sustainability

Article

A Bi-Objective Fuzzy Credibilistic Chance-Constrained Programming Approach for the Hazardous Materials Road-Rail Multimodal Routing Problem under Uncertainty and Sustainability

Yan Sun [1,*], **Xinya Li** [2], **Xia Liang** [1,*] **and Cevin Zhang** [3]

[1] School of Management Science and Engineering, Shandong University of Finance and Economics, Jinan 250014, China
[2] Institute of Technology, Shandong TV University, Jinan 250010, China; xylisdtvu@bjtu.edu.cn
[3] School of Engineering Sciences in Chemistry, Biotechnology and Health, KTH Royal Institute of Technology, 14156 Huddinge, Sweden; chenzh@kth.se
* Correspondence: sunyanbjtu@163.com (Y.S.); susanliangxia@163.com (X.L.)

Received: 8 April 2019; Accepted: 26 April 2019; Published: 4 May 2019

Abstract: Hazardous materials transportation involves extensive risk and cannot be avoided in practice. An advanced routing, however, can help to reduce the risk by planning the best transportation routes for hazardous materials that can make effective tradeoffs between the risk objective and the economic objective. In this study, we explore the hazardous materials routing problem in the road-rail multimodal transportation network with a hub-and-spoke structure, in which the risk is measured by the multiplication of population exposure and the associated volume of hazardous materials, and minimizing the total risk of all the transportation orders of hazardous materials is set as the risk objective. It is difficult to estimate the population exposure exactly during the routing decision-making process, which results in its uncertainty. In this study, we formulate the uncertain population exposure from a fuzzy programming perspective by using triangular fuzzy numbers. Moreover, the carbon dioxide emission constraint is formulated to realize the sustainable transportation of hazardous materials. To optimize the problem under the above framework, we first establish a bi-objective fuzzy mixed integer nonlinear programming model, and then develop a three-stage exact solution strategy that the combines fuzzy credibilistic chance constraint, linearization technique, and the normalized weighting method. Finally, a computational experiment is carried out to verify the feasibility of the proposed method in dealing with the problem. The experimental results indicate that tradeoffs between the two conflicting objectives can be effectively made by using the Pareto frontier to the hazardous materials routing problem. Furthermore, the credibility level and carbon dioxide emission cap significantly influence the hazardous materials routing optimization. Their effects on the optimization result are quantified by using sensitivity analysis, which can draw some useful insights to help decision makers to better organize the hazardous materials road-rail multimodal transportation under uncertainty and sustainability.

Keywords: hazardous materials routing; road-rail multimodal transportation; bi-objective optimization; uncertainty; credibilistic chance-constrained programming; carbon dioxide emissions

1. Introduction

1.1. Background

Hazardous materials transportation plays an important role in the transportation industry and has been given remarkable importance over the last decades [1]. Compared with regular goods, hazardous materials own at least one of the five dangerous characteristics including corrosivity, toxicity, ignitability, reactivity and infectivity [2,3], which lead to severe consequences that harm people, property, and environment, once associated accidents occur [4]. Therefore, the hazardous materials transportation is associated with tremendous risk that can cause human life and economic losses [5]. However, it is difficult to avoid transporting hazardous materials due to the fact that many hazardous materials, e.g., gasoline and petroleum, considerably influence both people's daily lives and the development of relative industries [6], and the locations where they get produced and consumed are geographically separated [4]. According to Du et al. [7], there are trillions of ton-miles of hazardous materials that are transported annually all over the world. Especially in China, as indicated by Xin et al. [8], the volume of hazardous materials transportation has reached up to ~400 million tons per year and ~95% of hazardous materials need to be transported. Simultaneously, China suffers a lot from transportation accidents involving hazardous materials [9].

As a result, the question of how to effectively manage the hazardous materials transportation to reduce risk has drawn great attention from government, transportation providers and demanders as well as transportation planners. The U.S. Hazardous Materials Transportation Uniform Safety Act of 1993 strongly acknowledged the route decision-making as an effective way to reduce risk from hazardous materials transportation [10]. Since then, the hazardous materials routing problem has become one of the spotlights in the transportation planning field [11].

1.2. Literature Review

In the transportation practice, hazardous materials transportation is dominated by roads. Roads serve the distribution of the majority of hazardous materials [9]. For example, in China, the road serves ~82% of the hazardous materials transportation [8]. Consequently, the majority of the current studies on the optimization of the hazardous materials transportation are in the context of the road transportation network. In the operational level, large numbers of studies focus on the vehicle routing problem (VRP) for the hazardous materials transportation, e.g., Bula et al. [12], Du et al. [13], Ma et al. [14], and Kheirkhah et al. [15]. In these studies, the traditional VRP models are modified into a hazardous materials transportation scenario in which a risk objective is formulated to minimize the transportation risk and a bi-objective optimization is carried out to make tradeoffs between the economic objective and risk objective by using the Pareto frontier analysis [16]. Moreover, the vehicle location-routing problem (LRP) for the hazardous wastes transportation also draws some attention, e.g., Ardjmand et al. [17], Zhao et al. [18], Asgari et al. [19] and Alumur and Kara [20]. In the LRP literature, the involved location problem refers to siting the facilities/centers used to store, treat, and dispose of the hazardous materials (e.g., used oil) with a certain level of capacities and technologies [18,20]. Simultaneously, there are many articles that are interested in the network design problem (NDP) for the hazardous materials road transportation, e.g., Esfandeh et al. [21], Fontaine and Minner [22], Kara and Verter [23], and Sun et al. [24]. The relative NDP belongs to the tactical level of transportation planning and has a longer planning horizon than VRP and LRP. Generally, only origin-to-destination pairs and corresponding volumes/demands of hazardous materials need to know to model NDP, while VRP and LRP should consider specific transportation orders as their optimization object. Although VRP, LRP, and NDP differ from each other in the above aspects, minimizing the costs and minimizing the risk are set as the optimization objectives of all these studies.

In the real world, compared with the road transportation that has already gained wide application, rail transportation become considerably popular in hazardous materials transportation due to its better reliability. Such significant characteristics can reduce risk and improve safety in transportation [25]. Furthermore, the combination of road and rail in transportation can integrate the accessibility advantage of road transportation in short/medium-distance distribution and economy and reliability advantage of rail transportation in long-hauling [26,27]. Therefore, road-rail multimodal transportation has been used in hazardous materials transportation and received an increasing freight volume, especially in the United States [1,28]. Moreover, some studies, e.g., Bubbico et al. [5,29], have demonstrated the superiority of road-rail multimodal transportation in hazardous materials transportation. However, as indicated by Erkut et al. [4], Verma and Verter [27], and Assadipour et al. [30], the road-rail multimodal transportation of hazardous materials does not get enough investigation that matches its advantages.

Currently, the relative literature on optimizing hazardous materials road-rail multimodal transportation is limited. Xie et al. [1] presented a representative study on the hazardous materials multimodal location-routing problem, in which a bi-objective nonlinear model is designed and a linear reformulation method is developed to solve the problem. Inspired by Xie et al.'s study [1], Jiang et al. [31] explored the same problem based on a multicommodity flow model. Compared with the above two articles that only consider origins, destinations and volumes of the transportation orders of hazardous materials, an improvement on the above two articles was achieved by Verma and Verter [27]. In their study, a lead time constraint is considered when planning the rail-truck intermodal transportation of hazardous materials, so that the delivery time from a shipper to a receiver will satisfy a deadline. In another paper published by Verma et al. [32], a bi-objective optimization framework is proposed for routing the rail-truck intermodal transportation with hazardous materials, in which various train services are provided for the route selection. Then Assadipour et al. [3] improved Verma's studies [27,32] on hazardous materials rail-truck intermodal transportation planning by considering the terminal congestion risk. Since the rail transportation is operated according to fixed schedules in the real world, Sun et al. [3] emphasized that schedule-based constraints that are neglected by the above-mentioned articles should be formulated to design feasible hazardous materials multimodal routes that can match the operations of the real-world transportation system. Besides the hazardous materials multimodal (location and) routing problem, the relative NDP also draws attention by Mohammadi et al. [33] and Assadipour et al. [28].

1.3. The Research Gap between the Literature and the Hazardous Materials Multimodal Transportation Practice

The hazardous materials multimodal routing problem deserves more attention from the transportation planning field than the current condition. Although some achievements have already been gained by the above studies, there is still a great research gap between the literature and the hazardous materials multimodal transportation practice on three aspects: (1) Proposing a more applicable risk assessment, (2) realizing sustainability of hazardous materials transportation, and (3) building a more suitable multimodal transportation system. The first and last aspects of the research gap derive from the demand for transportation practices on improving the feasibility of the hazardous materials road-rail multimodal routing. The second aspect results from the public concern on lowering carbon dioxide emissions to achieve sustainable transportation for hazardous materials. How the three aspects of the research gap emerge as follows.

First of all, risk assessment is an important work for routing hazardous materials. In general, the risk can be defined as the undesirable consequence caused by the accidents of hazardous materials [34]. Since people is one of the most important actors and stakeholders of transportation activities, they are faced with considerable risks that would harm their life. Consequently, the question of how to reduce the risk associated with people is always the core task of the hazardous materials routing and is formulated as one of the multiple objectives in the optimization modeling. From the viewpoint of people, the risk can be further described by two dimensions: (1) The number of people that will be potentially harmed once accidents of hazardous materials transportation happen, i.e., population exposure, and (2) the degree of the potential harm [3]. Accordingly, the risk can be measured by the multiplication of population exposure and associated volume of hazardous materials.

Obviously, population exposure is an important parameter used to measure risk, regardless of a road transportation scenario or a road-rail multimodal transportation scenario. In the existing literature, population exposure is treated as a deterministic parameter. However, it is widely known that the road-rail multimodal routing decision making is a task that should be done earlier than the actual transportation begins [35]. During the advanced decision-making process, the population mobility makes it extremely difficult to obtain exact relative data and results in the imprecise characteristic of the population exposure estimation. Consequently, the population exposure is uncertain during the practical routing decision making. As claimed by Sun et al. [26,36], both overestimation and underestimation exist when using deterministic values to measure uncertain parameters, which will reduce the feasibility of the routing. In practical decision making, decision makers usually get relative data that varies in a certain range [37]. In this case, it is easier for decision makers to use fuzzy set theory to value the uncertain population exposure by using a triangular fuzzy number that contains the most pessimistic estimation, the most likely estimation and the most optimistic estimation [38].

Secondly, sustainability raises growing concerns from both public and government all over the world, and has become an aim of the development of all industries [39]. As for the transportation industry, an effective approach to achieve sustainability is to realize green transportation by reducing carbon dioxide emissions [40–42]. As one of the biggest contributors to the carbon dioxide emissions, the transportation industry should seriously consider the restriction of carbon dioxide emissions in both the planning stage and practical operations [43]. To the best of our knowledge, there is no existing literature that considers reducing the carbon dioxide emissions when exploring neither the network design problem nor the routing problem of hazardous materials road-rail multimodal transportation. On contrary, such issue has been stressed by many studies on the multimodal routing problem of regular goods, and the majority of these studies focuses on using carbon tax regulation to reduce the carbon dioxide emissions [41,44–47].

However, besides the fact that it is difficult to clearly determine the value of carbon tax in practice, the effectiveness of carbon tax regulation is doubtful. Zhang et al. [47] pointed out that the performance of carbon tax regulation in the multimodal routing problem with low carbon consideration is sensitive to the case setting. Sun et al. [48] reported that the domination of the costs for accomplishing the transportation orders is transportation costs en route instead of a carbon tax, thus the carbon tax is insignificant to the optimization objective. As an alternative, it is worthwhile to formulate carbon dioxide emission constraint to realize the low carbon of hazardous materials road-rail multimodal routing. Although carbon dioxide emission constraint is not applied in the hazardous materials routing problem discussed by this study, it has already been employed in the reverse logistics network design problem and shows good feasibility [49].

Last but not least, when planning the hazardous materials road-rail multimodal routing problem, the decision makers need first to determine the type of consolidation network to model the transportation system [26,50]. A network can be a point-to-point network, a line network, a hub-and-spoke network or a collection-and-distribution network [50,51]. Among the four types, the hub-and-spoke network is most suitable to model the road-rail multimodal network [52,53], where the rail terminals serve as hubs and the origins and destination of hazardous materials transportation are spokes. The road-rail hub-and-spoke network is a three-stage full-truck-load transportation system, including pre-haul by road, long-haul by rail and end-haul by road [52,54]. Such door-to-door transportation chain comprehensively takes advantage of road transportation that has good mobility in short/medium-distance distribution and rail transportation that shows high-cost efficiency and reliability as well as massive capacity in long-distance transportation [26,55]. However, few studies associate the hazardous materials road-rail multimodal routing problem with a hub-and-spoke network that has been widely adopted in transportation practice.

1.4. Our Contributions to Bridging the Research Gap

In this study, we aim at enriching and enhancing the research on hazardous materials road-rail multimodal routing problem. Therefore, the research goal is to accomplish a bi-objective optimization for the hazardous materials road-rail multimodal routing problem that can help decision makers make an effective tradeoff between the economic objective and risk objective in practical transportation. To achieve the research goal, the above three aspects of the research gap should be bridged. Consequently, the following improvements to the existing literature that contributes to the same problem are realized in this study.

(1) The uncertainty of population exposure is considered when establishing the risk objective of the problem. Fuzzy set theory is used to deal with the uncertain issue and the fuzzy population exposure is represented by the triangular fuzzy number.

(2) Carbon dioxide emission constraint is formulated to reduce greenhouse gas emissions in the hazardous materials transportation to achieve sustainability. Sensitivity analysis is employed to explore the effect of the carbon cap on the hazardous materials routing problem.

(3) A hub-and-spoke network is used to represent the road-rail multimodal transportation system that carries out the hazardous materials transportation.

Furthermore, the routing problems in the transportation planning field should be optimization under specific formulation characteristics, regardless that the routing problem is for hazardous materials or regular goods [56]. Different studies address the routing problem under different formulation characteristics. In this study, we mainly consider the following four formulation characteristics to model the hazardous materials road-rail multimodal routing problem, including (1) determining optimization object, (2) modeling transportation modes, (3) setting optimization criterion, and (4) formulating network capacity. The proposed formulation characteristic framework also contributes to the research on the hazardous materials routing problem by providing a systematic modeling framework.

Considering the fuzziness of the problem, there should be a fuzzy programming model. The fuzziness also leads to the nonlinearity of the problem [48]. Furthermore, the complexity that results from formulating rail schedules and time windows also enhance the nonlinearity. As a result, we determine to construct a bi-objective fuzzy nonlinear programming model. As indicated by Tian and Cai [37] and Wang et al. [52], defuzziness should be first of all carried out, so that decision makers can obtain a crisp transportation plan. Xie at al. [1] and Sun et al. [41] point out linearization as a useful technique to solve the routing problem formulated by nonlinear programming model, since after model linearization, the problem can be effectively solved to gain its global optimal solution by exact solution algorithm that is automatically run by mathematical programming software. Therefore, an exact solution strategy that contains defuzziness, linearization, and will be developed by this study.

1.5. Organization of the Study

The remainder of this study is organized as follows. In Section 2, the above mentioned four formulation characteristics that are used to model our hazardous materials routing problem are systematically introduced. In Section 3, based on the extensions regarding the fuzzy population exposure, carbon dioxide emission constraint, and hub-and-spoke network, a fuzzy bi-objective mixed integer nonlinear programming model is developed to deal with the hazardous materials road-rail multimodal routing problem under given formulation characteristics. In Section 4, unlike the majority of the existing literature that focuses on the development of heuristic algorithms to solve the problem, we design a three-stage exact solution strategy that combines fuzzy credibilistic chance constraint, linearization technique, and normalized weighting method. In Section 5, the computational experiment is conducted to demonstrate the feasibility of the proposed method. Sensitivity analysis is utilized to reveal some managerial implications that can help decision makers better organize the hazardous materials road-rail multimodal transportation. Finally, the conclusions of this study are drawn in Section 6.

2. Formulation Characteristics of the Hazardous Materials Routing Problem

2.1. Determining Optimization Object: Multiple Transportation Orders

The hazardous materials road-rail multimodal routing can take single one transportation order or multiple transportation orders as its optimization object. Transportation orders contain the information on the origins, destinations, release instants at origins, volumes and due dates (can be represented by either time points or time windows) of transporting hazardous materials. Different transportation orders vary from each other in at least one of the above five aspects.

Since the multimodal transportation network is capacitated [57], it is obvious that the best routes for multiple orders are not the simple set of the independent best route for each order. In most cases, the decision makers need to serve more than one transportation order during the planning horizon [41]. From a viewpoint of network optimization, it is more practical to consider multiple transportation orders of hazardous materials. Besides, the routing problem with multiple transportation orders can be easily transformed into one with a single one order when the transportation order set containers only one order.

Therefore, the optimization object of our hazardous materials road-rail multimodal routing problem is multiple transportation orders. In this study, we use the symbols listed in Table 1 to denote the multiple transportation orders.

Table 1. Symbols that represent multiple transportation orders.

Parameters	Representations
P	Transportation order set.
p	Index of transportation order and $p \in P$.
o_p	Index of the origin of transportation order p.
d_p	Index of the destination of transportation order p.
q_p	Volume in ton of transportation order p.
$\Gamma^{p}_{release}$	Release instant of transportation order $]\varphi$ at origin o_{φ}.
$\left[\Gamma^{p-}_{due}, \Gamma^{p+}_{due}\right]$	Due date (represented by a time window) of accomplishing transportation order p. If the accomplishment of transportation order p is earlier than the lower bound Γ^{p-}_{due}, penalty costs should be paid to cover the additional storage, handling and maintenance of hazardous materials before they get further processed. However, it is not allowed that the transportation order is accomplished later than the upper bound Γ^{p+}_{due}, otherwise the processing of hazardous materials after transportation will be entirely disrupted.

2.2. Modeling Transportation Modes: Combination of Unscheduled and Scheduled Transportation Modes

In the vehicle routing problem for hazardous materials transportation, only one transportation mode, i.e., road transportation (mainly refer to trucks), is involved. The road transportation is unscheduled and thus has better mobility than rail transportation that should be run by prescribed schedules. Compared with vehicle routing problem, the multimodal routing problem is more complicated, since two different transportation modes are involved, i.e., unscheduled road transportation and scheduled rail transportation, and how to coordinate the two transportation modes is essential for the feasibility of the planned routes in practice.

Schedule of rail transportation should be modeled when optimizing the hazardous materials road-rail multimodal routing problem [26]. As summarized by our previous studies [1,21,46,48], the schedule regulates the following contents that the operation of a freight train should observe:

(1) Fixed running route of a freight train.
(2) Fixed operation time window of a freight train at a rail terminal, i.e., a time interval from the operation start instant to the operation cutoff instant.
(3) Fixed departure instant of a freight train from a rail terminal.
(4) Fixed arrival instant of a freight train at a rail terminal.
(5) Operational period of a freight train.

In the hub-and-spoke network, the road-rail multimodal transportation should have the following procedures in order to coordinate the two different kinds of transportation modes. Besides, considering that the hub-and-spoke network is a Full-Truck-Load (FTL) transportation system, the road transportation in this study implements the FTL strategy [54].

(1) *Pre-haul by road*. The hazardous materials of a transportation order start to get loaded on the trucks at their release instant at the origin. After being unloaded on the trucks, the hazardous materials can immediately depart from the origin.

(2) *Transshipment from road to rail*. After arriving at the rail terminal, the hazardous materials can immediately start to get unloaded from the trucks.

If the instant when the hazardous materials get unloaded from the truck is earlier than the lower bound of the operation time window of the selected freight train, the hazardous materials should wait until this instant and then start to get loaded on the train.

If the instant falls into the operation time window of the selected freight train, the loading operation can be immediately started.

It should be noted that the instant when the hazardous materials get loaded on the train should be later than the upper bound of the operation time window of the selected freight train.

(3) *Long-haul by rail*. After loading on the freight train, the hazardous materials should wait until the fixed departure instant of the train at the rail terminal, then leave the current terminal, and arrive at the successor terminal at the fixed arrival instant of the freight train.

(4) *Transshipment from rail to road*. After arriving at the terminal, the hazardous materials should wait until the lower bound of the operation time window of the freight train at the terminal and then start to get unloaded from the train. After unloaded from the train, the hazardous materials can immediately start to get loaded on the trucks.

(5) *End-haul by road*. After loading on the trucks, the hazardous materials can immediately depart from the terminal, arrive at the destination and finally get unloaded from the trucks, which means that the transportation order is accomplished.

In this study, we use the symbols listed in Table 2 to denote the road-rail multimodal transportation network.

Table 2. Symbols that represent the road-rail multimodal transportation network.

Parameters	Representations
N	Node set of the road-rail multimodal transportation network, including origins, destinations and rail terminals where transshipments are conducted.
A	Arc set of the road-rail multimodal transportation network.
S	Transportation service set of the road-rail multimodal transportation network.
$i,\ j,\ k$	Indices of the nodes and $i,\ j,\ k \in N$.
$m,\ n$	Indices of the transportation services and $m,\ n \in S$.
$(i,\ j)$	Directed arc from node i to node j and $(i,\ j) \in A$.
N_i^-	Set of the predecessor nodes to node i, and $N_i^- \subseteq N$.
N_i^+	Set of the successor nodes to node i, and $N_i^+ \subseteq N$.
S_{ij}	Set of transportation services on arc $(i,\ j)$ and $S_{ij} \subseteq S$.
R_{ij}	Set of freight trains on arc $(i,\ j)$ and $R_{ij} \subseteq S_{ij}$.
T_{ij}	Set of truck fleets on arc $(i,\ j)$ and $T_{ij} \subseteq S_{ij}$.
$\left[\Pi_i^{m-}, \Pi_i^{m+}\right]$	Fixed operation time window of freight train m at rail terminal i.
t_{ij}^m	Travel time in hour of truck fleet m on directed arc $(i,\ j)$.
d_{ij}^m	Travel distance in km of transportation service m on directed arc $(i,\ j)$.
t_i^m	Separate loading and unloading time per ton of transportation service m at node i.
Variables	**Representations**
w_i^p	0-1 variable: if node i is in the route for transporting transportation order p, $w_i^p = 1$; otherwise $w_i^p = 0$.
x_{ijm}^p	0-1 variable: if transportation service m on directed arc $(i,\ j)$ is used for transporting hazardous materials of transportation order p, $x_{ijm}^p = 1$; otherwise $x_{ijm}^p = 0$.
y_i^p	Non-negative variable: the instant when the hazardous materials of transportation order p arrive at node i.
z_{ijm}^p	Non-negative variable: the storage time of hazardous materials of transportation order p at rail terminal i before they get loaded on freight train m operated on directed arc $(i,\ j)$.

2.3. Setting Optimization Criterion: A Bi-Objective Optimization

In the routing problems for regular goods, economic objective, i.e., minimizing the costs created in the transportation activities, is the core objective of the hazardous materials transportation planning in the age of competition [58]. As for a multimodal transportation scenario in a hub-and-spoke network, the following kinds of costs will be created in the three-stage transportation process containing pre-haul, long-haul and end-haul:

(1) *Travel Costs* created by moving hazardous materials from origins to rail terminals by trucks (pre-haul), from rail terminals to another by rail (long-haul) and from rail terminals to destinations by trucks (end-haul).

(2) *Handling Costs* created by loading and unloading hazardous materials between freight trains and trucks to conduct transshipments at rail terminals.

(3) *Storage Costs* created by the early arrival of hazardous materials at rail terminals and waiting for the operation start instants of freight trains regulated by their schedules.

Additionally, according to the setting of the due dates of accomplishing the transportation orders, anther costs defined as follows should also be formulated.

(4) *Penalty Costs* created by accomplishing transportation orders earlier than the lower bound of the due date time windows. The penalty costs are linear to the degree of the earliness.

Above all, the objective function of the economic objective is constructed as Equation (1).

$$\text{Transportation Costs} + \text{Handling Costs} + \text{Storage Costs} + \text{Penalty Costs} \tag{1}$$

Risk objective is another important objective when the routing is for hazardous materials transportation. Risk assessment is thereby very important [59]. In the multimodal transportation of hazardous materials, the risk derives from the transportation process and transshipment process. As for a viewpoint of a node-arc network topology, the risk exists in both arcs where transportation is conducted and nodes where transshipment is realized [18]. Consequently, the risk of accomplishing the transportation orders of hazardous materials is assessed as Equation (2).

$$\text{Risk along Arcs} + \text{Risk around Nodes} \tag{2}$$

As claimed in Section 1, the risk is calculated by Equation (3) [3]. And in this study, we will design a bi-objective optimization for the hazardous materials road-rail multimodal routing problem to make an effective tradeoff between the economic objective and the risk objective.

$$\text{Fuzzy Population Exposure} \times \text{Associated Volume of Hazardous Materials} \tag{3}$$

In this study, we use the symbols listed in Table 3 to denote the parameters regarding costs and risk.

Table 3. Symbols that represent the parameters regarding costs and risk.

Parameters	Representations
c_{ij}^{m}	Transportation costs per ton per km of transportation service m on directed arc $(i,\ j)$.
c_m	Separate loading and unloading costs per ton of transportation service m.
$c_{storage}$	Storage costs per ton per hour.
$c_{penalty}$	Penalty costs per ton per hour.
$\widetilde{e}_{ijm}$	Fuzzy population exposure along directed arc $(i,\ j)$ when using transportation service m and $\widetilde{e}_{ijm} = \left(e_{ijm}^{1}, e_{ijm}^{2},\ e_{ijm}^{3}\right)$, where e_{ijm}^{1}, e_{ijm}^{2} and e_{ijm}^{3} are the most pessimistic, the most possible and the most optimistic values of $\widetilde{e}_{ijm}$, respectively.
$\widetilde{e}_{i}$	Fuzzy population exposure around node i and $\widetilde{e}_{i} = \left(e_{i}^{1}, e_{i}^{2},\ e_{i}^{3}\right)$. The representations of e_{i}^{1}, e_{i}^{2} and e_{i}^{3} are similar to those of e_{ijm}^{1}, e_{ijm}^{2} and e_{ijm}^{3}.

2.4. Formulating Network Capacity: A Complex Bundling Network

Although there exist some articles that focus on the uncapacitated multimodal routing problem [47,60], it is slightly possible that uncapacitated transportation networks exist in practice due to limited facilities and equipment (e.g., trucks, railway wagons, freight trains, drivers and transportation lines, etc.) in the network that can be used for the hazardous materials routing [36]. Moreover, a capacitated routing problem can be easily transformed into an uncapacitated one by setting the capacities as large enough positive numbers. As a result, we consider a capacitated road-rail multimodal transportation network in this study.

In a capacitated transportation network, bundling is the process that transports hazardous materials of different transportation orders in a common freight train or truck fleet and is one of the core businesses of transportation operators [61]. As a complex bundling network, the road-rail multimodal transportation system with a hub-and-spoke structure should consider the bundle capacity constraints in all of its pre-haul, long-haul, and end-haul.

The truck fleets conduct the road transportation in the pre-haul and end-haul processes. For a road transportation line, there is more than one truck fleet. Under the coordination of the multimodal transportation operators (MTO), the number of trucks in different original independent truck fleets on one road transportation line can be flexibly reassigned to carry the hazardous materials of different transportation orders. Therefore, we can integrate all the truck fleets in one road transportation line into a fleet group. Trucks in one fleet group can form various truck fleets according to the assignment of transportation orders to the road transportation line, on the condition that the volume of assigned hazardous materials does not exceed the bundle capacity of the truck fleet group. Furthermore, under FTL strategy, one truck fleet can only serve no more than one transportation order [54]. The above description is illustrated by Figure 1.

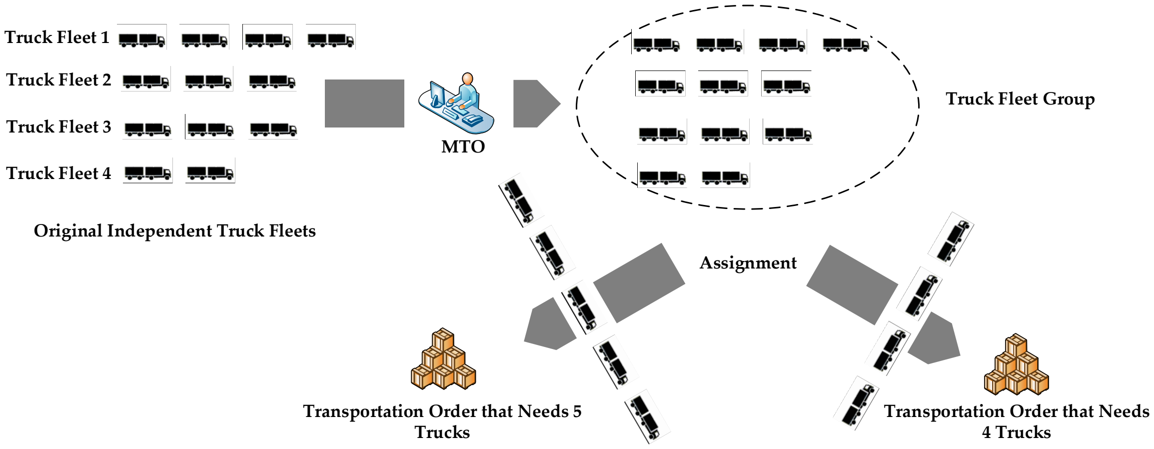

Figure 1. The operation of trucks on one road transportation line.

For the freight trains that are operated periodically, they might run more than one time during the planning horizon of the hazardous materials routing problem. For the convenience of modeling, the same freight trains that run in different periods are formulated as different train services that are represented by different indices [3,26,41,48], which can be seen in Figure 2. Consequently, the volume of hazardous materials assigned to a freight train that runs in a certain period should not exceed its bundle capacity.

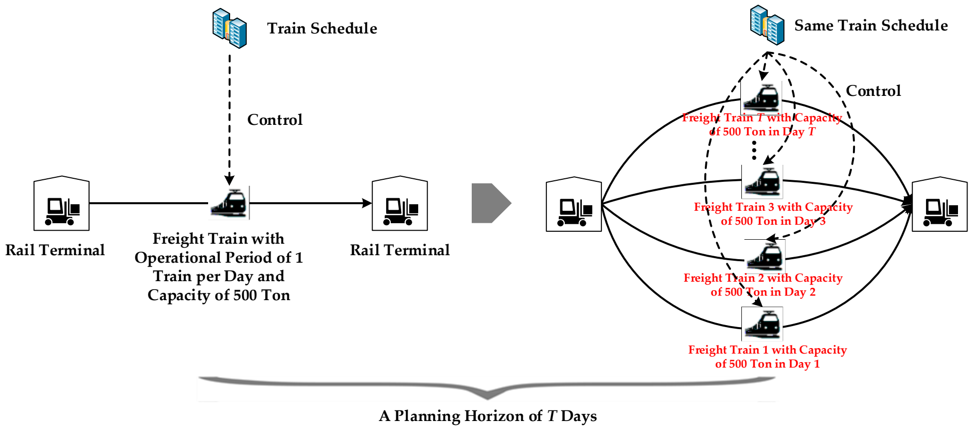

Figure 2. Formulation of the same freight trains in different periods.

Above all, in this study, we use cap_{ij}^{m} to denote the capacity in ton of transportation service m on arc $(i,\ j)$. For $m \in T_{ij}$, cap_{ij}^{m} is the capacity of all the trucks that the truck fleet group on arc $(i,\ j)$ can provide, while for $m \in R_{ij}$, cap_{ij}^{m} is the capacity of a freight train that run on arc $(i,\ j)$ in one of its periods.

3. Optimization Model

The current optimization model established in this section is similar to the one presented in our previous study [3]. However, compared with the previous one, significant improvements are made by the current model, including formulating the risk uncertainty with fuzzy population exposure, setting the road-rail multimodal transportation network as a hub-and-spoke network, building a carbon dioxide emission constraint for sustainable transportation, describing due dates as time windows, and considering the time consumption by the loading and unloading operations in the transportation process.

3.1. Assumptions to the Model

The following assumptions regarding transportation orders should be considered in order to establish a rigorous optimization model.

Assumption 1. *The hazardous materials of a transportation order will be prepared to get loaded at the corresponding release instant.*

Assumption 2. *A transportation order is accomplished once the associated hazardous materials get unloaded at the destination.*

Assumption 3. *It is not allowed that the transportation of the hazardous materials in a transportation order in a splittable way to ensure that each transportation order is integrated.*

3.2. Building Objective Functions

- Economic Objective

$$\begin{aligned}
\min \sum_{p\in P}\sum_{(i,\ j)\in A}\sum_{m\in S_{ij}} c_{ij}^{m}\cdot q_p\cdot d_{ij}^{m}\cdot x_{ijm}^{p} + \sum_{p\in P}\sum_{j\in N}\sum_{i\in N_i^-}\sum_{m\in S_{ij}} c_m\cdot q_p\cdot x_{ijm}^{p} \\
+ \sum_{p\in P}\sum_{j\in N}\sum_{k\in N_i^+}\sum_{n\in S_{jk}} c_n\cdot q_p\cdot x_{jkn}^{p} \\
+ \sum_{p\in P}\sum_{(i,\ j)\in A}\sum_{m\in R_{ij}} c_{storage}\cdot q_p\cdot z_{ijm}^{p} \\
+ \sum_{p\in P} c_{penalty}\cdot q_p\cdot \max\left\{\left(\left(y_{d_p}^{p} + \sum_{i\in N_{d_p}^-}\sum_{m\in S_{id_p}} t_{d_p}^{m}\cdot x_{id_pm}^{p}\right)\right., 0\right\}
\end{aligned} \quad (4)$$

- Risk Objective

$$\min \sum_{p\in P}\sum_{i\in N} w_i^p\cdot q_p\cdot \widetilde{e_i} + \sum_{p\in P}\sum_{(i,\ j)\in A}\sum_{m\in S_{ij}} x_{ijm}^p\cdot q_p\cdot \widetilde{e}_{ijm} \tag{5}$$

The first objective, i.e., the economic objective, is minimizing the total costs for accomplishing the multiple transportation orders of hazardous materials. The four formulas in different lines are the transportation costs, handling costs, storage costs and penalty costs, respectively. The second objective, i.e., the risk objective, is minimizing the total risk of all the transportation orders of hazardous materials.

3.3. Preseneting Constraints

$$\sum_{i\in N_i^-}\sum_{m\in S_{ij}} x_{ijm}^p - \sum_{k\in N_i^+}\sum_{n\in S_{jk}} x_{jkn}^p = -1 \quad \forall j = o_p \quad \forall p\in P \tag{6}$$

$$\sum_{i\in N_i^-}\sum_{m\in S_{ij}} x_{ijm}^p - \sum_{k\in N_i^+}\sum_{n\in S_{jk}} x_{jkn}^p = 0 \quad \forall j\in N\backslash\left\{o_p,\ d_p\right\} \quad \forall p\in P \tag{7}$$

$$\sum_{i\in N_i^-}\sum_{m\in S_{ij}} x_{ijm}^p - \sum_{k\in N_i^+}\sum_{n\in S_{jk}} x_{jkn}^p = 1 \quad \forall j = d_p \quad \forall p\in P \tag{8}$$

Equations (6)–(8) are the flow conservations of hazardous materials at origin, rail terminal (transshipping node), and destination, respectively.

$$y_{o_p}^p = \Gamma_{release}^p \quad \forall p\in P \tag{9}$$

Equation (9) is related to Assumption 1 in Section 2.1 that the hazardous materials of a transportation order start to get loaded at the corresponding release instant.

$$\sum_{m\in S_{ij}} x_{ijm}^p \le 1 \quad \forall p\in P \quad \forall (i,\ j)\in A \tag{10}$$

Equation (10) enforces Assumption 3 in Section 2.1 that ensures the integration of each transportation order of hazardous materials.

$$\begin{aligned} & y_j^p + \sum_{i\in N_j^-}\sum_{m\in S_{ij}} t_j^m\cdot q_p\cdot x_{ijm}^p + z_{jkn}^p + t_j^n\cdot q_p \\ & \le \Pi_j^{n+}\cdot x_{jkn}^p + \theta\cdot\left(1 - x_{jkn}^p\right) \end{aligned} \quad \forall p\in P \quad \forall (j,\ k)\in A \quad \forall n\in R_{ij} \tag{11}$$

Equation (11) is the fixed operation time window constraint where θ denotes a large enough positive number. It ensures that the instant when the hazardous materials get loaded on the selected freight train should be later than its upper bound of the operation time window.

$$\left(y_j^p + \sum_{i\in N_j^-}\sum_{m\in S_{ij}} t_j^m\cdot q_p\cdot x_{ijm}^p + t_j^n\cdot q_p + t_{jk}^n - y_k^p\right)\cdot x_{jkn}^p = 0 \quad \forall p\in P \quad \forall (j,\ k)\in A \quad \forall n\in T_{jk} \tag{12}$$

$$\left(\Pi_j^{m-} - y_j^p\right)\cdot x_{ijm}^p = 0 \quad \forall p\in P \quad \forall (i,\ j)\in A \quad \forall m\in R_{ij} \tag{13}$$

$$\begin{gathered} \left(\max\left\{\Pi_j^{n-} - \left(y_j^p + \sum_{i\in N_j^-}\sum_{m\in S_{ij}} t_j^m\cdot q_p\cdot x_{ijm}^p\right),\ 0\right\} - z_{jkn}^p\right)\cdot x_{jkn}^p = 0 \\ \forall p\in P \quad \forall (j,\ k)\in A \quad \forall n\in R_{ij} \end{gathered} \tag{14}$$

$$w_i^p = \begin{cases} \sum\limits_{j \in N_i^+} \sum\limits_{m \in S_{ij}} x_{ijm}^p & \forall p \in P \quad \forall i \in N \backslash \{o_p,\ d_p\} \\ 1 \quad \forall p \in P \quad \forall i \in \{o_p,\ d_p\} \end{cases} \tag{15}$$

Equations (12)–(15) are the compatibility requirement constraints among variables. Equations (12) and (13) separately compute the arrival instant of hazardous material of a transportation order at a node by road and rail. Especially for Equation (13), as stressed by Sun et al. [1,21,46,48], when using a freight train to transport hazardous materials, the effective arrival instant of hazardous material at the rail terminal should be the lower bound of the freight train's fixed operation time window, since the following unloading operation will start at this instant instead of the fixed arrival instant of the train. Equation (14) computes the storage time of hazardous materials of a transportation at a rail terminal before being transported by a freight train.

$$y_{d_p}^p + \sum_{i \in N_{d_p}^-} \sum_{m \in S_{id_p}} t_{d_p}^m \cdot q_p \cdot x_{id_p m}^p \le \Gamma_{due}^{p+} \quad \forall p \in P \tag{16}$$

Equation (16) is the constraint of the upper bound of the due date time window of the transportation order. It ensures that the accomplishment of each transportation order of hazardous materials does not exceed the corresponding upper bound of the due date time window.

$$\sum_{p \in P} q_p \cdot x_{ijm}^p \le cap_{ij}^m \quad \forall (i,\ j) \in A \quad \forall m \in S_{ij} \tag{17}$$

Equation (17) is the bundle capacity constraint that ensures the hazardous materials bundled in a common freight train or truck fleet group should not exceed the capacity.

$$\sum_{p \in P} \sum_{(i,j) \in A} \sum_{m \in S_{ij}} \pi_m \cdot q_p \cdot d_{ij}^m \cdot x_{ijm}^p \le cap_{emission} \tag{18}$$

Equation (18) is the carbon dioxide emission constraint where $cap_{emission}$ is the emission cap that should not be exceeded and π_m is the emission factor of transportation service m, i.e., the carbon dioxide emitted by transportation service m when moving one ton of goods one km. The left-hand formula of Equation (18) is established based on an activity-based method that has been widely utilized in calculation of greenhouse gas emissions [41,44,48,62,63].

$$w_i^p \in \{0,\ 1\} \quad \forall p \in P \quad \forall i \in N \tag{19}$$

$$x_{ijm}^p \in \{0,\ 1\} \quad \forall p \in P \quad \forall (i,\ j) \in A \quad \forall m \in S_{ij} \tag{20}$$

$$y_i^p \ge 0 \quad \forall p \in P \quad \forall i \in N \tag{21}$$

$$z_{ijm}^p \ge 0 \quad \forall p \in P \quad \forall (i,\ j) \in A \quad \forall m \in R_{ij} \tag{22}$$

Equations (19)–(22) are the domain constraints of the variables.

4. A Three-Stage Exact Solution Strategy

The optimization model presented in Section 3 is a bi-objective fuzzy mixed integer nonlinear programming model that contains imprecise information on Population Exposure. Due to its fuzziness, this model cannot be solved straightforwardly to obtain the crisp best road-rail multimodal routes for hazardous materials transportation. As a result, the fuzzy model should first of all be converted into a crisp model [37,64]. Furthermore, into order to gain the global optimal solutions to the problem by using exact solution algorithms (e.g., the Branch-and-Bound Algorithm) that can be effectively run by mathematical programming software (e.g., LINGO), the nonlinear model should be linearized to generate an equivalent linear model [1,21,46,48]. Finally, by solving the bi-objective mixed integer linear programming model by normalized weighting method, a Pareto frontier to the problem can be generated. According to the analysis above, we develop a three-stage exact solution strategy to solve the hazardous materials road-rail multimodal routing problem proposed in this study.

4.1. Step 1: Defuzziness by Fuzzy Credibilistic Chance-Constrained Programming

The risk objective function contains fuzzy parameters. The meaning of "min" of the risk objective function is not clear, since the values of fuzzy parameters are unknown when making the decision. Therefore, the risk objective function is not well-defined, which needs defuzziness to obtain a crisp objective.

Fuzzy chance-constrained programming can be applied to deal with fuzziness that exists in the objective function. Three fuzzy measures, i.e., possibility, necessity, and credibility measures, can be employed to construct the fuzzy chance-constrained programming [36,65]. Compared with the other two measures, fuzzy credibility measure is more suitable to evaluate the fuzzy incident due to its self-dual characteristic. Such self-dual measure ensures that a fuzzy incident must fail if its credibility equals 0, while must hold if its credibility equals 1 [66]. As a result, we select fuzzy credibilistic chance-constrained programming to address the fuzzy model.

By using fuzzy credibilistic chance-constrained programming, the risk objective function shown as Equation (5) can be revised as Equations (23) and (24).

$$\min \phi \tag{23}$$

$$\mathrm{Cr}\left\{\sum_{p\in P}\sum_{i\in N} w_i^p\cdot q_p\cdot \widetilde{e_i} + \sum_{p\in P}\sum_{(i,\ j)\in A}\sum_{m\in S_{ij}} x_{ijm}^p\cdot q_p\cdot \widetilde{e}_{ijm} \le \phi\right\} \ge \alpha \tag{24}$$

In Equation (23), ϕ is a variable and can be defined as a risk guarantee that can be offered to all the transportation orders of hazardous materials. In Equation (24), Cr{~} is the credibility of the fuzzy incident "~" in { }. $\alpha \in [0,\ 1]$ is the credibility confidence level that is set down based on the preference of the decision makers [67].

The formula in Cr{ } in the left-hand formula of Equation (24) can be transformed into Equation (25) according to the operational rule of fuzzy numbers [26].

$$\begin{aligned}(\phi - \sum_{p\in P}\sum_{i\in N} w_i^p\cdot q_p\cdot e_i^3 - \sum_{p\in P}\sum_{(i,\ j)\in A}\sum_{m\in S_{ij}} x_{ijm}^p\cdot q_p\cdot e_{ijm}^3,\ \phi - \sum_{p\in P}\sum_{i\in N} w_i^p\cdot q_p\cdot e_i^2 \\ - \sum_{p\in P}\sum_{(i,\ j)\in A}\sum_{m\in S_{ij}} x_{ijm}^p\cdot q_p\cdot e_{ijm}^2,\ \phi - \sum_{p\in P}\sum_{i\in N} w_i^p\cdot q_p\cdot e_i^1 \\ - \sum_{p\in P}\sum_{(i,\ j)\in A}\sum_{m\in S_{ij}} x_{ijm}^p\cdot q_p\cdot e_{ijm}^1) \ge 0\end{aligned} \tag{25}$$

According to Wang et al. [52], if a is a deterministic number and $\widetilde{b} = (b_1, b_2, b_3)$ is a triangular fuzzy number, $\mathrm{Cr}\left\{a \le \widetilde{b}\right\} \ge \alpha$ is equal to $2(1-\alpha)\cdot b_2 + (2\alpha - 1)\cdot b_1 \ge a$ when $\alpha \in (0.5,\ 1]$ and $2\alpha\cdot b_2 + (1-2\alpha)\cdot b_3 \ge a$ when $\alpha \in [0,\ 0.5]$. Consequently, we can modify Equation (24) as follows.

(1) If $\alpha \in [0,\ 0.5]$, Equation (24) is equivalent to Equation (26).

$$\begin{aligned}2\alpha\cdot\left(\phi - \sum_{p\in P}\sum_{i\in N} w_i^p\cdot q_p\cdot e_i^2 - \sum_{p\in P}\sum_{(i,\ j)\in A}\sum_{m\in S_{ij}} x_{ijm}^p\cdot q_p\cdot e_{ijm}^2\right) \\ +(1-2\alpha)\cdot\left(\phi - \sum_{p\in P}\sum_{i\in N} w_i^p\cdot q_p\cdot e_i^1 - \sum_{p\in P}\sum_{(i,\ j)\in A}\sum_{m\in S_{ij}} x_{ijm}^p\cdot q_p\cdot e_{ijm}^1\right) \ge 0\end{aligned} \tag{26}$$

(2) If $\alpha \in (0.5,\ 1]$, Equation (24) is equivalent to Equation (27).

$$\begin{gathered}2(1-\alpha)\cdot\left(\phi - \sum_{p\in P}\sum_{i\in N} w_i^p\cdot q_p\cdot e_i^2 - \sum_{p\in P}\sum_{(i,\ j)\in A}\sum_{m\in S_{ij}} x_{ijm}^p\cdot q_p\cdot e_{ijm}^2\right)\\ +(2\alpha-1)\cdot\left(\phi - \sum_{p\in P}\sum_{i\in N} w_i^p\cdot q_p\cdot e_i^3 - \sum_{p\in P}\sum_{(i,\ j)\in A}\sum_{m\in S_{ij}} x_{ijm}^p\cdot q_p\cdot e_{ijm}^3\right)\ge 0\end{gathered} \tag{27}$$

4.2. Step 2: Linearization

The function of penalty costs in the first objective function is piecewise due to $\max\{\Gamma_{due}^{p-} - (y_{d_p}^p + \sum_{i\in N_{d_p}^-}\sum_{m\in S_{id_p}} t_{d_p}^m\cdot x_{id_pm}^p),\ 0\}$ in it. Therefore, the first objective function is nonlinear. According to Sun et al. [48], it can be linearized as Equation (28) by adding an auxiliary variable ϑ_p and two auxiliary linear constraints shown as Equations (29) and (30).

$$\begin{gathered}\min \sum_{p\in P}\sum_{(i,\ j)\in A}\sum_{m\in S_{ij}} c_{ij}^m\cdot q_p\cdot d_{ij}^m\cdot x_{ijm}^p\\ +\sum_{p\in P}\sum_{j\in N}\sum_{i\in N_i^-}\sum_{m\in S_{ij}} c_m\cdot q_p\cdot x_{ijm}^p + \sum_{p\in P}\sum_{j\in N}\sum_{k\in N_i^+}\sum_{n\in S_{jk}} c_n\cdot q_p\cdot x_{jkn}^p\\ +\sum_{p\in P}\sum_{(i,\ j)\in A}\sum_{m\in R_{ij}} c_{storage}\cdot q_p\cdot z_{ijm}^p\\ +\sum_{p\in P} c_{penalty}\cdot q_p\cdot\vartheta_p.\end{gathered} \tag{28}$$

$$\vartheta_p \ge \Gamma_{due}^{p-} - \left(y_{d_p}^p + \sum_{i\in N_{d_p}^-}\sum_{m\in S_{id_p}} t_{d_p}^m\cdot q_p\cdot x_{id_pm}^p\right)\quad \forall p\in P \tag{29}$$

$$\vartheta_p \ge 0\quad \forall p\in P\ . \tag{30}$$

There exist multiplications of variables in Equations (12) and (13). Besides such multiplications, Equation (14) also contains a max function that is piecewise. Consequently, these three equations are nonlinear. According to Sun and Lang [41], linearization of these nonlinear equations is presented as follows.

Linear reformations of Equation (12) are Equations (31) and (32).

$$y_j^p + \sum_{i\in N_j^-}\sum_{m\in S_{ij}} t_j^m\cdot q_p\cdot x_{ijm}^p + t_j^n\cdot q_p + t_{jk}^n - y_k^p \ge \theta\cdot\left(x_{jkn}^p - 1\right)\quad \forall p\in P\quad \forall (j,\ k)\in A\quad \forall n\in T_{jk} \tag{31}$$

$$y_j^p + \sum_{i\in N_j^-}\sum_{m\in S_{ij}} t_j^m\cdot q_p\cdot x_{ijm}^p + t_j^n\cdot q_p + t_{jk}^n - y_k^p \le \theta\cdot\left(1 - x_{jkn}^p\right)\quad \forall p\in P\quad \forall (j,\ k)\in A\quad \forall n\in T_{jk}\ . \tag{32}$$

Equation (13) can be linearized as Equations (33) and (34), which is similar to the linearization of Equation (12).

$$\Pi_j^{m-} - y_j^p \ge \theta\cdot\left(x_{ijm}^p - 1\right)\quad \forall p\in P\quad \forall (i,\ j)\in A\quad \forall m\in R_{ij} \tag{33}$$

$$\Pi_j^{m-} - y_j^p \le \theta\cdot\left(1 - x_{ijm}^p\right)\quad \forall p\in P\quad \forall (i,\ j)\in A\quad \forall m\in R_{ij} \tag{34}$$

Equation (14) is equivalent to Equations (35) and (36).

$$\begin{gathered}z_{jkn}^p \ge \Pi_j^{n-} - \left(y_j^p + \sum_{i\in N_j^-}\sum_{m\in S_{ij}} t_j^m\cdot q_p\cdot x_{ijm}^p\right) + \theta\cdot\left(x_{jkn}^p - 1\right)\\ \forall p\in P\quad \forall (j,\ k)\in A\quad \forall n\in R_{ij}\end{gathered} \tag{35}$$

$$z_{jkn}^p \le \theta\cdot x_{jkn}^p\quad \forall p\in P\quad \forall (j,\ k)\in A\quad \forall n\in R_{ij} \tag{36}$$

4.3. Step 3: A Normalized Weighting Method to Generate the Pareto Frontier to the Problem

After Step 1 and Step 2, we can get a bi-objective mixed integer linear programming model whose optimization objectives are Equations (23) and (28) and constraints include Equations (6)–(11), (15)–(22), (26), (27), and (29)–(36). As for an optimization problem with two objectives and a common group of constraints, if the optimization of one objective automatically leads to the optimum of the other objective, it is not a bi-objective optimization problem and only has one optimal solution [68]. However, demonstrated by all the mentioned studies on hazardous materials routing problem, the economic objective and risk objective of the hazardous materials routing problem are in conflict with each other. The two objectives cannot achieve optimum simultaneously by one optimal solution, which means that any improvement of one objective will worsen the other one [69,70]. As a result, there is more than one solution to the bi-objective optimization of the hazardous materials road-rail multimodal routing problem. The solutions to the bi-objective optimization problem are named Pareto solutions, and these Pareto solutions form the Pareto frontier to the problem shown as Figure 3 [3,71].

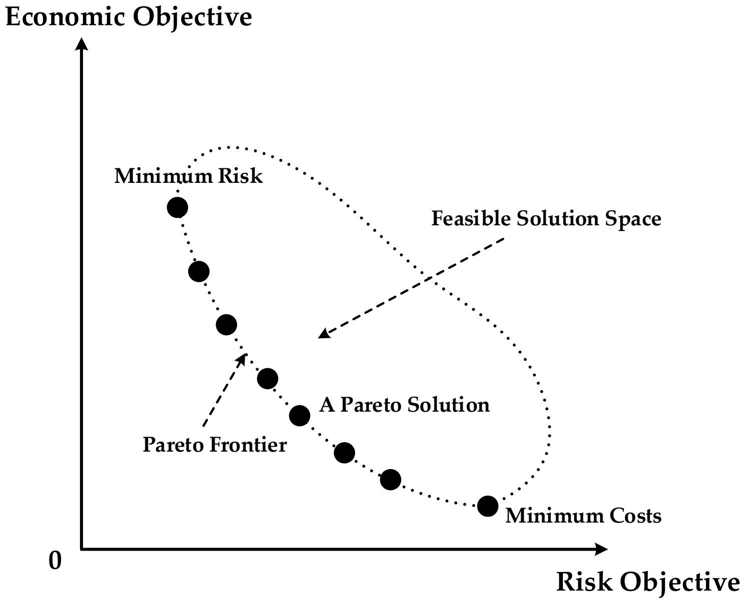

Figure 3. Solutions to the bi-objective optimization for the hazardous materials routing problem [3].

The normalized weighting method is widely used to generate the Pareto frontier to the bi-objective optimization problem [1]. It keeps the advantage of the traditional weighting method that is simple in the calculation, while it gets rid of the differences of the objectives in unit and magnitude that would influence the quality of the solutions when using the traditional weighting method [3,68].

Unlike the traditional weighting method that directly sum up the weighted objectives, the normalized weighting methods first of all calculate the respective optimal values of all the objectives. As for the specific problem discussed in this study, we use $g_{economic}$ and g_{risk} to denote the economic objective Equation (26) and risk objective Equation (21), respectively. By solving two single-objective optimization models that set Equations (26) and (21) as their respective objectives and share a common set of constraints including Equations (5)–(10), (14)–(22), (24), (25), and (27)–(34), we can obtain the optimal values of $g_{economic}$ and g_{risk}. Let $g_{economic}^{min}$ and g_{risk}^{min} represent the optimal economic objective value and the optimal risk objective value, respectively, the economic objective and risk objective can be separately normalized as $\frac{g_{economic}}{g_{economic}^{min}}$ and $\frac{g_{risk}}{g_{risk}^{min}}$. After the normalization, the two objectives become unitless and also have the same magnitude.

Then, different weights are distributed to the normalized objectives, which is the same as the operation of the traditional weighting method. Shown as Equation (37), the sum of the two weighted normalized objectives is the objective function of the new model that is used to generate the Pareto frontier. Weight combination (π_1, π_2) should satisfy Equations (38)–(40).

$$\min\left(\pi_1 \cdot \frac{g_{economic}}{g_{economic}^{min}} + \pi_2 \cdot \frac{g_{risk}}{g_{risk}^{min}}\right) \tag{37}$$

$$\pi_1 + \pi_2 = 1 \tag{38}$$

$$\pi_1 \in (0,\ 1] \tag{39}$$

$$\pi_2 \in [0,\ 1] \tag{40}$$

Finally, by manually modifying the value of π_1 from 0.01 to 1.0 with a step of 0.01, we can obtain the values of $g_{economic}$ and g_{risk} under every weight combination. Pareto solutions to the hazardous materials road-rail multimodal routing problem can be identified from all the objective value combinations $(g_{economic}, g_{risk})$ according to the definition.

5. Computational Experiment

5.1. Case Description

In this study, we presented a numerical case to demonstrate the feasibility of the proposed method in dealing with the hazardous materials road-rail multimodal routing problem and further draw some managerial implications. A road-rail multimodal transportation network with 12 nodes and 27 arcs is presented in Figure 4. The nodes in the transportation network include 3 origins, 3 destinations and 6 rail terminals where transshipment between rail and road transportation is conducted. There are 18 road transportation arcs (or lines) where the truck fleet groups implement FTL strategy. The 9 rail transportation arcs connect the 6 rail terminals in the transportation network, and there exists no less than one freight train that is operated periodically on each arc.

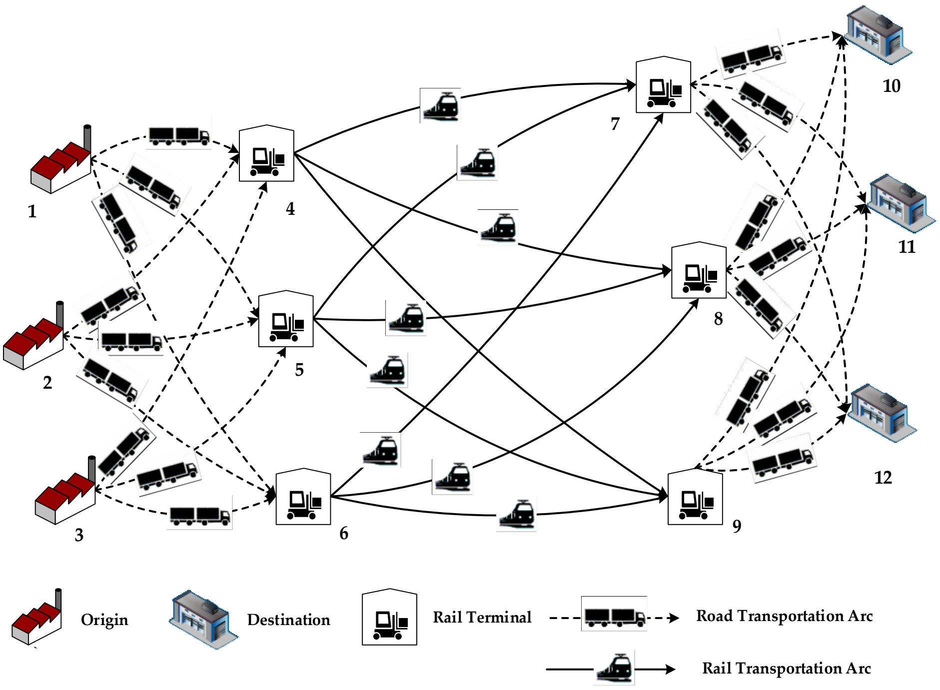

Figure 4. A road-rail multimodal transportation network for hazardous materials routing.

The schedules and travel distances of the freight trains operated on the rail transportation arcs of the road-rail multimodal transportation network are given in Table A1 in the Appendix A. The instants in this table are all discretized into real numbers for the convenience of modeling. For example, 4:30 in Day 1 is converted into 4.5, and 12:30 in Day 2 is converted into 26.5 (12.5 + 24 = 26.5). The separate loading and unloading time of road transportation (i.e., t_i^m, $\forall m \in R_{ij}$) is 0.05 h per ton.

The capacities, travel times, travel distances, and travel costs of the truck fleet groups on the road transportation arcs in the road-rail multimodal transportation network are given in Table A2 in the Appendix A. The separate loading and unloading time of road transportation (i.e., t_i^m, $\forall m \in T_{ij}$) is 0.1 h per ton.

Represented by triangular fuzzy numbers are, the fuzzy population exposures along the arcs and around the nodes in the road-rail multimodal transportation network are shown in Tables A3 and A4 in the Appendix A.

The costs parameters that are defined in Table 3, i.e., the transportation costs, the loading and unloading costs, the storage costs and the penalty costs, are given in Table 4.

Table 4. The values of the cost parameters defined in Table 3.

Transportation Mode	Transportation Costs in CNY per ton per km (C_{ij}^m)	Separate Loading and Unloading Costs in CNY per ton (C_m)	Storage Costs in CNY per ton per hour ($C_{storage}$)	Penalty Costs in CNY per ton per hour ($C_{penalty}$)
Rail	0.20	5.8	0.15	500
Road	0.75	5.5	/	

Data Source: Sun et al. [3].

In this study, the values of the emission parameters in the carbon dioxide emission constraint Equation (18) are shown in Table 5.

Table 5. The values of the emission parameters in Equation (18).

Transportation Mode	Emission Factor in ton per ton per km (π_m)	Emission Cap in Ton ($cap_{emission}$)
Rail	0.0000108	7.0
Road	0.0000443	

Data Source: Sun et al. [48].

In the case, we aim at serving 12 transportation orders of hazardous materials. The information on the transportation orders is presented in Table A5 in the Appendix A. Same as the discretization of the schedules of rail transportation, the release instants and due date time windows of the transportation orders of hazardous materials are all discretized into real numbers.

5.2. Computation Environment

In this study, all the computations for the hazardous materials road-rail multimodal routing problem are carried out under a given environment indicated by Table 6.

Table 6. Computation environment for the hazardous materials road-rail multimodal routing problem.

Programming Software	LINGO 12.0
Developer	LINDO Systems Inc., Chicago, IL, USA [72]
Implemented Algorithm	Standard Branch-and-Bound Algorithm
Solution State	Exact Solution(s) (Global Optimum)
Platform	ThinkPad Laptop with Intel Core i5-5200U, 2.20 GHz CPU, and 8 GB RAM

5.3. Parato Frontier to the Hazardous Materials Routing in the Numerical Case

First of all, the credibility confidence level α in Equation (24) is set to 0.9. Using the normalized weighting method to solve the bi-objective mixed integer linear programming model, we can obtain the Pareto frontier to the problem. The scale of the numerical case is indicated by Table 7. The computational time of such case is ~2.0 s, which is of high solution efficiency.

Table 7. Scale of the numerical case.

Number of Variables	Number of Integer Variables	Number of Constraints
1375	780	3905

Figure 5 illustrates the Pareto frontier to the numerical case. As we can see from Figure 5, the economic objective and the risk objective of the hazardous materials road-rail multimodal routing problem cannot research their respective optimum simultaneously, and the improvement of one objective must worsen the other one. Especially, compared with the Pareto solution corresponding to weight combination (0.99, 0.01), the one corresponding to weight combination (0.53, 0.47) can significantly reduce the costs of the hazardous materials routing by ~5.47% by slightly increasing its risk by ~1.39%.

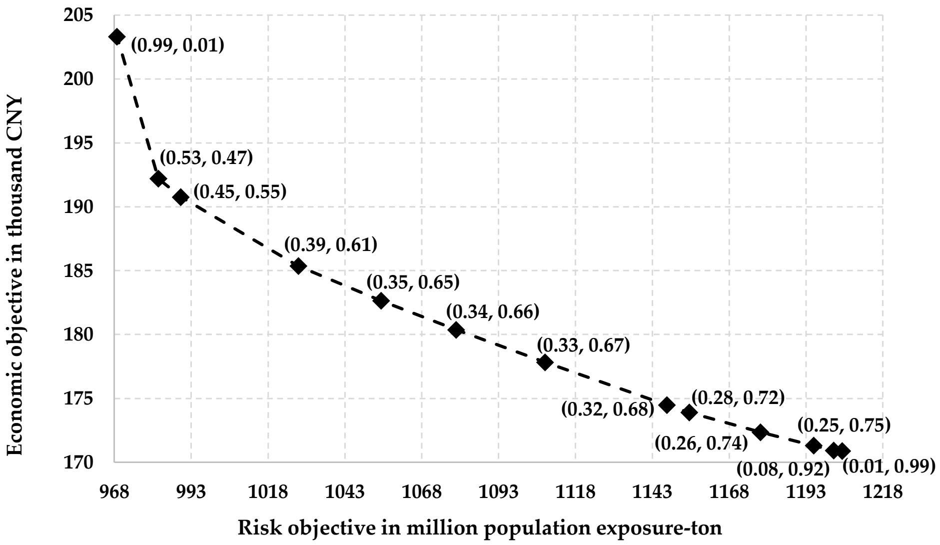

Figure 5. Pareto frontier to the numerical case when the credibility confidence is 0.9 and the emission cap is 7.0.

Based on the Pareto frontier, the decision makers can select one of the Pareto solutions as the multimodal transportation scheme for hazardous materials according to their preference towards the two objectives. For example, if the Pareto solution corresponding to weight combination (0.35, 0.65) is selected, the corresponding best road-rail multimodal routes for the hazardous materials transportation are illustrated in Table 8. In practice, decision makers can adopt multiple criteria decision-making methods to select the most suitable Pareto solution in a more precise way [73,74].

Table 8. The best road-rail multimodal routes when the weight combination is (0.35, 0.65).

Transportation Orders	Best Road-Rail Multimodal Routes
1	1– Truck fleet group 20 → 5 – Freight train 7 in Day 2 → 7 – Truck fleet group 28 → 10
2	1– Truck fleet group 19 → 4 – Freight train 7 in Day 2 → 8 – Truck fleet group 32 → 11
3	1– Truck fleet group 19 → 4 – Freight train 5 in Day 2 → 9 – Truck fleet group 35 → 11
4	1– Truck fleet group 20 → 5 – Freight train 8 in Day 2 → 7 – Truck fleet group 30 → 12
5	2– Truck fleet group 23 → 5 – Freight train 7 in Day 2 → 7 – Truck fleet group 28 → 10
6	2– Truck fleet group 23 → 5 – Freight train 8 in Day 2 → 7 – Truck fleet group 28 → 10
7	2– Truck fleet group 24 → 6 – Freight train 17 in Day 2 → 9 – Truck fleet group 35 → 11
8	2– Truck fleet group 24 → 6 – Freight train 17 in Day 2 → 9 – Truck fleet group 36 → 12
9	3– Truck fleet group 26 → 5 – Freight train 7 in Day 2 → 7 – Truck fleet group 28 → 10
10	3– Truck fleet group 27 → 6 – Freight train 17 in Day 2 → 9 – Truck fleet group 35 → 11
11	3– Truck fleet group 27 → 6 – Freight train 18 in Day 1 → 9 – Truck fleet group 36 → 12
12	3– Truck fleet group 27 → 6 – Freight train 17 in Day 2 → 9 – Truck fleet group 36 → 12

5.4. Sensitivity Analysis of the Hazardous Materials Routing with Respect to the Credibility Confidence

The credibility confidence in the fuzzy chance constraint Equation (24) is set by the decision makers subjectively when making the routing decision. As claimed by various studies in routing problems with fuzzy parameters [26,36,48], the value of the credibility confidence significantly influences the result of the routing optimization. In this study, we analyze the sensitivity of the Pareto frontier to the hazardous materials routing problem with respect to the credibility confidence. When the credibility confidence is separately set to 0.3, 0.6, 0.9 and 1, the corresponding 4 Pareto frontiers are illustrated in Figure 6.

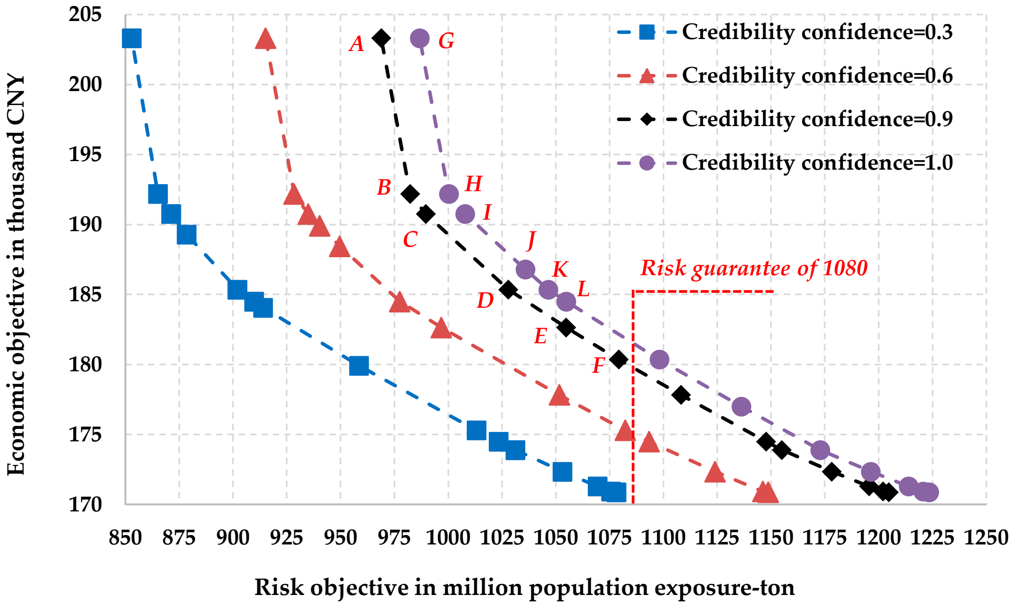

Figure 6. The sensitivity of the Pareto frontier with respect to the credibility confidence when the emission cap is 7.0.

As we can see from Figure 6, the Pareto frontier moves from left to right with the credibility confidence increasing. The risk objective is sensitive to the credibility confidence. It is an increasing function of the credibility confidence, i.e., the risk objective value increases with the credibility confidence increasing. It can be observed that if the decision makers prefer higher credibility of the hazardous materials routing, a larger risk guarantee should be offered to the served transportation orders of hazardous materials. However, the economic objective varies from 170891.4 CNY–203317.1 CNY, regardless of the value of the credibility confidence. The variation keeps unchanged. The economic objective is not relevant to the credibility confidence. Therefore, the economic objective is not sensitive to the uncertainty.

Based on Figure 5, the decision makers can make flexible routing decisions according to their preferences. For example, we assume that the risk guarantee that can be provided is 1080, and the decision makers want that the risk guarantee should be ensured with higher credibility that is no less than 0.9. In this case, Pareto solutions A, B, $C\ldots$ K and L on the Pareto frontiers corresponding to the credibility confidences of 0.9 and 1.0 all satisfy the risk requirement of decision makers. Then considering improving the economy, i.e., lowering the costs, of the hazardous materials routing, the decision makers can select Pareto solution F who owns the minimum economic objective value as the final transportation plan.

Additionally, when the credibility confidence is set to 1, the Pareto frontier is also the one generated by the deterministic model for the hazardous materials routing problem with risk certainty. Through the above example, we can draw the conclusion that the fuzzy model for the hazardous materials routing problem with risk uncertainty can help the decision makers find a more economic transportation scheme than the deterministic model under the same risk requirements.

5.5. Sensitivity Analysis of the Hazardous Materials Routing with Respect to the Emission Cap

As a hard constraint, the carbon dioxide emission constraint influences the hazardous materials road-rail multimodal routing problem. The emission cap is also determined by the decision makers subjectively. It should be noted that the following sensitivity is analyzed under a credibility confidence of 0.9. When the carbon dioxide emission cap is separately set to 5.8, 6.0, 6.4, and 7.0, the corresponding 4 Pareto frontiers are illustrated by Figure 7.

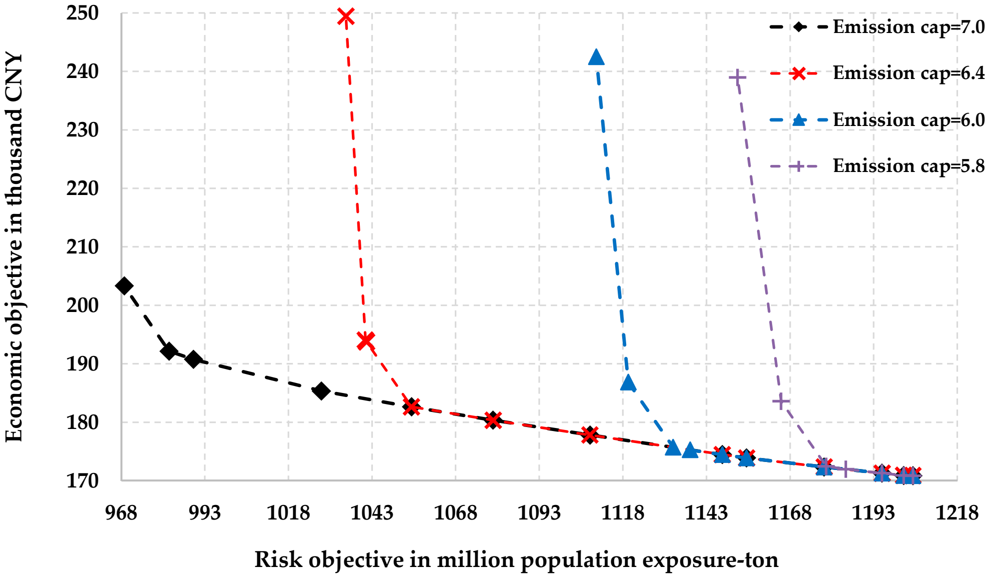

Figure 7. The sensitivity of the Pareto frontier with respect to the emission cap when the credibility confidence is 0.9.

As we can see from Figure 7, when the emission cap increases from 5.8 to 7.0, the upper section of the Pareto frontier where risk objective is attached with much more importance than the economic objective moves from left to right. However, the lower section of the Pareto frontier keeps relatively stable with the variation of the emission cap. Moreover, with the emission cap extending, the number of Pareto solution increase, which can provide decision makers with more candidates.

Indicated by Figure 7, if the decision makers attach more importance to the economic objective, the optimization result is not sensitive to the setting of the carbon dioxide emission cap. However, when the risk objective is more important than the economic objective, the optimization result becomes very sensitive to the carbon dioxide emission cap. Extending the carbon dioxide emission cap can help decision makers identify a more risk-efficient transportation scheme under the decision-making case that decision makers prefer as the risk objective.

6. Conclusions

In this study, we systematically investigate the hazardous materials road-rail multimodal routing problem that is a spotlight in the transportation planning field. The following three extensions are made in order to improve the problem optimization: (1) A hub-and-spoke network is used to represent the hazardous materials road-rail multimodal transportation network; (2) the uncertainty of the risk parameter, i.e., the population exposures, is considered. Triangular fuzzy numbers are used to formulate the fuzzy population exposures, and fuzzy credibilistic chance-constrained programming is adopted to build the fuzzy programming model for the hazardous materials routing problem under uncertainty. (3) Sustainability of the hazardous materials transportation is improved by formulating carbon dioxide emission constraint is formulated to reduce greenhouse gas emissions. Additionally, we propose a formulation characteristic framework to make problem modeling more rigorous. The framework includes four important formulation characteristics of the transportation modeling, including determining optimization object, modeling transportation modes, setting optimization criterion, and formulating network capacity. Above are the main contributions to the problem itself made by this study. As for solving the specific problem formulated by a bi-objective fuzzy mixed integer nonlinear programming model, we develop a three-stage exact solution strategy that combines fuzzy credibilistic chance constraint, linearization technique, and the normalized weighing method. Furthermore, sensitivity analysis is adopted by this study to quantify how uncertainty and sustainability influence the hazardous materials road-rail multimodal routing problem. The following managerial implications can be drawn by using the proposed method in this study, which is helpful for hazardous materials road-rail multimodal transportation organization.

(1) The economic objective and risk objective of hazardous materials road-rail multimodal routing problem are in conflict with each other. Improving one objective will worsen another. By using the Pareto frontier generated by our method, decision makers can make effective tradeoffs between the two objectives.

(2) Considering risk uncertainty resulting from fuzzy population exposure can help decision makers find a more economic transportation scheme than the study with risk certainty while keeping the same risk requirements.

(3) The credibility confidence influences the optimization result of the hazardous materials road-rail multimodal routing with fuzzy population exposure. The risk objective increases with the credibility confidence enhancing, while the economic objective is not sensitive to the credibility confidence.

(4) Larger risk guarantee should be offered to the transportation orders of hazardous materials if higher credibility of the hazardous materials routing is required by the decision makers.

(5) Carbon dioxide emission cap also influences the hazardous materials road-rail multimodal routing result, especially when the risk objective is attached more importance than the economic objective by the decision makers.

(6) Extending the carbon dioxide emission cap can improve the decision-making flexibility by providing decision makers with more Pareto solutions that can be set as transportation schemes. It can also help decision makers find a more risk-efficient transportation scheme when they prefer risk objective.

However, the routing problem is widely acknowledged to be an NP-hard problem. When the scale of the problem gets larger, the proposed solution method might be inefficient. Consequently, designing an intelligent algorithm, e.g., heuristic algorithm, will be one of our future works on the hazardous materials road-rail multimodal routing problem. Besides, using a normalized weight method to generate the Pareto frontier needs a lot of computation and is time-consuming. Therefore, finding another effective method is meaningful. It is worthwhile to try the ε-constraint method in our future work. Moreover, other sources of uncertainty, e.g., demand uncertainty, capacity uncertainty, and time uncertainty, will be discussed in our future work so that the problem formulation is more applicable. Some emerging technologies, e.g., Physical Internet [75], can be also discussed if they can be used to improve the hazardous materials road-rail multimodal routing.

Author Contributions: Y.S., X.L. (Xia Liang) and C.Z. proposed the topic explored in this paper. Y.S. and X.L. (Xia Liang) developed the mathematical model. Y.S. and C.Z. proposed the solution strategy for the problem. Y.S. and X.L. (Xinya Li) designed the numerical case. Y.S., X.L. (Xinya Li) and X.L. (Xia Liang) conducted the computation and sensitivity analysis in the case study. Y.S. and X.L. (Xinya Li) wrote the paper. X.L. (Xinya Li), X.L. (Xia Liang) and C.Z. thoroughly reviewed and improved the paper. All authors have discussed and contributed to the manuscript. All authors have read and approved the final manuscript.

Funding: This research was funded by the Project for Humanities and Social Sciences Research of Ministry of Education of China, grant number 19YJC630149, the Shandong Provincial Natural Science Foundation of China, grant number ZR2019BG006, the National Natural Science Foundation of China, grant number 71801142, and the Shandong Provincial Higher Educational Social Science Program of China, grant number J18RA053.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. The schedules of the freight trains in the network.

Freight Trains (m)	Train Routes ((i,j))	Operation Start Instants at Origins (Π_i^{m-})	Operation Cutoff Instants at Origins (Π_i^{m+})	Operation Start Instants at Destinations (Π_j^{m-})	Capacities (cap_{ij}^m)	Periods in Train per day	Travel Distances in km (d_{ij}^m)
1	(4, 7)	15	20	30	550	1	184
2	(4, 7)	6	13	22	583	1	184
3	(4, 8)	5	10	21	720	1	210
4	(4, 8)	3	11	24	750	1	210
5	(4, 9)	9	16	32	640	1	280
6	(4, 9)	14	21	36	610	1	280
7	(5, 7)	8	14	25	675	**1**	193
8	(5, 7)	13	19	31	710	1	193
9	(5, 8)	7	15	25	750	1	185
10	(5, 8)	10	16	27	650	1	185
11	(5, 9)	0	8	22	584	1	178
12	(5, 9)	6	15	25	540	1	178
13	(6, 7)	11	20	37	591	1	315
14	(6, 7)	14	19	40	630	1	315
15	(6, 8)	4	11	22	725	1	236
16	(6, 8)	8	16	30	690	1	236
17	(6, 9)	12	17	29	525	1	291
18	(6, 9)	15	23	35	570	1	291

Table A2. The capacities, travel times, and travel costs of the truck fleet groups in the network.

Truck Fleet Groups (m)	Arcs ((i,j))	Capacities in Ton (cap_{ij}^m)	Travel Times in Hour (t_{ij}^m)	Travel Distances in km (d_{ij}^m)
19	(1, 4)	300	1.5	68
20	(1, 5)	490	2.0	85
21	(1, 6)	400	5.0	120
22	(2, 4)	380	3.0	90
23	(2, 5)	460	2.8	105
24	(2, 6)	290	1.8	75
25	(3, 4)	320	5.6	114
26	(3, 5)	410	2.2	94
27	(3, 6)	340	2.0	100
28	(7, 10)	305	2.3	95
29	(7, 11)	410	3.2	118
30	(7, 12)	295	6.0	130
31	(8, 10)	350	4.3	106
32	(8, 11)	420	1.7	64
33	(8, 12)	442	2.4	93
34	(9, 10)	288	6.2	122
35	(9, 11)	390	3.7	102
36	(9, 12)	265	1.4	70

Table A3. The fuzzy population exposures along the arcs in the road-rail multimodal transportation network.

Transportation Arcs ((i, j))	**Fuzzy Population Exposures in Thousand People ($\tilde{e}_{ijm}$)**		
	e^1_{ijm}	e^2_{ijm}	e^3_{ijm}
(1, 4)	620.3	704.2	786.4
(1, 5)	710.6	758.0	816.5
(1, 6)	524.8	581.7	640.7
(2, 4)	395.1	470.6	520.4
(2, 5)	443.2	500.8	570.3
(2, 6)	603.5	683.2	748.6
(3, 4)	540.5	610.3	700.1
(3, 5)	570.0	632.7	696.5
(3, 6)	403.6	486.2	523.7
(4, 7)	551.0	650.8	689.5
(4, 8)	670.6	730.2	761.8
(4, 9)	445.8	554.8	570.4
(5, 7)	350.7	423.4	480.4
(5, 8)	660.5	703.5	750.8
(5, 9)	580.5	630.7	670.4
(6, 7)	365.1	410.0	430.8
(6, 8)	586.0	616.8	653.5
(6, 9)	368.5	402.6	440.3
(7, 10)	521.4	589.5	626.1
(7, 11)	510.9	596.0	630.8
(7, 12)	646.5	721.5	760.5
(8, 10)	410.5	442.3	500.4
(8, 11)	557.4	620.5	640.1
(8, 12)	584.7	650.2	710.8
(9, 10)	615.5	727.5	760.6
(9, 11)	311.8	350.7	387.0
(9, 12)	547.9	598.3	643.5

Table A4. The fuzzy population exposures around the nodes in the road-rail multimodal transportation network.

Nodes (i)	**Fuzzy Population Exposures in Thousand People ($\tilde{e}_i$)**		
	e^1_i	e^2_i	e^3_i
1	25.0	34.4	48.3
2	15.4	22.9	35.6
3	18.6	23.1	38.0
4	16.7	28.4	41.2
5	30.4	35.6	50.6
6	10.5	13.2	25.3
7	15.2	28.7	33.0
8	12.3	23.2	31.5
9	11.2	17.4	25.7
10	20.1	28.4	35.5
11	25.1	35.6	40.4
12	14.7	20.2	25.8

Table A5. Information on the transportation orders of the numerical case.

Transportation Orders (p)	Origins (o_p)	Destinations (d_p)	Volumes in ton (q_p)	Release Instants ($\Gamma^{p}_{release}$)	Due Dates ($[\Gamma^{p-}_{due}, \Gamma^{p+}_{due}]$)
1	1	10	30	4	[44, 62]
2	1	11	43	8	[54, 78]
3	1	11	53	10	[69, 95]
4	1	12	37	16	[73, 71]
5	2	10	61	3	[50, 70]
6	2	10	46	10	[65, 95]
7	2	11	65	9	[54, 77]
8	2	12	36	14	[58, 91]
9	3	10	70	7	[52, 72]
10	3	11	63	13	[70, 89]
11	3	12	41	3	[52, 60]
12	3	12	55	17	[60, 85]

References

1. Xie, Y.; Lu, W.; Wang, W.; Quadrifoglio, L. A multimodal location and routing model for hazardous materials transportation. *J. Hazard. Mater.* **2012**, *227*, 135–141. [CrossRef] [PubMed]
2. Zhao, J.; Huang, L.; Lee, D.H.; Peng, Q. Improved approaches to the network design problem in regional hazardous waste management systems. *Transport Res. E-Log.* **2016**, *88*, 52–75. [CrossRef]
3. Sun, Y.; Lang, M.; Wang, D. Bi-objective modelling for hazardous materials road–rail multimodal routing problem with railway schedule-based space–time constraints. *Int. J. Environ. Res. Public Health* **2016**, *13*, 762. [CrossRef] [PubMed]
4. Erkut, E.; Tjandra, S.A.; Verter, V. Hazardous materials transportation. *Oper. Res. Manag. Sci.* **2007**, *14*, 539–621.
5. Bubbico, R.; Maschio, G.; Mazzarotta, B.; Milazzo, M.F.; Parisi, E. Risk management of road and rail transport of hazardous materials in Sicily. *J. Loss Prev. Ind.* **2006**, *19*, 32–38. [CrossRef]
6. Verter, V.; Kara, B.Y. A path-based approach for hazmat transport network design. *Manag. Sci.* **2008**, *54*, 29–40. [CrossRef]
7. Du, J.; Yu, L.; Li, X. Fuzzy multi-objective chance-constrained programming model for hazardous materials transportation. *Int. J. Syst.* **2016**, *45*, 286–310. [CrossRef]
8. Xin, C.; Qingge, L.; Wang, J.; Zhu, B. Robust optimization for the hazardous materials transportation network design problem. *J. Comb. Optim.* **2015**, *30*, 320–334. [CrossRef]
9. Yang, J.; Li, F.; Zhou, J.; Zhang, L.; Huang, L.; Bi, J. A survey on hazardous materials accidents during road transport in China from 2000 to 2008. *J. Hazard. Mater.* **2010**, *184*, 647–653. [CrossRef]
10. Tarantilis, C.D.; Kiranoudis, C.T. Using the vehicle routing problem for the transportation of hazardous materials. *Oper. Res.* **2001**, *1*, 67. [CrossRef]
11. List, G.F.; Mirchandani, P.B.; Turnquist, M.A.; Zografos, K.G. Modeling and analysis for hazardous materials transportation: Risk analysis, routing/scheduling and facility location. *Transp. Sci.* **1991**, *25*, 100–114. [CrossRef]
12. Bula, G.A.; Prodhon, C.; Gonzalez, F.A.; Afsar, H.M.; Velasco, N. Variable neighborhood search to solve the vehicle routing problem for hazardous materials transportation. *J. Hazard. Mater.* **2017**, *324*, 472–480. [CrossRef] [PubMed]
13. Du, J.; Li, X.; Yu, L.; Dan, R.; Zhou, J. Multi-depot vehicle routing problem for hazardous materials transportation: A fuzzy bilevel programming. *Inf. Sci.* **2017**, *399*, 201–218. [CrossRef]
14. Ma, C.; Mao, B.; Xu, Q.; Hua, G.; Zhang, S.; Zhang, T. Multi-Depot Vehicle Routing Optimization Considering Energy Consumption for Hazardous Materials Transportation. *Sustainability* **2018**, *10*, 3519. [CrossRef]
15. Kheirkhah, A.; Navidi, H.; Messi Bidgoli, M. A bi-level network interdiction model for solving the hazmat routing problem. *Int. J. Prod. Res.* **2016**, *54*, 459–471. [CrossRef]
16. Das, A.; Mazumder, T.N.; Gupta, A.K. Pareto frontier analyses based decision making tool for transportation of hazardous waste. *J. Hazard. Mater.* **2012**, *227*, 341–352. [CrossRef] [PubMed]
17. Ardjmand, E.; Weckman, G.; Park, N.; Taherkhani, P.; Singh, M. Applying genetic algorithm to a new location and routing model of hazardous materials. *Int. J. Prod. Res.* **2015**, *53*, 916–928. [CrossRef]

18. Zhao, J.; Verter, V. A bi-objective model for the used oil location-routing problem. *Comput. Oper. Res.* **2015**, *62*, 157–168. [CrossRef]
19. Asgari, N.; Rajabi, M.; Jamshidi, M.; Khatami, M.; Farahani, R.Z. A memetic algorithm for a multi-objective obnoxious waste location-routing problem: A case study. *Ann. Oper. Res.* **2017**, *250*, 279–308. [CrossRef]
20. Alumur, S.; Kara, B.Y. A new model for the hazardous waste location-routing problem. *Comput. Oper. Res.* **2007**, *34*, 1406–1423. [CrossRef]
21. Esfandeh, T.; Batta, R.; Kwon, C. Time-dependent hazardous-materials network design problem. *Transp. Sci.* **2017**, *52*, 454–473. [CrossRef]
22. Fontaine, P.; Minner, S. Benders decomposition for the hazmat transport network design problem. *Eur. J. Oper.* **2018**, *267*, 996–1002. [CrossRef]
23. Kara, B.Y.; Verter, V. Designing a road network for hazardous materials transportation. *Transp. Sci.* **2004**, *38*, 188–196. [CrossRef]
24. Sun, L.; Karwan, M.H.; Kwon, C. Robust hazmat network design problems considering risk uncertainty. *Transp. Sci.* **2015**, *50*, 1188–1203. [CrossRef]
25. Verma, M.; Verter, V.; Gendreau, M. A tactical planning model for railroad transportation of dangerous goods. *Transp. Sci.* **2011**, *45*, 163–174. [CrossRef]
26. Sun, Y.; Liang, X.; Li, X.; Zhang, C. A Fuzzy Programming Method for Modeling Demand Uncertainty in the Capacitated Road–Rail Multimodal Routing Problem with Time Windows. *Symmetry* **2019**, *11*, 91. [CrossRef]
27. Verma, M.; Verter, V. A lead-time based approach for planning rail–truck intermodal transportation of dangerous goods. *Eur. J. Oper.* **2010**, *202*, 696–706. [CrossRef]
28. Assadipour, G.; Ke, G.Y.; Verma, M. A toll-based bi-level programming approach to managing hazardous materials shipments over an intermodal transportation network. *Transp. Res. Part. D* **2016**, *47*, 208–221. [CrossRef]
29. Bubbico, R.; Di Cave, S.; Mazzarotta, B. Risk analysis for road and rail transport of hazardous materials: A GIS approach. *J. Loss Prev. Ind.* **2004**, *17*, 483–488. [CrossRef]
30. Assadipour, G.; Ke, G.Y.; Verma, M. Planning and managing intermodal transportation of hazardous materials with capacity selection and congestion. *Transp. Res. Part. E.* **2015**, *76*, 45–57. [CrossRef]
31. Jiang, Y.; Zhang, X.; Rong, Y.; Zhang, Z. A multimodal location and routing model for hazardous materials transportation based on multi-commodity flow model. *Procedia Soc. Behav. Sci.* **2014**, *138*, 791–799. [CrossRef]
32. Verma, M.; Verter, V.; Zufferey, N. A bi-objective model for planning and managing rail-truck intermodal transportation of hazardous materials. *Transp. Res. Part. E.* **2012**, *48*, 132–149. [CrossRef]
33. Mohammadi, M.; Jula, P.; Tavakkoli-Moghaddam, R. Design of a reliable multi-modal multi-commodity model for hazardous materials transportation under uncertainty. *Eur. J. Oper.* **2017**, *257*, 792–809. [CrossRef]
34. Verma, M.; Verter, V. Railroad transportation of dangerous goods: Population exposure to airborne toxins. *Comput. Oper. Res.* **2007**, *34*, 1287–1303. [CrossRef]
35. Sun, Y.; Lang, M.; Wang, J. On solving the fuzzy customer information problem in multicommodity multimodal routing with schedule-based services. *Information* **2016**, *7*, 13. [CrossRef]
36. Sun, Y.; Zhang, G.; Hong, Z.; Dong, K. How uncertain information on service capacity influences the intermodal routing decision: A fuzzy programming perspective. *Information* **2018**, *9*, 24. [CrossRef]
37. Tian, W.; Cao, C. A generalized interval fuzzy mixed integer programming model for a multimodal transportation problem under uncertainty. *Eng. Optimiz.* **2017**, *49*, 481–498. [CrossRef]
38. Liang, T.F. Application of fuzzy sets to manufacturing/distribution planning decisions in supply chains. *Inf. Sci.* **2011**, *181*, 842–854. [CrossRef]
39. Yu, H.; Solvang, W. A stochastic programming approach with improved multi-criteria scenario-based solution method for sustainable reverse logistics design of waste electrical and electronic equipment (WEEE). *Sustainability* **2016**, *8*, 1331. [CrossRef]
40. Loo, B.P.; Li, L. Carbon dioxide emissions from passenger transport in China since 1949: Implications for developing sustainable transport. *Energy Policy* **2012**, *50*, 464–476. [CrossRef]
41. Sun, Y.; Lang, M. Modeling the multicommodity multimodal routing problem with schedule-based services and carbon dioxide emission costs. *Math. Probl. Eng.* **2015**, *2015*. [CrossRef]
42. Liao, C.H.; Tseng, P.H.; Lu, C.S. Comparing carbon dioxide emissions of trucking and intermodal container transport in Taiwan. *Transp. Res. Part D.* **2009**, *14*, 493–496. [CrossRef]

43. Li, H.; Lu, Y.; Zhang, J.; Wang, T. Trends in road freight transportation carbon dioxide emissions and policies in China. *Energy Policy* **2013**, *57*, 99–106. [CrossRef]
44. Chang, Y.T.; Lee, P.T.W.; Kim, H.J.; Shin, S.H. Optimization model for transportation of container cargoes considering short sea shipping and external cost: South Korean case. *Transport. Res. Rec.* **2010**, *2166*, 99–108. [CrossRef]
45. Demir, E.; Burgholzer, W.; Hrušovský, M.; Arıkan, E.; Jammernegg, W.; Van Woensel, T. A green intermodal service network design problem with travel time uncertainty. *Transport. Res. Part B.* **2016**, *93*, 789–807. [CrossRef]
46. Hrušovský, M.; Demir, E.; Jammernegg, W.; Van Woensel, T. Hybrid simulation and optimization approach for green intermodal transportation problem with travel time uncertainty. *Flex. Serv. Manuf. J.* **2018**, *30*, 486–516. [CrossRef]
47. Zhang, D.; He, R.; Li, S.; Wang, Z. A multimodal logistics service network design with time windows and environmental concerns. *PloS One* **2017**, *12*, e0185001. [CrossRef] [PubMed]
48. Sun, Y.; Hrušovský, M.; Zhang, C.; Lang, M. A time-dependent fuzzy programming approach for the green multimodal routing problem with rail service capacity uncertainty and road traffic congestion. *Complexity* **2018**, *2018*. [CrossRef]
49. Yu, H.; Solvang, W.D. A carbon-constrained stochastic optimization model with augmented multi-criteria scenario-based risk-averse solution for reverse logistics network design under uncertainty. *J. Clean. Prod.* **2017**, *164*, 1248–1267. [CrossRef]
50. Caris, A.; Macharis, C.; Janssens, G.K. Planning problems in intermodal freight transport: Accomplishments and prospects. *Transp. Plan. Technol.* **2008**, *31*, 277–302. [CrossRef]
51. Macharis, C.; Bontekoning, Y.M. Opportunities for OR in intermodal freight transport research: A review. *Eur. J. Oper.* **2004**, *153*, 400–416. [CrossRef]
52. Wang, R.; Yang, K.; Yang, L.; Gao, Z. Modeling and optimization of a road–rail intermodal transport system under uncertain information. *Eng. Appl. Artif. Intell.* **2018**, *72*, 423–436. [CrossRef]
53. Henderson, S.G.; Nelson, B.L. (Eds.) *Handbooks in Operations Research and Management Science: Simiulation*; Elsevier: Amsterdam, Netherlands, 2006; Volume 13.
54. Gonzalez-Feliu, J. Multi-stage LTL Transport Systems in Supply Chain Management. 2013. Available online: https://halshs.archives-ouvertes.fr/halshs-00796714/ (accessed on 4 May 2019).
55. Wolfinger, D.; Tricoire, F.; Doerner, K.F. A matheuristic for a multimodal long haul routing problem. *EURO J. Transp. Logist.* **2018**, 1–37. [CrossRef]
56. Sun, Y.; Lang, M.; Wang, D. Optimization models and solution algorithms for freight routing planning problem in the multi-modal transportation networks: A review of the state-of-the-art. *OJCE* **2015**, *9*, 714–723. [CrossRef]
57. Moccia, L.; Cordeau, J.F.; Laporte, G.; Ropke, S.; Valentini, M.P. Modeling and solving a multimodal transportation problem with flexible-time and scheduled services. *Networks* **2011**, *57*, 53–68. [CrossRef]
58. Forcina, A.; Petrillo, A.; Bona, G.D.; Felice, F.D.; Silvestri, A. An innovative model to optimise inventory management: A case study in healthcare sector. *Int. J. Serv. Oper. Manag.* **2017**, *27*, 549–568. [CrossRef]
59. Bona, G.D.; Silvestri, A.; Forcina, A.; Petrillo, A. Total efficient risk priority number (TERPN): A new method for risk assessment. *J. Risk Res.* **2018**, *21*, 1384–1408. [CrossRef]
60. Xiong, G.; Wang, Y. Best routes selection in multimodal networks using multi-objective genetic algorithm. *J. Comb. Optim.* **2014**, *28*, 655–673. [CrossRef]
61. Kreutzberger, E. Lowest cost intermodal rail freight transport bundling networks: Conceptual structuring and identification. *EJTIR* **2010**, *10*. [CrossRef]
62. Qu, Y.; Bektaş, T.; Bennell, J. Sustainability SI: Multimode multicommodity network design model for intermodal freight transportation with transfer and emission costs. *NETS* **2016**, *16*, 303–329. [CrossRef]
63. Winebrake, J.J.; Corbett, J.J.; Falzarano, A.; Hawker, J.S.; Korfmacher, K.; Ketha, S.; Zilora, S. Assessing energy, environmental, and economic tradeoffs in intermodal freight transportation. *J. Air Waste Manag. Assoc.* **2008**, *58*, 1004–1013. [CrossRef]
64. Özceylan, E.; Paksoy, T. Interactive fuzzy programming approaches to the strategic and tactical planning of a closed-loop supply chain under uncertainty. *Int. J. Prod. Res.* **2014**, *52*, 2363–2387. [CrossRef]
65. Zarandi, M.H.F.; Hemmati, A.; Davari, S. The multi-depot capacitated location-routing problem with fuzzy travel times. *Expert. Syst. Appl.* **2011**, *38*, 10075–10084. [CrossRef]

66. Zheng, Y.; Liu, B. Fuzzy vehicle routing model with credibility measure and its hybrid intelligent algorithm. *Appl. Math. Comput.* **2006**, *176*, 673–683. [CrossRef]
67. Mula, J.; Peidro, D.; Poler, R. The effectiveness of a fuzzy mathematical programming approach for supply chain production planning with fuzzy demand. *Int. J. Prod. Econ.* **2010**, *128*, 136–143. [CrossRef]
68. Boyer, O.; Sai Hong, T.; Pedram, A.; Mohd Yusuff, R.B.; Zulkifli, N. A mathematical model for the industrial hazardous waste location-routing problem. *J. Appl. Math.* **2013**, *2013*. [CrossRef]
69. Messac, A.; Ismail-Yahaya, A.; Mattson, C.A. The normalized normal constraint method for generating the Pareto frontier. *Struct. Multidiscip. Optim.* **2003**, *25*, 86–98. [CrossRef]
70. Mavrotas, G. Effective implementation of the ε-constraint method in multi-objective mathematical programming problems. *Appl. Math. Comput.* **2009**, *213*, 455–465. [CrossRef]
71. Yu, H.; Solvang, W. An improved multi-objective programming with augmented ε-constraint method for hazardous waste location-routing problems. *Int. J. Environ. Res. Pub. Heal.* **2016**, *13*, 548. [CrossRef]
72. Schrage, L. *LINGO User's Guide*; LINDO System Inc.: Chicago, IL, USA, 2006.
73. Liang, X.; Jiang, Y.; Liu, P. Stochastic multiple-criteria decision making with 2-tuple aspirations: A method based on disappointment stochastic dominance. *Int. T. Oper. Res.* **2018**, *25*, 913–940. [CrossRef]
74. Jiang, Y.; Liang, X.; Liang, H.; Yang, N. Multiple criteria decision making with interval stochastic variables: A method based on interval stochastic dominance. *Eur. J. Oper.* **2018**, *271*, 632–643. [CrossRef]
75. Sun, Y.; Zhang, C.; Dong, K.; Lang, M. Multiagent modelling and simulation of a physical internet enabled rail-road intermodal transport system. *Urban. Rail Transit.* **2018**, *4*, 141–154. [CrossRef]