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Research on Neutral Dynamic Network Cross-Efficiency Modeling for Low-Carbon Innovation Development of Enterprises

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Abstract: To evaluate the effectiveness of the low-carbon innovation development of enterprises, this paper proposes a neutral dynamic network cross-efficiency model and introduces the bootstrap sampling method to correct the model. The model categorizes the low-carbon green innovation R&D activities of enterprises into two distinct stages, as follows: the green R&D stage and the results transformation stage. It then assesses the efficiency of each stage and provides an overall efficiency rating. The model has been applied to a sample of listed Chinese iron and steel enterprises (CISES). The results of the study show that the overall efficiency of low-carbon innovation and development of CISES is on the low side, with the highest efficiency achieved in the green R&D stage, which is less than the lowest efficiency attained in the transformation stage, and most of the enterprises are in the stage of high green R&D and low transformation of the results. The ability of marketization of the R&D results still needs to be strengthened.

Keywords: low-carbon innovation development efficiency; dynamic networks; neutral cross-efficiency; bootstrap sampling methods

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1. Introduction

In the dual-carbon context, the innovation-driven green and low-carbon transformation of various industries has become the main theme of developing new quality productivity. The iron and steel industry (ISI) represents a significant foundation of China's national economy. It is also confronted with considerable challenges, and numerous steel enterprises globally have already established concrete carbon-neutral objectives [1]. In the actual production process, iron and steel enterprises (ISES) not only need to ensure the ultimate energy efficiency of ultra-low emissions, but they also need to ensure the production quality of the product; for this reason, it is necessary to carry out green carbon reduction transformation and upgrading, and it is necessary to enhance their own low-carbon development and innovation capacity to meet the needs of the actual enterprise [2]. Low-carbon innovation as a combination of innovation-driven and carbon reduction development is a key means to promote the green low-carbon transformation of the ISI, so the scientific evaluation of the development efficiency of low-carbon innovation in ISES is a key issue in the study of the green transformation of ISES.

This paper will focus on the efficiency of carbon reduction innovation development for ISES, considering the actual situation of ISES in terms of research and development, and the production process of multiple inputs and multiple outputs, measuring the relative efficiency and effectiveness of multiple enterprises. In the existing research, the

analysis methods focusing on efficiency mainly fall into two categories: parametric and nonparametric methods [3]. Parametric methods mainly include Regression Analysis, Stochastic Frontier Approach (SFA), etc. [4]. Cho et al. proposed a dynamic coefficient that combines multiple linear regression and optimization models to explore the impacts of natural disasters on the inventory-holding decisions of business managers [5]. Wang constructed a cross-country production model that incorporates the SFA approach to assess the relative R&D efficiency of different countries [6]. Non-parametric methods are mainly based on Data Envelopment Analysis (DEA) and its deformation [7]. Zhang et al. used an ultra-relaxed SBM model to assess the efficiency of provincial green development of iron and steel in China, and explored the factors affecting the efficiency of provincial green development through cluster analysis and the Tobit model [8]. Compared with the parametric method, which is applicable to multi-input and single-output cases, the DEA model is more suitable to a multi-input and multi-output (MIMO) case [9]. When facing the practical problems related to MIMO, compared with other MIMO methods, the DEA method is a non-parametric method, which does not require the prior specification of the functional relationship between inputs and outputs in advance, and the computational complexity is relatively low; it can also effectively respond to the dynamic changes in assessing the efficiency at different points in time. Therefore, the study will be based on the DEA model.

The DEA method has been widely applied in the assessment of efficiency in ISES [10–13]. In this study, the DEA model and its deformed models are self-assessment models, static models with 'black-box' characteristics, and even have the problem of the strong dependence of their results on samples. To solve these problems, Sexton et al. [14], Fare et al. [15], Tone and Tsutsui [16], and Simar et al. [17] put forth the cross-efficiency evaluation method, the network model (NDEA), the dynamic network model (DNDEA), and the bootstrap correction method, respectively. Sometimes the final evaluation results are not unique; for this reason, the related scholars combined the secondary goal of developing three benevolent, adversarial, and neutral strategies, and proposed the method of selecting one of the optimal weights from multiple sets of available weights and then carrying out a mutual evaluation after the self-assessment of the maximum efficiency, which has been widely applied [18,19].

All of the above models are optimized for only one or two main problems each, and do not solve the multiple problems faced by the basic DEA model at the same time. The focus of this paper is Chinese steel-listed enterprises, the relationship between which is intricate; the results produced by antagonistic and benevolent cross-efficiency are not trustworthy, while neutral cross-efficiency evaluations only focus on whether the decision is favorable to the value of the decision-making unit's evaluation, meaning the results are more trustworthy.

Therefore, when utilizing the DEA model to assess the efficiency of low-carbon innovation and development of CISES, this paper, in connection with the actual R&D and production situation and the sharing of input resources, considers combining the neutral cross-efficiency and the DNDEA model to construct a neutral dynamic network cross-efficiency model to assess the efficiency of green innovation of CISES. At the same time, the research sample capacity of Chinese steel-listed enterprises is small, and the data are few. The bootstrap simulation sampling method will be introduced to correct the above model.

2. Modelling

2.1. Dynamic Network DEA Self-Assessment Model

2.1.1. Construction of Self-Assessment Model

In this study, we refer to the DNDEA model constructed by Kou et al. [20], which fully integrates the dual identity of the carry-over variable and the connection variable linkers during the operation of the dynamic network system. However, since it is not possible to objectively measure the proportion of shared resources, this paper cites Kao and Hwang's [21] treatment of a two-stage network process in which the outputs of the first stage are used as inputs to the second stage, and the shared inputs are set to have the same multiplicative weights in both stages of the model.

We assume that the model is a classical two-stage network structure with T cycles and n homogeneous decision-making units (Figure 1).

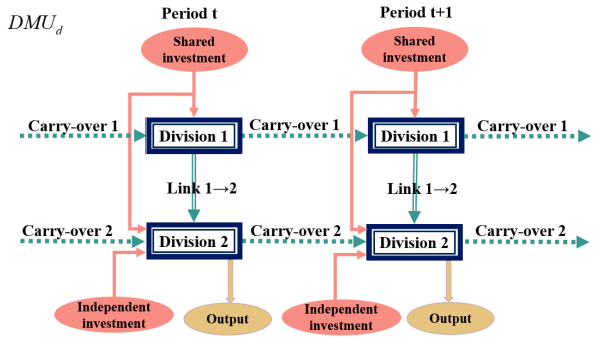


Figure 1. Two-stage dynamic network theory model diagram.

The following figure assumes that there are n homogeneous decision-making units $DMU_d(d = 1, \ldots, n)$ (Figure 2). DMU_d^{Nt} is the Nth stage of DMU_d in period t; x_{id}^t is the ith shared input of DMU_d in period t, where α_i^t is the proportion of sub-matching in period 1; z_{ad}^t is the ath linking variable between stage 1 and stage 2 of DMU_d in period t; k_{rd}^{1t} is the rth carry-over variable for DMU_d in period t, stage 1, and k_{sd}^{2t} is the sth carry-over variable for DMU_d in period t, stage 2; f_{bd}^t is the bth input of DMU_d in period t, stage 2; y_{md}^t is the mth output of DMU_d in period t, phase 2. $d = 1, \ldots, n$; $t = 1, 2, \ldots, T$; $N \in \{1, 2\}$; $i = 1, \ldots, I$; $a = 1, \ldots, A$; $r = 1, \ldots, R$; $s = 1, \ldots, S$; $b = 1, \ldots, B$; $m = 1, \ldots, M$.

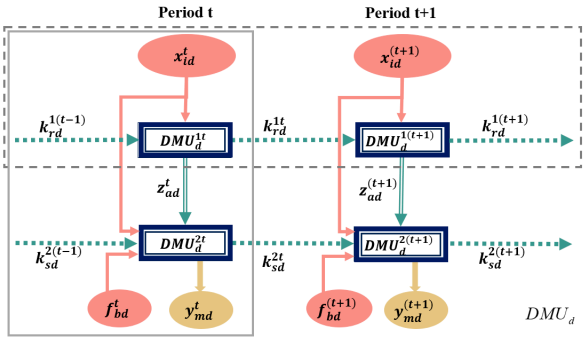


Figure 2. Mathematical structure of the two-stage dynamic network model.

For the entire dynamic network model, the linking variable (z_{ad}^t) in period t is both an output and an input in period 2; the carry-over variable (k_{rd}^{1t}) in period 1 in period t is both an output in period 1 and an input in period 1 (in period $t+1$); the carry-over variable (k_{sd}^{2t}) in period 1 in period t is both an output in period 2 in period t and an input in period 2 in period $t+1$.

Then, the θ_{dd}^{NT} formula that can define the overall self-assessment efficiency value of DMU_d is

$$\theta_{dd}^{NT} = \frac{\sum_{t=1}^{T}\left(\sum_{a=1}^{A}\varphi_{ad}z_{ad}^t + \sum_{r=1}^{R}\phi_{rd}^1 k_{rd}^{1t} + \sum_{m=1}^{M}v_{md}y_{md}^t + \sum_{s=1}^{S}\phi_{sd}^2 k_{sd}^{2t}\right)}{\sum_{t=1}^{T}\left(\sum_{i=1}^{I}u_{id}x_{id}^t + \sum_{r=1}^{R}\phi_{rd}^1 k_{rd}^{1(t-1)} + \sum_{a=1}^{A}\varphi_{ad}z_{ad}^t + \sum_{b=1}^{B}\eta_{bd}f_{bd}^t + \sum_{s=1}^{S}\phi_{sd}^2 k_{sd}^{2(t-1)}\right)} \quad (1)$$

We define the period's self-assessment efficiency value θ_{dd}^{Nt} formula for DMU_d as

$$\theta_{dd}^{Nt} = \frac{\sum_{a=1}^{A}\varphi_{ad}z_{ad}^t + \sum_{r=1}^{R}\phi_{rd}^1 k_{rd}^{1t} + \sum_{m=1}^{M}v_{md}y_{md}^t + \sum_{s=1}^{S}\phi_{sd}^2 k_{sd}^{2t}}{\sum_{i=1}^{I}u_{id}x_{id}^t + \sum_{r=1}^{R}\phi_{rd}^1 k_{rd}^{1(t-1)} + \sum_{a=1}^{A}\varphi_{ad}z_{ad}^t + \sum_{b=1}^{B}\eta_{bd}f_{bd}^t + \sum_{s=1}^{S}\phi_{sd}^2 k_{sd}^{2(t-1)}} \quad (2)$$

We define the self-assessed efficiency θ_{dd}^{1T} of DMU_d at stage 1 as

$$\theta_{dd}^{1T} = \frac{\sum_{t=1}^{T}\left(\sum_{a=1}^{A}\varphi_{ad}z_{ad}^{t} + \sum_{r=1}^{R}\phi_{rd}^{1}k_{rd}^{1t}\right)}{\sum_{t=1}^{T}\left(\sum_{i=1}^{I}u_{id}\alpha_{i}^{t}x_{id}^{t} + \sum_{r=1}^{R}\phi_{rd}^{1}k_{rd}^{1(t-1)}\right)} \tag{3}$$

We define the self-assessed efficiency θ_{dd}^{2T} of DMU_d at stage 2 as

$$\theta_{dd}^{2T} = \frac{\sum_{t=1}^{T}\left(\sum_{m=1}^{M}v_{md}y_{md}^{t} + \sum_{s=1}^{S}\phi_{sd}^{2}k_{sd}^{2t}\right)}{\sum_{t=1}^{T}\left(\sum_{i=1}^{I}u_{id}(1-\alpha_{i}^{t})x_{id}^{t} + \sum_{a=1}^{A}\varphi_{ad}z_{ad}^{t} + \sum_{b=1}^{B}\eta_{bd}f_{bd}^{t} + \sum_{s=1}^{S}\phi_{sd}^{2}k_{sd}^{2(t-1)}\right)} \tag{4}$$

We define the DMU_d's period self-assessed efficiency θ_{dd}^{1t} in stage 1 as

$$\theta_{dd}^{1t} = \frac{\sum_{a=1}^{A}\varphi_{ad}z_{ad}^{t} + \sum_{r=1}^{R}\phi_{rd}^{1}k_{rd}^{1t}}{\sum_{i=1}^{I}u_{id}\alpha_{i}^{t}x_{id}^{t} + \sum_{r=1}^{R}\phi_{rd}^{1}k_{rd}^{1(t-1)}} \tag{5}$$

We define the DMU_d's period self-assessed efficiency θ_{dd}^{2t} in stage 2 as

$$\theta_{dd}^{2t} = \frac{\sum_{m=1}^{M}v_{md}y_{md}^{t} + \sum_{s=1}^{S}\phi_{sd}^{2}k_{sd}^{2t}}{\sum_{i=1}^{I}u_{id}(1-\alpha_{i}^{t})x_{id}^{t} + \sum_{a=1}^{A}\varphi_{ad}z_{ad}^{t} + \sum_{b=1}^{B}\eta_{bd}f_{bd}^{t} + \sum_{s=1}^{S}\phi_{sd}^{2}k_{sd}^{2(t-1)}} \tag{6}$$

Therefore, in light of the assumption of constant returns to scale, the following overall self-assessment efficiency model for DMU_d is proposed:

$$\begin{aligned}
\max \quad & \theta_{dd}^{NT} = \frac{\sum_{t=1}^{T}\left(\sum_{a=1}^{A}\varphi_{ad}z_{ad}^{t} + \sum_{r=1}^{R}\phi_{rd}^{1}k_{rd}^{1t} + \sum_{m=1}^{M}v_{md}y_{md}^{t} + \sum_{s=1}^{S}\phi_{sd}^{2}k_{sd}^{2t}\right)}{\sum_{t=1}^{T}\left(\sum_{i=1}^{I}u_{id}x_{id}^{t} + \sum_{r=1}^{R}\phi_{rd}^{1}k_{rd}^{1(t-1)} + \sum_{a=1}^{A}\varphi_{ad}z_{ad}^{t} + \sum_{b=1}^{B}\eta_{bd}f_{bd}^{t} + \sum_{s=1}^{S}\phi_{sd}^{2}k_{sd}^{2(t-1)}\right)} \\
s.t. \quad & \frac{\sum_{t=1}^{T}\left(\sum_{a=1}^{A}\varphi_{ad}z_{aj}^{t} + \sum_{r=1}^{R}\phi_{rd}^{1}k_{rj}^{1t} + \sum_{m=1}^{M}v_{md}y_{mj}^{t} + \sum_{s=1}^{S}\phi_{sd}^{2}k_{sj}^{2t}\right)}{\sum_{t=1}^{T}\left(\sum_{i=1}^{I}u_{id}x_{ij}^{t} + \sum_{r=1}^{R}\phi_{rd}^{1}k_{rj}^{1(t-1)} + \sum_{a=1}^{A}\varphi_{ad}z_{aj}^{t} + \sum_{b=1}^{B}\eta_{bd}f_{bj}^{t} + \sum_{s=1}^{S}\phi_{sd}^{2}k_{sj}^{2(t-1)}\right)} \leq 1 \\
& (j = 1, \ldots, n) \\
& \frac{\sum_{a=1}^{A}\varphi_{ad}z_{aj}^{t} + \sum_{r=1}^{R}\phi_{rd}^{1}k_{rj}^{1t}}{\sum_{i=1}^{I}u_{id}\alpha_{i}^{t}x_{ij}^{t} + \sum_{r=1}^{R}\phi_{rd}^{1}k_{rj}^{1(t-1)}} \leqslant 1 \\
& \frac{\sum_{m=1}^{M}v_{md}y_{mj}^{t} + \sum_{s=1}^{S}\phi_{sd}^{2}k_{sj}^{2t}}{\sum_{i=1}^{I}u_{id}(1-\alpha_{i}^{t})x_{ij}^{t} + \sum_{a=1}^{A}\varphi_{ad}z_{aj}^{t} + \sum_{b=1}^{B}\eta_{bd}f_{bj}^{t} + \sum_{s=1}^{S}\phi_{sd}^{2}k_{sj}^{2(t-1)}} \leqslant 1 \\
& L_{i}^{t} \leqslant \alpha_{i}^{t} \leqslant H_{i}^{t} \\
& u_{id} \geqslant 0, \varphi_{ad} \geqslant 0, \phi_{rd}^{1} \geqslant 0, \phi_{sd}^{2} \geqslant 0, \eta_{bd} \geqslant 0, v_{md} \geqslant 0 \\
& (i = 1, \ldots, I; a = 1, \ldots, A; r = 1, \ldots, R; s = 1, \ldots, S; b = 1, \ldots, B; m = 1, \ldots, M)
\end{aligned} \tag{7}$$

where the first constraint is to indicate that the overall efficiency value of the evaluated unit d should be less than or equal to 1. The second constraint is to indicate that the efficiency

value of the evaluated unit d in stage 1 should be less than or equal to 1. The third constraint is to indicate that the efficiency value of the evaluated unit d in stage 2 should be less than or equal to 1. The fourth constraint is to indicate that the allocation ratio should be selected in the appropriate range according to the actual situation. And the fifth constraint is to indicate that the weight of model (7) should be greater than or equal to zero.

2.1.2. Solving the Self-Assessment Model

Model (7) is transformed equivalently by the Charnes–Cooper transformation of this model into the following linear programming form [22]:

$$\begin{aligned}
&\max\ \theta_{dd}^{NT} = \sum_{t=1}^{T}\left(\sum_{a=1}^{A}\delta_{ad}z_{ad}^{t} + \sum_{r=1}^{R}\psi_{rd}^{1}k_{rd}^{1t} + \sum_{m=1}^{M}\xi_{md}y_{md}^{t} + \sum_{s=1}^{S}\psi_{sd}^{2}k_{sd}^{2t}\right)\\
&s.t.\ \sum_{t=1}^{T}\left(\sum_{i=1}^{I}\mu_{id}x_{id}^{t} + \sum_{r=1}^{R}\psi_{rd}^{1}k_{rd}^{1(t-1)} + \sum_{a=1}^{A}\delta_{ad}z_{ad}^{t} + \sum_{b=1}^{B}\zeta_{bd}f_{bd}^{t} + \sum_{s=1}^{S}\psi_{sd}^{2}k_{sd}^{2(t-1)}\right) = 1\\
&\sum_{t=1}^{T}\left(\begin{array}{l}\sum_{a=1}^{A}\delta_{ad}z_{aj}^{t} + \sum_{r=1}^{R}\psi_{rd}^{1}k_{rj}^{1t} +\\ \sum_{m=1}^{M}\xi_{md}y_{mj}^{t} + \sum_{s=1}^{S}\psi_{sd}^{2}k_{sj}^{2t}\end{array}\right) - \sum_{t=1}^{T}\left(\begin{array}{l}\sum_{i=1}^{I}\mu_{id}x_{ij}^{t} + \sum_{r=1}^{R}\psi_{rd}^{1}k_{rj}^{1(t-1)} +\\ \sum_{a=1}^{A}\delta_{ad}z_{aj}^{t} + \sum_{b=1}^{B}\zeta_{bd}f_{bj}^{t} + \sum_{s=1}^{S}\psi_{sd}^{2}k_{sj}^{2(t-1)}\end{array}\right) \leqslant 0\\
&\quad (j = 1,\ldots,n)\\
&\qquad \sum_{a=1}^{A}\delta_{ad}z_{aj}^{t} + \sum_{r=1}^{R}\psi_{rd}^{1}k_{rj}^{1t} - \left(\sum_{i=1}^{I}\tau_{id}^{t}x_{ij}^{t} + \sum_{r=1}^{R}\psi_{rd}^{1}k_{rj}^{1(t-1)}\right) \leqslant 0\\
&\sum_{m=1}^{M}\xi_{md}y_{mj}^{t} + \sum_{s=1}^{S}\psi_{sd}^{2}k_{sj}^{2t} - \left(\begin{array}{l}\sum_{i=1}^{I}(\mu_{id}-\tau_{id}^{t})x_{ij}^{t} + \sum_{a=1}^{A}\delta_{ad}z_{aj}^{t}\\ +\sum_{b=1}^{B}\zeta_{bd}f_{bj}^{t} + \sum_{s=1}^{S}\psi_{sd}^{2}k_{sj}^{2(t-1)}\end{array}\right) \leqslant 0\\
&L_{i}^{t}\mu_{id} \leqslant \tau_{id}^{t} \leqslant H_{i}^{t}\mu_{id}\\
&\mu_{id} \geqslant 0, \delta_{ad} \geqslant 0, \psi_{rd}^{1} \geqslant 0, \psi_{sd}^{2} \geqslant 0, \zeta_{bd} \geqslant 0, \xi_{md} \geqslant 0\\
&(i = 1,\ldots,I; a = 1,\ldots,A; r = 1,\ldots,R; s = 1,\ldots,S; b = 1,\ldots,B; m = 1,\ldots,M)
\end{aligned} \tag{8}$$

According to the optimal weight combination $(\delta_{ad}^{*}, \psi_{rd}^{*1}, \xi_{md}^{*}, \psi_{sd}^{*2}, \mu_{id}^{*}, \zeta_{bd}^{*}, \tau_{id}^{*t})$ obtained from model (8), there is an overall self-assessment efficiency θ_{dd}^{NT} of DMU_d, which can be written as

$$\theta_{dd}^{NT} = \frac{\sum_{t=1}^{T}\left(\sum_{a=1}^{A}\delta_{ad}^{*}z_{ad}^{t} + \sum_{r=1}^{R}\psi_{rd}^{*1}k_{rd}^{1t} + \sum_{m=1}^{M}\xi_{md}^{*}y_{md}^{t} + \sum_{s=1}^{S}\psi_{sd}^{*2}k_{sd}^{2t}\right)}{\sum_{t=1}^{T}\left(\sum_{i=1}^{I}\mu_{id}^{*}x_{id}^{t} + \sum_{r=1}^{R}\psi_{rd}^{*1}k_{rd}^{1(t-1)} + \sum_{a=1}^{A}\delta_{ad}^{*}z_{ad}^{t} + \sum_{b=1}^{B}\zeta_{bd}^{*}f_{bd}^{t} + \sum_{s=1}^{S}\psi_{sd}^{*2}k_{sd}^{2(t-1)}\right)} \tag{9}$$

The period self-assessment efficiency θ_{dd}^{Nt} of DMU_d is

$$\theta_{dd}^{Nt} = \frac{\sum_{a=1}^{A}\delta_{ad}^{*}z_{ad}^{t} + \sum_{r=1}^{R}\psi_{rd}^{*1}k_{rd}^{1t} + \sum_{m=1}^{M}\xi_{md}^{*}y_{md}^{t} + \sum_{s=1}^{S}\psi_{sd}^{*2}k_{sd}^{2t}}{\sum_{i=1}^{I}\mu_{id}^{*}x_{id}^{t} + \sum_{r=1}^{R}\psi_{rd}^{*1}k_{rd}^{1(t-1)} + \sum_{a=1}^{A}\delta_{ad}^{*}z_{ad}^{t} + \sum_{b=1}^{B}\zeta_{bd}^{*}f_{bd}^{t} + \sum_{s=1}^{S}\psi_{sd}^{*2}k_{sd}^{2(t-1)}} \tag{10}$$

DMU_d's self-assessed efficiency θ_{dd}^{1T} at stage 1 is

$$\theta_{dd}^{1T} = \frac{\sum_{t=1}^{T}\left(\sum_{a=1}^{A}\delta_{ad}^{*}z_{ad}^{t} + \sum_{r=1}^{R}\psi_{rd}^{*1}k_{rd}^{1t}\right)}{\sum_{t=1}^{T}\left(\sum_{i=1}^{I}\tau_{id}^{*t}x_{id}^{t} + \sum_{r=1}^{R}\psi_{rd}^{*1}k_{rd}^{1(t-1)}\right)} \tag{11}$$

DMU_d's self-assessed efficiency θ_{dd}^{2T} at stage 2 is

$$\theta_{dd}^{2T} = \frac{\sum_{t=1}^{T}\left(\sum_{m=1}^{M}\xi_{md}^{*}y_{md}^{t}+\sum_{s=1}^{S}\psi_{sd}^{*2}k_{sd}^{2t}\right)}{\sum_{t=1}^{T}\left(\sum_{i=1}^{I}(\mu_{id}^{*}-\tau_{id}^{*t})x_{id}^{t}+\sum_{a=1}^{A}\delta_{ad}^{*}z_{ad}^{t}+\sum_{b=1}^{B}\zeta_{bd}^{*}f_{bd}^{t}+\sum_{s=1}^{S}\psi_{sd}^{*2}k_{sd}^{2(t-1)}\right)} \tag{12}$$

DMU_d's self-assessed efficiency θ_{dd}^{1t} for the period in stage 1 is

$$\theta_{dd}^{1t} = \frac{\sum_{a=1}^{A}\delta_{ad}^{*}z_{ad}^{t}+\sum_{r=1}^{R}\psi_{rd}^{*1}k_{rd}^{1t}}{\sum_{i=1}^{I}\tau_{id}^{*t}x_{id}^{t}+\sum_{r=1}^{R}\psi_{rd}^{*1}k_{rd}^{1(t-1)}} \tag{13}$$

DMU_d's self-assessed efficiency θ_{dd}^{2t} for the period in stage 2 is

$$\theta_{dd}^{2t} = \frac{\sum_{m=1}^{M}\xi_{md}^{*}y_{md}^{t}+\sum_{s=1}^{S}\psi_{sd}^{*2}k_{sd}^{2t}}{\sum_{i=1}^{I}(\mu_{id}^{*}-\tau_{id}^{*t})x_{id}^{t}+\sum_{a=1}^{A}\delta_{ad}^{*}z_{ad}^{t}+\sum_{b=1}^{B}\zeta_{bd}^{*}f_{bd}^{t}+\sum_{s=1}^{S}\psi_{sd}^{*2}k_{sd}^{2(t-1)}} \tag{14}$$

2.2. Neutral Dynamic Network Cross-Efficiency Modeling

2.2.1. Construction of Neutral Cross-Efficiency Model

The neutral-type secondary objective model was first proposed by Wang [23], whose main idea is that the decision-making unit, when deciding the input and output weights, focuses more on whether the weights are favorable for calculating its efficiency value. The neutral-type dynamic network cross-efficiency model constructed in this paper based on this is shown below.

$$\begin{aligned}
&\max\ W = \min_{\substack{a\in\{1,\ldots,A\}\\ r\in\{1,\ldots,R\}\\ m\in\{1,\ldots,M\}\\ s\in\{1,\ldots,S\}}} \frac{\sum_{t=1}^{T}\left(\varphi_{ao}z_{ao}^{t}+\phi_{ro}^{1}k_{ro}^{1t}+v_{mo}y_{mo}^{t}+\phi_{so}^{2}k_{so}^{2t}\right)}{\sum_{t=1}^{T}\left(\sum_{i=1}^{I}u_{io}x_{io}^{t}+\sum_{r=1}^{R}\phi_{ro}^{1}k_{ro}^{1(t-1)}+\sum_{a=1}^{A}\varphi_{ao}z_{ao}^{t}+\sum_{b=1}^{B}\eta_{bo}f_{bo}^{t}+\sum_{s=1}^{S}\phi_{so}^{2}k_{so}^{2(t-1)}\right)}\\
&s.t.\\
&\frac{\sum_{t=1}^{T}\left(\sum_{a=1}^{A}\varphi_{ao}z_{ad}^{t}+\sum_{r=1}^{R}\phi_{ro}^{1}k_{rd}^{1t}+\sum_{m=1}^{M}v_{mo}y_{md}^{t}+\sum_{s=1}^{S}\phi_{so}^{2}k_{sd}^{2t}\right)}{\sum_{t=1}^{T}\left(\sum_{i=1}^{I}u_{io}x_{id}^{t}+\sum_{r=1}^{R}\phi_{ro}^{1}k_{rd}^{1(t-1)}+\sum_{a=1}^{A}\varphi_{ao}z_{ad}^{t}+\sum_{b=1}^{B}\eta_{bo}f_{bd}^{t}+\sum_{s=1}^{S}\phi_{so}^{2}k_{sd}^{2(t-1)}\right)}=\theta_{dd}^{NT*}\\
&\frac{\sum_{t=1}^{T}\left(\sum_{a=1}^{A}\varphi_{ao}z_{aj}^{t}+\sum_{r=1}^{R}\phi_{ro}^{1}k_{rj}^{1t}+\sum_{m=1}^{M}v_{mo}y_{mj}^{t}+\sum_{s=1}^{S}\phi_{so}^{2}k_{sj}^{2t}\right)}{\sum_{t=1}^{T}\left(\sum_{i=1}^{I}u_{io}x_{ij}^{t}+\sum_{r=1}^{R}\phi_{ro}^{1}k_{rj}^{1(t-1)}+\sum_{a=1}^{A}\varphi_{ao}z_{aj}^{t}+\sum_{b=1}^{B}\eta_{bo}f_{bj}^{t}+\sum_{s=1}^{S}\phi_{so}^{2}k_{sj}^{2(t-1)}\right)}\leqslant 1\\
&(j=1,\ldots,n;j\neq o)\\
&\frac{\sum_{a=1}^{A}\varphi_{ao}z_{aj}^{t}+\sum_{r=1}^{R}\phi_{ro}^{1}k_{rj}^{1t}}{\sum_{i=1}^{I}u_{io}\alpha_{i}^{t}x_{ij}^{t}+\sum_{r=1}^{R}\phi_{ro}^{1}k_{rj}^{1(t-1)}}\leqslant 1\\
&\frac{\sum_{m=1}^{M}v_{mo}y_{mj}^{t}+\sum_{s=1}^{S}\phi_{so}^{2}k_{sj}^{2t}}{\sum_{i=1}^{I}u_{io}(1-\alpha_{i}^{t})x_{ij}^{t}+\sum_{a=1}^{A}\varphi_{ao}z_{aj}^{t}+\sum_{b=1}^{B}\eta_{bo}f_{bj}^{t}+\sum_{s=1}^{S}\phi_{so}^{2}k_{sj}^{2(t-1)}}\leqslant 1\\
&L_{i}^{t}u_{id}\leqslant\alpha_{i}^{t}u_{id}\leqslant H_{i}^{t}u_{id}\\
&u_{id}\geqslant 0,\varphi_{ad}\geqslant 0,\phi_{rd}^{1}\geqslant 0,\phi_{sd}^{2}\geqslant 0,\eta_{bd}\geqslant 0,v_{md}\geqslant 0\\
&u_{io}\geqslant 0,\varphi_{ao}\geqslant 0,\phi_{ro}^{1}\geqslant 0,\phi_{so}^{2}\geqslant 0,\eta_{bo}\geqslant 0,v_{mo}\geqslant 0(o=1,\ldots,n\ and\ o\neq d)\\
&(i=1,\ldots,I;a=1,\ldots,A;r=1,\ldots,R;s=1,\ldots,S;b=1,\ldots,B;m=1,\ldots,M)
\end{aligned} \tag{15}$$

where the partition in the objective function represents the value of the DMU in period t when the output indicator contains the ath $(a = 1, \ldots, A)$ linkage variable, the rth $(r = 1, \ldots, R)$ carry-over variable and the sth $(s = 1, \ldots, S)$ carry-over variable of stage 2, as well as the mth $(m = 1, \ldots, M)$ outputs for the $DMU_o (o = 1, \ldots, n \; and \; o \neq d)$ efficiency values. The objective function is the maximum value of the efficiency value of the output indicator that requires the smallest of these efficiency values..

The first constraint is to indicate that the weight combination $(u_{io}, \varphi_{ao}, \phi^1_{ro}, \phi^2_{so}, \eta_{bo}, v_{mo})$ should be such that the evaluated unit d satisfies the maximum efficiency, and θ^{NT*}_{dd} is the maximum value of θ^{NT}_{dd} in model (1). The second constraint is to indicate that the overall efficiency value of the evaluated unit o should be less than or equal to one. The third constraint is to indicate that the efficiency value of the evaluated unit o stage 1 should be less than or equal to 1. The fourth constraint is to indicate that the efficiency value of the evaluated unit o stage 2 should be less than or equal to 1. The fifth constraint is an indication that the allocation ratio should be chosen in an appropriate range according to the actual situation. In the sixth constraint, $u_{id}, \varphi_{ad}, \phi^1_{rd}, \phi^2_{sd}, \eta_{bd}, v_{md}$ are the weights obtained by solving model (7), indicating that these weights should be greater than or equal to zero. Under the seventh constraint, $\delta_{ao}, \psi^1_{ro}, \xi_{mo}, \psi^2_{so}, \mu_{io}, \zeta_{bo}, \tau^t_{io}$ are the weights of model (15), indicating that these weights should be greater than or equal to zero.

2.2.2. Solving the Neutral Cross-Efficiency Model

Model (15) is transformed equivalently by the Charnes–Cooper transformation of this model into the following linear programming form:

$$
\begin{aligned}
&\max W \\
&s.t. \\
&\sum_{t=1}^{T}\left(\begin{array}{l}\sum\limits_{a=1}^{A}\delta_{ao}z^t_{ad}+\sum\limits_{r=1}^{R}\psi^1_{ro}k^{1t}_{rd}+\\ \sum\limits_{m=1}^{M}\xi_{mo}y^t_{md}+\sum\limits_{s=1}^{S}\psi^2_{so}k^{2t}_{sd}\end{array}\right)-\theta^{NT*}_{dd}\cdot\sum_{t=1}^{T}\left(\begin{array}{l}\sum\limits_{i=1}^{I}\mu_{io}x^t_{id}+\sum\limits_{r=1}^{R}\psi^1_{ro}k^{1(t-1)}_{rd}+\sum\limits_{a=1}^{A}\delta_{ao}z^t_{ad}\\ +\sum\limits_{b=1}^{B}\zeta_{bo}f^t_{bd}+\sum\limits_{s=1}^{S}\psi^2_{so}k^{2(t-1)}_{sd}\end{array}\right)=0 \\
&\sum_{t=1}^{T}\left(\sum_{i=1}^{I}\mu_{io}x^t_{io}+\sum_{r=1}^{R}\psi^1_{ro}k^{1(t-1)}_{ro}+\sum_{a=1}^{A}\delta_{ao}z^t_{ao}+\sum_{b=1}^{B}\zeta_{bo}f^t_{bo}+\sum_{s=1}^{S}\psi^2_{so}k^{2(t-1)}_{so}\right)=1 \\
&\sum_{t=1}^{T}\left(\begin{array}{l}\sum\limits_{a=1}^{A}\delta_{ao}z^t_{aj}+\sum\limits_{r=1}^{R}\psi^1_{ro}k^{1t}_{rj}+\\ \sum\limits_{m=1}^{M}\xi_{mo}y^t_{mj}+\sum\limits_{s=1}^{S}\psi^2_{so}k^{2t}_{sj}\end{array}\right)-\sum_{t=1}^{T}\left(\begin{array}{l}\sum\limits_{i=1}^{I}\mu_{io}x^t_{ij}+\sum\limits_{r=1}^{R}\psi^1_{ro}k^{1(t-1)}_{rj}+\sum\limits_{a=1}^{A}\delta_{ao}z^t_{aj}\\ +\sum\limits_{b=1}^{B}\zeta_{bo}f^t_{bj}+\sum\limits_{s=1}^{S}\psi^2_{so}k^{2(t-1)}_{sj}\end{array}\right)\leqslant 0 \\
&(j=1,\cdots,n; j\neq o) \\
&\sum_{a=1}^{A}\delta_{ao}z^t_{aj}+\sum_{r=1}^{R}\psi^1_{ro}k^{1t}_{rj}-\left(\sum_{i=1}^{I}\tau^t_{io}x^t_{ij}+\sum_{r=1}^{R}\psi^1_{ro}k^{1(t-1)}_{rj}\right)\leqslant 0 \\
&\sum_{m=1}^{M}\xi_{mo}y^t_{mj}+\sum_{s=1}^{S}\psi^2_{so}k^{2t}_{sj}-\left(\begin{array}{l}\sum\limits_{i=1}^{I}(\mu_{io}-\tau^t_{io})x^t_{ij}+\sum\limits_{a=1}^{A}\delta_{ao}z^t_{aj}\\ +\sum\limits_{b=1}^{B}\zeta_{bo}f^t_{bj}+\sum\limits_{s=1}^{S}\psi^2_{so}k^{2(t-1)}_{sj}\end{array}\right)\leqslant 0 \\
&\sum_{t=1}^{T}\left(\varphi_{ao}z^t_{ao}+\phi^1_{ro}k^{1t}_{ro}+v_{mo}y^t_{mo}+\phi^2_{so}k^{2t}_{so}\right)-W\geq 0 \\
&L^t_i\mu_{id}\leqslant\tau^t_{id}\leqslant H^t_i\mu_{id} \\
&\mu_{id}\geqslant 0,\delta_{ad}\geqslant 0,\psi^1_{rd}\geqslant 0,\psi^2_{sd}\geqslant 0,\zeta_{bd}\geqslant 0,\xi_{md}\geqslant 0 \\
&\mu_{io}\geqslant 0,\delta_{ao}\geqslant 0,\psi^1_{ro}\geqslant 0,\psi^2_{so}\geqslant 0,\zeta_{bo}\geqslant 0,\xi_{mo}\geqslant 0,W\geq 0 \\
&(i=1,\ldots,I; a=1,\ldots,A; r=1,\ldots,R; s=1,\ldots,S; b=1,\ldots,B; m=1,\ldots,M)
\end{aligned}
\tag{16}
$$

A set of optimal weights $(\delta^*_{ao}, \psi^{*1}_{ro}, \xi^*_{mo}, \psi^{*2}_{so}, \mu^*_{io}, \zeta^*_{bo}, \tau^{*t}_{io})$ is obtained according to model (16), and there is an overall cross-efficiency θ^{NT}_{od} of decision unit DMU_o with respect to DMU_d that can be written as

$$
\begin{aligned}
&\theta^{NT}_{od}=\frac{\sum\limits_{t=1}^{T}\left(\sum\limits_{a=1}^{A}\delta^*_{ao}z^t_{ao}+\sum\limits_{r=1}^{R}\psi^{*1}_{ro}k^{1t}_{ro}+\sum\limits_{m=1}^{M}\xi^*_{mo}y^t_{mo}+\sum\limits_{s=1}^{S}\psi^{*2}_{so}k^{2t}_{so}\right)}{\sum\limits_{t=1}^{T}\left(\sum\limits_{i=1}^{I}\mu^*_{io}x^t_{io}+\sum\limits_{r=1}^{R}\psi^{*1}_{ro}k^{1(t-1)}_{ro}+\sum\limits_{a=1}^{A}\delta^*_{ao}z^t_{ao}+\sum\limits_{b=1}^{B}\zeta^*_{bo}f^t_{bo}+\sum\limits_{s=1}^{S}\psi^{*2}_{so}k^{2(t-1)}_{so}\right)} \\
&(d=1,\ldots,n;\; d\neq o)
\end{aligned}
\tag{17}
$$

The period cross-efficiency θ_{od}^{Nt} of the decision unit DMU_o with respect to DMU_d is

$$\theta_{od}^{Nt} = \frac{\sum_{a=1}^{A} \delta_{ao}^{*} z_{ao}^{t} + \sum_{r=1}^{R} \psi_{ro}^{*1} k_{ro}^{1t} + \sum_{m=1}^{M} \xi_{mo}^{*} y_{mo}^{t} + \sum_{s=1}^{S} \psi_{so}^{*2} k_{so}^{2t}}{\sum_{i=1}^{I} \mu_{io}^{*} x_{io}^{t} + \sum_{r=1}^{R} \psi_{ro}^{*1} k_{ro}^{1(t-1)} + \sum_{a=1}^{A} \delta_{ao}^{*} z_{ao}^{t} + \sum_{b=1}^{B} \zeta_{bo}^{*} f_{bo}^{t} + \sum_{s=1}^{S} \psi_{so}^{*2} k_{so}^{2(t-1)}} \tag{18}$$

The phase 1 cross-efficiency θ_{od}^{1T} of the decision unit DMU_o with respect to DMU_d is

$$\theta_{od}^{1T} = \frac{\sum_{t=1}^{T} \left(\sum_{a=1}^{A} \delta_{ao}^{*} z_{ao}^{t} + \sum_{r=1}^{R} \psi_{ro}^{*1} k_{ro}^{1t} \right)}{\sum_{t=1}^{T} \left(\sum_{i=1}^{I} \tau_{io}^{*t} x_{io}^{t} + \sum_{r=1}^{R} \psi_{ro}^{*1} k_{ro}^{1(t-1)} \right)} \tag{19}$$

The phase 2 cross-efficiency θ_{od}^{2T} of the decision unit DMU_o with respect to DMU_d is

$$\theta_{od}^{2T} = \frac{\sum_{t=1}^{T} \left(\sum_{m=1}^{M} \xi_{mo}^{*} y_{mo}^{t} + \sum_{s=1}^{S} \psi_{so}^{*2} k_{so}^{2t} \right)}{\sum_{t=1}^{T} \left(\sum_{i=1}^{I} (\mu_{io}^{*} - \tau_{io}^{*t}) x_{io}^{t} + \sum_{a=1}^{A} \delta_{ao}^{*} z_{ao}^{t} + \sum_{b=1}^{B} \zeta_{bo}^{*} f_{bo}^{t} + \sum_{s=1}^{S} \psi_{so}^{*2} k_{so}^{2(t-1)} \right)} \tag{20}$$

The period cross-efficiency θ_{od}^{1t} of the decision unit DMU_o with respect to DMU_d in phase 1 is

$$\theta_{od}^{1t} = \frac{\sum_{a=1}^{A} \delta_{ao}^{*} z_{ao}^{t} + \sum_{r=1}^{R} \psi_{ro}^{*1} k_{ro}^{1t}}{\sum_{i=1}^{I} \tau_{io}^{*t} x_{io}^{t} + \sum_{r=1}^{R} \psi_{ro}^{*1} k_{ro}^{1(t-1)}} \tag{21}$$

The period cross-efficiency θ_{od}^{2t} of the decision unit DMU_o with respect to DMU_d in phase 2 is

$$\theta_{od}^{2t} = \frac{\sum_{m=1}^{M} \xi_{mo}^{*} y_{mo}^{t} + \sum_{s=1}^{S} \psi_{so}^{*2} k_{so}^{2t}}{\sum_{i=1}^{I} (\mu_{io}^{*} - \tau_{io}^{*t}) x_{io}^{t} + \sum_{a=1}^{A} \delta_{ao}^{*} z_{ao}^{t} + \sum_{b=1}^{B} \zeta_{bo}^{*} f_{bo}^{t} + \sum_{s=1}^{S} \psi_{so}^{*2} k_{so}^{2(t-1)}} \tag{22}$$

Once the optimal weights for each DMU_d have been identified, the optimal weights are used to assess the efficiency values of other decision-making units DMU_o. A total of n^2 efficiency values are obtained, and the overall cross-efficiency matrix θ^{NT} can be obtained as

$$\theta^{NT} = \begin{bmatrix} \theta_{11}^{NT} & \theta_{12}^{NT} & \cdots & \theta_{1n}^{NT} \\ \theta_{21}^{NT} & \theta_{22}^{NT} & \cdots & \theta_{2n}^{NT} \\ \vdots & \vdots & \ddots & \vdots \\ \theta_{n1}^{NT} & \theta_{n2}^{NT} & \cdots & \theta_{nn}^{NT} \end{bmatrix} \tag{23}$$

According to the overall cross-efficiency matrix, the final overall cross-efficiency value of DMU_j can be taken as the arithmetic mean of all the efficiencies in the jth column.

Then, the overall cross-efficiency value $\hat{\theta}_j^{NT}$ of DMU_j is

$$\hat{\theta}_j^{NT} = \frac{1}{n} \sum_{d=1}^{n} \theta_{dj}^{NT} \quad j = 1, 2, \ldots, n \tag{24}$$

Similarly, the period cross-efficiency matrix θ^{Nt} is

$$\theta^{Nt} = \begin{bmatrix} \theta_{11}^{Nt} & \theta_{12}^{Nt} & \dots & \theta_{1n}^{Nt} \\ \theta_{21}^{Nt} & \theta_{22}^{Nt} & \dots & \theta_{2n}^{Nt} \\ \vdots & \vdots & \ddots & \vdots \\ \theta_{n1}^{Nt} & \theta_{n2}^{Nt} & \dots & \theta_{nn}^{Nt} \end{bmatrix} \quad (t = 1, \dots, T) \tag{25}$$

Then, the period cross-efficiency value $\hat{\theta}_j^{Nt}$ of DMU_j is

$$\hat{\theta}_j^{Nt} = \frac{1}{n} \sum_{d=1}^{n} \theta_{dj}^{Nt} \quad j = 1, 2, \dots, n \tag{26}$$

The stage cross-efficiency matrix θ^{eT} is

$$\theta^{eT} = \begin{bmatrix} \theta_{11}^{eT} & \theta_{12}^{eT} & \dots & \theta_{1n}^{eT} \\ \theta_{21}^{eT} & \theta_{22}^{eT} & \dots & \theta_{2n}^{eT} \\ \vdots & \vdots & \ddots & \vdots \\ \theta_{n1}^{eT} & \theta_{n2}^{eT} & \dots & \theta_{nn}^{eT} \end{bmatrix} \quad (e = 1, 2) \tag{27}$$

Then, the value of the stage-crossing efficiency $\hat{\theta}_j^{eT}$ of DMU_j is

$$\hat{\theta}_j^{eT} = \frac{1}{n} \sum_{d=1}^{n} \theta_{dj}^{eT} \quad j = 1, 2, \dots, n; \quad e = 1, 2 \tag{28}$$

The stage-period cross-efficiency matrix θ^{et} is

$$\theta^{et} = \begin{bmatrix} \theta_{11}^{et} & \theta_{12}^{et} & \dots & \theta_{1n}^{et} \\ \theta_{21}^{et} & \theta_{22}^{et} & \dots & \theta_{2n}^{et} \\ \vdots & \vdots & \ddots & \vdots \\ \theta_{n1}^{et} & \theta_{n2}^{et} & \dots & \theta_{nn}^{et} \end{bmatrix} \quad (e = 1, 2; t = 1, \dots, T) \tag{29}$$

Then, the value of the stage-crossing efficiency $\hat{\theta}_j^{et}$ of DMU_j is

$$\hat{\theta}_j^{et} = \frac{1}{n} \sum_{d=1}^{n} \theta_{dj}^{et} \quad j = 1, 2, \dots, n; \quad e = 1, 2 \tag{30}$$

So far, the specific steps for solving the neutral dynamic network cross-efficiency evaluation model are as follows:

Step 1. By solving model (8), the overall self-assessment efficiency value θ_{dd}^{NT}, the period self-assessment efficiency value θ_{dd}^{Nt}, the period self-assessment efficiency value θ_{dd}^{1t} in the first period, and the period self-assessment efficiency value θ_{dd}^{2t} in the second period of DMU_d are calculated $(d = 1, \dots, n)$;

Step 2. Substitute the above self-assessed efficiency value θ_{dd}^{NT} into the model (16) and solve to obtain the optimal solution $(\delta_{ao}^*, \psi_{ro}^{*1}, \xi_{mo}^*, \psi_{so}^{*2}, \mu_{io}^*, \zeta_{bo}^*, \tau_{io}^{*t})$ of the model;

Step 3. The model's optimal solution $(\delta_{ao}^*, \psi_{ro}^{*1}, \xi_{mo}^*, \psi_{so}^{*2}, \mu_{io}^*, \zeta_{bo}^*, \tau_{io}^{*t})$ is brought into Equations (17)–(22) to obtain the neutral overall cross-efficiency matrix θ^{NT}, the neutral period's cross-efficiency matrix θ^{Nt}, the neutral stage cross-efficiency matrix $\theta^{eT}(e = 1, 2)$, and the neutral stage period cross-efficiency matrix $\theta^{et}(e = 1, 2)$, respectively;

Step 4. The main diagonal elements in each cross-efficiency matrix are the self-assessment efficiency values corresponding to the first step, and the non-diagonal elements are the neutral-type cross-evaluation efficiency values that DMU_d evaluates for the remaining (n − 1) DMU_os. The final efficiency values are obtained by averaging each column of each type of neutral cross-efficiency matrix, e.g., the final overall cross-efficiency

value can be taken as the arithmetic mean of all efficiency values in column j of the overall cross-efficiency matrix $(d = 1, \ldots, n; o = 1, \ldots, n\ ; o \neq d)$.

2.3. Bootstrap Correction Model

The neutral dynamic network cross-efficiency model constructed in the previous section may not be statistically testable when faced with a small data set with a limited number of samples, so the bootstrap sampling method is introduced to correct the above model. Here, the overall cross-efficiency value $\hat{\theta}_d^{NT}$ is taken as an example, and the steps are as follows:

Step 1. Calculate the $DMU_d (d = 1, \ldots, n)$ raw efficiency estimates $\hat{\theta}_d^{NT}$ using the dynamic network cross-efficiency model in Section 2.2.2;

Step 2. Apply the bootstrap method to the initial efficiency value $\hat{\theta}_d^{NT}$ of n decision-making units to randomly and repeatedly extract n random efficiency values, to get a new sample group θ_{bd}^{*NT}, where b means the bth iteration, and θ_{bd}^{*NT} denotes that after the bth iteration $\hat{\theta}_1^{NT}$,...,$\hat{\theta}_n^{NT}$ the dth random value is $\hat{\theta}_n^{NT}$;

Step 3. Assuming that the original sample of DMU_d is $(x_{id}^t, z_{ad}^t, f_{bd}^t, k_{rd}^{1(t-1)}, k_{sd}^{2(t-1)}, z_{ad}^t, k_{rd}^{1t}, k_{sd}^{2t}, y_{md}^t)$, here, the adjustment formula for x_{id}^t is used as an example, and the following formula is used to calculate the simulation sample x_{bid}^{*t}.

$$x_{bid}^{*t} = \frac{\hat{\theta}_d^{NT}}{\theta_{bd}^{*NT}} \cdot x_{id}^t \quad d = 1, 2, \ldots, n \tag{31}$$

Step 4. Calculate the overall cross-efficiency value for the simulated sample $\hat{\theta}_{bd}^{NT}$;

Step 5. Repeat (2)–(4) above B times to produce a series of simulated random efficiency values $\hat{\theta}_{bd}^{*NT} (b = 1, \ldots, B)$.

Finally, by taking the mean for each set of simulated random efficiency values $\hat{\theta}_{bd}^{*NT} (b = 1, \ldots, B)$, we can simulate the original sample estimates.

The deviation value and the efficiency value after correction can be obtained by use of the following two equations:

The deviation calculation formula,

$$\overline{Bias}(\hat{\theta}_d^{NT}) = \frac{1}{B} \sum_{b=1}^{B} \hat{\theta}_{bd}^{*NT} - \hat{\theta}_d^{NT} \tag{32}$$

and efficiency value after correction,

$$\theta'^{NT}_d = \frac{1}{B} \sum_{b=1}^{B} \hat{\theta}_{bd}^{*NT} \tag{33}$$

3. Empirical Studies

3.1. Selection of the Indicator System

Cho et al. explored the dynamic effects of post-disaster dynamics based on differences in industry-averaged inventory turnover ratios representing product cycle durations [5]. Their approach relies only on inventory and cost of goods sold reports, and is applicable to a sample with extensive industry heterogeneity. Instead, this paper focuses on the efficiency of low-carbon innovation development in one industry (the steel industry). Therefore, this paper refers to the practices of several references on innovation efficiency in the field of steel [24–27], combines the two-stage innovation value chain theory [28], takes into account the heterogeneity and relevance of the enterprise's low-carbon innovation development in different stages, and divides the low-carbon green innovation R&D activities of listed ISES into the stage of green research and development (R&D) and the stage of transformation of results.

In the related literature evaluating the ISI based on the DEA model [29–33], the input indicators are generally selected as the number of employed persons, fixed investment,

R&D expenses, the number of new product development projects, the cost of digestion and absorption, and the cost of technological transformation, and the output indicators are generally selected as the numbers of scientific and technological theses, the number of applications for invention patents, the number of invention patents authorized, the new output value of new products, the sales revenue of new products, turnover in the technology market, main business income, total business income, and total profit.

Most scholars will choose invention patents as input indicators; however, there are not only green patents in invention patents. Combined with the actual situation of carbon reduction innovation development of CISES, this paper chooses to use green patents as research indicators to construct an evaluation index system for the low-carbon innovation development efficiency of listed steel companies (Table 1). There is also a two-stage dynamic network flowchart of low-carbon innovation and development activities of listed steel companies (Figure 3).

Table 1. Low-carbon innovation development efficiency evaluation index.

Segmentation by Stage	Classification	Specific Indicators
The green R&D stage	Shared Input	Amount of R&D investment Percentage of researchers
	Link Output	Net intangible assets Number of green patents obtained
	Carry-over Output	Number of invalid green patent applications
The results transformation stage	Independent Input	Net fixed assets
	Output	Percentage of employees other than R&D staff Gross operating income growth rate
	Carry-over	Stock of research and development costs

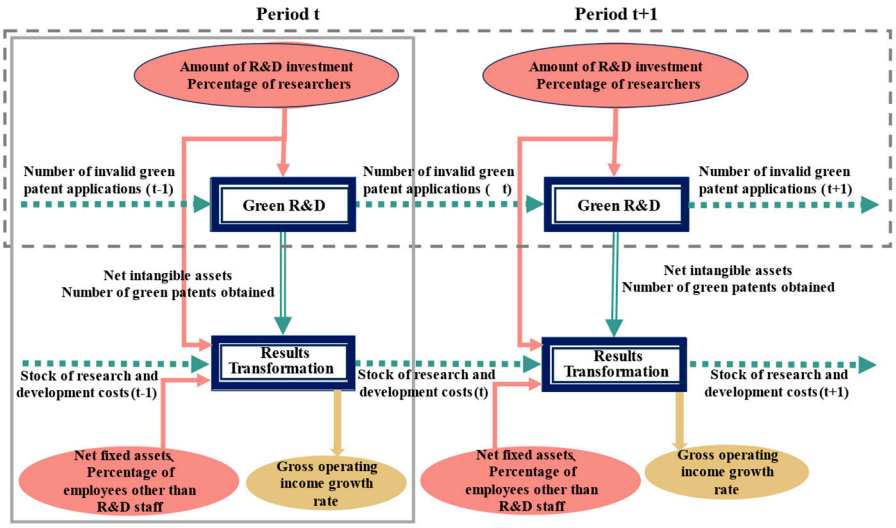


Figure 3. A dynamic network process for low-carbon innovation and development activities in listed steel companies.

3.2. Data Sources

This paper takes as its object of study the listed companies in China's ISI, which is an industrial sector dominated by industrial production activities such as ferrous metal mineral extraction and smelting and processing. As of 30 June 2024, there were 38 listed companies in the ISI. Based on data availability and the fact that the total number of decision-making units in DEA should be greater than two times the number of all indicators, this paper excludes ST shares from all listed enterprises, and selects as the research sample of listed enterprises ferrous metal smelting and rolling processing industries, as listed in

the industry classification system of the China Securities Regulatory Commission, which have been listed for at least three years, and possess data related to the development of carbon reduction innovation for the past three years. Through the above screening, a total of 25 listed companies in China's ISI were selected (Table 2).

Table 2. List of 25 listed steel companies after screening.

Certificate Code	Company Name	Certificate Code	Company Name
000708	CITIC Pacific Special Steel Group Co., Ltd.	600282	Nanjing Iron and Steel Co., Ltd.
000709	HBIS Company Limited	600295	Inner Mongolia Erdos Resources Co., Ltd.
000761	Bengang Steel Plates Co., Ltd.	600307	Gansu Jiu Steel Group Hongxing Iron and Steel Co., Ltd.
000825	Shanxi Taigang Stainless Steel Co., Ltd.	600399	Fushun Special Steel Co., Ltd.
000898	Angang Steel Company Limited	600408	Shanxi Antai Group Co., Ltd.
000932	Hunan Valin Steel Co., Ltd.	600569	Anyang Iron and Steel Inc.
000959	Beijing Shougang Co., Ltd.	600581	Xinjiang Bayi Iron and Steel Co., Ltd.
002075	Jiangsu Shagang Co., Ltd.	600782	Xinyu Iron and Steel Co., Ltd.
002110	Sansteel Minguang Co., Ltd., Fujian	600808	Maanshan Iron and Steel Company Limited
002756	Yongxing Special Materials Technology Co., Ltd.	601003	Liuzhou Iron and Steel Co., Ltd.
600010	Inner Mongolia Baotou Steel Union Co., Ltd.	601005	Chongqing Iron and Steel Company Limited
600126	Hang Zhou Iron and Steel Co., Ltd.	603878	Jiangsu Wujin Stainless Steel Pipe Group Co., Ltd.
600231	Lingyuan Iron and Steel Co., Ltd.		-

This paper takes the relevant data of these 25 listed companies in the ISI for 2019–2022 as the research sample, and the original data are obtained from the annual reports of each company, the China Science and Technology Statistical Yearbook, the China Statistical Yearbook, the China Research Data Service Platform (CNRDS), the CSMAR database, and the Juchao information database.

3.3. Model Application and Comparative Analysis

3.3.1. Analysis of Overall and Stage Efficiency

This section calculates various efficiency values based on the neutral dynamic network cross-efficiency model shown in Section 2.2, and corrects the model using a Bootstrap sampling method to obtain various efficiency values after correction. Due to the limitation of space, the overall cross-efficiency is taken as an example here, and the overall cross-efficiencies (Table 3) and stage cross-efficiencies (Table 4) before and after the amendment were compared for the low-carbon innovation development efficiencies of each of the 25 listed CISESs.

Table 3. Comparison of overall cross-efficiency before and after correction.

Serial Number	Certificate Code	Raw Overall Efficiency Value	Estimates of Overall Cross-Efficiency Corrected by Bootstrap	Bias	Ranking Comparison Before and After Correction
1	000708	0.2827	0.2707	0.0119	12/13
2	000709	0.1985	0.1867	0.0118	23/23
3	000761	0.1943	0.1627	0.0315	24/24
4	000825	0.1890	0.1531	0.0359	25/25
5	000898	0.2356	0.2332	0.0024	18/18
6	000932	0.2129	0.1966	0.0163	22/22
7	000959	0.2857	0.2851	0.0006	11/11
8	002075	0.3070	0.2966	0.0105	8/10
9	002110	0.3477	0.3582	0.0105	5/5
10	002756	0.2703	0.2312	0.0391	14/19
11	600010	0.2425	0.2432	0.0007	16/15

Table 3. *Cont.*

Serial Number	Certificate Code	Raw Overall Efficiency Value	Estimates of Overall Cross-Efficiency Corrected by Bootstrap	Bias	Ranking Comparison Before and After Correction
12	600126	0.4828	0.5077	0.0249	1/2
13	600231	0.2773	0.3236	0.0463	13/7
14	600282	0.2351	0.2353	0.0003	19/16
15	600295	0.2933	0.3178	0.0245	10/8
16	600307	0.2586	0.2511	0.0075	15/14
17	600399	0.4583	0.5112	0.0530	2/1
18	600408	0.4094	0.4643	0.0549	3/3
19	600569	0.3964	0.4226	0.0262	4/4
20	600581	0.2372	0.2254	0.0118	17/20
21	600782	0.2961	0.2806	0.0156	9/12
22	600808	0.2141	0.2091	0.0050	21/21
23	601003	0.2287	0.2337	0.0050	20/17
24	601005	0.3425	0.3420	0.0005	6/6
25	603878	0.3166	0.3132	0.0034	7/9
average value		0.2885	0.2902	0.0017	-

Table 4. Comparison before and after correction of stage cross-efficiency.

Serial Number	Certificate Code	Original Green R&D Stage Efficiency Value	Estimated Cross-Efficiency of Green R&D Stages Corrected by Bootstrap	Bias	The Efficiency Value of the Transformation Segment of the Original Results	Estimated Cross-Efficiency of the Results Transformation Phase, Corrected by Bootstrap	Bias
1	000708	0.1425	0.1081	0.0344	0.2972	0.2725	0.0247
2	000709	0.1365	0.1224	0.0141	0.1894	0.1777	0.0117
3	000761	0.1422	0.1336	0.0087	0.2060	0.1621	0.0439
4	000825	0.1423	0.1324	0.0099	0.1970	0.1508	0.0461
5	000898	0.1365	0.1257	0.0108	0.2496	0.2373	0.0123
6	000932	0.1427	0.1256	0.0171	0.2282	0.1998	0.0284
7	000959	0.1443	0.1274	0.0169	0.2712	0.2617	0.0094
8	002075	0.1432	0.1179	0.0253	0.2618	0.2446	0.0172
9	002110	0.1439	0.1231	0.0208	0.3805	0.3685	0.0119
10	002756	0.1071	0.0751	0.0321	0.2239	0.2122	0.0116
11	600010	0.1385	0.1235	0.0150	0.2933	0.2880	0.0054
12	600126	0.1415	0.1066	0.0350	0.3693	0.3724	0.0031
13	600231	0.1391	0.1232	0.0159	0.3045	0.3395	0.0350
14	600282	0.1458	0.1276	0.0182	0.2391	0.2306	0.0085
15	600295	0.1383	0.1101	0.0283	0.2547	0.2468	0.0079
16	600307	0.1378	0.1258	0.0120	0.2718	0.2587	0.0131
17	600399	0.1385	0.1074	0.0311	0.5090	0.5732	0.0642
18	600408	0.1054	0.1016	0.0038	0.3355	0.3412	0.0056
19	600569	0.1437	0.1219	0.0218	0.4862	0.4967	0.0104
20	600581	0.1441	0.1260	0.0182	0.1806	0.1753	0.0053
21	600782	0.1442	0.1219	0.0224	0.3304	0.2989	0.0315
22	600808	0.1462	0.1285	0.0177	0.2105	0.1956	0.0149
23	601003	0.1372	0.1266	0.0106	0.2276	0.2301	0.0025
24	601005	0.1441	0.1143	0.0299	0.2771	0.2635	0.0136
25	603878	0.1103	0.0792	0.0311	0.2239	0.2297	0.0059
average value		0.1374	0.1174	0.0200	0.2807	0.2731	0.0076

As can be observed from the data presented in Table 3 (2019–2022, average level of low-carbon innovation and development efficiency of the 25 companies listed in the ISI), the deviation caused by corrective action varies, as CITIC Special Steel (000708), Hegang (000709), Bensteel Plate (000761), TISCO Stainless (000825), Anshan Steel (000898), Valin Steel (000932), Shougang (000959), Shagang (002075), Yongxing Materials (002756), JISCO Hongxing (600307), Bayi Iron & Steel (600581), Sinosteel (600782), Maanshan Iron & Steel (600808), Chongqing Iron & Steel (601005), and Wuzhin Stainless (603878) show

negative deviations, indicating that the raw overall efficiency is overestimated. However, the bootstrap-corrected efficiency data show that Fushun Special Steel (600399) has the highest overall efficiency related to low-carbon innovation and development, but it is only 51.12 percent, which is still a big gap.

The mean value of the overall carbon reduction innovation development efficiency of the sample enterprises is 0.2902. During the evaluation period, the top ten CISESs in terms of overall efficiency value are Fushun Special Steel, Hangzhou Steel, Antex Group, Anyang Iron & Steel, Sangangang Minguang, Chongqing Iron & Steel, Ling Steel, Ordos, Wujin Stainless, and Shagang Steel, whose efficiency values are above the average value of efficiency. The aggregate efficacy of low-carbon innovation among the remaining CISESs has not yet attained the mean level of carbon reduction development efficiency. At the same time, there is a large gap in the level of efficiency between enterprises; TISCO stainless steel (000825) has the lowest efficiency of low-carbon innovation and development, at only 15.31 percent, and Fushun Special Steel (600399) shows too great a difference.

As shown in Table 4 (2019–2022, average level of efficiency of the stages of carbon reduction innovation and development of the 25 companies listed in the ISI), the deviations following correction are all lower, which indicates that the efficiency after the correction of deviation is better.

In the green R&D stage, Bensteel plate (000761) showed the highest stage efficiency, but only of 13.36%; green R&D efficiency was the lowest for Yongxing materials (002756), at only 7.51%, which is 43.79% lower than the efficiency of Bensteel plate (000761). In the transformation stage, Fushun Special Steel (600399) has shown the highest efficiency, at 57.32%; the lowest efficiency was achieved by TISCO Stainless (000825), at only 15.08%, which is 73.69% lower than that of Fushun Special Steel (600399)—a huge difference.

The mean values for the first-stage efficiency and second-stage efficiency of the low-carbon innovation development of the sampled steel companies in 2019–2022 are 0.1174 and 0.2807, respectively, with 17 sample companies exceeding the average of the first stage and 8 sample companies exceeding the average of the second stage. It can also be seen that the majority of the sample enterprises have greater efficiency in the second stage than in the first-stage, and the highest efficiency achieved in the first stage is lower than the lowest efficiency achieved in the second stage.

3.3.2. Relative Analysis of Types of Efficiency in Low-Carbon Innovation Development

In this paper, the mean values of the first stage and the second stage of the sampled steel enterprises for 2019–2022 are taken as the cut-off point, and the two stages of carbon reduction innovation development of the sample steel enterprises are divided into the two categories of high and low efficiency, while the 25 sampled enterprises are classified in relative terms, such that the efficiency of low-carbon innovation development is divided into four types (Figure 4).

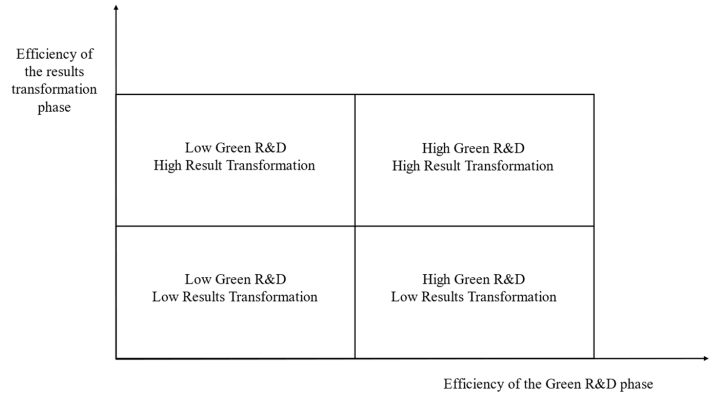


Figure 4. Low-carbon innovation development efficiency classification.

Based on the results shown in Table 4, the distribution of the types of low-carbon innovation development efficiency of the samples steel companies has been obtained (Figure 5). The numbers in Figure 5 correspond to the serial numbers of the listed steel companies in Tables 3 and 4.

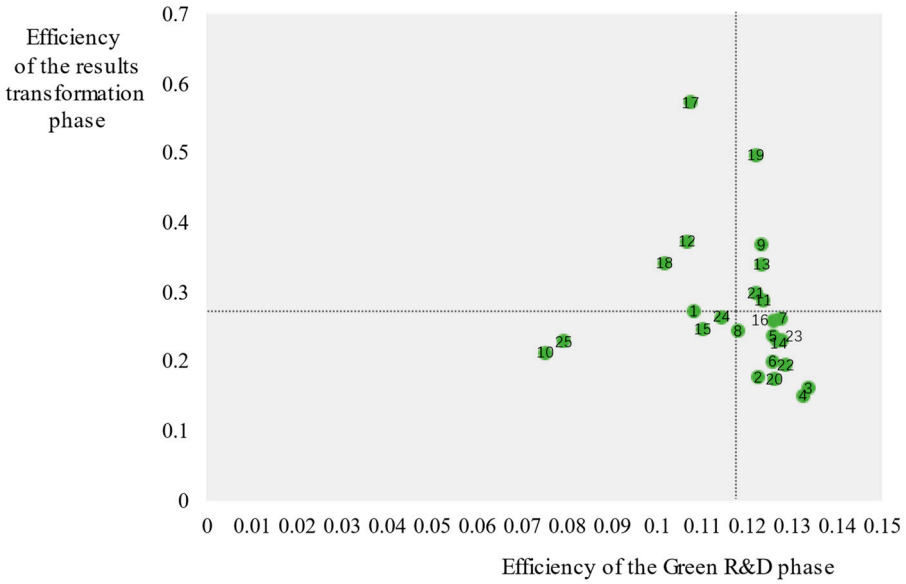


Figure 5. Distribution of low-carbon innovation development efficiency types among 25 listed steel companies, 2019–2022.

(1) The innovation and development of steel enterprises in the first quadrant is of the highly green R&D, high transformation type. As illustrated in Figure 5, five ISESs are located in the first quadrant for 2019–2022, accounting for 20% of all sample enterprises. Sangang Minguang, Baosteel, Lingsteel, Anyang Iron and Steel, and Xinsteel take the lead in both phases by virtue of their reasonable inputs and outputs, well-developed market environments, and stable outputs.

(2) The type of innovation and development of steel companies in the second quadrant is of the low-green, high-R&D results transformation type. As illustrated in Figure 5, there are only three ISESs located in the second quadrant during the 2019–2022 period, accounting for 12% of the number of all sample enterprises. Among them, Antai Group has formed a unique circular-economic industry by virtue of projects such as the microalgae carbon emission reduction system and the zero-carbon industrial park, and has achieved high efficiency in the results transformation stage. Hangzhou Steel has actively promoted digital economy projects, constructed a digital science and technology industrial eco-park, initiated an energy-saving and environmental protection strategy, and realized the transformation of green and intelligent manufacturing through the closure of its mid-level steelmaking base, which has also achieved high efficiency in the results transformation stage. Fushun Special Steel, through the implementation of an ultra-low emission transformation project, carried out a fully enclosed transformation of its scrap steel disposal yard and waste heat utilization transformation, and comprehensively implemented the application of intelligent manufacturing to achieve a high level of transformation. Therefore, the three ISESs should focus on improving the efficiency of R&D to enhance the overall level of low-carbon innovation and development of the enterprises.

(3) The type of innovation and development of steel enterprises in the third quadrant is of the low-green, R&D-low-results transformation type. As illustrated in Figure 5, there are five ISESs located in the third quadrant during the period 2019–2022, accounting for 20% of the number of all sample enterprises. These enterprises, CITIC Special Steel, Yongxing Materials, Erdos, Chongqing Iron and Steel, and Wujin Stainless, are at a lower efficiency level in both stages of the low-carbon innovation and development process. Therefore, these five

ISESs should look for problems from multiple perspectives in terms of green R&D innovation and results transformation to solve the double inefficiency issue in both stages.

(4) The type of innovation and development of steel companies in the fourth quadrant is of the high-green, R&D-low-results transformation type. As illustrated in Figure 5, during the 2019–2022 period, 12 ISESs were located in the fourth quadrant, accounting for as much as 48%. This indicates that with the support of the national dual-carbon policy, the listed CISESs are generally undergoing carbon reduction transformation, focusing on green R&D to develop more environmentally friendly production processes and materials. However, while these ISESs promote green R&D, the results are not transformed and applied, and the level of the results transformation is relatively low, which in turn affects the overall effect of the enterprises' low-carbon innovation and development. Therefore, these ISESs should focus on the relationship between their R&D results and the actual application market, to avoid the obstacles encountered in R&D in the process of actual application.

Overall, although the level of low-carbon green development of the CISESs is steadily improving, there is still a large gap in the level of efficiency between enterprises; TISCO stainless steel (000825) has the lowest efficiency of low-carbon innovation and development, at only 15.31 percent, and Fushun Special Steel (600399) shows too great a difference, with a gap of 35.81 percent. Each enterprise still needs to achieve fast technological innovation and resource integration, continue to improve the efficiency of its first stage (green R&D), promote the marketization of new achievements, promote the improvement of the overall efficiency of the low-carbon innovation and development of ISESs, and promote the harmonious low-carbon development of CISESs.

4. Conclusions and Recommendations

This paper firstly combines the current situation of low-carbon innovation development in China's ISIs with the ideas of the DNDEA model and the neutral cross-efficiency model, and proposes a neutral dynamic network cross-efficiency model. The model is used to evaluate the efficiency of the CISESs' carbon reduction innovation development. At the same time, we introduce the bootstrap sampling method to correct the model. Secondly, the low-carbon green innovation R&D activities of listed CISESs are divided into the green R&D stage and the results transformation stage. The proposed model is employed to evaluate the overall efficiency of the low-carbon innovation development of CISESs and the efficiency of each stage.

The assessment results show that the overall efficiencies of low-carbon innovation development in China's ISI are both low, and the highest efficiency in the first stage is lower than the lowest efficiency in the second stage, indicating that the low-efficiency value of the green R&D stage is the main factor affecting the overall low efficiencies of the sample of listed steel enterprises. Finally, the 25 enterprises were matched by type, and each type of enterprise was analyzed in detail. The results show that 48% of the listed steel enterprises belong to the high-green, R&D-low-results conversion type, indicating that the current Chinese listed enterprises have been conscious of promoting green R&D, but their ability to market the results of R&D still needs to be strengthened.

Based on the above conclusions and the current development situation of China's ISIs, the following recommendations are given:

(1) Enterprises should support and encourage innovation in the direction of low carbon and greenness, stimulate the interest of steel research workers in innovation, create a good atmosphere for innovation, cultivate the independent innovation ability of research workers, try to combine ideal research and development with reality, actively publicize their innovations, and promote the marketability of research and development results;

(2) Enterprises should rationally allocate low-carbon innovation resources, cultivate innovative high-end talents in enterprises, optimize the structural flow of inputs and outputs, and reduce the waste of innovation resources;

(3) The government should continue to maintain policy support, encourage enterprises to closely follow the industry's key core technologies for innovation and research and development, comprehensively advocate the development of the ISI in the direction of high-end, intelligence and greenness, and improve the level of efficiency of the low-carbon innovation and development of CISESs.

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