Ave. max%		Ave. min%	Ave. max%	Ave. min%	Ave. max%	
2109010	10.54	9.49	8.47	7.25	69.02	2.45	1.76	0.94	2.31	73.36
2109015	5.92	8.45	8.51	3.98	70.78	1.99	1.53	0.62	2.29	73.67
2108510	11.15	8.65	6.71	10.22	70.38	1.51	1.77	0.76	2.15	74.13
2108520	10.61	10.45	6.29	7.35	71.32	1.04	2.46	1.17	1.94	71.43
2108020	10.95	12.49	6.48	4.54	71.56	1.28	2.07	0.69	1.88	72.72
2108015	11.31	10.38	8.49	8.18	72.14	1.69	1.81	1.01	2.15	73.73
2159010	6.64	9.69	8.73	5.03	133.02	1.30	2.28	0.84	1.66	134.95
2159015	5.88	7.84	8.56	5.56	137.07	0.44	1.88	0.78	1.18	136.30
2158510	6.94	9.60	7.45	3.97	137.49	0.80	1.88	0.84	0.87	140.16
2158520	8.60	8.13	5.01	7.12	129.60	1.06	2.02	1.15	1.62	132.00
2158020	6.36	9.13	6.80	5.40	137.60	0.93	1.96	0.44	1.77	138.65
2158015	12.19	8.37	6.44	7.44	135.80	1.43	1.68	0.65	2.10	136.43
4109010	10.60	5.19	3.26	27.22	78.67	4.14	2.62	1.62	17.35	81.69
4109015	10.44	5.33	2.73	21.54	81.80	4.83	1.84	2.05	26.29	83.44
4108510	11.98	7.36	4.31	24.99	84.85	5.16	1.40	0.58	15.97	85.60
4108520	12.33	7.77	3.56	23.97	75.60	3.88	2.91	2.29	14.31	80.23
4108020	9.21	4.03	2.03	35.68	79.62	6.05	1.03	2.25	21.74	83.30
4108015	6.63	5.37	3.04	26.12	83.40	5.06	1.78	0.47	20.93	82.18
4159010	8.82	5.01	2.59	26.24	142.36	5.83	1.06	1.46	17.89	143.39
4159015	5.54	8.68	5.40	26.23	145.44	5.44	1.33	2.19	14.43	147.71
4158510	7.78	5.03	3.31	34.04	146.35	5.61	1.11	1.97	14.83	150.07
4158520	9.34	4.53	2.28	31.04	137.58	5.10	1.34	1.41	24.92	140.22
4158020	7.91	5.51	3.28	31.69	146.45	5.84	0.95	1.57	15.46	151.25
4158015	9.55	4.29	1.43	33.48	147.33	5.79	0.50	1.62	26.83	149.67
6109010	12.15	7.95	3.93	16.67	87.78	4.67	5.70	2.91	8.56	88.07
6109015	4.84	6.06	2.97	11.92	86.72	5.33	5.70	1.41	9.25	90.24
6108510	4.94	8.66	3.77	9.95	88.45	4.18	5.91	0.91	6.33	92.50
6108520	7.4	8.35	5.28	13	85.51	5.41	5.48	1.65	9.17	86.69
6108020	4.61	8.22	3.31	6.88	91.93	3.74	6.76	1.53	4.25	94.47
6108015	8.18	9.42	4.24	14.48	86.2	5.56	5.22	1.29	9.93	88.89
6159010	3.03	5.99	2.59	4.5	150.69	2.09	5.36	1.29	3.80	151.23
6159015	4.52	8.09	4.99	6.93	153.22	3.32	5.63	0.94	4.55	152.31
6158510	2.93	6.61	2.91	4.84	154.64	2.12	5.49	0.63	2.58	158.58
6158520	5.33	5.5	2.51	7.32	148.62	2.77	4.67	1.15	2.43	149.58
6158020	5.01	8.63	3.32	9.32	156.54	2.26	5.12	0.91	4.69	159.22
6158015	4.04	8.47	3.57	7.44	151.99	3.1	5.7	0.95	6.42	152.24

maximum of each objective value and the average solution time CPU(s) after the algorithm was run 30 times. From the results presented here, it is obvious that the average deviation of each objective value obtained by strategy II is relatively small under the same parameters and the fluctuation of the average deviation is also relatively small when changed NSGA-II parameters. The CPU is mainly related to the network scale and the population size, yet it is no meaningful relationship with the strategy selection. The analysis shows that strategy II has a desirable performance of stability in solving multi-objective multimodal transportation optimization problems under uncertainty.

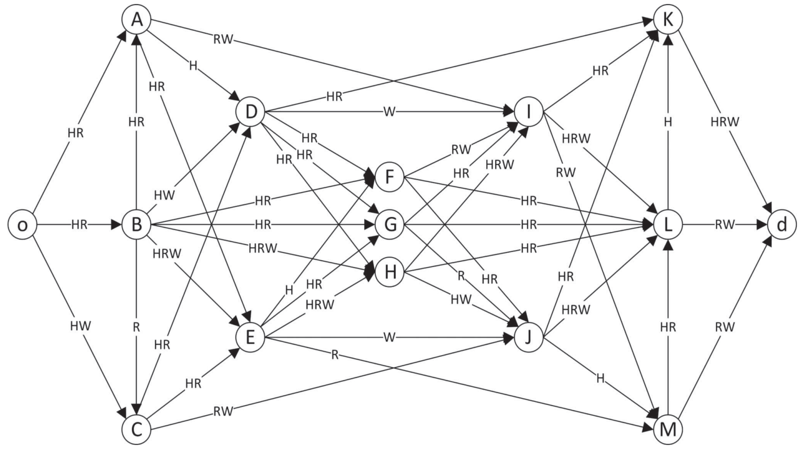

FIGURE 8. Multimodal transportation network.

TABLE 3. Parameters of transfer.

	Unit transferred duration between different mode of transportation (h)			Unit transferred cost between different modes of transportation (yuan)		
	Highway	Railway	Waterway	Highway	Railway	Waterway
Highway	1	1.5	2	30	30	40
Railway	1.5	2	4	30	40	50
Waterway	2	4	3	40	50	50

4.2. Problem instances

We assume, for simplicity, there are 100 tons of goods need to be transported from node o to node d through multimodal transportation. The structure of the multimodal transportation network is shown in Figure 8. The transfer data are shown in Table 3, Table 4 presents the data on the multimodal transportation network. Nodes A to M have a fixed timetable for each mode of transportation. The railway timetable is: 3:00; 6:00; 9:00; 12:00; 15:00; 18:00; 21:00. The waterway timetable is: 11:00; 18:00. The highway has no timetable. The departure time of the goods at the origin node is 7:30 am. The interval robust control parameters corresponding to all edges of highway, railway and waterway transportation duration are all set as 1, which indicates that the decision makers are pessimistic about the uncertain transportation duration. It is required to determine a reasonable route scheme to minimize the total duration and cost of multimodal transportation.

In this numerical instance, the population size is 100, the number of iterations is 200, Cross probability is 0.8 and mutation probability is 0.2 of the NSGA-II, and two different elite strategies (strategy I and strategy II) are employed. $\Re_1$ means Pareto Frontier solution set obtained by strategy I, which contains 8 solutions, $\Re_2$ means Pareto Frontier solution set obtained by strategy II, which contains 12 solutions. The distribution and convergence of its solution sets can be understood from Figure 9. In addition, it further reveals that there are five solutions which have the same objective function value in $\Re_1$ and $\Re_2$, and three of the solutions in $\Re_1$ are dominated by some of the solutions in $\Re_2$.

In the solved instances, 12 groups of non-dominant schemes have been obtained through strategy II as shown in Table 5, but there is no absolute advantage of each group scheme in transportation duration or cost. The results can be referenced for decision makers.

TABLE 4. Multimodal transportation network data.

Point pair; highway data; railway data; waterway data (data format: [transportation duration interval number (h)], cost (yuan/100TUD). ∼ means empty)	
EJ; ∼; ∼; [67,78], 442	EM; ∼; [59,70], 618; ∼
JM; [17,22], 2213; ∼; ∼	LK; [17,20], 1206; ∼; ∼
AD; [27,32], 1663; ∼; ∼	EF; [21,26], 571; ∼; ∼
BC; ∼; [85,96], 611; ∼	GJ; ∼; [65,77], 1078; ∼
DI; ∼; ∼; [89,107], 463	Md; ∼; [40,46], 1046; [104,115], 465
oA; [15,24], 971; [41,48], 674; ∼	oB; [16,21], 1100; [41,45], 653; ∼
AE; [18,25], 1037; [44,52], 475; ∼	AI; ∼; [34,40], 913; [116,120], 367
BD; [26,40], 1004; ∼; [92,103], 497	BF; [36,40], 1527; [63,67], 767; ∼
CD; [18,30], 1890; [54,64], 653; ∼	CE; [12,23], 923; [59,65], 681; ∼
DF; [41,44], 1158; [36,43], 663; ∼	DG; [37,41], 1193; [54,65], 460; ∼
DK; [43,46], 1397; [39,48], 528; ∼	EG; [26,37], 1900; [51,58], 472; ∼
FJ; [17,28], 1592; [35,45], 739; ∼	FL; [19,24], 1784; [45,57], 786; ∼
GL; [32,35], 1825; [38,46], 649; ∼	HJ; [33,45], 1818; ∼; [100,104], 409
IK; [9,21], 1817; [44,48], 459; ∼	IM; ∼; [33,45], 1098; [95,101], 367
Ld; ∼; [40,52], 1053; [69,73], 468	ML; [40,46], 1119; [48,54], 516; ∼
oC; [16,22], 1887; ∼; [100,111], 364	FI; ∼; [44,53], 888; [103,113], 466
BA; [35,43], 1029; [48,57], 782; ∼	GI; [41,48], 1803; [48,59], 671; ∼
BG; [37,47], 1350; [37,43], 423; ∼	HL; [16,25], 1608; [50,62], 716; ∼
CJ; ∼; [30,42], 1203; [85,97], 361	JK; [44,48], 1233; [55,63], 704; ∼
DH; [39,45], 1026; [38,46], 749; ∼	EH; [36,41], 1559; [54,57], 855; [112,115], 439
BE; [35,39], 1921; [46,55], 629; [64,76], 408	BH; [42,47], 1388; [37,41], 981; [65,74], 512
IL; [26,37], 1386; [43,51], 660; [66,76], 403	Kd; [11,20], 1557; [50,61], 879; [83,86], 528
HI; [23,32], 1909; [43,53], 624; [93,99], 522	JL; [27,35], 1140; [43,48], 728; [72,78], 397

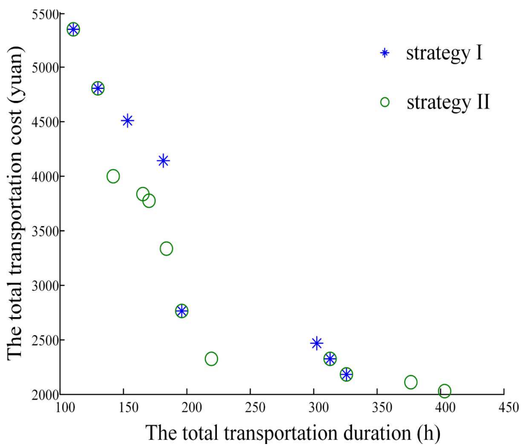

FIGURE 9. Distribution and convergence of Pareto Frontier solution sets under different solution strategies.

TABLE 5. Results of problem instance by solution strategy II.

	Route and mode of transportation	Total duration (h)	Total cost (yuan)
Scheme 1	o(H)A(R)I(H)K(H)d	110	5348
Scheme 2	o(H)A(H)D(R)K(H)d	130	4809
Scheme 3	o(H)A(R)I(R)K(H)d	142	4000
Scheme 4	o(R)B(H)D(R)K(H)d	166	3832
Scheme 5	o(H)A(H)E(R)M(R)d	170	3772
Scheme 6	o(H)A(R)I(R)K(R)d	184	3332
Scheme 7	o(H)B(R)G(R)L(W)d	196	2760
Scheme 8	o(R)B(R)G(R)L(W)d	220	2323
Scheme 9	o(R)A(W)I(R)L(W)d	313	2319
Scheme 10	o(R)A(W)I(R)K(W)d	326	2178
Scheme 11	o(W)C(W)J(R)K(W)d	377	2107
Scheme 12	o(R)A(W)I(W)M(W)d	403	2023

TABLE 6. Results of problem instance by solution strategy II when $\hbar^1_{i,j} = 1$, $\hbar^2_{i,j} = 0.5$ and $\hbar^3_{i,j} = 0.8$.

	Route and mode of transportation	Total duration (h)	Total cost (yuan)
Scheme 1	o(H)A(R)I(H)K(H)d	108	5348
Scheme 2	o(H)A(H)D(R)K(H)d	126	4809
Scheme 3	**o(H)B(H)D(R)K(H)d**	**138**	**4279**
Scheme 4	o(H)A(R)I(R)K(H)d	140	4000
Scheme 5	o(H)A(H)E(R)M(R)d	164	3772
Scheme 6	**o(R)A(R)I(R)K(H)d**	**164**	**3713**
Scheme 7	**o(H)B(R)G(R)L(R)d**	**167**	**3335**
Scheme 8	o(H)A(R)I(R)K(R)d	176	3332
Scheme 9	**o(H)A(R)E(R)M(R)d**	**190**	**3220**
Scheme 10	o(H)B(R)G(R)L(W)d	193	2760
Scheme 11	o(R)B(R)G(R)L(W)d	217	2323
Scheme 12	o(R)A(W)I(R)L(W)d	298	2319
Scheme 13	**o(R)A(W)I(W)L(W)d**	**322**	**2062**
Scheme 14	**o(W)C(W)J(W)L(W)d**	**385**	**1740**

Notes. The bold values are new ob-tained solutions after adjusting the robust parameters.

Robust control parameters can be adjusted to reflect the risk preferences of different decision makers. For example, $\hbar^1_{i,j} = 1$ and $\hbar^2_{i,j} = 0.5$ indicate as pessimistic about the transportation duration for highway and optimistic for railway and $\hbar^3_{i,j} = 0.8$ means the degree of risk decision preferences for waterway duration between pessimistic and optimistic. The scheme calculation results are shown in Table 6. Compared with Table 5, it can be seen that pareto solution set is variable under different robust control parameters.

5. CONCLUSIONS

In this paper, we establish a multi-objective multimodal transportation route robust optimization model with the minimum transportation duration and cost based on interval number under the uncertainty of transportation duration. NSGA-II with the elitist retention strategy is designed to solve the problem. High-quality solutions are obtained in numerical simulation, which confirms that the algorithm is effective in solving the bi-objective optimization problem. In the algorithm analysis, we propose a feasible method to evaluate the performance of the algorithm and the qualities of Pareto Frontier solution sets. The analysis indicates that adding the external archive strategy can improve the performance of the algorithm and the quality of the solutions. Decision makers can adjust robust control parameters to reflect their risk preference for uncertain transportation duration, and enable to balance the duration and cost interests based on the schemes. Finally, in future research, more efficient algorithms could be designed for the proposed problem in this paper to further improve the quality of the solutions.

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