A time-dependent fuzzy programming approach for the green multimodal routing problem with rail service capacity uncertainty and road traffic congestion

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Abstract: In this study, we explore an operational-level freight routing problem that aims to select the best routes to move containers through the road-rail multimodal service network. In response to the increasing demand for developing an environmentally friendly transportation, this study extends the multimodal routing problem into a green version by considering the CO_2 emissions. To improve the feasibility and reliability of the optimization model in addressing the practical problem, we consider the routing decision as a service-oriented planning and comprehensively formulate (1) multiple transportation orders, (2) schedule-based rail services whose capacities are uncertain during the decision process, (3) time-flexible road services that are often delayed due to the traffic congestion, and (4) specific customer demands with soft duedate time windows. By using the time-dependent travel time and triangular fuzzy numbers to separately describe the traffic congestion and capacity uncertainty, we establish a fuzzy chance-constrained mixed integer nonlinear programming model whose objective is to minimize the generalized costs for multiple transportation orders. Then a linearization-based exact solution strategy is designed, so that the problem can be effectively solved by any exact solution algorithm on any standard mathematical programming software. Finally, an empirical case based on the Chinese scenario is presented to demonstrate the feasibility of the proposed method. In the case study, sensitivity analysis, bi-objective optimization scenario analysis on CO_2 emissions and fuzzy simulation are adopted to draw some helpful conclusions which will further help the decision makers to better organize the multimodal transportation.

Keywords: green multimodal routing; capacity uncertainty; traffic congestion; fuzzy chance-constrained programming; nonlinear programming; linearization.

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1. Introduction

With the rapid development of globalization, growing companies are seeking for specialized partners all over the world to outsource their businesses and also for oversea markets to make more profit. International trade and accompanying global commodity circulation thus get significantly motivated during the last decades [1]. Supported by the transportation industry, this prosperity in turn results in the remarkable expansion of the transportation network from a limited region to the entire world. The expanded transportation network extends the distribution channels and enhances the difficulty of transportation organization from the viewpoint of economy, efficiency, reliability and environmental protection. The traditional unimodal transportation is no longer suitable for this situation. Meanwhile, an advanced transportation mode, namely the multimodal transportation, emerges in the transportation industry. It combines different transportation modes to generate origin-to-destination routes and integrates their respective advantages in the transportation process. Furthermore, by using containers with standardized dimensions, multimodal transportation can be highly mechanized and the efficiency of its operations at terminals as well as during transportation is greatly improved [2].

Many empirical case studies, e.g., Bookbinder et al. (1998) [3], Janic (2007) [4] and Liao et al. (2009) [5], have demonstrated the superiority of the multimodal transportation in the long-haul transportation setting. Nowadays, multimodal transportation is getting more and more popular and plays a crucial role in international trade. With the rapid promotion of multimodal transportation in practice, its "strategic-tactical-operational"-level planning problems accordingly become highlights in the transportation planning field [6,7].

Among various planning problems in different levels, the multimodal routing problem belongs to operational-level planning. It aims at selecting the best routes to move containers from their origins to destinations through the multimodal service network according to customer demands [2]. It is a combinatorial optimization problem that should comprehensively consider customer demands on lowering transportation cost and improving transportation efficiency, operations of different transportation services in the multimodal service network, national policy and public concern on environmental issues. The multimodal routing directly reflects the performance of the entire multimodal service network (e.g., economy, efficiency and reliability) and is also the foundation for solving other operational-level optimization problems (e.g., the pricing problem [8] and the revenue sharing problem [9]). Consequently, it has been attached great importance by both researchers and practitioners in recent years. Supporting practical decision-making on how to transport containers by using multimodal services is the ultimate objective of solving the multimodal routing problem. Therefore, improving the practicability is the most important principle when constructing the multimodal routing model.

Because the most significant characteristic of the multimodal transportation is its combination of different transportation modes, the first issue to be faced by the researchers is how to represent different transportation modes that match their respective operation situations. In this study, we focus on the rail-road multimodal transportation which is the most widely promoted mode in China. Therefore, the multimodal transportation specifically refers to the rail-road one.

Transportation modes can be generally classified into two categories, including the time-flexible mode represented by road services and the schedule-based mode represented by rail services. The fixed schedule of the rail service in China regulates the operation route of freight train, as well as its loading/unloading, classification/disassembly, arrival and departure operations at the railway stations. The transshipment of containers from road service to rail service should match the schedule of the rail service, otherwise the transshipment cannot be executed successfully, and the planned multimodal route will hence be infeasible in reality. Therefore, in order to avoid the situations where planned multimodal routes violate the schedules of the selected rail services, we should fully consider the constraints of the schedules on the route selection from the viewpoint of both space (fixed route) and time (fixed operation time).

Moreover, the multimodal routing decision is a task that should be done earlier than the actual transportation starts. So it is difficult to attain the complete information (e.g., travel time and capacity) on every transportation service [10], i.e., some operational parameters of some transportation services cannot be exactly described as deterministic numbers, which is the reason why uncertainty exists in the decision-making process. Addressing the uncertainty closely relates to the reliability of the planned multimodal routes and is a challenge for the decision makers.

Rail services are operated according to their fixed schedules that are planned by the railway dispatching sectors in advance. Generally, their operations with respect to the time are well under control and get less disruptions. Due to the limited effective length of the tracks in the railway stations and limited locomotive power, the freight trains are composed of a limited number of rail cars [11]. Rail services are hence capacitated, i.e., the number of containers that can be loaded on a train is finite. Therefore, it is necessary to consider the capacity constraint when making the multimodal routing decision. Compared with the operation time parameters, the available capacities of rail services show obvious uncertainty. The capacities of the rail services in the network are constantly changing, mainly because many other transportation processes that are difficult to predict will occupy part of the capacities [12]. If we just use deterministic capacities to build the capacity constraint, two consequences may happen in practice: (i) The planned multimodal routes are infeasible if the deterministic capacities are estimated to be too large, and (ii) The planned multimodal routes are not the actual best ones if the estimation is too small. Therefore, rail service capacity uncertainty is an important uncertain factor that should be considered in the decision-making process.

In this study, we assume that it is feasible to assign as many trucks as necessary to carry the containers. The road services thereby are uncapacitated and there is no uncertain issue for road service capacity. But their operations easily and frequently suffer from various disruptions, such as natural disasters (e.g., bad weather) and manmade disruptions (e.g., traffic accidents and congestion) [13]. Among these disruptions, road traffic congestion is the most common one especially in China when compared with others, because with the rapidly increasing traffic volume in recent years, the road traffic situation in China is getting worse. Road traffic congestion has already spread from metropolitan cities, e.g., Beijing and Shanghai, to large numbers of cities all over the country [14]. Road traffic congestion leads to the travel time uncertainty of the road services en route. Road traffic congestion usually delays the arrival of the containers at the nodes, further disrupts the transshipment if the containers have to take another transportation service (specifically rail service with fixed schedule) at the same node, and also possibly affects the arrival time of the containers at the destination that should satisfy the restriction of the corresponding duedate. Thus, road traffic congestion is another important uncertain factor that should be also considered in the decision-making process.

Today, the public awareness of environmentally friendly development increases [15], and the environmental issues have drawn considerable attention from the public and the government, especially in China which is a rapidly industrializing developing country [2]. Among the various environmental issues, global warming caused by greenhouse gas emissions is the most outstanding one and has been considered a tremendous threat to human sustainable development. CO_2 accounts for approximately 80% of the entire greenhouse gas emissions [5]. During recent decades, large numbers of countries have proposed regulations to ease the global warming by reducing CO_2 emissions. For example, in 2012, the National Development and Reform Commission of China proposed a pilot project on trading carbon emissions [2]. As for the transportation industry, it is widely acknowledged that the transportation sector is one of the biggest contributors to the CO_2 emissions [16,17], and related data in China is described by Li et al. (2013) [17]. Therefore, the transportation industry should accept this responsibility and consider controlling and optimizing the CO_2 emissions during the transportation planning stage to promote the development of an environmentally friendly transportation. In order to respond to these environmental requirements, in this study, we extend the multimodal routing problem into a green version by considering the CO_2 emissions.

Last but not least, customer demands are the core of the multimodal routing problem. The inclusion of the customer demands on improving the transportation economy and the transportation efficiency directly influences the results of the optimization model. In order to respond to the described challenges, the model presented in this study is oriented on the following key points:

(1) Use schedule-based services and time-flexible services to represent the rail and road services in the multimodal service network, respectively, and formulate the constraints of the schedules on the multimodal route selection.

(2) Formulate a piecewise linear function-based time-dependent travel time model to describe the road traffic congestion, and propose a fuzzy programming model to address the rail service capacity uncertainty to improve the reliability of the multimodal routing.

(3) Adopt the activity-based method to calculate the CO_2 emissions in the transportation process. Select a CO_2 emission charging method and a bi-objective optimization method to separately optimize the CO_2 emissions and compare their performance.

(4) Set multiple transportation orders as the optimization object and employ soft time windows to reflect the customer demand on transportation efficiency.

In Section 2, we present a detailed modelling framework on the above key points. The improvements of our settings compared to the existing multimodal routing literature are also indicated in this section. In Section 3, based on the proposed modelling framework, we establish a fuzzy chance-constrained mixed integer nonlinear programming model to mathematically describe the specific multimodal routing problem explored in this study. Since the proposed model is nonlinear, in Section 4, we design a linearization-based exact solution strategy to solve the problem and gain its exact solution. In Section 5, an empirical case study based on the Chinese scenario is given to demonstrate the feasibility of the methods in dealing with the practical problem. Also in the case study section, sensitivity analysis, bi-objective optimization scenario analysis on CO_2 emissions and fuzzy simulation are adopted to draw some conclusions which can further help the decision makers to better organize the multimodal transportation. Finally, the conclusions of this study are drawn in Section 6.

2. Modelling Framework

2.1. Modeling the transportation services

2.1.1. Road services under traffic congestion

In this study, we fully consider the flexibility of road services (container trucks) for the container transportation. The road services are formulated as an unscheduled and time-flexible transportation service. As a time-flexible service, road services possess following two characteristics [2,18]:

(1) When the containers arrive at the node by trucks, they can immediately get unloaded after arrival.

(2) After getting loaded on the trucks, the containers can immediately depart from the current node or they can wait until a planned departure time. By avoiding the road traffic congestion, the planned departure time at the current node should first ensure that the arrival time of the containers at the successive node does not exceed the loading operation cutoff time of the selected rail service at the same node, so that the transshipment can be successfully operated. Moreover, the planned departure time should also lower the inventory time at the current node to reduce the corresponding inventory costs. Under this situation, when using road service to move the containers from the current node to the successive one, we should first determine the planned departure time of trucks from the current node.

As stated in Section 1, the road services are disrupted by traffic congestion, and the influence of road traffic congestion is reflected by the travel time uncertainty. A few studies, e.g., Sun and Chen (2013) [19], Demir et al. (2015) [20] and Uddin and Huynh (2016) [13], adopted stochastic programming to formulate the multimodal service network problem under disruptions. However, in practical planning in China, due to the lack of reliable historical data, it is quite difficult to fit the probability distributions for the travel times of all road services in the multimodal service network. Besides, the fuzzy programming that uses fuzzy variables (usually triangular or trapezoidal numbers) to evaluate the uncertainty fails to represent the variation of the travel time of a road service en route with respect to the time of the day [21]. Therefore, to better match the Chinese scenario, we will use time-dependent travel time formulated by piecewise linear functions to model the road traffic congestion. By combining limited historical data and experiences from the experts, such travel times can be established. Figure 1 shows an example of the time-dependent travel time formulated by piecewise linear function. There are two peak hours from 9 am to 10 am and from 6 pm to 8 pm on the arc served by road services.

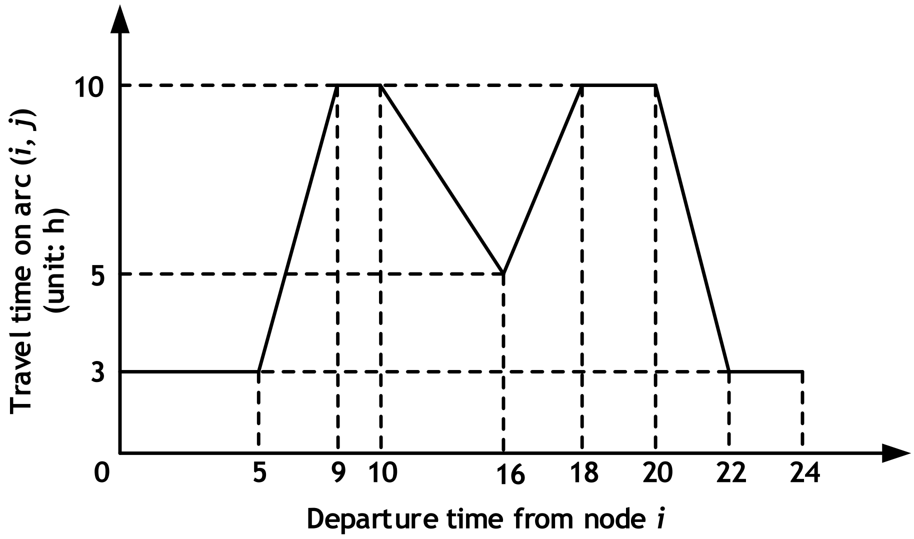

Figure 1. Time-dependent travel time formulated by piecewise linear function

2.1.2. Rail services with fixed schedules and capacity uncertainty

Currently in China, in order to promote the development of railway container transportation, block container trains have been extensively operated in the national railway transportation network and have become the main force of railway container transportation shortly after put into operation [2]. Thus, the rail services in this study specifically refer to the block container trains. Contrary to the time-flexible road services, rail services are operated according to fixed schedules. As for block container trains operated between their loading organization stations and unloading organization stations, their schedules regulate following contents:

(1) Operation time window at the loading/unloading organization station that regulates the operation start time and cutoff time regarding loading/unloading containers on/off the train;

(2) Scheduled departure/arrival time from/at the loading/unloading organization station;

(3) Operation period. For the convenience of modelling, same rail services in different operation periods are considered as different services.

Nowadays, in China, the loading/unloading operations of both road and rail services are highly mechanized, which significantly reduces the operation time of loading/unloading containers on/off the truck and train. Consequently, we assume that these times can be neglected in the multimodal routing modelling. Under this hypothesis, Figure 2 shows how schedules of rail services restrict the multimodal routing from the space-time viewpoint.

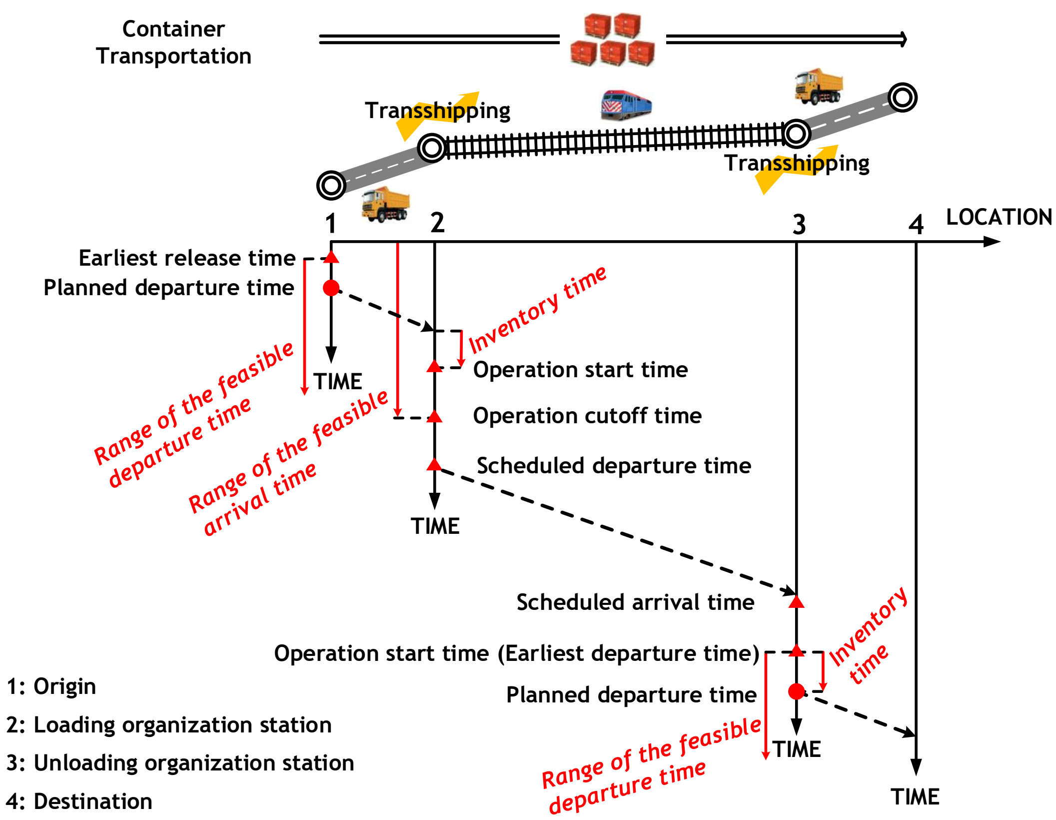

Figure 2. Diagram of a simple road-rail multimodal route

The origin-to-destination transportation process illustrated by Figure 2 is as follows.

(1) The containers will first depart from the origin (node 1) at the planned departure time that is not earlier than the earliest release time defined by the customer, and then arrive at the loading organization station (node 2).

(2) If the containers can be loaded on the train operated from node 2 to node 3, their arrival time at node 2 should be no later than the operation start time. If the arrival time is earlier than the operation start time, there will be an inventory period from the arrival time to the operation start time at node 2, and the containers should wait until the operation start time and then get loaded. Moreover, there exist a free-of-charge period [22]. Only when the inventory period is longer than this period, inventory costs will be created.

(3) After loaded on the train, the containers will wait until the scheduled departure time and then leave node 2 along with the train.

(4) The containers will arrive at the unloading organization station (node 3) at the scheduled arrival time of the train. However, they should wait until the operation start time of the train and then get unloaded. Therefore, the effective arrival time of the containers at node 3 is the operation start time instead of the scheduled arrival time.

(5) After unloaded from the train, the transportation organizer can select a planned departure time that is no earlier than the operation start time to move containers

to their destination (node 4).

During the transportation process, before the containers arrive at the destination, the inventory services are provided by the transportation providers. If the containers arrive too early to the destination, they have to be stored until the planned delivery date in a warehouse provided by the third-party inventory companies that can have different conditions in comparison to the transportation providers [23].

Our formulation for the constraints of the schedules on the multimodal route selection contributes to further development of the existing literature and better matches the Chinese scenario. Currently, the majority of the related articles neglects the constraints of the schedules and also considers rail services to be time-flexible. In these articles, the transshipment at the node is thereby simplified as a continuous "arrival-transshipping-departure" process with the transshipping time between different services known, e.g., Sun et al. (2008) [24], Jiang and Lu (2009) [25], Cai et al. (2010) [26], Zhang et al. (2011) [27], and Xiong and Wang (2014) [28].

There are different studies including schedules. Some studies, e.g., Liu et al. (2011) [29], Lin (2015) [30], Demir et al. (2015) [20] and Hrušovský et al. (2016) [16], only focus on the constraint of scheduled departure time on the route selection. Others, e.g., Chang (2007) [31], Moccia et al. (2011) [32] and Ayar and Yaman (2012) [22], also considered the scheduled service time windows of rail/waterway services at the terminals. However, their work cannot be directly utilized in the Chinese scenario due to the significant differences of schedules between China, the United States which is the scenario in Chang (2007) [31] and Italy which is the scenario in Moccia et al. (2011) [32] and between railway in this study and waterway involved in Ayar and Yaman (2012) [22].

As discussed in Section 1, the available capacity of a rail service is uncertainty. However, to the best of our knowledge, only a few study, e.g., Duan et al. (2012) [33], Wang (2016) [34], considered rail service capacity uncertainty in the transportation planning problems that they explored. Similar to the traffic congestion issue, the lacking of the historical data makes modelling of stochastic capacity infeasible. But on the contrary, the capacity uncertainty can be effectively expressed in a fuzzy way by using the triangular fuzzy variable represented by the minimum of the possible capacities, most possible capacity and maximum of the possible capacities, as it is illustrated by Figure 3. Similar to the traffic congestion issue, fuzzy capacity can be attained by limited historical data and expert experiences.

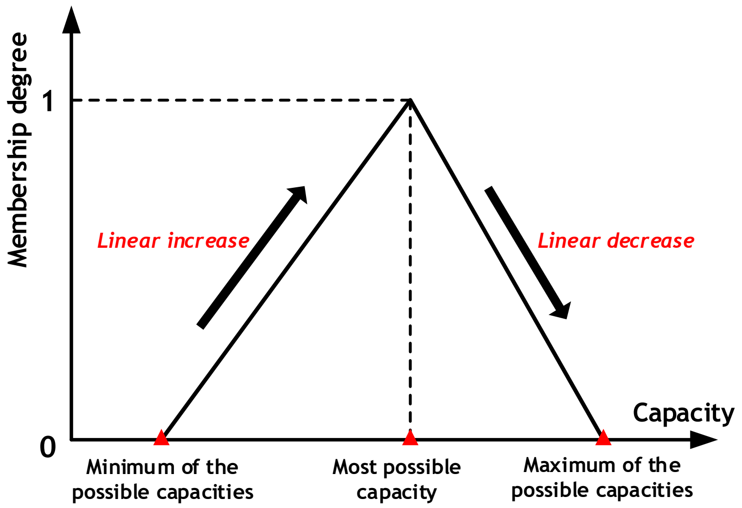

Figure 3. Diagram of the fuzzy capacity

2.1.3. Topological structure of the network

The topological structure of the multimodal service network is composed of nodes and arcs. The nodes represent the origins and destinations of various transportation orders as well as railway container stations where transshipments between rail services and road services are conducted. The arcs represent the tracks on which transportation services are operated. Related information on road and rail services, such as schedules, transportation distance and capacity, is regarded as the parameters of the nodes and arcs.

Considering the Chinese scenario, the rail services are the backbone for multimodal container transportation, while road services play an important role in origin pick-up and destination delivery. In some cases, road services also take direct origin-to-destination transportation. Figure 4 shows the basic topological structure of the multimodal service network. Overall, the network structure is similar to a hub-and-spoke network with multiple hubs where origins and destinations represent spokes while railway container stations represent hubs.

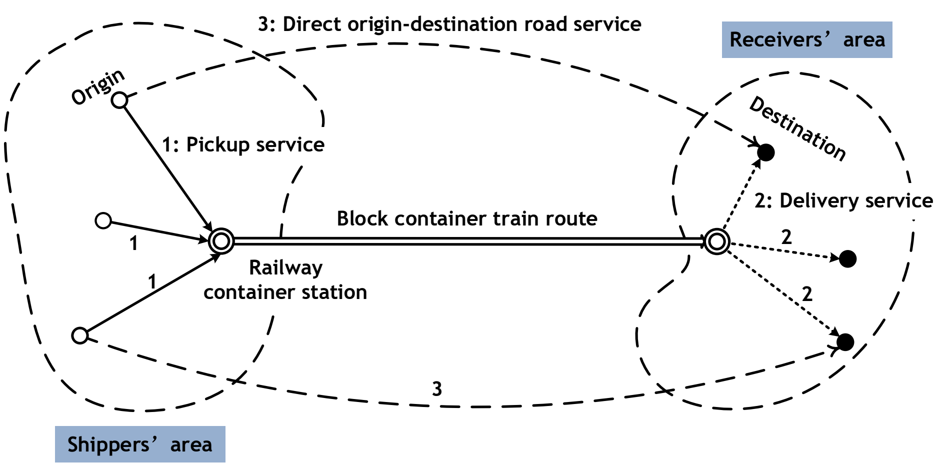

Figure 4. Basic topological structure of the multimodal service network

2.2. Modeling the CO_2 emissions

There are various models that can be utilized to calculate the CO_2 emitted by the transportation sector. Most of these proposed models contain large numbers of parameters regarding the fuel types, vehicle performance, driving status, traffic condition, geographical environment, etc. [20,35,36,37]. All of these parameters should be known in order to estimate the CO_2 emission accurately during the multimodal routing decision process. However, the multimodal routing is a task that is before the start of the transportation process. Furthermore many of these parameters are changing over time. As a result, it is quite challenging to attain all these values during the decision process, which largely reduces the feasibility of these methods in dealing with the practical problem.

As an alternative, the activity-based method that multiplies activity intensity (unit: TEU-km) with the CO_2 emission factor (unit: g/TEU-km) to calculate the total CO_2 emission [5] yields a better feasibility in transportation practice. This method has already been applied by scholars from various countries, e.g., China [2,38], Taiwan [5], South Korea [39], the United Kingdom [40] and the United States [41], to determine the CO_2 emission generated by transportation. Its wide application in turn also demonstrates its feasibility in this field. Therefore, we will adopt the activity-based method to compute the CO_2 emission in the multimodal service network.

The activity-based method calculates the total CO_2 emissions for a transportation service using the formula ($EM \cdot Q \cdot L$) where EM is the CO_2 emission factor of the transportation service (unit: g/TEU-km), Q is the volume of the containers carried by the transportation service (unit: TEU) and L is the corresponding transportation distance (unit: km).

In general, there are two approaches to optimize the CO_2 emissions, including (1) charging for CO_2 emissions and integrating CO_2 emission costs into the costs optimum objective, and (2) setting minimization of CO_2 emissions as an independent objective and conducting multi-objective optimization. The majority of the articles on optimizing CO_2 emissions in transportation adopts the first approach, e.g., Chang et al. (2010) [39], Zhang et al. (2011) [27], Wen et al. (2013) [42], Sun and Lang (2015) [2], Chen et al. (2015) [38], Demir et al. (2016) [20] and Hrušovský et al. (2016) [16]. While a few studies used the second approach, e.g., Sun and Chen (2013) [17] and Qu et al. (2016) [40] proposed a bi-objective optimization method with the objectives of minimizing the logistics costs and of minimizing the CO_2 emissions to solve the green multimodal routing problem and the green multimodal network design problem, respectively. It is difficult to distinguish which one is preferable based on the two approaches themselves. So in this study, we will adopt both approaches, so that we can obtain their respective optimization results.

In Section 4, we construct the optimization model based on the first approach. Then in Section 5, after testing the first approach, we will further test the second approach on the same empirical case. Through comparison, we can finally determine the better approach to optimize the CO_2 emissions for the given case.

2.3. Modeling the customer demands

Customer demands are represented by transportation orders known in advance. Each transportation order is characterized by its origin, destination, volume of containers, earliest release time of the containers at origin and duedate. The batch of containers of one transportation order cannot be split into several sub batches during the transportation process.

Generally, the duedate of the transportation order can be a time point or a time window [10]. Many studies, e.g., Verma et al. (2012) [43], Sun and Lang (2015a and 2015b) [2,44] and Sun et al. (2016) [18], considered the duedate as a time point and formulated a hard constraint that requires that the arrival time of the containers at the destination should not be later than the duedate. Other studies, e.g., Demir et al. (2016) [20] and Hrušovský et al. (2016) [16], modelled the duedate represented by the time point as a soft constraint, i.e., delayed delivery is allowed, but penalty costs will be created when delayed delivery of the containers emerges.

Today, with the remarkable development of many advanced manufacturing strategies (e.g., "Just in Time" Strategy), more and more companies consider that it is best if the products or materials can be delivered to them neither too early nor too late [10]. Under such consideration, the duedate in this study is a time window rather than a time point. The time window is described by a lower and an upper bound. For each transportation order, it is best if the arrival time of the corresponding containers falls within the time window. In this case, there will be no extra costs at the destination. However, if the containers arrive at the destination earlier than the lower bound, inventory costs will be created, because the early arrival leads to an inventory period of the goods before being further processed at the destination. If the arrival time is later than the upper bound, penalty costs should be charged for the delayed delivery.

3. Mathematical Model for the Multimodal Routing Problem

3.1. Notations

In this study, $G=(N,A,S)$ represents a road-rail multimodal service network in form of a directed graph, where N, A and S separately denote the node set, arc set and transportation service set in the network. For each transportation order k ($\forall k \in K$ where K is the transportation order set), its five attributes are represented as: origin o_k, destination d_k, volume q_k (unit: TEU), earliest release time t_{release}^{k} at origin and duedate $t_{\text{due}}^{k}=\left[\, t_k^{\mathrm{L}}, t_k^{\mathrm{U}}\right]$ where t_k^{L} and t_k^{U} are separately the lower bound and upper bound of the duedate time window. The rest of the symbols in the mathematical model and their respective representations are summarized as follows.

Indices	***Representations***
$i,\ j,\ h$	Indices of the nodes, $i,\ j$ and $h \in N$.
$s,\ r$	Indices of the transportation services, s and $r \in S$.
(h,i)	Directed arc from node h to node i, and $(h,i) \in A$.

(i,j)	Directed arc from node i to node j, and $(i,j) \in A$.
Sets	***Representations***
Γ_{ij}	Set of the rail services on arc (i,j).
Ω_{ij}	Set of the road services on arc (i,j).
S_{ij}	Set of the transportation services on arc (i,j), $S_{ij} = \Gamma_{ij} \cup \Omega_{ij}$ and $S_{ij} \subseteq S$.
$\delta^-(i)$	Set of the predecessor nodes to node i, and $\delta^-(i) \subseteq N$.
$\delta^+(i)$	Set of the successor nodes to node i, and $\delta^+(i) \subseteq N$.
Variables	***Representations***
w_{ijs}^k	Charged inventory time for transportation order k at node i before its containers are moved on arc (i,j) by service s, unit: h.
x_{ijs}^k	A binary variable. $x_{ijs}^k = 1$ if service s on arc (i,j) is used for transportation order k; $x_{ijs}^k = 0$ otherwise.
y_i^k	Arrival time of the containers of transportation order k at node i.
z_i^k	Planned departure time of the containers of transportation order k from node i.
n_i^k	A non-negative integer variable that indicates how many periods (24 hours) z_i^k exceeds.
t_{ijs}^k	Travel time of road service s on arc (i,j) when used for transportation order k, unit: h. $t_{ijs}^k = f_{ijs}\left(z_i^k\right)$ where f_{ijs} is the piecewise linear function of the travel time with respect to the corresponding planned departure time. Note that in this function, the input departure time z_i^k should fall within range [0, 24]. Otherwise it should be first normalized into such range before being input into the function.
Parameters	***Representations***
l_i^s	Loading/unloading operation start time of rail service s at node i.
u_i^s	Loading/unloading operation cutoff time of rail service s at node i.
$\tilde{v}_{ijs}$	Fuzzy available capacity of rail service s on arc (i,j) and $\tilde{v}_{ijs} = \left(v_{ijs}^{\min}, v_{ijs}^{\mathrm{M}}, v_{ijs}^{\max}\right)$ where $v_{ijs}^{\min} < v_{ijs}^{\mathrm{M}} < v_{ijs}^{\max}$, unit: TEU.
d_{ijs}	Travel distance of service s on arc (i,j), unit: km.
c_{ijs}	Unit transportation cost when service s is used to move containers on arc (i,j), unit: ￥/TEU.
c_s	Unit loading/unloading operation costs of service s, unit: ￥/TEU.
c_i^s	Unit inventory costs of transportation service s at node i, unit: ￥/TEU-h.
c_{dest}^k	Unit destination inventory costs for transportation order k, unit: ￥/TEU-h.
c_{pen}^k	Unit penalty costs for transportation order k caused by delayed delivery at its destination, unit: ￥/h.
c_{co_2}	Unit CO_2 emission costs, unit: ￥/g.

em_s	CO_2 emission factor for service s, unit: g/TEU-km.
τ_i^s	Free-of-charge inventory period of service s at node i, unit: h.
M	A significant large positive number.
α	Confidence in the fuzzy chance constraint.

3.2. A fuzzy chance-constrained MINLP model

The framework of the mathematical model is derived from the classical arc-node-based formulation that has been widely used in the routing problems of various research fields, e.g., telecommunication systems, manufacturing systems and internet service systems [1]. The mathematical model for the multimodal routing problem explored in this study is presented as follows. The proposed model is a combination of the fuzzy chance-constrained programming and the mixed integer nonlinear programming (MINLP).

Objective function:

$$\text{minimize} \sum_{k\in K}\sum_{(i,j)\in A}\sum_{s\in S_{ij}} c_{ijs}^k \cdot q_k \cdot x_{ijs}^k \tag{1}$$

$$+\sum_{k\in K}\sum_{i\in N}\left(\sum_{h\in\delta^-(i)}\sum_{r\in S_{hi}} c_r \cdot q_k \cdot x_{hir}^k + \sum_{j\in\delta^+(i)}\sum_{s\in S_{ij}} c_s \cdot q_k \cdot x_{ijs}^k\right) \tag{2}$$

$$+\sum_{k\in K}\sum_{(i,j)\in A}\sum_{s\in S_{ij}} c_i^s \cdot q_k \cdot w_{ijs}^k + \sum_{k\in K} c_{\text{dest}}^k \cdot q_k \cdot \max\{t_k^{\text{L}} - y_{d_k}, 0\} \tag{3}$$

$$+\sum_{k\in K} c_{\text{pen}}^k \cdot \max\{y_{d_k} - t_k^{\text{U}}, 0\} \tag{4}$$

$$+\sum_{k\in K}\sum_{(i,j)\in A}\sum_{s\in S_{ij}} c_{\text{co}_2} \cdot em_s \cdot q_k \cdot d_{ijs} \cdot x_{ijs}^k \tag{5}$$

Eqs.1-5 are successively the transportation costs en route, loading and unloading costs at the nodes, inventory costs, penalty costs caused by delayed deliveries at destinations and CO_2 emission costs. Their linear summation represents the generalized costs. The objective function minimizes the entire generalized costs for fulfilling multiple transportation orders by using multimodal transportation. This setting reflects the core of the multimodal routing which is to satisfy the customer demands that expect to accomplish their container transportation by the minimal monetary expenditure. Therefore, the multimodal routing in this study is a kind of service-oriented planning.

Subject to:

$$\sum_{j\in\delta^+(i)}\sum_{s\in S_{ij}} x_{ijs}^k - \sum_{h\in\delta^-(i)}\sum_{r\in S_{hi}} x_{hir}^k = \begin{cases} 1 & i = o_k \\ 0 & \forall i \in N\backslash\{o_k, d_k\} \\ -1 & i = d_k \end{cases} \quad \forall k \in K, \forall i \in N \tag{6}$$

$$\sum_{s\in S_{ij}} x_{ijs}^k \leq 1 \quad \forall k \in K, \forall (i,j) \in A \tag{7}$$

Eq.6 is the flow conservation constraint which ensures the continuity of the nodes and arcs on the planned routes, which is a common constraint in the node-arc-based formulation [1]. Eq.7 means that no more than one transportation service on one arc can be utilized to serve a transportation order. The combination of the two equations above ensures that containers in a transportation order are unsplittable, which is claimed in Section 2.3.

$$\mathrm{Cr}\left\{\sum_{k\in K} q_k \cdot x_{ijs}^k \leq \tilde{v}_{ijs}\right\} \geq \alpha \ \ \forall (i,j) \in A, \forall s \in \Gamma_{ij} \tag{8}$$

Eq.8 is the fuzzy chance constraint of the rail service capacity based on the fuzzy credibility theory [45]. In this equation, $\mathrm{Cr}\{\cdot\}$ represents the credibility of the event in $\{\cdot\}$. Eq.8 ensures that the credibility of the event that the entire loaded container volume on a rail service does not exceed its available capacity should not be lower than a predetermined confidence $\alpha \in [0,1]$. The value of α indicates the decision makers' preference for addressing the corresponding decision.

$$y_{o_k}^k = t_{\text{release}}^k \ \ \forall k \in K \tag{9}$$

Eq.9 assumes that the arrival time of the containers of transportation order k at the origin equals its earliest release time.

$$y_i^k \leq z_i^k \ \ \forall k \in K, \forall i \in N\backslash\{d_k\} \tag{10}$$

$$n_i^k = \lfloor z_i^k/24 \rfloor \ \ \forall k \in K, \forall i \in N\backslash\{d_k\} \tag{11}$$

$$t_{ijs}^k = f_{ijs}\left(z_i^k - 24 \cdot n_i^k\right) \ \ \forall k \in K, (i,j) \in A, \forall s \in \Omega_{ij} \tag{12}$$

$$\left(z_i^k + t_{ijs}^k - y_j^k\right) \cdot x_{ijs}^k = 0 \ \ \forall k \in K, \forall (i,j) \in A, \forall s \in \Omega_{ij} \tag{13}$$

Eqs.10-13 compute the arrival times of the containers of transportation order k at the nodes on the route by road services. First we determine the planned departure time of the containers at the current node i by Eq.10. Then we normalize such departure time into range [0, 24] by using the floor integral function Eq.11 and normalization formula $\left(z_i^k - 24 \cdot n_i^k\right)$, so that we can further generate the corresponding travel time t_{ijs}^k of the containers on arc (i,j) by road service s according to the piecewise linear function Eq.12. Finally, we can gain the arrival time of container flow k at the following node j by Eq.13.

$$\left(l_i^r - y_i^k\right) \cdot x_{hir}^k = 0 \ \ \forall k \in K, \forall (h,i) \in A, \forall r \in \Gamma_{hi} \tag{14}$$

Eq.14 computes the arrival times of the containers of transportation order k at the nodes on the route by rail services. As claimed in Section 2.1.2, l_i^r is the effective arrival time of containers at node i. Because we assume that loading/unloading time can be neglected, y_i^k is also the earliest departure time of containers at transshipping node i.

$$y_i^k \leq u_i^s \cdot x_{ijs}^k + M \cdot \left(1 - x_{ijs}^k\right) \ \ \forall k \in K, \forall (i,j) \in A, \forall s \in \Gamma_{ij} \tag{15}$$

Eq.15 is the rail service operation cutoff time constraint. It ensures that the arrival time of the containers of transportation order k at node i should not exceed the operation cutoff time of rail service s at the same node, if this rail service has to be used in order to move these containers on arc (i,j).

$$\left(\max\{l_i^s - y_i^k - \tau_i^s, 0\} - w_{ijs}^k\right) \cdot x_{ijs}^k = 0 \;\; \forall k \in K, \forall (i,j) \in A, \forall s \in \Gamma_{ij} \quad (16)$$

$$\left(\max\{z_i^k - y_i^k - \tau_i^s, 0\} - w_{ijs}^k\right) \cdot x_{ijs}^k = 0 \;\; \forall k \in K, \forall (i,j) \in A, \forall s \in \Omega_{ij} \quad (17)$$

Eqs.16 and 17 compute the charged inventory time of the containers of transportation order k at node i before being moved on arc (i,j) by a rail service and a road service, respectively. In Eq.17, especially if $i = o_k$ and $s \in \Omega_{ij}$, $\tau_i^s = 0$.

$$n_i^k \in \{0, 1, 2, \dots\} \;\; \forall k \in K, \forall i \in N \quad (18)$$

$$t_{ijs}^k \geq 0 \;\; \forall k \in K, (i,j) \in A, \forall s \in \Omega_{ij} \quad (19)$$

$$w_{ijs}^k \geq 0 \;\; \forall k \in K, \forall (i,j) \in A, \forall s \in S_{ij} \quad (20)$$

$$x_{ijs}^k \in \{0, 1\} \;\; \forall k \in K, \forall (i,j) \in A, \forall s \in S_{ij} \quad (21)$$

$$y_i^k \geq 0 \;\; \forall k \in K, \forall i \in N \quad (22)$$

$$z_i^k \geq 0 \;\; \forall k \in K, \forall i \in N \backslash \{d_k\} \quad (23)$$

Eqs.18-23 are the variable domain constraints.

4. An Exact Solution Strategy

4.1. Determining the solution strategy

The proposed mathematical model in Section 3.2 is easily understood, because it is established straightforwardly according to the settings of the specific multimodal routing problem. However, the mathematical model contains three categories of nonlinearity, including (1) fuzzy chance constraint as Eq.8, (2) piecewise linear constraint as Eq.12 and (3) general nonlinear components as Eqs. 3, 4, 13, 14, 16 and 17. Such nonlinearity increases the difficulty of the problem to be effectively solved by the exact solution algorithms (e.g., Branch-and-Bound Algorithm and Simplex Algorithm). Especially for the large-scale real-world problem, due to the nonlinearity, the solution to the problem will usually get into the local optimum, and massive computational time will be consumed to generate the solution. Therefore, if we can eliminate the nonlinearity of the model by designing the equivalent linear reformulations to the nonlinear equations in the model, then the problem can be solved with the help of the standard mathematical programming software (e.g., LINGO, CPLEX and GAMS) where exact solution algorithms can be implemented efficiently.

Although it is widely acknowledged that heuristic algorithms have better performance than the exact solution algorithms in dealing with the multimodal routing, which is known as an NP-hard problem, exact solution algorithms have two significant advantages. The first one is that they can test if the model observes the mathematical logic. The second is that they can provide an exact benchmark to verify the efficiency and accuracy of the heuristic algorithms [46]. Therefore, we devote this study to developing a linearization-based exact solution strategy to address the multimodal routing problem.

4.2. Model linearization technique

4.2.1. Crisp equivalent and linearization of the fuzzy chance constraint

From the definition of the fuzzy creditability, Eq.24 can be obtained where a is a deterministic number while $\tilde{b}$ is a triangular fuzzy number described by (b_1, b_2, b_3) and $b_1 < b_2 < b_3$. [47]:

$$\mathrm{Cr}\{a \leq \tilde{b}\} = \begin{cases} 1, & \text{if } a \leq b_1 \\ \dfrac{2b_2 - b_1 - a}{2(b_2 - b_1)}, & \text{if } b_1 \leq a \leq b_2 \\ \dfrac{b_3 - a}{2(b_3 - b_2)}, & \text{if } b_2 \leq a \leq b_3 \\ 0, & \text{if } a \geq b_3 \end{cases} \tag{24}$$

According to Eq.24, we can gain the crisp equivalency to the fuzzy chance constraint Eq.8 by replacing a with $\sum_{k\in K} q_k \cdot x_{ijs}^k$ and $\tilde{b}$ with $\tilde{v}_{ijs}$. However, the crisp equivalency is a piecewise linear function which is still essentially a nonlinear formula. Thus we conduct following modifications shown as Eqs. 25 and 26 to transform it into a pure linear function. After such modification, during the simulation process, we can use Eq.25 to substitute Eq.8 if $\alpha \in [0.5, 1]$, Eq.26 to substitute the same equation otherwise.

$$2(1-\alpha)\cdot v_{ijs}^{\mathrm{M}} + (2\alpha - 1)\cdot v_{ijs}^{\min} \geq \sum_{k\in K} q_k \cdot x_{ijs}^k \quad \text{if } 0.5 \leq \alpha \leq 1, \forall (i,j) \in A, \forall s \in \Gamma_{ij} \tag{25}$$

$$2\alpha\cdot v_{ijs}^{\mathrm{M}} - (2\alpha - 1)\cdot v_{ijs}^{\max} \geq \sum_{k\in K} q_k \cdot x_{ijs}^k \quad \text{if } 0 \leq \alpha \leq 0.5, \forall (i,j) \in A, \forall s \in \Gamma_{ij} \tag{26}$$

4.2.2. Linearization of the piecewise linear function

Similarly to Eq.24, the piecewise linear function $f_{ijs}(\cdot)$ is also nonlinear expression where $(\cdot)$ represents $(z_i^k - 24\cdot n_i^k)$ for the sake of conciseness. Let P_{ijs} represent the set of the linear segments of $f_{ijs}(\cdot)$, p the index of the segments ($p = 1, \ldots, |P_{ijs}|$) and $\left[tt_{ijs}^{kp-}, tt_{ijs}^{kp+}\right]$ the departure time interval corresponding to the linear segment $f_{ijs}^p(\cdot)$. Then $f_{ijs}(\cdot)$ has a universal formulation shown as Eq.27.

$$f_{ijs}(\cdot) = \begin{cases} f_{ijs}^1(\cdot), & \cdot \in \left[tt_{ijs}^{1-}, tt_{ijs}^{1+}\right] \\ & \vdots \\ f_{ijs}^p(\cdot), & \cdot \in \left[tt_{ijs}^{p-}, tt_{ijs}^{p+}\right] \\ & \vdots \\ f_{ijs}^{|P_{ijs}|}(\cdot), & \cdot \in \left[tt_{ijs}^{|P_{ijs}|-}, tt_{ijs}^{|P_{ijs}|+}\right] \end{cases} \quad \forall (i,j) \in A, \forall s \in \Omega_{ij} \tag{27}$$

To linearize the piecewise linear function Eq.27, the following procedures are conducted.

Step 1: Define a 0-1 variable φ_{ijs}^{kp}. $\varphi_{ijs}^{kp} = 1$, if $\left(z_i^k - 24 \cdot n_i^k\right)$ falls within $\left[tt_{ijs}^{p-}, tt_{ijs}^{p+}\right]$. $\varphi_{ijs}^{p} = 0$ otherwise. And φ_{ijs}^{p} should observe the following constraint.

$$\sum_{p \in P_{ijs}} \varphi_{ijs}^{kp} = 1 \ \forall k \in K, \forall (i,j) \in A, \forall s \in \Omega_{ij} \tag{28}$$

Step 2: Define two non-negative variables λ_{ijs}^{kp-} and λ_{ijs}^{kp+}, and distribute them to the lower bound tt_{ijs}^{p-} and upper bound tt_{ijs}^{p+} of the corresponding departure time interval $\left[tt_{ijs}^{p-}, tt_{ijs}^{p+}\right]$ as their weights. Hence we have following equations.

$$z_i^k - 24 \cdot n_i^k = \sum_{p \in P_{ijs}} \left(\lambda_{ijs}^{p-} \cdot tt_{ijs}^{p-} + \lambda_{ijs}^{p+} \cdot tt_{ijs}^{p+}\right) \ \ \forall k \in K, \forall (i,j) \in A, \forall s \in \Omega_{ij} \tag{29}$$

$$\lambda_{ijs}^{kp-} + \lambda_{ijs}^{kp+} = \varphi_{ijs}^{kp} \ \ \forall k \in K, \forall (i,j) \in A, \forall s \in \Omega_{ij}, \forall p \in P_{ijs} \tag{30}$$

$$\lambda_{ijs}^{kp+} \geq 0 \ \ \forall k \in K, \forall (i,j) \in A, \forall s \in \Omega_{ij}, \forall p \in P_{ijs} \tag{31}$$

$$\lambda_{ijs}^{kp-} \geq 0 \ \ \forall k \in K, \forall (i,j) \in A, \forall s \in \Omega_{ij}, \forall p \in P_{ijs} \tag{32}$$

Step 3: Modify the piecewise linear function as follows.

$$f_{ijs}\left(z_i^k - 24 \cdot n_i^k\right) = f_{ijs}\left[\sum_{p \in P_{ijs}} \left(\lambda_{ijs}^{kp-} \cdot tt_{ijs}^{p-} + \lambda_{ijs}^{kp+} \cdot tt_{ijs}^{p+}\right)\right]$$

$$= \sum_{p \in P_{ijs}} f_{ijs}\left(\lambda_{ijs}^{kp-} \cdot tt_{ijs}^{p-} + \lambda_{ijs}^{kp+} \cdot tt_{ijs}^{p+}\right)$$

$$= \sum_{p \in P_{ijs}} f_{ijs}^{p}\left(\lambda_{ijs}^{kp-} \cdot tt_{ijs}^{p-} + \lambda_{ijs}^{kp+} \cdot tt_{ijs}^{p+}\right)$$

$$= \sum_{p \in P_{ijs}} \left[\lambda_{ijs}^{kp-} \cdot f_{ijs}^{p}\left(tt_{ijs}^{p-}\right) + \lambda_{ijs}^{kp-} \cdot f_{ijs}^{p}\left(tt_{ijs}^{p+}\right)\right]$$

where $f_{ijs}^{p}\left(tt_{ijs}^{p-}\right)$ and $f_{ijs}^{p}\left(tt_{ijs}^{p+}\right)$ for $\forall (i,j) \in A, \forall s \in \Omega_{ij}, \forall p \in P_{ijs}$ are all known. Finally the pure linear equivalency to Eq.12 is shown as Eq.33.

$$t_{ijs}^{k} = \sum_{p \in P_{ijs}} \left[\lambda_{ijs}^{p-} \cdot f_{ijs}^{p}\left(tt_{ijs}^{p-}\right) + \lambda_{ijs}^{p-} \cdot f_{ijs}^{p}\left(tt_{ijs}^{p+}\right)\right] \ \ \forall k \in K, \forall (i,j) \in A, \forall s \in \Omega_{ij} \tag{33}$$

4.2.3. Linearization of other nonlinear components

Linear Reformulation 1: Eq.3 with nonlinear component $\sum_{k\in K} c^k_{\text{dest}} \cdot q_k \cdot \max\{t^{\text{L}}_k - y_{d_k}, 0\}$ can be linearized by Eqs.34-36 where g_k is a newly introduced variable.

$$\sum_{k\in K}\sum_{(i,j)\in A}\sum_{s\in S_{ij}} c^s_i \cdot q_k \cdot w^k_{ijs} + \sum_{k\in K} c^k_{\text{dest}} \cdot q_k \cdot g_k \tag{34}$$

$$g_k \geq t^{\text{L}}_k - y_{d_k} \quad \forall k \in K \tag{35}$$

$$g_k \geq 0 \quad \forall k \in K \tag{36}$$

If the containers arrive at the destination earlier than t^{L}_k, $t^{\text{L}}_k - y_{d_k} > 0$. Consequently, $\max\{t^{\text{L}}_k - y_{d_k}, 0\} = t^{\text{L}}_k - y_{d_k}$. According to Eqs.34 and 35, $g_k \geq t^{\text{L}}_k - y_{d_k}$. Minimization of Eq.34 will then lead to $g_k = t^{\text{L}}_k - y_{d_k}$. In this case, $\sum_{k\in K} c^k_{\text{dest}} \cdot q_k \cdot \max\{t^{\text{L}}_k - y_{d_k}, 0\}$ is equivalent to Eqs.34-35.

If the containers arrive at the destination later than t^{L}_k, $t^{\text{L}}_k - y_{d_k} < 0$. Consequently, $\max\{t^{\text{L}}_k - y_{d_k}, 0\} = 0$. According to Eqs.34 and 35, $g_k \geq 0$. Minimization of Eq.34 will then lead to $g_k = 0$. In this case, $\sum_{k\in K} c^k_{\text{dest}} \cdot q_k \cdot \max\{t^{\text{L}}_k - y_{d_k}, 0\}$ is also equivalent to Eqs.34-35.

Above all, the equivalency above is verified. Similarly, we have following linear reformulation.

Linear Reformulation 2: Nonlinear component $\sum_{k\in K} c^k_{\text{pen}} \cdot \max\{y_{d_k} - t^{\text{U}}_k, 0\}$ in Eq.4 can be linearized by Eqs.37-39 where σ_k is also a newly introduced variable.

$$\sum_{k\in K} c^k_{\text{pen}} \cdot \sigma_k \tag{37}$$

$$\sigma_k \geq y_{d_k} - t^{\text{U}}_k \quad \forall k \in K \tag{38}$$

$$\sigma_k \geq 0 \quad \forall k \in K \tag{39}$$

Linear Reformulation 3: Nonlinear constraint $n^k_i = \lfloor z^k_i/24 \rfloor \ \forall k \in K, \forall i \in N\backslash\{d_k\}$ (Eq.12) can be reformulated by linear constraints Eqs.40 and 41.

$$n^k_i \leq z^k_i/24 \quad \forall k \in K, \forall i \in N\backslash\{d_k\} \tag{40}$$

$$n^k_i > (z^k_i/24) - 1 \quad \forall k \in K, \forall i \in N\backslash\{d_k\} \tag{41}$$

We take $z^k_i = 60$ as example to verify the equivalency above. According to Eq.12, $n^k_i = \lfloor 60/24 \rfloor = \lfloor 2.5 \rfloor = 2$. Meanwhile, according to Eqs.47 and48, there exists $1.5 < n^k_i \leq 2.5$. Because n^k_i is a non-negative integer, finally $n^k_i = 2$. Consequently, the equivalency above is tenable.

Linear Reformulation 4: By using the same linearization technique, nonlinear constraints $(z^k_i + t^k_{ijs} - y^k_j) \cdot x^k_{ijs} = 0 \ \forall k \in K, \forall (i,j) \in A, \forall s \in \Omega_{ij}$ (Eq.13) and $(l^r_i - y^k_i) \cdot x^k_{hir} = 0 \ \forall k \in K, \forall (h,i) \in A, \forall r \in \Gamma_{hi}$ (Eq.14) can be reformulated by linear constraints Eqs.42-43 and 44-45, respectively.

$$z_i^k + t_{ijs}^k - y_j^k \geq M \cdot (x_{ijs}^k - 1) \;\; \forall k \in K, \forall (i,j) \in A, \forall s \in \Omega_{ij} \tag{42}$$

$$z_i^k + t_{ijs}^k - y_j^k \leq M \cdot (1 - x_{ijs}^k) \;\; \forall k \in K, \forall (i,j) \in A, \forall s \in \Omega_{ij} \tag{43}$$

$$l_i^r - y_i^k \geq M \cdot (x_{hir}^k - 1) \;\; \forall k \in K, \forall (h,i) \in A, \forall r \in \Gamma_{hi} \tag{44}$$

$$l_i^r - y_i^k \leq M \cdot (1 - x_{hir}^k) \;\; \forall k \in K, \forall (h,i) \in A, \forall r \in \Gamma_{hi} \tag{45}$$

Linear Reformulation 5: By using the same linearization form, nonlinear constraints $\left(\max\{0, l_i^s - y_i^k - \tau\} - w_{ijs}^k\right) \cdot x_{ijs}^k = 0 \;\; \forall k \in K, \forall (i,j) \in A, \forall s \in \Gamma_{ij}$ (Eq.16) and $\left(\max\{0, z_i^k - y_i^k - \tau\} - w_{ijs}^k\right) \cdot x_{ijs}^k = 0 \;\; \forall k \in K, \forall (i,j) \in A, \forall s \in \Omega_{ij}$ (Eq.17) can be reformulated by linear constraints Eqs.46-47 and 48-49.

$$w_{ijs}^k \geq M \cdot (x_{ijs}^k - 1) + (l_i^s - y_i^k - \tau_i^s) \;\; \forall k \in K, \forall (i,j) \in A, \forall s \in \Gamma_{ij} \tag{46}$$

$$w_{ijs}^k \leq M \cdot x_{ijs}^k \;\; \forall k \in K, \forall (i,j) \in A, \forall s \in \Gamma_{ij} \tag{47}$$

$$w_{ijs}^k \geq M \cdot (x_{ijs}^k - 1) + (z_i^k - y_i^k - \tau_i^s) \;\; \forall k \in K, \forall (i,j) \in A, \forall s \in \Omega_{ij} \tag{48}$$

$$w_{ijs}^k \leq M \cdot x_{ijs}^k \;\; \forall k \in K, \forall (i,j) \in A, \forall s \in \Omega_{ij} \tag{49}$$

For detailed proofs of Linear Reformations 4 and 5, readers can refer to Reference [2].

4.3. Improved linear reformulation

For the sake of readability, the improved linear reformulation derived from the mathematical model in Section 3.2 is summarized as follows.

Objective function:

Minimize (1)+(2)+(34)+(37)+(5)

Subject to:

Constraints (6), (7), (9), (10), (15), (18-23), (25), (26), (28-32), (40-49)

5. Empirical Case Study based on the Chinese Scenario

5.1. Case description

In this section, we present a real-world case to demonstrate the feasibility of the proposed model and exact solution strategy in optimizing the practical problem. This empirical case is oriented on a Chinese scenario. In this scenario, several consignments of containers need to be transported from the western inland cities (e.g., Lanzhou and Hohhot) to the eastern sea ports (e.g., Qingdao) through the road-rail multimodal service network.

In the multimodal service network, “road services” refer to the container trucks and “rail services” refer to the block container trains. The topological structure of the multimodal service network is shown in Figure 5. In the multimodal service network, there are 10 periodically operated rail services (block container trains) and 15 road services (container trucks). The schedules of the rail services and the time-dependent travel times of the road services are separately presented in Appendix A and Appendix B in the supplemental file. Note that all the values in Appendix A and Appendix B are expressed as real numbers, e.g., 10:30 is rewritten as 10.5 and 5:00 at the second day of the planning horizon is as 29 (24+5). Other times in different days can be expressed in the same way.

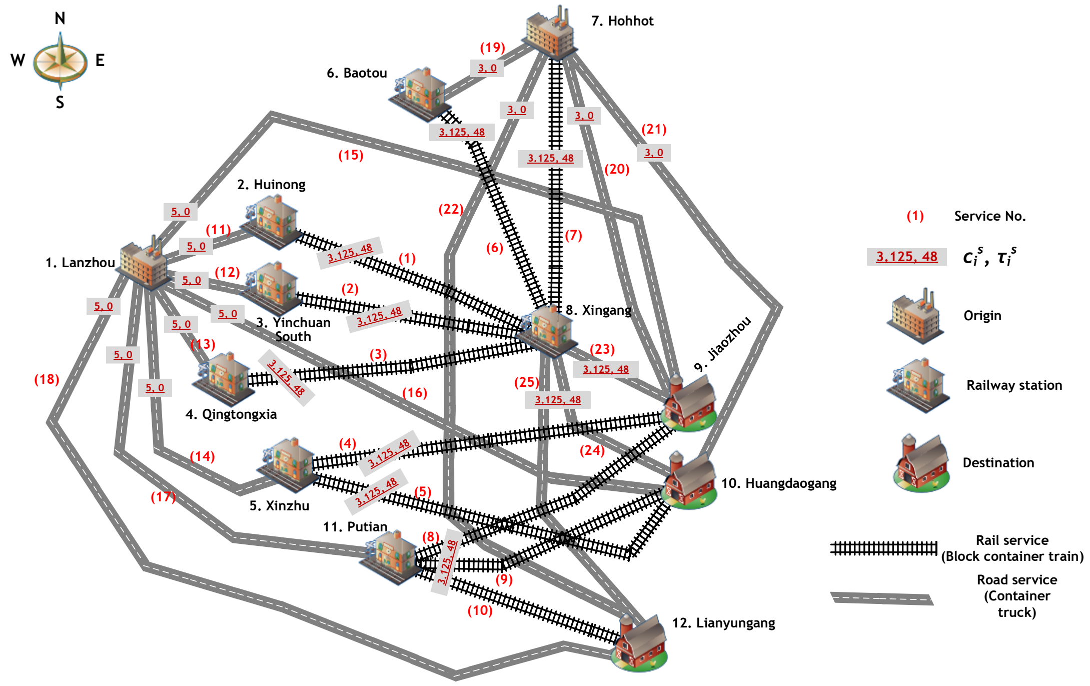

Figure 5. Multimodal service network for the empirical case

There are 10 transportation orders within a short-term planning horizon. The containers in these orders need to be transported from Lanzhou and Hohhot (inland cities in Northwest China) to Jiaozhou and Huangdaogang (sea ports in Qingdao, Shandong Province), and Lianyungang (a sea port in Jiangsu Province) through the multimodal service network shown in Figure 5. The detailed information on the multiple transportation orders is given in Appendix C in the supplemental file. Note that in Appendix C, if the destination inventory costs equal zero, it means that the receivers have their own inventory facilities and there is no need to rent them from other warehouse companies.

5.2. Parameter setting

The unit transportation costs en route (unit: ¥/TEU) regarding the two transportation services are determined by Eq.50.

$$c_{ijs}^{k} = \begin{cases} c_{\text{rail}}^{1} + c_{\text{rail}}^{2} \cdot d_{ijs} & s \in \Gamma_{ij} \\ c_{\text{road}}^{2} \cdot d_{ijs} & s \in \Omega_{ij} \end{cases} \quad \forall k \in K, \forall (i,j) \in A, \forall s \in S_{ij} \tag{50}$$

As can be seen in Eq.50, the unit transportation costs for rail services en route include two parameters: c_{rail}^{1} which is the costs related to the container volume (unit: ¥/TEU) and c_{rail}^{2} which is the costs related to the turnover of the containers (the multiplication of the container volume and corresponding transportation distance, unit: ¥/TEU-km). For road services, such costs only relates to one parameter c_{road}^{2} which is similar to c_{rail}^{2} (unit: ¥/TEU-km). The values of all these parameters above are regulated by the Ministry of Transport of China and China Railway Corporation [48].

20 ft ISO containers are utilized to contain goods in the empirical case. According to 2015 China Railway Statistical Bulletin [49], the national railways consumed 15.69 million tons of the standard coal and accomplished 33,503.67 hundred million ton-kilometers of freight transportation. The unit CO_2 emission rate of the standard coal is 0.69 and approximately 92% carbon is conversed into CO_2. Assuming that the 20 ISO containers are all fully loaded (each container weights 24 ton), we can then calculate the CO_2 emission factor of rail service as the following formula [50] where 44 is the molecular weight of one CO_2 molecule and 12 is the atomic weight of one C atom.

$$\frac{15.69 * 24}{33503.67 * 10^{2}} * 0.69 * 92\% * \frac{44}{12} * 10^{6} = 262\ (\mathrm{g/TEU-km})$$

Similarly, by using the data from 2015 China Transportation Industry Development Statistical Bulletin [51], we can also gain the CO_2 emission factor of road services which is 1,064 g/TEU-km. The values of all the parameters in the empirical case are summarized as shown in Table 1. In addition, the values of the unit inventory costs of transportation services at the nodes (c_i^s) and the free-of-charge inventory periods of services at the nodes (τ_i^s) are all presented in Figure 5. When the nodes are specifically the railway stations, all the corresponding c_i^s=3.125 ¥/TEU and τ_i^s= 48 h. When the nodes are the origins of the transportation orders, c_i^s varies based on the locations of the nodes and τ_i^s= 0 h if $s \in \Omega_{ij}$.

Table 1. Values of the parameters in the empirical case

Parameter	Description	Value	Unit
c_{rail}^{1}	Railway costs parameter regarding the volume of the containers	500	¥/TEU
c_{rail}^{2}	Railway costs parameter regarding the turnover of the containers	2.025	¥/TEU-km
c_{road}^{2}	Road costs parameter regarding the turnover of the containers	6	¥/TEU-km
c_s	Unit loading/unloading operation costs of the transportation services	25* 195**	¥/TEU
$c_{\mathrm{co_2}}$	Unit CO_2 emission costs	50***	¥/ton
α	Confidence in the fuzzy chance constraint (Eq.8)	0.9	--
em_s	CO_2 emission factors for the transportation services	1064* 262**	g/TEU-km

* Road service; ** Rail service.

*** Suggested by the research group at Chinese Academy of Environmental Planning [52].

5.3. Simulation environment

Described by the linearized programming model shown in Section 4.3, the empirical case can be solved by any exact solution algorithms, e.g., Branch-and-Bound Algorithm and Simplex Algorithm. In this study, we adopt the Branch-and-Bound Algorithm to solve the problem. The algorithm is conducted by the mathematical programming software LINGO 12 designed by LINDO Systems Inc., Chicago, IL, USA [53] on a ThinkPad Laptop with Intel Core i5-5200U 2.20 GHz CPU 8 GB RAM. The scale of the empirical case is indicated by Table 2.

Table 2. Scale of the empirical case problem

Total variables	Integer variables	Constraints
5,829	1,980	8,417

5.4. Optimization result and multimodal route illustration

The optimization result of the empirical case and the performance of the exact solution strategy is shown in Table 3.

Table 3. Optimization result and strategy performance

Solution algorithm	Solver state	Best solution	Computational time
Standard Branch-and-Bound Algorithm	Global Optimum	¥ 1,575,559	1 min 06 sec*

*Average value of 10 times simulation.

The structure of the minimal generalized costs for the multiple transportation orders is illustrated by Figure 6 where C1 to C5 are successively the transportation costs en route, loading/unloading operation costs, inventory costs, penalty costs and the CO_2 emission costs, which also correspond to Eq.1 to Eq.5 in the objective function.

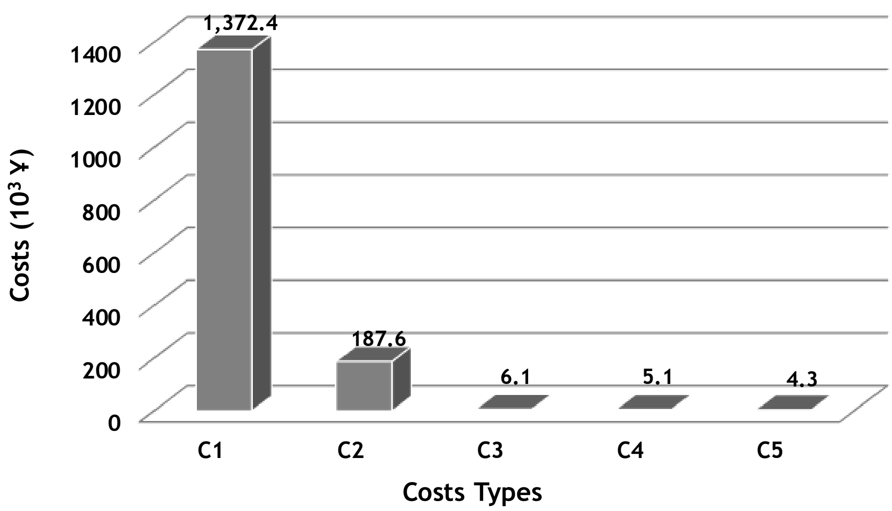

Figure 6. Structure of the minimal generalized costs

The best routes for the containers in the multiple transportation orders are given in Table 4. According to the planned routes, the accomplishments of 4 transportation orders satisfy their duedate time windows exactly.

Table 4. Best routes in the empirical case

No.	Best multimodal routes	Arrival time
1	Lanzhou {28} — (14) — Xinzhu — (4) — Jiaozhou	130.4
2	Lanzhou {37} — (14) — Xinzhu — (4) — Jiaozhou	130.4**
3	Lanzhou {111} — (14) — Xinzhu — (5) — Huangdaogang	214.6
4	Lanzhou {15} — (17) — Putian — (10) — Lianyungang	79**
5	Lanzhou {90} — (17) — Putian — (10)— Lianyungang	175**
6	Hohhot — (7) — Xingang {96} — (23) — Jiaozhou	106.9**
7	Hohhot — (7) — Xingang {101.5} — (23) — Jiaozhou	106.9
8	Hohhot — (7) — Xingang {148} — (23) — Jiaozhou	72*
9	Hohhot — (7) — Xingang {192} — (23) — Jiaozhou	72*
10	Hohhot {72} — (19) — Baotou — (6) — Xingang {171.5} — (25) — Lianyungang	186

*Early delivery; **Delayed delivery; Numbers in { }: Planned departure time

5.5. Case discussion

5.5.1. Sensitivity of the multimodal routing with respect to the CO_2 emissions

First of all, we analyze the effect of the CO_2 emissions on the multimodal routing. Let the unit emission costs vary from 50 to 100, the sensitivity of the multimodal routing result with respect to this variation can be seen in Figure 7. Figure 7 shows that the CO_2 emission costs increase linearly due to the fact that the emission volume is a constant (87.1 ton), while the rest of the generalized costs stay constant with the unit emission costs increasing. Even though we continue the simulation until the unit emission costs reach up to 1,000, which is obviously infeasible in practice (According to the formulation of Chinese Academy of Environmental Planning [52], the feasible unit emission costs should reach up to 100 at 2030), the sensitivity still keeps the same tendency as shown in Figure 7. It means that the best routes in the empirical case do not modify when the emission costs vary and are hence insensitive to this variation. Therefore, charging for CO_2 emissions within a reasonable range is not particularly helpful to promote the green multimodal transportation, at least in this empirical case.

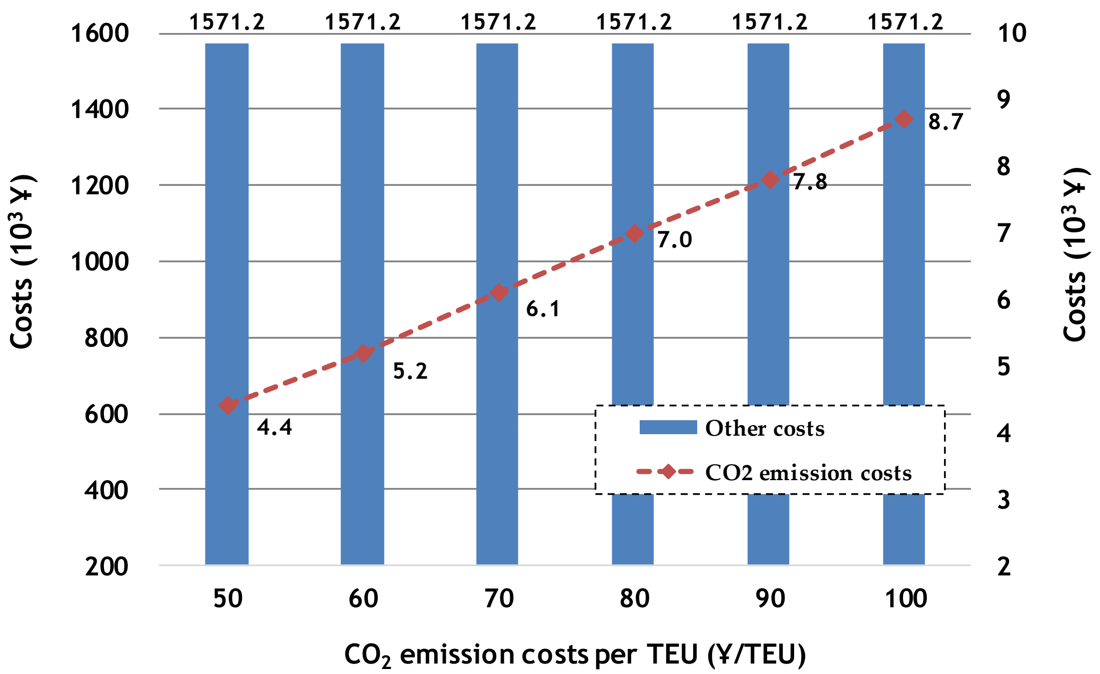

Figure 7. Sensitivity of the multimodal routing with respect to the CO_2 emissions

5.5.2. Bi-objective optimization scenario regarding CO_2 emissions

Furthermore, we modify the proposed model into a bi-objective optimization model with the objectives of minimizing the generalized costs (Z_1=Eq.1+Eq.2+Eq.3+Eq.4) and of minimizing the CO_2 emissions (Z_2=Eq.51).

$$\text{minimize} \sum_{k \in K} \sum_{(i,j) \in A} \sum_{s \in S_{ij}} em_s \cdot q_k \cdot d_{ijs} \cdot x_{ijs}^k \tag{51}$$

Using the widely utilized Weighted Sum Method [36] defined in Eqs.52 and 53, we can solve the bi-objective optimization problem and generate its Pareto solutions shown in Figure 8. Especially, compared with the last Pareto solution, the second last one can lower the CO_2 emissions from 87.1 to 83.7 by 3.90% and causes only a slight increase of the generalized costs from 1,571.2 to 1,586.0 by 0.94%.

$$\text{minimize} \;\; \omega \cdot Z_1 + (1 - \omega) \cdot Z_2 \tag{52}$$

$$0 < \omega \leq 1 \tag{53}$$

By comparing Figure 8 with Figure 7, we can conclude that bi-objective optimization approach is much more effective than charging for CO_2 emissions in helping decision makers to control and optimize the CO_2 emissions in the multimodal service network.

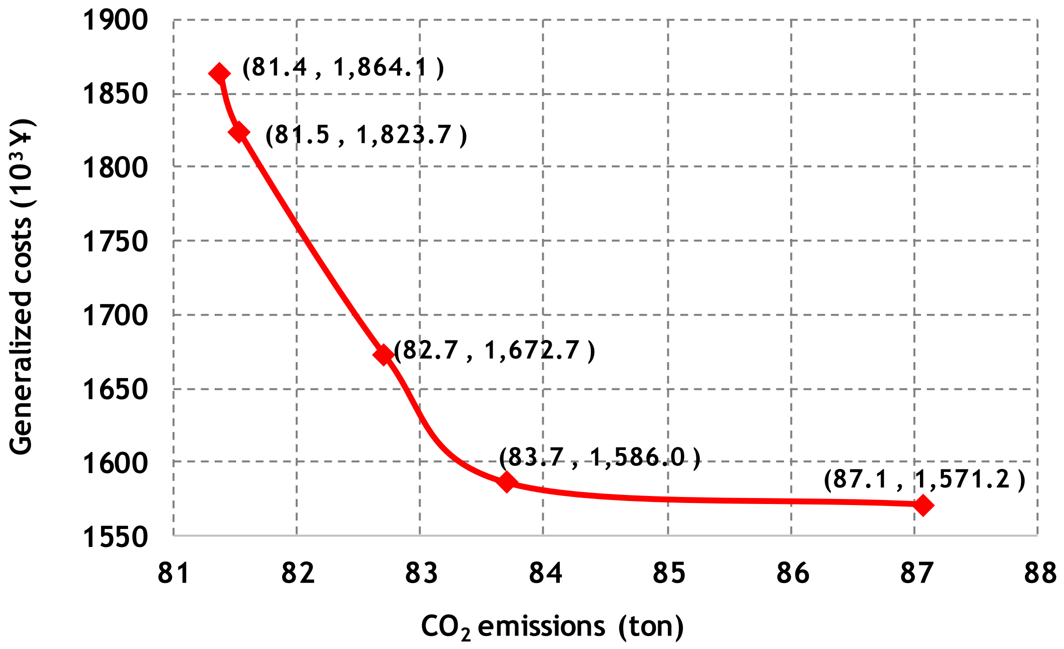

Figure 8. Pareto solutions to the bi-objective optimization problem

5.5.3. Sensitivity of the multimodal routing with respect to the confidence

Confidence α in the fuzzy chance constraint (Eq.8) is set by the decision makers and reflects their preference for the reliability of the multimodal routing such that all the loaded volume of a rail service does not exceed its carrying capacity. Its value has a remarkable effect on the optimization result of the multimodal routing, which can be investigated by using sensitivity analysis. Let α vary from 0.1 to 1.0 with a step size of 0.1, we can obtain the sensitivity of the multimodal routing result (indexed by the minimal generalized costs) with respect to such variation, which can be seen in Figure 9. We can also draw some helpful insights from Figure 9 summarized as follows.

(1) Overall, larger values of confidence α will lead to larger generalized costs for the best routes.

(2) The variation of the generalized costs with respect to the confidence is stepwise. In this case study, the multimodal routing is sensitive to the confidence when its value exceeds 0.3.

(3) The economy and reliability of the multimodal routing cannot reach their respective optimum simultaneously. The economy will be sacrificed if the decision makers decide to improve the reliability of the planned best routes, and vice versa.

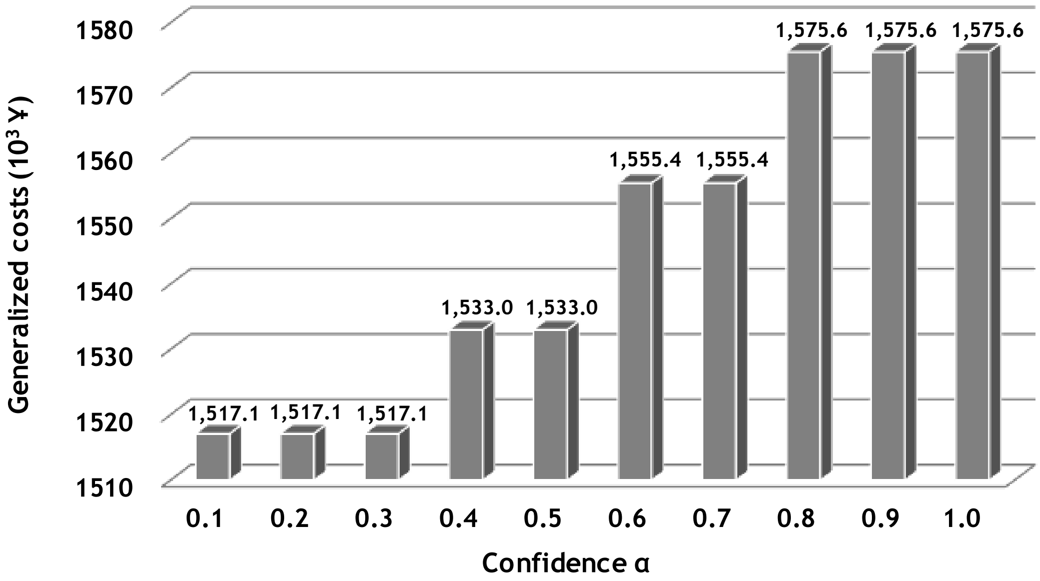

Figure 9. Sensitivity of the multimodal routing with respect to the confidence

5.5.4. Fuzzy simulation

During the decision-making process regarding the multimodal routing, it is challenging for decision makers to determine an objective confidence value. In order to help them to select reasonable confidence values, fuzzy simulation is adopted in this study.

The fuzzy simulation simulates the actual deterministic transportation scenario by randomly generating the carrying capacities of rail services according to the membership degree of the triangular fuzzy numbers (see in Figure 3). The simulation process is shown in Figure 10 [8].

Step 1: **For** $(\boldsymbol{i},\boldsymbol{j}) \in \boldsymbol{A},\ \boldsymbol{s} \in \boldsymbol{\Gamma_{ij}}$

Step 2: Generate a random number $v_{ijs} \in \left[v_{ijs}^L, v_{ijs}^U\right]$;

Step 3: Calculate its membership degree:

$$\mu_{\tilde{v}_{ijs}}(v_{ijs}) = \begin{cases} \frac{v_{ijs}-v_{ijs}^L}{Q_{ijs}^M-Q_{ijs}^L}, & \text{if } v_{ijs}^L \le v_{ijs} \le v_{ijs}^M \\ \frac{v_{ijs}^U-v_{ijs}}{Q_{ijs}^U-Q_{ijs}^M}, & \text{if } v_{ijs}^M \le v_{ijs} \le v_{ijs}^U \\ 0, & \text{otherwise} \end{cases};$$

Step 4: Generate a random number $\pi \in [0,1]$;

Step 5: **If** $\boldsymbol{\mu}(\boldsymbol{v_{ijs}}) \ge \boldsymbol{\pi}$

$v_{ijs} \rightarrow$ the actual carrying capacity of rail service $s \in \Gamma_{ij}$;

Step 6: **Otherwise**

Repeat Step 2 to Step 5;

Step 7: **End**

Step 8: **End**

Figure 10. Fuzzy simulation process

After the simulation, we can first gain deterministic carrying capacities v_{ijs} for $(i,j) \in A$, $s \in \Gamma_{ij}$. Eq.8 can be consequently transformed into a general carrying capacity constraint as Eq.54.

$$\sum_{k \in K} q_k \cdot x_{ijs}^k \leq v_{ijs} \quad \forall (i,j) \in A, \forall s \in \Gamma_{ij} \tag{54}$$

Then we can check if the planned routes given by the fuzzy programming model satisfy Eq.15 or not. If the planned routes satisfy this constraint, we define them as a successful plan, otherwise a failed plan. The fuzzy simulation should be conducted several times.

In this study, we ran the simulation 50 times, and the fuzzy simulation result is shown in Figure 11. As we can see from Figure 11, the successful times of the planned routes increase remarkably when the confidence value changes from 0.7 to 0.8. Although the generalized costs increase approximately by 1.29%, the success ratio of the planned routes considerably increases from 26% to 100% by more than 3.8 times when the confidence value is set to 0.8 instead of 0.7.

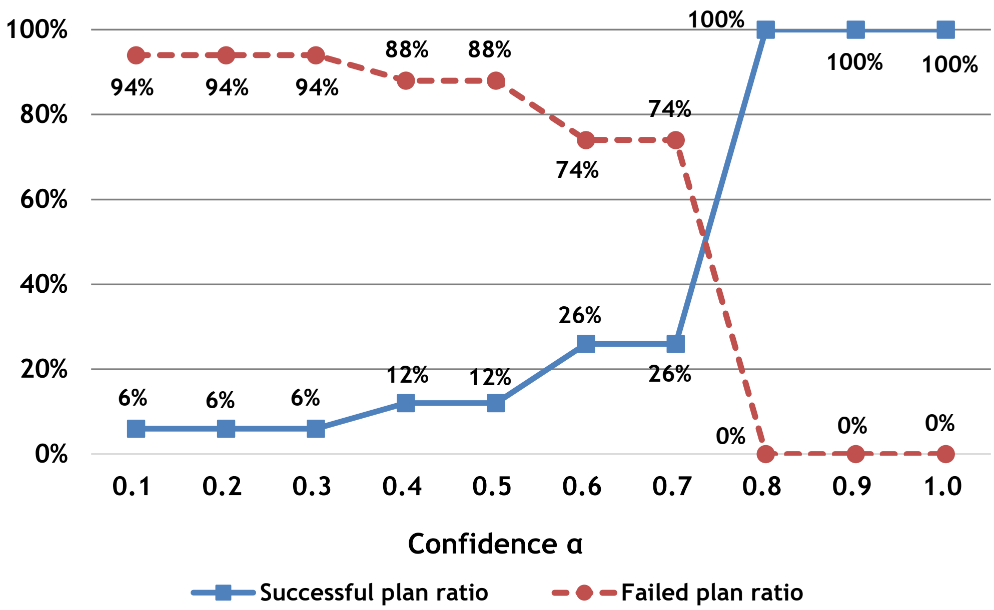

Figure 11. Fuzzy simulation result regarding confidence α

We can further achieve the optimization results of the 50 deterministic problems formulated by the linearized model with Eqs. 25 and 26 replaced by Eq.54. The optimization results are presented in Appendix D in the supplemental file. Such results can be considered as the actual best routes. By comparing the actual best routes with the planned ones, we can find the confidence value that best matches the actual transportation.

In the 50 fuzzy simulations, the best actual routes whose generalized costs are equal to ¥ 1,575,559 emerge 38 times that account for 76% of the entire simulation times (see in Figure 12). That is to say, such routes are the most likely best ones in the practical transportation. The planned best routes given by the fuzzy programming model with confidence values of 0.8, 0.9 and 1.0 match the most likely best actual routes better than others. Above all, the best values of the confidence in this empirical case are 0.8, 0.9 and 1.0.

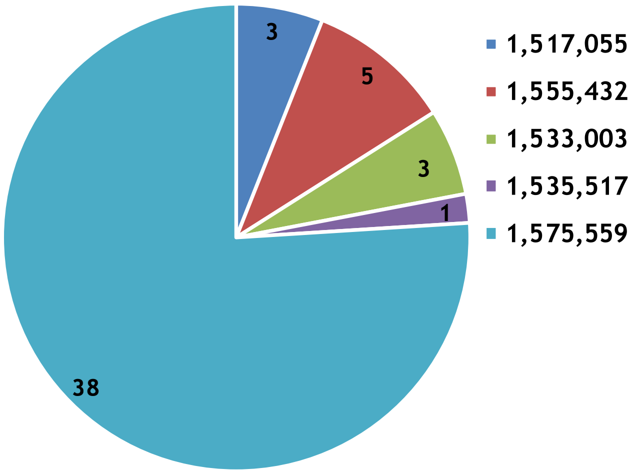

Figure 12. Ratios of the optimization results in the 50 fuzzy simulations

6. Conclusions

Nowadays, the multimodal transportation has been widely promoted all over the world, and its routing optimization has been attached great importance by both researchers and practitioners. Meanwhile, the public concern on environmental protection raises, and environmentally friendly development gets tremendous highlights in almost every industry. Therefore, it is valuable to combine multimodal routing with the environmental views. In practice, the complex multimodal service network challenges the practicability of the multimodal routing modelling.

In this study, in order to enable the multimodal routing problem to better match the sustainable tendency and the practical transportation scenario, we extend and develop this problem by considering (1) sustainable transportation on controlling CO_2 emissions, (2) schedule-based rail services with capacity uncertainty, and (3) time-flexible road service influenced by traffic congestion. Moreover, multiple transportation orders, soft duedate time window and customer demand orientation are all formulated in this study. By using time-dependent travel time formulated by the piecewise linear function and triangular fuzzy numbers in order to separately address the traffic congestion and the uncertain capacities, we construct a time-dependent fuzzy programming model to describe the specific problem. A linearization-based exact solution strategy is proposed to solve the problem with the help of the mathematical programming software. An empirical case is designed to demonstrate the feasibility of the method in dealing with the practical problem. Sensitivity analysis, bi-objective optimization analysis and fuzzy simulation are comprehensively adopted to draw many helpful insights for decision-making.

For further improvement to this study, we will test the feasibility of the exact solution strategy in dealing with a larger-scale empirical case. If the test result is not satisfactory, we will try to design some advanced intelligent solution algorithms (e.g., heuristic algorithms) with higher solution efficiency, so that the problem can be effectively optimized and routing suggestions can be provided to the decision makers in time when the problem scale gets larger.

References

[1] Sun, Y., Lang, M., & Wang, D. (2015) Optimization models and solution algorithms for freight routing problem in the multi-modal transportation networks: A review of the state-of-the-art. *The Open Civil Engineering Journal*, 9(1), 714-723. http://dx.doi.org/10.2174/1874149501509010714

[2] Sun, Y., & Lang, M. (2015). Modeling the multicommodity multimodal routing problem with schedule-based services and carbon dioxide emission costs. *Mathematical Problems in Engineering*, 2015, Article ID 406218, 21 pages. http://dx.doi.org/10.1155/2015/406218

[3] Bookbinder, J. H., & Fox, N. S. (1998). Intermodal routing of Canada-Mexico shipments under NAFTA. *Transportation Research Part E: Logistics and Transportation Review*, 34(4), 289-303. https://doi.org/10.1016/S1366-5545(98)00017-9

[4] Janic, M. (2007). Modelling the full costs of an intermodal and road freight transport network. *Transportation Research Part D: Transport and Environment*, 12(1), 33-44. https://doi.org/10.1016/j.trd.2006.10.004

[5] Liao, C. H., Tseng, P. H., & Lu, C. S. (2009) Comparing carbon dioxide emissions of trucking and intermodal container transport in Taiwan. *Transportation Research Part D: Transport and Environment*, 14(7), 493-496. https://doi.org/10.1016/j.trd.2009.05.002

[6] Caris, A., Macharis, C., & Janssens, G. K. (2008). Planning problems in intermodal freight transport: accomplishments and prospects. *Transportation Planning and Technology*, 31(3), 277-302. http://dx.doi.org/10.1080/03081060802086397

[7] Macharis, C., & Bontekoning, Y. M. (2004). Opportunities for OR in intermodal freight transport research: A review. *European Journal of operational research*, 153(2), 400-416. https://doi.org/10.1016/S0377-2217(03)00161-9

[8] Liu, D., & Yang, H. (2012). Dynamic pricing model of container sea-rail intermodal transport on single OD line. *Journal of Transportation Systems Engineering and Information Technology*, 12(4), 122-127. https://doi.org/10.1016/S1570-6672(11)60216-X

[9] Liu, D., Yang, H., & Zhang, Y. (2013). Slot allocation optimization model for multi-node container sea-rail intermodal transport. *Journal of Transportation Systems Engineering & Information Technology*, 13(2), 164-171. http://www.tseit.org.cn/en/y2013/v13/i2/164

[10] Sun, Y., Lang, M., & Wang, J. (2016). On Solving the Fuzzy Customer Information Problem in Multicommodity Multimodal Routing with Schedule-Based Services. *Information*, 7(1), Article ID 13, 16 pages. http://dx.doi.org/10.3390/info7010013

[11] Ceselli, A., Gatto, M., Lübbecke, M. E., Nunkesser, M., & Schilling, H. (2008). Optimizing the cargo express service of Swiss Federal railways. *Transportation Science*, 42(4), 450-465. 10.1287/trsc.1080.0246

[12] Lei, Z. L. (2008). Study on the Theory of Carrying Capacity Reliability of Railway Networks. *Journal of China Railway Society*, 30(4), 84-88. http://dx.chinadoi.cn/10.3321%2fj.issn%3a1001-8360.2008.04.016

[13] Uddin, M. M., & Huynh, N. (2016). Routing Model for Multicommodity Freight in an Intermodal Network Under Disruptions. *Transportation Research Record: Journal of the Transportation Research Board*, (2548), 71-80. http://dx.doi.org/10.3141/2548-09

[14] Wang, Y., & Hang, Y. (2016). Index System of Traffic Congestion Evaluation in Beijing Based on Big Data. *Journal of Transportation Systems Engineering and Information Technology*, 16(4): 231-240. http://www.tseit.org.cn/EN/Y2016/V16/I4/231

[15] Yu, H., & Solvang, W. D. (2016). 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*, 8(12), Article ID 1331, 28 pages. http://dx.doi.org/10.3390/su8121331

[16] Hrušovský, M., Demir, E., Jammernegg, W., & Van Woensel, T. (2016). Hybrid simulation and optimization approach for green intermodal transportation problem with travel time uncertainty. *Flexible Services and Manufacturing Journal*, 1-31. 10.1007/s10696-016-9267-1

[17] Li, H., Lu, Y., Zhang, J., & Wang, T. (2013). Trends in road freight transportation carbon dioxide emissions and policies in China. *Energy Policy*, 57, 99-106. https://doi.org/10.1016/j.enpol.2012.12.070

[18]Sun, Y., Lang, M., & Wang, D. (2016). Bi-objective modelling for hazardous materials road-rail multimodal routing problem with railway schedule-based space-time Constraints. *International Journal of Environmental Research and Public Health*, 13(8), Article ID 762, 31 pages. http://dx.doi.org/10.3390/ijerph13080762

[19]Sun, B., & Chen, Q. (2013, July). The routing optimization for multi-modal transport with carbon emission consideration under uncertainty. In *Control Conference (CCC), 2013 32nd Chinese* (pp. 8135-8140). IEEE. http://ieeexplore.ieee.org/abstract/document/6640875/

[20] Demir, E., Burgholzer, W., Hrušovský, M., Arıkan, E., Jammernegg, W., & Van Woensel, T. (2016). A green intermodal service network design problem with travel time uncertainty. *Transportation Research Part B: Methodological*, 93, 789-807. https://doi.org/10.1016/j.trb.2015.09.007

[21] Jabali, O., Woensel, T., & de Kok, A. G. (2012). Analysis of travel times and CO2 emissions in time – dependent vehicle routing. *Production and Operations Management*, 21(6), 1060-1074. http://onlinelibrary.wiley.com/doi/10.1002/atr.216/full

[22] Ayar, B., & Yaman, H. (2012). An intermodal multicommodity routing problem with scheduled services. *Computational Optimization and Applications*, 1-23. 10.1007/s10589-011-9409-z

[23] Wang, X., Chi, Z. B., & Ge, X. L. (2011). Research and analysis for time-limited multimodal transport model of vehicle. *Application Research of Computer*, 28(2), 563-

565.
http://dx.chinadoi.cn/10.3969%2fj.issn.1001-3695.2011.02.044

[24] Sun, H., Li, X., & Chen, D. (2008, September). Modeling and solution methods for viable routes in multimodal networks. In *Management of Innovation and Technology, 2008. ICMIT 2008. 4th IEEE International Conference on* (pp. 1384-1388). IEEE.
https://doi.org/10.1109/ICMIT.2008.4654573

[25] Jiang, J., & Lu, J. (2009). Research on optimum combination of transportation modes in the container multimodal transportation system. In *Logistics: The Emerging Frontiers of Transportation and Development in China* (pp. 693-698).
http://dx.doi.org/10.1061/40996(330)99

[26] Cai, Y., Zhang, L., & Shao, L. (2010, January). Optimal multi-modal transport model for full loads with time windows. In *Logistics Systems and Intelligent Management, 2010 International Conference on* (Vol. 1, pp. 147-151). IEEE.
https://doi.org/10.1109/ICLSIM.2010.5461448

[27]Zhang, J., Ding, H. W., Wang, X. Q., Yin, W. J., Zhao, T. Z., & Dong, J. (2011, July). Mode choice for the intermodal transportation considering carbon emissions. In *Service Operations, Logistics, and Informatics (SOLI), 2011 IEEE International Conference on* (pp. 297-301). IEEE.
https://doi.org/10.1109/SOLI.2011.5986574

[28] Xiong, G., & Wang, Y. (2014). Best routes selection in multimodal networks using multi-objective genetic algorithm. *Journal of Combinatorial Optimization*, 28(3), 655-673.
https://link.springer.com/article/10.1007/s10878-012-9574-8

[29] Liu, J., He, S. W., Song, R., & Li, H. D. (2011). Study on optimization of dynamic paths of intermodal transportation network based on alternative set of transport modes. *Journal of the China Railway Society*, 33(10), 1-6.
http://en.cnki.com.cn/Article_en/CJFDTOTAL-TDXB201110002.htm

[30] Lin, F. (2015). Optimal intermodal transport path planning based on martins algorithm. *Journal of Southwest Jiaotong University*, 50(3), 543-549.
10.3969/j.issn.0258-2724.2015.03.025

[31] Chang, T. S. (2008). Best routes selection in international intermodal networks. *Computers & Operations Research*, 35(9), 2877-2891.
https://doi.org/10.1016/j.cor.2006.12.025

[32] Moccia, L., Cordeau, J. F., Laporte, G., Ropke, S., & Valentini, M. P. (2011). Modeling and solving a multimodal transportation problem with flexible-time and scheduled services. *Networks*, 57(1), 53-68.
http://onlinelibrary.wiley.com/doi/10.1002/net.20383/full

[33] Duan, G., Lu, Y. R., Chen, L., Li, Y. Z., He, R. C. (2012). Optimization of Railway Empty Container Allocation under Uncertain Environment. *Journal of Lanzhou Jiaotong University*, 30(4):84-88.
http://xb.lzjtu.edu.cn/CN/abstract/abstract420.shtml

[34] Wang, X. (2016). Stochastic resource allocation for containerized cargo transportation networks when capacities are uncertain. *Transportation Research Part E: Logistics and Transportation Review*, 93, 334-357.
https://doi.org/10.1016/j.tre.2016.06.004

[35] Demir, E., Bektaş, T., & Laporte, G. (2011). A comparative analysis of several vehicle emission models for road freight transportation. *Transportation Research Part D: Transport and Environment*, 16(5), 347-357.
https://doi.org/10.1016/j.trd.2011.01.011

[36] Demir, E., Bektaş, T., & Laporte, G. (2014). The bi-objective pollution-routing problem.

European Journal of Operational Research, 232(3), 464-478.
https://doi.org/10.1016/j.ejor.2013.08.002

[37] Bektaş, T., & Laporte, G. (2011). The pollution-routing problem. *Transportation Research Part B: Methodological*, 45(8), 1232-1250.
https://doi.org/10.1016/j.trb.2011.02.004

[38] Chen, L., Lin, B., Wang, L., Wen, X., & Li, J. (2015). Transfer of freight flow between highway and railway based on carbon emissions. *Journal of Southeast University (Natural Science Edition)*, (5), 1002-1007.
http://dx.chinadoi.cn/10.3969%2fj.issn.1001-0505.2015.05.032

[39] Chang, Y. T., Lee, P., Kim, H. J., & Shin, S. H. (2010). Optimization model for transportation of container cargoes considering short sea shipping and external cost: South Korean case. *Transportation Research Record: Journal of the Transportation Research Board*, (2166), 99-108.
http://dx.doi.org/10.3141/2166-12

[40] Qu, Y., Bektaş, T., & Bennell, J. (2016). Sustainability SI: multimode multicommodity network design model for intermodal freight transportation with transfer and emission costs. *Networks and Spatial Economics*, 16(1), 303-329.
10.1007/s11067-014-9227-9

[41] Winebrake, J. J., Corbett, J. J., Falzarano, A., Hawker, J. S., Korfmacher, K., Ketha, S., & Zilora, S. (2008). Assessing energy, environmental, and economic tradeoffs in intermodal freight transportation. *Journal of the Air & Waste Management Association*, 58(8), 1004-1013.
http://dx.doi.org/10.3155/1047-3289.58.8.1004

[42] Wen, X., Lin, B., He, S., Zhang, J., & Li, J. (2013). The optimization model for flow assignment and routing plan in integrated transportation based on carbon emissions. *Transactions of Beijing Institute of Technology*, 33(S1), 5-8.
http://journal.bit.edu.cn/zr/ch/reader/view_abstract.aspx?file_no=2013S102&flag=1

[43] Verma, M., Verter, V., & Zufferey, N. (2012). A bi-objective model for planning and managing rail-truck intermodal transportation of hazardous materials. *Transportation research part E: Logistics and Transportation Review*, 48(1), 132-149.
https://doi.org/10.1016/j.tre.2011.06.001

[44] Sun, Y., & Lang, M. (2015). Bi-objective optimization for multi-modal transportation routing planning problem based on Pareto optimality. *Journal of Industrial Engineering and Management*, 8(4), 1195.
http://dx.doi.org/10.3926/jiem.1562

[45] Liu, B., & Iwamura, K. (1998). Chance constrained programming with fuzzy parameters. *Fuzzy sets and systems*, 94(2), 227-237.
https://doi.org/10.1016/S0165-0114(96)00236-9

[46] Tang, D., & Palekar, U. S. (2011). Scheduling large-scale micro/nano biochemical testing: Exact and heuristic algorithms. *Computers & Operations Research*, 38(6), 942-953.
https://doi.org/10.1016/j.cor.2010.10.006

[47] Cao, E., & Lai, M. (2009). A hybrid differential evolution algorithm to vehicle routing problem with fuzzy demands. *Journal of Computational and Applied Mathematics*, 231(1), 302-310.
https://doi.org/10.1016/j.cam.2009.02.015

[48] China Railway 95306 website, available at:
http://hyfw.95306.cn/hyinfo/action/JgxxAction_index?type=1 (accessed on 7.9.2017).

[49]National Railway Administration of People's Republic of China, 2016, available at:

http://www.nra.gov.cn/xwzx/zlzx/hytj/201603/t20160303_21466.shtml (accessed on 7.9.2017).
[50] Yu, J., Lin, G., & He, H. (2013). Carbon Emissions of Container Transportation with Costs and Time Constraints Consideration. *Henan Science*, (11), 2035-2041. http://dx.chinadoi.cn/10.3969%2fj.issn.1004-3918.2013.11.044
[51]Ministry of Transport of the People's Republic of China, 2016, available at: http://zizhan.mot.gov.cn/zfxxgk/bnssj/zhghs/201605/t20160506_2024006.html (accessed on 7.9.2017).
[52] Wang, J., Yan, G., Jiang, K., Liu, C., & Ge, C. (2009). The study on China's carbon tax policy to mitigate climate change. *China Environmental Science*, 29(1), 101-105. http://dx.chinadoi.cn/10.3321%2fj.issn%3a1000-6923.2009.01.020
[53] Schrage, L. (2006). LINGO user's guide. *LINDO System Inc., Chicago, IL*.