Research Article

Identifying Interindustry CO₂ Emissions Transfer Structure Using Network Methods

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People's production and life have been inseparable from the consumption of various products, which often directly or indirectly release CO₂. As CO₂ emissions can transfer among industries, the identification and classification of the industries that release CO₂ directly or indirectly can contribute to curbing the CO₂ emissions. This paper proposes an input-output-based methodology to measure CO₂ emissions transfer caused by linkages between industries in an economy and constructs the network topology in terms of the remarkable coefficients of interindustry CO₂ emissions transfer. We classify all industries according to the role played in the emissions transfer process, and the network is represented by a "Bow-Tie" structure. In the visualization expression, it is easy to find the star nodes and the transmission paths of CO₂ emissions among industries. Finally, the method is applied to the case of China. Empirical results indicate that the method developed in this paper provides new tools for the study of industrial CO₂ emissions theory.

1. Introduction

CO₂ is one of the main greenhouse gases, which contribute to climate change. A country's CO₂ emissions are caused by people's daily life and the production of various goods and services. Reducing the CO₂ emissions associated with production has received wide attention [1]. People's production and life have been inseparable from the consumption of various goods and services, which often directly and indirectly release CO₂ [2, 3]. In an economy, the identification and classification of industries according to direct and indirect CO₂ emissions are helpful for decision-makers to curb CO₂ emissions.

Industries with more direct CO₂ emissions (such as power production and metal smelting) often become the focus of CO₂ emissions reduction. Since interindustry CO₂ emissions transfer is an objective existence, indirect emissions should not be ignored [4, 5]. Indirect CO₂ emissions from an industry are not caused in its production process, but by its requirements involved in the industrial chains. The

production of an industry often requires a variety of products, and these intermediate inputs also release CO₂ due to the combustion of fossil fuels in their production process, resulting in indirect emissions [6, 7]. For example, some industries may consume a great deal of power rather than fossil fuels, which result in indirect CO₂ emissions as electric power industry emits a lot of CO₂ during its production process. The responsibility for these emissions should not be the electric power industry, but those industries that need power. People usually ignore indirect emissions and pay less attention to the industries emitting less CO₂ directly. In case the intermediate inputs emit much CO₂ during the production process, they should also bear responsibility. Input-output analysis is one of the basic tools for solving such a question [8, 9]. Valuable as the input-output analysis is, it nevertheless takes into consideration only the quantitative analysis. In fact, we should not only know the total amount of CO₂ emissions, but also know emissions transfer among industries. It is important to find out the significant inter-industry transmission paths of emissions for decision-

makers to formulate CO₂ emissions reduction strategies. At this point, the structural analysis is equally important at least. The network is one of the most popular methods to study structures [10].

There are a few papers using the network theory to analyze the CO₂ transfer networks. As a powerful tool for revealing characteristics and roles of structural correlation, Social Network Analysis (SNA) has been widely used in both economic and environment [11, 12]. Liu and Xiao [13] investigated 2004–2017 provincial industrial carbon emissions of China with the modified gravity model combined with SNA. They constructed spatial correlation network and found out its influencing factors with the help of Quality Assurance Procedure of SNA. Lv et al. [14] used the multiregional input-output and SNA methods to investigate China's embodied carbon transfer across provinces. Wang et al. [15] identified the critical sectors that are critical for the CO₂ emissions in value chains based on eigenvector approaches. Wang et al. [16] developed a research framework combining semiclosed input-output analysis with network analysis to investigate interdependencies between households and industrial sectors. Zhang et al. [17] constructed the CO₂ emission network of an urban agglomeration in the Yangtze River middle reaching megalopolis and proposed a multilevel analysis framework based on social network analysis.

Some scholars apply the complex network analysis method to the analysis of interindustry carbon transfer. Wang et al. [18] calculated the interprovincial sectoral linkages of embodied CO₂ in 2012 and 2015 in China and described the clustering feature visualized and identified the transfer media sectors with complex networks. Jiang et al. [19] established a global carbon emissions transfer network to identify the impact of the structural role of sectors on carbon emissions. Some scholars combine networks with other models to analyze the carbon emission of industries. Duan et al. [20] combined multiregion input-output (MRIO) analysis and ecological network analysis (ENA) to assess China's carbon flow and identified key carbon reduction areas and sectors. He et al. [21] used the modified gravity model on carbon emissions from China's power sector to build a spatial correlation network.

Based on graph theory, this paper uses qualitative input-output analysis method to analyze the industrial structure of CO₂ emissions. In the context of network analysis, it is obvious that industries become vertices, and directed edges represent the significant CO₂ emissions transfers between industries. And the network is termed the Industrial CO₂ Emissions Transfer Network (ICETN) in this paper. In order to construct the network, the starting point is to define and calculate the linkage coefficients of interindustry CO₂ emissions transfer through input-output analysis. Then, according to the significance linkages, the corresponding ICETN is established. Furthermore, all industries are classified, and the network is expressed with a "Bow-Tie" structure. With this representation, it becomes easy to identify various CO₂ emissions transfer paths. The methods developed in this paper are applied to the case of China. Empirical results indicate that the methods provide new

tools for the study of CO₂ emissions theory and expand the horizon and application of interindustry CO₂ emissions transfer research.

The main contribution of this paper is as follows. (1) From the perspective of qualitative input-output, the ICETN model proposed in this paper reveals the effect of carbon emissions among industries in an economy and describes the correlation structure and individual characteristics of networks. (2) The paper proposed a new method to identify the bow-tie structure of CO₂ transfer network. According to the relationship between an industry and the others, this paper classifies all industries into cycle industries, input industries, reception industries, parallel industries, edge industries, and isolated industries, which belong to different parts of the bow-tie structure respectively.

The rest of this paper is structured as follows. Section 2 introduces the concept and calculation method of coefficients of interindustry CO₂ emissions transfer. Sections 3 and 4 show the methods to construct the ICETN and to identify the bow-tie structure, respectively. Section 5 presents our empirical results. In Section 6, the summary and conclusions are provided.

2. Coefficients of Interindustry CO₂ Emissions Transfer

During the production process of an industry, CO₂ emissions are released directly due to the combustion of fossil fuels. But these are not all CO₂ emissions. It needs products from various industries, which also emit CO₂ emissions during their productions, as shown in Figure 1. When industry i supplies products to j , it also emits CO₂ due to the input. The responsibility for these emissions should be borne by industry j . In other words, industry i transfers the responsibility to industry j . Similarly, industry j transfers the responsibility to industry k . Likewise, the CO₂ emissions transfer relationships among industries become very complex in an economy.

Now, we analyze CO₂ emissions based on the input-output technique in an economy. Consider the input-output table shown in Table 1. X denotes the $n \times n$ matrix of interindustry flows, x the column vector of total outputs, and e the column vector of the total CO₂ emissions from each industry. A prime denotes transposition. The matrix of input coefficients is given by $A = X\hat{x}^{-1}$, where $\hat{x}$ is used to denote a diagonal matrix of x .

Let us start with direct emissions. For any specific industry, such as j , in its production process, it emits CO₂ directly due to the combustion of fossil fuels. The total output of industry j is expressed as x_j , and the total emissions as e_j . Then, the CO₂ emissions of one unit output can be calculated as

$$e_j^u = \frac{e_j}{x_j}, \quad (j = 1, 2, \dots, n). \quad (1)$$

These are the direct emissions. We also need to calculate the CO₂ emissions from the intermediate inputs. For any intermediate input industry i , its production also requires

FIGURE 1: CO₂ emissions transfer among industries.

TABLE 1: Input-output table.

	n production industries	Final demand	Totals
n production industries	X	f	x
Primary inputs	v'	d	$v' + d$
Totals	x'	—	—
Emissions	e'	—	—

burning fossil fuels and emits CO₂. Similarly, its emissions of one-unit output can be calculated as $e_i^u = e_i/x_i$. The element x_{ij} of x_i denotes the inputs from industry i to j and e_{ij} the CO₂ emissions for producing x_{ij} . The emissions e_{ij} can be calculated as

$$e_{ij} = e_i^u \times x_{ij}. \quad (2)$$

From the input-output theory, the backward linkage indicator gives the total amount of inputs obtained from the production industries for producing one unit of total output. Similarly, the CO₂ emissions linkage indicator gives the total amount of CO₂ emissions from the production industries for one unit of total output. Here, the coefficients of interindustry CO₂ emissions transfer are defined as follows.

For industry i and j , in order to produce one unit output of industry j , a certain number of inputs from industry i are needed. The coefficient of CO₂ emissions transfer between industry i and j refers to the total amount of direct CO₂ emissions from industry i for the inputs to produce one unit output of industry j , expressed in c_{ij} :

$$c_{ij} = \frac{e_{ij}}{x_j}, \quad (i, j = 1, 2, \dots, n). \quad (3)$$

We substitute equation (2) into (3):

$$c_{ij} = e_i^u \times \frac{x_{ij}}{x_j}, \quad (i, j = 1, 2, \dots, n). \quad (4)$$

In the input-output analysis, a_{ij} denotes the backward linkage coefficient, the total amount of inputs obtained from

industry i that is required to produce one unit of total output in industry j , $a_{ij} = x_{ij}/x_j$. Then, we get

$$c_{ij} = e_i^u \times a_{ij}, \quad (i, j = 1, 2, \dots, n), \quad (5)$$

where a_{ij} can be calculated according to the input-output table; e_i^u can be calculated from equation (1). In equation (1), e_i , the amount of CO₂ directly emitted from industry i , can be calculated according to the Energy Statistical Yearbook. There are three kinds of fossil fuels that belong to primary energy (coal, crude oil, and natural gas) and five belong to secondary energy (coke, gasoline, kerosene, diesel oil, and fuel oil). The direct CO₂ emissions of various industries can be calculated as $\sum_{s=1}^8 u_s(i) \times f_s$, where $u_s(i)$ is the total amount of the energy s consumed by industry i , which can be found from the Energy Statistical Yearbook. f_s is the CO₂ emissions coefficient of the energy s .

Obviously, the coefficient c_{ij} is positively correlated with a_{ij} and e_i^u . The higher the coefficients, the greater the intensity of CO₂ emissions transfer between industries. Within each industry, one unit of production might cause lower or higher emissions, depending on the technology and/or process used.

Equation (5) can be rewritten in a matrix form for all industries. If $C(n \times n)$ is the coefficients matrix of interindustry CO₂ emissions transfer, A the $(n \times n)$ matrix of technical coefficients, and $\hat{e}^u(n \times n)$ the diagonal matrix generated by e_i^u ($n \times 1$), then

$$C = \hat{e}^u A. \quad (6)$$

3. Industrial CO₂ Emissions Transfer Networks

Industrial linkages lead to CO₂ emissions transfer linkages among industries, as described in Part 2. The coefficients of interindustry CO₂ emissions transfer describe the strengths of linkages. Although there are CO₂ emissions transfers among most industries, it can be found that there are great differences in quantity. The linkages with significant quantitative account for a small part of the total but play a decisive role. In order to analyze the overall structure, it is important to identify these linkages and analyze them

qualitatively. This paper establishes the network according to these significant linkages, named the Industrial CO₂ Emissions Transfer Network (ICETN).

This idea of qualitative analysis comes from qualitative input-output analysis (QIOA). Some scholars believe that if questions of structure and structural evolution are concerned, a qualitative approach is of greater significance [22]. QIOA has been developed by Campbell [23], Holub et al. [24], and some further papers following those mentioned above [25–28]. The basic concept of QIOA consists of binary transformation of the entries of input-output table, according to a defined filter rate.

After a critical threshold found first, the linkages that are greater than the threshold are selected. These linkages are integrated to form a network. As shown in Figure 2(a), v_1-v_5 are industries. The edges between them represent linkages, and the linkage coefficients as the weights on the edges. When the critical threshold w_{45} is determined, selecting the linkages whose coefficients are greater than w_{45} , as shown in Figure 2(b), we get the network.

The selection of threshold is the key of discussion. There are two methods: exogenous critical value determined by experience and endogenous critical value determined by calculation. Regarding the average value used as the critical value, Campbell [23] simplified the industrial relationship in Washington (1963). If the coefficient between the two industries is greater than the average value, it is regarded as the existence of industrial correlation; otherwise, it does not exist. Aroche Reyes [28] established the correlation relationship with the empirical value 5 as the critical value in the process of important coefficient analysis. Schnabl [22] proposed the method of minimum flow analysis (MFA) based on the traditional QIOA. Zhao et al. [25] proposed a simpler method to calculate the endogenous critical value with the tool of Thomas Weaver index.

After comparing various methods, this paper decides to use Pareto's 80/20 rule to determine the threshold. Pareto's 80/20 rule states that about 80% of all effects stem from 20% of all causes for many events [29–31], which has been applied in a variety of fields, such as economics [32, 33], where its validity and usefulness have been demonstrated. Given that the Pareto rule conceptually contrasts the contribution of the vital few with that of the trivial many, it is used in this paper to establish the ICETN.

Specifically, all coefficients of interindustry CO₂ emissions transfer in an economy are arranged from high to low, and the top 20% are taken as significant ones. When the coefficient between any two industries, such as industry i and j , ranks the top 20%, the linkage from industry i and j is seen as significant. There is a directed edge between them, from industry i to j , and the corresponding element in the adjacency matrix is 1. Otherwise, the coefficient is not in the top 20%, there is no edge, and the element in the adjacency matrix is 0. When a diagonal element is 1, a loop is formed. It means that the industry circulates internally. Since we focus on analyzing interindustry linkages, we do not consider them in this paper. So, the diagonal elements of the adjacency matrix should be set as 0. A schematic diagram of an ICETN is shown in Figure 3.

Denote the adjacency matrix of the network in Figure 2

$$\text{as } Z, Z = \begin{bmatrix} 0 & 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}. \text{ As } z_{12} = 0, \text{ there is no edge}$$

from industry v_1 to v_2 in Figure 1. And $z_{13} = 1$, there is an edge from industry v_1 to v_3 . The rest are similar.

4. Industries Classification and “Bow-Tie” Structure Representation of an ICETN

4.1. Industries Classification. Different subgraphs reflect special features of CO₂ emissions transfer in an ICETN. One of the most important subgraphs in an ICETN is the cycle subgraphs, also known as the strongly connected subgraphs, as shown in Figure 4.

As shown in Figure 4, industry 1, industry 2, and industry 3 form a cycle subgraph. There is a path between any two industries at least. When CO₂ emissions in any industry change, they will affect the other two. Since there are mutually accessible paths between any two vertices, the industries in the cycle subgraph are closely related. When the CO₂ emissions of any industry increase or decrease, the responsibility will be transferred to the other industries along directed paths and reach the initial one. The effect circulates with decreasing strength until it finally disappears. The impact among industries is no longer in the form of a straight line, but repeated in cycle modes. As a result, a change of CO₂ emissions in any industry has a greater impact on the whole network. In a network, there may be several cycle structures. The Strongly Connected Kernel, the core of the network, is the strongly connected subgraph with the most industries.

Theoretically, in a network, some industries are upstream of the Strongly Connected Kernel and transfer CO₂ emissions to the kernel. Some are downstream and receive CO₂ emissions from the kernel. Some have no connection paths with the kernel but connect the above two types of industries. Some only receive CO₂ emissions from the first type of industries or only transfer CO₂ emissions to the second ones. The industries that are not related to all the previous ones are isolated industries. In this paper, these industries are named as input industries, reception industries, parallel industries, edge industries, and isolated industries, respectively. Together with the cycle ones in the Strongly Connected Kernel, there are six types of industries in an ICETN. In fact, some types of industries may not exist.

4.2. “Bow-Tie” Structure Representation of an ICETN. From the above analysis, an ICETN contains six types of industries at most. If a network is drawn according to this classification, the network can be represented as a model that CO₂ emissions transfer from the input industries to the cycle or parallel ones, then to the reception industries. This

FIGURE 2: Schematic diagram of ICETN construction.

FIGURE 3: Schematic diagram of an ICETN.

FIGURE 4: A cycle structure.

representation can visually describe the types of industries, and the linkages within them.

The “Bow-Tie” structure of a network is a visual representation. It decomposes a connected directed network (or a weakly connected giant in a disconnected network) into five parts, namely, the Strongly Connected Kernel, “In” part, “Out” part, Tube, and Tendril, as shown in Figure 5.

Being the largest strongly connected subgraph in a network, the Strongly Connected Kernel is the core of a network [34–37]. There are mutually reachable paths between any two vertices in the kernel. The “In” part consists of vertices pointing to the Strongly Connected Kernel; the “Out” part is pointed out by the Strongly Connected Kernel; the vertices of the Tube are pointed out by the “In” part, pointing to the “Out” part; the vertices of the Tendril are pointed out by the “In” part, or to the “Out” part. There must be no vertices from the “Out” part to the “In” part;

otherwise, they all belong to the Strongly Connected Kernel. This “Bow-Tie” structure can clearly represent the overall structure of a network, as shown in Figure 5.

The “Bow-Tie” structure representation is applied to the ICETN. The industries in the largest cycle subgraph belong to the Strongly Connected Kernel, the input industries to the “In” part, the reception ones to the “Out” part, parallel ones to the Tube, and edge ones to the Tendril. The isolated industries are not included in a “Bow-Tie” structure.

In this classification, each type of industries plays a different role. The cycle industries in the Strongly Connected Kernel are the core of the network. Any change in them will circulate among the kernel and affect the reception industries again and again. The “In” part industries are located at the entrance of the network. They can impact the Strongly Connected Kernel, and further, the “Out” part. The edge industries on the Tendril are in relatively short paths and have only a small impact on the whole system. The “Tube” industries connect the “In” part and the “Out” part, and their changes are transmitted in one direction. The reception industries and the isolated ones have little impact on the whole structure.

4.3. Identifying Various Types of Industries in an ICETN.

It is necessary to identify the types of industries for drawing the “Bow-Tie” structure of an ICETN. As the core of a network, the Strongly Connected Kernel should be identified first.

4.3.1. Identifying the Strongly Connected Kernel. Idea: all strongly connected subgraphs in an ICETN are found, among which the largest one is the Strongly Connected Kernels. In any strongly connected subgraph, there must be a directed path at least between any two vertexes. A strongly connected subgraph will become a complete subgraph if we draw a directed edge between any two vertices when there are paths. With all elements being 1, it is easy to recognize the adjacency matrix of a complete subgraph.

FIGURE 5: The “Bow-Tie” structure.

For an ICETN N , $N = (V, E)$, where V represents all industrial set, and E is the edge set. As the network includes n industries, the adjacency matrix $Z = (z_{ij})_{n \times n}$. If $z_{ij} = 1$, there is a directed edge $\vec{ij}$ from industry i to j ; otherwise, $z_{ij} = 0$, and there is no edge.

First, the corresponding extended network N^* should be built. When there are paths in N , there will be an edge in N^* . The network N contains n industries, so the maximum distance between any two industries does not exceed $n - 1$. Z^* , and the adjacency matrix of N^* can be obtained by Boolean operation ($1 \oplus 1 = 1$, $1 \oplus 0 = 1$, $1 \otimes 1 = 1$, $1 \otimes 0 = 0$) from the adjacency matrix Z .

$$Z^* = \#(Z + Z^2 + \dots + Z^{n-1}), \quad (7)$$

where Z^* is the basis for identifying the Strongly Connected Kernel. The identification steps are as follows:

Step 1: $k \leftarrow -1$, $l_k \leftarrow 0$.

Step 2: $j \leftarrow k + 1$.

Step 3: determine whether $Z^*_{kj} = 1$ and $Z^*_{jk} = 1$ at the same time. If yes, industries k and j belong to set V_{l_k} , $l_k \leftarrow l_k + 1$, and then go to the next step; if no, go to the next step directly.

Step 4: $j \leftarrow j + 1$, judge j :

- (1) If $j < n + 1$, return to Step 3; otherwise,
- (2) Judge k . If $k < n$, then $k \leftarrow k + 1$, and return to Step 2; otherwise,

Step 5: terminate.

The obtained set V_{l_k} is the industry set of the strongly connected subgraph in an ICETN. The set $V_{l_k^*}$ corresponding to the maximum value l_k^* contains the most industries, and it is the Strongly Connected Kernel industry set.

4.3.2. Identification of Other Parts. In order to identify the other types of industries, the Strongly Connected Kernel C is condensed into point c , and the condensation graph is constructed. In adjacency matrix Z , the rows and columns of the elements in C are added into one row and one column by

Boolean operation, and the adjacency matrix Z^{**} of the condensation graph is obtained. For each industry, its type is identified according to its association with the concentration point c . If there is an industry whose elements in row and column are all 0, it must be an isolated industry. The other parts are identified as follows:

Step 1: in Z^{**} , in the row c , if there is an industry i_Δ with $Z^{**}(ci_\Delta) = 1$, then industry i_Δ belongs to the “Out” part. In the column c , if there is an industry j_Δ with $Z^{**}(j_\Delta c) = 1$, then industry j_Δ belongs to the “In” part.

Step 2: in the row i_Δ , if there is an industry $i_{\Delta+1}$ with $Z^{**}(i_\Delta i_{\Delta+1}) = 1$, then industry $i_{\Delta+1}$ belongs to the “Out” part; in the column j_Δ , if there is an industry $j_{\Delta+1}$ with $Z^{**}(j_\Delta j_{\Delta+1}) = 1$, then industry $j_{\Delta+1}$ belongs to the “In” part.

Step 3: let $\Delta = \Delta + 1$, repeat Step 2 until there is no $Z^{**}(i_\Delta i_{\Delta+1})$ or $Z^{**}(j_\Delta j_{\Delta+1})$, and find all the “Out” part and “In” part industries.

Step 4: in Z^{**} , in the column of “Out” part industry i_Δ , if there is an industry k_Δ with $Z^{**}(k_\Delta i_\Delta) = 1$, then k_Δ belongs to Tendril industry; similarly, in the row of “In” part industry j_Δ , if there is an industry l_Δ with $Z^{**}(j_\Delta l_\Delta) = 1$, then industry l_Δ belongs to Tendril.

Step 5: if $k_{\Delta+1}$ and $l_{\Delta+1}$ are found with $Z^{**}(k_{\Delta+1} k_\Delta) = 1$ or $Z^{**}(l_\Delta l_{\Delta+1}) = 1$ in the column k_Δ and the row l_Δ , $k_{\Delta+1}$ or $l_{\Delta+1}$ belongs to the Tendril industry. Set $\Delta = \Delta + 1$, repeat Step 5 until there is no $Z^{**}(k_{\Delta+1} k_\Delta)$ or $Z^{**}(l_\Delta l_{\Delta+1})$, and find all the Tendril industries.

Step 6: in the “Bow-Tie” structure, the remaining industries are the Tube industries. Come to the end.

5. The Industrial CO₂ Emissions Transfer Network of China

The ICETN of China is constructed based on China’s Input-output Table (<https://data.stats.gov.cn/ifnormal.htm?u=/files/html/quickSearch/trcc/trcc01.html&h=740>) and Energy Statistics Yearbook (China Energy Statistical Yearbook is edited by the Industrial Transportation Statistics

Department of the National Bureau of Statistics. Since 2008 edition, it has been published by China Statistics Press and released to the public at home and abroad) in 2015. In order to facilitate the comparison, the Input-output Table is kept consistent with the industries divided in China's Energy Statistics Yearbook. Some industries in the Input-output Table are merged in this paper. In the 2015 Input-output Table, "General Equipment" and "Professional Equipment" are merged; "Transport, Warehousing and Postal," "Wholesale, Retail and Accommodation, Food and Beverage," and "Other Industries" are merged. The specific industries and corresponding codes are shown in Table 2.

5.1. Analysis of the Coefficients of Interindustry CO₂ Emissions Transfer. According to formulas (1)–(6), the coefficients of interindustry CO₂ emissions transfer of China are calculated in 2015. List the top 30, as shown in Table 3.

From Table 3, in the top 30 coefficients, there are 12 coefficients whose starting point is industry 22 (electricity, heat production, and supply). It shows that industry 22 transfers much CO₂ emissions to other industries by inputting their products into other industries. Next are industry 11 (petroleum processing, coking, and nuclear fuel processing) and industry 14 (metal smelting and calendaring and processing), with 7 and 5 coefficients, respectively. In other words, 80% of CO₂ emissions in the top 30 coefficients comes from the three industries. It is important to improve technology and reduce the direct CO₂ emissions of the three industries or reduce the use of products from these three industries for emissions reduction.

In order to further study the change rule of coefficients, the top 50 coefficients are listed, as shown in Figure 6. It can be seen that the first three numbers have a large gap. Then, the curve gradually flattened, and the variation trend weakened, especially after the 40th coefficient. Since most of the coefficients are very small, it is necessary to select some significant coefficients to study the interindustry structural characteristics.

5.2. Analysis of the Industrial CO₂ Emissions Transfer Network. According to the method of Part 2, China's coefficients of interindustry CO₂ emissions transfer are calculated. Among the 784 linkage coefficients, 156 are at the top 20%, including 16 internal circulation coefficients. The ICETN of China in 2015 is constructed by the other 140 significant correlations, as shown in Figure 7.

5.2.1. Analysis of the Basic Characteristics of the ICETN of China. From the analysis of China's ICETN in 2015, it can be found that there are no isolated industries. There are 15 industries with out-degrees of 0; that is, more than half of the industries are in the "Out" part. They only receive but not transfer CO₂ emissions to others. The network consists of two cycle structures: one is the Strongly Connected Kernel, which contains 10 industries, namely, No. 2, 3, 4, 5, 11, 12, 13, 14, 22, and 26; the other only contains two industries, namely, No. 1 and 6. The maximum out-degree is 27, and the maximum in-degree is 8, as shown in Table 4.

5.2.2. Degrees of Industries and Star Node Industries. The degree of an industry refers to the number of industries linked with it. Out-degree of an industry is the number of industries, which it pointed to, and in-degree the number of other industries pointing to it. The industries with large degrees become star nodes. Those with high out-degrees are the output star node industries, and those with high in-degrees are the input star node industries. The degrees of industries in China's ICETN are shown in Table 5.

(1) Out-degree Star Industries. From China's ICETN in 2015, the out-degrees of industries have significant differences from each other. The out-degrees of 15 industries are 0. The out-degrees of the top three industries are all more than 20, and these industries become the typical star nodes. Figure 8 shows the top two out-degree star industries, industries 22 and 26.

(2) In-degree Star Industries. The in-degrees of nodes reflect how many industries they receive CO₂ emissions from. Compared with the out-degree, there are relatively small differences in in-degrees. The industry with the largest in-degree is industry 21 (arts and crafts and other manufacturing industries (including waste materials)), and its in-degree is 8. The next are No.13 (nonmetallic mineral products industry), No. 5 (nonmetallic mineral and other mining and dressing industry), and No. 14 (metal smelting and rolling processing industry), with the in-degrees all 7, as shown in Figure 9. These industries receive much CO₂ from others and bear the responsibility of indirect CO₂ emissions.

5.2.3. "Bow-Tie" Structure of China's ICETN. According to the method proposed above, the industries of China are classified, and the "Bow-Tie" structure network diagram is drawn, as shown in Figure 10(a).

(1) Cycle Structures. According to the classification, China's ICETN only includes two types of industries. One is in the Strongly Connected Kernel, and the other is in the "Out" part. The strongly connected kernel contains 10 industries, as shown in Figure 10(b). Industries 1 and 6 also form a cycle structure, as can be seen from Figure 10(a), but they belong to the "Out" part.

Within a cycle structure, there are interindustry cycle linkages of CO₂ emissions. In each cycle, the leading industries provide significant CO₂ emissions for subsequent industries, and the subsequent industries in turn provide significant CO₂ emissions for the leading industries. Such a cycle increases the effect of individual industries in CO₂ emissions. The circle degree is an important index to measure the role of an industry in a circle structure [38, 39]. The circle degree of an industry refers to the number of cycles across the industry. The greater the circle degree is, the greater the role the industry plays in the cycle. The circle degree of industry 11 (petroleum processing, coking, and nuclear fuel processing industry), industry 14 (metal smelting and rolling processing industry), and industry 2 (coal mining and washing industry) rank in the top three, so these three industries are at the center of the cycle.

TABLE 2: Combined industries and codes.

Codes	Industries
1	Agriculture, forestry, animal husbandry and fishery
2	Coal mining and washing industry
3	Oil and gas extraction industry
4	Metal mining and dressing industry
5	Mining and dressing industry of nonmetallic mines and other mines
6	Food manufacturing and tobacco processing industry
7	Textile industry
8	Textile, clothing, shoes, hats, leather, down and its products
9	Wood processing and furniture manufacturing
10	Paper printing and cultural and educational sporting goods manufacturing industry
11	Petroleum processing, coking and nuclear fuel processing industries
12	Chemical industry
13	Nonmetallic mineral products industry
14	Metal smelting and rolling processing industry
15	Metal products industry
16	General and special equipment manufacturing industry
17	Transportation equipment manufacturing industry
18	Electrical machinery and equipment manufacturing industry
19	Communication equipment, computer and other electronic equipment manufacturing industry
20	Instrument and instrument and cultural office machinery manufacturing industry
21	Arts and crafts and other manufacturing industries (including waste products)
22	Production and supply of electricity and heat
23	Gas production and supply industry
24	Water production and supply industry
25	Construction industry
26	Transportation, warehousing and postal services
27	Wholesale, retail, accommodation, and catering
28	Other industries

TABLE 3: Coefficients of interindustry CO₂ emissions transfer ranked in the top 30.

Rank	c_{ij} (t/10000 RMB)	Industry i	Industry j
1	2.9632	22	22
2	1.1517	22	24
3	0.7816	14	14
4	0.7114	11	11
5	0.6760	22	4
6	0.6490	14	15
7	0.6420	11	26
8	0.6251	11	3
9	0.6074	2	2
10	0.5151	14	18
11	0.4618	22	14
12	0.4471	22	5
13	0.4263	2	22
14	0.3670	22	3
15	0.3601	11	12
16	0.3550	22	2
17	0.3332	22	13
18	0.3283	22	15
19	0.3084	11	14
20	0.3083	12	12
21	0.3046	14	16
22	0.3007	22	12
23	0.2911	11	5
24	0.2830	13	13
25	0.2724	22	11
26	0.2681	13	25
27	0.2598	14	25
28	0.2417	11	4
29	0.2307	2	23
30	0.2193	22	23

FIGURE 6: Coefficients of interindustry CO₂ emissions transfer ranked in the top 50.

FIGURE 7: The industrial CO₂ emissions transfer network of China in 2015.

TABLE 4: Basic characteristics of ICETN in 2015.

Item	Quantity and industry code
Edge	140
Self-cycle industry	10 (no. 22, 14, 11, 2, 12, 13, 26, 7, 10, 23, 6, 4, 9, 21, 1, 16)
Out-degree is 0	15 (no. 4, 5, 8, 15, 16, 17, 18, 19, 20, 21, 23, 24, 25, 27)
The top three industries with the largest out-degree	3 (no. 22, 26, 12 with degree 27, 25, 22, respectively)
In-degree ≥ 7	4 (no. 21, 13, 14, 5 with degree 8, 7, 7, 7, respectively)
Cycle structure	2

(2) *The Longest Path.* The directed paths in a ICETN represent the paths of CO₂ emissions transfer among industries. In one path, the starting industry transfers CO₂ emissions out. As the transmitters, the intermediate industries receive CO₂ emissions and pass them back. The terminal ones are the receiver. The longest path represents the path through which CO₂ emissions pass among the most industries. In a circle structure, there is a mutually reachable path between any industries. In China's

ICETN, there are 10 industries in the Strongly Connected Kernel. The CO₂ emissions from any industry can be transferred to all others. On the longest path in the network, after transferring to all the industries in the kernel, the CO₂ emissions are transferred to the small cycle structure consisting of industries 1 and 6, then to industry 7, finally to industries 8, 10, and 21, as shown in Figure 10(a).

5.3. Summary. As can be seen from the above calculation results, the coefficients of interindustry CO₂ emissions transfer, and the network built from them, are good tools for studying the interindustry structural characteristics. They provide a basis for the formulation of CO₂ emission reduction policies.

According to the calculation results, the industries were divided into two categories, cycle industries and reception ones. Among the reception industries, more than half of them are only recipients of carbon emission responsibility, which only receive carbon emissions from the others and do not pass them on. There is also a small cycle structure in reception industries, composed of industries 1 and 6. The

TABLE 5: The degrees, out-degrees, and in-degrees of industries in China's ICETN.

Industry codes	Degrees	Out-degrees	In-degrees
1	7	3	4
2	15	10	5
3	7	2	5
4	7	1	6
5	9	2	7
6	4	1	3
7	7	3	4
8	4	0	4
9	6	0	6
10	6	0	6
11	24	19	5
12	27	22	5
13	16	9	7
14	23	16	7
15	6	0	6
16	5	0	5
17	5	0	5
18	5	0	5
19	5	0	5
20	5	0	5
21	8	0	8
22	30	27	3
23	5	0	5
24	4	0	4
25	6	0	6
26	27	25	2
27	3	0	3
28	4	0	4

FIGURE 8: Out-degree star industries.

FIGURE 9: In-degree star node industries.

FIGURE 10: (a) “Bow-Tie” structure of China’s ICETN. (b) The strongly connected kernel.

strongly connected kernel, the largest cycle structure, contains 10 industries. The circle degree is an important index to describe the roles of various industries in the cycle structure. The circle degree of industry 11 (petroleum processing, coking, and nuclear fuel processing industry), industry 14 (metal smelting and rolling processing industry), and industry 2 (coal mining and washing industry) are the top three. There are also obvious star node industries in the network. Different measures should be taken for different types of industries.

6. Conclusions

It is widely known that CO₂ emissions can be transferred among industries because of the industrial linkages. In this paper, the coefficients of interindustry CO₂ emissions transfer are proposed to analyze the relationships among industries. Then, the industrial CO₂ emissions transfer network is constructed according to the significant coefficients. Furthermore, the industries are classified, and the network is expressed with a “Bow-Tie” structure. Some subgraphs of the network are analyzed. In the case study, based on the Input-output Table and the Energy Statistics Yearbook of China in 2015, China’s industrial CO₂ emissions transfer network is constructed and analyzed. From the calculation examples and results, the methods in this paper provide new contents and methods for the theory of industrial CO₂ emissions.

In order to reduce CO₂ emissions, different measures should be taken for out-degree and in-degree star node industries. For the out-degree star industries, such as industry 22 (electricity, heat production, and supply), the key should be to take measures to reduce the direct CO₂ emissions. For the in-degree star industries, it is important to reduce the consumptions of its related industries.

Although all belong to circular structure, we still need to take different measures for cycle industries. The industries with large circle degrees, such as industry 11 (petroleum processing, coking, and nuclear fuel processing), should be the focus of attention. We could try to reduce their direct emissions or reduce their use. For the longest path, we should try to shorten its length.

The reception industries account for half of the total. For them, the focus should not be on reducing their direct CO₂

emissions, but on reducing the consumption from high emission industries.

Further research needs to complement our findings along different dimensions. First, the analysis of network characteristics could be further deepened. Moreover, the significant coefficients of interindustry CO₂ emissions transfer are not the same, and most of them are quite different. In the process of building the network, the weight of edges could be considered.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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