International Journal of Scientific Engineering and Science
Volume 3, Issue 4, pp. 30-36, 2019. ISSN (Online): 2456-7361

Prediction of Carbon Emission Effects Caused by Industrial Segments Restructure in China

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Abstract— *This paper reclassifies the industrial segments in China based on the goals of low-carbon economy. Applying a dynamic multi-objective model, it predicts efficiency of carbon emission after the adjustment of industrial sector restructure in the following 5 five years, and provides some theoretical supports for policy establishments. As shown by this research, the industrial reorganization and restructuring may well coordinate the triangle relations among "carbon reduction-economic rise-employment growth", which universally magnify the effects of carbon reduction. Based on the investigation and analysis via multi-objective optimization model, we conclude to the carbon emission effects on different classes of industries*.

Keywords— *Industry sector restructure; carbon emission reduction; low-carbon economy; dynamic multi-objective model*.

I. Introduction

According to the data issued by the National Bureau of statistics, the total energy consumption in China reached 36.2 million tons of standard coal in 2014, with a carbon emission of about 90 million tons, accounting for 29% of the global total, and the situation of energy saving and emission reduction is very severe. As early as 1991, Grossman & Krueger [1] pointed out three possible channels for economic growth to affect the environment, namely scale effect, technological effect and structural effect. In order to investigate this structural effect, Debabrata Talukdar and other (2001) [2] and Jorgenson (2007) [3] are based on the panel data of developing countries to analyze the effects of industrial structure adjustment on carbon emissions. According to the mainstream empirical analysis method in this field, the research of domestic scholars can be classified into the following categories: First, a method based on IPAT equation and its variable form. Zhou X. [4] and Tian X. [5] adopt provincial panel data to analyze the relationship between the industrial structural transformation and carbon dioxide emission according to the different expansion forms of the model. Two, structural decomposition analysis method based on input output table. Pan X. F. and Shu T. and Xu D. W. [6] and Tian Y. S. [7] combined with input-output tables, using structural decomposition analysis method to study the changes in the carbon emission intensity of China's manufacturing industry. Third, a method of exponential decomposition analysis. Lv Z. Q. [8] used the logarithmic mean Divisia exponential decomposition method proposed by Ang Chai [9], Xia Y. Q. [10] used LMDI decomposition method to predict the impact of industrial structure changes on carbon emissions. In addition, Ren J. L. and so on used the LMDI decomposition model and LEAP model to analyze the impact factors of industrial carbon emission in the high efficient eco economic zone of the Yellow River Delta and forecast the scenario. Four, other methods. Chen Y. G. [11] and so on put forward the "open P curve" hypothesis of the industrial structure and the evolution of carbon emission intensity. Zhang W. and Wang S. H. [12] use the path analysis to clarify the relationship between the three industrial proportions and their relationship with carbon intensity; Zhu Y. B. [13] and Wang Z. set up an optimization model for the Division door span, and optimize the industrial structure under the guidance of consumer preference. Li K.I. [14] used the dynamic panel smoothing transformation model to analyze the impact of industrial structure on the environmental Kuznets curve (EKC) of China's provinces.

Most studies think that most industries have great differences in energy consumption and carbon emission intensity. The adjustment of industrial structure and optimization and upgrading will have a stable impact on carbon emissions, and the change space of industrial output value is limited. The optimization and upgrading of its internal structure will play a key role in the development of a low carbon economy. However, the previous empirical research on the impact of industrial structure adjustment on carbon emissions is not much, and most of them focus on the analysis of the relationship between them. The neglect of industrial structure adjustment will involve many aspects of the low carbon economic system, and the structural adjustment from the perspective of energy conservation and emission reduction is likely to break the already reached comprehensive. It fits the state of economic balance.

In this paper, a multi-objective optimization model is proposed, which takes the dynamic input-output balance equation as the main constraint and the goal function of a group of socioeconomic development targets, and is based on this model to predict the carbon emission effect of China's industrial structure adjustment in the next few years. Different from the past, this research not only classifies industrial subdivision industry according to multiple targets, but also measures the carbon emission efficiency of industrial structure adjustment by constructing a dynamic input-output model, and connects the present and future of economic development to ensure that the forecast results are more consistent with the economic operation state.

II. Classification of Industrial Industry and Estimation of Carbon Emissions

The "2010 China input and output extension table" is the latest and most detailed input-output table of China so far. Therefore, it is regarded as an important basis for the classification of industry, which divides the industrial sector into 47 categories, and the 2011 China Statistical Yearbook subdivides the industrial sector into 42 industries and two data sources. The caliber is slightly different. In order to facilitate the calculation of the relevant index values, we first sort out the industry categories and classify them into 31 categories, as shown in Table 1. The development characteristics of these industries are different from the process, the production process and the technical level, and there are great differences in many aspects, such as energy consumption, greenhouse gas emission, absorption of employment, and promoting economic growth. From the three economic development targets of reducing carbon, promoting growth and increasing employment, it can be further developed for many industrial industries. The classification and reduction of the number of industries will help to explain the evolution of industrial structure and its impact on carbon emissions more concisely, accurately and clearly.

TABLE 1. Classification of industrial industries based on multi-objectives

Industry Type (8 types)	Industrial Industry (31 types)	Industry Number
Category I industry high carbon emissions - high value-added rate - high employment industry	Coal mining and washing, oil and natural gas extraction, paper and printing, power and heat production and supply, gas production and supply.	Five
Category II industry: high carbon emissions - high value-added rate - low employment industry	Nonmetallic mineral products industry	one
Category III industry high carbon emissions low value-added rate - high employment industry	Chemical raw materials and chemical products manufacturing industry	one
Category IV industry: high carbon emissions - low value-added rate - low employment industry	Petroleum processing, coking and nuclear fuel processing, ferrous metal smelting and calendering processing, non-ferrous metal smelting and calendering processing industry.	three
Category V industry low carbon emissions low value-added rate low employment industry	Manufacturing of food and alcoholic beverages, wood processing and wood, bamboo, rattan, brown goods and furniture manufacturing, and metal products industry.	three
Category VI industry low carbon emissions low value-added rate - high employment industry	Leather, fur, feather (cashmere) and its products industry, cultural and educational sports goods manufacturing, rubber, plastic products, transportation equipment manufacturing, electrical machinery and equipment manufacturing, communication equipment, computer and other electronic equipment manufacturing industry	six
Category VII industry low carbon emissions - high value-added rate - low employment industry	Black metal mining, non-metallic ore and other mining and selection, tobacco products industry, medicine, chemical fiber manufacturing and other chemical industry, handicraft, waste recycling processing industry and other manufacturing industry	five
Category VIII industry low carbon emissions - high value-added rate - high employment industry	Non-ferrous metal mining, textile, textile and clothing, shoes, cap manufacturing, general equipment manufacturing, special equipment manufacturing, instrument and culture, office machinery manufacturing, water production and supply industry	seven

According to the 2011 China Input-Output Statement Extension Table and the 2011 China Statistical Yearbook, the total output carbon dioxide emissions of 10,000 Yuan (the ratio of total energy consumption carbon dioxide emissions to total output in 2010 at the current price) of each industry are calculated respectively, expressed in u, per ton/10,000 Yuan, and the value-added rate of each industry. It refers to the ratio of industrial added value to total output in 2010, expressed in v, and the number of employees with total output of 10,000 Yuan (referring to the ratio of the number of employees with total output at the end of the year in 2010, expressed in w, unit: people / 10,000 Yuan), respectively, with these three indicators as the coordinate axis, drawing three industrial sectors Dimensional distribution graph. According to the median of each index value, roughly determine the dividing value of high and low areas: u = 0.1, v = 0.2 and w = 0.005, according to which make three mutually perpendicular planes, divide the space into eight areas, as shown in Figure 1. Obviously, the points representing different industries are unevenly dispersed in different regions, and each region falls somewhat. These industries are divided into eight categories. The specific results are shown in Table 1.

In addition, the IPCC (2007) [13] refers to the three methods of estimating the carbon emissions from the combustion of fossil fuels for the consumption of carbon dioxide produced by the consumption of petrochemical energy in human production activities.

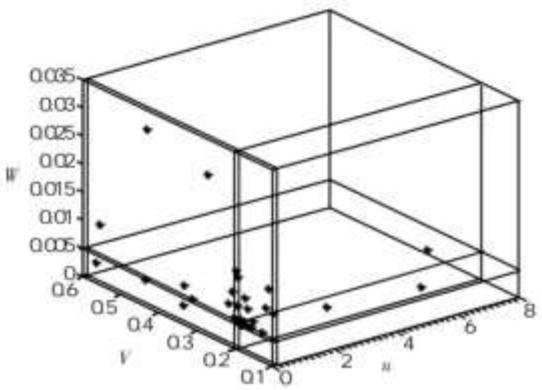

Fig. 1. Three space map of the industrial distribution

The first method of this paper is to estimate the carbon dioxide emissions according to the amount of energy consumption and the default emission factor. Although the accuracy is insufficient, it is simple and applicable. It needs to be explained that the carbon emission estimates are aimed at 8 kinds of petrochemical energy: raw coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil and natural gas; the carbon

International Journal of Scientific Engineering and Science
Volume 3, Issue 4, pp. 30-36, 2019. ISSN (Online): 2456-7361

emission factor of the energy is multiplied by the average low-calorie factor, that is, the carbon emission corresponding to the unit energy consumption; carbon emissions should be used. Equal to the energy consumption multiplied by the carbon emission factor.

III. MODEL CONSTRUCTION

3.1. Objective Function

The adjustment of industry development and industrial structure should be adapted to the development of a low carbon economy as far as possible. It should not aggravate the grim nature of the employment situation. Moreover, the excessive or slow growth of industrial output is unfavorable. The optimization of industrial structure should be beneficial to the national economic security, social stability, low carbon environmental protection and the development of other industries. Therefore, the article designs the objective function from four aspects: total economic volume, carbon emissions, total employment, and the comprehensive balance between industries. Because one of the characteristics of the optimization problem in the time dimension is that its criterion function is additive and separable, then the four objective functions of the dynamic optimization model all choose the corresponding cumulative value.

3.1.1. The target of economic growth

Internationally, GDP is usually used to measure national income. The largest target value in the planning period is the first objective function. It is expressed as:

$$maxTGDP = \sum_{t=1}^{k} e^T [X(t) - A(t)^T X(t)] \tag{1}$$

Where $t \in \{1, 2, \ldots, K\}$, e=[1, 1, …, 1]^T is a unit column vector. The table 1 shows that the production department can be classified into 9 categories of industries, in which industrial production departments include 8 industries (I, II, III, IV, V, VI, VII, VIII), and the rest of the non-industrial industries are included in category IX industry. According to this division, $X(t)$ represents the total production of various industries in phase t. Out vector, $[X_1(t), X_2(t), \ldots X_n(t)]^T$, n=9, so $A(t)=(a_{ij}(t))_{nxn}$ indicates that the direct consumption coefficient matrix in the t phase should also be transformed according to the new industry classification.

3.1.2. The target of carbon emission control

Under the low carbon development mode, the basic goal of industrial restructuring is to control or reduce carbon emissions, which can be expressed as follows:

$$minTCE = \sum_{t=1}^{k} C(t) X(t) \tag{2}$$

In the above formula, $C(t)$ is the row vector of carbon emission intensity of various industries in the period t: $[C_1(t), C_2(t), \ldots, C_n(t)]$. $C_n(t)=M_1 / N_1$, where M_1 is the total energy consumption emissions in phase t of category n industry, N_1 is the total output of phase category n industry)

3.1.3. The goal of full employment

Labor employment is one of the social problems that are closely related to the development of the industry. The third objective function is the maximum cumulative value of the total amount of employment in the planning period. The expression is as follows:

$$maxTPE = \sum_{t=1}^{k} L(t) \times X(t) \tag{3}$$

In the above formula, $L(t)$ is the row vector of labor coefficient of various industries in the period t: $[L_1(t), L_2(t), \ldots, L_n(t)]$. $L_n(t)= M_2 / N_2$, where M_2 is the number of employees in urban units at the end of stage t of category n industry, N_2 is the total output of phase of category n, representing the number of employees at the end of the town period of the total output of category t category n industry units.

3.1.4. The objective of comprehensive economic balance

The comprehensive economic balance is the basis of the benign development of the low carbon economic system, which requires the coordinated development of various industries and as much as possible to reduce the degree of imbalances. The objective function is as follows:

$$minTDV = \sum_{t=1}^{K} e^T [d_+(t) + d_-(t)] \tag{4}$$

In the formula, $d_+(t) = [d_{+1}(t), d_{+2}(t), \ldots, d_{+n}(t)]^T$, $d_-(t) = [d_{-1}(t), d_{-2}(t), \ldots, d_{-n}(t)]^T$. They represent the positive and negative deviation vectors of the dynamic input-output equilibrium equations for various industries in phase t, $d_{+i}(t)$ and $d_{-i}(t)$ (i = 1, 2,...), respectively. The sum of (n) is used to measure the degree of imbalance of class I industry in the period t, then the minimum sum of the positive and negative variables in all kinds of industry in the planning period is used as the objective function, which can be used to describe the most possible balance of the comprehensive economy.

3.2. Constraint conditions

3.2.1. Dynamic input-output balance constraint

The dynamic input-output balance constrains the complex dynamic equilibrium between input and output (or production and consumption) in each production department. In a real economy, the balance is a basic equilibrium or trend, and the input and output are difficult to be completely equal, and there will be some deviations. So the expression of this constraint is as follows:

$$X(t-1) = A(t-1)X(t-1) + B(t-1) + Y(t-1) - d_+(t-1) + d\_(t-1) \tag{5}$$

In the above formula, $t \in \{1, 2, \ldots, K\}$, when t-1=0, it indicates the base period, $B(t) = (b_{ij}(t))_{nxn}$ indicates the investment coefficient matrix according to the new industry classification t period, $Y(t)=[Y_1(t), Y_2(t), \ldots, Y_n(t)]^T$ is the column vector for the sum of final consumption expenditure and net exports of various industries in phase t. Here, the dynamic input-output balance constraint in phase t is composed of the dynamic input-output equilibrium equations of all kinds of industries, and the corresponding positive and negative deviation vectors can make the equation have a certain elasticity, which is more consistent with the actual economic development and is easy to get a stable solution.

3.2.2. GDP growth constraint

In order to ensure the increasing material and cultural needs of the people, we should take into account the

International Journal of Scientific Engineering and Science
Volume 3, Issue 4, pp. 30-36, 2019. ISSN (Online): 2456-7361

constraints on the increase in value-added industries. So the expression of this constraint is as follows:

$$e^T\left[X(t)-A(t)^T X(t)\right] \geq \left(1+\bar{g}\right) e^T\left[X(t-1)-A(t-1)^T X(t-1)\right] \quad (6)$$

Where $t \in \{1, 2, \ldots, K\}, \bar{g}$ represents the annual growth rate of GDP during the planning period.

3.2.3. Energy consumption and carbon emission constraints

In order to achieve the basic goal of controlling carbon emissions and energy consumption, the constraints of energy consumption and carbon emissions must be met:

$$\frac{E(t)X(t)}{e^T[X(t)-A(t)^T X(t)} \leq (1+N)^t E_o, t \in \{1, 2, \ldots, K\}$$

$$\frac{C(t)X(t)}{e^T[X(t)-A(t)^T X(t)} \leq (1+M)^t C_o, t \in \{1, 2, \ldots, K\}$$

In the above formula, $E(t)$ is the row vector $[E_1(t), E_2(t), \ldots, E_n(t)]$, $E_n(t)$ which constitutes the total output energy consumption of various industries in phase t. $E_n(t)=M_3 / N_3$, where M_3 is the total amount of energy consumption in phase t of category n industry, N_3 is the total output of phase t of category n industry, representing total output of the total output of the category t phase n industry unit. N indicates the average growth rate of GDP energy consumption in the production unit during the planning period, and E_o is the energy consumption of the unit GDP production unit based on the base period. M indicates the average growth rate of energy consumption carbon emissions by unit GDP production unit in the planning period, and C_o is the unit production sector energy consumption carbon emissions for the unit production sector based on C_o.

3.2.4. Labor restraint

If the structural shortage of labor resources is ignored, in order to ensure the demand for labor in various industries and ensure the stability of the employment situation, the expression of the constraints is as follows:

$$L(t)\, X(t) \geq (1+H)t\, L_o, t \in \{1, 2, \ldots, K\} \quad (7)$$

In the formula, H represents the average growth rate of total employment in the planning period, and L is the total amount of actual employment in the base period.

3.2.5. Nonnegative constraints

$$X(t) \geq 0,\ Y(t) \geq 0,\ d_+(t) \geq 0,\ d_-(t) \geq 0,\ t \in \{1, 2, \ldots, K\} \quad (8)$$

Using Y as an endogenous variable can overcome the artificial nature of exogenous variables and make the results more in line with the economic operation process.

3.3. Parameter estimation

3.3.1. Direct consumption coefficient matrix A(t)

The direct consumption coefficient matrix $A(0)$ of the base year is obtained directly from the Chinese input-output table for a year, and $A(t)$ ($t \in \{1, 2, \ldots, K, \ldots\}$) is obtained in order for the revision of $A(0)$, at present, the international popular direct consumption coefficient revision techniques include expert investigation, RAS correction, Lagrange undetermined coefficient method and key coefficient method. Among them, the subjective randomness of the expert investigation method is stronger, and the accuracy depends entirely on the evaluation method of the experts; the correction method must be eliminated directly. The coefficient of consumption will be influenced by two aspects of substitution and consumption as a hypothesis, and it is required that the intermediate use and material consumption of the departments in each period are known, and in unknown circumstances, their superiority cannot be embodied; and the Lagrange undetermined coefficient method is only suitable for a short time in the planning period, and a larger error will be produced in the long-term prediction. The key coefficient law only revises the coefficient from the angle of mathematical analysis and does not relate to economic theory.

This paper combines the mature Markov method with the input-output analysis method. It can not only modify the direct consumption coefficient matrix according to the known information, but also can compare the prediction results under different circumstances. Markov process is a stochastic dynamic process with the characteristics of "no aftereffect". If the transfer probability matrix is constant, the process will reach a stable state. Using this principle, the coefficient revision formula: $P_t^T = P^T_o \lambda^t$ ($t \in \{1, 2, \ldots, K\}$), in which, P_t represents the ratio coefficient matrix of phase t, and $P_o = \begin{bmatrix} A_o & Q_o \\ J_o & W_o \end{bmatrix}$ represents the initial state of the ratio coefficient matrix, and λ is the transfer probability matrix. According to the finished base period input-output Table 2,

TABLE 2. The composition of the ratio coefficient matrix P of the base period

<table>
<tr><td rowspan="2"></td><td colspan="5">Intermediate Products</td><td>Final Product</td><td>Total Output Value</td></tr>
<tr><td>Class I Industrial Industry</td><td>Class II Industrial Industry</td><td></td><td>Class VIII Industrial Industry</td><td>Class IX Industrial Industry</td><td>Accumulation and Consumption Total</td><td></td></tr>
<tr><td>Category I Industrial Industry</td><td colspan="5" rowspan="5">The direct consumption coefficient matrix of the first quadrant A_0</td><td rowspan="5">The ratio coefficient matrix Q_0 of the II quadrant</td><td>…</td></tr>
<tr><td>Category II Industrial Industry</td><td>…</td></tr>
<tr><td>…</td><td>…</td></tr>
<tr><td>Category VIII Industrial Industry</td><td>…</td></tr>
<tr><td>Category IX Industrial Industry</td><td>…</td></tr>
<tr><td>Added Value Add Up</td><td colspan="5">The ratio coefficient matrix J0 of the III quadrant</td><td>The ratio coefficient matrix W_0 of the IV quadrant</td><td>…</td></tr>
<tr><td>Total Input</td><td>…</td><td>…</td><td>…</td><td>…</td><td>…</td><td>…</td><td>…</td></tr>
</table>

A_o is calculated by the direct consumption coefficient formula, and the numbers in the other matrices Q_o and J_o can be calculated according to the similar method, as the proportion of each part in the total output, for example, the matrix J is composed of the proportion of all kinds of industry added value to its total output value. The determination of the transfer probability matrix lambda follows a series of hypotheses: with the progress of technological innovation and energy saving technology and the improvement of productivity level, the transfer and substitution of production factors among various industries is objective, and more and more high carbon emissions products will be replaced by low carbon emissions products.

3.3.2. The investment coefficient matrix B(t)

The investment coefficient matrix is the core constraint of the above models. Due to the instability of investment, the determination of matrix is difficult. It is assumed that for the same product, the demand for the intermediate products of various industries is the same as the demand for its investment products, and the lag of investment is taken into account, $b_{ij}(t) = s_i(t)a_{ij}(t) / x_j(t+1)$, t = 1, 2..., K. In the K formula, $\Delta s_i(t)$ represents the investment in phase t of phase I industry, and Δx_j $(t+1)$ indicates the total output increase of phase I industry t-1 phase than the t stage.

IV. EXAMPLES OF APPLICATIONS

4.1. Parameter setting and model solving

Based on the relevant year's China statistical yearbook and input-output table, with 2010 as the base period and 2011-2020 as the planning period, the values of various parameters in the model are estimated according to the constant prices in 2010. At present, there are only the input-output tables of the subdivided industries in 2002, 2005, 2007 and 2010. In order to ensure the consistent statistical caliber, the estimation basis of some parameters is limited to the sample data at different intervals in these four years. Therefore, $C(t)$, $I(t)$ and $E(t)$ use the GM (1,1) grey model with unequal time intervals to estimate year by year. According to the industrial industry classification based on multi-objective above, the input-output table in 2010 can be sorted and calculated to obtain the direct consumption coefficient matrix $a(0)$ for the base year, and then the direct consumption coefficient matrix $a(t)(t$=1, 2, ..., 10) for 2011-2020 can be predicted by combining Markov method with input-output analysis method.

$\Delta S_i(t)$, $\Delta X_j(t+1)$ and G_i all adopt weighted average values of various industries from 2002-2005, 2005-2007, and 2007-2010. According to the twelfth five-year plan for China's national economic and social development, set the values of $\bar{g}$, N, M and H to ensure the smooth realization of the development goals. The values of E_o, C_o and L_o can be calculated according to the 2011 China statistical yearbook and China energy statistical yearbook. The solution process is as follows:

First, the objective functions (1) and (3) are transformed into two minimization problems, as follows:

$$minTGDP = -\sum_{t=1}^{K} e^T \left[X(t) - A(t)^T X(t) \right] \tag{9}$$

$$minTPE = -\sum_{t=1}^{K} L(t) \times X(t) \tag{10}$$

Secondly, after the dimensionless treatment of each target, the weighted sum of multiple targets is taken as a single target by using the linear weighting method. Considering that China is currently facing the great pressure of growth, employment, pollution control and coordinated development at the same time, the weight of each target function is 1 / 4.

Finally, MATLAB software is used to call the function linprog to solve the problem.

4.2. Analysis of prediction results

In general, according to the predicted value of industrial structure adjustment in the planning period (Table 3), carbon emissions are sensitive to industrial structure adjustment on the premise of ensuring steady growth in economic aggregate and employment level in the next few years. in 2010-2020, the average annual growth rate of carbon emissions is controlled within 5 %, and the control target of carbon emission intensity (carbon emissions per unit GDP of production energy consumption) has been successfully achieved, from 2.28 tons / 10,000 Yuan to 1.56 tons / 10,000 Yuan (with no price change in 2010). In the next few years, the adjustment direction of industrial structure is as follows:

TABLE 3. The predicted value of industrial structure adjustment in the planning period

	Actual Value In 2010	Forecast For 2015	Forecast For 2018	Forecast For 2020
	A proportion of total industrial output	A proportion of total industrial output	A proportion of total industrial output	A proportion of total industrial output
Class I industry	12.26%	5.00%	6.75%	4.21%
Class II industry	5.17%	6.89%	7.98%	13.24%
Class III industry	5.63%	6.78%	7.98%	12.47%
Class IV industry	14.49%	5.87%	8.08%	9.46%
Class V industry	13.05%	20.86%	20.06%	21.32%
Class VI industry	25.68%	19.03%	16.04%	13.24%
Class VII industry	7.36%	15.65%	13.77%	11.21%
Class VIII industry	16.36%	19.93%	19.34%	16.86%
Carbon emissions (ten thousand tons)	913407	1163934	1350327	1416526
GDP (billion Yuan)	401202	617299	799420	907111
Number of urban end-of-term employees (thousand people)	130515	190883	228634	240432

International Journal of Scientific Engineering and Science
Volume 3, Issue 4, pp. 30-36, 2019. ISSN (Online): 2456-7361

Note: For the sake of consistency of statistical standards, GDP in 2010 is the total value added of various industries in the input-output table of that year. Therefore, the estimated GDP in each year is different from that in the statistical yearbook, and the GDP is unchanged in 2010. Carbon emission refers to the total carbon dioxide emission from energy consumption in the production sector, excluding the carbon emission from the living sector.

Firstly, the main industries that have shown a general downward trend in their share of total industrial output are class I industry, class IV industry and class VI industry, which belong to high carbon emission-high added value rate-high employment industry, high carbon emission - low added value rate-low employment industry, low carbon emission-low added value rate-high employment industry, respectively. Among them, class I and class IV industry both experienced a rapid decline first and then a slight increase, especially the latter, which decreased sharply from 14.49% in 2010 to 5.87% in 2015 and then rose to 9.46 % in 2020. As can be seen from Table 3, these two types of industries, including petroleum processing, coking and nuclear fuel processing, ferrous metal smelting and calendering processing, are all typical high energy consumption and high carbon emission industries. Greatly reducing their proportion may play a significant role in controlling the growth of carbon emission in the short term. However, considering the basic position of these industries and the coordinated development among them, especially with the accelerated development and utilization of new energy and energy conservation and emission reduction technologies in recent years, in the long run, their carbon emission intensity will show a gradually decreasing trend and the industrial characteristics of high carbon emission will no longer be prominent. Therefore, the decline in their proportion will slow down year by year.

Secondly, the proportion of class II, III, and V industries shows an upward trend. They belong to high carbon emission - high added value rate - low employment industry, high carbon emission - low added value rate - high employment industry, low carbon emission - low added value rate - low employment industry, respectively. The expansion of their respective proportions will only promote the realization of a certain goal, but will hinder the realization of the other two goals. Nevertheless, when the promotion of the current one exceeds the obstruction of the latter, moderate scale expansion is still the inevitable choice in the short term. For example, the increase in the proportion of food and alcoholic beverage manufacturing, wood processing, wood, bamboo, rattan, brown products and furniture manufacturing, metal products and other industries helps to control the growth of carbon emissions, but has little contribution to economic growth and employment absorption. Therefore, the moderate expansion of the development scale of these industries is a balanced choice after weighing and choosing the pros and cons. In addition, category VII and VIII industries belong to low carbon emission - high added value rate - low employment industry and low carbon emission - high added value rate - high employment industry, respectively. Their respective proportions have gone through the process of rising, but they began to fall back after that. As the pace of scientific and technological innovation accelerates and low carbon energy is widely used, the inherent advantages of these two industries in reducing carbon emission and promoting growth may exist for a long time, but the differences between them and other industries are likely to narrow. In order to maintain the comprehensive economic balance, the trend of the scale expansion of these industries will definitely slow down.

In short, industrial structure adjustment is a complex system project, involving all aspects of the economic and Social Council. There are conflicts and shields among the various objectives of the optimization problem. While promoting growth, it is inevitable that it will bring great pressure to reduce emissions and consumption. Moreover, industries with strong economic impetus may not be able to absorb enough jobs, but they cannot ignore or give up any reasonable development objective. There is no denying that the adjustment of industrial structure is conducive to coordinating economic growth, full employment and carbon emission control as much as possible, fully realizing the goal of carbon reduction, and finally reaching the Pareto optimal state.

V. CONCLUSION

To sum up, the main conclusions of the article include the following:

First, according to the forecast results, on the premise of achieving the carbon emission control target, through the optimization of the industrial structure, China can still maintain a growth rate of about 8 % in the next five years. the total number of new jobs in cities and towns exceeds 49 million. at the same time, the overall response of carbon emissions to the adjustment of the industrial structure is relatively sensitive: the average annual growth rate of carbon emissions is controlled within 5 %, and the cumulative decrease in carbon emission intensity also exceeds 17 %. It can be seen that the three sub-goals of reducing carbon emissions, promoting economic growth and expanding employment are interdependent and mutually restricted. to coordinate the relationship among them through the optimization of industrial structure can play a certain carbon reduction effect.

Second, in the low-carbon development mode, most of class I and IV industrial sectors show the characteristics of high energy consumption and high emission, which can greatly reduce their proportion in the short term. however, in the long term, the key lies in the vigorous development and promotion of energy-saving and emission-reduction technologies, and the need to use high-level environmental protection technologies to transform the traditional production process. Because if the technology for eliminating pollution is not improved and pollution is controlled only by limiting production and halting production, the effect is not only limited, but also seriously affects the coordinated development of other related industries due to the vacillation of its basic position.

Thirdly, although non-metallic mineral products industry, chemical raw materials and chemical products manufacturing industry belong to high carbon emission industry, they have made outstanding contributions to economic growth and employment expansion respectively. as for them, moderate scale expansion is still the inevitable choice in the short term.

In addition, with the accelerating pace of scientific and technological innovation and the widespread use of low-carbon energy in various industries, especially those with high energy consumption and high emission, the advantages of class VII and VIII industries including ferrous metal mining, non-metallic mining and other mining, tobacco products, non-ferrous metal mining, textile, textile and clothing, shoes, cap manufacturing and general equipment manufacturing in energy conservation and emission reduction are no longer so prominent, and their expansion trend will gradually slow down.

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