Quantitative analysis and scenario prediction of energy-consumption carbon emissions in urban agglomerations in China: Case of Beijing-Tianjin-Hebei region

Min Yu 1, Fuyan Liu 1, Mengdi Shu 2, Jinpeng Liu 2,3 and Chao Chen 2

1 Economic and Technological Research Institute, State Grid Zhejiang Electric Power Corporation, Hangzhou 310000, China;
2 School of Economics and Management, North China Electric Power University, Beijing 102206, China.
3 Email: hbdlljp@163.com

Abstract. China’s economy has entered a period of new normal, which brings an opportunity for the development of a green and low-carbon economy and environmental protection. In order to solve the contradiction between economic development and environmental protection in Beijing-Tianjin-Hebei region, Chinese government decided to adjust and optimize the urban layout and spatial structure of Beijing-Tianjin-Hebei region. Therefore, it is imperative to systematically analyse the factors affecting energy-consumption carbon emissions in Beijing-Tianjin-Hebei region to explore the relationship between factors and carbon emission intensity. This paper determined the influencing factors and conducted a systematic comparative analysis on energy-consumption carbon emissions in Beijing-Tianjin-Hebei region. Combined with BP neural network model, scenario prediction of energy-consumption carbon emissions in Beijing-Tianjin-Hebei region during the “13th Five-Year Plan” period was designed to further clarifying the key influencing factors. The results showed that energy intensity is the key influencing factor of energy-consumption carbon emissions in Beijing-Tianjin-Hebei region. In order to achieve the target of carbon emission reduction in Beijing-Tianjin-Hebei region during the “13th Five-Year Plan” period, which is 0.67, it is critical to promote supply-side structural reform.

1. Introduction

At present, the world's energy structure has undergone profound adjustments with the relationship between supply and demand generally eased. A new round of energy revolution has flourished. As the world's second-largest economy, the growth rate of GDP in China has declined yearly during the “12th Five-Year Plan” period (2011-2015) which stayed at around 6.8%. At the same time, the growth rate of China's energy consumption has slowed down, and the issue of development quality and efficiency has become more prominent. Therefore, the energy transformation is a long and arduous task with structural reforms on the supply side urgently needed [1]. The period of “13th Five-Year Plan” is the decisive stage for building a well-to-do society in an all-round way. It is also the accelerating period for enhancing China’s energy revolution, making every effort to promote the transformation of energy production and utilization methods in order to building a clean, low-carbon, safe and efficient modern energy system [2]. This is a major historic mission of the energy revolution in China.
With the fast-developing technologies, the air pollution caused by heavy industry and car emissions hasn’t been severer than ever before in the history, especially in the Northern China [3]. And the particular matters in the haze are the mostly attributed causes for pneumonia and lung cancer. Beijing-Tianjin-Hebei region, as one of the most densely populated and industrially developed regions in China, is an important engine for stimulating China’s economic development. However, due to the high proportion of coal in energy consumption structure in Beijing-Tianjin-Hebei region, the total discharge of pollutants far exceeds the environmental capacity. The contradiction between economic development and environmental protection is prominent, constraining the coordinated development process of Beijing-Tianjin-Hebei region. The data showed that the average annual carbon emission in Beijing-Tianjin-Hebei region accounted for about one-fifth of China’s total carbon emission. The total carbon emissions of Beijing residents were volatile, and the difference between rural and urban carbon emissions was increasing[4]. And the annual average concentration of PM2.5 in 2016 presented the spatial distribution of “serious pollution in the southeast and lighter in the northwest”, forming Beijing-Tianjin-Tangshan and Shijiazhuang-Xingtai-Handan these two heavy pollution belts [5].

Because of natural conditions, economic environment, there is a big difference in the influence factors of carbon emissions of different countries or regions, so individual analysis is in great request. As for models, academics preferred to use models such as the Logarithmic Mean Divisia Index (LMDI), Kaya (IPAT) and STIRPAT to study the influential factors of carbon emissions. A concentration index called the Kakwani index can be used to measure the regional disparity of CO2 emissions [6]. The STIRPAT model combined with the use of the panel and time-series data can be used to analyze the factors affecting carbon emissions. The results show that the key impact factor (KIF) at global level is affluence, followed by technology and population in the order of their impacts on carbon emission [7]. Reduced energy intensity and the urbanization were the main factors mitigating carbon emissions too [8]. A decomposition analysis method, LMDI, is introduced to analyze the factors that may affect CO2 emission in the industrial sectors in China. The analytic result showed that population is the main driving force that push the increase of industrial CO2 emission [9].Therefore, it is imperative to clarify the control targets such as the total amount and intensity of carbon emissions in Beijing-Tianjin-Hebei region during the “13th Five-Year Plan” period. And on the basis of studying the characteristics of carbon emissions in Beijing-Tianjin-Hebei region, factors affecting energy-consumption carbon emissions in Beijing-Tianjin-Hebei region are systematically analyzed. We can explore the change law of energy-consumption carbon emissions in Beijing-Tianjin-Hebei region, so that relevant regulatory policies and measures can be proposed in a targeted manner, which contributes to the realization of low-carbon coordinated development in Beijing-Tianjin-Hebei region. Furthermore, it helps to lay a solid foundation and deepen the advancement of energy revolution.

2. Analysis on factors affecting regional energy-consumption carbon emissions

2.1. Study on the mechanism of energy-consumption carbon emissions

System dynamics is based on feedback control theory. It uses computer simulation technology to combine quantitative and qualitative analysis effectively. Starting from the whole system, it combined with the information feedback behaviors in complex systems, searched and studied the relevant influencing factors within the system, also it mainly be used to deal with non-linear, multivariable and multiple feedback complex system problems.

The paper introduced a system dynamics model with high order, nonlinearity, and multiple feedbacks and built up a system model of influencing factors of the energy-consumption carbon emissions in Beijing-Tianjin-Hebei region. This model covered economy, energy, and society modules. By analyzing the internal mechanism of the energy-consumption carbon emissions factors in Beijing-Tianjin-Hebei region, a feedback diagram of the energy-consumption carbon emissions system in Beijing-Tianjin-Hebei region can be drawn.
Based on the system model of influencing factors of the energy-consumption carbon emissions in Beijing-Tianjin-Hebei region, combined with index selection principles of reliability, measurability, and scientific, this paper selected population density, per capita GDP, energy intensity, and industrial added value as the main influencing factors of the energy-consumption carbon emissions in Beijing-Tianjin-Hebei region. Among them, population density is a key factor in the social model that can reflect the population of Beijing-Tianjin-Hebei region. The key factor of the economic module is per capita GDP, which reflects changes in the level of personal wealth and can also reflect the level of regional economic development. As the key factor of the energy module, energy intensity and industrial added value reflect energy consumption per unit of GDP and industrial output value after deducting the value of material consumption, respectively. Studying the quantitative relationship between the above four factors and carbon emission intensity will help us to analyse the current situation of the energy-consumption carbon emissions in Beijing-Tianjin-Hebei region thoroughly. And it conduces to provide an effective basis for government policy formulation in the future.

2.2. Quantitative analysis on factors affecting energy-consumption carbon emissions

| Indicator                      | Symbol | Definition                                                        | Unit                                |
|--------------------------------|--------|-------------------------------------------------------------------|-------------------------------------|
| Carbon emission intensity      | I      | Increased carbon emissions per unit GDP                          | 10 kilo-tons /10 kilo-yuan          |
| Population density            | P      | Population living on land per unit region                        | Man per square kilometer            |
| Per capita GDP                | A      | The ratio of the gross domestic product achieved to the resident population within its scope | yuan                                |
| Energy intensity              | T1     | The amount of energy consumed per unit of GDP                    | kg of standard coal equivalent /10 kilo-yuan |
| Industrial added value        | T2     | The industrial output value after deducting the value of material consumption | a hundred million yuan              |

|            | I     | P     | A           | T1     | T2         |
|------------|-------|-------|-------------|--------|------------|
| 2006       | 1.03  | 442   | 24194.20    | 1.34   | 8369.27    |
| 2007       | 0.94  | 449   | 28809.10    | 1.21   | 9569.28    |
| 2008       | 0.85  | 458   | 34022.70    | 1.06   | 11259.95   |
| 2009       | 0.82  | 467   | 36960.50    | 1.03   | 13442.11   |
| 2010       | 0.77  | 482   | 43732.30    | 0.90   | 13909.07   |
| 2011       | 0.68  | 490   | 52074.90    | 0.80   | 16728.88   |
| 2012       | 0.63  | 497   | 57348.30    | 0.75   | 20250.02   |
| 2013       | 0.56  | 504   | 57282.17    | 0.71   | 21928.96   |
| 2014       | 0.52  | 510   | 60019.01    | 0.67   | 23447.76   |
| 2015       | 0.49  | 513   | 62247.93    | 0.64   | 24156.60   |
| 2016       | 0.46  | 516   | 66588.93613 | 0.60   | 23319.71   |
In 1994, based on the I-PAT model, York and other people proposed a random special form-STIRPAT model. The STIRPAT model is expressed as: \( I = aP^bA^cT^d e \). Among them, I, P, A, T indicate the environmental impact, demographic factors, wealth factors, and technical factors respectively while b, c, and d are the coefficients of population, wealth, and technical factors. Meanwhile, a is the model coefficient and e is the random error term. Because the STIRPAT model is a non-linear multi-equation, a linear model is built as shown below by evaluating the logarithm of both sides of the model in order to facilitate the calculation.

All indicator data in this paper is from China City Statistical Yearbook and the China Energy Statistical Yearbook. The description of each indicator in the model is shown in Table 1. The data of each indicator in the model is shown in Table 2.

### 3. Scenario prediction based on BP neural network model

#### 3.1. Scenario design

![Scenario Diagram](image)

Figure 1. Parametric diagram of scenario simulation.

Neural network is an artificial intelligence learning system which simulates biological neural networks. It is usually formed by connecting multiple interconnected network nodes in a certain way. Compared with the traditional prediction model, the BP (Back Propagation) neural network model has a strong ability of nonlinear mapping and fault tolerance, and it is suitable for solving complex problems of internal mechanisms. With strong self-learning, self-adaptive and generalization ability, the learning outcomes which the network learned can be applied to solve similar problems.

As shown in the Figure 1, different scenario simulation parameters can be got from setting different standards for the following four indicators.

Based on parameter setting of the four indicators above, 16 possible national economic development scenarios in Beijing-Tianjin-Hebei region during the "13th Five-Year Plan" period can be set where population density, per capita GDP, and energy intensity and industrial added value are denoted by A, B, C, and D. As shown in the Table 3, "0" represents that an indicator takes a low rate in the scenario while "1" represents that an indicator takes a high rate in the scenario.

#### 3.2. Comparison and analysis based on predictive study

This paper used indicators’ original data during the period of "11th Five-Year Plan" to "12th Five-Year Plan" (2006-2015) in Beijing-Tianjin-Hebei region as a training sample to train BP neural networks. Then each indicator’s actual data in 2012-2016 was taken as the test sample to test the trained BP neural network model.
Based on the 16 scenarios established above, the carbon emission intensity of Beijing-Tianjin-Hebei region in 2020 can be predicted by applying the trained BP neural network model. And the difference between the predicted and target values can be seen in Figure 2.

**Table 3.** Matrix diagram of parameter setting of 16 scenarios

| Scenario | P | A | T1 | T2 |
|----------|---|---|----|----|
| 1        | 0 | 0 | 0  | 0  |
| 2        | 0 | 0 | 0  | 1  |
| 3        | 0 | 0 | 1  | 1  |
| 4        | 0 | 1 | 1  | 1  |
| 5        | 0 | 0 | 1  | 0  |
| 6        | 0 | 1 | 0  | 0  |
| 7        | 1 | 0 | 0  | 0  |
| 8        | 0 | 1 | 0  | 1  |
| 9        | 0 | 1 | 1  | 0  |
| 10       | 1 | 0 | 0  | 0  |
| 11       | 1 | 0 | 1  | 0  |
| 12       | 1 | 1 | 0  | 0  |
| 13       | 1 | 0 | 1  | 1  |
| 14       | 1 | 1 | 0  | 1  |
| 15       | 1 | 1 | 1  | 0  |
| 16       | 1 | 1 | 1  | 1  |

**Figure 2.** Prediction results of carbon emission intensity in Beijing-Tianjin-Hebei region in 2020 under different scenarios.

In Scenario 2, 3, 48, 9, 10, 12, 13 and 14, Beijing-Tianjin-Hebei region can achieve the goal of reducing carbon emission intensity to 0.67 and below in 2020. Among them, Scenario 2 has the best effect on control of carbon emission intensity with a reduction of 46.27% compared with the target value. Scenario 14 is following with a reduction of 40.30% compared with the target value. Scenario 16 has the worst effect on control of carbon emission intensity, and its prediction value of carbon emission intensity exceeds the target value by 217.91%. It can be seen that no matter what the change trend of per capita GDP and population density is, promoting technological progress and industrial transformation and upgrading is the key to reducing carbon emission intensity.
4. Conclusions and recommendations

Based on the "13th Five-Year Plan" and the development of Beijing-Tianjin-Hebei region during the period of "11th Five-Year Plan" to "12th Five-Year Plan ", this paper used system dynamics and STIRPAT model to determine the influencing factors and conducted a systematic comparative analysis on energy-consumption carbon emissions in Beijing-Tianjin-Hebei region. Combined with BP neural network model, scenario prediction of energy-consumption carbon emissions in Beijing-Tianjin-Hebei region during the "13th Five-Year Plan" period was designed to further clarifying the key influencing factors. Taking regression and prediction results into account, energy intensity is the key influencing factor of energy-consumption carbon emissions in Beijing-Tianjin-Hebei region. In order to achieve the target of carbon emission reduction in Beijing-Tianjin-Hebei region during the “13th Five-Year Plan” period, which is 0.67, it is critical to upgrade the technological level of clean energy and further promote industrial transformation and upgrading.

Based on the results mentioned above, the future strategies of carbon emission mitigation for policymakers are provided below. Going forward, Beijing-Tianjin-Hebei region will continue to put into practice the vision of innovative, coordinated, green, open and inclusive development. It's necessary to adapt to and steer the new normal of economic development, push forward supply-side structural reform, accelerate the building of a new system for an open economy, drive economic development with innovation, and achieve sustainable development. The government should focus on five priority tasks-cutting overcapacity, reducing excess inventory, deleveraging, lowering costs, and strengthening areas of weakness-thereby improving the composition of supply and promoting the misalignment and coordinated development of internal industrial functions in Beijing-Tianjin-Hebei region.

Acknowledgment

This study is supported by the National Natural Science Foundation of China (NSFC) (71501071), Beijing Social Science Fund (16YJC064) and the Fundamental Research Funds for the Central Universities (2018ZD14,2017MS059).

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