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CO_2 Emission Efficiency Analysis of Rail-Water Intermodal Transport: A Novel Network DEA Model

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Abstract: How to evaluate the carbon emission efficiency of multimodal transport is an important issue of public concern, and this article attempts to solve it with a network data envelopment analysis (DEA) model. DEA is a method to evaluate the efficiency of homogeneous decision-making units (DMUs). First, this article studies the efficiency decomposition and efficiency aggregation of the general network structure for DEA model. In efficiency decomposition, the relationship between system efficiency and division efficiency is discussed; whereas in efficiency aggregation, the division tendency brought about by the definition of weights is analyzed. Then, a reasonable and single compromise solution to division efficiency scores is investigated while the system efficiency remains optimal. Finally, a two-stage network DEA model of rail-water intermodal transport is established with carbon dioxide (CO_2) emissions as an undesirable output. Based on this model, the rail-water intermodal transport efficiencies of 14 ports in China in 2015 are evaluated by the methods of efficiency decomposition, efficiency aggregation, and non-cooperation. The results show that Rizhao Port, Tangshan Port, Nanjing Port, and Zhuhai Port have set an example to other ports. Qinhuangdao Port, Ningbo-Zhoushan Port, Guangzhou Port, and Beiliang Port need to improve the efficiency of railway transportation. Beibu Gulf port, Zhanjiang Port, Dalian Port, Lianyungang Port, Yantai Port, and Yichang Port should optimize their intermodal system. In addition, Yantai Port and Yichang Port urgently need to improve the port efficiency in low-carbon operation. The network DEA model constructed in this article can be further applied to the efficiency evaluation of multi-link supply chains, and the empirical results can provide a reference for the efficiency evaluation of ports in China.

Keywords: network DEA; carbon dioxide; rail-water intermodal transport; undesirable output

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1. Introduction

In addition to global warming, glacier melting, and sea level rise, the greenhouse effect has caused extreme weather disasters such as floods, droughts and hurricanes and thus become the focus of the world's attention. Among all the gases leading to the greenhouse effect, CO_2 accounts for the largest proportion and is the primary source of the greenhouse effect [1]. The transportation sector is one of the major sectors of fossil fuel consumption and a major source of greenhouse gases like CO_2. Global transport emitted 8222 Mt of CO_2 in 2019, making it the world's second-largest source of carbon emissions after electricity and heat producers, according to data from the International Energy Agency. Therefore, reasonable planning of the transportation sector and active transformation to a low-carbon development mode are of great significance to global CO_2 emission reduction [2].

In China, roads, railways, waterways, and other modes of transportation all have a considerable scale, but these modes are unbalanced in proportion. Low-carbon transport modes such as railways and waterways are underutilized [3]. Compared with a single method of transportation, multimodal transport has the advantages of larger transportation capacity, higher operation efficiency, fewer exhaust emissions, and lower cost, and has become a preferred transportation method, especially in medium- and long-distance transportation. Therefore, the development of multimodal transport can not only relieve traffic pressure and optimize transport structure, but also further enhance the economic and environmental benefits of transport [4,5]. Multimodal transport can convert carbon costs into economic benefits. Transportation companies should therefore try to formulate reasonable transportation plans under the premise of low-carbon economy and low-carbon transportation, which will largely contribute to the reduction in fossil fuel consumption and CO_2 emissions [6,7]. Multimodal transport has become an important means to achieve sustainable economic and social development because of its inherent advantages. Rail-water intermodal transport is a typical representative of multimodal transport. Thus, this article will carry out a case study based on the rail-water intermodal transport in China.

To further improve operations and reduce transportation carbon emissions, it is important to identify specific divisions that lead to transportation inefficiencies by evaluating the efficiency of rail-water intermodal transport. Most existing studies on the efficiency evaluation of multimodal transport focus on land and air transportation, and few focus on rail-water intermodal transport. Moreover, the existing studies mainly analyze the overall situation of the multimodal transport system rather than the internal structure of the system. The network DEA model can evaluate the relative effectiveness of comparable units of the same type through linear programming, which has obvious advantages in analyzing the internal structure and efficiency of the system [8,9]. At present, the DEA is rarely used to study the internal structure of multimodal transport. Therefore, it is of great theoretical and practical significance to adopt the network DEA model to evaluate the efficiency of rail-water intermodal transport. This can expand the application of network DEA. Moreover, it helps to identify inefficient divisions and links, so corresponding improvement measures can be taken to further reduce CO_2 emissions [10].

The research aim of this article is to evaluate the efficiency of rail-water intermodal transport using a novel network DEA model, identify inefficient divisions, and propose corresponding improvement measures. In this article, a network DEA model with an intermediate product and undesirable output is established. The process of rail-water intermodal transport is divided into two production stages: railway and port. The CO_2 emissions from port are regarded as undesirable output. The system and stage efficiency of rail-water intermodal transport is calculated by the methods of efficiency decomposition, efficiency aggregation, and non-cooperation.

The rest of this article is arranged as follows. Section 2 is the literature review. Section 3 presents the efficiency decomposition and aggregation in the network DEA model. Section 4 introduces the non-cooperative two-stage network DEA model. Section 5 is an empirical study on the rail-water intermodal transport in China. Section 6 shows the conclusion and directions of future research.

2. Literature Review

2.1. Development of the Network DEA Model

Färe and Grosskopf [11] first named the DEA model, considering the system's internal structure as the network DEA model. Many scholars have conducted research on network DEA models with different structural types. For example, Castelli et al. [12] discussed the decision unit with a two-stage structure, which is a basic model, and Tone and Tsutsui [13] took a more in-depth study of the basic model and proposed a slacks-based network DEA model to study intermediate products. Then, Fukuyama and Weber [14] extended the slacks-based network DEA model by adding undesirable outputs.

The efficiency measurement method of the network DEA model mainly includes multiplication and addition. Many scholars have studied the application and deficiency of multiplication and addition. When the network system is a simple series structure and there is no external input in the second stage, the solution of the multiplication method is relatively simple. For example, Kao and Hwang [15] proposed a multiplicative decomposition method for two-stage models, in which the system efficiency is the product of the two-stage efficiencies. However, when there is external input in the second stage, the efficiency evaluation model obtained by the multiplication method is highly nonlinear and the solution is difficult. To solve this nonlinear model, Chen and Zhu [16] studied second-order cone programming and demonstrated that it could be used to solve all two-stage nonlinear network DEA models under the multiplication method.

In addition to the multiplication method, the addition method is also commonly used. Chen et al. [17] proposed an additive decomposition method for two-stage models, which was extended to general network structures by Cook et al. [18]. In the addition method, the system efficiency is a weighted average of the stage efficiencies. Among them, the weight can represent the relative importance of the stage, and there are different methods for selecting the weight. Chen et al. [17] and Cook et al. [18] used the ratio of stage input to total input to represent the weight. Nevertheless, Despotis et al. [19] and Ang and Chen [20] both demonstrated that the weight selection method proposed by Chen et al. [17] tends to favor the importance of the second stage. For this problem, Michali et al. [21] proved that the favor of stage in the two-stage model does not exist under variable returns to scale.

In the research on network DEA models in recent years, some scholars have proposed new efficiency measurement methods and network structure forms. For example, Wu et al. [22] proposed a heuristic algorithm for transforming a nonlinear model into a parametric linear model under a non-cooperative framework, and they also proposed a two-stage network structure with shared input resources. Chao et al. [23] used a dynamic network DEA model to study the efficiency of large-container-shipping companies. Sotiros et al. [24] proposed the notion of dominance in division efficiency in network DEA models. Lozano and Khezri [25] proposed a minimal improvement method for network DEA in both the cooperative and the non-cooperative cases. The minimal improvement method refers to determining the projection direction to minimize the relative distance to the boundary. Lee [26] defined loss as total input minus total output, and dissected network systems based on the concept of loss. These new contents provide more possibilities for the research of network DEA models. Previous studies have analyzed common network structures and efficiency measurement methods, which have laid the foundation for developing network DEA models. However, these studies mainly focused on general structures and cannot be applied to specific industries and production scenarios. This article expands the method of Kao [27], Michali et al. [21], and Koronakos et al. [28], expands the research scope, and applies it to the carbon emissions of multimodal transport.

2.2. Application of Network DEA in the Efficiency Evaluation of Transportation Carbon Emissions

Carbon emissions in the transportation sector are a crucial link in the world's carbon reduction process. Using the network DEA model to evaluate the efficiency of transportation carbon emissions can effectively identify the inefficient divisions within the transportation system, which is conducive to carbon emission reduction in the transportation sector. Some scholars have studied the application of the network DEA model in the efficiency evaluation of carbon emissions from transportation. In the aviation sector, Cui and Li [29] evaluated the efficiency of 22 international airlines from 2008 to 2012 by using a network DEA model including both an operational stage and a carbon reduction stage. Based on efficiency evaluation, Cui [30] calculated the maximum expected output according to the total reduced carbon emissions of 28 airlines. In the application process, there may be a special case where the input or output is negative. For this special case, Cui and Jin [31] adopted a new network DEA model that can handle negative data to measure the carbon efficiency of 25 global airlines from 2008 to 2018.

In water transportation, the main players include ports, shipping companies, and administrations. For the ports, Chang and Park [32] proposed a new DEA model for measuring undesirable outputs such as carbon emissions and applied it to the ports of South Korea. For the shipping companies, Chen et al. [33] used the network centralized DEA model to analyze the route resource allocation of a Taiwanese shipping company. For the administrations, Tovar and Wall [34] applied the DEA model to estimate the environmental efficiencies of 28 Spanish port authorities in 2016, with CO_2 emissions as an undesirable output.

In land transportation, for cargo transportation, Liu et al. [35] proposed a parallel slack-based DEA model and used it to evaluate the overall efficiency of China's land transportation sector and the efficiency of railway and road transportation when CO_2 emissions are considered. They found an obvious regional imbalance in the environmental efficiency of land transport in China. For a more in-depth analysis, some scholars combine the DEA model with other models. Liu et al. [36] combined the non-radial DEA model with window analysis to measure the energy efficiency of the highway and railway sectors in 30 provinces in China. They then used the Tobit regression model to analyze the factors affecting energy environmental efficiency. In addition, for passenger transport, Kang et al. [37] used a two-stage network DEA model to measure the efficiency of public transport systems considering CO_2 emissions.

At present, the application of network DEA in the efficiency evaluation of transportation carbon emission is concentrated on a single mode of transport, and the evaluation of multimodal transport is lacking. Compared with a single mode of transport, multimodal transport has higher operation efficiency, larger transportation volume, and lower cost. It can reduce fossil fuel consumption and thus CO_2 emissions. Evaluating the carbon emission efficiency of multimodal transport is conducive to optimizing the transportation structure, giving full play to the advantages of intermodal transport, and reducing transportation carbon emissions.

2.3. Carbon Emissions in Multimodal Transport Research

Multimodal transport can improve economic and environmental benefits during transportation and reduce CO_2 emissions. Thus, the carbon emission in multimodal transport has attracted increasing attention from scholars. Some scholars mainly consider the impact of cost. For example, Kim et al. [38] studied the relationship between transportation cost and CO_2 emissions and proposed to balance the relationship. In transportation costs, some scholars have conducted research on specific environmental costs. Stanley et al. [39] introduced environmental costs into the freight dispatching system to form an integrated network design model and verified the model with an actual railway freight network. Qu et al. [40] considered the specific CO_2 emission cost and constructed a nonlinear programming model for demand determination. In addition to costs and carbon emissions, transportation time is an important factor in multimodal transport. Bauer et al. [41] and Demir et al. [42] added the analysis of transportation time. Bauer et al. [41] analyzed the relationship between CO_2 emissions, cost, and time; pointed out that a reasonable path can reduce greenhouse gas emissions in the process of multimodal transport; and established an optimization model under carbon emission constraints from the perspective of the government and enterprises. Analyzing the relationship among cost, carbon emission, and time is conducive to promoting their coordinated development, and modeling them as an objective function can yield a more direct conclusion. Demir et al. [42] took the minimum cost, time, and emission as the objective functions, considered the uncertainty of travel time in a green multimodal transport service network, and then adopted a sample approximation method to solve. In addition to transportation time, transportation distance is also an important factor. Accorsi et al. [43] studied the site selection of outlets in the food supply chain from the perspective of low-carbon economy and discussed the relationship among carbon emission, cost, and the transportation distance of goods.

Some scholars have compared the carbon emissions of different modes of transportation. Both the choice of transport mode and the coordination of companies have a certain impact on CO_2 emissions; Benjaafar et al. [44] pointed this out and combined low-carbon issues with logistics operations, using a mathematical model to demonstrate the significance of decision making in logistics operations for carbon reduction. Among all modes of transport, road transport has the highest carbon emissions; Gerilla et al. [45] demonstrated this with the example of CO_2 emissions from manufacturers to middlemen. To reduce road transport to reduce carbon emissions, Liao et al. [46] took carbon emissions as an optimization objective and designed a transport mode selection model that can reduce road transport. It is an effective means to replace road transport with other transport modes such as shipping and railways. Chen et al. [47] focused on coastal shipping services, a low-carbon alternative to road transport. As for the railways, Rodrigues et al. [48] demonstrated that the use of railways instead of road transport could significantly reduce the total carbon emissions from transport, then Rodrigues et al. [49] conducted an empirical analysis using British container shipping as an example. Compared with single-road transport, multimodal transport is more effective in reducing emissions. Mostert et al. [50] conducted a comparative analysis of multimodal transport and road transport from both economic and environmental aspects, reflecting the advantages of multimodal transport. Then, Heinold and Meisel [51] conducted large-scale simulations of road transport and multimodal transport and estimated emission rates, further demonstrating the emission reduction effect of multimodal transport. Among different transport modes, road transport has the highest carbon emissions, railway and shipping have lower emissions, and multimodal transport has the most obvious emission reduction effect.

Currently, in the research on the carbon emission of multimodal transport, the network DEA model is rarely used to evaluate the carbon emission efficiency. Multimodal transport is a multi-link process, and the links can be regarded as multiple evaluation units. Therefore, network DEA is suitable for evaluating the efficiency of multimodal transport.

In previous studies, some scholars applied the network DEA model to evaluate the transportation sector's carbon emission efficiency, but most focused on a single mode of transportation. Few scholars have used the network DEA model in the research on the carbon emission of multimodal transport. This article chooses the network DEA model to evaluate the carbon emission efficiency of multimodal transport for these reasons: First, DEA is widely used to measure the efficiency of decision-making units relative to the production frontier. Its most significant advantage is that it is nonparametric, allowing multiple inputs and outputs to be included in the production model. Second, compared with other methods, network DEA considers the intermediate products and the relationship between sub-divisions and provides more diagnostic information and a more detailed analysis level for the system. The network DEA model's efficiency evaluation results are also considered more effective [13,52]. Third, the inefficient rail-water intermodal transport system and the corresponding inefficient divisions can be found using the network DEA model. The inefficient divisions are the resources for the whole system's inefficiency, which helps propose targeted improvement measures.

The possible innovations of this article are as follows. First, this article studies the efficiency decomposition and efficiency aggregation of the general network structure for the DEA model. In efficiency decomposition, the relationship between system efficiency and division efficiency is discussed, whereas in efficiency aggregation, the division tendency brought about by the definition of weights is analyzed. Second, a reasonable and single compromise solution for the division efficiency score is investigated under the condition that the system efficiency of the multi-stage network DEA model remains optimal. Third, the CO_2 emission efficiency of rail-water intermodal transport is evaluated by using the efficiency decomposition, efficiency aggregation, and non-cooperative methods of the network DEA model.

3. Efficiency Decomposition and Aggregation in the Network DEA Model

The system's internal structure contains intermediate products and the relationships between sub-divisions, and the model considering the internal structure can provide more diagnostic information and a more detailed analysis level. The efficiency evaluation results are also considered to be more accurate. Ignoring the internal structure of the system can lead to different and sometimes misleading results [13,52]. To evaluate the efficiency of a rail-water intermodal transport system with and without considering the internal structure, respectively, the methods of efficiency decomposition and efficiency aggregation were selected for the study. The efficiency decomposition measures the system efficiency from the inputs supplied from outside and the outputs produced to outside, and then derives the relationships between the system efficiency and the division efficiencies. The efficiency aggregation defines the relationships first, and then measures the system and division efficiencies based on these [27].

Consider the general structure for network systems composed of Q divisions in Kao [27]. Denote X_{ij}^q and Y_{sj}^q as the ith input, $i \in \{1, 2, \ldots, I\}$, supplied from outside, and the sth final output, $s \in \{1, 2, \ldots, S\}$, produced from the qth division, $q = 1, \ldots, Q$, of the jth DMU, $j = 1, \ldots, n$, respectively. Further, denote Z_{gj}^{ab} as the gth intermediate product produced by division a for division b to use, $g \in \{1, 2, \ldots, G\}$. Denote v_i, e_s, and w_g as the weights of variables and u_q as the free variable under variable returns to scale. The specific structure is shown in Figure 1.

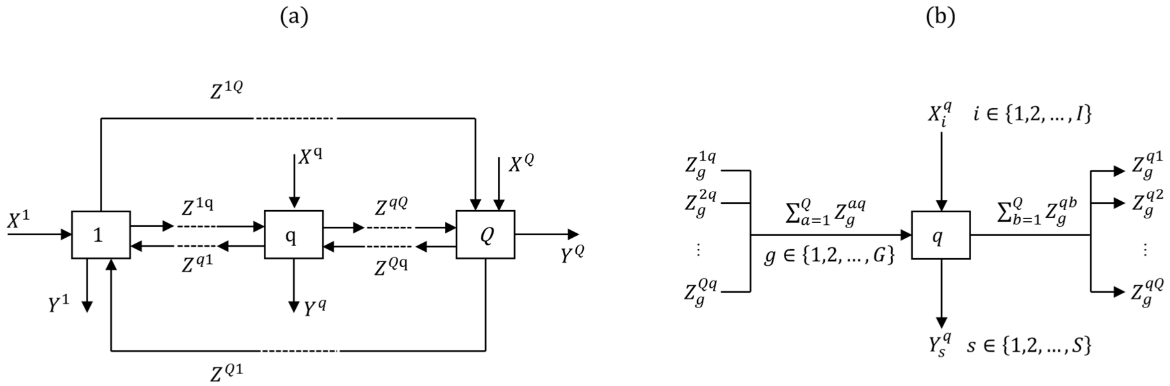

Figure 1. (**a**) The general structure of the network system. (**b**) The qth division in the system.

3.1. Efficiency Decomposition

The input-oriented efficiency decomposition model for measuring the system efficiency under variable returns to scale can be formulated as:

$$\begin{aligned} E_o^{D*} &= max \ \frac{\sum_{q=1}^{Q}\left(\sum_{s=1}^{S} e_s Y_{so}^q + u_q\right)}{\sum_{q=1}^{Q}\sum_{i=1}^{I} v_i X_{io}^q} \\ \text{s.t. } E_{qj} &= \frac{\sum_{s=1}^{S} e_s Y_{sj}^q + \sum_{g=1}^{G} w_g\left(\sum_{b=1}^{Q} Z_{gj}^{qb}\right) + u_q}{\sum_{i=1}^{I} v_i X_{ij}^q + \sum_{g=1}^{G} w_g\left(\sum_{a=1}^{Q} Z_{gj}^{aq}\right)} \le 1 \\ &u_q \text{ free in sign } q = 1, \ldots, Q \ j = 1, \ldots, n \\ &v_i, e_s, \ w_g \ge 0 \end{aligned} \tag{1}$$

The objective function E_o^D of the model (1) is the ratio of the final output to the outside input. Each constraint represents the division efficiency E_{qj}, respectively. Note that the multipliers v, e, and w of X, Y, and Z are the same in all divisions, and the same intermediate product Z has the same multiplier w no matter whether it plays the role of an input or output. Because all the intermediate inputs are equal to all the intermediate outputs, $\sum_{q=1}^{Q}\left[\sum_{g=1}^{G} w_g(\sum_{a=1}^{Q} Z_{gj}^{aq})\right] = \sum_{q=1}^{Q}\left[\sum_{g=1}^{G} w_g(\sum_{b=1}^{Q} Z_{gj}^{qb})\right]$. The constraint $\frac{\sum_{q=1}^{Q}\left(\sum_{s=1}^{S} e_s Y_{sj}^q + u_q\right)}{\sum_{q=1}^{Q}\sum_{i=1}^{I} v_i X_{ij}^q} \le 1$ is redundant because it can be derived from the division efficiency constraint.

Definition 1. *DMU$_o$ is considered to be system-efficient if and only if* $E_o^{D*} = 1$.

Kao [27] discussed the relationship between system efficiency and division efficiency in three special network structures; this article will discuss the relationship between system efficiency and division efficiency in the general network structure. Because $\sum_{q=1}^{Q}\left[\sum_{g=1}^{G} w_g(\sum_{a=1}^{Q} Z_{gj}^{aq})\right] =$

$\sum_{q=1}^{Q}\left[\sum_{g=1}^{G} w_g(\sum_{b=1}^{Q} Z_{gj}^{qb})\right]$, for the DMU$_o$: $\left[\sum_{q=1}^{Q}\sum_{i=1}^{I} v_i X_{io}^{q} - \sum_{q=1}^{Q}\left(\sum_{s=1}^{S} e_s Y_{so}^{q} + u_q\right)\right] = \sum_{q=1}^{Q}\left[\sum_{i=1}^{I} v_i X_{io}^{q} + \sum_{g=1}^{G} w_g(\sum_{a=1}^{Q} Z_{go}^{aq}) - \left(\sum_{s=1}^{S} e_s Y_{so}^{q} + u_q\right) - \sum_{g=1}^{G} w_g(\sum_{b=1}^{Q} Z_{go}^{qb})\right]$. Divide both sides of this formula by $\sum_{q=1}^{Q}\sum_{i=1}^{I} v_i X_{io}^{q}$ at the same time and the relationship between system efficiency and division efficiency can be obtained as follows:

$$\begin{gathered}(1-E_o^D) = \sum_{q=1}^{Q}(1-E_{qo})P_q' \\ \text{where } P_q' = \frac{\sum_{i=1}^{I} v_i X_{io}^{q} + \sum_{g=1}^{G} w_g(\sum_{a=1}^{Q} Z_{go}^{aq})}{\sum_{q=1}^{Q}\sum_{i=1}^{I} v_i X_{io}^{q}}\end{gathered} \tag{2}$$

The three network systems mentioned in Kao [27] also meet Formula (2).

3.2. Efficiency Aggregation

In efficiency decomposition, the system efficiency is the ratio of the final output to the outside input. In efficiency aggregation, system efficiency is defined as a function of division efficiencies. For the additive form, the system efficiency is defined as a weighted average of the division efficiencies, $E_o^A = \sum_{q=1}^{Q} P_q E_{qo}$, where $P_q \geq 0$, with $\sum_{q=1}^{Q} P_q = 1$. Kao [27] defined the weight associated with a division as the proportion of the aggregate input of this division in that of all divisions, that is, $P_q = \frac{\sum_{i=1}^{I} v_i X_{io}^{q} + \sum_{g=1}^{G} w_g(\sum_{a=1}^{Q} Z_{go}^{aq})}{\sum_{q=1}^{Q}\left[\sum_{i=1}^{I} v_i X_{io}^{q} + \sum_{g=1}^{G} w_g(\sum_{a=1}^{Q} Z_{go}^{aq})\right]}$.

Ang and Chen [20] and Despotis et al. [19] showed that, under constant returns to scale, this definition of the weights results in a non-increasing relationship between them, i.e., $P_1 \geq P_2$, for some network systems. This results in giving higher priority to the first division.

Due to this problem, this article will study the weighting relationship under variable returns to scale. The system efficiency is:

$$\begin{aligned} E_o^A &= \sum_{q=1}^{Q} P_q E_{qo} \\ &= \sum_{q=1}^{Q}\left\{\frac{\sum_{i=1}^{I} v_i X_{io}^{q} + \sum_{g=1}^{G} w_g\left(\sum_{a=1}^{Q} Z_{go}^{aq}\right)}{\sum_{q=1}^{Q}\left[\sum_{i=1}^{I} v_i X_{io}^{q} + \sum_{g=1}^{G} w_g\left(\sum_{a=1}^{Q} Z_{go}^{aq}\right)\right]} \times \frac{\sum_{s=1}^{S} e_s Y_{so}^{q} + \sum_{g=1}^{G} w_g\left(\sum_{b=1}^{Q} Z_{go}^{qb}\right) + u_q}{\sum_{i=1}^{I} v_i X_{io}^{q} + \sum_{g=1}^{G} w_g\left(\sum_{a=1}^{Q} Z_{go}^{aq}\right)}\right\} \\ &= \frac{\sum_{q=1}^{Q}\left[\sum_{s=1}^{S} e_s Y_{so}^{q} + \sum_{g=1}^{G} w_g(\sum_{b=1}^{Q} Z_{go}^{qb}) + u_q\right]}{\sum_{q=1}^{Q}\left[\sum_{i=1}^{I} v_i X_{io}^{q} + \sum_{g=1}^{G} w_g(\sum_{a=1}^{Q} Z_{go}^{aq})\right]}\end{aligned} \tag{3}$$

The efficiency aggregation model is as follows:

$$\begin{gathered} E_o^{A*} = max\ \frac{\sum_{q=1}^{Q}\left[\sum_{s=1}^{S} e_s Y_{so}^{q} + \sum_{g=1}^{G} w_g(\sum_{b=1}^{Q} Z_{go}^{qb}) + u_q\right]}{\sum_{q=1}^{Q}\left[\sum_{i=1}^{I} v_i X_{io}^{q} + \sum_{g=1}^{G} w_g(\sum_{a=1}^{Q} Z_{go}^{aq})\right]} \\ \text{s.t. } E_{qj} = \frac{\sum_{s=1}^{S} e_s Y_{sj}^{q} + \sum_{g=1}^{G} w_g(\sum_{b=1}^{Q} Z_{gj}^{qb}) + u_q}{\sum_{i=1}^{I} v_i X_{ij}^{q} + \sum_{g=1}^{G} w_g(\sum_{a=1}^{Q} Z_{gj}^{aq})} \leq 1 \\ u_q \text{ free in sign } q = 1, \ldots, Q\ j = 1, \ldots, n \\ v_i, e_s,\ w_g \geq 0 \end{gathered} \tag{4}$$

Applying the Charnes–Cooper transformation [53], the model (4) can be transformed into a linear one and solved.

Definition 2. *DMU$_o$ is considered to be system-efficient if and only if* $E_o^{A*} = 1$.

According to the inequality constraint of the model (4), the following formula can be obtained:

$$\sum_{i=1}^{I} v_i X_{ij}^{q} + \sum_{g=1}^{G} w_g(\sum_{a=1}^{Q} Z_{gj}^{aq}) \geq \sum_{s=1}^{S} e_s Y_{sj}^{q} + \sum_{g=1}^{G} w_g(\sum_{b=1}^{Q} Z_{gj}^{qb}) + u_q \tag{5}$$

Consider any two divisions, i.e., q_1 and q_2, using Formula (5), and the following inequality can be obtained:

$$\begin{aligned} &P_{q_1} - P_{q_2} \\ &= \frac{\sum_{i=1}^{I} v_i X_{ij}^{q1} + \sum_{g=1}^{G} w_g (\sum_{a=1}^{Q} Z_{gj}^{aq1})}{\sum_{q_1=1}^{Q}\left[\sum_{i=1}^{I} v_i X_{ij}^{q1} + \sum_{g=1}^{G} w_g (\sum_{a=1}^{Q} Z_{gj}^{aq1})\right]} - \frac{\sum_{i=1}^{I} v_i X_{ij}^{q2} + \sum_{g=1}^{G} w_g (\sum_{a=1}^{Q} Z_{gj}^{aq2})}{\sum_{q_1=1}^{Q}\left[\sum_{i=1}^{I} v_i X_{ij}^{q1} + \sum_{g=1}^{G} w_g (\sum_{a=1}^{Q} Z_{gj}^{aq1})\right]} \\ &= \frac{\sum_{i=1}^{I} v_i X_{ij}^{q1} + \sum_{g=1}^{G} w_g (\sum_{a=1}^{Q} Z_{gj}^{aq1}) - \sum_{i=1}^{I} v_i X_{ij}^{q2} - \sum_{g=1}^{G} w_g (\sum_{a=1}^{Q} Z_{gj}^{aq2})}{\sum_{q_1=1}^{Q}\left[\sum_{i=1}^{I} v_i X_{ij}^{q1} + \sum_{g=1}^{G} w_g (\sum_{a=1}^{Q} Z_{gj}^{aq1})\right]} \\ &\geq \frac{\sum_{s=1}^{S} e_s Y_{sj}^{q1} + \sum_{g=1}^{G} w_g (\sum_{b=1}^{Q} {Z_{gj}^{q1}}^{b}) + u_{q_1} - \sum_{i=1}^{I} v_i X_{ij}^{q2} - \sum_{g=1}^{G} w_g (\sum_{a=1}^{Q} Z_{gj}^{aq2})}{\sum_{q_1=1}^{Q}\left[\sum_{i=1}^{I} v_i X_{ij}^{q1} + \sum_{g=1}^{G} w_g \left(\sum_{a=1}^{Q} Z_{gj}^{aq1}\right)\right]} = H \end{aligned} \quad (6)$$

In inequality (6), for convenience, use H to represent the last fraction. The denominator of H is positive, and the sign of the numerator depends on the values of the optimal weights and the scalar u_q. Therefore, the sign of H is different for the different DMUs. That means that there is no non-increasing relationship between weights, and the definition of the weights will not give higher priority to any division under variable returns to scale.

In efficiency aggregation, the system efficiency is a weighted average of division efficiencies, and Kao [27] defined the weight as a proportion. Under constant returns to scale, this definition will give higher priority to some divisions for some network systems. However, under variable returns to scale, this definition will not lead to any tendency in the production process [21]. As such, the empirical study is carried out under variable returns to scale.

3.3. A Single Compromise Solution for the Division Efficiency Score

In a network structure, through the evaluation of system efficiency and division efficiency, inefficient divisions that affect the system efficiency can be identified, and targeted improvement suggestions can be put forward. However, the division efficiency scores may not be unique when the system efficiency is optimal. The non-uniqueness of division efficiency is not conducive to the identification of inefficient divisions, so it is necessary to find a way to obtain a reasonable compromise solution for division efficiency. Koronakos et al. [28] proposed a compromise programming method to obtain a reasonable compromise division efficiency. This article adopts the weighted min–max method to make the compromise division efficiency as close as possible to the highest efficiency score that the division can achieve and as far away from the lowest efficiency score as possible. Koronakos et al. [28] analyzed 2 and 3 divisions, and we now consider multiple divisions. The following section takes the efficiency decomposition of a multi-division series structure as an example to study.

Consider a series network structure with Q divisions, as shown in Figure 2. Denote X_{ij} as the ith outside input in the first division, $i \in \{1, 2, \ldots, I\}$, of the jth DMU, $j = 1, \ldots, n$, respectively, and Y_{sj} as the sth final output in the Qth division, $s \in \{1, 2, \ldots, S\}$. Further, denote Z_{gj}^{q} as the gth intermediate product produced by the qth division for the $q + 1$th division to use, $g \in \{1, 2, \ldots, G\}$. Denote v_i, e_s, and w_g as the weights of the variables and v_i', e_s', and w_g^* as the corresponding weights after Charnes–Cooper transformation.

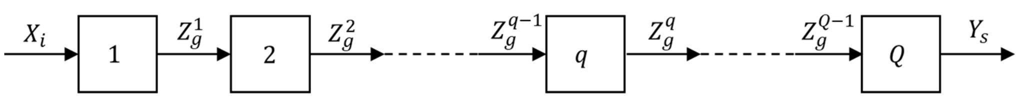

Figure 2. A series network structure.

Using the efficiency decomposition model for measuring the system efficiency (model 1), the optimal system efficiency E_o^* can be obtained. By maximizing the efficiency of a division under the condition of keeping the system efficiency optimal, the highest efficiency score $E^{+}_{q'o}$ of the division can be obtained. When $q' = 2, \ldots, Q-1$, the specific model is as follows:

$$\begin{gathered}
E^{+}_{q'o} = max \frac{\sum_{g=1}^{G} w_g^{q'} Z_{go}^{q'}}{\sum_{g=1}^{G} w_g^{q'-1} Z_{go}^{q'-1}} \\
\text{s.t. } E_{1j} = \frac{\sum_{g=1}^{G} w_g^{1} Z_{gj}^{1}}{\sum_{i=1}^{I} v_i X_{ij}} \leq 1 \\
E_{qj} = \frac{\sum_{g=1}^{G} w_g^{q} Z_{gj}^{q}}{\sum_{g=1}^{G} w_g^{q-1} Z_{gj}^{q-1}} \leq 1 \; q = 2, \ldots, Q-1 \\
E_{Qj} = \frac{\sum_{s=1}^{S} e_s Y_{sj}}{\sum_{g=1}^{G} w_g^{Q-1} Z_{gj}^{Q-1}} \leq 1 \\
j = 1, \ldots, n \\
\frac{\sum_{s=1}^{S} e_s Y_{so}}{\sum_{i=1}^{I} v_i X_{io}} = E_o^{*} \\
v_i, e_s, w_g \geq 0
\end{gathered} \tag{7}$$

When $q' = 1$, the objective function is $E^{+}_{1o} = max \frac{\sum_{g=1}^{G} w_g^{1} Z_{go}^{1}}{\sum_{i=1}^{I} v_i X_{io}}$. When $q' = Q$, the objective function is $E^{+}_{Qo} = max \frac{\sum_{s=1}^{S} e_s Y_{so}}{\sum_{g=1}^{G} w_g^{Q-1} Z_{go}^{Q-1}}$. The constraints remain the same.

Using the Charnes-Cooper transformation, the linear form of model (7) is as follows:

$$\begin{gathered}
E^{+}_{q'o} = max \sum_{g=1}^{G} w_g^{*q'} Z_{go}^{q'} \\
\text{s.t. } \sum_{g=1}^{G} w_g^{*q'-1} Z_{go}^{q'-1} = 1 \\
\sum_{g=1}^{G} w_g^{*1} Z_{gj}^{1} - \sum_{i=1}^{I} v_i' X_{ij} \leq 0 \\
\sum_{g=1}^{G} w_g^{*q} Z_{gj}^{q} - \sum_{g=1}^{G} w_g^{*q-1} Z_{gj}^{q-1} \leq 0 \; q = 2, \ldots, Q-1 \\
\sum_{s=1}^{S} e_s' Y_{sj} - \sum_{g=1}^{G} w_g^{*Q-1} Z_{gj}^{Q-1} \leq 0 \\
j = 1, \ldots, n \\
\frac{\sum_{s=1}^{S} e_s' Y_{so}}{\sum_{i=1}^{I} v_i' X_{io}} = E_o^{*} \\
v_i', e_s', w_g^{*} \geq 0
\end{gathered} \tag{8}$$

Similarly, the lowest efficiency score $E^{-}_{q'o}$ of each division can be obtained while keeping the system efficiency optimal. When $q' = 2, \ldots, Q-1$, the specific model is as follows:

$$\begin{gathered}
E^{-}_{q'o} = \min \sum_{g=1}^{G} w_g^{*q'} Z_{go}^{q'} \\
\text{s.t. } \sum_{g=1}^{G} w_g^{*q'-1} Z_{go}^{q'-1} = 1 \\
\sum_{g=1}^{G} w_g^{*1} Z_{gj}^{1} - \sum_{i=1}^{I} v_i' X_{ij} \leq 0 \\
\sum_{g=1}^{G} w_g^{*q} Z_{gj}^{q} - \sum_{g=1}^{G} w_g^{*q-1} Z_{gj}^{q-1} \leq 0 \; q = 2, \ldots, Q-1 \\
\sum_{s=1}^{S} e_s' Y_{sj} - \sum_{g=1}^{G} w_g^{*Q-1} Z_{gj}^{Q-1} \leq 0 \\
j = 1, \ldots, n \\
\frac{\sum_{s=1}^{S} e_s' Y_{so}}{\sum_{i=1}^{I} v_i' X_{io}} = E_o^{*} \\
v_i', e_s', w_g^{*} \geq 0
\end{gathered} \tag{9}$$

When $q' = 1$ or Q, the model is similar to the highest efficiency. Thus, when the system efficiency is kept optimal, the highest efficiency score E_q^{+} and the lowest efficiency score E_q^{-} of each division are obtained, $q = 1, 2, \ldots, Q$. Note that the division efficiency score is unique when E_q^{+} and E_q^{-} are equal. Then, the weighted min-max method is used to obtain a reasonable compromise division efficiency. The specific model is as follows:

$$
\begin{gathered}
min\left\{max\left[\lambda_1\left(E^{+}_{1o}-\sum_{g=1}^{G} w_g^{*1} Z_{go}^{1}\right),\lambda_2\left(E^{+}_{2o}-\frac{\sum_{g=1}^{G} w_g^{*2} Z_{go}^{2}}{\sum_{g=1}^{G} w_g^{*1} Z_{go}^{1}}\right),\ldots,\lambda_Q\left(E^{+}_{Qo}-\frac{\sum_{s=1}^{S} e'_s Y_{so}}{\sum_{g=1}^{G} w_g^{*Q-1} Z_{go}^{Q-1}}\right)\right]\right\} \\
\text{s.t. } \sum_{i=1}^{I} v'_i X_{io} = 1 \\
\sum_{g=1}^{G} w_g^{*1} Z_{gj}^{1} - \sum_{i=1}^{I} v'_i X_{ij} \le 0 \\
\sum_{g=1}^{G} w_g^{*q} Z_{gj}^{q} - \sum_{g=1}^{G} w_g^{*q-1} Z_{gj}^{q-1} \le 0 \; q = 2,\ldots,Q-1 \\
\sum_{s=1}^{S} e'_s Y_{sj} - \sum_{g=1}^{G} w_g^{*Q-1} Z_{gj}^{Q-1} \le 0 \\
j = 1,\ldots,n \\
\frac{\sum_{s=1}^{S} e'_s Y_{so}}{\sum_{i=1}^{I} v'_i X_{io}} = E_o^{*} \\
v'_i, e'_s, w_g^{*} \ge 0
\end{gathered} \tag{10}
$$

In model (10), the weight $\lambda_q = \frac{1}{E^{+}_{qo}-E^{-}_{qo}}$, $q = 1,2,\ldots,Q$. By introducing an auxiliary variable δ, the model (10) can be equivalently transformed into the following model:

$$
\begin{gathered}
\min\delta \\
\text{s.t. } \lambda_1\left(E^{+}_{1o}-\sum_{g=1}^{G} w_g^{*1} Z_{go}^{1}\right) \le \delta \\
\lambda_q\left(E^{+}_{qo}-\frac{\sum_{g=1}^{G} w_g^{*q} Z_{go}^{q}}{\sum_{g=1}^{G} w_g^{*q-1} Z_{go}^{q-1}}\right) \le \; q = 2,\ldots,Q-1 \\
\lambda_Q\left(E^{+}_{Qo}-\frac{\sum_{s=1}^{S} e'_s Y_{so}}{\sum_{g=1}^{G} w_g^{*Q-1} Z_{go}^{Q-1}}\right) \le \delta \\
\sum_{i=1}^{I} v'_i X_{io} = 1 \\
\sum_{g=1}^{G} w_g^{*1} Z_{gj}^{1} - \sum_{i=1}^{I} v'_i X_{ij} \le 0 \\
\sum_{g=1}^{G} w_g^{*q} Z_{gj}^{q} - \sum_{g=1}^{G} w_g^{*q-1} Z_{gj}^{q-1} \le 0 \; q = 2,\ldots,Q-1 \\
\sum_{s=1}^{S} e'_s Y_{sj} - \sum_{g=1}^{G} w_g^{*Q-1} Z_{gj}^{Q-1} \le 0 \\
j = 1,\ldots,n \\
\frac{\sum_{s=1}^{S} e'_s Y_{so}}{\sum_{i=1}^{I} v'_i X_{io}} = E_o^{*} \\
v'_i, e'_s, w_g^{*} \ge 0
\end{gathered} \tag{11}
$$

The model can be solved by bisection search, that is, searching the value of δ in [0, 1] [54]. Assuming that the optimal solution of model (11) is $\left(\hat{v}'_i, \hat{e}'_s, \hat{w}_g^{*}\right)$, the system efficiency and the single compromise division efficiency are as follows:

$$
\begin{gathered}
\hat{E}_o = \frac{\sum_{s=1}^{S} \hat{e}'_s Y_{so}}{\sum_{i=1}^{I} \hat{v}'_i X_{io}} = E_o^{*} \\
\hat{E}_{1o} = \frac{\sum_{g=1}^{G} \hat{w}_g^{*1} Z_{go}^{1}}{\sum_{i=1}^{I} \hat{v}'_i X_{io}} \\
\hat{E}_{qo} = \frac{\sum_{g=1}^{G} \hat{w}_g^{*q} Z_{go}^{q}}{\sum_{g=1}^{G} \hat{w}_g^{*q-1} Z_{go}^{q-1}} \; q = 2,\ldots,Q-1 \\
\hat{E}_{Qo} = \frac{\sum_{s=1}^{S} \hat{e}'_s Y_{so}}{\sum_{g=1}^{G} \hat{w}_g^{*Q-1} Z_{go}^{Q-1}}
\end{gathered} \tag{12}
$$

$\hat{E}_{1o}, \hat{E}_{qo}$ and $\hat{E}_{Qo}$ are reasonable and single compromise solutions for the division efficiency scores while the system efficiency remains optimal.

4. Non-Cooperative Two-Stage Network DEA Model

Efficiency decomposition and efficiency aggregation are two methods of measuring system efficiency. This section considers a two-stage system with undesirable output (see Figure 3). Denote X_{ij}^{1} as the ith outside input in the first stage, $i \in \{1,2,\ldots,I\}$, of the jth DMU, $j = 1,\ldots,\ n$, respectively, and X_{dj}^{2} as the dth outside input in the second stage, $d \in \{1,2,\ldots,D\}$. Then, denote Y_{sj}^{1} as the sth final output in the second stage, $s \in \{1,2,\ldots,S\}$, and Y_{lj}^{2} as the lth undesirable output in the second stage, $l \in \{1,2,\ldots,L\}$.

Further, denote Z_{gj} as the gth intermediate product produced by the first stage for the second stage to use, $g \in \{1, 2, \ldots, G\}$. Denote v_i, k_d, e_s, m_l and w_g as the weights of the variables, u_1 and u_2 as the free variables under variable returns to scale, and v'_i, k'_d, e'_s, m'_l, w'_g, u'_1 and u'_2 as the corresponding weights and free variables after Charnes-Cooper transformation.

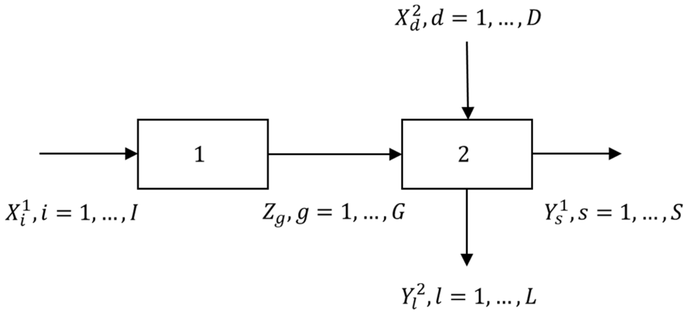

Figure 3. A two-stage system with undesirable output.

This article treats undesirable outputs as normal inputs. This is a common practice for dealing with undesirable outputs, and the model aims to decrease normal inputs and undesired outputs [21,55,56]. The efficiency decomposition model under variable returns to scale can be formulated as:

$$\begin{array}{c} E_o^{D*} = max \ \frac{\sum_{s=1}^{S} e_s Y_{so}^1 + u_1 + u_2}{\sum_{i=1}^{I} v_i X_{io}^1 + \sum_{d=1}^{D} k_d X_{do}^2 + \sum_{l=1}^{L} m_l Y_{lo}^2} \\ \text{s.t. } \frac{\sum_{g=1}^{G} w_g Z_{gj} + u_1}{\sum_{i=1}^{I} v_i X_{ij}^1} \le 1 \\ \frac{\sum_{s=1}^{S} e_s Y_{sj}^1 + u_2}{\sum_{g=1}^{G} w_g Z_{gj} + \sum_{d=1}^{D} k_d X_{dj}^2 + \sum_{l=1}^{L} m_l Y_{lj}^2} \le 1 \\ v_i, k_d, e_s, m_l, w_g \ge 0 \\ j = 1, \ldots, n \ u_1, u_2 \text{ free in sign.} \end{array} \tag{13}$$

Similar to model (1), the constraint $\frac{\sum_{s=1}^{S} e_s Y_{sj}^1 + u_1 + u_2}{\sum_{i=1}^{I} v_i X_{ij}^1 + \sum_{d=1}^{D} k_d X_{dj}^2 + \sum_{l=1}^{L} m_l Y_{lj}^2} \le 1$ is redundant. Applying the Charnes-Cooper transformation, the model (13) can be transformed into a linear one:

$$\begin{array}{c} E_o^{D*} = max \ \sum_{s=1}^{S} e'_s Y_{so}^1 + u'_1 + u'_2 \\ \text{s.t. } \sum_{g=1}^{G} w'_g Z_{gj} - \sum_{i=1}^{I} v'_i X_{ij}^1 + u'_1 \le 0 \\ \sum_{s=1}^{S} e'_s Y_{sj}^1 - \sum_{g=1}^{G} w'_g Z_{gj} - \sum_{d=1}^{D} k'_d X_{dj}^2 - \sum_{l=1}^{L} m'_l Y_{lj}^2 + u'_2 \le 0 \\ \sum_{i=1}^{I} v'_i X_{io}^1 + \sum_{d=1}^{D} k'_d X_{do}^2 + \sum_{l=1}^{L} m'_l Y_{lo}^2 = 1 \\ v'_i, k'_d, e'_s, m'_l, w'_g \ge 0 \\ j = 1, \ldots, n \ u'_1, u'_2 \text{ free in sign.} \end{array} \tag{14}$$

The efficiency aggregation model can be formulated as:

$$\begin{array}{c} E_o^{A*} = max \ \frac{\sum_{g=1}^{G} w_g Z_{go} + u_1 + \sum_{s=1}^{S} e_s Y_{so}^1 + u_2}{\sum_{i=1}^{I} v_i X_{io}^1 + \sum_{g=1}^{G} w_g Z_{go} + \sum_{d=1}^{D} k_d X_{do}^2 + \sum_{l=1}^{L} m_l Y_{lo}^2} \\ \text{s.t. } \frac{\sum_{g=1}^{G} w_g Z_{gj} + u_1}{\sum_{i=1}^{I} v_i X_{ij}^1} \le 1 \\ \frac{\sum_{s=1}^{S} e_s Y_{sj}^1 + u_2}{\sum_{g=1}^{G} w_g Z_{gj} + \sum_{d=1}^{D} k_d X_{dj}^2 + \sum_{l=1}^{L} m_l Y_{lj}^2} \le 1 \\ v_i, k_d, e_s, m_l, w_g \ge 0 \\ j = 1, \ldots, n \ u_1, u_2 \text{ free in sign.} \end{array} \tag{15}$$

Similarly, the model (15) can be transformed into a linear one by the Charnes–Cooper transformation.

In practice, the importance of the two stages in the system may not be the same, and one stage may be a more important leader stage and the other a secondary follower stage. For example, cargo handling is primary in the port production process and the port collecting and distributing are secondary. This leader–follower two-stage structure is called the non-cooperative network DEA model [22]. In the non-cooperative network DEA model, first calculate the optimal efficiency of the leader stage, then calculate the efficiency of the follower stage when the efficiency of the leader stage remains optimal (adding it to the constraints).

Assuming stage 1 as the leader, under variable returns to scale, the efficiency of stage 1 is as follows:

$$\begin{gathered} E_{1o}^{1*} = max \ \frac{\sum_{g=1}^{G} w_g Z_{go} + u_1}{\sum_{i=1}^{I} v_i X_{io}^1} \\ \text{s.t. } \frac{\sum_{g=1}^{G} w_g Z_{gj} + u_1}{\sum_{i=1}^{I} v_i X_{ij}^1} \le 1 \\ v_i, w_g \ge 0 \\ j = 1, \ldots, n \ u_1 \text{ free in sign.} \end{gathered} \tag{16}$$

Using the Charnes-Cooper transformation, the linear form of model (16) is as follows:

$$\begin{gathered} E_{1o}^{1*} = max \ \sum_{g=1}^{G} w'_g Z_{go} + u'_1 \\ \text{s.t. } \sum_{g=1}^{G} w'_g Z_{gj} - \sum_{i=1}^{I} v'_i X_{ij}^1 + u'_1 \le 0 \\ \sum_{i=1}^{I} v'_i X_{io}^1 = 1 \\ v'_i, w'_g \ge 0 \\ j = 1, \ldots, n \ u'_1 \text{ free in sign.} \end{gathered} \tag{17}$$

The efficiency of stage 2 (follower) is calculated as follows:

$$\begin{gathered} E_{2o}^{1*} = max \ \frac{\sum_{s=1}^{S} e_s Y_{so}^1 + u_2}{\sum_{g=1}^{G} w_g Z_{go} + \sum_{d=1}^{D} k_d X_{do}^2 + \sum_{l=1}^{L} m_l Y_{lo}^2} \\ \text{s.t. } \frac{\sum_{g=1}^{G} w_g Z_{go} + u_1}{\sum_{i=1}^{I} v_i X_{io}^1} = E_{1o}^{1*} \\ \frac{\sum_{g=1}^{G} w_g Z_{gj} + u_1}{\sum_{i=1}^{I} v_i X_{ij}^1} \le 1 \\ \frac{\sum_{s=1}^{S} e_s Y_{sj}^1 + u_2}{\sum_{g=1}^{G} w_g Z_{gj} + \sum_{d=1}^{D} k_d X_{dj}^2 + \sum_{l=1}^{L} m_l Y_{lj}^2} \le 1 \\ v_i, k_d, e_s, m_l, w_g \ge 0 \\ j = 1, \ldots, n \ u_1, u_2 \text{ free in sign.} \end{gathered} \tag{18}$$

where E_{1o}^{1*} is the optimal efficiency of stage 1. Similarly, model (18) can be transformed into the linear form using the Charnes-Cooper transformation:

$$\begin{gathered} E_{2o}^{1*} = max \ \sum_{s=1}^{S} e'_s Y_{so}^1 + u'_2 \\ \text{s.t. } \sum_{g=1}^{G} w'_g Z_{go} - E_{1o}^{1*} \sum_{i=1}^{I} v'_i X_{io}^1 + u'_1 = 0 \\ \sum_{g=1}^{G} w'_g Z_{gj} - \sum_{i=1}^{I} v'_i X_{ij}^1 + u'_1 \le 0 \\ \sum_{s=1}^{S} e'_s Y_{sj}^1 - \sum_{g=1}^{G} w'_g Z_{gj} - \sum_{d=1}^{D} k'_d X_{dj}^2 - \sum_{l=1}^{L} m'_l Y_{lj}^2 + u'_2 \le 0 \\ \sum_{g=1}^{G} w'_g Z_{go} + \sum_{d=1}^{D} k'_d X_{do}^2 + \sum_{l=1}^{L} m'_l Y_{lo}^2 = 1 \\ v'_i, k'_d, e'_s, m'_l, w'_g \ge 0 \\ j = 1, \ldots, n \ u'_1, u'_2 \text{ free in sign.} \end{gathered} \tag{19}$$

Definition 3. *DMU_o is stage-k-efficient if and only if* $E_{ko}^{1*} = 1, k = 1,\ 2.$

When stage 2 is the leader, the efficiency of stage 2 is:

$$
\begin{gathered}
E_{2o}^{2*} = max \ \frac{\sum_{s=1}^{S} e_s Y_{so}^1 + u_2}{\sum_{g=1}^{G} w_g Z_{go} + \sum_{d=1}^{D} k_d X_{do}^2 + \sum_{l=1}^{L} m_l Y_{lo}^2} \\
\text{s.t.} \ \frac{\sum_{s=1}^{S} e_s Y_{sj}^1 + u_2}{\sum_{g=1}^{G} w_g Z_{gj} + \sum_{d=1}^{D} k_d X_{dj}^2 + \sum_{l=1}^{L} m_l Y_{lj}^2} \le 1 \\
k_d, e_s, m_l, w_g \ge 0 \\
j = 1, \ldots, n \ u_2 \text{ free in sign.}
\end{gathered} \tag{20}
$$

The efficiency of stage 1 (follower) is calculated as follows:

$$
\begin{gathered}
E_{1o}^{2*} = max \ \frac{\sum_{g=1}^{G} w_g Z_{go} + u_1}{\sum_{i=1}^{I} v_i X_{io}^1} \\
\text{s.t.} \ \frac{\sum_{s=1}^{S} e_s Y_{so}^1 + u_2}{\sum_{g=1}^{G} w_g Z_{go} + \sum_{d=1}^{D} k_d X_{do}^2 + \sum_{l=1}^{L} m_l Y_{lo}^2} = E_{2o}^{2*} \\
\frac{\sum_{g=1}^{G} w_g Z_{gj} + u_1}{\sum_{i=1}^{I} v_i X_{ij}^1} \le 1 \\
\frac{\sum_{s=1}^{S} e_s Y_{sj}^1 + u_2}{\sum_{g=1}^{G} w_g Z_{gj} + \sum_{d=1}^{D} k_d X_{dj}^2 + \sum_{l=1}^{L} m_l Y_{lj}^2} \le 1 \\
v_i, k_d, e_s, m_l, w_g \ge 0 \\
j = 1, \ldots, n \ u_1, u_2 \text{ free in sign.}
\end{gathered} \tag{21}
$$

Similar to the previous, models (20) and (21) can be solved in linear form by the Charnes-Cooper transformation.

5. Empirical Study

5.1. Rail-Water Intermodal Transport in China

In recent years, China has vigorously promoted port rail-water intermodal transport, such as the automatic transformation of terminals, the breaking of information barriers for intermodal transport, and the upgrading of transfer equipment, which has further improved the matching degree of vehicles, ships, and cargoes. Faced with the complex and changeable external environment, local port groups have actively coordinated with local governments and railway departments to ensure the stable operation of port rail-water intermodal transport through the introduction of relevant policies [57,58]. Using the DEA model to evaluate the efficiency of China's rail-water intermodal transport can identify specific divisions that lead to inefficiencies in transportation, further improve operations, promote the development of multimodal transport, and reduce transport carbon emissions [59].

5.2. Rail-Water Intermodal Transport Model Considering CO_2 Emission

A two-stage network DEA model of rail-water intermodal transport is constructed, and the port CO_2 emission is regarded as an undesirable output, as shown in Figure 4. Rail-water intermodal transport includes two parts: railway transportation and waterway transportation. The two parts are connected and transshipped to complete the transportation together. Stage 1 of the network system is transporting goods by rail, and stage 2 is loading and unloading goods in ports.

This article summarizes the relevant literature, as shown in Table 1. Based on this literature, combined with the actual situation of this case and the availability of data, the specific variables of the rail-water intermodal transport system have been determined. The length of railways and railway labor are the inputs of stage 1. The railway−port freight volumes are considered the intermediate products and refer to the volume of goods transported by railway to the port. The berth quantity and port labor are the outside inputs of stage 2. The port cargo throughput and carbon dioxide emissions are the desirable output and undesirable output of stage 2, respectively. In the rail-water intermodal transport system, the carbon emission mainly comes from the port. Compared with the port, the carbon emission of the railway is very small and is not considered here.

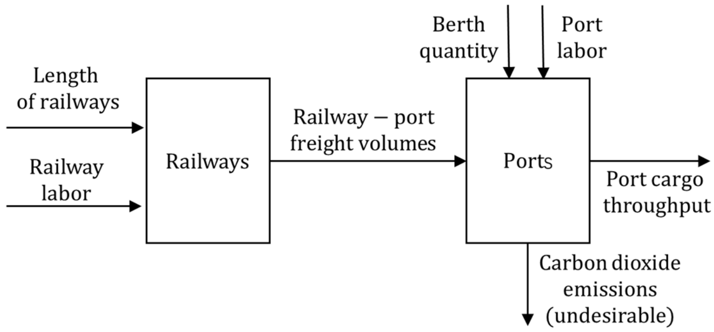

Figure 4. Two-stage network structure of rail-water intermodal transport.

Table 1. References for variable selection [21,60–65].

Literature	System	Variables	Orientation	Area
Cantos et al., 1999	Railway	Inputs: ▪ Number of workers ▪ Consumption of energy ▪ Number of locomotives ▪ Number of passenger carriages ▪ Number of freight cars ▪ Number of kilometers of track Outputs: ▪ Passenger-km ▪ Tonnes-km	Input-oriented	Europe
Wanke and Kalam Azad, 2018	Railway	Inputs: ▪ Railway route length ▪ Number of locomotives ▪ Number of freight wagons Outputs: ▪ Freight (thousand tonnes) ▪ Freight km	Input-oriented	Asia
Michali et al., 2021	Railway	Inputs: ▪ Costs ▪ Length of Lines ▪ Total Wagons Outputs: ▪ Freight MT-km ▪ Passengers M-km ▪ Lden $\geq$ 55 dB	Input-oriented	Europe
Tongzon, 2001	Port	Inputs: ▪ Number of berths ▪ Number of cranes ▪ Number of tugs ▪ Stevedoring labor ▪ Terminal area Outputs: ▪ Throughput ▪ Ship working rate (TEU/h)	Input-oriented	Worldwide

Table 1. *Cont.*

Literature	System	Variables	Orientation	Area
Barros, 2003	Port	Inputs: ▪ Number of workers ▪ Book value of the assets Outputs: ▪ Ships ▪ Movement of freight ▪ Gross gage ▪ Break-bulk cargo ▪ Containerized freight ▪ Solid bulk ▪ Liquid bulk	Input-oriented	Portugal
Almawsheki and Shah, 2015	Port	Inputs: ▪ Terminal area ▪ Quay length ▪ Quay crane ▪ Yard equipment ▪ Maximum draft Outputs: ▪ Throughput	Input-oriented	Middle-east
Saeedi et al., 2019	Multimodal transport	Inputs: ▪ Total terminal area ▪ Length of tracks ▪ No. of tracks ▪ No. of cranes ▪ No. of stackers Outputs: ▪ Value of intermodal freight transport service	Input-oriented	Europe

This article evaluates the CO_2 emission efficiency of rail-water intermodal transport systems in 14 Chinese ports in 2015. The 14 ports are members of the China Association of Port Railway Branch (a branch of the China Ports & Harbours Association). The China Ports & Harbours Association is the only national industry organization in the Chinese port industry, and its members are all over the coastal and riverine regions of China. It is typical and representative to study the 14 members of the China Association of Port Railway Branch.

The data sources and specific values of variables are shown in Tables 2 and 3. Since there is no official authoritative port carbon emission data, and only "China City CO_2 Emissions Dataset (2012)" and "China City Greenhouse Gases Emissions Dataset (2015)" have been published so far, the data of Emissions Dataset (2015) is used. Since 2015, there has been no significant change in the data of many variables. Recently, much of the relevant literature has also used the data of the 2010s. As such, the data for 2015 is still of reference value. Note that the carbon emission in the Emissions Dataset (2015) is part of all, and is not completely accurate. However, it has little impact on the whole, and the data can still reflect the general situation of port emissions. Moreover, this study can provide an illustrative case for the novel network DEA model and a practical idea for future related research.

Table 2. Data sources.

Variable	Data Sources
Length of railways	China Ports Yearbook
Railway labor	Annual Report
Railway—port freight volumes	China Ports Yearbook
Berth quantity	China Statistical Yearbook
Port labor	Annual Report
Port cargo throughput	China Statistical Yearbook
Carbon dioxide emissions	China City Greenhouse Gases Emissions Dataset (2015)

Table 3. Specific values of variables.

2015	Length of Railways (km)	Railway Labor	Railway—Port Freight Volumes (10,000 Tons)	Berth Quantity	Port Labor	Port Cargo Throughput (10,000 Tons)	Carbon Dioxide Emissions (10,000 Tons)
Qinhuangdao Port	170.00	1692	4328.00	72	11,993	25,309.00	23.90
Rizhao Port	158.00	1100	4400.00	53	5389	33,707.36	52.90
Beibu Gulf port	85.50	353	3229.00	256	3119	20,482.00	44.52
Zhanjiang Port	110.00	976	3038.00	174	6765	22,036.11	37.76
Tangshan Port	19.86	412	2780.00	97	2675	49,285.00	132.92
Dalian Port	124.85	830	2270.00	222	8235	41,482.00	136.28
Lianyungang Port	86.30	455	2733.00	77	8982	21,074.90	29.87
Ningbo-Zhoushan Port	54.50	521	2016.20	624	12,289	88,929.50	654.49
Yantai Port	24.50	335	1794.25	98	8995	25,163.00	142.18
Guangzhou Port	41.70	366	910.00	715	9970	52,095.67	35.01
Beiliang Port	51.00	101	432.10	11	819	1368.00	3.73
Yichang Port	21.00	154	335.10	579	3022	7776.00	18.44
Nanjing Port	15.00	823	161.65	346	2745	22,218.00	12.12
Zhuhai Port	17.69	73	289.00	147	2883	11,208.78	137.08

5.3. Results

In the above model, stage 1 measures the efficiency of railways in China's rail-water intermodal transport system, and stage 2 evaluates the efficiency of ports, taking into account CO_2 emissions. The railway can concentrate the goods from the hinterland to the port and transport them out by ships. The railway guarantees the smooth operation of the port, which is conducive to improving the shipping capacity. In the rail-water intermodal transport system of this article, the 14 selected railway companies are all subsidiaries of the corresponding port enterprises. The port is the main transportation link, and the railway is the subsidiary link. Therefore, it is assumed that stage 2 is the leader and stage 1 is the follower. Under variable returns to scale, the efficiency of the system and the two stages is evaluated using the efficiency decomposition, efficiency aggregation, and non-cooperative methods described above. The specific calculation results are shown in Figure 5.

According to the calculation results and definitions 1, 2, and 3, the following conclusions can be drawn. In the cases of efficiency decomposition and efficiency aggregation, the system efficiency value is 1 or less than 1 at the same time, and the effectiveness of the system is consistent. However, the system efficiency obtained by the efficiency decomposition model is equal to or lower than that by the efficiency aggregation model because the system efficiency of the efficiency decomposition model ignores the internal process of the network system. It can be seen that the results of the efficiency aggregation model considering the internal structure are more accurate and realistic. The system's internal structure contains intermediate products and the relationships between sub-divisions, and the model considering the internal structure can provide more diagnostic information and a more detailed analysis level. The efficiency evaluation results are also considered to be more accurate. Ignoring the internal structure of the system can lead to different and sometimes misleading results.

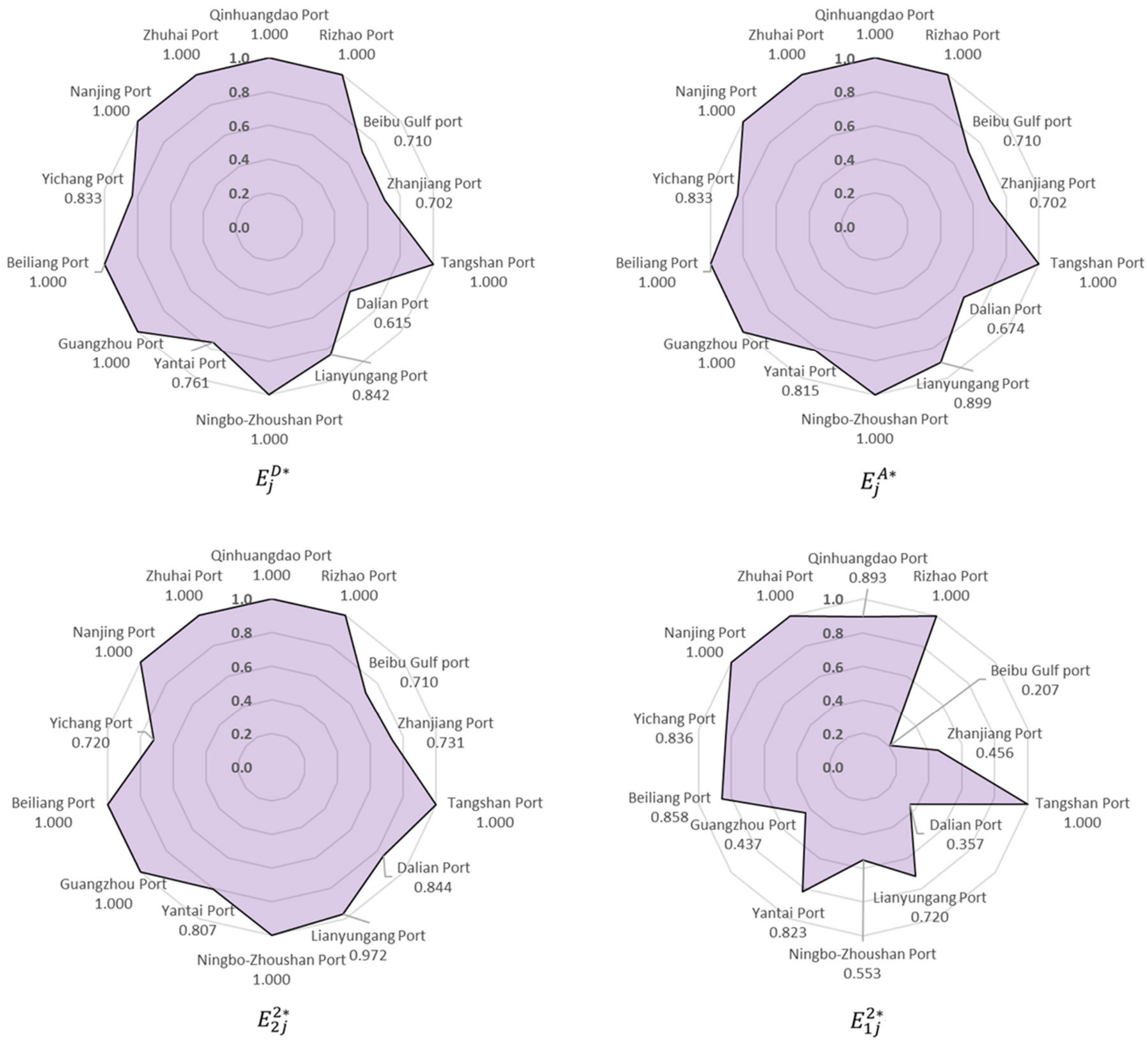

Figure 5. Calculation results of system efficiency and stage efficiency.

The system efficiency values of Qinhuangdao Port, Rizhao Port, Tangshan Port, Ningbo-Zhoushan Port, Guangzhou Port, Beiliang Port, Nanjing Port, and Zhuhai Port are 1, indicating that they are efficient. By contrast, the system efficiency values of Beibu Gulf port, Zhanjiang Port, Dalian Port, Lianyungang Port, Yantai Port, and Yichang Port are smaller than 1, indicating that they are inefficient. This implies that the operation and management of the entire multimodal transport system are at a low level, and the cooperation between different modes of transport is not ideal. The main reasons are the low operation efficiency and high cost of each logistics link, the lack of a unified multimodal transport information platform, and the low level of logistics information services. In addition, the lack of unified multimodal industry standards and regulations is also an important reason for the inefficiency of the system.

As for Rizhao Port, Tangshan Port, Nanjing Port, and Zhuhai Port, the efficiency values of the system and two stages are 1, indicating that they are efficient. As for Qinhuangdao Port, Ningbo-Zhoushan Port, Guangzhou Port, and Beiliang Port, the efficiency values of the system and stage 2 are 1 and efficient, yet the efficiency value of stage 1 is below 1 and inefficient. These indicate that railways are under-resourced in railway lines and workers, the management level of the railway transport is low, and the management department does not pay enough attention to the railway stage. With stage 2 as the leader and stage 1 as the follower, for Yantai Port and Yichang Port, the efficiency of stage 2 is lower than that of stage 1. This indicates that the port's facilities and manpower input are insufficient and the low-carbon operation performance is poor. The main reasons are that the energy structure of the port needs to be optimized, the utilization rate of electric energy needs to be improved, and there is a lack of new technology and equipment. In addition, the weak low-carbon awareness of employees is also an important reason for the poor performance of operations.

5.4. Discussion

According to the calculation results, Qinhuangdao Port, Ningbo-Zhoushan Port, Guangzhou Port, and Beiliang Port are only inefficient at the railway stage. To improve the efficiency of railway transport, it is necessary to increase the number of railway special lines and vehicles. In addition, the government should introduce encouraging policies to improve the management level of railway transport.

Beibu Gulf port, Zhanjiang Port, Dalian Port, Lianyungang Port, Yantai Port, and Yichang Port are smaller than 1 in system efficiency, which means they are inefficient. Thus, they need to optimize the entire multimodal transport system from the following aspects. First, it is necessary to optimize the operation mode of rail-water intermodal transport, improve the operation efficiency of logistics links such as ports and railways, and shorten railway transportation time to reduce transportation costs. Second, railways and ports should jointly build a multimodal transport information platform, unify multimodal transport standards, realize data interconnection and sharing, and enhance the logistics information services throughout the rail-water intermodal transport. Third, industry standards for multimodal transport should be introduced and relevant state departments should formulate laws and regulations applicable to multimodal transport to improve the standard specifications for different goods and operations and strengthen the coordination between different modes of transport.

With the port as the leader, the port efficiency of Yantai Port and Yichang Port is lower than the railway efficiency. This shows that they need to enhance the low-carbon operation efficiency of the ports from the following aspects. First, it is necessary to optimize the energy structure of ports, enhance the construction and upgrading of shore power, and promote the electrification of mechanical equipment such as port vehicles and container-handling equipment. Second, it is necessary to strengthen new technology research and equipment upgrading, introduce the Internet of Things and energy-saving equipment into the port, reduce unreasonable work procedures and plans, and optimize management methods. Third, the low-carbon awareness of personnel should be enhanced by introducing the low-carbon concept into on-the-job training and strengthening environmental protection publicity.

Overall, Rizhao Port, Tangshan Port, Nanjing Port, and Zhuhai Port are efficient in the whole system and both stages. Other ports should learn from them and take measures from the aspects of energy structure, technological innovation, and management standards to promote green and low-carbon development of multimodal transport.

6. Conclusions

This article constructs a specific network DEA model to evaluate the efficiency of rail-water intermodal transport in China. The main contributions of this article are as follows. First, in the general network structure, the efficiency decomposition, efficiency aggregation, and single compromise division efficiency are discussed. Second, the CO_2 emission efficiency in rail-water intermodal transport is evaluated by the efficiency decomposition, efficiency aggregation, and non-cooperative methods of network DEA.

First, this article studies the efficiency decomposition and efficiency aggregation of general network structures. Specifically, in efficiency decomposition, the relationship between system efficiency and division efficiency is discussed. In efficiency aggregation, the division tendency brought about by the definition of weights is discussed. Subsequently, a reasonable and single compromise solution for the division efficiency score is discussed under the condition that the system efficiency remains optimal. Finally, this article establishes a two-stage network DEA model for rail-water intermodal transport with CO_2 emission as an undesirable output. Based on this model, the rail-water intermodal transport efficiency of 14 ports in China in 2015 is evaluated by the methods of efficiency decomposition, efficiency aggregation, and non-cooperation. According to the calculation results, Qinhuangdao Port, Ningbo-Zhoushan Port, Guangzhou Port, and Beiliang Port are only inefficient at the railway stage, so it is necessary to improve the efficiency of railway transportation. Moreover, the system efficiency of Beibu Gulf port, Zhanjiang Port, Dalian Port, Lianyungang Port, Yantai Port, and Yichang Port is less than 1, which indicates that they are inefficient and thus need to optimize the entire multimodal transport system. With the port as the leader, the port efficiency of Yantai Port and Yichang Port is lower than the railway efficiency. In this case, they are in urgent need of improvement of the low-carbon operation efficiency of the port. In general, Rizhao Port, Tangshan Port, Nanjing Port, and Zhuhai Port are efficient in the system and two stages, so other ports need to learn from them.

In the future, further research can be carried out in the following aspects. First, a more practical network DEA model considering more stages can be established, and the model can be used to analyze the multimodal transport chains with multiple transshipment and transport links. Second, the model can be applied to other efficiency evaluations of supply chains. For example, the network DEA model could be used to evaluate the performance of manufacturers and sellers or analyze the environmental performance of goods storage and logistics. Third, the multi-period model can be used to analyze the dynamic trend of multimodal transport efficiency. Multi-period network DEA can not only horizontally compare the efficiency of different multimodal transport systems in the same time period, but also vertically compare the efficiency of a multimodal transport system in different time periods.

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