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Low-Carbon Water–Rail–Road Multimodal Routing Problem with Hard Time Windows for Time-Sensitive Goods Under Uncertainty: A Chance-Constrained Programming Approach

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Abstract: In this study, a low-carbon freight routing problem for time-sensitive goods is investigated in the context of water–rail–road multimodal transportation. To enhance the on-time transportation of time-sensitive goods, hard time windows are employed to regulate both pickup and delivery services at the start and end of their transportation. The uncertainty of both the demand for time-sensitive goods and the capacity of the transportation network are modeled using L-R triangular fuzzy numbers in the routing process to make the advanced routing more feasible in the actual transportation. Based on the carbon tax policy, a fuzzy linear optimization model is established to address the proposed problem, and an equivalent chance-constrained programming formulation is then obtained to make the solution to the problem attainable. A numerical experiment is carried out to verify the feasibility of incorporating the carbon tax policy, uncertainty, and water–rail–road multimodal transportation to optimize the low-carbon freight routing problem for time-sensitive goods. Furthermore, a multi-objective optimization is used to reveal that lowering the transportation costs, reducing the carbon emissions, and avoiding the risk are in conflict with each in the routing. We also analyze the sensitivity of the optimization results concerning the confidence level of the chance constraints and the uncertainty degree of the uncertain demand and capacity. Based on the numerical experiment, we draw several conclusions to help the shipper, receiver, and multimodal transportation operator to organize efficient water–rail–road multimodal transportation for time-sensitive goods.

Keywords: multimodal routing problem; time-sensitive goods; carbon emissions; time windows; uncertainty; fuzzy linear optimization model; chance-constrained programming

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1. Introduction

With the development of agile manufacturing, speed-to-market deliveries, and efficient supply chain management, customers are attaching greater importance to the timeliness of transportation, which is leading to higher demand for the transportation of time-sensitive goods. Time-sensitive goods should be transported punctually from their origins to their destinations, and customers are willing to pay high costs to accomplish this [1]. Hence, it is important for freight companies to make profits and maintain their competitiveness by providing high-quality transportation services for time-sensitive goods. In transportation practice, water–rail–road multimodal transportation (WRRMT) makes full use of the three transportation service modes to carry out goods transportation, and the respective advantages of the different transportation service modes can be effectively combined to improve the economics, timeliness, and environmental sustainability of the transportation service [2]. Therefore, WRRMT is suitable for the transportation of time-sensitive goods. Before transportation is carried out, a rigorous transportation route scheme should be planned in advance to guide the shipper, receiver, and multimodal transportation operator

(MTO) in the organization of transportation. Consequently, the routing problem for time-sensitive goods in the context of WRRMT should be investigated to ensure their on-time transportation while improving the service level in terms of economics, reliability, and environmental sustainability.

The current transportation optimization studies have paid little attention to time-sensitive goods. Tang and Li [1] explored a two-phase container slot allocation problem for time-sensitive goods under demand uncertainty and proposed a stochastic integer programming model. Azadian et al. [3] presented a dynamic routing problem for time-sensitive goods in a stochastic air network, where the problem is addressed based on real-time delay information, random trip times, and flight availability. Yang et al. [4] classified the goods based on their time sensitivity; employed hard and soft time windows to regulate the transportation of time-sensitive goods and regular goods, respectively; and discussed the multimodal routing problem of the two kinds of goods.

Currently, studies on the multimodal routing problem (MRP) have mainly focused on the scenario of the transportation of regular goods. To improve the timeliness of the MRP, some works have considered the minimization of the transportation time as their optimization objective. Sun and Lang [5] and Xiong and Wang [6] carried out a bi-objective optimization for the MRP, taking the minimization of costs and time as their objectives, and found that the two objectives are in conflict with each other. Similar objectives were also adopted by Chang [7] when modeling an international intermodal route selection problem. A study by Vale and Ribeiro [8] considered reduction in the carbon emissions and transportation time as the objectives of their MRP optimization. However, when the transportation is serving agile manufacturing, speed-to-market deliveries, and efficient supply chain management, enhancing the timeliness of transportation should aim for on-time transportation instead of least-time transportation [9,10], especially for time-sensitive goods. Therefore, the concept of time windows has been widely adopted in the MPR literature, among which the soft time window is the most commonly used form [11]. This allows for transportation to violate the time window under the condition that the violation is penalized. In this case, the transportation might start or end at any time within the planning horizon [12]. Thus, a soft time window enhances the flexibility of the MRP, and its utilization can be found in many studies, e.g., references [13–15]. However, the time-sensitive goods depend on on-time transportation, and their transportation is stricter than that of regular goods. As stated by Yang et al. [4], the transportation of time-sensitive goods should follow hard time windows. Only a few articles have used hard time windows for the MRP [16,17], but they still refer to regular goods. Furthermore, the on-time transportation of time-sensitive goods is determined by on-time pickup and delivery at the start and end of their transportation. Therefore, the pickup and delivery of time-sensitive goods should both be restricted by hard time windows. Currently, only Sun et al. [18,19] and Ge and Sun [20] have comprehensively considered the pickup and delivery time windows in their studies on the MRP. However, their models still refer to soft time windows, which are not suitable for routing time-sensitive goods.

The water–rail–road multimodal routing problem for time-sensitive goods (WRRMRPTSG) should be determined before their transportation begins. Due to rapid changes in the market and a lack of effective communication to exchange information among shipper, receiver, MTO, carriers, and terminal operators, the demand for time-sensitive goods is difficult to precisely determine when planning their transportation route [21]. Simultaneously, it is difficult for the transportation network to remain at a stable capacity, since the capacity is influenced by various factors related to humans, machines, and the environment [22]. Therefore, the capacity of the transportation network is constantly changing and difficult to predict accurately. As a result, the exact data of the demand and capacity cannot be obtained when planning the transportation route for time-sensitive goods, and therefore, the uncertainty of both the demand and capacity in the WRRMRPTSG needs to be addressed. When collecting data, we were able to obtain limited historical data of the uncertain parameters under different conditions, which helped us to easily model the uncertain parameters as fuzzy numbers. To the best of our knowledge, no studies have addressed the WRRMRPTSG under uncertainty (specifically, fuzziness) of demand and capacity. For the MRP related to regular goods, formulations of one of the two uncertain parameters using fuzzy numbers have been widely considered by a large number of studies, e.g., references [11,13,16] for fuzzy demand and references [14,18–20,22] for fuzzy capacity. In these studies, the uncertainty of demand and capacity was modeled by trapezoidal or triangular fuzzy numbers, and the fuzzy ranking method or chance-constrained programming method was utilized to model the problem. A comprehensive consideration of fuzzy demand and fuzzy capacity has not been highlighted by the relevant studies, and only a few works can be found [23]. However, Sun's study [23] was related to the transportation of regular goods considering soft time windows and neglected carbon emission reduction.

Based on the review of the literature, we can conclude that the WRRMRPTSG is still a young research field, and the modeling of the MRP for regular goods cannot be directly used in the WRRMRPTSG in terms of time windows and uncertain conditions. Moreover, the environmental sustainability of transportation has become increasingly important, since the carbon emissions produced by transportation account for a large portion of the total carbon emissions [24]. Therefore, low-carbon multimodal transportation planning has been a main focus in the literature [25,26]. Therefore, this study also takes lowering carbon emissions into account to realize the environmentally sustainable transportation of time-sensitive goods. Currently, the carbon tax policy is the most widely used approach to reduce carbon emissions. It has been implemented in many countries, e.g., Sweden, Denmark, Canada, and Japan [27]. It has also been applied to various problems related to sustainable transportation, logistics, and supply chain management, e.g., network design problems [28], routing problems [29], and location problems [30]. There are also studies showing that carbon tax policy reduces more carbon emissions than the carbon cap-and-trade policy [31]. Considering the above, this study assesses the effect of the carbon tax policy on lowering the carbon emissions of the WRRMRPTSG. Carbon tax policy imposes a tax rate on the carbon emissions of the transportation of time-sensitive goods, and converts the emissions into the costs, which are part of the cost objective of the WRRMRPTSG. This study uses activity-based method [32] to calculate the carbon emissions of the transportation, where the emissions of transportation are calculated by multiplying the intensities of the transportation activities and their carbon emission factors.

To summarize, this study extends the first author's previous works on the MRP for regular goods [11,20,22] and specifically focuses on a novel low-carbon water–rail–road multimodal routing problem with hard time windows for time-sensitive goods under uncertainty (LCWRRMRPHTWTSGU). The following contributions are made.

(1) The timeliness of pickup and delivery services is enhanced by using hard time windows to achieve the on-time transportation of time-sensitive goods.
(2) The carbon tax policy is incorporated into the WRRMRPTSG to reduce the carbon emissions of the transportation of time-sensitive goods, and the feasibility of the carbon tax policy is verified.
(3) The uncertain demand for time-sensitive goods and the uncertain capacity of the transportation network are formulated as L-R triangular fuzzy numbers (LRTFNs), and the resulting uncertain delivery time caused by demand uncertainty is further modeled as the LRTFN.
(4) A fuzzy linear optimization model is proposed whose objective is to minimize the total costs, including the transportation costs and carbon tax, and a solvable chance-constrained programming reformulation for the model is built.
(5) A numerical experiment is presented to verify the feasibility of the LCWRRMR-PHTWTSGU, analyze the relationship of the various objectives, and draw some conclusions that help to organize efficient WRRMT for time-sensitive goods.

2. Problem Description

Time-sensitive goods are defined as goods whose quality is considerably influenced by time (e.g., fresh food) [1], or products and raw materials, whose pre- and post-transportation processing employs the "Just-in-Time" strategy. Time-sensitive goods depend on on-time transportation to ensure their quality and support their pre- and post-transportation processing. If the transportation is early or delayed, the quality and market prices of the time-sensitive goods will be affected, and their processing will be disrupted. In these cases, a hard time window is more suitable than a soft time window, flexible time window, or the lead time in formulating the LCWRRMRPHTWTSGU. In this study, we consider that the on-time transportation of the time-sensitive goods requires on-time pickup and delivery services. Consequently, hard time windows are used to regulate both the pickup time and delivery time of time-sensitive goods in the LCWRRMRPHTWTSGU.

The timeliness of transporting time-sensitive goods means on-time transportation instead of least-time transportation in this study. Although yielding the lowest speed compared to rail and road transportation, water transportation should be considered in the transportation of time-sensitive goods due to its advantages of a large capacity and high economy. Thus, the use of water transportation, which increases the transportation times, might lead to the on-time delivery of time-sensitive goods. Consequently, the WRRMT is considered in this study for the routing of time-sensitive goods.

To summarize, the MTO should adopt WRRMT to move the batch of time-sensitive goods from their origin to their destination based on the time windows proposed by the shipper and receiver. According to the requirements of hard time windows, the pickup (departure) of the time-sensitive goods from their origin should be within the shipper's time window. After WRRMT, the delivery (arrival) of time-sensitive goods at their destination should be within the receiver's time window. Consequently, the LCWRRMRPHTWTSGU refers to not only transportation service mode selection and transportation route design, but also pickup time planning.

WRRMT requires the batch of goods to be unsplittable, so that they can be picked up from the shipper and delivered to the receiver once. Before transportation, the demand, origin, destination, and time windows are provided to the MTO by the shipper and receiver. The MTO then builds the transportation network, of which the nodes, arcs, and transportation service modes are known, and plans the routing oriented to the customers' requirements. This study considers the demand and capacity to be uncertain, while the other parameters are deterministic. The deterministic parameters include the travel distances, travel speeds, travel cost rates, and carbon emission factors of the transportation service modes, the unit operation times, operation cost rates, carbon emission factors to transfer goods between different transportation service modes, and the carbon tax rate.

In this study, we comprehensively formulate the uncertainty of demand and capacity as fuzzy numbers. Unlike the majority of the relevant studies that have employed regular fuzzy numbers, this study adopts LRTFNs to model the uncertainty of the demand and capacity. Currently, only Ge and Sun [20] have taken advantage of such fuzzy numbers in the MRP under uncertainty. However, their study only considered the capacity uncertainty, adopted soft time windows for pickup and delivery, and neglected the low-carbon target. Compared to regular fuzzy numbers, LRTFNs can adopt left- and right-hand spread ratios to model the uncertainty degree of an uncertain parameter [20], where the influence of the uncertainty degree on the LCWRRMRPHTWTSGU can be analyzed to obtain some managerial insights. An LRTFN can be generally represented by $\widetilde{r} = (r, \lambda, \delta)_{LR}$, where r is the mean value, and λ and δ are the left- and right-hand spreads, respectively. A detailed introduction to LRTFNs can be found in the study by Gao and Feng [33].

According to Ge and Sun [20], the uncertainty degree of $\widetilde{r}$ can be shown as spread ratios λ/r and δ/r. Increases (decreases) in the λ/r and δ/r improve (reduce) the uncertainty degree of $\widetilde{r}$. Using an LRTFN, all the possible values of an uncertain parameter under different conditions can be captured by the routing model. In the WRRMT, the transfer time of sensitive-time goods depends on the unit operation time of the selected transfer types at the node and the demand for the time-sensitive goods. Therefore, the uncertainty of demand results in the uncertainty of the transfer time, and further leads to the uncertainty of the delivery time of the time-sensitive goods. The uncertain delivery time is also an LRTFN. To summarize, L-R triangular fuzzy demand (LRTFD), L-R triangular fuzzy capacity (LRTFC), and L-R triangular fuzzy delivery time (LRTFDT) exist in the mathematical model.

3. Mathematical Model

3.1. Symbols

(1) Symbols of the transportation network.

Let $G = (N, A, S)$ denote the transportation network, where N is the node set indexed by h, i, and j; A is the arc set indexed by (i, j), which is an arc from node i to node j; and S is the transportation service mode set indexed by k and m. N_i^- and N_i^+ separately represent the predecessor and successor node sets to node i, respectively, and $N_i^- \subseteq N$ and $N_i^+ \subseteq N$. S_i and S_{ij} are the sets of transportation service modes linking node i and running on arc (i, j), respectively, and $S_i \subseteq S$ and $S_{ij} \subseteq S$.

(2) Symbols of the parameters.

We have l_{ijm}, v_{ijm}, e_{ijm}, and $\tilde{w}_{ijm} = (w_{ijm}, \lambda_{ijm}, \delta_{ijm})_{LR}$ to successively represent the travel distance in km, the travel speed in km/h, the carbon emission factor in kg/(TEU·km), and the LRTFC in TEU of transportation service mode m on arc (i, j). For transportation service mode m on arc (i, j), c_{ijm}^1 represents its travel cost rate in CNY/TEU, and c_{ijm}^2 is its travel cost rate in CNY/(TEU·km). t_i^{km}, c_i^{km}, e_i^{km}, and $\tilde{w}_i^{km} = \left(w_i^{km}, \lambda_i^{km}, \delta_i^{km}\right)_{LR}$ denote, respectively, the operation time in hr/TEU, the operation cost rate in CNY/TEU, the carbon emission factor in kg/TEU, and the LRTFC in TEU of transferring goods from transportation service mode k to transportation service mode m at node i. p_{tax} is the carbon tax rate in CNY/kg.

(3) Symbols of the transportation order.

n_o and n_d index the origin and destination of the time-sensitive goods, respectively, and $n_o \in N$ and $n_d \in N$. $\tilde{q} = (q, \lambda\prime, \delta\prime)_{LR}$ is the LRTFD in TEU of the time-sensitive goods. $[a^-, a^+]$ and $[b^-, b^+]$ are the hard time windows for the pickup and delivery services, respectively.

(4) Symbols of the variables.

x_{ijm} denotes a 0–1 variable that is 1 when transportation service mode m on arc (i, j) is selected to move the goods, and 0 otherwise. y_i^{km} is also a 0–1 variable that equals 1 when the goods are transferred from transportation service mode k to transportation service mode m at node i. $\tilde{z}$ represents the LRTFDT, where z is used to define its mean value and is non-negative. u is a non-negative variable showing the pickup time of the time-sensitive goods at the destination.

3.2. Fuzzy Linear Optimization Model

Using the symbols defined above, we built a fuzzy mixed integer linear optimization model for the LCWRRMRPHTWTSGU discussed in this study.

$$\begin{aligned} \min & \sum_{(i,\,j)\in A} \sum_{m\in S_{ij}} \left(c_{ijm}^1 + c_{ijm}^2 \cdot l_{ijm}\right) \cdot \tilde{q} \cdot x_{ijm} + \sum_{i\in N} \sum_{k\in S_i} \sum_{m\in S_i} c_i^{km} \cdot \tilde{q} \cdot y_i^{km} \\ & + p_{\text{tax}} \cdot \left(\sum_{(i,\,j)\in A} \sum_{m\in S_{ij}} e_{ijm} \cdot l_{ijm} \cdot \tilde{q} \cdot x_{ijm} + \sum_{i\in N} \sum_{k\in S_i} \sum_{m\in S_i} e_i^{km} \cdot \tilde{q} \cdot y_i^{km} \right) \end{aligned} \tag{1}$$

such that

$$\sum_{h\in N_i^-} \sum_{k\in S_{hi}} x_{hik} - \sum_{j\in N_i^+} \sum_{m\in S_{ij}} x_{ijm} = \begin{cases} -1 & i = n_o \\ 0 & \forall i \in N \backslash \{n_o,\ n_d\} \\ 1 & i = n_d \end{cases} \tag{2}$$

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

$$\sum_{k \in S_i} \sum_{m \in S_i} y_i^{km} \leq 1 \quad \forall i \in N \backslash \{n_o,\ n_d\} \tag{4}$$

$$\sum_{j \in N_i^+} x_{ijm} = \sum_{k \in S_i} y_i^{km} \quad \forall i \in N \backslash \{n_o,\ n_d\} \quad \forall m \in S_i \tag{5}$$

$$\sum_{h \in N_i^-} x_{hik} = \sum_{m \in S_i} y_i^{km} \quad \forall i \in N \backslash \{n_o,\ n_d\} \quad \forall k \in S_i \tag{6}$$

$$a^- \leq u \leq a^+ \tag{7}$$

$$z = u + \sum_{(i,\ j) \in A} \sum_{m \in S_{ij}} \frac{l_{ijm}}{v_{ijm}} \cdot x_{ijm} + \sum_{i \in N} \sum_{k \in S_i} \sum_{m \in S_i} t_i^{km} \cdot q \cdot y_i^{km} \tag{8}$$

$$\tilde{z} = \left(z, \sum_{i \in N} \sum_{k \in S_i} \sum_{m \in S_i} t_i^{km} \cdot \lambda\prime \cdot y_i^{km}, \sum_{i \in N} \sum_{k \in S_i} \sum_{m \in S_i} t_i^{km} \cdot \delta' \cdot y_i^{km} \right)_{LR} \tag{9}$$

$$b^- \leq \tilde{z} \leq b^+ \tag{10}$$

$$x_{ijm} \cdot \tilde{q} \leq \tilde{w}_{ijm} \quad \forall (i,j) \in A \quad \forall m \in S_{ij} \tag{11}$$

$$y_i^{km} \cdot \tilde{q} \leq \tilde{w}_i^{km} \quad \forall i \in N \backslash \{n_o,\ n_d\} \quad \forall k \in S_i \quad \forall m \in S_i \tag{12}$$

$$x_{ijm} \in \{0,1\} \quad \forall (i,\ j) \in A \quad \forall m \in S_{ij} \tag{13}$$

$$y_i^{km} \in \{0,1\} \quad \forall i \in N \backslash \{n_o,\ n_d\} \quad \forall k \in S_i \quad \forall m \in S_i \tag{14}$$

$$u \geq 0 \tag{15}$$

$$z \geq 0 \tag{16}$$

In the proposed model above, Equation (1) is the objective that aims to minimize the total costs of accomplishing the transportation of time-sensitive goods. It consists of the transportation costs (travel costs and transfer costs) and the carbon emission costs (i.e., carbon tax). Equations (2)–(6) are the basic constraints formulated in the MPR that require the goods to be unsplittable [11,20,22]. Equation (2) is the equilibrium constraint of the flow of goods. Equations (3) and (4) ensure that the time-sensitive goods are unsplittable in both the travel process on the arcs and the transfer process at the nodes. Equations (5) and (6) ensure that the route yields a smooth connection between the travel process and the transfer process. It should be noted that this model takes $y_i^{km} = 1$ when there are $\sum_{h \in N_i^-} x_{hik} = 1$, $\sum_{j \in N_i^+} x_{ijm} = 1$, and $k = m$, which further enhances Equations (5) and (6) in ensuring a smooth "node-arc-node" structure of the planned route. However, in this case, $y_i^{km} = 1$ does not lead to an increase in the costs, time, and carbon emissions of the route, since c_i^{km}, t_i^{km}, and e_i^{km} are all set to zero when $k = m$. Equation (7) is the pickup time window constraint that regulates the departure of the time-sensitive goods from their origin. Equation (8) calculates the mean value of the LRTFDT of the time-sensitive goods. Equation (9) determines the representation of the LRTFDT. Equation (10) is the delivery time window constraint that regulates the delivery time of the time-sensitive goods at the destination, where the left- and right-hand spreads of the LRTFDT are presented. Equations (11) and (12) are the capacity constraints and ensure that the capacities of the selected transportation service modes and selected transfer types can bear the demand for time-sensitive goods. Equations (13)–(16) are the variable domain constraints.

4. Model Defuzzification

The mathematical model constructed in Section 3.2 cannot be solved directly, since it contains imprecise information in Equations (1) and (10)–(12). Therefore, defuzzification of the proposed model should be carried out to make the problem solvable. Thus, the best solution to the LCWRRMRPHTWTSGU can be obtained to provide the shipper, receiver, and MTO with the transportation scheme for time-sensitive goods, including the planned pickup time, the selected transportation service modes, and the transportation route.

This study used the well-known chance-constrained programming technique [34] to carry out defuzzification of the model. The basic operation of chance-constrained programming is to use the expected value operator and the chance-constrained operator to deal with the fuzzy objective(s) and fuzzy constraint(s), respectively [35]. To avoid the overly optimistic or pessimistic routing decisions, it is suitable to establish chance constraints using the credibility measure that indicates the compromised attitude of the decision makers. This has been extensively acknowledged by a large number of relevant studies in various research fields [36–39]. The chance constraints of Equations (10)–(12) are as follows:

$$\mathrm{Cr}\left\{\tilde{z} \geq b^-\right\} \geq \varphi \tag{17}$$

$$\mathrm{Cr}\left\{\tilde{z} \leq b^+\right\} \geq \varphi \tag{18}$$

$$\mathrm{Cr}\left\{x_{ijm} \cdot \tilde{q} \leq \tilde{w}_{ijm}\right\} \geq \varphi \quad \forall (i,j) \in A \quad \forall m \in S_{ij} \tag{19}$$

$$\mathrm{Cr}\left\{y_i^{km} \cdot \tilde{q} \leq \tilde{w}_i^{km}\right\} \geq \varphi \quad \forall i \in N \backslash \{n_o,\ n_d\} \quad \forall k \in S_i \quad \forall m \in m_i \tag{20}$$

In the above equations, φ is the confidence level preferred by customers, which is usually in the range of [0.5, 1.0]. These equations indicate that the credibility that the fuzzy events hold should not be lower than a minimum feasibility degree. Given an LRTFN $\tilde{r} = (r, \lambda, \delta)_{LR}$, where there is $r - \lambda \geq 0$ and a deterministic number η satisfying $\eta \geq 0$, we can obtain Equations (21) and (22) with reference to Peykani et al. [40].

$$\mathrm{Cr}\left\{\tilde{r} \geq \eta\right\} = \begin{cases} 1 & \text{if } r - \lambda \geq \eta \\ \frac{r+\lambda-\eta}{2\lambda} & \text{if } r - \lambda \leq \eta \leq r \\ \frac{r+\delta-\eta}{2\delta} & \text{if } r \leq \eta \leq r + \delta \\ 0 & \text{if } r + \delta \leq \eta \end{cases} \tag{21}$$

$$\mathrm{Cr}\left\{\tilde{r} \leq \eta\right\} = \begin{cases} 0 & \text{if } r - \lambda \geq \eta \\ \frac{\eta-r+\lambda}{2\lambda} & \text{if } r - \lambda \leq \eta \leq r \\ \frac{\eta+\delta-r}{2\delta} & \text{if } r \leq \eta \leq r + \delta \\ 1 & \text{if } r + \delta \leq \eta \end{cases} \tag{22}$$

The distributions of Equations (21) and (22) are illustrated in Figure 1. Considering a confidence level φ in the range of [0.5, 1.0], we obtained Equations (23) and (24), which remove the fuzziness of the fuzzy constraints.

$$\mathrm{Cr}\left\{\tilde{r} \geq \eta\right\} \geq \varphi \Longleftrightarrow r + (1 - 2\varphi) \cdot \lambda \geq \eta \tag{23}$$

$$\mathrm{Cr}\left\{\tilde{r} \leq \eta\right\} \geq \varphi \Longleftrightarrow r + (2\varphi - 1) \cdot \delta \leq \eta \tag{24}$$

According to Equations (23) and (24), the crisp chance constraint representations of Equation (10) are as follows:

$$\mathrm{Cr}\left\{\tilde{z} \geq b^-\right\} \geq \varphi \Longleftrightarrow z + (1 - 2\varphi) \cdot \lambda' \geq b^- \tag{25}$$

$$\mathrm{Cr}\left\{\tilde{z} \leq b^+\right\} \geq \varphi \Longleftrightarrow z + (2\varphi - 1) \cdot \delta' \leq b^+ \tag{26}$$

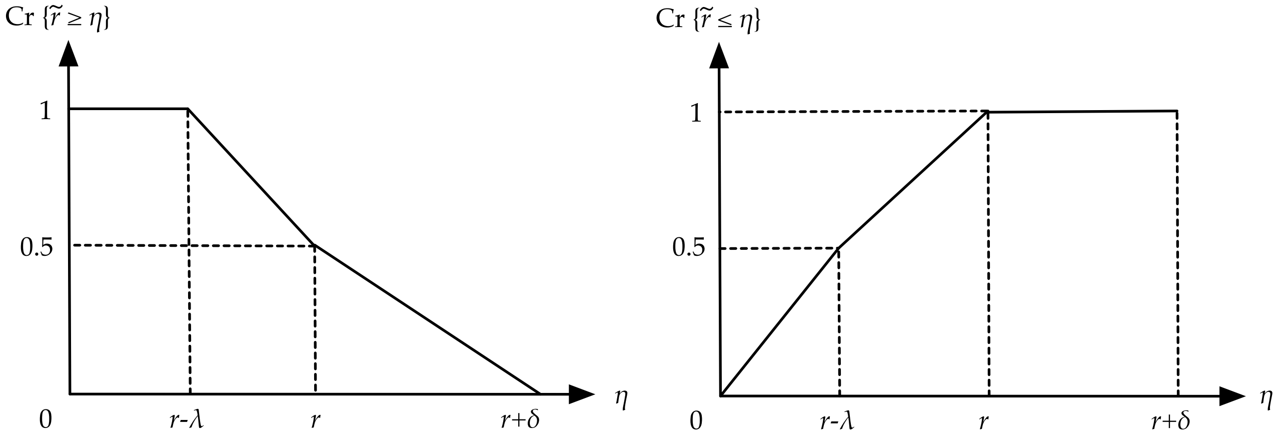

Figure 1. Distributions of Equations (21) and (22).

According to Giallanza et al. [41], we can rewrite Equation (19) as Equation (27).

$$\begin{aligned} &\mathrm{Cr}\left\{ x_{ijm} \cdot \widetilde{q} \leq \widetilde{w}_{ijm} \right\} \geq \varphi \\ \Longrightarrow\ &\mathrm{Cr}\left\{ \widetilde{w}_{ijm} - x_{ijm} \cdot \widetilde{q} \geq 0 \right\} \geq \varphi \\ \Longrightarrow\ &\mathrm{Cr}\left\{ \left(w_{ijm} - x_{ijm} \cdot q, x_{ijm} \cdot \delta' + \lambda_{ijm}, x_{ijm} \cdot \lambda' + \delta_{ijm} \right)_{LR} \geq 0 \right\} \geq \varphi \end{aligned} \tag{27}$$

Then, according to Equation (23), Equation (19) can be reformulated as Equation (28).

$$w_{ijm} - x_{ijm} \cdot q + (1 - 2\varphi) \cdot \left(x_{ijm} \cdot \delta' + \lambda_{ijm} \right) \geq 0 \quad \forall (i, j) \in A \quad \forall m \in S_{ij} \tag{28}$$

Similarly, the crisp chance constraint of Equation (20) is Equation (29).

$$w_i^{km} - y_i^{km} \cdot q + (1 - 2\varphi) \cdot \left(y_i^{km} \cdot \delta' + \lambda_i^{km} \right) \geq 0 \quad \forall i \in N \backslash \{ n_o,\ n_d \} \quad \forall k \in S_i \quad \forall m \in S_i \tag{29}$$

After defuzzification of the fuzzy constraints, the expected value operator is used to address the fuzzy objective. According to Xu and Zhou [35], the expected value of the LRTFD $\widetilde{q} = (q, \lambda', \delta')_{LR}$ under a credibility measure is given by Equation (30).

$$\mathrm{E}\left[\widetilde{q} \right] = \frac{4q + \delta' - \lambda'}{4} \tag{30}$$

By replacing $\widetilde{q}$ in Equation (1) with $\mathrm{E}\left[\widetilde{q} \right]$, we can obtain the crisp objective of the LCWRRMRPHTWTSGU, which is formulated as Equation (31).

$$\begin{aligned} \min \sum_{(i,\ j) \in A} \sum_{m \in S_{ij}} \left(c_{ijm}^1 + c_{ijm}^2 \cdot l_{ijm} \right) \cdot \frac{4q + \delta' - \lambda'}{4} \cdot x_{ijm} + \sum_{i \in N} \sum_{k \in S_i} \sum_{m \in S_i} c_i^{km} \cdot \frac{4q + \delta' - \lambda'}{4} \cdot y_i^{km} \\ + p_{\mathrm{tax}} \cdot \left(\sum_{(i,\ j) \in A} \sum_{m \in S_{ij}} e_{ijm} \cdot l_{ijm} \cdot \frac{4q + \delta' - \lambda'}{4} \cdot x_{ijm} + \sum_{i \in N} \sum_{k \in S_i} \sum_{m \in S_i} e_i^{km} \cdot \frac{4q + \delta' - \lambda'}{4} \cdot y_i^{km} \right) \end{aligned} \tag{31}$$

To summarize, after defuzzification of the fuzzy optimization model, we generated a chance-constrained linear optimization model for the LCWRRMRPHTWTSGU. The objective of this crisp model is Equation (31), and the constraints of the model are Equations (2)–(8), (11)–(16), (25), (26), (28) and (29). This model can be solved using the Branch-and-Bound algorithm implemented by mathematical programming software Lingo, with which the global optimum solution to the LCWRRMRPHTWTSGU can be found.

5. Numerical Experiment

5.1. Numerical Case Design and Optimization

In this study, we continued to use and modify the transportation network presented by Sun and Lang [5] to carry out a numerical experiment. The structure of the transportation network is shown in Figure 2. The values of the travel distances of the transportation service modes, and the mean values of the LRTFCs of both transportation service modes and transfer operations in the transportation network refer to this work [5]. The values of the other parameters of the transportation network can be found in Tables A1 and A2 with reference to the existing studies that are based on the Chinese scenario [20,22].

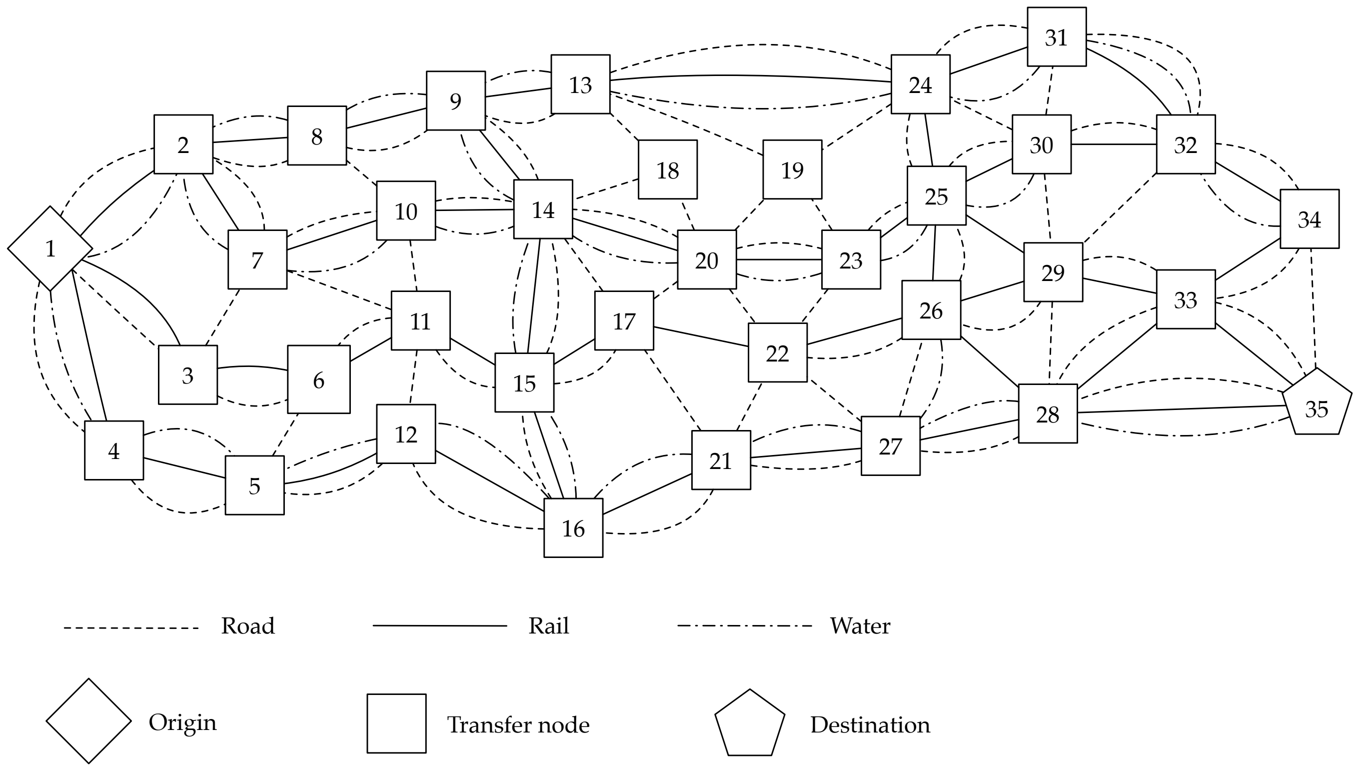

Figure 2. Transportation network in the numerical experiment [5].

In the numerical experiment, a batch of time-sensitive goods was transported from node 1 to node 35. The pickup time window of the time-sensitive goods at node 1 was from 5:00 a.m. to 10:00 a.m. on day 1, and their delivery time window at node 35 was from 6:00 p.m. to 10:00 p.m. on day 2. The mean value of the LRTFD of the time-sensitive goods was 30 TEU. The carbon tax rate in the numerical experiment was set to CNY 2/kg, that is, 0.2 of the value determined by Yuan et al. [42].

We assumed that the left- and right-hand spread ratios for the LRTFD of the time-sensitive goods and the LRTFCs of the transportation network were all 20%, and we changed the confidence level from 0.5 to 1.0 in a step of 0.1. The total costs of the best WRRMT routes under different confidence levels are listed in Table 1.

Table 1. Total costs of the best WRRMT routes under different confidence levels.

Confidence Levels	0.5	0.6	0.7	0.8	0.9	1.0
Total Costs (CNY)	187,786	188,970	188,970	191,463	220,145	254,131

According to Table 1, the improvement of the confidence level corresponded to the increase in the total costs of the best WRRMT route. The total costs of the best WRRMT route were especially sensitive to the confidence level when the value of the confidence level changed from 0.7 to 1.0. Transportation planning is an advanced task and the transportation conditions are constantly changing from the planning stage to the beginning of the actual transportation. Therefore, the planned WRRMT route for time-sensitive goods might fail in the actual transportation due to violation of the capacity constraint or the hard time window constraint. To prevent the risk that the planned WRRMT route implemented in the actual transportation will violate the above constraints, the risk-averse shipper and receiver prefer higher confidence levels to enhance the two kinds of constraints. In these situations, they need to increase their transportation budget. Table 1 provides a reference for the shipper and the receiver to balance the economics and risks of the transportation of the time-sensitive goods.

5.2. Feasibility Verification of the LCWRRMRPHTWTSGU

Currently, there have been no studies on the LCWRRMRPHTWTSGU. Therefore, we verified its feasibility in this work. First of all, we analyzed the performance of the carbon tax policy in lowering the carbon emissions of the transportation of time-sensitive goods. In this verification, we obtained the WRRMT routes that yielded the minimum carbon emissions using Equation (32) as the objective and Equations (2)–(8), (11)–(16), (25), (26), (28) and (29) as the constraints. Then, we compared the carbon emissions of the WRRMT routes under carbon tax policy and under carbon emission minimization. The results are shown in Figure 3.

$$\min F_1 = \sum_{(i,\,j)\in A} \sum_{m\in S_{ij}} e_{ijm}\cdot l_{ijm}\cdot \frac{4q+\delta\prime-\lambda\prime}{4}\cdot x_{ijm} + \sum_{i\in N} \sum_{k\in S_i} \sum_{m\in S_i} e_i^{km}\cdot \frac{4q+\delta\prime-\lambda\prime}{4}\cdot y_i^{km} \quad (32)$$

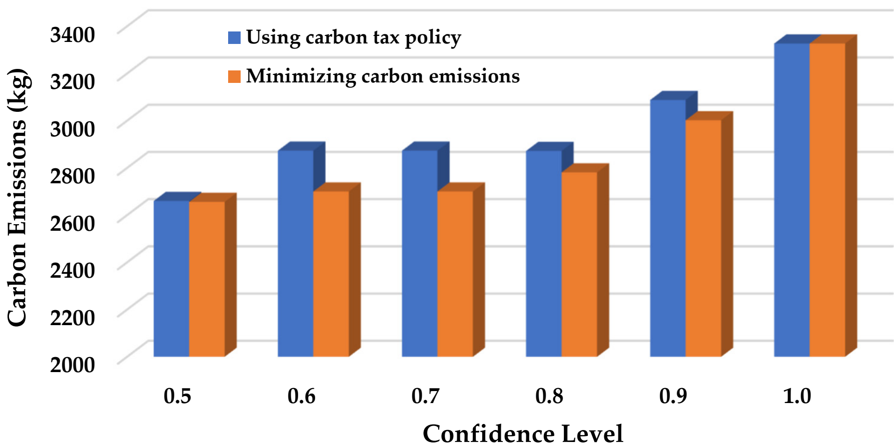

Figure 3. Comparison of the carbon emission reduction of carbon tax policy and carbon emission minimization method on the LCWRRMRPHTWTSGU.

As can be seen in Figure 3, the two methods showed a similar performance in reducing the carbon emissions of the WRRMT route. The average gap in the carbon emissions between the two methods under different confidence levels was about 3.2%. We can conclude that the carbon tax policy was effective at lowering carbon emissions in the LCWRRMRPHTWTSGU.

Furthermore, we verified the feasibility of considering uncertainty by comparing it to the optimization result given using deterministic modeling. We use the mean values of the LRTFC and LRTFD to construct a deterministic transportation condition. Under this condition, the deterministic linear optimization model for the WRRMRPTSG can be established by replacing $\tilde{q}$, $\tilde{w}_{ijm}$, and $\tilde{w}_i^{km}$ with q, w_{ijm}, and w_i^{km}, respectively, and removing Equation (9) from the fuzzy linear optimization model in Section 3.2. After solving the deterministic model using Lingo, we obtained the best WRRMT route, whose total costs were CNY 187,786. The best WRRMT route given by the deterministic model was the same as that given by the chance-constrained linear optimization model under a confidence level of 0.5. Although the deterministic model can plan a WRRMT route with the lowest costs, its optimization results yield a high risk when used in the actual transportation due to a relatively low confidence level. Therefore, this WRRMT route will not be accepted by the risk-averse shipper and receiver.

However, considering the uncertainty of demand and capacity, as addressed by the chance-constrained linear optimization model, provides a solid approach for the risk-averse shipper and receiver to avoid the risk by improving the confidence level. Furthermore, various WRRMT routes are available for the shipper and receiver, and they can select the most suitable one according to their attitude toward risk. Consequently, modeling the uncertainty of demand and capacity improves the flexibility of the WRRMRPTSG, and should be highlighted by the research.

Furthermore, we verified whether the use of WRRMT is suitable for time-sensitive goods. In this verification, we compared the performance of the WRRMT and unimodal rail transportation in the transportation routing of time-sensitive goods. The reason for using rail transportation for comparison is that this transportation service mode yields medium costs, speed, and carbon emissions compared to the road and water. The total costs of the best transportation routes using multimodal and unimodal transportation in the transportation network shown in Figure 2 under different confidence levels are illustrated in Figure 4. It should be noted that it is infeasible to obtain the best transportation route for time-sensitive goods using unimodal rail transportation when the confidence level is 1.0.

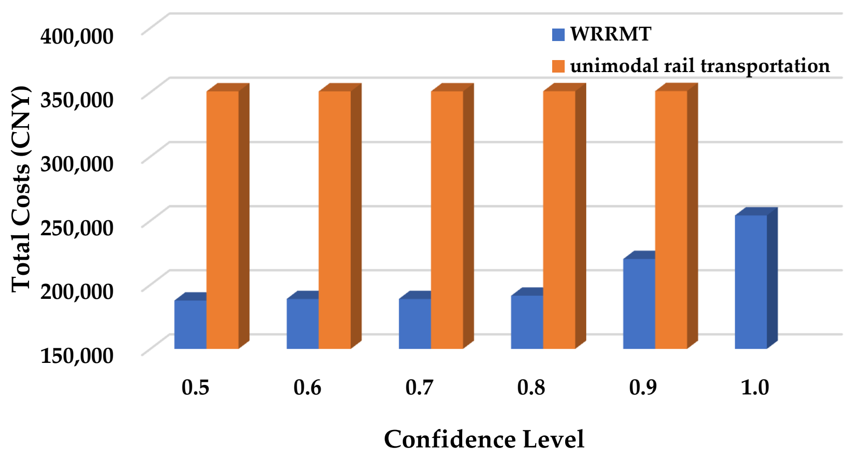

Figure 4. Total costs of the transportation routes for time-sensitive goods using the WRRMT and unimodal rail transportation.

Figure 4 indicates that, compared to unimodal rail transportation, using the WRRMT can significantly reduce the total costs of the transportation of the time-sensitive goods under different confidence levels. Furthermore, if the shipper and receiver are extremely risk-averse, a feasible transportation route might be unattainable when using unimodal rail transportation. Therefore, WRRMT is a suitable transportation service for the transportation of time-sensitive goods.

5.3. Multi-Objective Optimization Analysis of the LCWRRMRPHTWTSGU

In China, a nationwide carbon tax policy has not been implemented. Therefore, the carbon tax is not enforced for the transportation of time-sensitive goods by the government. In this case, a multi-objective optimization model for the LCWRRMRPHTWTSGU can be used. This model takes Equations (32) and (33) as its objectives and adopts Equations (2)–(8), (11)—(16), (25), (26), (28), and (29) as the constraints.

$$\min F_2 = \sum_{(i,\,j)\in A} \sum_{m\in S_{ij}} \left(c^1_{ijm} + c^2_{ijm} \cdot l_{ijm}\right) \cdot \frac{4q + \delta\prime - \lambda\prime}{4} \cdot x_{ijm} + \sum_{i\in N} \sum_{k\in S_i} \sum_{m\in S_i} c^{km}_i \cdot \frac{4q + \delta\prime - \lambda\prime}{4} \cdot y^{km}_i \tag{33}$$

The payoff table of the multi-objective optimization for the LCWRRMRPHTWTSGU under different confidence levels is given in Table 2

Table 2. Payoff table of the multi-objective optimization for the LCWRRMRPHTWTSGU.

Confidence Levels	Minimize F_1		Minimize F_2	
	F_2 (CNY)	F_1 (kg)	F_2 (CNY)	F_1 (kg)
0.5	196,588	2656	181,010	8203
0.6	199,389	2700	181,010	8203
0.7	199,389	2700	181,010	8203
0.8	191,154	2781	184,205	8255
0.9	216,080	3002	213,969	3088
1.0	247,476	3327	237,186	8649

As can be seen in Table 2, improving the confidence level increased both the lowest transportation costs (F_2) and the minimum carbon emissions (F_1) in the single-objective optimization of the LCWRRMRPHTWTSGU. Furthermore, under different confidence levels, the two objectives (i.e., lowering the transportation costs and reducing the carbon emissions) of the multi-objective optimization could not reach their respective optimums simultaneously. Therefore, the two objectives are conflicting with each other, and there are Pareto solutions to the LCWRRMRPHTWTSGU under multi-objective optimization. To summarize, avoiding risk, lowering transportation costs, and reducing carbon emissions are in conflict with each other. Such a conclusion also matches the findings of Li et al.'s work [22]. The weighted sum method can be used to find the Pareto solutions to the LCWRRMRPHTWTSGU. For example, the Pareto solutions under a confidence level of 0.6 are presented in Table 3.

Table 3. Pareto solutions to the LCWRRMRPHTWTSGU under a confidence level of 0.6.

Pareto Solution No.	1	2	3	4
Transportation Costs (CNY)	199,389	191,458	183,223	181,010
Carbon Emissions (kg)	2700	2729	2873	8203

According to Table 3, compared to Pareto solution 4, using Pareto solution 3 can reduce the carbon emissions by about 65% and only lead to an increase in the transportation costs of about 1.2%. Therefore, Pareto solution 3 is more suitable than Pareto solution 4, since it yields significant environmental sustainability in the transportation of time-sensitive goods.

5.4. Influence of the Uncertainty Degree on the LCWRRMRPHTWTSGU

In this analysis, we assumed that the shipper and receiver were risk-averse, and that they preferred a high confidence level of 0.9. In this case, we continued to assume that the left- and right-hand spreads of the LRTFD and LRTFCs were all equal, increased the spread ratio from 5% to 30% in a step of 5%, and calculated the total costs of the best WRRMT routes for the time-sensitive goods. The results are shown in Table 4.

Table 4. Total costs of the best WRRMT routes for time-sensitive goods under different spread ratios.

Spread Ratios (%)	5	10	15	20	25	30
Total Costs (CNY)	211,957	211,957	214,438	244,851	280,751	infeasible

According to Table 4, increasing the spread ratio that represents the improvement in the uncertainty degree resulted in increases in the total costs of the time-sensitive goods. The significant improvement in the uncertainty degree might make the LCWRRMRPHTWTSGU infeasible, which is in agreement with the findings of Ge and Sun [20]. Table 4 clearly shows that when the shipper and receiver would like to reduce risks by maintaining a high confidence level in the chance constraints while saving transportation budget, they should find methods to reduce the uncertainty degrees of the uncertain demand and capacity:

(1) The shipper and receiver should build effective communication and negotiation strategies with each other and pay attention to the real-time changes in the supply and demand in the market, so that they can reduce the uncertainty degree of the uncertain demand for time-sensitive goods.
(2) The MTO should pay attention to the capacity stability of the carriers and terminal operators in the water–rail–road multimodal transportation network. After receiving the transportation order of time-sensitive goods, the MTO should use these with adequate and stable capacities at a high priority to build the transportation network, so that the uncertainty degree of the uncertain capacity of the network can be reduced. This suggestion is also emphasized by Ge and Sun [20] in the MRP for regular goods.

6. Conclusions

In this study, we explored a low-carbon water–rail–road multimodal routing problem for time-sensitive goods that has not been highlighted in the transportation planning field. Based on the characteristics of time-sensitive goods and routing optimization, the following considerations are included in the problem optimization:

(1) Hard time windows are used to realize the on-time pickup and delivery services for time-sensitive goods to ensure on-time transportation.
(2) Carbon tax policy is employed to reduce the carbon emissions of the WRRMT for time-sensitive goods.
(3) The uncertainty of both the demand and the capacity is incorporated into the routing to make the planned route more feasible in actual transportation.

Based on the above considerations, this study proposes a novel LCWRRMRPHTWTSGU, where LRTFNs are adopted to model the uncertainty, and the uncertainty degrees of the uncertain parameters are defined. To address such a problem, we constructed a chance-constrained linear optimization model based on the credibility measure whose global optimum solution can be easily obtained. A numerical experiment revealed the following conclusions:

(1) WRRMT is a suitable transportation service for the transportation of time-sensitive goods under uncertainty of demand and capacity.
(2) Modeling the uncertainty enables a flexible routing optimization, and helps the risk-averse shipper and receiver to reduce risks by improving the confidence level and prepare enough transportation budget.
(3) Carbon tax policy is effective in reducing the carbon emissions of WRRMT for time-sensitive goods. Lowering transportation costs, reducing carbon emissions, and avoiding risk are in conflict with each other.
(4) Reducing the uncertainty degrees of the uncertain demand and capacity is a promising way to help the shipper and receiver to reduce risks while saving transportation budget.

However, this study only considered the carbon tax policy in the LCWRRMRPHTWTSGU. Other carbon emission reduction methods, e.g., mandatory carbon emission policy [42] and carbon cap-and-trading policy [43], have not been discussed in the research. Therefore, our future work will model multiple carbon emission reduction methods and focus on their comparison to help the MTO to find the best method to achieve the transportation of time-sensitive goods with the highest environmental sustainability. Furthermore, multi-source uncertainty covering the aspects of speed, time, capacity, and demand should be considered to realize improved reliability, for which modeling the uncertain variables based on LRTFNs is challenging. Last but not least, we should formulate the fixed service time windows of the transfer nodes in the LCWRRMRPHTWTSGU to make the multimodal transportation process modeled in the routing better match the real-world transportation organization.

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Data Availability Statement: All data generated or analyzed during this study are included in this paper and reference [5], which is open access.

Conflicts of Interest: Mr. Min Li is employee of the company Shandong Zhonghe Carbon Emission Service Center CO. LTD. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Appendix A

Table A1. Travel cost rates, speeds, and carbon emission factors of transportation service modes.

	c^1_{ijm}(CNY/TEU)	c^2_{ijm}(CNY/(TEU·km))	v_{ijm}(km/h)	e_{ijm}(kg/(TEU·km))
Rail	500	2.03	60	0.076
Road	15	8	80	2.480
Water	950	0	30	0.088

Table A2. Cost rates, times, and carbon emission factors of different transfer types (the number sequence means c_i^{km} (CNY/TEU)/t_i^{km} (min/TEU)/e_i^{km} (kg/TEU)).

	Rail	**Road**	**Water**
Rail	0/0/0	5/4/5.06	7/8/5.80
Road	5/4/5.06	0/0/0	10/6/5.54
Water	7/8/5.80	10/6/5.54	0/0/0

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