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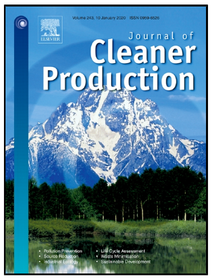

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Regional Multimodal Logistics Network Design Considering Demand Uncertainty and CO_2 Emission Reduction Target: A System-Optimization Approach

Abstract: This paper investigates an interesting regional multimodal logistics network design problem with CO_2 emission reduction target and uncertain demands in the context of urban cluster development. From the perspective of system optimization, a regional logistics network involves a centralized logistics authority and a centralized carrier, where the logistics authority concerns the regional logistics network configuration in terms of the number, location and scale of logistics parks and the subsidies of rail transportation links, and the carrier's decisions include the choice of transportation route for each logistics demand. Given a determined logistics demand pattern, this multi-stakeholder decision making problem is first formulated as a bi-level programming model followed by its equivalent mathematical programming with equilibrium constraints (MPEC) to depict the leader-follower behaviors. To capture the risk aversion level of the logistics authority in uncertain demand environment, an improved adjustable robust optimization method is proposed, including an individual control parameter and providing an exact expression of the maximum satisfaction probability. Computational results and related impact analysis demonstrate that the proposed models and solution methods are effective, which can provide the beneficial theory basis and practice guide for the green and sustainable development of regional logistics.

Keywords: regional logistics network, multimodal transport, multi-stakeholder, robust optimization

1. Introduction

The growth and expansion of urbanization clusters have the significant impact on the regional and national and economic development. However, they inevitably lead to the negative social and environmental externalities. According to the report of the U.S. Environmental Protection Agency (2016), urban areas account for about 80% of carbon emissions from human activities, and the transport sector is a major source of such emissions, accounting for nearly 26%. Moreover, the Intergovernmental Panel on Climate Change (2014) predicts that vehicle emissions on a business-as-usual basis could account for 60% of all permissible emissions by 2050, of which freight transportation contributes 36%. To reduce the effects of human activities on the environment, implementing the green or low-carbon strategies in various industries has become the consensus of the international community (Cai et al., 2019). Although 157 of the 197 parties have ratified the Paris Agreement and pledged to set targets to reduce greenhouse gas emissions, only 16 countries have set in place the sector-specific emissions reduction targets (Nachmany, 2018). Thus, how to plan and design a high-performance and low-carbon regional logistics network in response to climate change is a daunting challenge to the economic development of urban clusters, and it is also the motivation of this study.

Urban cluster is a highly developed spatial form integrated three or more geographically adjacent cities, and it is also the center of production and consumption (Fang and Yu, 2017). Most of the inter-city freight caused by urban activities is transported from its origins to destinations through freight transshipment services (Hao et al., 2015). Planning or designing an effective regional logistics network for such trips is challenging because these demands are closely related to the industrial layout and consumption patterns. More specifically, the distribution and total amount of logistics demands are hard to predict accurately (Gan et al., 2018). In addition, the long-term decisions that involve investing in or subsidizing logistics infrastructures need to be made before the logistics demand occurs. All of these imply that the regional logistics network planners have to face a complicated and highly uncertain external environment rather than the generally assumed deterministic environment.

The main ways to reduce the negative effects of logistics activities on the environment and human health are the low-carbon planning and operations of logistics network and the transformation of existing freight transport modes. As the key components in the regional logistics network, logistics parks are designed as the freight transshipment hubs to achieve switching points for the inter-modal freight flows and also to provide the function of distribution centers. According to the fifth national logistics park survey (China Federation and Logistics and Purchasing, 2018), the total number and scale of logistics parks in China increased by 117% and

123%, respectively, from 2012 to 2018. There are many issues behind this remarkable growth, including unplanned expansion and unwise investment and lack of planning guide. It is therefore imperative to optimally plan and design the number, location and capacity of logistics parks and improve the effectiveness of a regional logistics network (Yang et al., 2016). Despite that hub location problems have received widespread attention in the past thirty years, there are some research gaps in the layout of regional logistics facilities, particularly regarding the interactions among urban cluster planning, multimodal transport and land-use.

Compared with the sole road transportation, the multimodal transportation is a new tendency in recent years. In the multimodal logistics network, freight shippers, carriers and logistics authorities (planners) are the three key stakeholders. From the perspective of planners, the multimodal transportation could promote regional development by providing diversified services and reduce carbon emissions at the same time. Moreover, to achieve a binding emission reduction target, the logistics authority (government) may require the carrier to use the low-carbon transport modes (Sheng et al., 2017). Nevertheless, the carrier's choice in both transport mode and route in a regional logistics network is highly impacted by transport cost, transport time and the location of origin-destination (O-D) demands (Zhang et al., 2018b). Therefore, the interests and objectives of the logistics authority and the carrier involved in the regional logistics system are different and sometimes even conflicting. Hence, a system optimum perspective that considers the relationship between the logistics authority and the carrier as well as their choice preferences under different policies is essential.

This study aims to design a regional multimodal logistics network from the system optimum perspective in the context of urban cluster development, which takes into account the following four prominent features arising from the development of urban cluster: uncertain logistics demand pattern, CO_2 emission reduction target, subsides and multiple stakeholders. Given a pre-determined logistics demand pattern, this multi-stakeholder decision-making problem is formulated as an interesting bi-level programming model and its equivalent mathematical programming with equilibrium constraints (MPEC). In the upper-level decision problem, the objective of logistics authority is to maximize the total flows routing in logistics parks and rail transport links subject to the given budget and CO_2 emission reduction target constraints. In the lower-level problem, the carrier minimizes the total generalized transportation cost subject to logistics demand and capacity constraints. Meanwhile, an improved robust optimization approach is proposed to capture the risk aversion level of the logistics authority in the uncertain demand environment. Compared with the approximate probability boundary shown by Bertsimas and Sim (2004), this study provides an exact expression of the maximum satisfaction probability. Moreover, we address the effects of the key parameters of the proposed robust model on the regional logistics network design, and some management insights are obtained to develop a green regional logistics network with uncertain demand.

The remainder of this paper is organized as follows. Section 2 reviews the relevant recent studies. Section 3 introduces the assumptions, notations and the representation of a regional multimodal logistics network. Section 4 presents the deterministic and robust optimization models for the regional multimodal logistics network design problem. In Section 5, the proposed robust optimization techniques are applied in a real-world study, and some managerial insights are obtained. Finally, conclusions are drawn in Section 6.

2. Literature Review

The existing studies can be divided into four clusters: (i) urban cluster logistics, (ii) multimodal logistics network design, (iii) logistics network design with environmental concerns, and (iv) network design under box uncertainty.

2.1 Urban cluster logistics

As a new regional unit participating in global competition, the urban cluster determines the new pattern of global economic development (Fang and Yu, 2017). In this context, an efficient and reliable regional logistics system is critical to ensure the sustainable development of a particular region economy (Aljohani and Thompson, 2016). The literature is replete with qualitative works that consider logistics spatial distribution and structure, logistics aggregation and collaboration, and the interrelationship of regional logistics and regional economy. Therein, Van den Heuvel et al. (2013) analyzed land allocation policies by means of a survey conducted in the south of the Netherlands. They found that municipalities do not actively stimulate spatial concentration of logistics firms, although both aldermen and public administration employees acknowledge that co-location of logistics firms can lead to benefits. Raimbault (2019) addressed the relationship between regional economic and regional logistics system based on the case study of the Paris region. The findings showed that evolutions of spatial planning policies and of logistics metropolitan politics show significant effect on the forms of political involvement in inland ports development. Therefore, logistics clusters are significantly important for companies and governments to improve regional logistics system performances. And coordination and collaboration are the essential part for creating harmony to achieve sustainability of urban cluster due to the economies of scale of logistics agglomeration (Rivera et al., 2016). Han et al. (2018) addressed the effects of urban agglomeration economies on carbon emissions based on the theory of agglomeration economies, and they found that both specialization and diversification agglomeration can significantly promote carbon emission reduction in local and neighboring cities through the agglomeration externalities. Zhang et al. (2018a) and Jiang et al. (2019) have considered the green or low-carbon strategies of logistics activities and applied optimization methods to plan/design a regional logistic network in the context of urban cluster development.

2.2 Multimodal logistics network design

Logistics network design and sustainable logistics management policies are two important aspects for developing a low-carbon regional logistics system. The former involves determining the optimal configuration of logistics infrastructure, whereas the latter mostly refers to subsidies for green transport modes or CO_2 emission taxes (Zhang et al., 2018b). Among all the configuration patterns of regional logistics network design, the configuration pattern based on multi-mode is the most widely applied in recent years (Wang, 2008). The multimodal logistics network design is a new branch of hub-and-spoke problems. O'Kelly (1987) first formulated the hub-and-spoke problem as an uncapacitated single allocation p-hub median problem. To obtain more realistic settings of hub networks, scholars have explored various extensions recently, including hub capacity constraints and hub network design, such as considering hub capacity limitations and congestion (Azizi et al., 2018), competing hub networks (Xu et al., 2018), hierarchical hub network (Dukkanci and Kara, 2017) and multimodal hub network (Tsao and Linh, 2018). Multimodal hubs are designated as nodes in a multimodal network composed of highway, railway and other transportation modes. To this regard, Alumur et al. (2012) studied a multimodal hub location and hub network design problem by relaxing the complete hub network assumption while considering cost and different types of service qualities. The authors postulated that the number of hubs was predetermined and ignored the multimodal transfer activities at hubs. These may not be realistic. For practical purposes, Meng and Wang (2011) addressed a multimodal logistics network design problem with multi-stakeholder and multi-type containers by considering the congestion effects and the multimodal transfer activities at hubs. The results shown that the performance of the proposed hybrid genetic algorithm is significantly better than the exhaustive enumeration algorithm in terms of computation time and solution quality. In order to obtain a global optimal solution, Wang and Meng (2017) proposed a branch-and-bound based algorithm to solve the discrete intermodal freight transport network design problem. For a comprehensive review of multimodal freight network design, interested readers can refer to the references (Crainic et al., 2018; SteadieSeifi et al., 2014). Even though these studies capture some important features of multimodal logistics network design, few of them considers the unique features of regional multimodal logistics network design with subsidies and carbon emissions target considered in this study.

2.3 Logistics network design with environmental concerns

Logistics network design problems have been extensively studied, but its environmental impact has been considered only recently (Govindan and Soleimani, 2017). To reduce the impact of logistics activities on the environment, Eskandarpour et al. (2015) suggested the use of low-carbon policies (such as caps and transactions, carbon taxes and subsidies) in the logistics network design phase. Waltho et al. (2019), in their comprehensive review of low-carbon policies for logistics network design, pointed out that most of the existing studies focused on the green logistics network design under given cap-and-trades or carbon taxes the perspective of manufacturing enterprises or third-party logistics service providers. Different from enterprise logistics, regional logistics belongs to social logistics and its planner is the regional management authority (government) that formulates low-carbon policies (Cui et al., 2015). Therefore, it is valuable to that consider the low-carbon policy design in regional logistics network. Therein, Iannone (2012) empirically studied a range of conditions to achieve private and social cost efficiency of port hinterland container distribution in a regional logistics system. They found that the greenhouse gas emissions can be effectively reduced by taking some low-carbon policies such as carbon taxes, modal shifts and improvements of rail services. Recently, Zhang et al. (2018b) proposed a bi-level optimization model combining logistics infrastructure investments and green transport mode subsidies to achieve given carbon emission targets in a regional logistics network. The results suggested that low-carbon policies are significantly affect the layout of logistics nodes in the logistics network. These studies have not considered the effect of logistics demand uncertainty on policymakers.

2.4 Network design under box uncertainty

According to the known degree of parameters information, decision-making environments are classified into three categories: (i) All parameters are deterministic and known, which is called deterministic environments; (ii) Some parameters are random, and their probability distributions are known, which is called stochastic environments; and (iii) Some parameters are random, but their probability distributions are unknown, which is called uncertain environments (Rosenhead et al., 1972). To solve the mathematical programming problems in uncertain environments, Soyster (1973) first proposed a robust optimization method based on the worst-case scenario. Although this method is too conservative, it lays a foundation for the development of robust optimization. Subsequently, Mulvey et al. (1995) introduced a robust optimization method based on the finite scenario sets. Compared with Soyster's method, this method reduces the conservatism of the solutions. Based on the works of Soyster (1973) and Mulvey et al. (1995), Bertsimas and Sim (2004) established a new robust optimization framework, and pointed out that the two key techniques of robust optimization are selecting uncertain set and obtaining the robust counterpart of the origin problem. Because the box set has more advantage than the other uncertainty sets in probability calculation and robust counterpart model, it is widely used in logistics network planning, power grid scheduling, aircraft route planning and other fields (Gabrel et al., 2014). Therein, Ghaffari-Nasab et al. (2015) investigated a robust hub-and-spoke network design problem in which demand uncertainty is modeled with a box uncertainty. They consider that the number of establishing hubs is not fixed and take the sum of the cost of establishing hubs and the transportation cost of all goods as the objective function. However, they do not consider demand uncertainty in the objective function, but use the nominal demand value. Zetina et al. (2017) presented a robust uncapacitated hub location problem with box uncertainty, and use a budget to control the maximum number of uncertain demands in the objective function. Despite this, they ignore the capacity limitations of the hubs. In addition, the above studies based on the complete network assumption seem somewhat restrictive, especially considering that the transport links of an actual logistics network are affected by geographical environment, policy constraints, administrative divisions and other practical conditions. To this regard, Martins de Sá et al. (2018) studied a single-mode multiple allocation incomplete hub location problem with box uncertainty. Nevertheless, these studies do not consider the degree of risk aversion of the decision maker in logistics network design under uncertainty, and its minor changes may make the original design plan meaningless.

3. Assumptions, Notations and Network Representations

3.1. Assumptions and Notations

To facilitate the problem description and regional logistics network modeling, the necessary assumptions are presented below:

(i) Region: The target region for this study is an urban cluster with common interests and destiny, which is a highly integrated group composed of several geographically adjacent cities (e.g. the Greater Paris region of France, the Yangtze River Delta urban cluster of China and the Pittsburg-Chicago region of United States) (Fang and Yu, 2017).

(ii) Nodes: As shown in Fig. 1(a), there are three different types of nodes in regional logistics network, i.e. extra-regional virtual transit hubs, potential logistics parks, and origins and destinations of demand. As the name implies, the extra-regional virtual transit hub is a special virtual transit hub or a demand node outside the study region, which is applied to describe the logistics activities between the inside and outside of the study region. In addition, considering the impact of geographical and administrative characteristics on logistics park location planning, the service area of each logistics park is limited to the city where it is located.

(iii) Links: There are two types of links in the regional multimodal logistics network, that is, road segments and rail tracks. Without loss of generality, a road segment is available between all nodes, but a rail track is only allowed to be used between logistics parks, and between logistics parks and extra-regional virtual transit hubs. In this study, only railway transportation has capacity limitations.

(iv) Demands: According to the geographical scope of Origin-destination nodes of logistics demand (O-Ds), the logistics demand can be divided into inter-regional and intra-regional demand. Specifically, the intra-regional demand is divided into inter-city demand and intra-city demand. Since logistics parks are rarely used for intra-city demand, this study only considers the inter-regional logistics demand, as well as inter-city logistics demand.

(v) Routes: O-D routes from origin nodes to destination ones are associated with O-D pairs, which may be connected with direct routes (not via logistics parks) or transfer routes that visit logistics parks. Due to city restrictions on vehicles, Heavy goods vehicles (HGVs) cannot be used for a direct transport routes. As shown in Fig. 1(b), there exists three alternative transport service routes for logistics carriers: (1) direct transport service routes by Light goods vehicles (LGVs) , (2) combined transport service routes by HGVs and LGVs, and (3) combined transport service routes by railway and LGVs. The transfer is only serviced in logistics parks during combined transport.

(vi) Cost: It is assumed that the carrier can transport freight (e.g., containers) by direct transport and combined transport, and make decisions on freight transport routes according to the time cost, transport cost and subsidy of each route.

(vii) CO_2 emissions: Freight transportation is largely driven by fossil fuel combustion, resulting in emissions of greenhouse gases (GHG) including carbon dioxide (CO_2), nitrogen dioxide (NO_x) and sulfur oxide (SO_x). This study is a strategic-tactical planning, which adopts the activity-based function proposed by McKinnon and Piecyk (2010) to estimate the carbon footprint of a transport operation. The unit CO_2 emission of transport mode $m \in M$ can be calculated as Eq. (1).

$$E_a^m = e_m d_a \tag{1}$$

where e_m denotes the average CO_2 emission factor per unit turnover by transport mode $m \in M$ and d_a denotes the length of transport link $a \in A$.

The rationale for adopting this CO_2 emissions function is that it is commonly used by logistics authorities to make strategic decisions (Zhang et al., 2018b). It has the advantage of including variables that measure the mode of transport and the corresponding transport distance, while ignoring factors that are difficult to measure or calculate in detail, such as the filling rate and fuel type of vehicles for each mode of transport (McKinnon and Piecyk, 2010). Note that the CO_2 emissions calculated by Eq. (1) are CO_2 equivalent emissions of greenhouse gases generated by transport activities.

(viii) Carbon reduction target (rate): Suppose the country has set a carbon reduction target for the transportation sector (Chang and Park, 2016). It is the index to evaluate the ratio of the CO_2 emissions reduction amount $\left(E_0 - E_1\right)/E_0$ in a logistics system, where E_0 and E_1 represent the CO_2 emissions of the regional logistics system without and with implementations of green logistics network design and incentive measures by logistics authorities.

(ix) Stakeholders: From the perspective of system optimization, the stakeholders in a regional logistics system involve a centralized logistics authority and a centralized carrier. In the context of national carbon reduction target, the logistics authority is committed to maximizing the total flow of low-carbon transport routes in the regional logistics system through low-carbon design (such as planning logistics parks and subsidies for rail transportation). Because of the commercial nature of freight transportation, the carrier is rational and aims to minimize the generalized cost of transportation activities in the system.

To improve the readability of this study, a detailed notations and descriptions is given in Table 1.

(Insert Table 1 here)

3.2. Network representations

In this section, the representation of a regional multimodal logistics network is presented, which can be used by the logistics authority to make network design decisions.

Physical network. As shown in Fig. 1(a), let K denote the set of cities in the study region. Denote P_k and I_k as the set of potential logistics parks and demand nodes in the city $k \in K$, respectively. Thus, the set of potential logistics parks and the set of demand nodes in the urban cluster are represented by $P = \bigcup_{k\in K} P_k$ and $I = \bigcup_{k\in K} I_k$, respectively. Denote by H the set of extra-regional virtual transit hubs.

Denote $M = \{1,2,3\}$ as the set of transport modes, where ‘‘1”, ‘‘2”and ‘‘3”, represent the Light Goods Vehicles (LGVs), Heavy Goods Vehicles (HGVs) and Railways respectively, which are shown as Fig. 1(b). Let $A_{HP}^{M} = \{a_{h,p}^{m} \mid h \in H, p \in P, m \in M\}$ denote the set of all the possible bi-directional links between extra-regional virtual transit hubs and potential logistics parks. Similarly, define $A_{P}^{M} = \{a_{p,l}^{m} \mid p \in P_k, l \in P \setminus P_k, k \in K, m \in M\}$ as the set of all the possible bi-directional links between potential logistics parks in different cities. Let $A_{I}^{1} = \{a_{i,j}^{1} \mid i \in I_k, j \in I \setminus I_k, k \in K, m = 1\}$ denote the set of all the possible bi-directional links between demand nodes in different cities. Denote by $A_{PI}^{1} = \{a_{p,i}^{1} \mid p \in P_k, i \in I_k, k \in K, m = 1\}$ the set of all the possible bi-directional links between potential logistics parks and demand nodes in the same cities. Let $A_{HI}^{1} = \{a_{h,i}^{1} \mid h \in H, i \in I, m = 1\}$ denote the set of all the possible bi-directional links between extra-regional virtual transit hubs and demand nodes.

Thus, the regional logistics physical network can be illustrated by an directed graph $\mathsf{G} = (\mathsf{N}, \mathsf{A})$, where $\mathsf{N} = H \cup P \cup I$ is the set of nodes, and $\mathsf{A} \equiv A_{HP}^{M} \cup A_{P}^{M} \cup A_{I}^{1} \cup A_{PI}^{1} \cup A_{HI}^{1}$ is the set of bi-directional links.

Operational network. For each logistics park $p \in P$, there may be two types of transfer activities: road-road and road-rail. Let $A_{PM}^{T} = \{b_{p}^{m,1} \mid p \in P, m \in M\}$ denote the set of all the possible transfer links at potential logistics. Define $N = \mathsf{N}$ is the set of nodes, and $A = \mathsf{A} \uplus A_{PM}^{T}$ is the set of bi-directional links. Then, we denote by $G = (N, A)$ the regional logistics operational network generated from $\mathsf{G} = (\mathsf{N}, \mathsf{A})$.

(Insert Fig. 1 here)

Feasible sets of route. Denote by $\mathsf{O} \subset N$ the set of origin nodes, and $\mathsf{D} \subset N$ the set of destinations nodes. Define $W \subset \mathsf{O} \times \mathsf{D}$ as the set of origin-destination (O–D) pairs. For any $(o,d) \in W$, denote by $R_{o,d}^{D}$ and $R_{o,d}^{T}$ as the sets of direct transport routes and transfer transport routes connecting (o,d) pair, respectively. Let $R_{o,d} = R_{o,d}^{D} \cup R_{o,d}^{T}$ be the set of all transport routes connecting (o,d) pair. Boolean variables are introduced to capture the connection between nodes. Define $\delta_{o,d}^{a,r}$ be one if transport route $r \in R_{o,d}$ traverses $a \in A$; zero otherwise. Define $\delta_{o,d}^{p,r}$ be one if transport route $r \in R_{o,d}$ traverses $p \in P$; zero otherwise. Define $\delta_{p,r}^{b}$ be one if transfer transport route $r \in R_{o,d}^{T}$ traverses $p \in P$ and using transfer arc $b \in A_{PM}^{T}$; zero otherwise. Let $q_{o,d}$ denote the total demand on all routes $r \in R_{o,d}$ between O–D pair $(o,d) \in W$.

As shown in Fig. 1(b), for each inter-regional logistics demand $q_{h,i}, (h,i) \in W_0$, the set of direct transport routes can be represented by $R_{h,i}^{D} = \left\{ r \mid \delta_{h,i}^{a_{h,i}^{1},r} = 1, \sum_{a \in A_{HI}^{M}} \delta_{h,i}^{a,r} = 1 \right\}$, and the set of transfer transport routes can be represented by

$$R_{h,i}^{T}=\left\{r \mid \delta_{h,i}^{a_{h,p}^{m},r}=1,\delta_{p,r}^{b}=1,\delta_{h,i}^{a_{p,i}^{1},r}=1,\delta_{h,i}^{a_{h,p}^{m},r}\cdot\delta_{p,r}^{b}\cdot\delta_{h,i}^{a_{p,i}^{1},r}=1,\sum_{a\in A_{HP}^{M}}\delta_{h,i}^{a,r}=1,\sum_{b\in A_{PM}^{T}}\delta_{p,r}^{b}=1,\sum_{a\in A_{PI}^{M}}\delta_{h,i}^{a,r}=1,p\in P_{k}\right\}.$$

Similarly, for each inter-city logistics demand $q_{i,j},(i,j)\in W\setminus W_0$, the set of direct transport routes can be represented by $R_{i,j}^{D}=\left\{r \mid \delta_{i,j}^{a_{i,j}^{1},r}=1,\sum_{a\in A_{I}^{M}}\delta_{i,j}^{a,r}=1\right\}$, and the set of transfer transport routes can be represented by $R_{i,j}^{T}=\left\{\begin{array}{l} r \mid \delta_{i,j}^{a_{i,p}^{1},r}=1,\delta_{p,r}^{b}=1,\delta_{i,j}^{a_{p,l}^{m},r}=1,\delta_{l,r}^{b}=1,\delta_{i,j}^{a_{l,j}^{1},r}=1,\delta_{i,j}^{a_{i,p}^{1},r}\cdot\delta_{p,r}^{b}\cdot\delta_{i,j}^{a_{p,l}^{m},r}\cdot\delta_{l,r}^{b}\cdot\delta_{i,j}^{a_{l,j}^{1},r}=1,\sum_{a\in A_{PI}^{M}}\delta_{i,j}^{a,r}=1,\\ \sum_{b\in A_{PM}^{T}}\delta_{p,r}^{b}=1,\sum_{a\in A_{P}^{M}}\delta_{p,l}^{a,r}=1,\sum_{b\in A_{PM}^{T}}\delta_{p,r}^{b}=1,\sum_{a\in A_{PI}^{M}}\delta_{i,j}^{a,r}=1,p\in P_k,l\in P_o,k\neq o \end{array}\right\}$.

Generalized transportation cost. The generalized cost functions to transport unit shipment through direct transport or combined transport routes can be calculated as follows.

For direct transport of inter-regional logistics demand,

$$C_{h,i}^{D,r}=\sum_{a\in A_{HI}^{1}}\delta_{h,i}^{a,r}\left(c_a+\pi t_a\right)\quad\forall r\in R_{h,i}^{D},(h,i)\in W_0 \tag{2}$$

For direct transport of inter-city logistics demand,

$$C_{i,j}^{D,r}=\sum_{a\in A_{I}^{1}}\delta_{i,j}^{a,r}\left(c_a+\pi t_a\right)\quad\forall r\in R_{i,j}^{D},(i,j)\in W\setminus W_0 \tag{3}$$

For transfer transport of inter-regional logistics demand,

$$\begin{aligned}C_{h,i}^{T,r}=&\sum_{a\in A_{PI}^{1}}\delta_{h,i}^{a,r}\left(c_a+\pi t_a\right)+\sum_{b\in A_{PM}^{T}}\delta_{p,r}^{b}\left(c_b+\pi t_b\right)+\sum_{a\in A_{HP}^{M}}\delta_{h,i}^{a,r}\left[c_a\left(1-y_a\right)+\pi t_a\right]\\&\forall r\in R_{h,i}^{T},(h,i)\in W_0\end{aligned} \tag{4}$$

For transfer transport of inter-city logistics demand,

$$\begin{aligned}C_{i,j}^{T,r}=&\sum_{a\in A_{PI}^{1}}\delta_{i,j}^{a,r}\left(c_a+\pi t_a\right)+\sum_{b\in A_{PM}^{T}}\delta_{p,r}^{b}\left(c_b+\pi t_b\right)+\sum_{a\in A_{P}^{M}}\delta_{i,j}^{a,r}\left[c_a\left(1-y_a\right)+\pi t_a\right]\\&\forall r\in R_{i,j}^{T},(i,j)\in W\setminus W_0\end{aligned} \tag{5}$$

where c_a and t_a denote the transport cost and time on the transport link $a\in A$, respectively. c_b and t_b denote the transfer cost and time at the logistics park $p\in P$, respectively. Parameter π is the value of time. y_a is the subsidy rate variable made by the logistics authority for rail transport link $a\in A_{HP}^{2}\cup A_{P}^{2}$. Eq. (2) and Eq. (3) show that for direct transport, the generalized cost contains the time cost and transport cost for freight transported through the links in each route. Eq. (3) and Eq. (4) show that for transfer transport, the generalized cost contains the following three terms: the transport cost between the demand nodes and the transfer nodes, the park transfer cost, and the transport cost between the transfer nodes.

CO_2 emissions of transportation. The CO_2 emission functions for transporting one unit of freight through direct transport and transfer transport routes are shown as follows.

For direct transport of inter-regional logistics demand,

$$E_{h,i}^{D,r}=\sum_{a\in A_{HI}^{M}}\delta_{h,i}^{a,r}e_1 d_a\quad\forall r\in R_{h,i}^{D},(h,i)\in W_0 \tag{6}$$

For direct transport of inter-city logistics demand,

$$E_{i,j}^{D,r}=\sum_{a\in A_{I}^{M}}\delta_{i,j}^{a,r}e_1 d_a\quad\forall r\in R_{i,j}^{D},(i,j)\in W\setminus W_0 \tag{7}$$

For transfer transport of inter-regional logistics demand,

$$E_{h,i}^{T,r}=\sum_{m\in M}\sum_{a\in A_{HP}^{M}}\delta_{h,i}^{a,r}e_m d_a+\sum_{a\in A_{PI}^{1}}\delta_{h,i}^{a,r}e_1 d_a\quad\forall r\in R_{h,i}^{T},(h,i)\in W_0 \tag{8}$$

For transfer transport of inter-city logistics demand,

$$E_{i,j}^{T,r}=\sum_{a\in A_{PI}^{1}}\delta_{i,j}^{a,r}e_1 d_a+\sum_{m\in M}\sum_{a\in A_{P}^{M}}\delta_{i,j}^{a,r}e_m d_a+\sum_{a\in A_{PI}^{1}}\delta_{i,j}^{a,r}e_1 d_a\quad\forall r\in R_{i,j}^{T},(i,j)\in W\setminus W_0 \tag{9}$$

where e_m denotes the average CO_2 emission per unit turnover by transport mode $m\in M$ and d_a denotes the length of transport link $a\in A$. Eq. (6) and Eq. (7) show that for direct transport, the CO_2 emissions contain the emissions for freight transported through the links in each route. Eq. (8) and Eq. (9) show that for transfer transport, the CO_2 emissions contain the emissions between each route through between the demand nodes and the transfer nodes, and between the transfer nodes.

4. Problem Description and Model Building

This study aims at modeling a regional multimodal logistics network from the system optimum perspective in the context of urban cluster development by taking into account the four prominent features arising from the urban cluster development: uncertain logistics demand pattern, CO_2 emission reduction target, subsides and multiple stakeholders. Given a determined logistics demand pattern, this problem is typically formulated as a Stackelberg game. As shown in Fig. 2, a bi-level programming model can be built to describe the leader-follower behaviors between the logistics authority and the carrier in the regional multimodal logistics system. As the leader, the logistics authority attempts to maximize the total flows routing in logistics parks and rail transport links by planning the investment capacity of logistics parks and determining the subsidy rates on rail transport links. After given the investment and subsidy policies by the logistics authority, the carrier develops route-based freight transportation assignments to minimize the generalized transportation cost of the logistics system. To capture the risk aversion level of the logistics authority in uncertain demand environment, an improved adjustable robust optimization method is proposed, which introduces an individual control parameter and provides an exact expression for the maximum satisfaction probability. Therefore, this study can simultaneously solve the following major research issues:

(i) In a multi-stakeholder regional logistics system, how do the logistics authority and the carrier achieve their respective objectives?

(ii) How can the logistics authority make decisions within a highly uncertain demands environment?

(iii) When implementing the national emission reduction target, how can the logistics authority maximize the total flow of low-carbon transport routes in the regional logistics system? and

(iv) How to determine the number, location and capacity of logistics parks, and the subsidy rate for the railway transportation links?

4.1 Bi-level programming model

To facilitate modeling, this section assumes that the logistics demands are known and pre-determined. The regional multimodal logistics network design problem considering CO_2 emission reduction target can be formulated as the following bi-level programming model.

$$\begin{aligned}\underset{\mathbf{X,Y,Z}}{Max} & \sum_{(h,i)\in W_0}\sum_{r\in R_{h,i}^T} f_{h,i}^{T,r} + \sum_{(i,j)\in W\setminus W_0}\sum_{r\in R_{i,j}^T} f_{i,j}^{T,r} + \sum_{(h,i)\in W_0}\sum_{r\in R_{h,i}^T}\sum_{a\in A_{HP}^3}\delta_{h,i}^{a,r} f_{h,i}^{T,r} \\ & + \sum_{(i,j)\in W\setminus W_0}\sum_{r\in R_{i,j}^T}\sum_{a\in A_P^3}\delta_{i,j}^{a,r} f_{i,j}^{T,r} - \theta\sum_{k\in K}\sum_{p\in P_k} x_p^k - \varpi\sum_{a\in A_{HP}^3\cup A_P^3} y_a c_a\end{aligned} \tag{10}$$

subject to

$$V_{\min} z_p^k \le x_p^k \le M z_p^k \quad \forall p\in P_k, k\in K \tag{11}$$

$$0 \le y_a \le \Phi \quad \forall a\in A_{HP}^3 \cup A_P^3 \tag{12}$$

$$c_0\sum_{k\in K}\sum_{p\in P_k} x_p^k + \sum_{a\in A_{HP}^3\cup A_P^3} y_a c_a v_a \le B \tag{13}$$

$$\frac{E_0 - E_1}{E_0} \ge \phi_E \tag{14}$$

$$x_p^k \ge 0 \quad \forall p\in P_k, k\in K \tag{15}$$

$$z_p^k \in \{0,1\} \quad \forall p\in P_k, k\in K \tag{16}$$

$$\begin{aligned}E_1 = & \sum_{(h,i)\in W_0}\sum_{r\in R_{h,i}^D} E_{h,i}^{D,r} f_{h,i}^{D,r} + \sum_{(i,j)\in W\setminus W_0}\sum_{r\in R_{i,j}^D} E_{i,j}^{D,r} f_{i,j}^{D,r} + \sum_{(h,i)\in W_0}\sum_{r\in R_{h,i}^T} E_{h,i}^{T,r} f_{h,i}^{T,r} \\ & + \sum_{(i,j)\in W\setminus W_0}\sum_{r\in R_{i,j}^T} E_{i,j}^{T,r} f_{i,j}^{T,r}\end{aligned} \tag{17}$$

$$E_0 = \sum_{(h,i)\in W_0}\sum_{r\in R_{h,i}^D} e_1 d_a q_{h,i} + \sum_{(i,j)\in W\setminus W_0}\sum_{r\in R_{i,j}^D} e_1 d_a q_{i,j} \tag{18}$$

where $\mathbf{X}$ is a decision vector defined as $\mathbf{X} := \left(x_p^k, p \in P_k, k \in K\right)$, which means a set of investment capacity for logistics park $p \in P$ in city $k \in K$; $\mathbf{Y}$ is a decision vector defined as $\mathbf{Y} := \left(y_a, a \in A_{HP}^3 \cup A_P^3\right)$, which means a set of subsidy rate for rail transport link $a \in A_{HP}^3 \cup A_P^3$; $\mathbf{Z}$ is a vector defined as $\mathbf{Z} := \left(z_p^k, p \in P_k, k \in K\right)$, representing a set of binary decision variables of whether logistics park $p \in P_k$ is established in city $k \in K$; and $\mathbf{f}$ is a vector defined as $\mathbf{f} := \left(f_{o,d}^r, r \in R_{o,d}, (o,d) \in W\right)$, representing a set of flow assignment plans determined by the following equivalent minimization problem:

$$\begin{aligned} \underset{\mathbf{f}}{Min} \quad & \sum_{(h,i)\in W_0} \sum_{r \in R_{h,i}^D} C_{h,i}^{D,r} f_{h,i}^{D,r} + \sum_{(i,j)\in W \setminus W_0} \sum_{r \in R_{i,j}^D} C_{i,j}^{D,r} f_{i,j}^{D,r} + \sum_{(h,i)\in W_0} \sum_{r \in R_{h,i}^T} C_{h,i}^{T,r} f_{h,i}^{T,r} \\ & + \sum_{(i,j)\in W \setminus W_0} \sum_{r \in R_{i,j}^T} C_{i,j}^{T,r} f_{i,j}^{T,r} \end{aligned} \tag{19}$$

subject to

$$\sum_{r \in R_{h,i}^D} f_{h,i}^{D,r} + \sum_{r \in R_{h,i}^T} f_{h,i}^{T,r} \geq \overline{q}_{h,i} \quad \forall (h,i) \in W_0 \quad : \alpha_{h,i} \tag{20}$$

$$\sum_{r \in R_{i,j}^D} f_{i,j}^{D,r} + \sum_{r \in R_{i,j}^T} f_{i,j}^{T,r} \geq \overline{q}_{i,j} \quad \forall (i,j) \in W \setminus W_0 \quad : \beta_{i,j} \tag{21}$$

$$\sum_{(h,i)\in W_1} \sum_{r \in R_{h,i}^T} \delta_{h,i}^{p,r} f_{h,i}^{T,r} + \sum_{(i,j)\in W_2} \sum_{r \in R_{i,j}^T} \delta_{i,j}^{p,r} f_{i,j}^{T,r} \leq x_p^k \quad \forall p \in P_k, k \in K \quad : \gamma_p^k \tag{22}$$

$$\sum_{(h,i)\in W_0} \sum_{r \in R_{h,i}^T} \delta_{h,i}^{a,r} f_{h,i}^{T,r} \leq v_a \quad \forall a \in A_{HP}^3 \quad : \eta_a \tag{23}$$

$$\sum_{(i,j)\in W \setminus W_0} \sum_{r \in R_{i,j}^T} \delta_{i,j}^{a,r} f_{i,j}^{T,r} \leq v_a \quad \forall a \in A_P^3 \quad : \mu_a \tag{24}$$

$$f_{h,i}^{D,r} \geq 0 \quad \forall r \in R_{h,i}^D, (h,i) \in W_0 \quad : \varphi_{h,i}^{D,r} \tag{25}$$

$$f_{h,i}^{T,r} \geq 0 \quad \forall r \in R_{h,i}^T, (h,i) \in W_0 \quad : \varphi_{h,i}^{T,r} \tag{26}$$

$$f_{i,j}^{D,r} \geq 0 \quad \forall r \in R_{i,j}^D, (i,j) \in W \setminus W_0 \quad : \kappa_{i,j}^{D,r} \tag{27}$$

$$f_{i,j}^{T,r} \geq 0 \quad \forall r \in R_{i,j}^T, (i,j) \in W \setminus W_0 \quad : \kappa_{i,j}^{T,r} \tag{28}$$

The upper-level objective function (10) seeks to maximize total flows, including flows into logistics parks (terms 1 and 2) and rail transport links (terms 3 and 4), and penalty flows (terms 5 and 6). The penalty terms 5 and 6 are added to the objective function to prevent blind investment in logistics parks and subsidies for railway transportation. Especially, parameters θ and ϖ are smaller than the marginal value for handling one additional unit of flow. Constraint (11) ensures that logistics park is constructed if and only if its construction processing capacity is not less than the minimum construction processing capacity $V_{\min}$, where parameter M is a large value. Inequality (12) is subsidy rate constraints, where Φ is the maximum subsidy rate. Constraint (13) enforces the total budget limitation for the investments and subsidies, in which parameter c_0 denotes the unit construction cost per unit of processing capacity at logistics park, parameter B denotes the total budget and v_a denotes the maximum capacity of rail transport link $a \in A_{HP}^3 \cup A_P^3$. Based on the assumption viii, constraint (14) ensures that the designed regional logistics system meets the national carbon reduction target ϕ_E. Constraint (15) is the positive capacity variables. Constraint (16) defines the binary variables. Equations (17) and (18) represent the total CO_2 emissions of the regional logistics system with and without low-carbon strategy design, respectively.

The lower-level objective function (19) seeks to minimize total generalized cost of regional logistics system, including time cost and transportation cost. Constraints (20) and (21) ensure that the volume distribution plan is not less than the actual logistics demand. Constraint (22) enforces the capacity limitation of the logistics parks and rail transport links, respectively. Constraints (23) and (24) enforce the capacity limitation of the rail transport links. Constraints (25)-(28) are the positive flow variables. Notations $\alpha_{h,i}, \beta_{i,j}, \gamma_h, \varphi_{h,i}^{D,r}, \varphi_{h,i}^{T,r}, \kappa_{i,j}^{D,r}$ and $\kappa_{i,j}^{T,r}$ are dual variables.

(Insert Fig. 2 here)

4.2 Mixed-integer linear programming (MILP) model

The lower-level route-based flows assignment problem is a linear programming problem, and the optimal solution can be expressed by its complementary slackness conditions. To facilitate the analysis of the decision-making behavior of the logistics authority, the above bi-level programming model can be equivalent to the following MPEC problem.

$$(SD)\ \underset{\mathbf{X},\mathbf{Y},\mathbf{Z},\mathbf{f}}{Max} \sum_{(h,i)\in W_0}\sum_{r\in R_{h,i}^T} f_{h,i}^{T,r} + \sum_{(i,j)\in W\setminus W_0}\sum_{r\in R_{i,j}^T} f_{i,j}^{T,r} + \sum_{(h,i)\in W_0}\sum_{r\in R_{h,i}^T}\sum_{a\in A_{HP}^3}\delta_{h,i}^{a,r} f_{h,i}^{T,r} + \sum_{(i,j)\in W\setminus W_0}\sum_{r\in R_{i,j}^T}\sum_{a\in A_P^3}\delta_{i,j}^{a,r} f_{i,j}^{T,r} - \theta\sum_{k\in K}\sum_{p\in P_k} x_p^k - \varpi\sum_{a\in A_{HP}^3\cup A_P^3} y_a c_a \quad (29)$$

subject to constraints (2)-(9), (11)-(18) and

$$\partial L/\partial f_{h,i}^{D,r} = C_{h,i}^{D,r} - \alpha_{h,i} - \varphi_{h,i}^{D,r} = 0 \quad \forall r\in R_{h,i}^D, (h,i)\in W_0 \quad (30)$$

$$\partial L/\partial f_{h,i}^{T,r} = C_{h,i}^{T,r} - \alpha_{h,i} - \sum_{k\in K}\sum_{p\in P_k}\gamma_p^k \delta_{h,i}^{p,r} - \sum_{a\in A_{HP}^2}\eta_a\delta_{h,i}^{a,r} - \varphi_{h,i}^{T,r} = 0 \quad \forall r\in R_{h,i}^T, (h,i)\in W_0 \quad (31)$$

$$\partial L/\partial f_{i,j}^{D,r} = C_{i,j}^{D,r} - \beta_{i,j} - \kappa_{i,j}^{D,r} = 0 \quad \forall r\in R_{i,j}^D, (i,j)\in W\setminus W_0 \quad (32)$$

$$\partial L/\partial f_{i,j}^{T,r} = C_{i,j}^{T,r} - \beta_{i,j} - \sum_{k\in K}\sum_{p\in P_k}\gamma_p^k \delta_{i,j}^{p,r} - \sum_{a\in A_P^2}\mu_a\delta_{i,j}^{a,r} - \kappa_{i,j}^{T,r} = 0 \quad \forall r\in R_{i,j}^T, (i,j)\in W\setminus W_0 \quad (33)$$

$$0 \le \sum_{r\in R_{h,i}^D} f_{h,i}^{D,r} + \sum_{r\in R_{h,i}^T} f_{h,i}^{T,r} - \bar{q}_{h,i} \perp \alpha_{h,i} \ge 0 \quad \forall (h,i)\in W_0 \quad (34)$$

$$0 \le \sum_{r\in R_{i,j}^D} f_{i,j}^{D,r} + \sum_{r\in R_{i,j}^T} f_{i,j}^{T,r} - \bar{q}_{i,j} \perp \beta_{i,j} \ge 0 \quad \forall (i,j)\in W\setminus W_0 \quad (35)$$

$$0 \le x_p^k - \sum_{(h,i)\in W_1}\sum_{r\in R_{h,i}^T}\delta_{h,i}^{p,r} f_{h,i}^{T,r} - \sum_{(i,j)\in W_2}\sum_{r\in R_{i,j}^T}\delta_{i,j}^{p,r} f_{i,j}^{T,r} \perp \gamma_p^k \ge 0 \quad \forall p\in P_k, k\in K \quad (36)$$

$$0 \le v_a - \sum_{(h,i)\in W_0}\sum_{r\in R_{h,i}^T}\delta_{h,i}^{a,r} f_{h,i}^{T,r} \perp \eta_a \ge 0 \quad \forall a\in A_{HP}^3 \quad (37)$$

$$0 \le v_a - \sum_{(i,j)\in W\setminus W_0}\sum_{r\in R_{i,j}^T}\delta_{i,j}^{a,r} f_{i,j}^{T,r} \perp \mu_a \ge 0 \quad \forall a\in A_P^3 \quad (38)$$

$$0 \le f_{h,i}^{D,r} \perp \varphi_{h,i}^{D,r} \ge 0 \quad \forall r\in R_{h,i}^D, (h,i)\in W_0 \quad (39)$$

$$0 \le f_{h,i}^{T,r} \perp \varphi_{h,i}^{T,r} \ge 0 \quad \forall r\in R_{h,i}^T, (h,i)\in W_0 \quad (40)$$

$$0 \le f_{i,j}^{D,r} \perp \kappa_{i,j}^{D,r} \ge 0 \quad \forall r\in R_{i,j}^D, (i,j)\in W\setminus W_0 \quad (41)$$

$$0 \le f_{i,j}^{T,r} \perp \kappa_{i,j}^{T,r} \ge 0 \quad \forall r\in R_{i,j}^T, (i,j)\in W\setminus W_0 \quad (42)$$

Constraints (30) -(42) are the lower-level complementary slack conditions, where constraints (34)-(42) are complementary constraints. As an example, complementary constraint (42) denotes $f_{i,j}^{T,r} \ge 0, \kappa_{i,j}^{T,r} \ge 0$ and $f_{i,j}^{T,r}\kappa_{i,j}^{T,r} = 0$. Since the above MPEC problem is a nonlinear programming problem with complementary constraints, it is difficult to solve it by general nonlinear optimization methods. Therefore, a disjunctive constraints approach proposed by Fortuny-Amat and McCarl (1981) is applied to convert complementary constraints (34)-(42) into linear constraints, then, the above MPEC problem is reformulated as a MILP problem which can be solved by MILP solvers. By way of an example, for complementary constraint (42): $0 \le f_{i,j}^{T,r} \le \chi_{i,j}^{T,r}\Psi_{i,j}^{T,r}$, $0 \le \kappa_{i,j}^{T,r} \le \left(1-\chi_{i,j}^{T,r}\right)\Theta_{i,j}^{T,r}$, $\chi_{i,j}^{T,r} \in \{0,1\}$, where $\Psi_{i,j}^{T,r}$ and $\Theta_{i,j}^{T,r}$ are large values that place no restrictions on $f_{i,j}^{T,r}$ and $\kappa_{i,j}^{T,r}$ when $\chi_{i,j}^{T,r}$ is one or zero, respectively.

4.3 Robust optimization model

The purpose of robust optimization is to find such a feasible solution that satisfies all constraints for any logistics demand and makes the objective function optimal. Let the uncertain demand $\tilde{\mathbf{q}} = \left(\tilde{q}_{o,d}, (o,d)\in W\right)$ varying in a given nonempty compact convex set Ω . Suppose the uncertain demand $\tilde{\mathbf{q}}$ falls in a box (interval) uncertainty set. Specifically, $\tilde{\mathbf{q}} = \bar{\mathbf{q}} + \boldsymbol{\rho}\bullet\hat{\mathbf{q}} \in \Re^{|W|} : \boldsymbol{\rho}\in[0,1]^{|W|}$, where $\bar{\mathbf{q}}$ and $\hat{\mathbf{q}}$ are the lower-bound and upper bound of uncertain demand $\tilde{\mathbf{q}}$, and $\boldsymbol{\rho}$ is demand uncertainty vector used to evaluated the degree of conservatism of the decision maker (Ben-Tal et al., 2004). Then, the robust counterpart (RC) model of the deterministic MPEC problem is stated as follows.

$$\begin{aligned}(RC)\ \underset{\mathbf{X,Y,Z,f}}{Max} & \sum_{(h,i)\in W_0}\sum_{r\in R_{h,i}^T} f_{h,i}^{T,r} + \sum_{(i,j)\in W\setminus W_0}\sum_{r\in R_{i,j}^T} f_{i,j}^{T,r} + \sum_{(h,i)\in W_0}\sum_{r\in R_{h,i}^T}\sum_{a\in A_{HP}^3}\delta_{h,i}^{a,r} f_{h,i}^{T,r} \\ & + \sum_{(i,j)\in W\setminus W_0}\sum_{r\in R_{i,j}^T}\sum_{a\in A_P^3}\delta_{i,j}^{a,r} f_{i,j}^{T,r} - \theta\sum_{k\in K}\sum_{p\in P_k} x_p^k - \varpi\sum_{a\in A_{HP}^3\cup A_P^3} y_a c_a\end{aligned} \tag{43}$$

subject to constrains (1)-(8), (10)-(17), (29)-(32), (35)-(41), and

$$E_0 = \sum_{(h,i)\in W_0}\sum_{r\in R_{h,i}^D} e_0 d_a\left(\overline{q}_{h,i} + \hat{q}_{h,i}\right) + \sum_{(i,j)\in W\setminus W_0}\sum_{r\in R_{i,j}^D} e_0 d_a\left(\overline{q}_{i,j} + \hat{q}_{i,j}\right) \tag{44}$$

$$0 \le \sum_{r\in R_{h,i}^D} f_{h,i}^{D,r} + \sum_{r\in R_{h,i}^T} f_{h,i}^{T,r} - \left(\overline{q}_{h,i} + \hat{q}_{h,i}\right) \perp \overline{\alpha}_{h,i} \ge 0 \quad \forall (h,i)\in W_0 \tag{45}$$

$$0 \le \sum_{r\in R_{i,j}^D} f_{i,j}^{D,r} + \sum_{r\in R_{i,j}^2} f_{i,j}^{T,r} - \left(\overline{q}_{i,j} + \hat{q}_{i,j}\right) \perp \overline{\beta}_{i,j} \ge 0 \quad \forall (i,j)\in W\setminus W_0 \tag{46}$$

Note that equations (44)-(46) are the robust counterpart regarding the demand uncertainty of (18), (33) and (34), respectively. Since the above robust counterpart model requires all decision variables to be feasible for all values of uncertain demand, it may lead to an overly conservative solution. Inspired by this, a control parameter Γ proposed by Bertsimas and Sim (2004) was applied to reduce the conservatism of the robust counterpart model and to obtain a relatively satisfactory solution, but the degree of risk aversion of the decision maker in uncertain environment was not considered. Risk aversion is a concept in economics, finance, and psychology that explains the behavior of the decision maker in uncertain situations. Define $\Gamma_0 = \sum_{(h,i)\in W_0}\rho_{h,i} + \sum_{(i,j)\in W\setminus W_0}\rho_{i,j}$ as the summation of all uncertain elements in vector $\boldsymbol{\rho}$, and it satisfies $\Gamma_0 \le \Gamma$ where overall control parameter $\Gamma(\Gamma > 0)$ denotes the degree of overall conservatism of logistics authority in dealing with uncertain demands. For each uncertain variable $\rho_{o,d}, \forall (o,d)\in W$, Let deviation parameter $\varepsilon_{o,d} = \left|\rho_{o,d} - \Gamma / (|W|)\right| / |1-0|$ measures how far from the nominal average value its values typically are, where $|W|$ is the number of uncertain variables, $\Gamma / (|W|)$ is the nominal average value of all uncertain variables under the control parameter Γ, and $|1-0|$ denotes the maximum interval length value of each uncertain variables. In order to facilitate the model solution and fairness, it is assumed that each deviation parameters satisfy the condition $\varepsilon_{o,d} \le \varepsilon, \forall (o,d)\in W$, where individual control parameter $\varepsilon(0 \le \varepsilon \le 1)$ denotes the degree of the logistics authority's risk aversion in dealing with deviations from each deviation parameters. The higher the individual control parameter, the lower the risk aversion level of logistics authority. In particular, when ε is equal to 0, the decision maker is extremely risk averse; on the contrary, when ε is equal to 1, the decision maker is extremely risk preference. In summary, overall control parameter Γ is used to measure the overall demand uncertainty of regional logistics system. On this basis, individual control parameter ε is used to measure the uncertainty of each uncertain demand. Then the RC model is rewritten into the following adjustable robust counterpart (ARC) model.

$$\begin{aligned}(ARC)\ \underset{\mathbf{X,Y,Z,f}}{Max} & \sum_{(h,i)\in W_0}\sum_{r\in R_{h,i}^T} f_{h,i}^{T,r} + \sum_{(i,j)\in W\setminus W_0}\sum_{r\in R_{i,j}^T} f_{i,j}^{T,r} + \sum_{(h,i)\in W_0}\sum_{r\in R_{h,i}^T}\sum_{a\in A_{HP}^3}\delta_{h,i}^{a,r} f_{h,i}^{T,r} \\ & + \sum_{(i,j)\in W\setminus W_0}\sum_{r\in R_{i,j}^T}\sum_{a\in A_P^3}\delta_{i,j}^{a,r} f_{i,j}^{T,r} - \theta\sum_{k\in K}\sum_{p\in P_k} x_p^k - \varpi\sum_{a\in A_{HP}^3\cup A_P^3} y_a c_a\end{aligned} \tag{47}$$

subject to constraints (2)-(9), (11)-(18), (30)-(33), (36)-(42) and

$$E_0 = \sum_{(h,i)\in W_0}\sum_{r\in R_{h,i}^D} e_0 d_a\left(\overline{q}_{h,i} + \rho_{h,i}\hat{q}_{h,i}\right) + \sum_{(i,j)\in W\setminus W_0}\sum_{r\in R_{i,j}^D} e_0 d_a\left(\overline{q}_{i,j} + \rho_{i,j}\hat{q}_{i,j}\right) \tag{48}$$

$$0 \le \sum_{r\in R_{h,i}^D} f_{h,i}^{D,r} + \sum_{r\in R_{h,i}^T} f_{h,i}^{T,r} - \left(\overline{q}_{h,i} + \rho_{h,i}\hat{q}_{h,i}\right) \perp \overline{\alpha}_{h,i} \ge 0 \quad \forall (h,i)\in W_0 \tag{49}$$

$$0 \le \sum_{r\in R_{i,j}^D} f_{i,j}^{D,r} + \sum_{r\in R_{i,j}^2} f_{i,j}^{T,r} - \left(\overline{q}_{i,j} + \rho_{i,j}\hat{q}_{i,j}\right) \perp \overline{\beta}_{i,j} \ge 0 \quad \forall (i,j)\in W\setminus W_0 \tag{50}$$

$$\sum_{(h,i)\in W_0}\rho_{h,i} + \sum_{(i,j)\in W\setminus W_0}\rho_{i,j} \le \Gamma \tag{51}$$

$$\left|\rho_{h,i} - \Gamma / (|W|)\right| \le \varepsilon, \forall (h,i)\in W_0 \tag{52}$$

$$\left|\rho_{i,j} - \Gamma / \left(|W|\right)\right| \leq \varepsilon, \forall (i,j) \in W \setminus W_0 \tag{53}$$

$$\forall \boldsymbol{\rho} \in [0,1]^{|W|} \tag{54}$$

It is clear by the construction of adjustable robust counterpart model that if the sum of the elements of the uncertain vector $\boldsymbol{\rho}$ is not greater than the overall control parameter Γ and each deviation parameter $\varepsilon_{o,d}$ of uncertain demand $\tilde{q}_{o,d}, (o,d) \in W$ is not greater than the individual control parameter ε, then the solution of the ARC problem will remain feasible. However, compared with the original uncertainty set $\tilde{Q}$, the ARC model may violate some constraints and have no solution with a certain probability. Therefore, the parameter Γ and ε combined control the trade-off between the objective function of the uncertain problem and the probability of violation.

Let $\left(\mathbf{X}^*_{\Gamma,1}, \mathbf{Y}^*_{\Gamma,1}, \mathbf{Z}^*_{\Gamma,1}, \mathbf{f}^*_{\Gamma,1}, \boldsymbol{\rho}^*_{\Gamma,1}\right)$ be an set of optimal solutions of ARC model corresponding to the given control pair $(\Gamma, \varepsilon = 1)$, where $\varepsilon = 1$ denotes the logistics authority tend to design regional logistics networks without risk preference restrictions. Given the overall control parameter Γ, If demand uncertainty parameters $\rho_{o,d}, (o,d) \in W$ are *independent and uniformly distributed random variables* on $[0,1]$, then the maximum probability of satisfying the demand constraint (54) is as follows:

$$\Pr_\Gamma = \Pr\left(\Gamma_0 \leq \Gamma\right) = \begin{cases} \dfrac{1}{|W|!} \displaystyle\sum_{j=0}^{\lfloor \Gamma \rfloor} (-1)^j \binom{|W|}{j} (\Gamma - j)^{|W|}, & \Gamma < |W| \\ 1, \quad \Gamma \geq |W| \end{cases} \tag{55}$$

Where $\lfloor \Gamma \rfloor$ represents the greatest integer less than or equal to Γ. Equation (55) is the probability that the uncertain vector $\boldsymbol{\rho}$ satisfies the constraint (51) under the given the overall control parameter Γ. The probability calculation formula (55) is similar to but different from that described in Bertsimas and Sim (2004). It is an exact expression for the maximum probability boundary, not an approximate one. For detailed proofs for the above probability, the reader can refer to the paper (Lugannani and Rice, 1980).

Define $\Pr_{o,d}(\Gamma, \varepsilon)$ as the individual probability of each uncertain demand $\tilde{q}_{o,d}, (o,d) \in W$ satisfying the demand constraints (49)-(53) under control pair (Γ, ε). Then, it is calculated as follows:

$$\begin{aligned} \Pr_{o,d}(\Gamma, \varepsilon) &= \Pr\left\{\left(\tilde{q}_{o,d} \leq \bar{q}_{o,d} + \rho^{*(o,d)}_{\Gamma,1} \hat{q}\right) \cap \left(\varepsilon_{o,d} \leq \varepsilon\right) \cap \left(\Gamma_0 \leq \Gamma\right)\right\} \\ &= \Pr\left\{\left(\rho_{o,d} \leq \rho^{*(o,d)}_{\Gamma,1}\right) \cap \left(\Gamma / \left(|W|\right) - \varepsilon \leq \rho_{o,d} \leq \Gamma / \left(|W|\right) + \varepsilon\right)\right\} \\ &= \begin{cases} \Pr\left\{\max\left(\Gamma / \left(|W|\right) - \varepsilon, 0\right) \leq \rho_{o,d} \leq \Gamma / \left(|W|\right) + \varepsilon\right\}, & \Gamma / \left(|W|\right) + \varepsilon \leq \rho^{*(o,d)}_{\Gamma,1} \\ \Pr\left\{\max\left(\Gamma / \left(|W|\right) - \varepsilon, 0\right) \leq \rho_{o,d} \leq \rho^{*(o,d)}_{\Gamma,1}\right\}, & \max\left(\Gamma / \left(|W|\right) - \varepsilon, 0\right) \leq \rho^{*(o,d)}_{\Gamma,1} \leq \Gamma / \left(|W|\right) + \varepsilon \\ 0, \quad \rho^{*(o,d)}_{\Gamma,1} \leq \max\left(\Gamma / \left(|W|\right) - \varepsilon, 0\right) \end{cases} \end{aligned} \tag{56}$$

From equation (56), the individual control parameter ε greatly affects the probability of each uncertain demand $\tilde{q}_{o,d}, (o,d) \in W$. To describe the effect of individual control parameter ε on feasible solutions of the ARC problem, the weighted arithmetic mean (WAM) is introduced as its evaluation index, which is described as follows.

$$WAM(\varepsilon \mid \Gamma) = \frac{\sum_{(o,d) \in W} \left(\sigma^{\Gamma,\varepsilon}_{o,d} \rho^{*(o,d)}_{\Gamma,1}\right)}{\sum_{(o,d) \in W} \rho^{*(o,d)}_{\Gamma,1}} \tag{57}$$

where $\sigma^{\Gamma,\varepsilon}_{o,d} = \max(\rho^{*(o,d)}_{\Gamma,1} - \Gamma / \left(|W|\right) - \varepsilon, 0) + \max\left(\Gamma / \left(|W|\right) - \varepsilon, 0\right)$ is the length of the interval of each uncertain demand $\tilde{q}_{o,d}, (o,d) \in W$ that violate the constraints (52) and (53).

5. Case Study

To examine the impacts of uncertain control parameters on the decisions, the proposed models and solution methods were tested on a regional logistics network of the Changsha-Zhuzhou-Xiangtan City Cluster, Hunan Province, China. The models were implemented and solved with the optimization solver Cplex using Yalmip package in Matlab platform. All computational experiments reported in this study are conducted on a single-thread of an Intel Core I7-2600 (3.40 GHz) processor with 8 GB of available RAM. All default options for the solver remain unchanged except for the optimality gap tolerances set to zero.

5.1 Data and parameter settings

As depicted in Fig. 3, the regional logistics network of the Changsha-Zhuzhou-Xiangtan City Cluster consists of 35 nodes, 864 paths and 56 O-D pairs. The total budget should not exceed ¥1 billion per year. The logistics authority plans to make a unified plan on the number and capacity of 14 candidate logistics parks in the regional logistics system of the urban cluster, as well as the subsidy rate of railway transportation link. Shortest distance between two nodes using different modes of transport, inter-regional O-D demand, inter-city O-D demand and parameters relating to means of transports are mainly listed in Appendix Tables 2-6. In addition, the value of time is ¥15 per hour. The minimum construction processing capacity of candidate logistics parks is 4 million tons per year. The maximum subsidy rate is 30%. The unit construction cost per unit of processing capacity at logistics parks is ¥5 per ton-year. The national carbon reduction target is 60%. In the computational experiments, the railway has the capacity constraint, and its maximum capacity is 2 million tons per year.

(Insert Fig. 3 here)

5.2. Results and discussions

Uncertain control parameters control the conservative level of the robust solution to achieve an expected robustness level. In this section the overall control parameter Γ is considered to vary between 5 and 55 with step size of 5 and the individual control parameter ε is considered to vary between 0 and 1 with step size of 0.1. The performance and solution quality of the proposed robust optimization method with respect to the uncertain control parameters are tested. It is divided into two parts: evaluating the effectiveness of the proposed robust model and analyzing the regional network design performance under the combination of uncertain parameters. To illustrate the effectiveness of the proposed robust model, as shown in Fig. 4, the accurate bound (55) is compared with the exponential distribution bound proved by Bertsimas and Sim (2004), and the effect of different control parameter combinations on the WAM is formulated. Next, the robust network design solutions for different control parameter combinations are reported in Figs. 5-8.

The first part of the tests aims to analyze the validity of the accurate bound (55) and the impact of the risk aversion level of the decision maker on the decisions. Control-based solution method proposed by Bertsimas and Sim (2004) is a tailor-made technique for box uncertainty optimization problem, and an exponential distribution is used to approximate the maximum satisfaction probability. One of its key operations is how to choose appropriate overall control parameter to balance the robustness of the robust model and the maximum satisfaction probability of the solution. However, the probability of exponential distribution calculation may be overly optimistic, and this method does not take into account the risk aversion of the decision maker. As shown in Fig. 4(a), a notable result is that it is not necessary to set the overall control parameter as high as possible in order to satisfy the maximum satisfaction probability of the solution. If it is set too large, the solution is too robust, resulting in wasted resources. On the contrary, the solution is not robust enough to meet uncertain demands. For instance, by setting the overall control parameter for the test problem at about 35, the maximum satisfaction probability calculated by the three probability bounds is almost 100%. In addition, when $\Gamma = 25$, the probability calculated by using exponential bound, accurate bound and normal distribution bound is 98%, 1.0% and 0.95%, respectively. According to mathematical statistics theory, when $\Gamma = 25$, the probability does not exceed 3%. This proves that the probability calculated by the exponential distribution boundary is too optimistic, but the accurate bound and normal distribution bound are reasonable and almost the same order of magnitude. One advantage of the accurate bound is that it does not require repeated random sampling, so it is easier to calculate than the normal distribution bound based on sample statistics.

(Insert Fig. 4 here)

(Insert Fig. 5 here)

Moreover, the degree of risk aversion of the decision maker plays an important role in decision making under uncertain environments. As illustrated in Fig. 4(b), given the overall control parameter Γ, the WAM increases as the individual control parameter ε decrease. This general trend can be explained by the fact that the decision maker use risk aversion to counter the uncertainty of each O-D demand. For example, the minimum value (ε=0) corresponds to the extreme risk aversion of the decision maker. It is expected that the uncertain budget (overall control parameters) is evenly distributed to each O-D demand. Furthermore, it is observed from Figs. 5-7 that the individual control parameter can significantly affect the robustness of robust model. This reveals that when making decisions in an uncertain environment, the decision maker should consider both the degree of conservatism of the robust counterpart model (Γ) and the degree of risk aversion of the decision maker (ε), rather than ignoring the latter. Based on the aforementioned discussion, the proposed robust optimization method is effective and feasible, and can provide references for network design under uncertain environments.

The next goal of this test is to analyze the design performance of regional low-carbon network under the combination of uncertain parameters. It can be seen from Fig. 5(a) that increasing the degree of conservatism of the robust counterpart model (Γ) or the degree of risk aversion of the decision maker (ε) results in greater values of the ARC objective function. This is an expected outcome, because as the value of Γ or ε increases, the solution can better tolerate fluctuations in demand, resulting in more robust routing assignment and park construction decisions (see Figs. 6-8). Not surprisingly, the curves of the total cost including investment and subsidies, total construction investment and total construction scale of logistics parks have the same shape as the objective functions. Given the value of Γ, the ARC objective function increases with ε, but is only significantly affected when ε is less than 0.5. This again reveals that the risk aversion of the logistics authority can effectively regulate the robustness of logistics network design. In addition, the total increment of the objective function affected parameter ε by in the Γ direction presents the characteristics of high in the middle and low on both sides, which also represents risk-return for the decision maker. Therefore, when the value of Γ is very small or very large, the logistics authority is not suitable to increase the risk investments.

(Insert Fig. 6 here)

The actual carbon emission reduction rate is an important standard to measure the sustainable development of regional logistics in the context of the national carbon reduction target. As is displayed in Fig. 5(b), the actual carbon emissions reduction rate $\left(1-E_1/E_0\right)$ of the regional logistics network decreases with the increase of the overall control parameter Γ. For instance, when $\varepsilon=0$, from $\Gamma=5$ to $\Gamma=55$, the actual carbon emissions reduction rate is reduced from 64.5% to 60.6%, a 6 percent decrease. This reveals an interesting insight: in the allocation of limited resources, individuals with superior conditions will have priority. Given the overall control parameter Γ, the logistics authority tends to prioritize the allocation of quota (uncertainty) to the O-D demand that actually reduces carbon emissions when making decisions. With the increase of Γ, the competition of resources is constantly weakened, and the allocation amount of each O-D demand tends to mean. For this reason, the individual control parameter ε is introduced to measure the risk level of uncertain allocation. In addition, the actual carbon emission reduction rate is related to the proportion of different types of transportation routes. As illustrated in Fig. 1(b), the logistics carrier can transport freight by three types of routes: light truck direct transport, heavy truck transfer transport and railway transfer transport. In general, the largest amount of carbon emissions from transporting unit freight at the same distance is the first type, followed by the second type, and the smallest is the third type. However, the logistics carrier is rational when choosing transport routes, that is, the routes with the lowest cost, not the routes with the lowest carbon emissions. Therefore, in order to meet the national carbon emission target, the logistics authority needs to adopt low-carbon measures to reduce the cost of low-carbon transport routes.

(Insert Fig. 7 here)

Fig. 6 presents the comparison results of total flows and its composition for different ε values as a function of Γ. The results show that increasing the value of ε has little effect on the total flows in the regional logistics system, but it can effectively change the distribution of flows in different transportation routes and reduce carbon emissions. This is because the total flows is mainly controlled by the parameter Γ, while the flow route distributions is controlled by both the parameters Γ and ε. Moreover, the size of Γ value directly affects the layout of logistics parks (see Figs. 7(c), 7 (d) and 8). As shown in Figs. 7(a) and (d), with the increase of Γ value, more conservative logistics park layout and cost are needed to counter the uncertainty of total demand and further change the route distributions of O-D demand. In detail, the total number of logistics parks to be configured in the regional logistics network is 8 or 9, because the No. 20 logistics park may not be built (Fig. 8). Here, City 1 will build parks 5, 7 and 8, city 2 will build parks 19, (20) and 21, and city 3 will build parks 28, 29 and 30. The Γ value is too small, which means that the layout of the logistics parks fails to meet the uncertain demand, resulting in large flows will be served by direct transport routes that generate high carbon emissions. On the contrary, Γ value is too large, which will leave a lot of logistics facilities idle. Therefore, it is necessary to set a reasonable Γ value for the low-carbon and sustainable development of regional logistics. On the other hand, with the increase of ε value, the share of direct transport routes with high carbon emission can be effectively reduced, while the share of transfer routes with low carbon emission can be increased (Fig. 6). Moreover, Fig. 7(b) illustrates the total subsides for railway transport links taken from these experiments fluctuates between ¥33.6 million/year and ¥37.4 million/year. These confirm the fact that the logistics authority controls the distribution of flows on different types of routes and reduces the negative externalities of logistics activities on the environment by adjusting the deviation of each uncertain O-D demand (ε) and the subsidies of the railway transportation links.

5.3 Combined effect of CO_2 reduction target and subsidy rate on the regional logistics network design

In order to evaluate the effect of the national carbon reduction target ϕ_E and the maximum subsidy rate Φ on the green design of regional logistics network, we solve the ARC model for the national carbon reduction targets ranging from 30% to 70% for five the maximum subsidy rates of 0%, 10%, 20%, 30% and 40% with the overall control parameter $\Gamma = 35$ and individual control parameter $\varepsilon = 0.3$.

(Insert Fig. 8 here)

(Insert Fig. 9 here)

It can be observed from Fig. 9(a) that if $\Phi = 0\%$ and $\Phi = 10\%$, the value of ϕ_E in the feasible region of ARC model can reach 55%; if $\Phi = 20\%$, the value of ϕ_E can reach 60%; and if $\Phi = 30\%$ and $\Phi = 40\%$, the value of ϕ_E can reach 65%. Therefore, the increase of Φ value can increase the value range of carbon emission reduction target ϕ_E in the feasible region of ARC model. This also implies that higher value of Φ is needed to meet the higher CO_2 reduction target. As presented in Fig. 9, if the value of ϕ_E is fixed, the ARC objective function value increases as the value of Φ increases, but the required total costs (investment and subsidies) and total construction scale of logistics parks decrease first and then increase. On the other hand, given the value of Φ, the ARC objective function value and the required total costs increase as the value of ϕ_E increases, but the growth rate of the ARC objective function value is greater than that of the required total costs. This is because higher values of Φ or ϕ_E results in a more protected solution through subsidizing or building more logistics parks and change the transportation structure (Figs. 9(c)-(f)). Therefore, With the increase of Φ or ϕ_E, more subsidies and logistics parks would be invested to hedge against the transshipment flows and thus higher level of environmental protection is achieved.

Furthermore, the logistics authority is more concerned about how to achieve the predetermined national carbon reduction target with less cost. As shown in Fig. 9(b), if the national carbon reduction target ϕ_E is no more than 52.5%, the most appropriate subsidy rate boundary Φ is set to 10%; if the value of ϕ_E is greater than 52.5% and no more than 55%, the boundary Φ is set to 0%; if the value of ϕ_E is greater than 55% and no more than 60%, the boundary Φ is set to 20%; if the value of ϕ_E is greater than 60% and no more than

65%, the boundary Φ is set to 30%; and if the value of ϕ_E is greater than 65%, there is no boundary value Φ that satisfies this condition. According to the above analysis, the national carbon reduction target is closely related to the setting of the maximum subsidy rate. When the national carbon reduction target is less than a certain threshold (e.g. 52.5%), the total cost of the regional logistics network under a small subsidy rate boundary is lower than that under no subsidy rate boundary. However, when the national carbon reduction target larger than a certain threshold (e.g. 55%), a higher level of subsidy must be provided to achieve the stringent CO_2 reduction targets. Besides, between these two thresholds (e.g., 52.5%-55%), it is possible that the total cost without subsidy is lower than the total cost with subsidy.

6. Conclusions

One of the most critical strategic decisions in a regional logistics network design is to determine the network configuration of logistics parks and the transportation strategy, which has significant impacts on the sustainability of regional economy and environment. This is a comprehensive design problem due to the multiple stakeholders, the balance between environmental protection and economic development, and the uncertainty of future logistics demands. This study investigated a regional multimodal logistics network design problem with CO_2 emission reduction target and uncertain demands in the context of urban cluster development. A novel bi-level programming model was developed for the proposed regional multimodal logistics network design problem with deterministic demand which considered the realistic constraints such as CO_2 emission reduction target, budget and capacity. To facilitate the analysis of the decision-making behavior of the logistics authority, the developed bi-level programming model was transformed to its equivalent MPEC. Based on the method proposed by Bertsimas and Sim (2004), by introducing individual control parameter Γ to describe the risk aversion level of the decision maker, an improved adjustable robust optimization model was built to simultaneous control the conservative level of the adjustable robust model (Γ) and the risk aversion level of the decision maker (ε). After that, the proposed models and solution methods were tested in an urban cluster of China and solved by Cplex solver.

The case study shows that the proposed robust optimization method is an effective approach to address the regional multimodal logistics network design problem with uncertain demands. However, the actual carbon reduction rate decreases as the overall control parameters increase, due to the increased flow of direct routes in the logistics system. Furthermore, the low-carbon design measures vary significantly with the changing in control parameters. Considering the general nature of regional logistics network design, the below management insights have been identified.

(i) In the multi-stakeholder regional logistics system, each stakeholder exhibits different behaviors in the process of seeking to achieve its own objectives. Game-theoretical model is an effective approach to describe the inherent relationship among the multiple stakeholders. In order to promote the sustainable development of regional logistics and achieve mutual benefit, it is a wise choice to use the game-theoretical model to analyze the decision-making behavior of the logistics authority and the carrier and design coordination measures. As the leader, the logistics authority needs to design corresponding low-carbon measures (such as planning logistics parks and subsidizing rail transport) to reasonably guide the carrier to choose low-carbon transport routes. Since the logistics carrier is rational when choosing transport routes, that is, the routes with the lowest cost, not the routes with the lowest carbon emissions. Therefore, the logistics authority can change the carrier's transportation behavior through low-carbon measures without damaging the interests of the carrier.

(ii) The adjustable robust optimization method is an effective method to cope with decision problems under uncertainty environments by selecting reasonable control parameters is the key to measure its performance. The overall control parameter balances the relationship between model robustness and solution robustness. The logistics authority should set it in a reasonable range because too small will lead to the robust solution that is difficult to resist uncertainty, while too large will cause too conservative robust model and a lot of waste of logistics resources. Moreover, when assigning uncertainty budgets, the logistics authority tends to prioritize the allocation of quota (uncertainty) to the O-D demand that actually reduces carbon emissions. Such preference choices may not be in line with real-world changes in logistics demands and bear significant risks. To adjust the risk level of uncertain allocation, the individual control parameter should also be focused so that the rationality and sustainability of regional logistics system can be dramatically improved.

(iii) In general, the strict carbon reduction rate may result in higher subsidy levels and logistics network configurations. In order to reduce the impact of freight transport on the environment, it is an effective measure for the logistics authority to develop multimodal transport system and increase the subsidy rate of railway transport. In addition, some macro policies such as strengthening low-carbon awareness and developing incentives can be advocated to rationally guide the carrier to choose green transport routes.

Further research can be suggested as follows. First, this study focuses only on the aggregated carbon emissions. It is necessary to consider more detailed measurement methods of different types of transport modes, speeds and weights. Secondly, the competition and cooperation involving more than two players is worth investigating. Finally, the multi-period planning of regional logistics network with demand uncertainty may be more realistic.

Declaration of interest: None.

Appendix: Tables 2-6

(Insert Tables 2-6 here)

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Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Figures

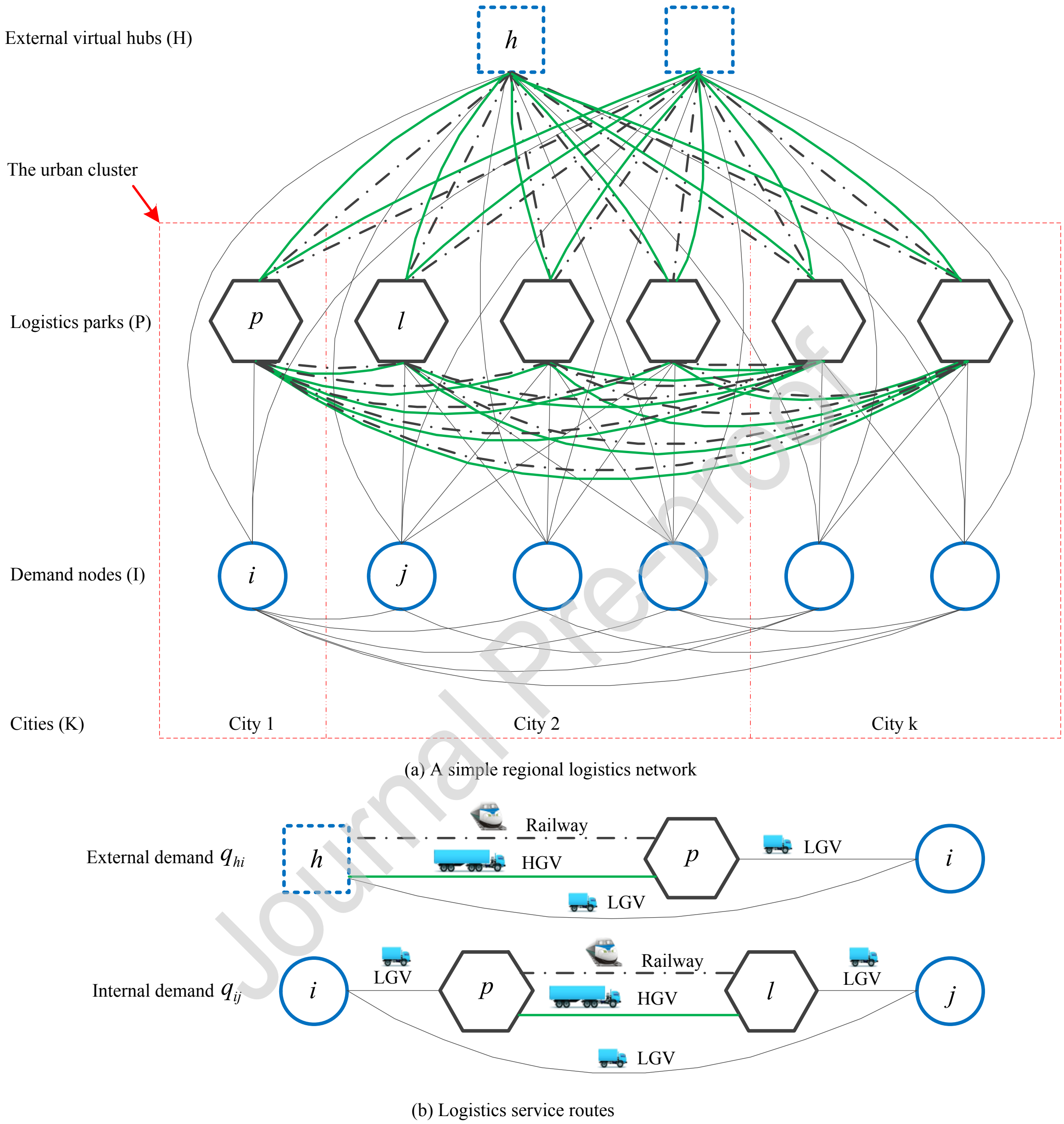

Fig. 1. Network representation of a regional logistics system: **(a)** A simple regional logistics network; **(b)** Logistics service routes.

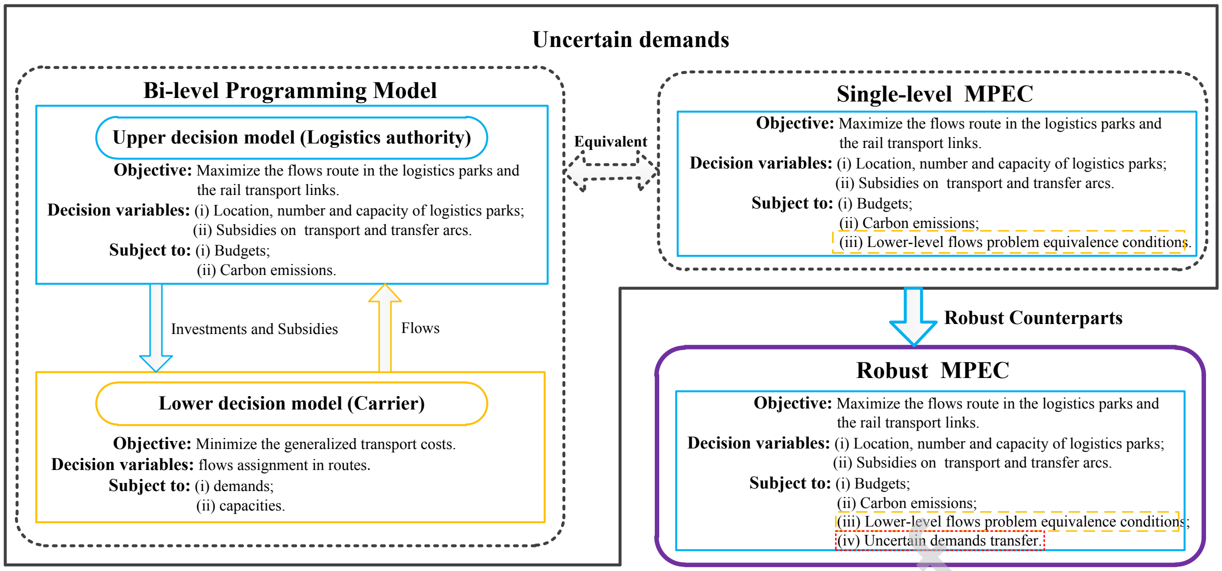

Fig. 2. A robust decision framework of the regional logistics system with uncertain demand.

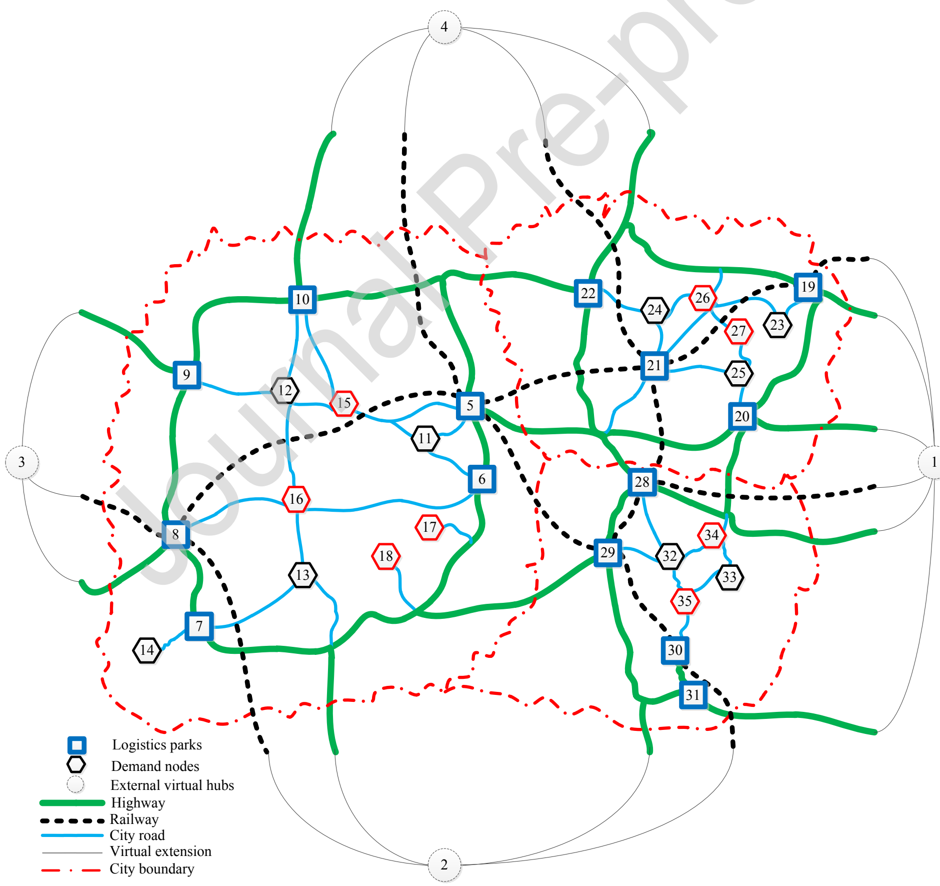

Fig. 3. The regional logistics network of the Changsha-Zhuzhou-Xiangtan City Cluster

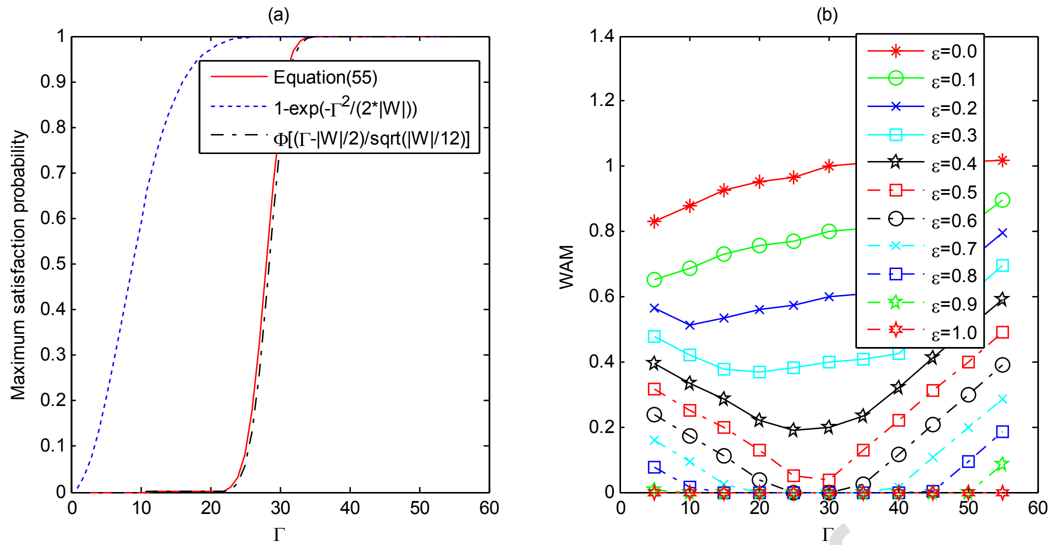

Fig. 4. Comparison of probability bounds and weighted arithmetic mean (WAM) for different ε values as a function of Γ: **(a)** Probability bounds; **(b)** Weighted arithmetic mean (WAM).

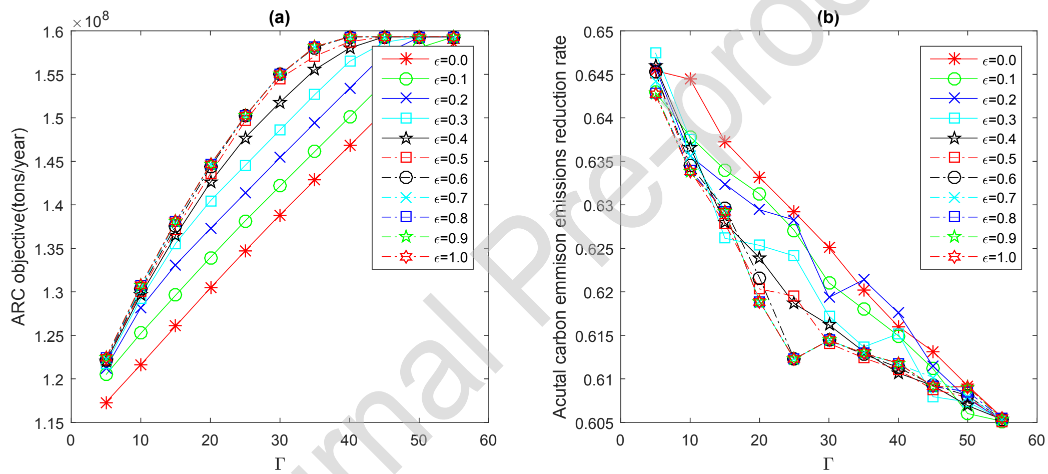

Fig. 5. Comparison of ARC objective function value and actual carbon emissions reduction rate for different ε values as a function of Γ: **(a)** ARC objective function value; **(b)** Actual carbon emissions reduction rate.

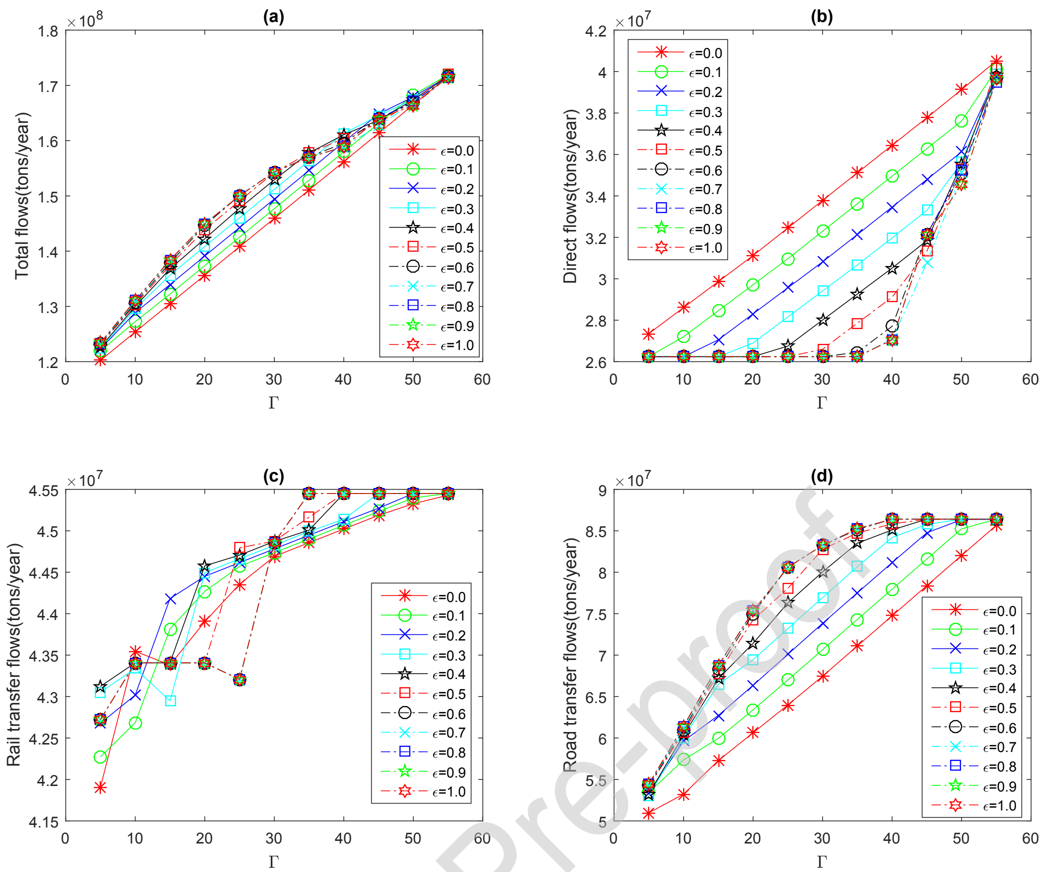

Fig. 6. Comparison of various flows for different ε values as a function of Γ: **(a)** Total flows; **(b)** Direct flows; **(c)** Rail transfer flows; **(d)** Road transfer flows.

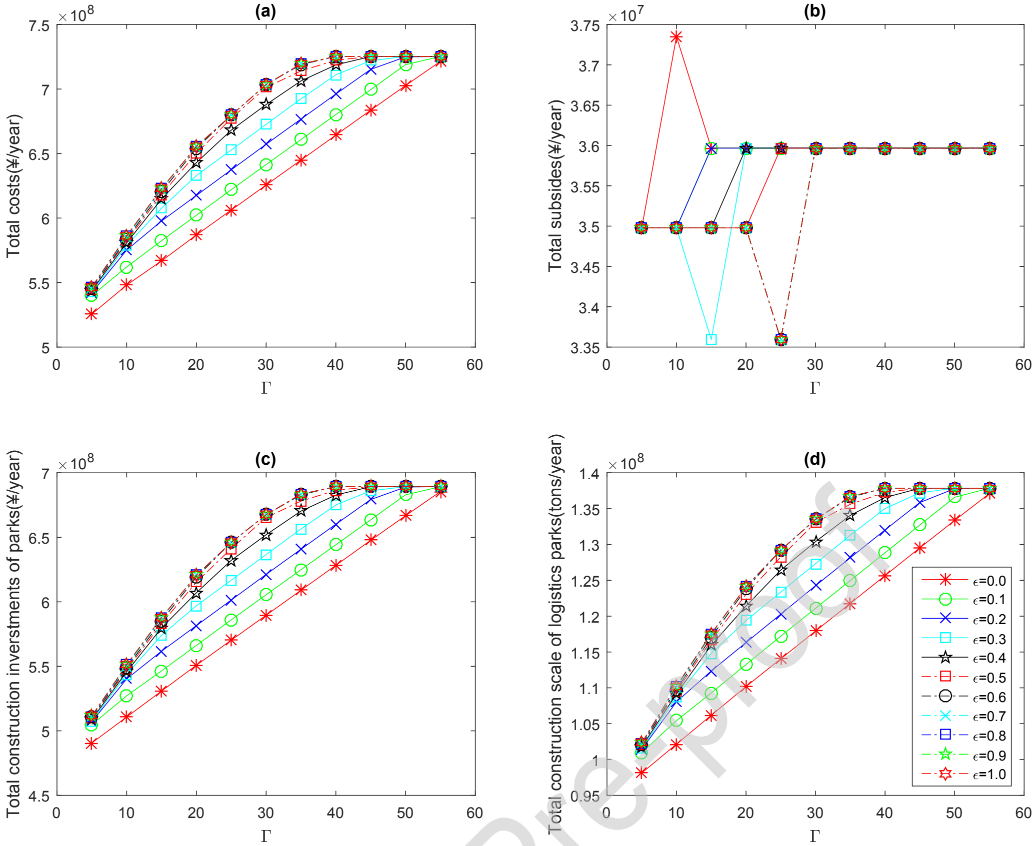

Fig. 7. Comparison of total costs and subsides of regional system, and construction of logistics parks for different ε values as a function of Γ: **(a)** Total costs; **(b)** Total subsides; **(c)** Total construction investments of logistics parks; **(d)** Total construction scale of parks.

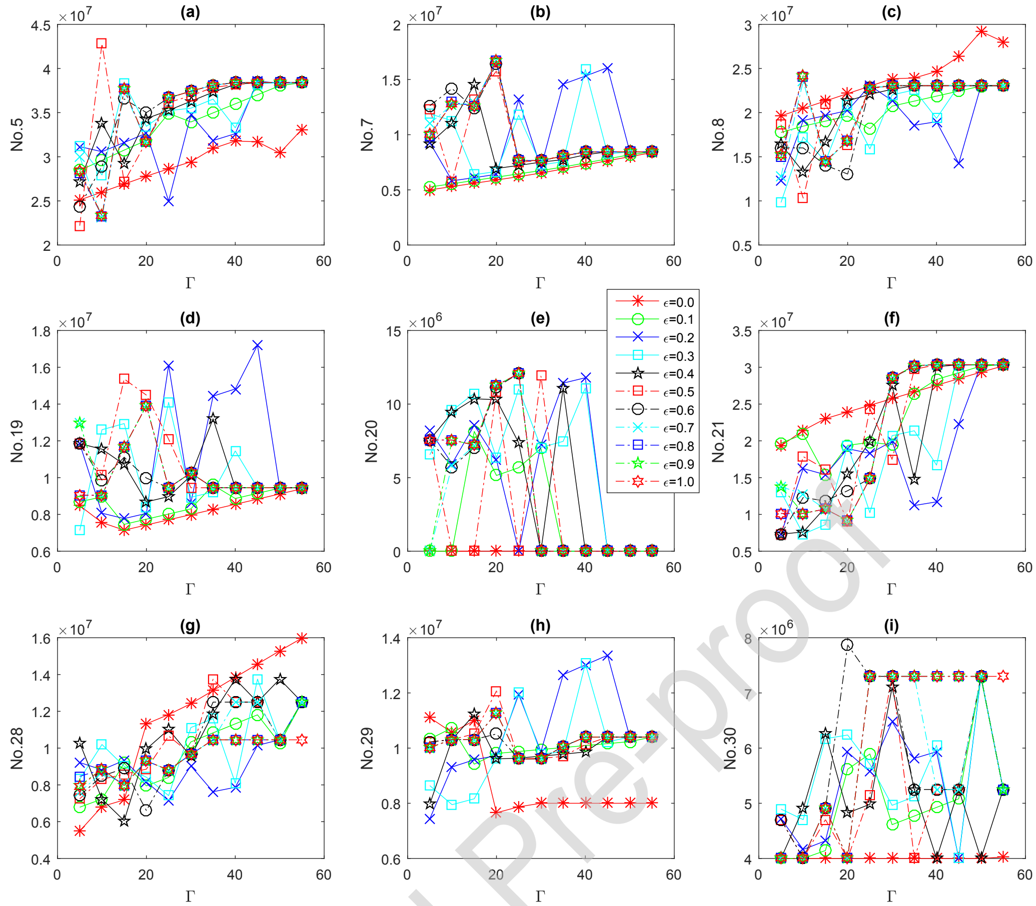

Fig. 8. Comparison of construction scale of logistics parks for different ε values as a function of Γ: **(a)** No. 5 park; **(b)** No. 7 park; **(c)** No. 8 park; **(d)** No. 19 park; **(e)** No. 20 park; **(f)** No. 21 park; **(g)** No.28 park; **(h)** No. 29 park; **(i)** No. 30 park.

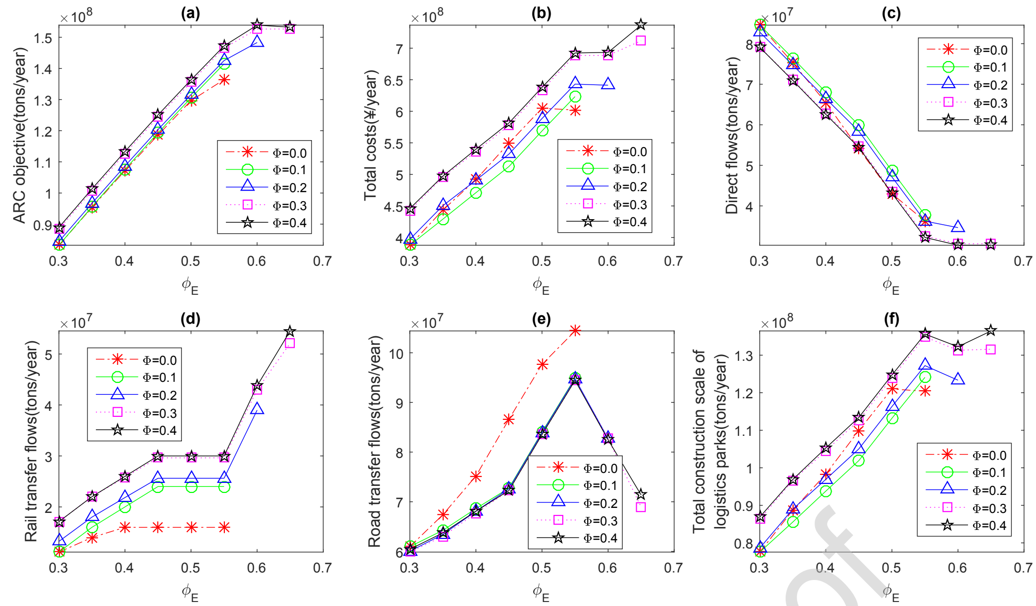

Fig. 9. Comparison of regional green logistics network design for different Φ values as a function of ϕ_E: **(a)** ARC objective value; **(b)** Total costs; **(c)** Direct flows; **(d)** Rail transfer flows; **(e)** Road transfer flows; **(f)** Total construction scale of parks.

Highlights

- A robust regional multimodal logistics network design problem is studied.
- Multi-stakeholder decision behavior is modeled as a novel bi-level programming model.
- An improved robust optimization framework is developed to handle box uncertainty.
- Management insights into multimodal green logistics network design are provided.

Tables

Table 1. Notations

Notation	Description
Sets	
K	set of cities in the study region
N	set of all nodes
P	set of potential logistics parks
I	set of demand nodes
H	set of extra-regional virtual transit hubs
P_k	set of potential logistics parks in the city $k \in K$, $\bigcup_{k\in K} P_k = P$
I_k	set of demand nodes in the city $k \in K$, $\bigcup_{k\in K} I_k = I$
M	set of modes
A	set of all bi-directional links
A_{HP}^{M}	set of all the possible bi-directional links between extra-regional virtual transit hubs and potential logistics parks.
A_{P}^{M}	set of all the possible bi-directional links between potential logistics parks in different cities
A_{I}^{1}	set of all the possible bi-directional links between demand nodes in different cities
A_{PI}^{1}	set of all the possible bi-directional links between potential logistics parks and demand nodes in the same cities
A_{HI}^{1}	set of all the possible bi-directional links between extra-regional virtual transit hubs and demand nodes
A_{PM}^{T}	set of all the possible transfer links at potential logistics
O	set of origin nodes
D	set of destinations nodes
W	set of all logistics origin-destination (O–D) pairs
W_0	set of inter-regional logistics origin-destination (O–D) pairs.
$R_{o,d}^{D}$	set of all direct transport routes connecting O–D pair $(o,d) \in W$
$R_{o,d}^{T}$	set of all transfer transport routes connecting O–D pair $(o,d) \in W$
$R_{o,d}$	set of all transport routes connecting O–D pair $(o,d) \in W$
$\tilde{\mathbf{q}}$	Set of uncertain demand (tons/year)
$\bar{\mathbf{q}}$	the lower-bound of the uncertain demand (tons/year)
$\hat{\mathbf{q}}$	the upper bound of uncertain demand (tons/year)
$\boldsymbol{\rho}$	demand uncertainty vector used to evaluated the degree of conservatism of the decision maker
Parameters	
$\delta_{o,d}^{a,r}$	one if transport route $r \in R_{o,d}$ traverses $a \in A$; zero otherwise
$\delta_{o,d}^{p,r}$	one if transport route $r \in R_{o,d}$ traverses $p \in P$; zero otherwise
$\delta_{p,r}^{b}$	one if transfer transport route $r \in R_{o,d}^{T}$ traverses $p \in P$ and using transfer arc $b \in A_{PM}^{T}$; zero otherwise
$q_{o,d}$	the total demand on all routes $r \in R_{o,d}$ between O–D pair $(o,d) \in W$ (tons/year)

Notation	Description
c_a	transport cost on the transport link $a \in A$ (¥/ton)
t_a	transport time on the transport link $a \in A$ (h)
c_b	transfer cost at the logistics park $p \in P$ (¥/ton)
t_b	transfer time at the logistics park $p \in P$ (h)
π	the value of time (¥/h)
e_m	the average CO_2 emission per unit turnover by transport mode $m \in M$ (kg/ton-km)
d_a	the length of transport link $a \in A$ (km)
$V_{\min}$	the minimum construction processing capacity (tons/year)
Φ	the maximum subsidy rate
c_0	unit construction cost per unit of processing capacity at logistics park (¥/ton-year)
B	the total budget (¥/year)
v_a	the maximum capacity of rail transport link $a \in A_{HP}^3 \cup A_P^3$ (tons/year)
ϕ_E	the national carbon reduction target
Γ	the degree of overall conservatism of logistics authority in dealing with uncertain demands
ε	the degree of the logistics authority's risk aversion in dealing with deviations from each deviation parameters
Decision variables	
$\mathbf{X}$	set of investment capacity for logistics park $p \in P$ in city $k \in K$, $\mathbf{X} := \left(x_p^k, p \in P_k, k \in K\right)$
$\mathbf{Y}$	set of subsidy rate for rail transport link $a \in A_{HP}^3 \cup A_P^3$, $\mathbf{Y} := \left(y_a, a \in A_{HP}^3 \cup A_P^3\right)$
$\mathbf{Z}$	set of binary decision variables of whether logistics park $p \in P_k$ is established in city $k \in K$, $\mathbf{Z} := \left(z_p^k, p \in P_k, k \in K\right)$
$\mathbf{f}$	set of flow assignment plans determined by the carrier $\mathbf{f} := \left(f_{o,d}^r, r \in R_{o,d}, (o,d) \in W\right)$

Table 2. Shortest distance between two nodes by HGV (LGV) (km)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35
1	0	614	856	646	487	487	521	522	518	499	494	507	506	525	503	508	492	501	438	447	457	463	441	456	447	451	447	460	465	459	458	458	451	452	457
2	614	0	716	776	403	400	387	397	414	418	401	410	385	385	406	401	391	388	411	397	404	413	409	409	403	413	406	391	384	373	367	382	381	384	379
3	856	716	0	338	402	405	387	380	372	385	398	383	399	384	388	388	405	400	441	440	428	418	439	427	438	429	436	432	432	443	447	439	445	443	441
4	646	776	338	0	373	377	391	381	363	358	375	366	392	393	370	376	385	388	375	385	377	366	375	372	380	369	377	388	395	407	413	398	400	398	401
5	487	403	402	373	0	4	38	36	32	18	7	20	27	44	16	21	13	21	50	41	31	26	46	32	41	37	41	30	30	42	47	36	42	41	39
6	487	400	405	377	4	0	38	36	33	22	8	22	25	43	17	21	11	19	49	39	30	27	46	32	40	38	40	28	27	39	44	34	40	39	36
7	521	387	387	391	38	38	0	10	27	40	31	29	15	5	27	20	29	20	86	75	67	65	83	70	76	75	77	61	56	63	65	63	69	69	64
8	522	397	380	381	36	36	10	0	18	33	28	21	19	13	22	15	30	22	85	75	66	62	82	68	76	73	76	62	58	67	70	65	72	71	66
9	518	414	372	363	32	33	27	18	0	20	26	12	31	30	16	16	33	30	80	72	62	55	77	63	72	67	72	61	60	71	75	67	73	72	69
10	499	418	385	358	18	22	40	33	20	0	17	12	35	45	13	21	28	31	61	55	44	36	58	44	54	48	53	47	48	60	65	54	60	58	57
11	494	401	398	375	7	8	31	28	26	17	0	15	21	36	10	14	10	15	57	47	38	34	53	40	48	45	48	35	34	45	50	41	47	46	43
12	507	410	383	366	20	22	29	21	12	12	15	0	26	33	5	10	23	23	69	61	50	44	65	51	61	56	60	50	49	60	65	56	62	61	58
13	506	385	399	392	27	25	15	19	31	35	21	26	0	20	22	16	15	6	73	60	53	52	69	56	62	62	63	46	41	48	51	48	54	54	49
14	525	385	384	393	44	43	5	13	30	45	36	33	20	0	32	24	34	25	91	79	72	70	88	75	81	80	82	66	61	67	69	67	74	74	68
15	503	406	388	370	16	17	27	22	16	13	10	5	22	32	0	8	18	18	65	56	46	41	62	48	57	53	56	45	44	55	59	51	57	56	53
16	508	401	388	376	21	21	20	15	16	21	14	10	16	24	8	0	18	14	71	61	52	47	67	53	61	59	62	49	46	56	60	53	60	59	55
17	492	391	405	385	13	11	29	30	33	28	10	23	15	34	18	18	0	9	57	46	38	37	54	41	47	47	48	32	29	38	42	36	42	41	37
18	501	388	400	388	21	19	20	22	30	31	15	23	6	25	18	14	9	0	67	55	47	46	63	50	56	56	57	41	36	45	48	43	50	49	44
19	438	411	441	375	50	49	86	85	80	61	57	69	73	91	65	71	57	67	0	16	19	25	3	17	12	13	9	29	37	43	47	34	32	29	36
20	447	397	440	385	41	39	75	75	72	55	47	61	60	79	56	61	46	55	16	0	12	23	13	15	5	16	9	14	21	27	31	18	17	14	21
21	457	404	428	377	31	30	67	66	62	44	38	50	53	72	46	52	38	47	19	12	0	12	16	5	10	10	10	13	21	31	36	22	24	21	25
22	463	413	418	366	26	27	65	62	55	36	34	44	52	70	41	47	37	46	25	23	12	0	22	9	20	12	18	22	29	41	47	32	35	32	35
23	441	409	439	375	46	46	83	82	77	58	53	65	69	88	62	67	54	63	3	13	16	22	0	14	8	10	6	25	33	40	44	31	29	27	33
24	456	409	427	372	32	32	70	68	63	44	40	51	56	75	48	53	41	50	17	15	5	9	14	0	11	6	9	18	26	36	42	27	28	25	30
25	447	403	438	380	41	40	76	76	72	54	48	61	62	81	57	61	47	56	12	5	10	20	8	11	0	11	4	17	25	32	37	23	22	19	25
26	451	413	429	369	37	38	75	73	67	48	45	56	62	80	53	59	47	56	13	16	10	12	10	6	11	0	8	23	31	41	46	31	32	29	34
27	447	406	436	377	41	40	77	76	72	53	48	60	63	82	56	62	48	57	9	9	10	18	6	9	4	8	0	20	28	35	40	26	26	23	29
28	460	391	432	388	30	28	61	62	61	47	35	50	46	66	45	49	32	41	29	14	13	22	25	18	17	23	20	0	8	19	24	10	14	12	13
29	465	384	432	395	30	27	56	58	60	48	34	49	41	61	44	46	29	36	37	21	21	29	33	26	25	31	28	8	0	13	19	7	14	13	9
30	459	373	443	407	42	39	63	67	71	60	45	60	48	67	55	56	38	45	43	27	31	41	40	36	32	41	35	19	13	0	6	9	11	13	7
31	458	367	447	413	47	44	65	70	75	65	50	65	51	69	59	60	42	48	47	31	36	47	44	42	37	46	40	24	19	6	0	15	15	18	12
32	458	382	439	398	36	34	63	65	67	54	41	56	48	67	51	53	36	43	34	18	22	32	31	27	23	31	26	10	7	9	15	0	7	7	3
33	451	381	445	400	42	40	69	72	73	60	47	62	54	74	57	60	42	50	32	17	24	35	29	28	22	32	26	14	14	11	15	7	0	3	6
34	452	384	443	398	41	39	69	71	72	58	46	61	54	74	56	59	41	49	29	14	21	32	27	25	19	29	23	12	13	13	18	7	3	0	7
35	457	379	441	401	39	36	64	66	69	57	43	58	49	68	53	55	37	44	36	21	25	35	33	30	25	34	29	13	9	7	12	3	6	7	0

Table 3. Shortest distance between two nodes by railway (km)

	1	2	3	4	5	8	19	21	28	29	30
1	0	-	-	-	450	482	405	422	425	429	424
2	-	0	-	-	372	367	379	373	361	355	344
3	-	-	0	-	372	350	407	395	399	399	409
4	-	-	-	0	344	351	346	348	359	364	376
5	450	372	372	344	0	-	46	28	27	27	39
8	482	367	350	351	-	0	79	61	57	54	62
19	405	379	407	346	46	79	0	-	26	34	39
21	422	373	395	348	28	61	-	0	12	19	29
28	425	361	399	359	27	57	26	12	0	-	-
29	429	355	399	364	27	54	34	19	-	0	-
30	424	344	409	376	39	62	39	29	-	-	0

Table 4. Inter-regional O–D demand (10,000 tons/year).

Origin	Destination	Demand	Origin	Destination	Demand
1	11	[300, 450]	3	11	[230, 345]
1	12	[400, 600]	3	12	[320, 480]
1	13	[380, 570]	3	13	[380, 570]
1	14	[350, 525]	3	14	[310, 465]
1	23	[240, 360]	3	23	[300, 450]
1	24	[220, 330]	3	24	[270, 405]
1	25	[270, 405]	3	25	[280, 420]
1	32	[270, 405]	3	32	[230, 345]
1	33	[350, 525]	3	33	[250, 375]
2	11	[60, 90]	4	11	[170, 255]
2	12	[160, 240]	4	12	[290, 435]
2	13	[280, 420]	4	13	[340, 510]
2	14	[80, 120]	4	14	[210, 315]
2	23	[110, 165]	4	23	[250, 375]
2	24	[80, 120]	4	24	[190, 285]
2	25	[120, 180]	4	25	[190, 285]
2	32	[70, 105]	4	32	[160, 240]
2	33	[90, 135]	4	33	[190, 285]

Table 5. Inter-city O–D demand (10,000 tons/year).

Origin	Destination	Demand	Origin	Destination	Demand
15	26	[300, 450]	17	26	[190, 285]
15	27	[70, 105]	17	27	[40, 60]
15	34	[250, 375]	17	34	[150, 225]
15	35	[170, 255]	17	35	[110, 165]
16	26	[280, 420]	18	26	[120, 180]
16	27	[70, 105]	18	27	[30, 45]
16	34	[240, 360]	18	34	[100, 150]
16	35	[160, 240]	18	35	[70, 105]
26	34	[150, 225]	27	34	[180, 270]
26	35	[200, 300]	27	35	[240, 360]

Table 6. Estimated parameters of transport modes.

transport mode	Speed (km/h)	Unit cost (¥/ton-km)	average unit emission (kg/ton-km)	Transfer (by LGV)	
				Unit flow transfer cost (¥/ton)	Unit flow transfer time (h/ton)
LGV	60	0.4	0.283	-	-
HGV	60	0.32	0.132	0.5	0.2
Railway	45	0.25	0.022	1	0.4

(source: Qu et al. (2016); Zhang et al. (2018b))