Journal of Cleaner Production 172 (2018) 2793–2810

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Regional carbon emission evolution mechanism and its prediction approach driven by carbon trading – A case study of Beijing

Jin-peng Liu*, Xu-bei Zhang, Xiao-hua Song

School of Economics and Management, North China Electric Power University, Beijing, 102206, China

ARTICLE INFO

Article history:
Received 18 June 2017
Received in revised form
11 November 2017
Accepted 18 November 2017
Available online 20 November 2017

Keywords:
Regional carbon emission trading
Evolution mechanism
Measurement and prediction method
Scenario analysis

ABSTRACT

Resources and environmental issues have become the main obstacles to the global sustainable development. For example, the global warming and paroxysmal environmental problems induced by fossil energy consumption are highlighted in recent years. As a big energy consumption and carbon emission country, China has tried to establish and implement the carbon emission trading mechanism in order to adjust the economic development patterns, optimize the energy structure and fulfill the emission goals. This mechanism has played a certain role in guiding and supporting the energy saving and carbon emission reduction. With the wide popularization and acceptance of low-carbon and green development, the advantages and the benefits of regional carbon emission trading mechanism will gradually show up with more trading activities and enterprise participation. Therefore, it's imperative to explore the carbon emission trading mechanism and provide relative suggestions for government and enterprises. For analyzing the carbon emission trading mechanism in China, the development situations of economy, energy and policy were reviewed firstly. Then, based on the direct and indirect emissions, the carbon emission measurement method was used to study the emission trends of Beijing and pilot areas. With the system dynamics analysis model, the key factors and evolution circuits influential to the carbon emission mechanism were identified from the aspects of society, energy, economy and environment. The factors were further selected by extended STIRPAT model and ridge regression model in order to construct the BP Neural Network prediction model of carbon emissions. Meanwhile, take Beijing as an example, seven different development scenarios were set to test the rational levels of carbon emissions in the next five years. At last, with the prediction and scenario analysis results, some policy advices were discussed and provided theoretical and practical references for reasonable and efficient carbon emission trading.

1. Introduction

The remarkable shortage of resources and environmental problems caused by economic development and social construction has become an important bottleneck of sustainable development. China's resource-environment problems are particularly prominent in the process of maintaining rapid economic growth (Chuai et al., 2014). As shown in Fig. 1, the ratios of fossil energy consumptions were still high in recent years.

The rapid economic growth mode with high energy consumption in China caused a huge amount of carbon emissions, which has hindered the sustainable development of the economy. In 2011, China accounted for about a third of the world's carbon emissions (see Fig. 2) (Lin and Sun, 2010). According to the International Energy Agency (IEA) forecasting, China's carbon dioxide emissions will rise to 11.615 billion tons in 2030, accounting for 48.6% of the global new emission increments (IEA, 2010). Since the Paris Climate Agreement came into effect, the global energy conservation and emission reduction has entered a new stage. In the 13th five-year plan, China proposed to actively control carbon emissions and implement emissions-reduction commitments. How to balance the development of economic construction and carbon emission control is an important issue in China at this stage.

The full implementation of domestic carbon dioxide emissions trading has become an important way and practical choice for the realization of China's energy-saving and emission reduction targets and low-carbon development (Lo, 2013). Carbon trading can drive companies to spontaneously accelerate technological innovation

* Corresponding author.
E-mail address: hbdlljp@163.com (J.-p. Liu).

https://doi.org/10.1016/j.jclepro.2017.11.133

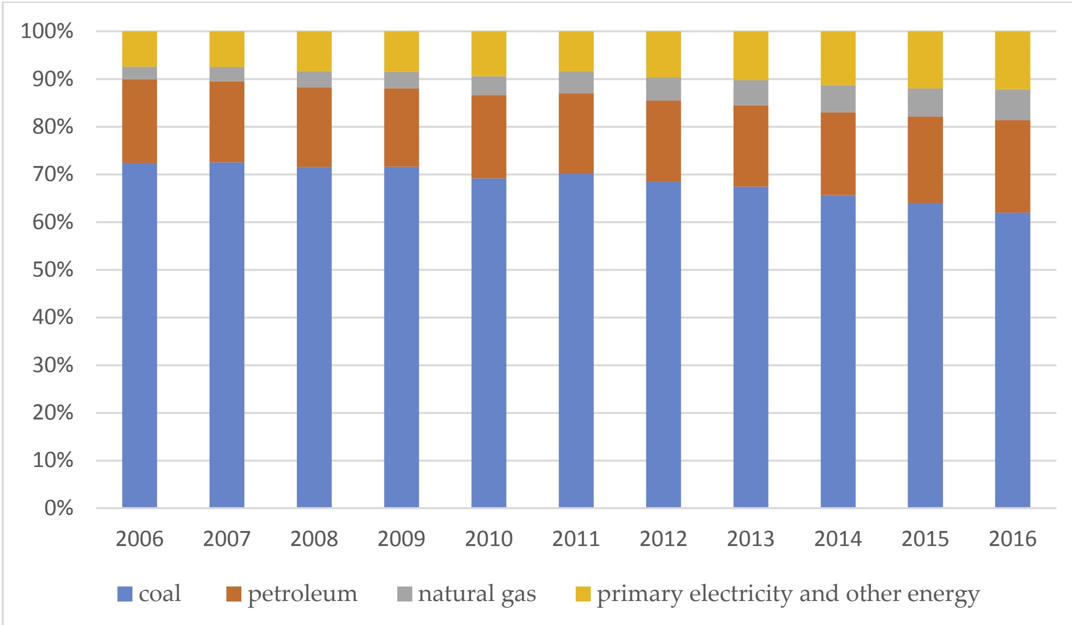

Fig. 1. Structure of China's primary energy consumption.
Source: China's National Bureau of Statistics.

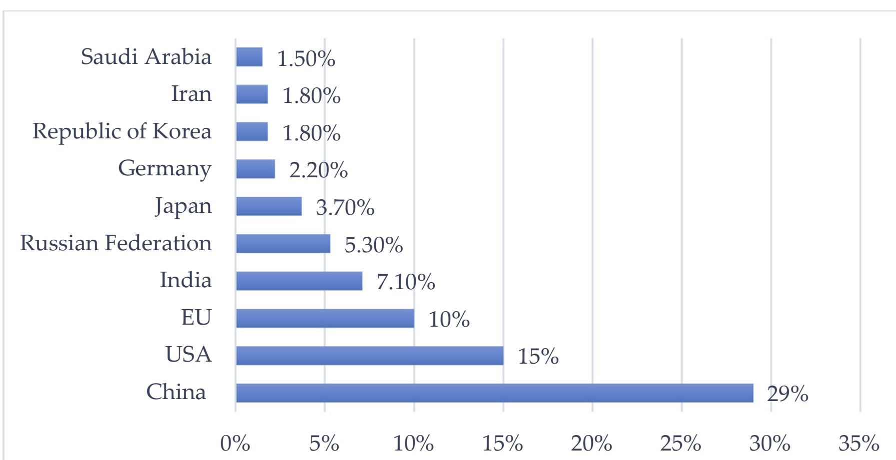

Fig. 2. Top ten emitters in the world 2011(Source: The World Bank).

and coordinate capital operations by market mechanisms on the road of reducing emissions quickly and inexpensively (Wang and Wang, 2015). At present, most of China's enterprises are still on the bottom of the international carbon market value chain, and it is urgent to raise the initiative of enterprises in carbon emissions reducing. Therefore, the establishment of a unified, orderly domestic carbon emissions trading market is essential. As shown in Table 1, China has been committed to domestic carbon trading market construction and has promulgated a series of policy measures as a buttressing support. The national carbon emissions trading market, which covers 24 industries such as coal production, power generation, steel and civil aviation, will be officially launched in 2017. China is set to become the world's largest carbon trading market, and carbon emissions management will usher in a new model.

At the same time, China covers a large territory so that the distinction among population density, economic development level, industrial structure, energy consumption levels and other aspects leads to regional differences in carbon emissions (Ren et al., 2015). How to maximize the potential of carbon emission reduction and promote the steady, green and efficient growth of the region without breaking through the environmental carrying capacity of each region is an important consideration for the formulation of regional emission reduction policies and the determination of the carbon quota. Since 2013, 7 provinces and cities such as Beijing, Tianjin and Shanghai were selected as pilot areas for carbon emissions trading. Up to March 2016, the total turnover of National Certified Emission Reduction (CCER) in seven pilot markets exceeded $ 1.3 billion (Zeng, 2016). In a way, pilot projects contributed to the pilot regional carbon emissions reduction, and provides a guide for the national carbon market development.

However, on the current stage, China's carbon trading is guided by governments in some particular industries relying on political or non-marketable measures, i.e. 2C pattern (Command and

Control). A mature carbon trading mechanism dominated by the market fully reflecting the monetary value on carbon emissions has not formed across the board in China. Meanwhile, for example, lack of pricing mechanism for carbon emission trading was also blocking the system development. For fulling this marketization and ensuring the objectivity of monetization, the regional carbon emission evolution mechanism should be explored as a basis to help the government to find great motivator and identify the possible market size of carbon emission. With the development trend prediction of carbon emission, the carbon financial markets, even the carbon capital markets, can be constructed by the supports of market-oriented trading mechanism under reasonable supervision.

In this context, our paper will pay great attention to regional development characteristics to explore the mechanism of regional carbon emission evolution, measurement and development forecasting methods, as well as analyze the enormous potential and development feasibility of regional emission reduction driven by the development of carbon emissions trading in China. It may provide a certain method and practice reference for the scientific setting of sub-regional rational carbon emission control objectives and the establishment of systematic and efficient emission reduction mechanism.

2. Literature review

With the carbon emission reduction pressure increasing, the government and researchers focus far more on carbon emissions. A considerable amount of research has been done. Based on different research perspectives and methods, interaction among regional carbon emissions, economy and energy consumption as well as key influence factors were carried out by domestic and foreign scholars. They are trying to figure out the efficient path of carbon reduction that is appropriate for region development.

Carbon emissions are mainly from the burning of fossil fuels which has a close relationship with energy consumption, economic growth. Shahzad et al. (2016) examined the cointegration relationship between Pakistan's carbon emissions, energy consumption, trade liberalization and financial development from 1977 to 2011 using the ARDL Boundary Inspection Cointegration Program. The results showed that carbon emissions and energy consumption were inverted U-type relationship. Park and Hong (2013) analyzed South Korea's economic growth, carbon dioxide emission, and energy consumption using the Markov switching model. Al-Mulali et al. (2013) explored the bi-directional long run relationship between energy consumption, Carbon Dioxide emission, and economic growth in the Latin American and Caribbean countries. The study arrived at different results. While 60% of the countries have a positive bi-directional long run relationship between energy consumption, Carbon Dioxide emission, and economic growth, the others have mixed results. Dogan and Seker (2016) analyzed the influence of the real income, renewable energy consumption, nonrenewable energy consumption, trade openness and financial development on CO_2 emissions in the Environmental Kuznets Curve (EKC) model for the top countries listed in the Renewable Energy Country Attractiveness Index by employing heterogeneous panel estimation techniques with cross-section dependence. By using the FMOLS and the DOLS, we also find that increases in renewable energy consumption, trade openness and financial development decrease carbon emissions while increases in nonrenewable energy consumption contribute to the level of emissions.

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. Groot et al. (2009) used a concentration index called the Kakwani index to measure the regional disparity of CO_2 emissions. Shuai et al. (2017) combined the STIRPAT model with the use of the panel and time-series data to analyze the impacts of population, affluence and technology on the carbon emission of 125 countries at different income levels over the period of 1990–2011. 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. 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. Xu et al. (2016) decomposed the factors that affect carbon emissions at a multi-regional level. Jung et al. (2012) undertook a decomposition analysis to identify the factors driving energy-related CO_2 emissions in five regions of South Korea. Reduced energy intensity, was the main factor mitigating carbon emissions. Wang et al. (2016) studied the relationship between urbanization and carbon emission for the BRICS countries within the period 1985–2014. They believed that urbanization could induce the increase of carbon emission for the BRICS countries. A decomposition analysis method, LMDI, is introduced by Quick (2014) to analyze the factors that may affect CO_2 emission in the industrial sectors in China. The analytic result showed that population is the main driving force that push the increase of industrial CO_2 emission. The influence factors of agricultural carbon emissions were studied

Table 1
List of important incentive policies of carbon trading market in China.

Time	Title	Publishing sector	Key focus
2011.1	Notice of the pilot project on the carbon emission permits trade	National Development and Reform Commission of China	7 provinces (cities) were selected as pilot cities for carbon trading. The government began to cultivate and build carbon trading platform in these areas to ensure the smooth progress of the pilot work.
2012.6	Interim Measures for the administration of voluntary reductions in greenhouse gas emissions	National Development and Reform Commission of China	Encouragement of voluntary GHG emissions reductions based on project-based GHG emissions
2014.5	Low-carbon development plan for year 2014–2015	the State Council of China	Expedite development of low-energy low-emission industries. Acceleration on key carbon reduction projects of manufacturing, construction, transportation, public institutions and so on.
2014.12	Interim measures for carbon trading management	National Development and Reform Commission of China	Carbon emissions trading should adhere to the combination of government's guidance and market rules so that the government can strengthen the control of greenhouse gas emissions, regulate the carbon emissions trading market operation.
2016.1	The work plan for controlling greenhouse gas emissions during the 13th five-year period	the State Council of China	The total amount of carbon emissions must be effectively controlled. During the 13th Five-Year Plan period, China should gradually establish a national carbon emissions trading regulations and start the operation of the national carbon emissions trading market.

based on STIRPAT model, and the corresponding countermeasures were put forward by Gao et al. (2016).

The urgency of energy saving and emission reduction makes carbon trading a global carbon management measure (Raux et al., 2015). However, studies above do not provide much attention to the latest changes of carbon emission in the current status because of booming global carbon trading market. The benefits of the carbon market are obvious for developing countries with large energy consumption (Cui et al., 2014). Wu et al. (2014) used the DSGE model simulation to study the impact of the carbon emissions trading market on China's economy, and they believed that a unified carbon emissions market could reduce the total output of carbon emissions. But the cost of carbon trading depends on a lot of uncertain conditions of market, companies are not very well-motivated in carbon trading (Johnson and Heinen, 2004). Zhao et al. (2016) conducted an empirical survey on carbon prices, trading volume, market liquidity and information transparency of China's seven carbon trading pilot cities and found that China's carbon trading market efficiency needs to be improved. At this stage, the lack of real-time carbon prices and leading spot transactions makes the function of China's carbon trading market can not be fully displayed. China's rapid integration of the carbon markets still seems to need a relatively long time (Li and Lu, 2015). There are still many obstacles to the reduction of carbon dioxide emissions based on the establishment of the national carbon trading market. It is necessary to carry out specific analysis in the region, and to explore the key impetus and practical obstacles to promote the carbon trading reduction. For these reasons, this paper launched a related research in the following sections.

In summary, there is a substantial number of existing literature on the carbon emission measurement, the impact factors and the peak value of carbon emissions. Further analysis of regional carbon emission reductions driven by carbon trading is of immense value. Therefore, in the context of prosperous carbon trading, this paper, combined with the regional carbon emission characteristics, is intended to rationalize the potential of regional emission reduction, carry out regional carbon emission diagnosis and prediction research, and explore the evolution mechanism and development trend, so as to provide the assist force for scientific and efficient regional emission reduction.

3. Methodology

3.1. Research system

This paper takes the regional carbon emission as the research object, and carries out quantitative diagnosis analysis, evolvement laws and development tendency prediction relatively thoroughly under the background of carbon trading. The concrete research contents proceed as follows.

First, based on the analysis of carbon emission in China, this paper analyzes the development of regional carbon emission by means of data mining analysis and comparative research, and then puts forward the regional carbon emission evolution mechanism analysis on the base of system dynamics, STIRPAT and ridge regression model. Through the development diagnostic analysis and evolution mechanism research, this paper builds a BP neural network of regional carbon emission development tendency forecast by feat of scenario prediction analysis, and takes Beijing as an example of the regional empirical study, proposes to find out optimized carbon emission reduction path and policy recommendations. The overall research framework and technical route are shown in Fig. 3.

3.2. Method

3.2.1. System dynamics model

System dynamics was first proposed by Prof. Forrester of the Massachusetts Institute of Technology in 1956 (Forrester, 1969). It was introduced to China in the late 1970s and has made great achievements in regional and urban planning, energy management, and industrial research. Systems dynamics theory strongly believes in this idea: the system must have a structure, and the structure of the system determines its function. It argues that the root of the problem should be found from the internal structure of the system based on the feedback characteristics of the elements within the system, rather than using external disturbances or random events to illustrate the nature of the system. It also firmly believes that many of the variables within the system have causal links in their interaction. The systematic interconnection of feedback poses the structure of the system, which is the fundamental determinant of system behavior (Machado et al., 2015).

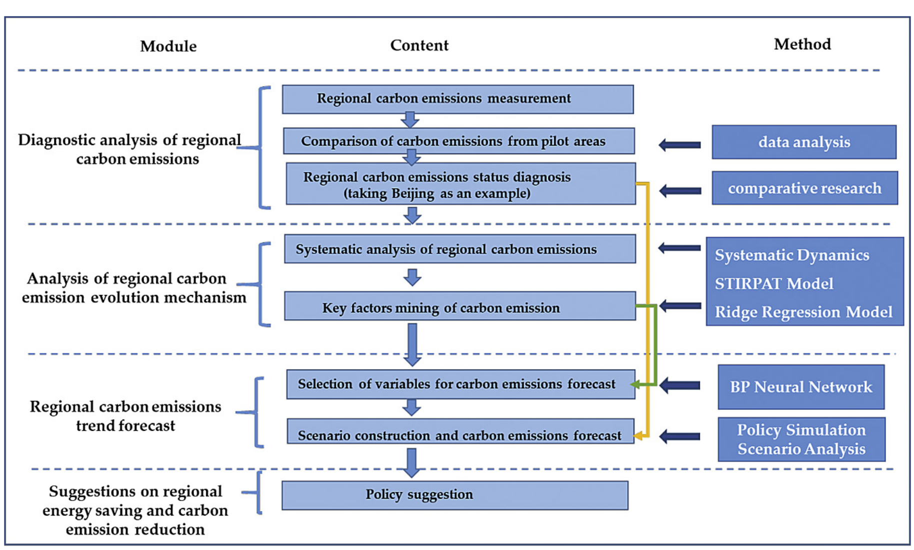

Fig. 3. Framework diagram of this paper ideas.

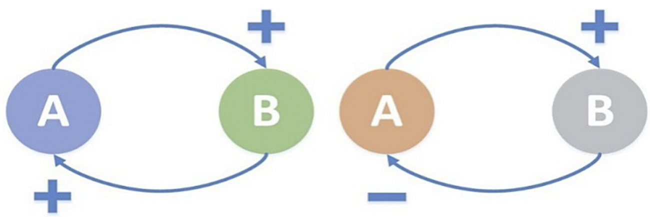

Fig. 4. Positive (negative) feedback loop.

The relationship between the causes and outcomes of the elements in the system is called a causal relationship. It can be described by the connection of the causal elements and the direction of the arrow. When both the cause and the outcome move in the same direction, this relationship is called the positive causal relationship, and is represented by "+". On the contrary, it is called negative causal relationship. When multiple causal chains are connected end to end, they form a causal feedback loop. As shown in Fig. 4, the causal feedback loop can be divided into positive feedback and negative feedback. The causal circuit diagram (CLD) composed of multiple feedback loops can clearly show the complex causal relationship between multiple variables, and extract the key elements that affect the structure of the system. It simplifies the problem of high order, nonlinear, multiple feedback complex time-varying systems (Coyle, 1996). Regional carbon emissions are affected by multiple factors, involving multiple responses to economic, environmental, and demographic systems. The use of the system dynamics model can help us to better comb the regional link between the factors of carbon emissions, grasp the dynamic evolution mechanism.

3.2.2. STIRPAT model

The prototype of Stochastic Impacts by Regression on Population, Affluence, and Technology model (STIRPAT) was presented by American ecologists Ehrlich and Comnoner in the 1970s (Roberts, 2011). IPAT model (I = PAT) can be used to study the relationship between economic activity and environmental stress where I, P, A and T respectively represent the environmental impact, population, affluence and technology. The analytical framework of the IPAT model is simple, intuitive and open. It is widely used on environmental issues because it covers three major influencing factors of population, economy and technology. However, the "I = PAT" model still has some limitations (Wang et al., 2017). For example, change the assignment of a factor will directly lead to value changes of other factors in the analysis. Therefore, in order to solve the above problems, A nonlinear stochastic regression STIRPAT model was established based on IPAT model. The standard form is shown in equation (1).

$$I = aP^bA^cT^de \tag{1}$$

In formula (1): a is the constant term of the model. I, P, A and T represent the index of the population, the wealth and the technology of the environmental impact, the population, the wealth and the technical level respectively, and e is the model error term.

In practical use, the STIRPAT model can also increase the social factors or other control factors to analyze its impact on the environment, but the added variables are conceptually consistent with the multiplicative forms in the formula. In general, the STIRPAT model is transformed into a logarithmic form:

$$lnI = lna + blnP + clnA + dlnT + lne \tag{2}$$

The derived STIRPAT model is suitable for the analysis of carbon emissions affected by multiple factors such as population, economy, and technology. The coefficient of the model can reflect the impact of indicators on carbon emissions.

3.2.3. Ridge regression model

Due to the existence of multiple collinearity among the explanatory variables, the variance of the parameter estimation in the model is large, which makes the effect of the ordinary least squares estimation method unsatisfactory (Erickson, 1981). In 1962, A.E.Hoerl first proposed a method to improve the general least squares estimation, Ridge Estimate (Hoerl and Kennard, 2000). The economic variables that affect carbon emissions usually interact with each other, so their collinearity is high and is likely to result in pseudo-regression. So as to solve this problem, this paper uses the method of ridge regression to overcome the influence of multi-collinearity by regression diagnosis and independent variable selection.

When $|X'X| \approx 0, X'X + KI, K > 0$, the closeness to singularity is small. After normalizing the data, we still count the normalized matrix as X and define the estimated parameters $\widehat{\beta}(k)$ as a ridge regression estimate:

$$\widehat{\beta}(K) = \left(X'X + KI\right)^{-1} X'y \tag{3}$$

In equation (3), K is the ridge parameter. When $K = 0$, $\widehat{\beta}(k)$ is the least squares estimation, so $0 < k < 1$.

3.2.4. BP neural network

Artificial neural network is an information processing system that imitates the function and structure of biological nervous system. The BP network, proposed by the team of scientists led by Rinehart and McClelland in 1986, is a multi-layer feedforward network trained by error back propagation algorithm and is one of the most widely used neural network models (Windsor et al., 2005). The BP network can learn and store a large number of input-output pattern mappings without having to reveal the mathematical equations describing the mapping relationships beforehand. The neural network uses the back-propagation method to constantly adjust the network weights and thresholds so that the sum of the squared errors of the network is minimized. BP neural network model topology includes input layer, hide layer and output layer as shown in Fig. 5.

The input and output layers are the independent variable X and the dependent variable Y respectively, and the middle layer is the assignment process of the input value. The BP algorithm is roughly calculated in two steps:

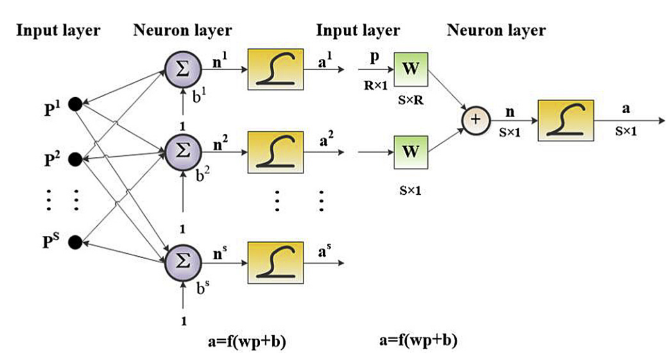

Fig. 5. BP neural network structure.

(1) Forward propagation. The values are entered from the input layer, arbitrarily multiplied by the middle layer, and then the output value is obtained at the output layer. The output value will be compared with the expected value. If they are not equal, the entire network will enter the process of reverse propagation.
(2) Reverse propagation. This process returns the error of the output value to the expected value according to the original path and passes it again by the correction weight (w). The process stops when the error value reaches the specified accuracy (Lee, 2004). Because of its strong non-linear mapping ability and adaptive ability, BP neural network is especially suitable for solving the complicated carbon problem of internal mechanism, and the predicted value is closer to the real value.

4. Regional carbon emission measurement and development level analysis

In order to explore the evolutionary patterns and trends of regional carbon emissions, it is necessary to know carbon emissions measurement and the status quo. Therefore, this paper firstly clarifies the method of regional carbon emission and carries out the diagnosis analysis of carbon emission in typical regions.

4.1. Quantitative measurement of regional carbon emissions

Regional carbon dioxide emissions usually include direct emissions and indirect emissions (Fig. 6). Direct emission of carbon dioxide mainly refers to emission generated by fossil fuel combustion from fixed facilities, public vehicle passenger transport, and urban rail transit mobile facilities in the region. In the process of industrial production and waste disposal, a significant amount of direct carbon dioxide emissions is also generated. Indirect emission of carbon dioxide is the emission from fossil fuels burning during the power generation that are implied in the interregional power consumption in the area.

As we all know, clean energy consumption will barely lead to carbon dioxide emissions, and fossil fuels consumption for distinct power generation has been included in the total amount in the region. Taking end-use and effective emissions as benchmarks for research, this paper will focus on the total direct consumption of fossil fuels and the fossil energy consumption in the power generation process implied in the external transmission. According to the "Guidance on Carbon Dioxide Accounting and Reporting for Beijing Enterprises (2015)", as shown in Fig. 7, in this paper, the regional carbon emissions calculation is divided into two parts, namely, the direct emission of fossil fuel combustion, and the hidden carbon dioxide emissions come from the transmission of electricity.

(1) Direct emissions

The direct carbon dioxide emissions from fossil fuel combustion are calculated according to formula (4).

$$E_c = \sum_{i=1}^{I} A_i F \tag{4}$$

where E_c is carbon dioxide emission (tCO2), A_i is the amount of heat released by the ith fossil fuel (TJ), F_i is the emission factor for the ith fuel (tCO2/TJ), i is the fossil fuel type, I is the quantity of fossil fuel types. In particular, F_i can be calculated via equation (5)

$$F_i = C_i \times \alpha_i \times \rho \tag{5}$$

where F_i is the direct emission factor of the ith fossil fuel (tCO_2/TJ), C_i is the calorific value carbon content per unit of the ith fossil fuel (tC/TJ). a_i is the carbon oxidation rate (%), and ρ is the ratio of the molecular weight of carbon dioxide to carbon in a constant value of 44/12.

(2) Indirect emissions

The indirect carbon dioxide emissions from interregional power generation are calculated according to formula (6).

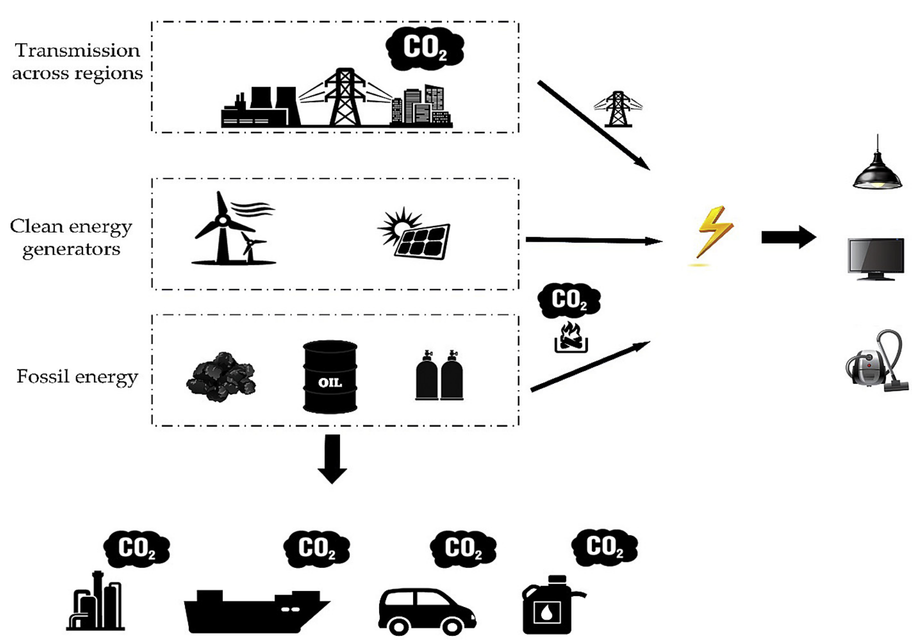

Fig. 6. Regional carbon source framework.

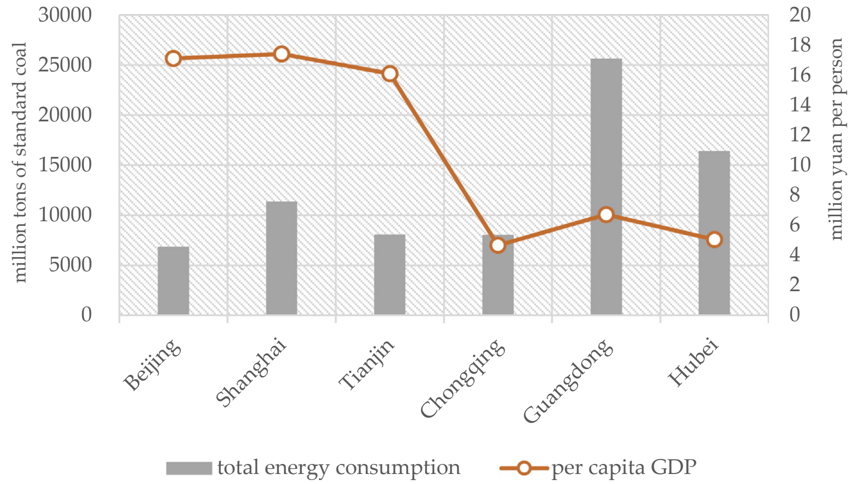

Fig. 7. Overview of carbon trade pilot areas in the year of 2015.
Source: China's National Bureau of Statistics.

$$E_d = D \times f_g \times p \tag{6}$$

where E_d is the amount of carbon dioxide emissions (tCO_2), D is the regional power consumption amount (MWh). f_g is the indirect emission coefficient of power consumption with value of 0.604 (tCO_2/MWh). p is the percentage of interregional transmission electricity consumption (%).

(3) Total carbon dioxide emissions

$$E = E_c + E_d \tag{7}$$

In equation (7), E is the total amount of carbon dioxide emissions in the region.

In this paper, the carbon footprint of the region is estimated by summing up the carbon emissions generated by direct energy consumption in the region and indirect energy consumption lay hidden in interregional transmission power generation. The scope and calculation of this assessment are larger than those of the past, which are only calculated for direct emissions. But it is consistent with international prevailing rules and increasingly being used at home and abroad for recent studies (Repo et al., 2015).

4.2. Diagnostic analysis of carbon emissions trading in the pilot area

The development of regional carbon trading pilot marks the beginning of China's pioneering and crucial step in the use of market mechanisms to promote emissions reduction. In addition to Beijing, six provinces and cities such as Tianjin, Shanghai and Guangdong have launched a regional carbon trading market by using different quota trading mechanisms. The pilots are located in the north, central and western regions and the southern coastal areas. Although the quantity of pilot areas is small, but the pilot areas have a huge base of GDP, population, energy consumption as well as a certain regional representation in the level of economic development, resource distribution and carbon emissions. As shown in Fig. 7, the energy consumption of the pilot areas is quite different.

Guangdong's energy consumption is about four times that of Beijing, but its GDP per person is less than half that of Beijing. Compared the two giant cities Beijing and Shanghai, while the population and economic development level is relatively close, but the total energy consumption of Beijing was significantly lower than Shanghai. Therefore, the diagnosis and comparison of these typical areas can help us to better understand the actual efficiency of carbon emissions reduction in Beijing. It also lays the foundation for the development of carbon emissions in China, and helps to explore the evolution of carbon emissions in the region.

According to the calculation method of carbon emission in section 4.1, this paper calculated the carbon emission intensity of other carbon emission pilot areas from 2008 to 2015 based on the energy consumption data in the provincial statistical yearbooks. The results are shown in Fig. 8. The carbon intensity of each pilot area showed a significant downward trend, of which the lowest carbon intensity in Beijing. In the pilot areas, the reduction effects of carbon emissions driven by the current carbon trading mechanism were obvious. The regional carbon emissions show a faster attenuation trend under the carbon trading.

From the results in Figs. 7 and 8, Beijing consumed less energy and produced more GDP compared with other pilot cities. Its carbon emission intensity level showed the typicality. In a short period, Beijing will be an ideal reference object to other cities. Thus, Beijing will be selected as a typical city to analyze the development status of carbon emission in order to mine the key factors and plan reasonable analysis scenes influential to the carbon emission. A carbon emission diagnose for Beijing contains its energy consumption structure, industrial structure, carbon intensity and so on. The specific analysis are as follows in section 4.3.

4.3. Diagnostic analysis of regional carbon emissions in Beijing

As China's political, economic and cultural center, Beijing is a typical region with high carbon emission. By the end of 2016, Beijing has more than 20 million inhabitants, 5.619 million motor vehicles, and the city's annual carbon emissions generated more than 50 million tons. Beijing's economic and energy structure determines the carbon emissions show a wide coverage and high degree of dispersion characteristics, and has distinctive regional characteristics (Chen et al., 2013). In the region, thermal power production and supply enterprises, power production enterprises, cement manufacturing enterprises, petrochemical production enterprises and transportation enterprises are the main sources of carbon dioxide emissions. As shown in Fig. 9, coal and natural gas still dominate energy consumption in Beijing.

Considering with the influences of Beijing city development

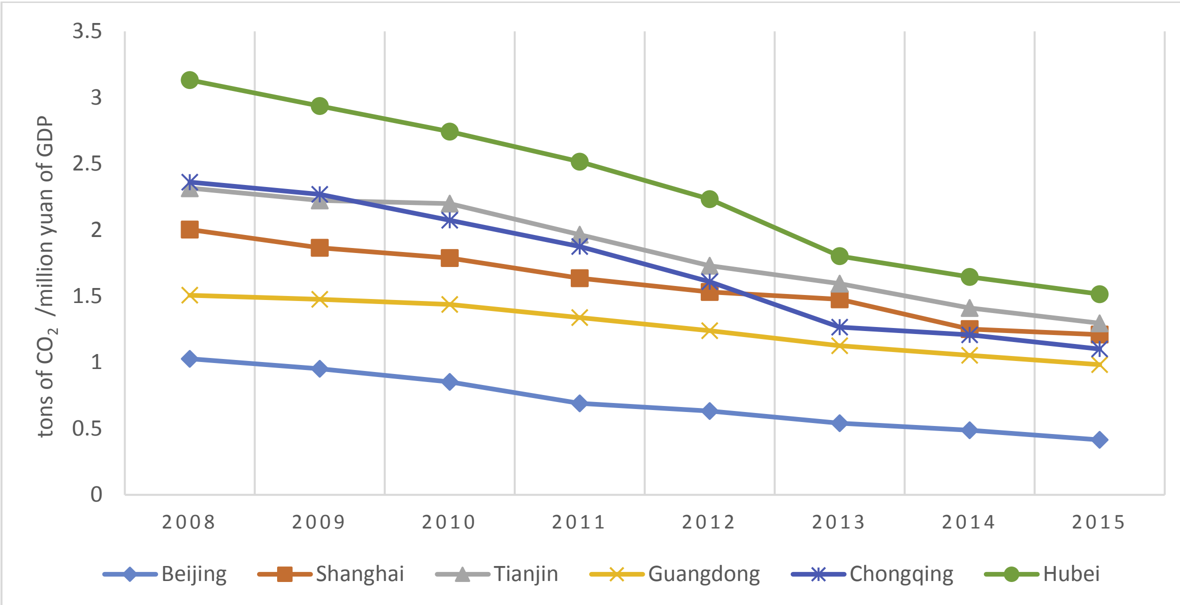

Fig. 8. Comparison of carbon emission intensity in carbon pilot areas from 2008 to 2014.
Source: China's National Bureau of Statistics.

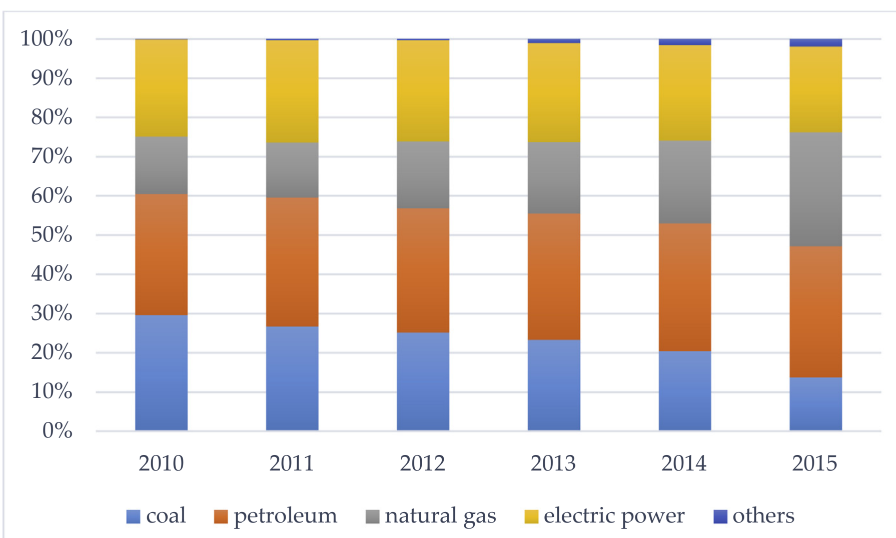

Fig. 9. Energy consumption structure of Beijing from 2010 to 2015.
Source: Beijing Statistical Yearbook 2016.

plan, the industrial structure has adjusted and optimized gradually as shown in Fig. 10. In 2016, the tertiary industry ratio has increased to 80.3%.

Beijing, as a typical area of industrial structure adjustment and carbon emissions trading pilot, is a typical city with scarce resources but large energy consumption. Each year it receives a large amount of trans-regional power transmission. In the summer of 2016, which created the peak load history of the Beijing power grid, the proportion of trans-regional power was 63% (Wang, 2017). Beijing became the first city in China to generate all electricity from clean energy sources, as the entire thermal power plants were shut down in March 2017. The act will reorient the way that energy drives the development of cities, and will strongly promote carbon emissions control and industrial restructuring. Carbon trading also brings something new to emissions control. According to the Beijing carbon emission power electronic trading platform, the cumulative quota for the Beijing carbon trading market in 2016 was 12.59 million tons, with a turnover of 474 million yuan. As shown in Fig. 11, Carbon trading has brought significant reductions in emissions.

According to the calculation method of regional carbon dioxide emission proposed in the 4.4 section of this paper, the carbon emission is calculated and analyzed by using the relevant data of Beijing statistical yearbook. The annual trans-regional power ratio is calculated according to the 60% level in the region. The types of primary energy consumption in Beijing include eight categories such as raw coal, coke, gasoline, fuel oil, kerosene and natural gas. Meanwhile, carbon intensity refers to the amount of carbon dioxide

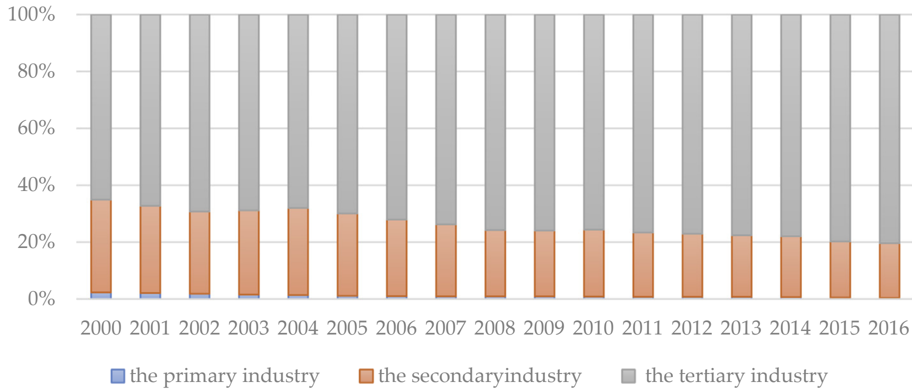

Fig. 10. Industrial structure of Beijing in 2000–2016.
Source: Beijing Municipal Bureau of Statistics.

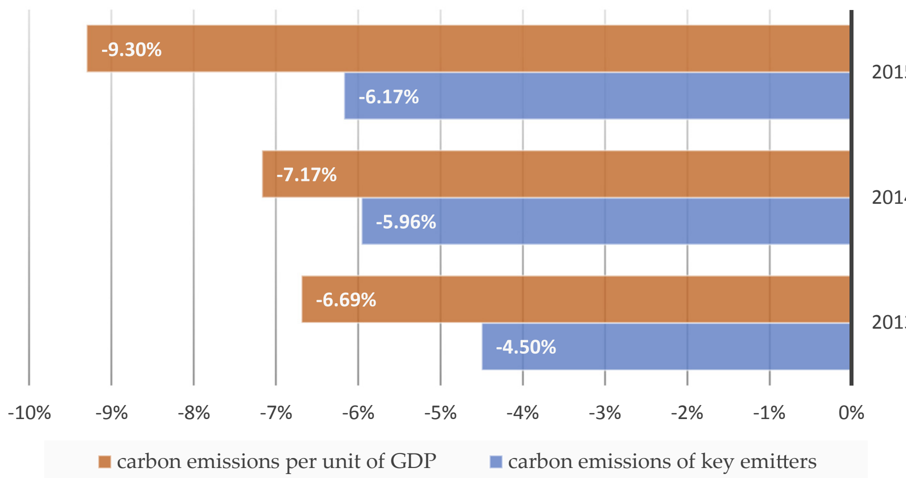

Fig. 11. Emission reduction effect after the implementation of carbon trading in Beijing.
Source: Beijing Municipal Bureau of Statistics.

emitted per unit of GDP. In order to the relationship between economy development and carbon emissions in the region, the carbon emissions and carbon intensity in Beijing are both shown in Fig. 12.

In Fig. 12, Beijing's carbon dioxide emissions show a certain development regularity. Before 2003, carbon emissions showed a slow upward trend. Since 2003, with the rapid economic growth, China has become the world's second largest economy. At the same

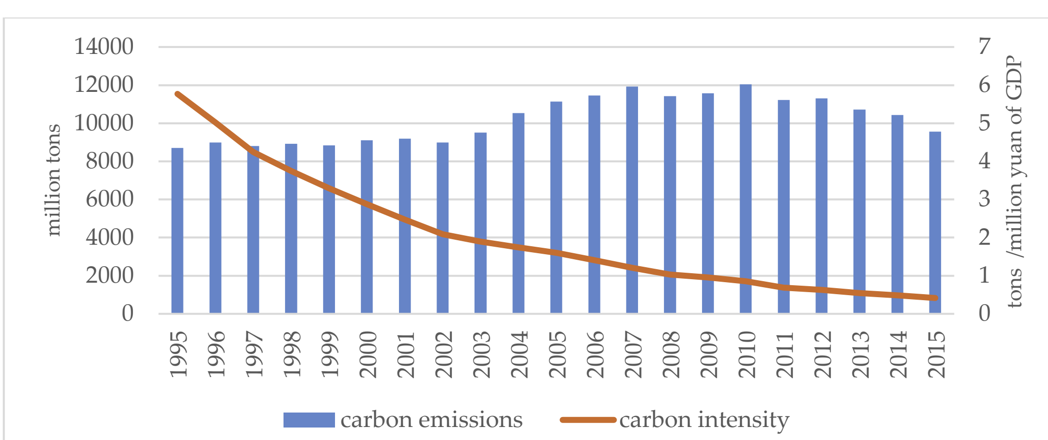

Fig. 12. Carbon emission and carbon intensity in Beijing from 1995 to 2015.

time, China has become one of the biggest players in greenhouse gas emissions. In this context, after 2003, Beijing's carbon emissions grew faster and peaked in 2010. From 2003 onwards, to reduce the amount of coal used and improve environmental quality, Beijing began to implement the electric heating reform project. In addition, the government provided a dedicated support the development of high-tech energy-saving environmental protection industry and regional industrial structure adjustment from the policy, capital, technology and other aspects. So, the total amount of carbon emissions gradually decreased. After the start of the carbon trading pilot in 2013, the total amount of carbon emissions in Beijing declined rapidly.

For further exploring the relationship between economy development and carbon emission in Beijing, the GDP growth rate and carbon intensity reduction rate are also compared in Fig. 13. In general, while economic growth is accompanied by a decline in carbon dioxide emissions, the region has achieved a relatively low carbon development model. The intensity of carbon emissions in Beijing continued to decrease during the whole period. By 2015, the intensity of carbon emissions in Beijing was 0.41 tons/million, which only accounted for 7 percent the rate of those in 1995. As shown in Fig. 11, when comparing Beijing's carbon intensity and real GDP, it was found that the decline in carbon emission intensity before 2008 was much lower than the GDP growth rate. Yang et al. (2017) argued that the actual reduction in carbon dioxide can only be achieved when the rate of decline in carbon intensity is greater than the growth rate of GDP. After 2008, the gap is narrowing. In the last three years, the decline in carbon intensity in Beijing is higher than the GDP growth rate, which means that Beijing has achieved actual carbon emissions reduction. Above all, Beijing's energy-saving and emission reductions have achieved remarkable results, but there is still room for further deepening.

5. Regional carbon emission influencing factors mining and evolution mechanism analysis

Based on the measurement and development diagnostic analysis of regional carbon emission in the previous sections, different regions show a different development trend. The process of the evolution is affected by the numerous factors in economy, environment, and population. On the whole, the influencing factors include the level of economic development, energy structure, policy mechanism, etc. From the regions of view, the influencing factors also cover the income level, the energy structure, and the residents' energy-consuming habits. All these constitute a complex impact on the structural system, and form an inherent evolution mechanism with development regularity. System dynamics is applied to the dynamic behavior of complex feedback system. It can be used to find and study the relevant influencing factors in the system. It has been widely used in the analysis of complex systems such as country, region and industry. Therefore, this paper uses the concept of system dynamics to analyze the evolution mechanism of regional carbon emission, and excavates the key influencing factors of carbon emission on the basis of deep analysis of the complex environmental system inside and outside the regional carbon emission.

In accordance with the principle of determining the boundaries of the system, the regional carbon emission analysis system should

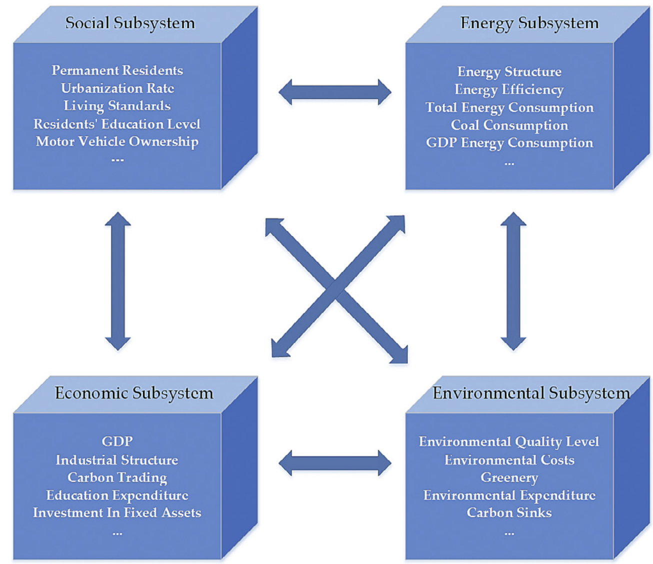

Fig. 14. Carbon emissions system frame.

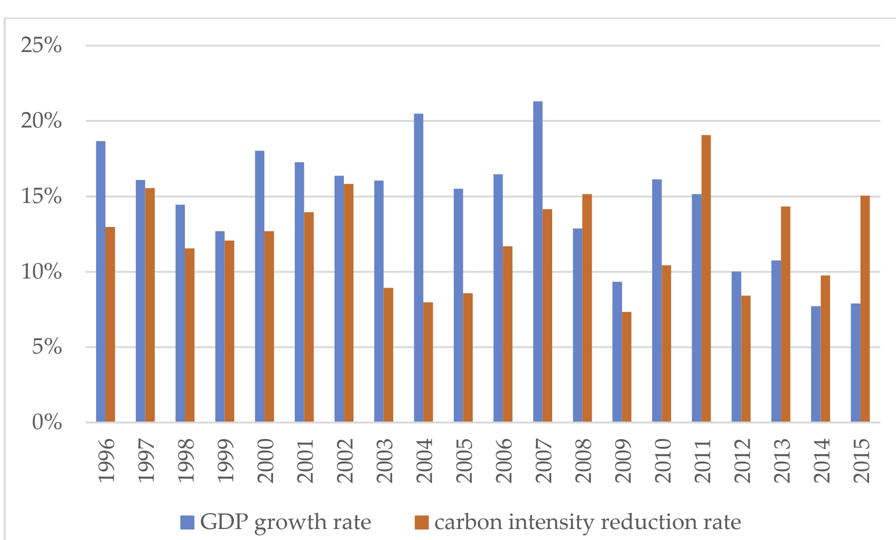

Fig. 13. Comparison of GDP growth rate and carbon intensity reduction rate.

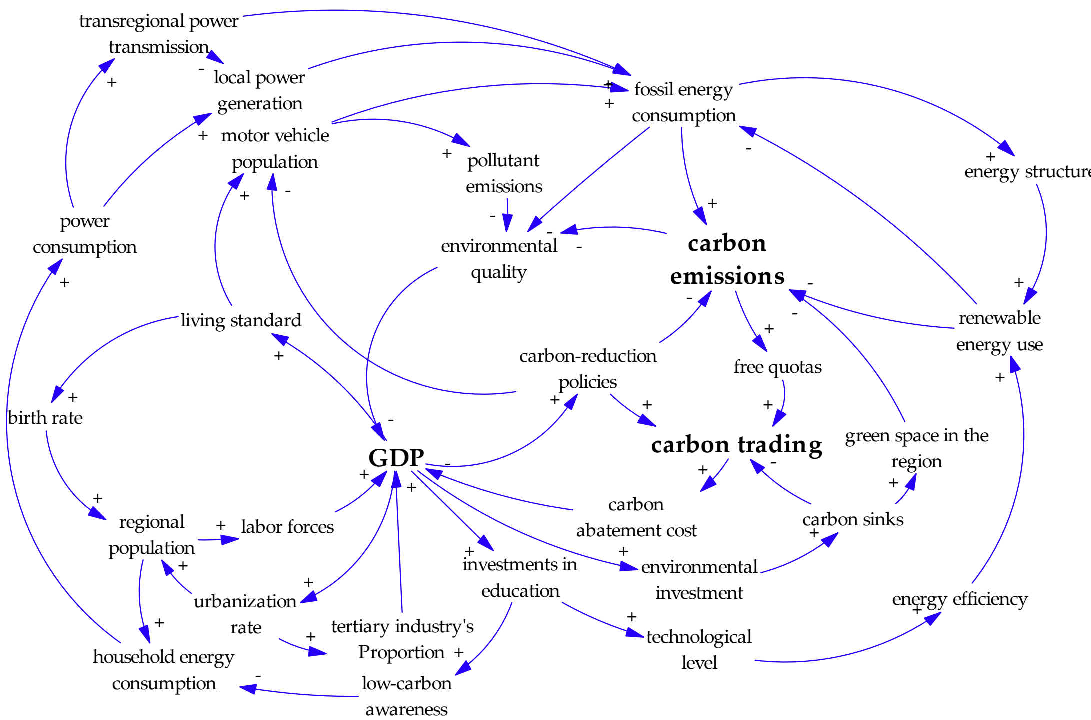

Fig. 15. Causal Loop Diagram of region carbon emissions.

cover four components: economic subsystem, environmental subsystem, energy subsystem and social subsystem (see Fig. 14), which mainly contains the key variables such as GDP, energy structure and environmental expenditure.

According to the system dynamics analysis theory, there are complicated causal feedback relations among the subsystems and the key variables. For example, economic development will stimulate the consumption of energy, while the growth of energy consumption contributes to carbon dioxide emissions. Therefore, according to the interactions between carbon emissions and four subsystems, this paper takes the interaction mechanism of the internal elements of each subsystem into account, and builds the causal loop diagram of regional carbon emission evolution based on the system dynamics principle (see Fig. 15).

There are multiple feedback loops in the causal loop diagram. Based on the analysis of the causal loop diagram of system dynamics, this paper takes two main balancing circuits as an example to illustrate the evolution mechanism of carbon emissions:

(1) GDP → (+) living standard → (+) birth rate → (+) regional population → (+) household energy consumption → (+) power consumption → (+) local electricity production → (+) fossil energy consumption → (+) carbon emissions → (−) environmental quality → (−) GDP

Economic development promotes the improvement of economic living standards in the region. And a high standard of living can stimulate the expansion of the population. Obviously, the increase of resident population makes the household energy consumption go up rapidly and stimulates the electricity consumption in the region. As a result, power generation is further expanded because of the growing demand for electricity. The energy structure in most areas of China is dominated by coal. Under these circumstances, electricity production has led to more fossil energy consumption and increased carbon emissions and other pollutants emissions.

(2) Carbon emissions → (+) free quotas → (+) carbon trading → (+) carbon abatement cost → (−) GDP → (+) carbon reduction policies → (−) carbon emissions

In the context of high-carbon emissions, the increase in the total quota available for carbon trading has stimulated the enthusiasm of enterprises to participate in carbon trading and contributed to the vigorous development of carbon trading. At the same time, carbon trading has a certain impact on the enterprise's carbon abatement cost, development strategies and market competitions. The government will actively adjust carbon reduction policies in line with the development of the industry so as to meet the market development law, ensure the normal operation of enterprises and promote the realization of carbon emission targets.

In general, the continuous development of the regional economy has not only promoted the expansion of urban scale and population growth, but also brought a new round of energy consumption growth, which eventually led to high carbon dioxide emissions in the region. From an overall perspective, improvement in regional energy structure and industrial structure, as well as the use of renewable energy sources can significantly reduce carbon dioxide emissions. From an individual perspective, fostering low carbon awareness among residents and promoting their "Green" lifestyle will also make a great contribution to energy saving and carbon dioxide emission reduction. In addition, the government's energy-saving emission reduction policy guidance and carbon trading market will become an important driving force.

6. Regional carbon emissions prediction analysis

Due to the complexity and variability of the regional carbon emissions, this paper predicts the carbon emissions by using the BP neural network model with strong adaptability and strong anti-interference based on the evolution mechanism and influencing factors digging in the previous sections. In order to improve the accuracy of BP neural network prediction, it is necessary to reduce

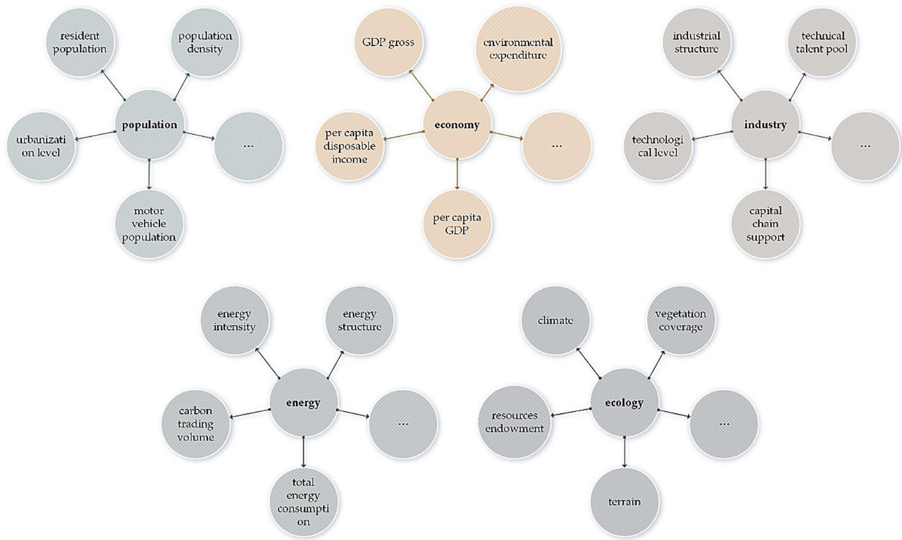

Fig. 16. Decomposition of carbon emission factors.

the number of input layers. Therefore, the main influencing factors of carbon emission need to be screened. In this paper, the key factors of carbon emission are extracted by STIRPAT model firstly. According to the STIRPAT fitting equation, this paper sets up various development scenarios and compares the trends of carbon emissions under different scenarios.

6.1. Influencing factors selection of carbon emissions

The regional carbon emissions mechanism analysis system built by System dynamics can be further concretized and plotted (Fig. 16). Because the traditional IPAT model can not describe the degree of mutual influence between variables, this paper uses the extended STIRPAT model to analyze the influencing factors of carbon emission, and use the ridge regression method to analyze the correlation between the influencing factors and carbon emission.

In STIRPAT model, population, asset and technology are the basic independent variables. However, in order to suit the development situation in Beijing, the variables in the STIRPAT model should be decomposed into more specific indexes. In particular, Beijing is a megalopolis with thriving and robust service-oriented tertiary industry which is different with some cities relying on the secondary industry for economy development. Meanwhile, its urbanization rate and vehicle amount are much bigger than other cities which makes Beijing take more pressures on carbon emission reduction. In recent years, with the advances of energy-saving emission reduction and carbon emissions trading, the intensity and total amount of carbon emissions in Beijing have been effectively controlled. Therefore, the variables reflecting the actual development of Beijing should be adopted and extended in the STIRPAT model, such as energy consumption of tertiary industry, urbanization, quantity of vehicle, and so on. Considering with the development characteristics of Beijing and the integrity of data, the specific selection of variables is shown in Table 2.

The eventual expanded STIRPAT carbon emission model is shown in Equation (8):

$$\begin{aligned} \ln I = \ln a + b_1 lnP_1 + b_2 lnP_2 + b_3 lnP_3 + b_4 lnP_4 + c_1 lnD_1 \\ + c_{21} lnD_2 + d_1 lnG_1 + d_2 lnG_2 + d_3 lnG_3 + d_4 lnG_4 + h_1 lnH_1 \\ + lne \end{aligned} \tag{8}$$

This paper use SPSS software to test the above model with multiple linear regression. As shown in Table 3, the model passed a significant test at the level of 1%, and the D.W. value was close to 2 which indicated that there is no sequence correlation.

Table 3
The model parameters of multivariate linear regression.

R	R^2	Adjusted R^2	Standard error	D.W.
0.992a	0.984	0.970	0.02747	1.555

Table 2
Main variables of STIRPAT model.

Extracting factors	Variables	Variables representation	Variables name	Units
Environment	I	level of carbon emissions	carbon emissions	million tons
Population	P1	population gross	resident population	ten thousand people
	P2	urbanization level	urbanization rate	%
	P3	quantity of vehicle	motor vehicles population	million vehicles
	P4	energy utilization of residents	household energy consumption	million tons of standard coal
Regional economy	D1	scale of economic growth	per capita of GDP	yuan per person
Industrial structure	D2	the present situation of the tertiary industry	proportion of the tertiary industry	%
Energy	G1	energy structure	annual consumption of coal	million tons
	G2	total energy consumption	total energy consumption of the secondary industry	million tons of standard coal
	G3		total energy consumption of tertiary industry	million tons of standard coal
	G4	level of carbon trading activity	carbon trading volume	ton
Ecotype	H1	ecological effect	urban greening coverage	%

Table 4
The collinearity of variables.

Variables	Tolerance	Variance inflation factor
P1	0.0038	260.5386
P2	0.0100	99.7845
P3	0.0021	469.2202
P4	0.0015	684.4472
D1	0.0020	496.1204
D2	0.0047	213.7228
G1	0.1210	8.2622
G2	0.0941	10.6307
G3	0.0019	528.9109
G4	0.0657	15.2170
H1	0.0054	185.8357

Although the model passed the significance test, as shown in Table 4, the diagnosis showed that there was a high degree of collinearity between the explanatory variables in the regression equation.

The variance expansion factor of most variables is greater than 10. The maximum variance inflation factor is 684. In this case, the least square method (LSM) may cause a pseudo-regression.

In order to improve the accuracy of regression analysis, this paper uses the ridge regression estimation method to re-estimate the model. Ridge regression is a biased estimation regression method designed for data with high degree of multicollinearity. It can obtain more scientific and effective regression coefficients at the expense of partial information and lower precision by abandoning the unbiasedness, so it is much more robust to the ill conditioned data than the least square method. Therefore, this paper carries out ridge trace analysis for all 12 explanatory variables. The result is shown in Fig. 17, where the horizontal axis represents ridge parameter K, and the vertical axis represents the regression coefficient.

It can be seen from the above figure that when the ridge parameter K is greater than 0.02, the regression coefficients of the explanatory variables tend to be stationary (with the horizontal line as the asymptote), and the regression coefficient is not economically absolute. As a result, the ridge parameter is determined to be 0.02. The regression equation is shown in equation (9).

$$\begin{aligned}\ln I = & -4.4700 - 0.0763 lnP_1 + 1.7796 lnP_2 + 0.0048 lnP_3 \\ & + 0.0985 lnP_4 + 0.0030 lnD_1 - 0.2426 lnD_2 + 0.0504 lnG_1 \\ & + 0.7957 lnG_2 + 0.0008 lnG_3 + 0.0055 lnG_4 + 0.0389 lnH_1\end{aligned} \tag{9}$$

The equation passed integral significance inspection. The total resident population and the proportion of the third industry are negatively related to carbon emissions. From the perspective of regression coefficients, five explanatory variables have profound influence on carbon emissions: resident population, urbanization rate, and household energy consumption, proportion of the tertiary industry and total energy consumption of the secondary industry. Among them, the urbanization rate is the most significant influencing factor. And carbon trading volume and urban greening rate also play a positive role in regional carbon emission reduction to a certain extent.

6.2. BP neural network prediction model

The feedforward network based on BP algorithm can approximate any nonlinear function with arbitrary precision, and the prediction of short-term carbon emission is effective. Therefore, this paper chose BP neural network as the analysis model to forecast the carbon emissions of Beijing in 2020. Based on the STIRPAT model, five key influencing factors of carbon emission are selected, which reduced the input layer of BP neural network and helps to improve the prediction accuracy. This paper constructs a variety of development scenarios and forecasts the future carbon emissions based on different development scenarios so as to improve the s rationality of the forecast and truly reflect the realistic forecast trend of regional carbon emission.

6.2.1. Scenario setting

The implementation of the strategic positioning of the capital city and construction of the world-class harmonious and livable city may depend on the critical stage of the "13th Five-Year Plan" period. According to the newly introduced "Beijing Urban Master Plan (2016–2030) (Draft)" in 2017, by 2020, Beijing will take the lead in achieving a comprehensive well-off society, its non-capital power can also be cleared. Beijing-Tianjin-Hebei region coordinated development of the situation will also be initially achieved.

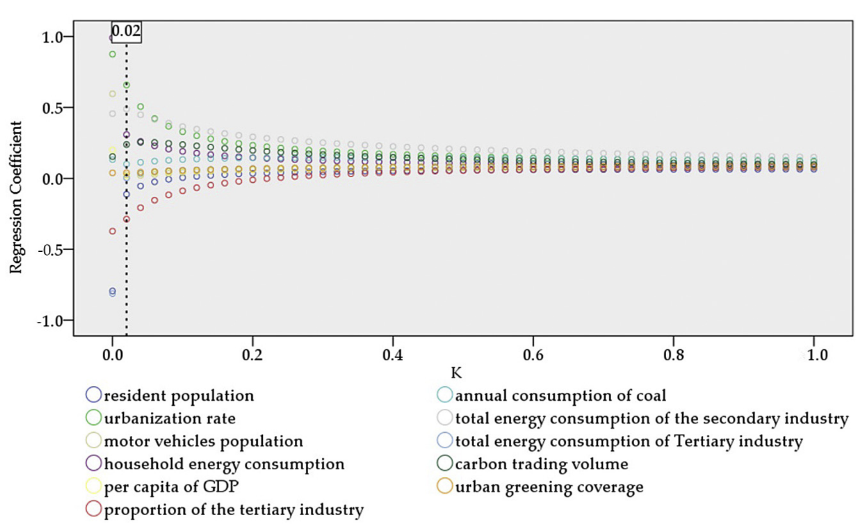

Fig. 17. Ridge regression analysis.

Table 5
The main influencing factors of carbon emissions and the planning objectives.

Key influencing factors	Values in the end of 2015	The average growth rate in the last five years	Planning and development goals for 2020
Resident population	9552.52 Million people	2.04%	the population of Beijing will not exceed 23 million people by 2020 and stay a long-term stability
Urbanization rate	86.51%	0.13%	improve the quality of urbanization, and accelerate the urbanization rate of household population
Household energy consumption	79.70%	1.09%	the proportion of the tertiary industry added value accounted for more than 80%
Proportion of the tertiary industry	1552.7 million tons of standard coal	4.58%	same as national energy development plan average annual energy consumption growth rate stabilized at around 2.5%
Total energy consumption of the secondary industry	1902.7 million tons of standard coal	−4.21%	

Based on the five key influencing factors of carbon emission, this paper sets out different development scenarios to forecast the carbon emission trends according to the relevant planning objectives of Beijing's regional development.

According to the plan, as shown in Table 5, in 2020, Beijing will adhere to regional collaboration and urban-rural integration to further optimize the urban space and industrial layout, and strengthen space management, enhance the overall efficiency and livability of the city. The size of the resident population will be effectively controlled and the degree of effective urbanization will be further improved. Affected by the population expansion and the increasing level of urbanization, the total living energy consumption will be further increased. Under the premise that the tertiary industry has become the dominating industry of Beijing, a further increase of the tertiary industry ratio will reduce energy consumption of secondary industry. In summary, this paper sets up seven scenarios for comparison analysis, as shown in Table 6.

The reference scenario is based on the planned target growth rates in the Beijing Urban Master Plan and the average annual growth rate of the indicators in the past five years. It emphasizes coordinated development within the region. With the appropriate control of population size and energy consumption, Beijing will actively enhance the level of effective urbanization and lift the proportion of the tertiary industry in GDP. With the reference scenario as a reference, the rates of increase in other scenarios are set. In the population expansion scenario, the resident population maintained a high growth rate, which led to the vigorous increase of the total energy consumption. The urbanization rate of rapid urbanization scenario is set double compared to the reference one. In the energy-saving scenario, this paper sets the average annual growth rate of household energy consumption by 2% while keeping other variables consistent with the reference scenario. In the developed tertiary industry, the increase in the proportion of the tertiary industry has led to a decrease both in the proportion of the secondary industry and the total energy consumption. Total energy consumption of the secondary industry is set to a lower growth rate in the low industrial energy consumption scenario. Carbon trading is mainly aimed at the carbon emissions of business units, household energy consumption is not included in the scope of transactions. Therefore, in the active carbon trading scenario setting, the high-emission secondary industry is inhibited. On the contrary, the tertiary industry will develop rapidly. The results of the carbon emissions prediction in seven different scenarios can reflect changes in carbon emission reductions under varied influences.

6.2.2. Prediction under different scenarios

Based on the selection of key variables in section 6.1, this paper chooses five input nodes of BP neural network, which are resident population, urbanization rate, household energy consumption, proportion of the tertiary industry and total energy consumption of the secondary industry. The amount of carbon emissions is selected as the output node.

According to Kolmogrov theorem, if the amount of hidden node is enough, the neural network with a hidden layer can be approximated by any precision of a nonlinear function. Therefore, this paper uses a three-layer multi-input single-output BP network with a hidden layer to establish a prediction model. In the design process of the neural network, if the number of hidden neurons is too large, it will cause a large amount of network computation and prone to over-fitting problems. On the contrary, if the number of neurons is too small, the network performance will be affected to achieve the desired results. The number of hidden neurons in the network is closely related to the complexity of the actual problem, the number of neurons in the input and output layers, and the setting of the expected error. In this paper, equation (10) is used to select the number of hidden neurons.

$$\iota = \sqrt{n+m} + a \tag{10}$$

where n is the number of neurons in the input layer, m is the number of neurons in the output layer, and a is the constant between [1,10]. The number of neurons should be in the range of

Table 6
Assumption for different development scenarios.

Key influencing factors	Reference scenario	Population expansion scenario	Rapid urbanization scenario	Energy-saving scenario	Developed tertiary industry	Low industrial energy consumption scenario	Active carbon trading scenario
Resident population	1.17%	2.04%	1.17%	1.17%	1.17%	1.17%	1.17%
Urbanization rate	0.26%	0.26%	0.50%	0.26%	0.26%	0.26%	0.26%
Household energy consumption	2.50%	4.58%	2.50%	2.00%	2.50%	2.50%	2.50%
Proportion of the tertiary industry	1.09%	1.09%	1.09%	1.09%	2.18%	1.09%	2.18%
Total energy consumption of the secondary industry	−4.21%	−4.21%	−4.21%	−4.21%	−5%	−5.00%	−5.50%

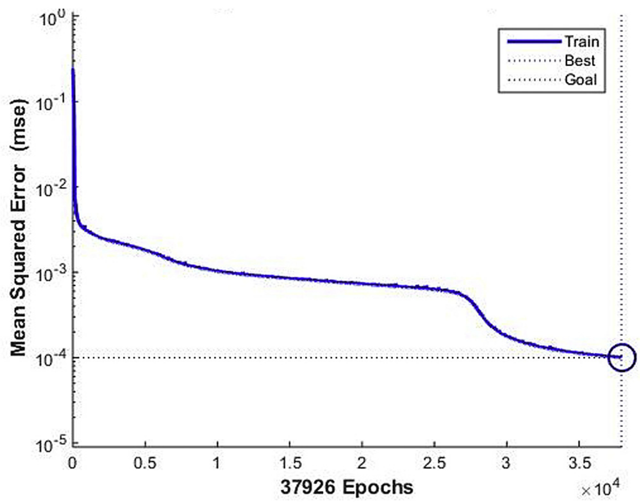

Fig. 18. BP neural network training results.

[4,12]. In this case, the number of hidden neurons is set to 8. This paper set up three layers of BP neural network structure as 5-8-1 eventually. Limited to the statistical data, all 20 samples were used in the prediction from 1995 to 2016. Under the confidence level of 0.10, 18 samples (accounted for 80%) were used as training samples and 4 samples (accounted for 20%) were used for testing. With normalized sample data, they entered the network where the parameters have been set. As shown in Figs. 18 and 19, the network completed learning after 37926-time learnings to achieve the desired error of 10^{-4}. On the constraint of mean squared error, the uncertainty of this BP network has been improve significantly.

In this paper, BP neural network is used to predict the carbon emission in Beijing from 2017 to 2020. The prediction results in different scenarios are shown in Fig. 20.

6.3. Discussion of scenario analysis results

In this paper, the reference scenario is set as a benchmark to carry out comparative analysis with the other six scenarios so as to arrive at the most scientific trend of carbon emissions in Beijing. It

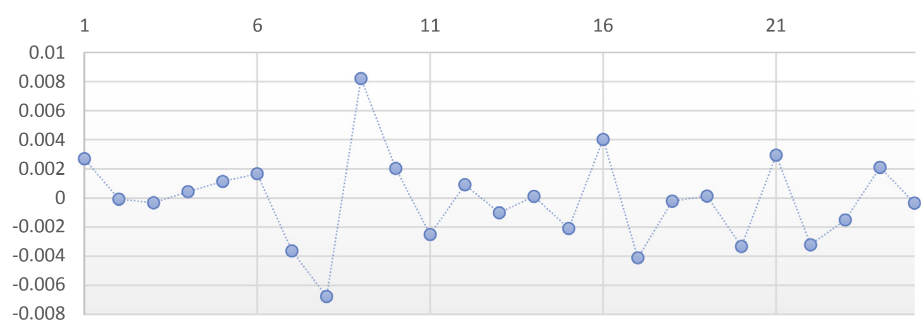

Fig. 19. Sample training error.

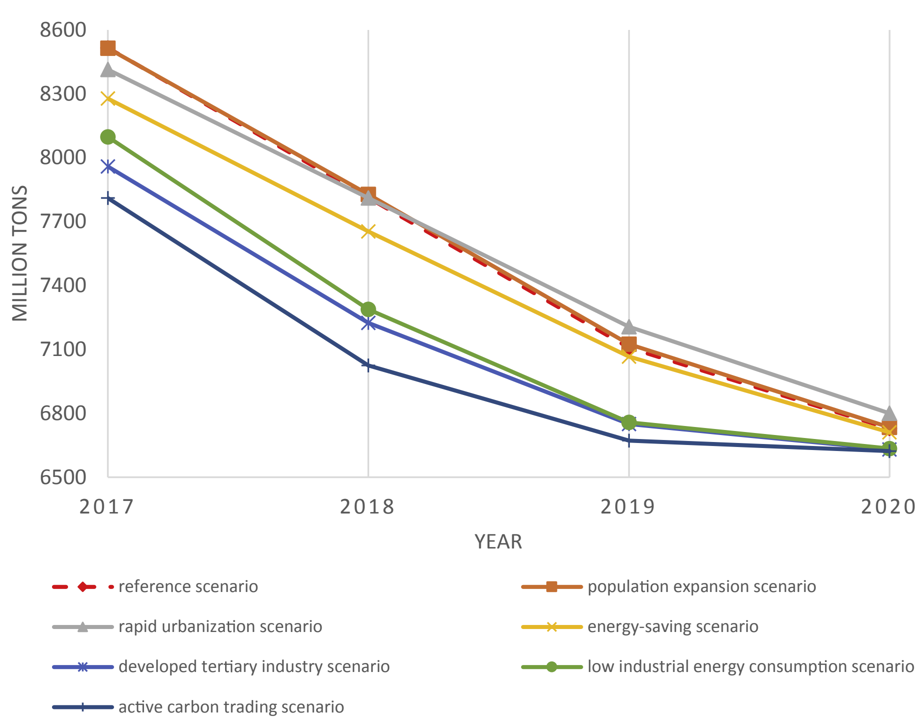

Fig. 20. Forecast of carbon emissions from 2016 to 2020 under different scenarios.

can be seen from Fig. 20 that the total carbon emissions in Beijing show a downward trend under the seven scenarios, but the decline rate and the final emission reductions are different. The results of the discussion are as follows:

(1) In the reference scenario, the limitation of permanent population and energy consumption, as well as the enhancement of urbanization level and the third industry proportion allows a significant reduction in carbon emissions. This development set may in accordance with the requirements of the low carbon development for Beijing, which can produce a certain effect on reduction. But some influences can still be imposed much more stringent control to produce significant emission reductions since they are relatively conservative now.

(2) There are only two scenarios where the predicted carbon emissions exceed the reference scenario: population expansion scenario and rapid urbanization scenario. Among them, the rapid urbanization scenario owns the highest forecast carbon emissions. So, the promotion of urbanization and population expansion will affect the progress of carbon emission reduction to a certain extent. From the perspective of the impact level, the difference between the population expansion scenario and the reference scenario is small, so the rise of the resident population is not the most important incentive for the significant increase in regional carbon emissions. The rapid advance of urbanization may have a greater impact on regional carbon emissions comparing with population. Urbanization not only brings a simple population increase and concentration, but also the industry agglomeration and the resulting increase in energy consumption. Therefore, in the process of regional carbon emission reduction, improving the quality of urbanization and optimizing the urban development structure have become a key to further reduction work.

(3) The degree of carbon emissions reduction caused by the tertiary industry expansion and industrial energy consumption retrenchment is significantly bigger than household energy consumption reduction, which can explain that both the proportion enhance of tertiary industry and the secondary industry energy consumption reduction are effective measures for energy saving and emission reduction in Beijing.

(4) Compared with other scenarios, difference in carbon emissions between active carbon emissions scenario and the reference scenario gets the first place which shows that the active carbon trading contributes greatly to the reduction in emissions. The direct impact of carbon trading on secondary and tertiary industry energy-saving promotes a substantial decline in regional carbon emissions. How to stimulate the development of carbon trading and enhance the enthusiasm of market parties have become a new breakthrough in reduction work.

7. Advices for regional carbon emissions reduction policies driven by carbon trading

Combined with regional carbon emission evolution mechanism and trend prediction research, recommendations for regional carbon emissions optimization policy are proposed as follows.

(1) Carbon trading must be valued because it has a vital role in promoting energy conservation. At the same time, regional carbon trading policies should be treated differently according to local conditions. In the current China's national carbon trading market, the Chinese government still dominates. Carbon trading process requires the total amount of allocation, quota allocation, certification registration, trading, penalties and other corresponding processes. Combined with the establishment of the carbon trading mechanism in the pilot area, it can be seen from Fig. 21 that the government can actively intervene and guide the relevant processes to promote the large-scale development of carbon trading.

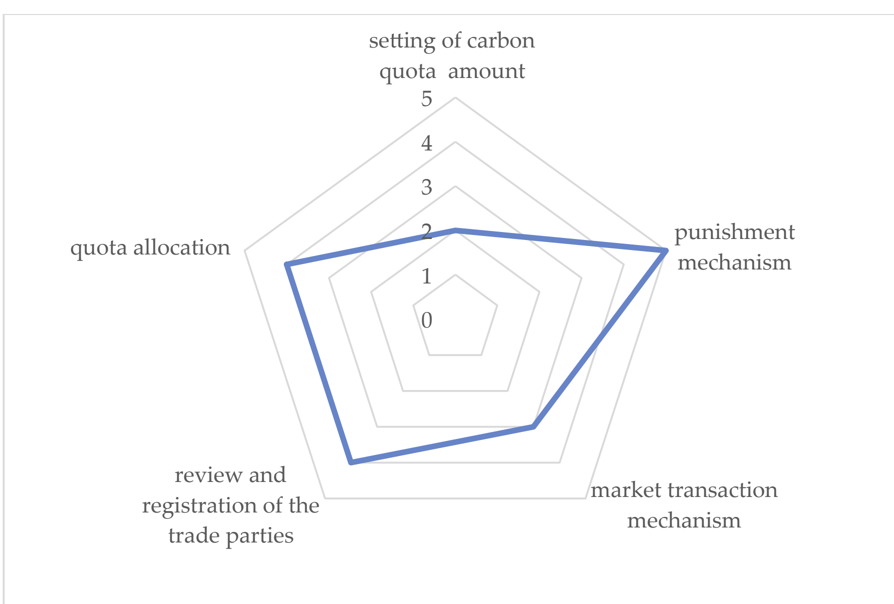

Fig. 21. Degree of influence of government intervention in carbon trading.

From the analysis result, industrial enterprises are an important source of carbon dioxide emissions as well as an important participant in carbon trading market. Therefore, to different types of carbon dioxide emission reduction units, the government should set the emission reduction coefficient scientifically at distinction treatment principles considering with the different, industrial characteristics. The quota application conditions and thresholds should be also adjusted flexibility, but strictly satisfy the management of total carbon emission amount and the quota distribution. In addition, to strictly regulate management of carbon emissions trading and quota allocation, application conditions and threshold for quota adjustment should also be determined. At the same time, it is also very important to perfect the pricing mechanism of the carbon trading market and combine the advantages of the administrative means and the market mechanism. Market-based regulation should be used for parties with little reduction potential. On the contrary, the government should implement a mandatory emission reduction measures for high-emission enterprises and increase the penalties for breach of contract, thus reducing the overall cost of the community while promoting the further development of low-carbon economy.

(2) The improvement of urbanization quality and level is of great significance to regional carbon emission control. The empirical analysis results show that urbanization has a significant role in promoting carbon dioxide emissions. It is feasible to carry out scientific and rational urban low-carbon development plan to develop centralized, compact and group-type urban spatial layout model to reduce carbon emissions. Optimizing the regional layout while constructing green buildings and low-carbon transport system, promote green travel also help to reduce the intensity of carbon emissions in the region.

(3) In the context of increasing population, the guidance of low carbon behavior is an important way to achieve energy saving and emission reduction in the region. With the rapid development of China's economy and the loosening of population policies, in the next period, the total urban population will continue to grow which will further stimulate resources and energy demand. Therefore, a reasonable guide to residents of energy consumption, and actively adjust the residents can use habits to support regional carbon emissions optimization control. So a reasonable guide to the residents of energy consumption, and active adjustment for the residents' habits can support the further optimization of regional carbon emissions.

Conflicts of interest

We have no conflicts of interest to declare.

Acknowledgments

This study is supported by the National Natural Science Foundation of China (NSFC) (71501071), China Postdoctoral Science Foundation (2014M550937), Ministry of Education in China Project of Humanities and Social Sciences (14JF005), Beijing Social Science Fund (16YJC064) and the Fundamental Research Funds for the Central Universities (2017MS059).

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