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Feasible Region Evaluation of Urban Industry Development for Achieving the Carbon Peak and Neutrality

Bingjie Li¹, Xiaoyan Hu¹, Hu Li¹, Sheng Wang^{2*}, Hao Chen², Yahui Ma² and Fenghua Zou²

¹ Jiangsu Economic Research Institute, State Grid Jiangsu Electric Power Co., Ltd, Nanjing, Jiangsu, 210000, China

² State Grid (Suzhou) City & Energy Research Institute Co., Ltd, Suzhou, Jiangsu, 215000, China

Email: wangsheng_zju@zju.edu.cn

Abstract. The carbon peak/neutrality is one of the most concerning matters recently for both government and energy enterprises. With the establishment of new low-carbon-orientated policies, the development of urban industries should be comprehensively reviewed. For achieving the carbon peak and neutrality, this paper proposes techniques to forecast the carbon emission for the industry sector, and evaluate the feasible region of the urban industry development. First, an improved STIRPAT model is developed to analyze the relations between carbon emission and various impact factors. Then, the carbon emission of the industrial sector is forecast. Moreover, an optimization model is developed to analyze the feasible region of different factors around the forecast point. Finally, the industries in Suzhou are analyzed as an example to validate the proposed technique.

1. Introduction

With the worldwide concern for greenhouse gas emissions, China is now undergoing a transition towards low-carbon development and energy utilization. On Sep 22, 2020, in the General Debate of the Seventy-fifth United Nations General Assembly, President Xi announced the vision of Carbon Peak and Carbon Neutrality in China. It is stated in the “Thirteenth Five-Year Plan for Controlling Greenhouse Gas Emissions” that the Jiangsu province has promised a 20.5% reduction in the carbon emission intensity (CEI). City, as a basic unit to implement the policies, is facing the pressure of bettering the energy and industry structures for lower carbon emission.

Recently, extensive research effort has been paid to the topics of carbon emission measuring, impact factor analysis, and carbon emission forecast. The carbon emission of China from 1997 to 2015 were calculated in [1]. A decomposition of the CO₂ emissions in Guangdong province, China, based on a multi-sectoral approach was studied in [2]. The decomposition relations between the carbon emission of the electricity generations and the economic in China was analyzed in [3] using the LMDI method. The driving forces of the carbon emission of Turkey’s transportation sector, the commercial building sector, and the industrial sector in Shanghai, China, were investigated in [4], [5], and [6], respectively. The CO₂ emissions in China from fossil energy were studied in [7]. A hybrid algorithm for predicting the carbon emission was proposed in [8] based on an improved lion swarm optimizer.

However, the researches above focus on the investigation of the current situation and the future development of carbon emission. They give suggestions on the future energy-related policies, or future development of industries, etc., merely intuitively based on the results. Few studies have devised the



pathway towards the low-carbon future and provided quantitative analysis and executable guide. A low-carbon plan was devised for a district in Shanghai, China in [9] using the STIRPAT model. The carbon emission of Shanghai was analyzed in [10], and the pathway to an optimal economic structure was studied based on STIRPAT and NSGA-II. The feasible path of the carbon emission peak in China's construction sector was assessed in [11]. These studies optimized the impact factors to accelerate the progress of reaching the carbon emission peak.

However, with the given goal of reducing carbon emission and its intensity, the development of urban economy, scale, industry, etc., must face invisible restraints. Sometimes they even contradict the basic policy of cities. For example, the workforce is the foundation of urban development, while it is also a driving force for the carbon emission increase. It is apparently unreasonable to strictly limit the scale of the population in exchange for the reduction of carbon emission. Therefore, we need to carefully balance among various variables that affect the carbon emission and determine the feasible region of these factors, which is also vital to the city's development. Moreover, the circumstance is always evolving and uncertain, for which we need to count in determining the feasible region of urban industry development.

Therefore, under the national policies on controlling the total amount of carbon emission, and the CEI, this paper proposed a technique to forecast the carbon emission, as well as evaluate the feasible region of urban industry development. First, an improved STIRPAT is developed to analyze the relations between carbon emission and various impact factors. Then, the carbon emission of the industrial sector is forecast. Moreover, an optimization model is developed to study the feasible region of various factors around the forecast point. Finally, the industries in Suzhou are analyzed as an example to validate the proposed technique.

2. Carbon Emission Forecasting

2.1. Carbon Emission Evaluation

Based on the energy consumptions of the industry sector, the energy-related carbon emission can be calculated as:

$$c_t = \sum_{i \in I} \sum_{j \in J} ec_{i,j,t} \times NCV_i \times O_{i,j} \times CC_i / F_i \quad (1)$$

Where c_t is the carbon emission in year t . I and J are the sets of energy type and industry sector, respectively. $ec_{i,j,t}$ is the energy consumption of energy i in sector j in year t . NCV_i is the caloric value of energy i . $O_{i,j}$ is the oxygenation efficiency of energy i in sector j . CC_i is the CO₂ emissions per net caloric value produced by energy i [12]. F_i is the conversion coefficient to standard coal.

2.2. Carbon Emission Forecasting Based on the Improved STIRPAT Model

To predict carbon emission, the impact factors must be specified. The Kaya equation is usually used to decompose the impact factor of carbon emissions into population, economy, and energy consumption intensity. However, to investigate more thoroughly, the Kaya equation is extended to incorporate more factors:

$$\begin{aligned} c_t &= \sum_{i \in I} \sum_{j \in J} c_{i,j,t} \\ &= \sum_{i \in I} \sum_{j \in J} p_t \times \frac{p_t^I}{p_t} \times \frac{g_t}{p_t^I} \times \frac{ec_{i,j,t}}{ec_{j,t}} \times \frac{g_{j,t}}{g_t} \times \frac{ec_{j,t}}{g_{j,t}} \times \frac{c_{i,j,t}}{ec_{i,j,t}} \\ &= \sum_{i \in I} \sum_{j \in J} p_t \times A_t \times B_t \times C_{i,j,t} \times D_{j,t} \times E_{j,t} \times F_{i,j,t} \end{aligned} \quad (2)$$

where p_t is the population in year t . p_t^I is the population that works for the second industry. g_t is the GDP. Therefore, the impact factor of the carbon emission can be classified into seven categories, namely, population, population structure A_t , average GDP contribution for second industry B_t , energy structure $C_{i,j,t}$, industry structure $D_{j,t}$, energy consumption intensity $E_{j,t}$, carbon emission factor $F_{i,j,t}$.

Based on these impact factors, the STIRPAT model can be extended to forecast carbon emission in the future in a more detailed way. In the traditional STIRPAT or IPAT models, the dependant variable (such as carbon emission) is fitted concerning the absolute values of the independent variables. However, the dimensionalities of the independent and dependant variables cannot match in this manner. Moreover, different dimensionality will lead to different absolute values, which may cause accuracy issues. Therefore, suppose the carbon emission factors do not change. Instead of taking their absolute values, we fit based on their relative rate of change:

$$\frac{C_{i,j,t+1}}{C_{i,j,t}} = \varepsilon_{i,j} \left(\frac{A_{t+1}}{A_t}\right)^{a_{i,j}} \left(\frac{B_{t+1}}{B_t}\right)^{b_{i,j}} \left(\frac{C_{i,j,t+1}}{C_{i,j,t}}\right)^{c_{i,j}} \left(\frac{D_{j,t+1}}{D_{j,t}}\right)^{d_{i,j}} \left(\frac{E_{j,t+1}}{E_{j,t}}\right)^{e_{i,j}} \left(\frac{p_{t+1}}{p_t}\right)^{f_{i,j}} \tag{3}$$

where $a_{i,j}$, $b_{i,j}$, $c_{i,j}$, $d_{i,j}$, $e_{i,j}$, $f_{i,j}$ are the fit coefficients of the impact factors. $\varepsilon_{i,j}$ is the error coefficient.

After taking logarithms for both sides, (3) becomes:

$$\begin{aligned} \ln C_{i,j,t+1} &= \ln C_{i,j,t} + \ln \varepsilon_{i,j} + (f_{i,j} - a_{i,j}) \ln p_{t+1} + (a_{i,j} - f_{i,j}) \ln p_t + (a_{i,j} - b_{i,j}) \ln p_{t+1}^I \\ &\quad + (b_{i,j} - a_{i,j}) \ln p_t^I + (b_{i,j} - d_{i,j}) \ln g_{t+1} + (d_{i,j} - b_{i,j}) \ln g_t + c_{i,j} \ln ec_{i,j,t+1} - c_{i,j} \ln ec_{i,j,t} \\ &\quad + (e_{i,j} - c_{i,j}) \ln ec_{j,t+1} + (c_{i,j} - e_{i,j}) \ln ec_{j,t} + (d_{i,j} - e_{i,j}) \ln g_{j,t+1} + (e_{i,j} - d_{i,j}) \ln g_{j,t} \end{aligned} \tag{4}$$

Fit the curve using the least square method, and we can obtain the values of fit coefficients.

3. Feasible Region of Urban Industry Development

After obtaining all the fit coefficients, the carbon emission at any year t can be forecast as:

$$\begin{aligned} C_t &= \sum_{i \in I} \sum_{j \in J} C_{i,j,t_0} \prod_{\tau=t_0+1}^t \left(\varepsilon_{i,j} \left(\frac{A_{\tau+1}}{A_{\tau}}\right)^{a_{i,j}} \left(\frac{B_{\tau+1}}{B_{\tau}}\right)^{b_{i,j}} \left(\frac{C_{i,j,\tau+1}}{C_{i,j,\tau}}\right)^{c_{i,j}} \left(\frac{D_{j,\tau+1}}{D_{j,\tau}}\right)^{d_{i,j}} \left(\frac{E_{j,\tau+1}}{E_{j,\tau}}\right)^{e_{i,j}} \left(\frac{p_{\tau+1}}{p_{\tau}}\right)^{f_{i,j}} \right) \\ &= \sum_{i \in I} \sum_{j \in J} C_{i,j,t_0} \varepsilon_{i,j}^{t-t_0} \left(\frac{A_t}{A_{t_0}}\right)^{a_{i,j}} \left(\frac{B_t}{B_{t_0}}\right)^{b_{i,j}} \left(\frac{C_{i,j,t}}{C_{i,j,t_0}}\right)^{c_{i,j}} \left(\frac{D_{j,t}}{D_{j,t_0}}\right)^{d_{i,j}} \left(\frac{E_{j,t}}{E_{j,t_0}}\right)^{e_{i,j}} \left(\frac{p_t}{p_{t_0}}\right)^{f_{i,j}} \end{aligned} \tag{5}$$

where t_0 is the base year.

Under the urgent requirement of the carbon peak and neutrality, the provincial government usually establishes policies to restrain the carbon emission quantity and intensity of the city. Then, according to the last section, the development of urban industries must be restrained within a certain region. The feasible region is formed as a polyhedron in a high-dimension space. For quantifying the feasible region of urban development, the following optimization problems are solved for determining the upper and lower boundaries of a certain factor, when other factors are given, which is equivalent to the projection of the polyhedral feasible region to a certain plane. Suppose we need to obtain the upper and lower boundaries of the energy structure for energy i in sector j in year t , $C_{i,j,t}^{\max}$ and $C_{i,j,t}^{\min}$, respectively:

$$C_{i,j,t}^{\max} = \arg \max \{C_{i,j,t}\}, C_{i,j,t}^{\min} = \arg \min \{C_{i,j,t}\} \tag{6}$$

Subject to (5), and the following nontrivial constraints:

- 1) Carbon emission quantity and intensity constraints:

$$0 \leq c_t \leq (1 + \alpha^q) c_{t_0} \quad (7)$$

$$0 \leq c_t / g_t \leq (1 + \alpha^i) c_{t_0} / g_{t_0} \quad (8)$$

2) Economic growth constraints:

$$g_t \geq (1 + \beta)^{t-t_0} g_{t_0} \quad (9)$$

3) Energy and industry structure constraints:

$$ec_t = \sum_{i \in I} ec_{i,t} = \sum_{i \in I} \sum_{j \in J} ec_{i,j,t}, g_t = \sum_{i \in I} g_{i,t} = \sum_{i \in I} \sum_{j \in J} g_{i,j,t} \quad (10)$$

$$ec_t \geq (1 + \varphi)^{t-t_0} ec_{t_0} \quad (11)$$

4) Other given boundary conditions:

$$p_t = (1 + \gamma)^{t-t_0} p_{t_0} \quad (12)$$

$$p_t^I = \gamma_t^I p_t \quad (13)$$

$$g_{j,t} = g_{j,t_0} / g_{t_0} \times g_t \quad (14)$$

Where a^q and α^i are the permitted carbon emission quantity and intensity growth rates, respectively. β is the annual growth rate of GDP published in the government report. φ is the average energy consumption growth rate. γ is the natural growth rate of the population. γ_t^I is the proportion of people that work for the second industry in year t .

4. Source of Data

The population and its structure, industry structure, as well as energy consumption are from Suzhou statistical yearbook. The carbon emission factors are from the IPCC's guide on greenhouse gas emission. The conversion factor to the standard coal is from the China energy statistical yearbook.

5. Case Studies

5.1. Forecast of the Carbon Emission of Suzhou's Industrial Sector

To validate the effectiveness of the proposed improved STIRPAT model, the errors of the regression are presented in figure 1. As we can see, the errors are properly controlled within an acceptable range. 87.69% of the errors are controlled within 0.5%, which validates the effectiveness of the proposed improved STIRPAT model. On the other hand, we can also observe that different energies show different ranges of error. For example, the errors of coke, gasoline, electricity are relatively smaller, which indicates that the prediction of the carbon emission from these energies is relatively more accurate.

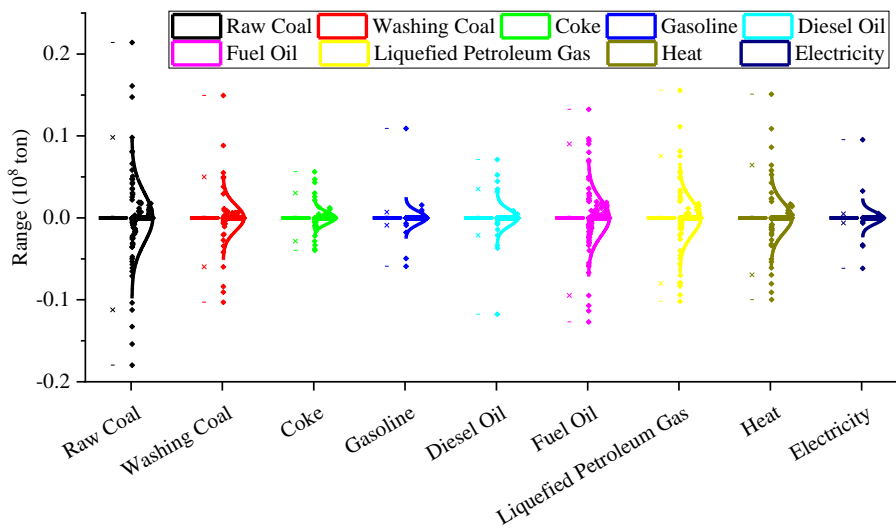


Figure 1. Errors of the multiple linear regression.

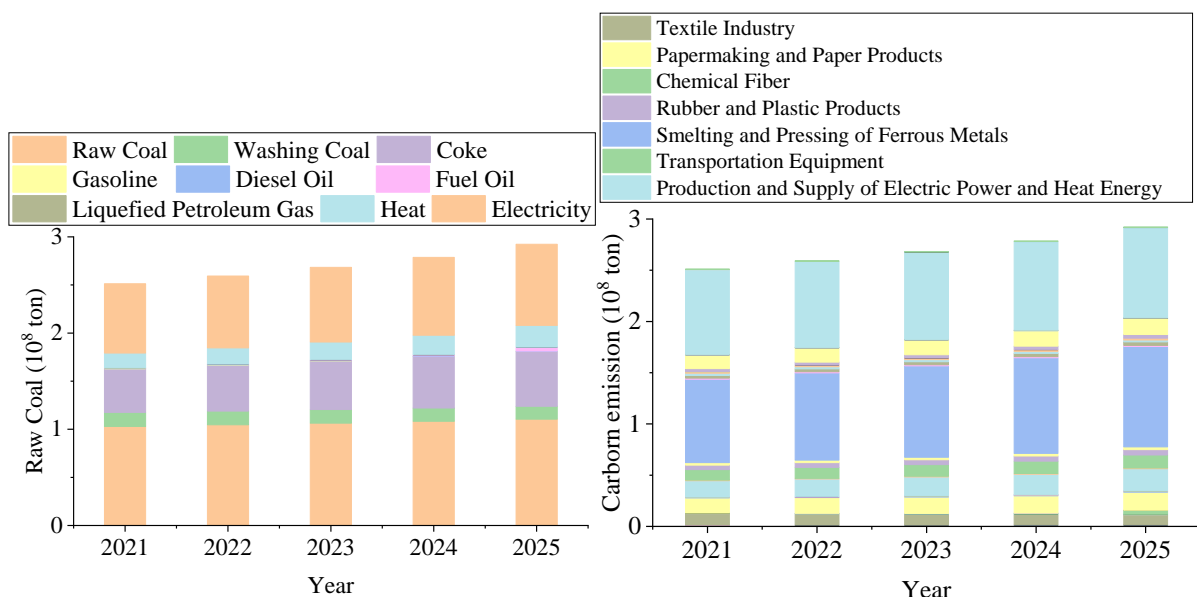


Figure 2. (a) carbon emission forecast by energy type; (b) carbon emission forecast by industry sector.

Assuming in the “Fourteenth Five-Year Plan”, the growth of the impact factors studied in this paper, e.g., population, economic growth, etc., are the same as in the average growth rates in the last ten years, the forecast structure of the carbon emission of Suzhou’s industrial sector are presented in Fig.2. As presented in figure 2(a), the amount of carbon emission increases steadily in the next five years, with an average growth rate of 3.86%. The energy structure is still optimizing, as the proportion of the gas emission from raw coal decreases from 40.97% in 2021 to 37.79% in 2025. The carbon emissions of the leading industry in Suzhou are marked in figure 2(b). The share of heavy industry, such as smelting and pressing of ferrous metals, is still increasing slightly, from 32.41% in 2021 to 33.51% in 2025.

5.2. Feasible Region of Suzhou’s Industry Development

The feasible region of Suzhou’s industry development is investigated in this section in the aspects of various energy structures. The impact of the CEI limitations on the energy consumption of coal

products is compared in figure 3(a). Four scenarios are compared. In scenario A, no measure is adopted to restrain the CEI. It is the same as the average CEI in the past ten years. In scenario B, the CEI should reduce in the “Fourteenth Five-Year Plan” by the same amount in the “Thirteenth Five-Year Plan”, which is 20.5% for Jiangsu province. In scenario C, the CEI is slightly controlled with a reduction of 5%. In scenario D, moderate measures are taken, and the CEI is planned to be reduced by 10%.

As we can see, the feasible regions of energy structures are different in different scenarios. In figure 3(a), with the limitation of CEI growing tighter, the feasible region of the coal product consumption also becomes tighter. From scenario A to scenario B, the lower and upper boundaries for the coal product consumption decreases by 48.15% and 68.03%, respectively. This is because the coal-related energy sources are not carbon-efficient, as they will produce more carbon emissions than other fossil fuels, gas, for example, when generating the same amount of energy. Therefore, the use of coal will be stricter with the progression to the carbon peak and neutrality. On the other hand, the feasible region of the electricity consumption slightly expands with the stricter control of CEI. The upper and lower boundaries increase by 2089.38% and 462.41%, respectively. This is because electricity is a clean energy source, which will be more dominated with energy reform in the future.

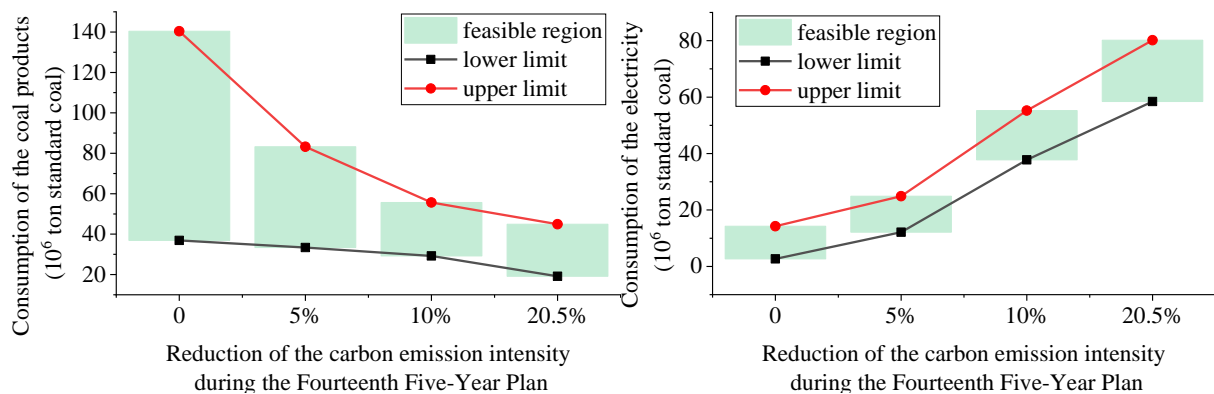


Figure 3. (a) feasible region of the consumption of the coal products under the control of CEI; (b) feasible region of the consumption of the electricity under the control of CEI.

6. Conclusions

With the gradually established low-carbon-orientated policies, the development of urban industries will be faced with more severe challenges. Under this circumstance, the forecasting method and feasible region evaluation of urban industry development for achieving the carbon peak and neutrality are developed in this paper. The large industries in Suzhou are analyzed as an example.

Observing from the case studies, we can find that though the carbon emission will be growing steadily in the Fourteenth Five-Year Plan, the carbon emission will however be controlled. The energy and industry structures are, and will be undergoing a substantial restructure in the foreseen future. On the other hand, the feasible region of the consumption of coal products is gradually narrowing, while the feasible region of the electricity consumption is expanding. Energy substitution is one of the feasible solutions towards low-carbon energy utilization. The technique developed in this paper can provide a useful tool for government decision-makers and industry enterprises to devise energy policies and reactions in advance.

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