Multimodal Transportation Routing Optimization Considering Schedule Constraints and Uncertain Time

Tingyu Wang, Cunjie Dai, Haijun Li, Runyu Wu

Abstract—**Given the constraints of schedule and the uncertainty of time, the practical needs of operators regarding transportation modes and routing selection are more effectively addressed through the utilization of multiple modes for freight transportation within a transportation network. A bi-objective integer planning model has been developed, focusing on the transportation demand of the operator. The model considers the variability in travel time between nodes and the transfer time associated with various modes of transportation. Its objective is to minimize both total cost and time while treating the freight arrival time as a constraint. The uncertainty planning model is further elucidated through three criteria: optimistic, expected, and pessimistic. The varying risk attitudes of different operators inform these criteria. The modal is subsequently resolved using the Gurobi solver. This study utilizes the transportation demand of Lanzhou-Ningbo Zhoushan Port to create a series of multimodal transportation routings based on various weight combinations. It further examines the impacts of arrival time, schedule constraints, risk attitude, and departing time on the selection outcomes of transportation routing. The findings of this paper may serve as a reference for decision-making by multimodal transportation operators in the development of transportation plans.**

Index Terms—**Multimodal Transportation, Arrival Time, Routing Optimization, Schedule Constraints, Uncertainty Analysis.**

I. Introduction

With the expansion of international commerce, the need for delivery services has increased. This has become logistics a crucial element in integrating production and consumption, hence facilitating international commerce [1]. However, pinpointing a unique mode of transportation that satisfies diverse transportation requirements has been challenging, necessitating the use of a combination of multiple modes.

Multimodal transportation means the strategic integration of several transportation modes, such as road, railway, maritime, and aerial, through the harmonious combination of two or more of these modalities. This freight method entails the conveyance of commodities from origin to destination [2]. Consequently, it facilitates the optimal utilization of various modes while enhancing the allocation of transportation resources. Furthermore, it can substantially decrease transportation duration and expenses. Primarily, multimodal transportation improves logistics efficiency. Currently, the share of multimodal transportation in China stands at merely 2.9% ; the nation's comprehensive transportation growth remains uneven and insufficient, necessitating the advancement of high-quality development through complete transformation [3].

Cost optimization is the primary focus of multimodal transportation research, encompassing several factors like transportation costs, transfer costs, inventory costs, carbon tax costs, etc. [4] The cost reduction approach, a crucial metric of transportation efficiency and economic advantage, fosters the ongoing improvement of logistics plans, facilitates optimal resource utilization, and enhances the overall effectiveness of the transportation chain. Global supply chains are complicated, and the concept of sustainable development has prompted further examination of multimodal transportation beyond just cost considerations. Currently, academics are examining it from a broader spectrum of perspectives, including time efficiency [5], low-carbon environmentalism [6], and risk management [7].

Time is a crucial metric that holds substantial importance in the analysis of multimodal transportation. Swift adaptation to market need and the minimization of freight transit duration are crucial for enhancing corporate competitiveness and client contentment. The allocated time window guarantees that freight may arrive or leave within a specific period, thereby fulfilling client requirements and enhancing satisfaction. It is divided into two categories: the hard time window and the soft time window [8]. For time-sensitive freight, such as fresh produce and medicines, it is crucial to guarantee that the commodities are transported within a precisely defined time frame to avert cargo damage. Conversely, for non-time-sensitive freight, such as general items and raw materials, there exists a degree of flexibility. Although modifications to the transportation duration are permitted within a certain range, it is crucial to comply with the stipulated time frame criteria as precisely as feasible.

In addition, the schedule must be adhered to for the railway, water, and air transport processes [5], guarantee punctuality

Manuscript received July 16, 2024; revised November 5, 2024.

This research was supported by the Natural Science Foundation of Gansu Province (23JRRA858)

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and dependability, optimize the distribution of transportation resources, enhance customer service, and bolster safety management, etc. However, once they are missed, they have to wait for the next departure [9].

Numerous types of uncertainty exist in actual transportation. The multimodal transportation planning issue primarily involves uncertainties in transfer time, volume, and consumer demand [6]. Weather extremes, congestion, seasonal demand, and equipment breakdowns [6] often result in temporal unpredictability. In light of the many uncertainties inherent in the multimodal transportation process, a rational and effective approach has been formulated.

This paper presents the following contributions. (1) The process begins with the development of a bi-objective integer programming model that incorporates time restrictions and uncertainty. (2) The mathematical example of the Lanzhou-Ningbo Zhoushan Port is optimized by considering the operators' risk attitudes and three criteria of uncertain variables. These criteria are used to convert mathematical modalities into corresponding equivalent forms. (3) The impact of arrival time, schedule constraints, risk attitude, and departing time on transportation routing decisions is examined.

In the subsequent section, "Literature Review", a literature review on time windows, schedules, and uncertainty is given and the research work of this paper is described. "Problem Description" defines the study's scope and formulates the problem's hypothesis. "Model Formulation" builds a bi-objective integer programming model with uncertain temporal variables and applies three uncertainty theory criteria to convert the model into a deterministic form. An analysis of the effects of arrival time, schedule constraints, risk attitude, and departure time on the optimization of multimodal transport routing is conducted in the "Case Study" for the Lanzhou-Ningbo Zhoushan Port example, which provides technical assistance to operators in formulating transportation plans. In the last "Conclusion", the conclusion of this paper is given.

II. Literature Review

Among the many research results, the content of concern is focused on different aspects. For example, D. Kirchler et al. [10] studied the shortest routing problem of intermodal transport; E. H. Laaziz et al. [11] focused on the service network design problem to build an efficient transportation network; B. Dong et al. [12] focused on the low-carbon problem in the transportation process; and G. Y. Ke [7] considered the intermodal transportation problem of dangerous freight. However, transportation time is not only directly correlated with the level of transportation costs but also crucial to factors such as delivery of goods without delay, customer satisfaction, and market competitiveness.

Specifically, the time window necessitates the delivery of the service within the desired timeframe; any early arrival will be met with a wait, and any late arrival will be penalized or denied. At each node, D. Emrah et al. [13] take into account the earliest and latest possible departure times for any mode of transportation. These times serve as boundaries, defining a time window. This time window, in turn, imposes constraints on the departure time of that particular node. M. Verma et al. [4] study the multimodal transportation of hazardous goods under delivery cycle constraints. Z. Li et al. [14] consider not only the latest arrival time but also the earliest departure time, which requires that the starting time of departure is later than the time window while the terminal node's arrival time is earlier than the window. S. Fazayeli et al. [15] set penalties for exceeding the time window limit to improve customer satisfaction, as did Y. Zhao et al. [16], L. Moccia et al. [2] simulated an actual truck pickup and delivery service with a time window.

Y. Sun et al. [8] considered truck transportation time as trapezoidal fuzzy numbers on this basis and also considered the railroad transportation schedule constraints, which are closer to the real transportation environment. Because in real life, railroad transportation usually has a fixed schedule, and once it is missed, it must wait for the next departure time [9]. The schedule constraint not only affects the freight's departure time to the next node after reloading but also generates additional storage costs due to the freight being stranded at the transshipment node [5]. S. Liu et al. [17] also considered schedule constraints, and A. Baykasoğlu et al. [18] also explored periodic departure schedules and compared the effects of flexible formation trains and schedule trains on routing.

In most multimodal transportation studies, the various influencing factors are usually regarded as constant values, ignoring the uncertainties caused by congestion, emergencies, seasonal changes, market dynamics, and weather conditions in the actual transportation process. H. Zhang et al. [6] described the demand uncertainty with a trapezoidal fuzzy number, and the interval number describes the time uncertainty. M. Li et al. [19] explained the uncertainty in demand using probability values and stochastic interval numbers. They also looked into the uncertainty in the price of the carbon tax and used a hybrid fireworks algorithm with a gravitational search factor to solve the model. X. Zhang et al. [20] describe the uncertainty of time using a normal distribution, while a few studies concentrate on the uncertainty of network structure [17] and the uncertainty of carbon emission factors [21], offering a comprehensive view of decision analysis and optimization in the multimodal transport field. There are also many methods to deal with uncertainty transformation, such as opportunity constraints [8], robust optimization [19], Monte Carlo simulation [20], etc. Nonetheless, limited research exists regarding transformation utilizing three criteria for uncertain variables.

Research in this domain is deficient because of the complex interaction of arrival time, schedule, and uncertainty factors in multimodal transportation, which complicates management efforts. Examining it from the perspective of the operator's risk attitude presents a significant challenge. A comprehensive examination of all components enhances the precision of modeling and forecasting multimodal transportation while also providing valuable insights for improved decision-making, increased efficiency, and cost reduction.

This paper constructs a bi-objective integer planning model that considers schedule constraints under the uncertainty of multimodal transportation operators' demand. The optimization routings for the Lanzhou-Ningbo Zhoushan

Port example are found using various combinations of weights, taking into account the risk attitude of operators. The modalities are transformed into equivalent forms using three criteria based on uncertain variables, respectively. The effects of arrival time, schedule constraints, risk attitude, and departing time on the results of transportation routing are further analyzed. The study's results can serve as a reference for multimodal transportation operators when formulating their transportation plans.

TABLE I displays the distinctions between this paper's research and the related literature.

III. PROBLEM DESCRIPTION

In the realm of global trade, the efficiency of transportation has become a vital determinant of competitiveness. However, the single mode of transportation for long-distance travel still falls short in meeting the diverse needs of customers. Consequently, to mitigate this issue, multimodal transportation has been used, integrating railway, road, water, and air resources, thereby enhancing transit efficiency and facilitating trade. The model is constructed from the operator's perspective, thoroughly considering arrival time, scheduling, and temporal variability in the transportation process. To ensure its feasibility in terms of time and space, the following assumptions are established:

(1) The multimodal transportation network and routings are fixed.

(2) Only one mode of transportation can be selected between two nodes, and up to one transfer of freight occurs at each node. Any node other than the origin and destination may be used as a transfer node.

(3) Capacity between nodes cannot be split, and arc transportation capacity and node transfer capacity are sufficiently large.

(4) Transportation time and transfer time in the process are uncertain, and uncertainty variables are introduced to represent them.

IV. MODEL FORMULATION

A. Model Parameters

A directed acyclic graph $G=(N,S,A)$ is a graphical depiction of a multimodal transportation network consisting of three primary elements: The set of transportation nodes N, the collection of transportation modes S, and the arcs A that connect them.

Each node in this network has the flexibility to choose from any of the transportation modes available in set S. This selection process determines the associated transportation time for the journey.

Moreover, when a transfer in modes occurs at a transfer node, an additional transfer duration is required. The duration of the transfer is dependent on the mode change and the characteristics of the transfer node.

If railway transport is chosen, the freight needs to be departed according to its schedule. Currently, delays will occur owing to scheduling limitations, and vehicle transport does not account for these limits. Fig. 1 illustrates the temporal connection of each node, and also, taking into account the actual transportation procedure, the latest permissible arrival time for the freight will be established, therefore imposing a time window constraint. The symbols are described in TABLE II.

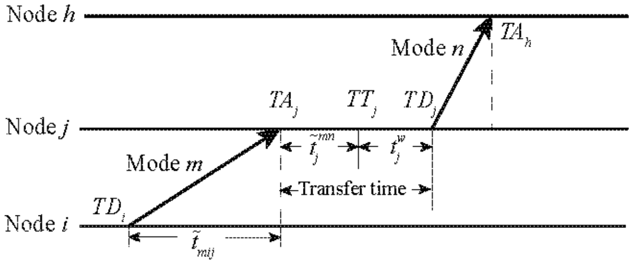


Fig. 1. Schematic diagram of node time

B. Mathematical Model

B.1 Objective function

The paper examines the optimization of freight transportation from origin to destination from the perspective of a multimodal operator, emphasizing the reduction of operating costs and the improvement of arrival efficiency. In the domain of multimodal transportation, a key goal is to determine the most economical option, which includes the routing expenses of various transportation modes and the transfer costs at intermediate points.

$$Minf_1=\sum_{m}^{S}\sum_{i}^{N}\sum_{j}^{N}x_{ij}^{m}c_{ij}^{m}qd_{ij}^{m}+\sum_{m}^{S}\sum_{n}^{S}\sum_{j}^{N}y_{j}^{mn}c_{j}^{mn}q \tag{1}$$

TABLE I
LITERATURE REVIEW

Article	Objective	Time window	Schedule	Uncertainty	Risk attitude	Solution methodology
Demir et al. [13]	Bi-objective	Yes	Yes	No	No	CPLEX
M. Verma et al. [4]	Bi-objective	Yes	No	No	No	CPLEX
Z. Li et al. [14]	Single-objective	Yes	No	No	No	HKSDP
Y. Sun et al. [8]	Bi-objective	Yes	Yes	Time	No	LINGO
Y. Peng et al. [5]	Bi-objective	Yes	Yes	Time and cost	No	NAGA-II
A. Baykasoğlu et al. [18]	Multi-objective	No	Yes	No	No	LINGO
H. Zhang et al. [6]	Multi-objective	No	No	Demand and time	No	Sparrow search
M. Li et al. [19]	Single-objective	No	No	Time and cost	No	FAGSO
X. Zhang et al. [20]	Single-objective	No	No	Demand and time	No	CA-GA
This paper	Bi-objective	Yes	Yes	Time	Yes	Gurobi

※ HKSDP: A Kernel Search and Dynamic Programming Hybrid Heuristic[5]

FAGSO: A Hybrid Fireworks Algorithm with Gravitational Search Operator[19]

TABLE II
SYMBOL DESCRIPTION

Symbol	Description
Set	
N	The set of nodes, $N=\{1,2,\cdots,N\}$, $i,j,h\in N$, o is the original node, d is the destination node, and $N\backslash\{o,d\}$ is the transition node.
S	The set of transportation modes, $S=\{1,2\}$,1 for railway, 2 for road, $m,n\in S$
A	The set of arcs, $(i,j)\in A$
Parameters	
q	Number of containers(unit: carton)
c_{ij}^{m}	Transportation costs for transportation m by mode from node i to node j (unit: CNY/(carton・kilometer))
c_{j}^{mn}	Transfer cost from transportation mode m to transportation mode n at the node j (unit: CNY/carton)
d_{ij}^{m}	Transportation distance from node i to node j by transportation mode m (unit: kilometer)
$\tilde{t}_{mij}$	Uncertain transportation time from node i to node j by mode m of transportation(unit: minute)
$\tilde{t}_{j}^{mn}$	Uncertain transfer time from transportation mode m to transportation mode n at the node j (unit: minute)
t_{j}^{w}	Waiting time at the node j due to the schedule(unit: minute)
TA_j	The arrival time at the node j
TT_j	The time of transshipment completed at the node j
TD_j	The departing time at the node j
T^*	Arrival time
SD_{ij}	The departing time of trains from node i to node j
M	A very large number
Decision variables	
x_{ij}^{m}	0-1 decision variables, if from node i to node j by transportation mode m, $x_{ij}^{m}=1$, or $x_{ij}^{m}=0$
y_{j}^{mn}	0-1 decision variables, if from transportation mode m to n at node j , $y_{j}^{mn}=1$, or $y_{j}^{mn}=0$

Additionally, it is important to take into account the total transportation time of the task, which includes both the transportation and the transfer times. The transfer time consists of the transshipment time and the waiting time.

$$Minf_2=\sum_{i}^{N}\sum_{j}^{N}\sum_{m}^{S}x_{ij}^{m}\tilde{t}_{mij}+\sum_{j}^{N}\sum_{m}^{S}\sum_{n}^{S}y_{j}^{mn}(\tilde{t}_{j}^{mn}q+t_{j}^{w}) \quad (1)$$

B.2 Constraints

$$\sum_{m}^{S}x_{ij}^{m}\leq 1 \quad \forall(i,j)\in A \quad (3)$$

$$\sum_{m}^{S}\sum_{n}^{S}y_{j}^{mn}\leq 1 \quad \forall j\in N\backslash\{o,d\} \quad (4)$$

$$\sum_{m}^{S}\sum_{j}^{N}x_{ij}^{m}-\sum_{m}^{S}\sum_{j}^{N}x_{ji}^{m}=\begin{cases}1 & i=o\\ -1 & i=d\\ 0 & i=N\backslash\{o,d\}\end{cases} \quad (5)$$

$$\sum_{i}^{N}x_{ij}^{m}=\sum_{n}^{S}y_{j}^{mn} \quad \forall j\in N\backslash\{o,d\},\forall m\in S \quad (6)$$

$$\sum_{j}^{N}x_{ij}^{n}=\sum_{m}^{S}y_{i}^{mn} \quad \forall i\in N\backslash\{o,d\},\forall n\in S \quad (7)$$

$$\begin{aligned}&\tilde{t}_{mij}\leq TA_j-TD_i+M(1-x_{ij}^{m})\\&\forall i\in N\backslash\{d\}, j\in N\backslash\{o\}, i\neq j, m\in S\end{aligned} \quad (8)$$

$$\begin{aligned}&\tilde{t}_{j}^{mn}q\leq TT_j-TA_j+M(1-y_{j}^{mn})\\&\forall j\in N\backslash\{o,d\}, m\in S, n\in S\end{aligned} \quad (9)$$

$$\sum_{i}^{N}\sum_{j}^{N}\sum_{m}^{S}x_{ij}^{m}\tilde{t}_{mij}+\sum_{j}^{N}\sum_{m}^{S}\sum_{n}^{S}y_{j}^{mn}(\tilde{t}_{j}^{mn}q+t_{j}^{w})\leq T^* \quad (10)$$

$$TD_j=SD_{jh}x_{jh}^{1}+TT_j(1-x_{jh}^{1})\forall j\in N\backslash\{o,d\}, h\neq j, n\in S \quad (11)$$

$$x_{ij}^{m}\in\{0,1\} \quad \forall(i,j)\in A,\forall m\in S \quad (12)$$

$$y_{j}^{mn}\in\{0,1\} \quad \forall j\in N\backslash\{o,d\},\forall m,n\in S \quad (13)$$

Among them, Eq. (3) indicates that not more than one mode of transportation is used between two nodes, Eq. (4) indicates that the number of transshipments at the transshipment node is not more than one, Eq. (5) indicates the flow balance, Eqs. (6) and (7) indicate the compatibility constraints, and Eq. (8) indicates the time when the freight departs from the node i and arrives at the node j through the mode of transportation m . Eq. (9) represents the moment when the freight completes the changing at the transshipment node j, Eq. (10) is the freight arrival time constraint, Eq. (11) represents the departing time under the schedule constraints of railway transportation at the node j, and Eqs. (12) and (13) are the decision variables.

C. Model Processing

C.1 Clarification of uncertain variables

In the above model, $\tilde{t}_{mij}$ and $\tilde{t}_{j}^{mn}$ are uncertain variables that cannot be used directly in the calculation of transportation time and need to be clarified.

Theorem 1[22]: The uncertainty distribution Φ of an uncertain variable, $\mathcal{M}$ is an uncertain measure, $\Re$ is the whole number of real numbers, ξ is defined by

$$\Phi(x)=\mathcal{M}\{\xi\leq x\} \quad \forall x\in\Re \quad (14)$$

Theorem 2[23]: Let ξ be an uncertain variable with regular uncertainty distribution $\Phi(\alpha)$. Then the inverse function $\Phi^{-1}(\alpha)$ is called the inverse uncertainty distribution of ξ .

Theorem 3[23]: Let $\xi_1,\xi_2,\cdots,\xi_n$ be independent uncertain variables with regular uncertainty distributions $\Phi_1, \Phi_2, \cdots, \Phi_n$ respectively. If f is a continuous and strictly increasing function, then $\xi = f(\xi_1, \xi_2, \cdots, \xi_n)$ has an inverse uncertainty distribution:

$$\Psi^{-1}(\alpha) = f(\Phi_1^{-1}(\alpha), \Phi_2^{-1}(\alpha), \cdots, \Phi_n^{-1}(\alpha)) \quad (15)$$

The constraints Eqs. (8) to (10) are transformed into the form of uncertainty measures, and the objective function f_2 is transformed into the same form as Eq. (8).

$$\mathcal{M}\left\{\sum_i^N \sum_j^N \sum_m^S x_{ij}^m \tilde{t}_{mij} + \sum_j^N \sum_m^S \sum_n^S y_j^{mn} (\tilde{t}_j^{mn} q + t_j^w) \le T^*\right\} \ge \lambda \quad (16)$$

$$\begin{aligned} &\mathcal{M}\left\{\tilde{t}_{mij} \le TA_j - TD_i + M(1 - x_{ij}^m)\right\} \ge \gamma \\ &\forall i \in N \setminus \{d\}, j \in N \setminus \{o\}, m \in S \end{aligned} \quad (17)$$

$$\begin{aligned} &\mathcal{M}\left\{\tilde{t}_j^{mn} q \le TT_j - TA_j + M(1 - y_j^{mn})\right\} \ge \eta \\ &\forall j \in N \setminus \{o, d\}, m \in S, n \in S \end{aligned} \quad (18)$$

where λ, γ, η is the confidence level, and $0 < \lambda, \gamma, \eta \le 1$.

Definition 1[25]: Let ξ be an uncertain variable. $\mathcal{M}$ is an uncertainty measure of ξ with confidence level α for any real number r.

(1) The optimistic value of ξ is defined by:

$$\xi_{\sup}(\alpha) = \sup\{r \mid \mathcal{M}\{\xi \ge r\} \ge \alpha\}, \alpha \in (0,1] \quad (19)$$

(2) The expected value of ξ is defined by:

$$\xi_E = \int_0^{+\infty} \mathcal{M}\{\xi \ge r\} dr - \int_{-\infty}^0 \mathcal{M}\{\xi \le r\} dr \quad (20)$$

(3) The pessimistic value of ξ is defined by:

$$\xi_{\inf}(\alpha) = \inf\{r \mid \mathcal{M}\{\xi \le r\} \ge \alpha\}, \alpha \in (0,1] \quad (21)$$

Proposition 1[25]: Let ξ be an uncertain variable with continuous uncertainty distribution Φ. Then for any real number r, there are

$$\Phi(r) = \mathcal{M}\{\xi \le r\}, 1 - \Phi(r) = \mathcal{M}\{\xi \ge r\} \quad (22)$$

According to Definition 1, it can be obtained

$$\xi_{\sup}(\alpha) = \sup\{r \mid 1 - \Phi(r) \ge \alpha\}, \alpha \in (0,1] \quad (23)$$

$$\xi_E = \int_0^{+\infty} (1 - \Phi(r)) dr - \int_{-\infty}^0 \Phi(r) dr \quad (24)$$

$$\xi_{\inf}(\alpha) = \inf\{r \mid \Phi(r) \ge \alpha\}, \alpha \in (0,1] \quad (25)$$

Theorem 4[23]: Let ξ, η be independent uncertain variables with finite expected values. Then for any real numbers a, b, there are

$$E(a\xi + b\eta) = aE(\xi) + bE(\eta) \quad (26)$$

Lemma 1[27]: Given a real number λ, an uncertain variable η, and ξ, η are independent of each other, there are

(1) $\lambda \ge 0$, $(\lambda\xi)_{\sup}(\alpha) = \lambda\xi_{\sup}(\alpha), (\lambda\xi)_{\inf}(\alpha) = \lambda\xi_{\inf}(\alpha)$.

(2) $\lambda < 0$, $(\lambda\xi)_{\sup}(\alpha) = \lambda\xi_{\sup}(\alpha), (\lambda\xi)_{\inf}(\alpha) = \lambda\xi_{\inf}(\alpha)$.

(3) $(\xi + \eta)_{\sup}(\alpha) = \xi_{\sup}(\alpha) + \eta_{\sup}(\alpha)$,

$(\xi + \eta)_{\inf}(\alpha) = \xi_{\inf}(\alpha) + \eta_{\inf}(\alpha)$.

On the above, the operator can then select the corresponding criterion for the transformation of uncertain variables according to his risk attitude.

C.2 Multi-objective to single-objective

Because of the dimension of cost and duration, the linear weighting approach is not a workable method for the issue. The ideal point method, however, is based on constructing an ideal point that meets each objective dimension [28], then searching for the most feasible solution that is closest to that ideal point under the constraints and finally constructing a single-objective plan with deviation minimization as the objective function.

If the optimal solution of k objectives X_{ij}^*, f_i^* is identical, then multi-objective planning will be optimally solved, thus concluding the algorithm. Otherwise, the transformation must be executed.

$$MinF = \sum_i^k \omega_i [(f_i(x) - f_i^*) / f_i^*] \quad \forall \omega_i \ge 0, \sum_i^k \omega_i = 1 \quad (27)$$

C.3 Complete model

The objective function is

$$\begin{aligned} &MinF = \omega_1 [(f_1 - f_1^*) / f_1^*] \\ &+ \omega_2 [(f_2 - f_2^*) / f_2^*] \\ &\forall \omega_1 + \omega_2 = 1, \omega_1, \omega_2 \ge 0 \end{aligned} \quad (28)$$

Marking $\Phi_{mij}(\alpha)$ and $\Gamma_{jmn}(\alpha)$ as the uncertainty distributions of $\tilde{t}_{mij}$ and $\tilde{t}_j^{mn}$, respectively, so $\Phi_{mij}^{-1}(\alpha)$ and $\Gamma_{jmn}^{-1}(\alpha)$ is the uncertainty inverse distributions, Eqs. (16)~(18) can be further transformed. The constraints are as follows.

Under the optimistic value criterion, the constraints are Eq. (3) to Eq. (7), Eq. (11) to Eq. (13), Eq. (30) to Eq. (32)

$$\begin{aligned} &Minf_2 = \sum_i^N \sum_j^N \sum_m^S x_{ij}^m \Phi_{mij}^{-1}(1 - \lambda) \\ &+ \sum_j^N \sum_m^S \sum_n^S y_j^{mn} [\Gamma_{jmn}^{-1}(1 - \lambda) q + t_j^w] \end{aligned} \quad (29)$$

$$\begin{aligned} &\sum_i^N \sum_j^N \sum_m^S x_{ij}^m \Phi_{mij}^{-1}(1 - \lambda) \\ &+ \sum_j^N \sum_m^S \sum_n^S y_j^{mn} [\Gamma_{jmn}^{-1}(1 - \lambda) q + t_j^w] \le T^* \end{aligned} \quad (30)$$

$$\begin{aligned} &\Phi_{mij}^{-1}(1 - \gamma) \le TA_j - TD_i + M(1 - x_{ij}^m) \\ &\forall i \in N \setminus \{d\}, j \in N \setminus \{o\}, m \in S \end{aligned} \quad (31)$$

$$\begin{aligned} &q\Gamma_{jmn}^{-1}(1 - \eta) \le TT_j - TA_j + M(1 - y_j^{mn}) \\ &\forall j \in N \setminus \{o, d\}, m \in S, n \in S \end{aligned} \quad (32)$$

The constraints under the expected value criterion are Eq. (3) to Eq. (7), Eq. (11) to Eq. (13), Eq. (34) to Eq. (36)

$$f_2 = E(\lambda) \quad (33)$$

$$\begin{aligned} E(\lambda) = &\sum_i^N \sum_j^N \sum_m^S x_{ij}^m \left(\int_0^{+\infty} (1 - \Phi_{mij}(T^*)) d(T^*)\right) \\ &+ \sum_i^N \sum_j^N \sum_m^S x_{ij}^m \left(\int_{-\infty}^0 \Phi_{mij}(T^*) d(T^*)\right) \\ &+ q \cdot \sum_j^N \sum_m^S \sum_n^S y_j^{mn} \left(\int_0^{+\infty} (1 - \Phi_{mij}(T^*)) d(T^*)\right) \\ &+ q \cdot \sum_j^N \sum_m^S \sum_n^S y_j^{mn} \left(\int_{-\infty}^0 \Phi_{mij}(T^*) d(T^*)\right) + \sum_j^N \sum_m^S \sum_n^S y_j^{mn} t_j^w \end{aligned} \quad (34)$$

$$E(\gamma)=\int_0^{+\infty}(1-\Phi_{mij}(a))d(a)+\int_{-\infty}^{0}\Phi_{mij}(a)d(a)$$
$$+\int_0^{+\infty}(1-\Gamma_{mij}(a))d(a)+\int_{-\infty}^{0}\Gamma_{mij}(a)d(a) \quad (35)$$
$$\forall i\in N\setminus\{d\}, j\in N\setminus\{o\}, m\in S$$

$$E(\eta)=q(\int_0^{+\infty}(1-\Phi_{jmn}(b))d(b)+\int_{-\infty}^{0}\Phi_{jmn}(b)d(b)$$
$$+\int_0^{+\infty}(1-\Gamma_{jmn}(b))d(b)+\int_{-\infty}^{0}\Gamma_{jmn}(b)d(b)) \quad (36)$$
$$\forall j\in N\setminus\{o,d\}, m\in S, n\in S$$

Where

$a=TA_j-TD_i+M(1-x_{ij}^m)$, $b=TT_j-TA_j+M(1-y_j^{mn})$.

Under the pessimistic value criterion, the constraints are Eq. (3) to Eq. (7), Eq. (11) to Eq. (13), Eq. (38) to Eq. (40)

$$f_2=\sum_i^N\sum_j^N\sum_m^S x_{ij}^m\Phi_{mij}^{-1}(\lambda)$$
$$+\sum_j^N\sum_m^S\sum_n^S y_j^{mn}[\Gamma_{jmn}^{-1}(\lambda)q+t_j^w] \quad (37)$$

$$\sum_i^N\sum_j^N\sum_m^S x_{ij}^m\Phi_{mij}^{-1}(\lambda)$$
$$+\sum_j^N\sum_m^S\sum_n^S y_j^{mn}[\Gamma_{jmn}^{-1}(\lambda)q+t_j^w]\le T^* \quad (38)$$

$$\Phi_{mij}^{-1}(\gamma)\le TA_j-TD_i+M(1-x_{ij}^m)$$
$$\forall i\in N\setminus\{d\}, j\in N\setminus\{o\}, m\in S \quad (39)$$

$$q\Gamma_{jmn}^{-1}(\eta)\le TT_j-TA_j+M(1-y_j^{mn})$$
$$\forall j\in N\setminus\{o,d\}, m\in S, n\in S \quad (40)$$

V. Case Study

A. Parameters Setting

A company in Lanzhou (o , noted as node 1) has 30 standard containers of freight to be transported to Ningbo-Zhoushan Port (d , noted as node 13) through the intermodal transportation network in 2. Considering the freight volume and geographic location and other factors, selected Chengdu, Xi'an, Chongqing, Zhengzhou, Wuhan, Changsha, Nanchang, Wuhu, Shanghai, Jiaxing, Hangzhou, the 11 cities as a transshipment node $2,3,\ldots,12$, at least one mode of transportation between adjacent cities can be accessed, if the choice of highway transport, arrived at the transshipment node can be directly away from the mode of transport or change, while the railway transportation will be subject to the node of the schedule constraints. A specialized technique is used to record time intervals in order to enable discrete management of time. For instance, the commencement of transportation at 8:00 is designated as 0 minutes, whereas 10:45 is recorded as 165 minutes from the starting point. Similarly, transportation starting at 9:00 the following day is marked as 1500 minutes, relative to the initial reference time.

Considering that different modes of transportation have different pricing methods, checking the 95306 website gives the unit cost of transportation of a standard container by railway, as shown in TABLE III, which also gives obedience to the linear uncertainty distribution of transportation time [6] and the departing time [31].

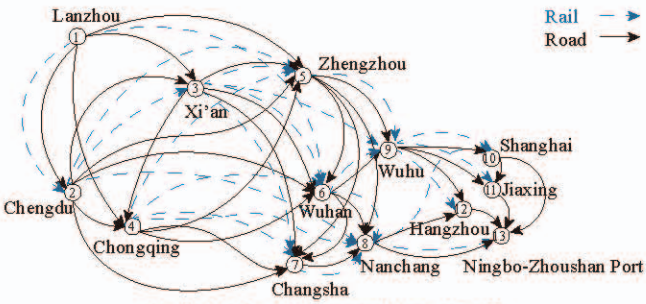


Fig. 2. Multimodal transportation network

TABLE III
RAILWAY UNIT COST, TIME, AND DEPARTING TIME

Arc	Cost (CNY/carton)	Time (minute)	Departing Time
1-2	4340	[3945,3960]	18:15
1-6	6474	[3499,3514]	18:15
2-3	3630	[2781,2796]	20:21
2-5	5551	[4391,4406]	13:49
2-8	7334	[4381,4396]	20:59
3-5	2374	[1679,1694]	20:57
3-6	3595	[5031,5046]	10:20
3-7	5163	[5710,5725]	09:32
3-9	4823	[4299,4314]	14:16
4-5	2374	[5270,5285]	04:21
4-6	3595	[4941,4956]	17:57
4-7	4971	[2151,2166]	10:21
4-8	6184	[3477,3492]	17:57
5-9	3409	[1900,1915]	21:19
6-8	1839	[1010,1025]	18:20
6-9	2508	[1230,1245]	18:56
7-8	2033	[990,1005]	04:44
8-10	3648	[940,955]	20:22
8-13	3359	[3313,3328]	22:10
9-10	1989	[1820,1835]	00:38
9-11	1786	[1780,1795]	20:59
9-12	1585	[1710,1725]	00:52

The unit cost of road transport is calculated according to the basic price plus the mileage price, which can be obtained from the article [29] $c_{ij}^2=15+8d_{ij}^2$. The distance between the nodes of each city is referred to Gaode map. Since road transport is greatly affected by weather, congestion, etc., different forms of uncertainty variables are used to describe the time change [6], part of which obeys the zigzag uncertainty distribution and part of which obeys the linear uncertainty distribution, as shown in TABLE IV.

B. Numerical Results

The departing time of the origin is set to be 18:15 on July 1st, which is recorded as 0 minutes, and the arrival time is 18:15 on July 7th, i.e., $T^*=10080$, and the value of weight ω_1 is taken from 0 to 1 at intervals of 0.1. The algorithm is implemented by the Gurobi solver invoked by the Python language, and the running environment is a personal PC with a CPU APPLE M1 Pro and 8GB of RAM.

(1) Numerical results based on optimistic value criterion

The optimistic value criterion focuses on the most favorable outcome, reflecting the risky attitude of the operator who tends to take risks in pursuit of greater returns. It is suitable for operators with a high tolerance for risk.

TABLE VI's results, obtained with confidence level

$\alpha = 0.6$, are displayed in Fig. 3(a), along with the cost and time changes, and the routing plan is shown in Fig. 4.

As can be seen from the results, Plan 4 has the lowest cost, 360555 CNY, and Plan 1 has the shortest time, only 2317 minutes. Comparison with Plan 4 reveals that Plan 3 has increased transportation efficiency by 24%. Costs have only increased by 6%, a relatively small change, while Plan 2 has a significant reduction in transportation time by 43%. Yet costs have only increased by 17%, compared to Plan 1, which has a significant reduction in transportation time by 72%, and a significant increase in costs by 53%. In terms of the choice of mode of transportation, the railway is more attractive for time-insensitive freight due to its economic advantages, and flexible road transport is more appropriate for time-sensitive and value-added freight.

Specifically, railway transport, with arc (1,6) instead of arc (1,5) of road transport, offers a significant cost reduction, an obvious economic advantage, and a demonstration of its economic advantages in comparison to plan 2 and plan 1. Comparing plan 2, plan 3, and plan 4, their routing is consistent, and the main difference is the mode of transportation. From node 6 to node 9, road transport makes transportation efficiency increased by 25%, and the cost increased by 10%; from node 9 to node 12 choosing the road transport time savings of 24%, the cost only increased by 6%, highlighting the advantages of road transport in short-distance transportation. Therefore, multimodal transportation operators need to make the appropriate choice depending on the situation with the freight.

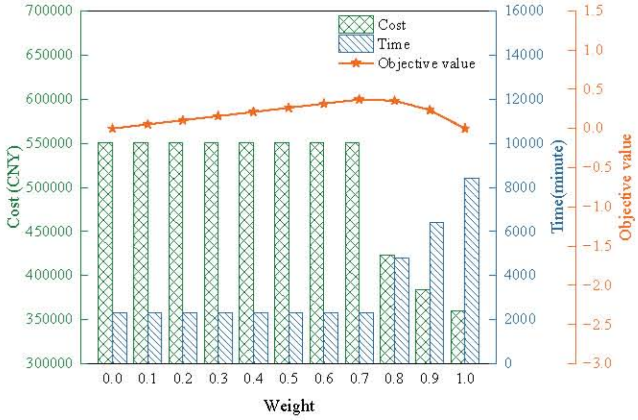
TABLE IV
ROAD UNIT COST AND TIME

Arc	Cost (CNY/carton)	Time (minute)
1-2	870	[713,940,1029]
1-3	670	[543,730,791]
1-4	980	[795,1060,1870]
1-5	1145	[939,1245,1350]
2-3	743	[618,803,891]
2-4	308	[231,328,356]
2-5	1203	[983,1303,1412]
2-6	1159	[950,1259,1364]
2-7	1193	[975,1293,1402]
3-4	712	[574,772,837]
3-5	481	[381,541,565]
3-6	740	[595,800,867]
3-7	1004	[813,1084,1195]
4-5	1156	[947,1256]
4-6	868	[711,948]
4-7	905	[739,985]
5-6	509	[402,549,595]
8-10	3648	[940,955]
8-13	3359	[3313,3328]
5-7	802	[662,862,935]
5-8	838	[689,898,995]
5-9	698	[564,758,821]
6-7	332	[269,352,382]
6-8	346	[280,366,398]
6-9	478	[379,518,562]
7-8	337	[273,357]
8-12	528	[416,568,616]
8-13	661	[536,721,781]
9-10	354	[287,354,406]
9-11	304	[228,324,352]
9-12	295	[222,295,342]
10-11	108	[81,108,118]
10-13	230	[173,230,271]
11-13	171	[129,171]
12-13	157	[118,157]

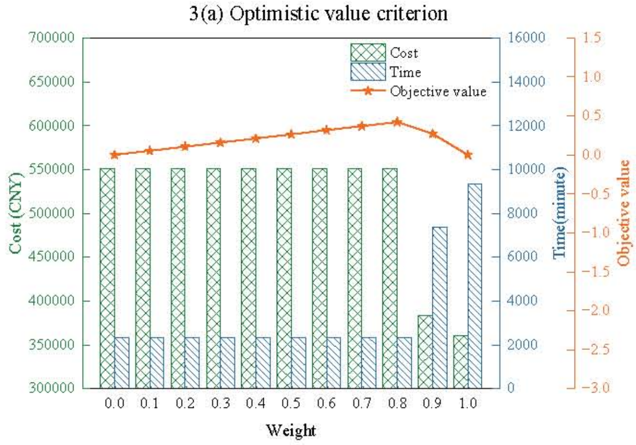
TABLE V
TRANSFER COST(CNY/CARTON) AND TIME(MINUTE/CARTON)

Node	Railway-Railway	Railway-Road	Road-Railway	Road-Road
1	0/0	0/0	0/0	0/0
2	0/0	195/[40,48]	195/[40,48]	0/0
3	0/0	195/[40,48]	195/[40,48]	0/0
4	0/0	195/[40,48]	195/[40,48]	0/0
5	0/0	195/[40,48]	195/[40,48]	0/0
6	0/0	195/[40,48]	195/[40,48]	0/0
7	0/0	195/[40,48]	195/[40,48]	0/0
8	0/0	195/[40,48]	195/[40,48]	0/0
9	0/0	195/[40,48]	195/[40,48]	0/0
10	0/0	195/[40,48]	195/[40,48]	0/0
11	0/0	195/[40,48]	195/[40,48]	0/0
12	0/0	195/[40,48]	195/[40,48]	0/0
13	0/0	0/0	0/0	0/0

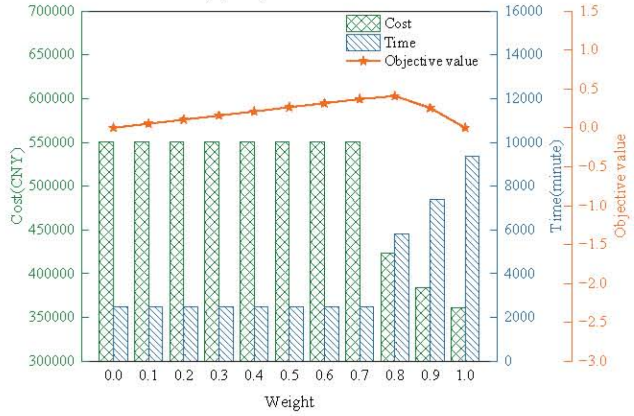
※ Cost/Time



3(a) Optimistic value criterion



3(b) Expected value criterion



3(c) Pessimistic value criterion

Fig. 3. Optimization results of the three criteria

TABLE VI
OPTIMIZATION RESULTS of MULTIMODAL ROUTING BASED on OPTIMISTIC VALUE CRITERION

Plan	ω_1	Routing	Modes	Cost(CNY)	Time(minute)
1	0~0.7	1-5-9-12-13	Road-road-road-road	550860	2317
2	0.8	1-6-9-12-13	Railway-road-road-road	423315	4805.2
3	0.9	1-6-9-12-13	Railway-railway-road-road	383820	6407
4	1	1-6-9-12-13	Railway-railway-railway-road	360555	8402.6

TABLE VII
OPTIMIZATION RESULTS of MULTIMODAL ROUTING BASED on EXPECTED VALUE CRITERION

Plan	ω_1	Routing	Modes	Cost(CNY)	Time(minute)
1	0~0.8	1-5-9-12-13	Road-road-road-road	550860	2346.5
2	0.9	1-6-9-12-13	Railway-railway-road-road	383820	7345
3	1	1-6-9-12-13	Railway-railway-railway-road	360555	9332

TABLE VIII
OPTIMIZATION RESULTS of MULTIMODAL ROUTING BASED on PESSIMISTIC VALUE CRITERION

Plan	ω_1	Routing	Modes	Cost(CNY)	Time(minute)
1	0~0.7	1-5-9-12-13	Road-road-road-road	550860	2482.4
2	0.8	1-6-9-12-13	Railway-road-road-road	423315	5824.6
3	0.9	1-6-9-12-13	Railway-railway-road-road	383820	7389.8
4	1	1-6-9-12-13	Railway-railway-railway-road	360555	9361.4

Fig. 4. Routings for the optimistic value criterion

(2) Numerical results based on the expected value criterion

By figuring out the average expected value under various scenarios, the expected value criterion is used to measure risk. TABLE VII displays the transportation plan, and Fig. 3(b) exemplifies the divergence in both cost and travel duration across different plans.

Plan 3 has the lowest total cost, 360555 CNY, and Plan 1 has the shortest total time, 2346.5 minutes. Comparison with Plan 3 reveals that Plan 2 transportation time improves by 21% , and cost increases by only 6% , while Plan 1 transportation time improves by 75% and cost increases by 53% . For time-sensitive freight, plan 2 is efficient and can be more efficient at less cost.

(3) Numerical results based on the pessimistic value criterion

The pessimistic value criterion focuses on the most unfavorable outcome and is suitable for operators who have a lower tolerance for risk or are more robust and conservative. The confidence level A of the pessimistic value criterion yields the transportation plans shown in TABLE VIII, with the transportation cost and time results as in Fig. 3(c). Plan 4 has the lowest total cost, 360555 CNY, and Plan 1 has the shortest total time, 2482.4 minutes.

(4) Comparison of the results of the three criteria

Upon examining each criterion separately, an inverse correlation between cost and time becomes apparent, suggesting that minimizing costs often translates to reduced efficiency. Given that enhancing transportation efficiency necessitates substantial capital investments, striking a balance between achieving efficiency gains and managing cost escalations during decision-making is crucial. It ensures optimal resource allocation and attainment of the most beneficial outcomes.

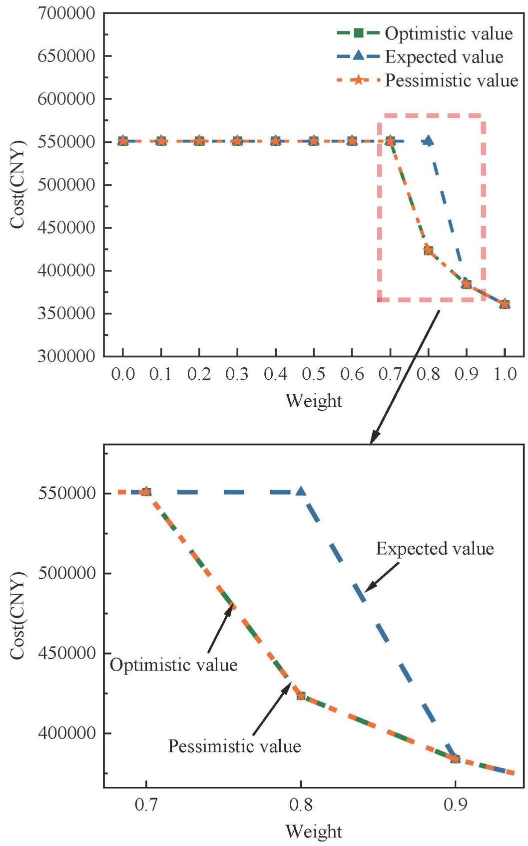
Further, a side-by-side comparison of the three criteria, as shown in Fig. 5, provides insight into the differences and impacts between them. Fig. 5(a) presents the variation in transportation costs, Fig. 5(b) the variation in transportation time, and Fig. 5(c) the variation in the value of the objective function.

From a cost perspective, both the optimistic and pessimistic value criteria produce an overall cost that is essentially equivalent, but slightly exceeds the cost associated with the expected value criterion.

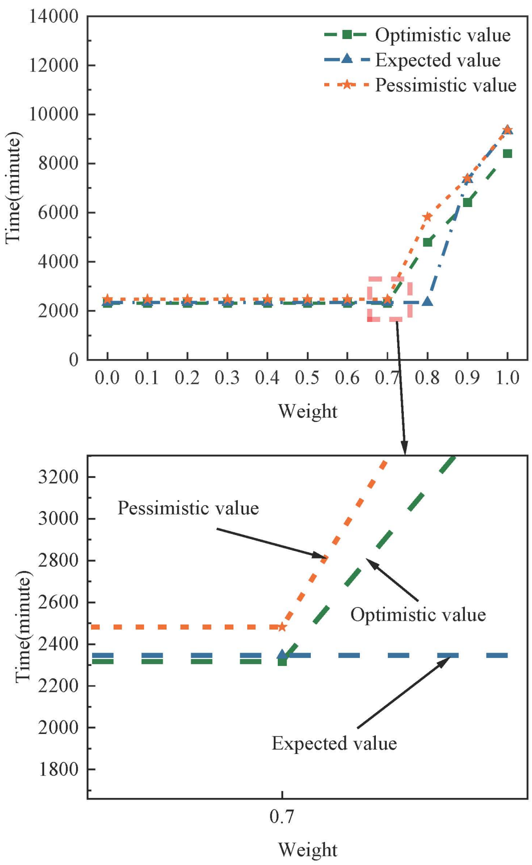
From a temporal perspective, when $\omega_1 \le 0.7$, the optimistic value criterion yields a shorter duration compared to the expected value criterion, both of which significantly fall below the pessimistic value criterion, albeit with relatively minor discrepancies. Conversely, $\omega_1 \ge 0.8$, the time disparity among the three criteria becomes strikingly evident. Lastly, when $\omega_1 = 0.8$, the expected value criterion emerges as the most efficient, boasting the shortest timeframe, which surpasses both the optimistic and pessimistic value criteria, underscoring its superiority in terms of minimizing time consumption.

From the objective value perspective, all three variations exhibit identical outcomes. It demonstrates that various risk attitudes play a significant role in the selection of transportation options.

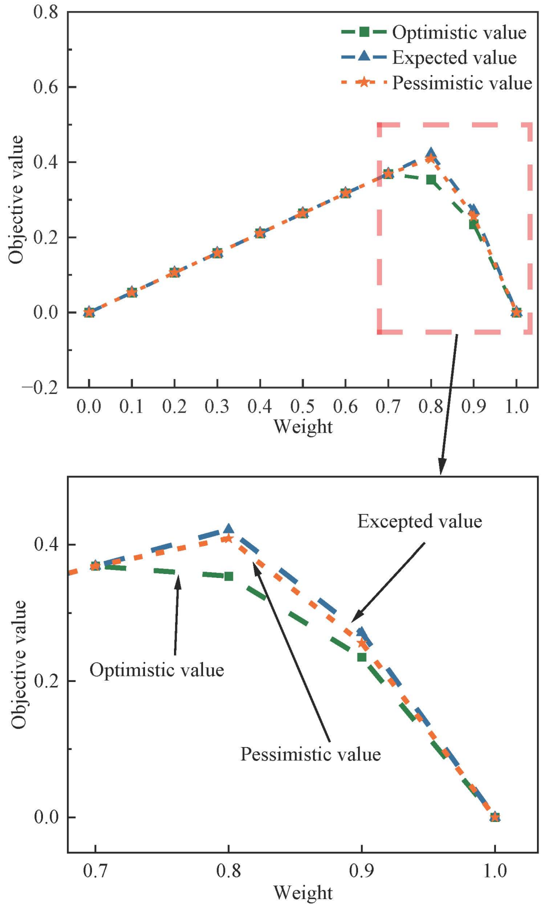
From the above mentioned, under different value criteria, the transportation plans differ significantly when $\omega_1 \ge 0.8$. Multimodal transportation operators must exercise discretion in tailoring their decisions to the ever-evolving circumstances, selecting optimal transportation schemes for individual freight consignments. This strategic approach enables them to dynamically adapt to the volatile market demands and the intensified competitive landscape, ensuring resilience and competitiveness in a dynamic industry.



5(a) Cost



5(b) Time



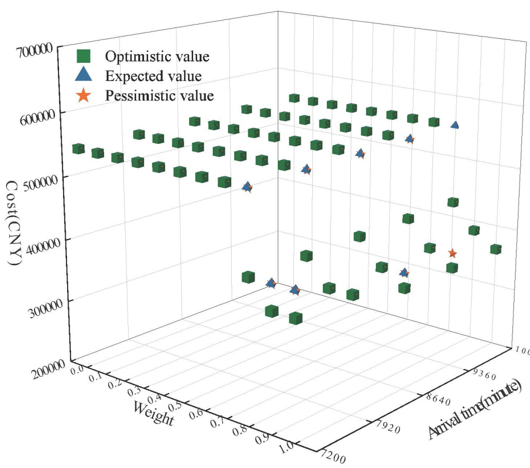
5(c) Objective value

Fig. 5. Changes under different criteria

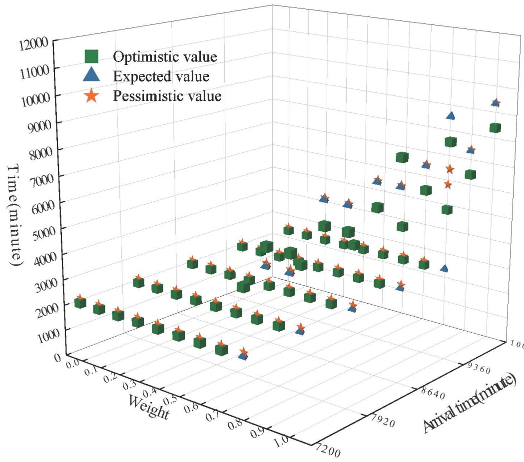
C. *Sensitivity Analysis*

(1) Sensitivity analysis of arrival time

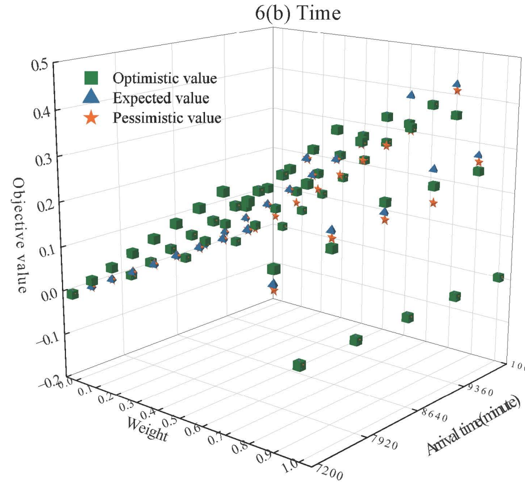
Fig. 6 shows that when the arrival time is changed while all other variables stay the same, the cost, time, and objective values are very sensitive to changes in the arrival time, no matter what evaluation criteria were used. It means that a small change in arrival time affects them significantly, and the change in time is more obvious. Specifically, costs decrease as the arrival time increases, while time increases simultaneously. Thus, operators have the flexibility to choose different transportation plans depending on the arrival time of the freight.



6(a) Cost



6(b) Time



6(c) Objective value

Fig. 6. Sensitivity analysis of arrival time

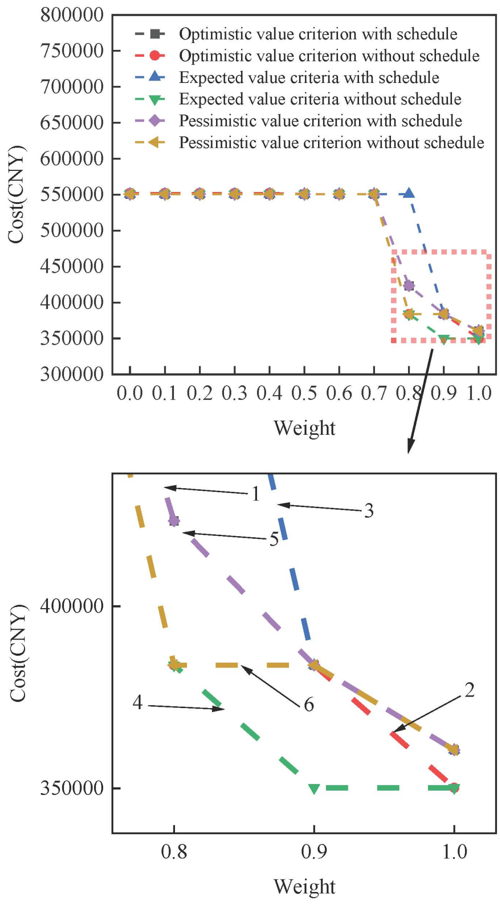
(2) Sensitivity analysis of schedule constraints

The findings provided in Fig. 7 demonstrate the comparison of the impact of having or not scheduling on the optimum routing while keeping every other variable constant.

The influence of schedule on transportation cost and transportation time cannot be overlooked, as evidenced by the fact that when considering schedule constraints, transportation cost and time are both greater than when not. Therefore, in multimodal transportation routing optimization, setting a reasonable schedule is of enormous significance to the development of transportation plans.

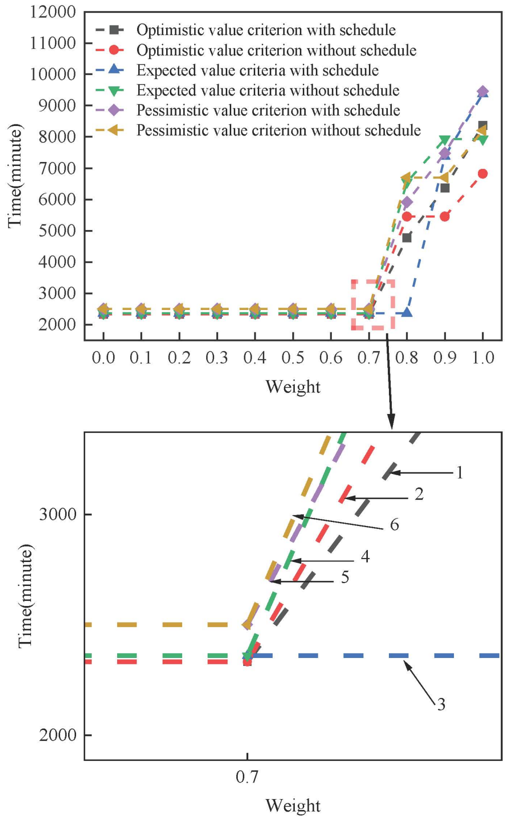
(3) Sensitivity analysis of confidence α based on optimism value criterion

The outcomes shown in Fig. 8 can be obtained. It finds out that when the confidence level α rises, the cost rises as well, and transfer time decreases when $\omega_1 \leq 0.8$. Most of them change drastically at $\alpha = 0.9$, which indicates that $\alpha = 0.9$ is the key point. When $\omega_1 \geq 0.9$, variations in the confidence level remain inconsequential to the cost, while the sole consequence is a marginal reduction in the required time as it escalates. It may be because the change in time caused by the change in the confidence level is not as large as the effect of the schedule and arrival time, so it is not enough to change the original transportation plan, and this α is not binding.

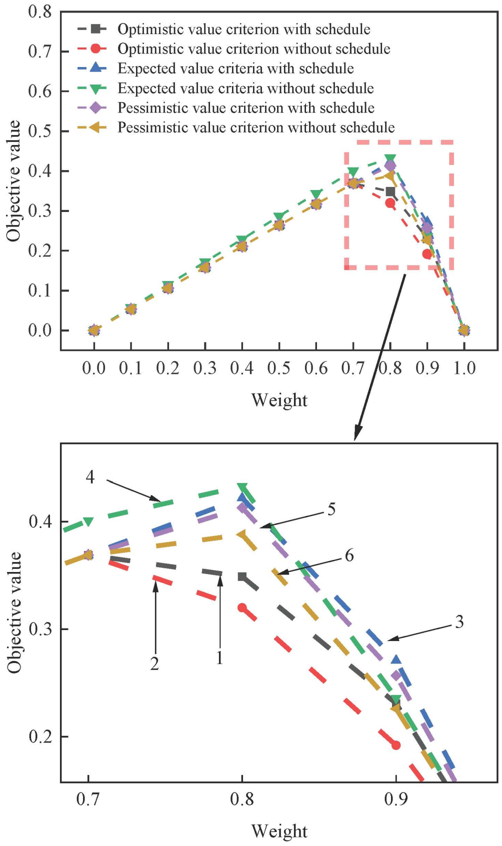


7(a) Cost

※ 1:Optimistic value with schedule
2:Optimistic value without schedule
3:Expected value with schedule
4:Expected value without schedule
5:Pessimistic value with schedule
6:Pessimistic value without schedule

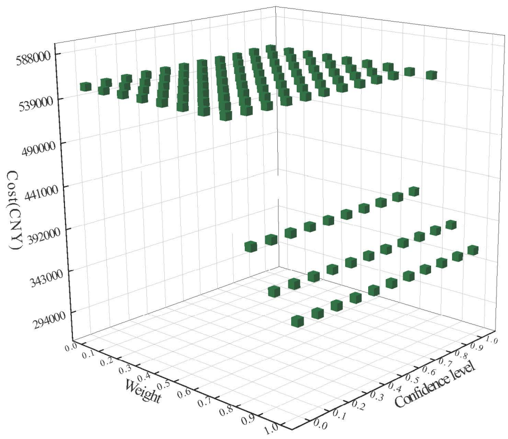


7(b) Time

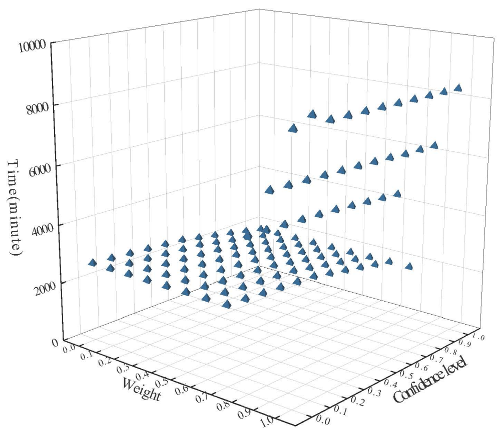


7(c) Objective value

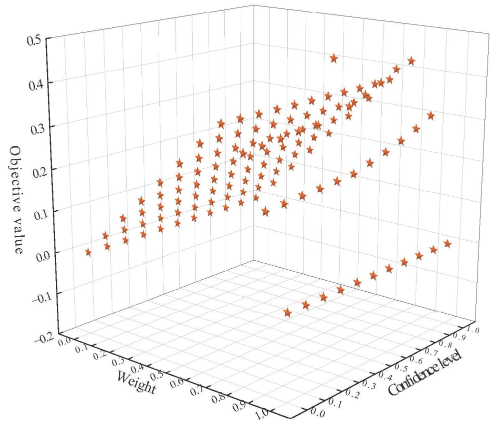
Fig. 7. Sensitivity analysis of schedule constraints



8(a) Cost



8(b) Time



8(c) Objective value

Fig. 8. Sensitivity analysis of optimism criterion confidence level α

Therefore, in practice, operators need to combine various factors to determine the appropriate confidence level, improve transportation efficiency, reduce transportation costs, and arrange a reasonable transportation plan.

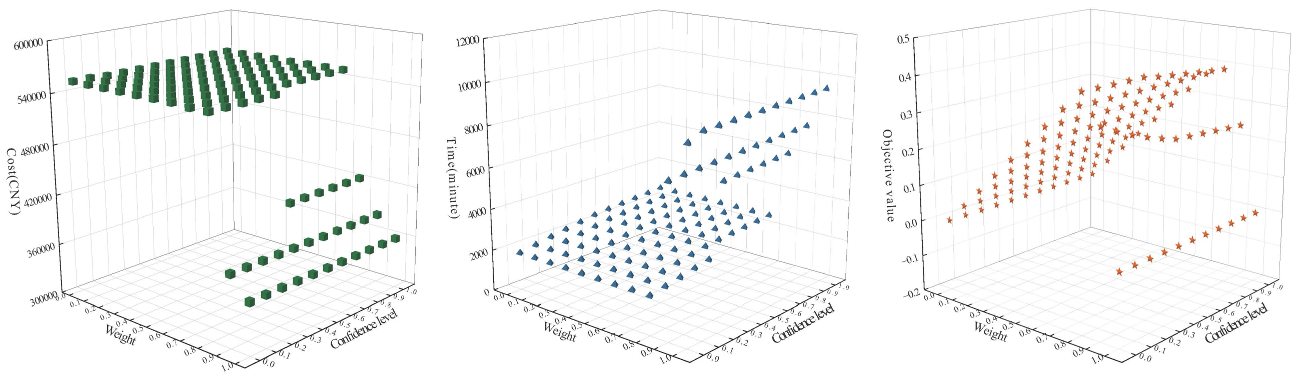
(4) Sensitivity analysis of confidence based on pessimistic value criterion

Other parameters remain unchanged, increasing from 0 to 1 at intervals of 0.1 and adjusting the value of the pessimistic value criterion confidence level α ; the results shown in Fig. 9 can be obtained. When $\omega_1 = 0.7, 0.9, 1$, the change in confidence level α does not cause a change in the transportation plan, but only a slight increase in transportation time. Other values are taken, the degree of confidence rises, the cost will decrease, and the time grows. The critical point of the pessimistic value criteria is at $\alpha = 0.2$ since there has been a significant shift there. Therefore, different confidence levels can provide more choices for operators and effectively reduce transportation costs.

(5) Sensitivity analysis of different departing time

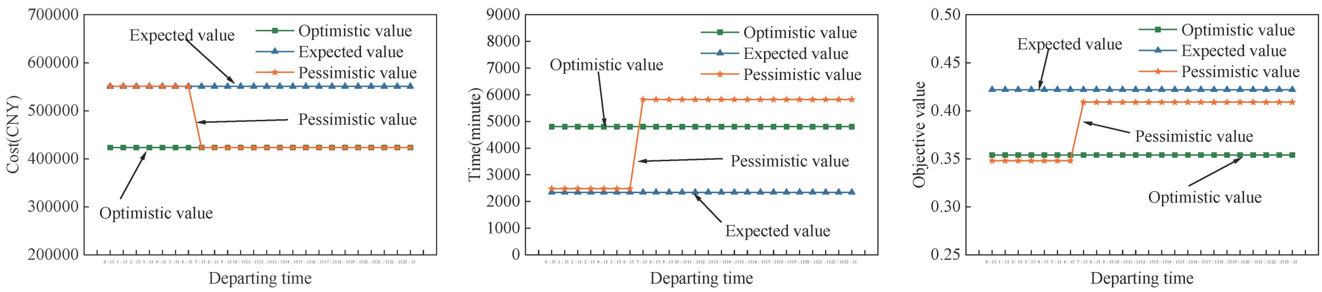
In actual transportation, different departing times can also impact route selection. Under consideration of schedule constraints, arriving at the transit station one hour earlier may increase the possibility of catching a train that departs at an earlier time, while arriving one hour later may result in missing the train that goes first and thus having to wait to travel on a subsequent train. Other things being equal, the impact of different departing times on route selection is analyzed by considering the impact of 24 departing times on cost, time, and objective values in comparison, starting at 0:15 and 60-minute intervals.

It can be seen from the results that the departing time does not affect the routing solution when $\omega_1 = 0, 0.1, \cdots, 0.7$. When $\omega_1 = 0.8$, the routing solution under the pessimistic value criterion as in Fig. 10(a) starts to change, and the transportation cost is lower when departing at 7:15 and later, but the efficiency decreases. When $\omega_1 = 0.9, 1$, as in Figs. 10(b) and 10(c) the routing schemes under all three criteria change, and it can be found that both 6:15 and 7:15 are key points. Results from the above not only offer a valuable reference for optimizing the railway schedule but also offer the operator invaluable advice when selecting the delivery time of road transport.

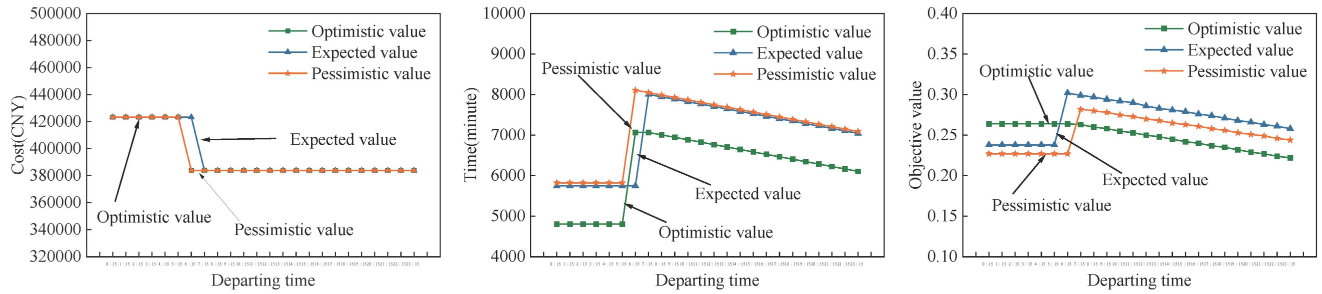


9(a) Cost 9(b) Time 9(c) Objective value

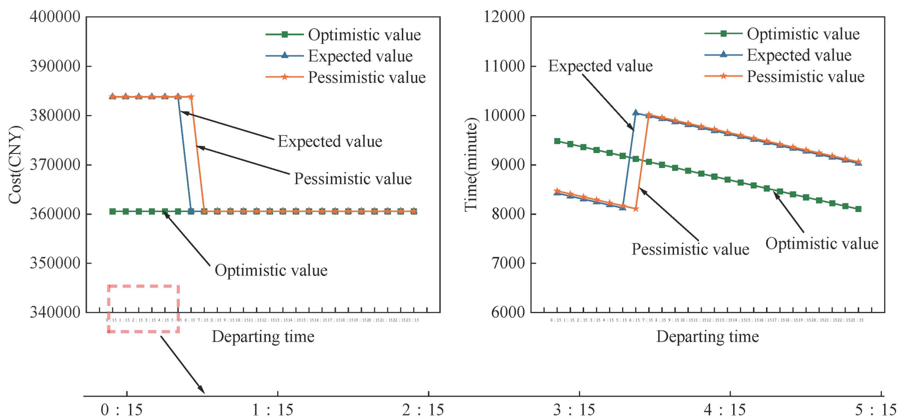
Fig. 9. Sensitivity analysis of pessimistic criterion confidence level α



10(a) $\omega_1 = 0.8$



10(b) $\omega_1 = 0.9$



10(c) $\omega_1 = 1$

Fig. 10. Sensitivity analysis of departing time

VI. Conclusion

The capacity of multimodal transportation to significantly improve transportation efficiency and decrease associated costs is considerable. The principal conclusions derived from the analysis performed in this research are presented below.

1) Factors like arrival time, schedule constraints, and time uncertainty were evaluated and determined to significantly impact transportation costs and time. For time-insensitive freight, train transportation is preferable due to its economic benefits; conversely, for time-sensitive freight of higher value, flexible road transit is more economical. It serves as a crucial reference for multimodal operators to tailor their transport solutions to the specific requirements of the freight.

2) The comparative examination of the optimization outcomes for the three uncertainty variable criteria

reveals that distinct criteria yield varying transportation options, thereby assisting operators in making informed selections aligned with their risk preferences.

3) The sensitivity analysis reveals that shipment arrival time, schedule constraints, and departing time significantly influence routing selection. Additionally, the confidence levels of both the optimistic and pessimistic value criteria impact variations in transportation costs and times, thereby providing robust support for the optimization of multimodal transportation schemes.

4) While the findings of this research offer a valuable reference for optimizing transportation routing under uncertain conditions, the dynamic nature of reality necessitates additional research to enhance both the theoretical framework and practical implementation of multimodal transportation.

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