Front. Econ. China 2021, 16(3): 569–587
https://doi.org/10.54605/fec20210307

RESEARCH ARTICLE

Chunzi Wang[a], **Mingxiong Zhu**[a]

Scenario Prediction of China's Natural Gas Consumption and Carbon Emissions in the Next Ten Years

Abstract Based on Johansen Cointegration Test, this paper sheds light on the long-run equilibrium relationship between natural gas consumption, gas production, and GDP in China. Three different natural gas demand scenarios of low, medium and high rates in the next ten years are considered, and a Neural Network Autoregression Model is used to predict the future carbon dioxide emission. We conclude: (1) In all three scenarios, the growth rates of natural gas consumption are all higher than those of natural gas production, while the gap between demand and domestic supply will gradually turn broader and China will largely rely on imports ; (2) In the scenario of low-rate economic growth, natural gas consumption will grow slowly, and it will be difficult to realize the carbon emission reduction targets by 2030 due to low-rate substitution of natural gas for coal; (3) If medium-rate to high-rate economic growth sustains, coupled with rapid increase in natural gas consumption and production, China's Carbon Emission Reduction Targets for 2030 can be achieved with high-rate substitution of natural gas for coal.

Keywords carbon dioxide emission, gas consumption, Johansen Cointegration Test, Neural Network Autoregression Model (NNAR)
JEL Classification Q3, Q4

Received September 22, 2020

[a] School of Statistics and Management, Shanghai University of Finance and Economics, Shanghai 200433, China
E-mail: wczsufe@163.com (Chunzi Wang, corresponding author), mxzhu@mail.shufe.edu.cn (Mingxiong Zhu)

1 Introduction

1.1 Background and Significance of the Research Work

A substantial volume of carbon dioxide is emitted when coal, petroleum and other fossil fuels are burned, leading to global warming and destruction of the ecological balance. To reduce carbon emissions on a global scale has become the consensus of all countries in the world.

On September 22, 2020, the Chinese Government pledged at the 75th Session of the UN General Assembly that China would introduce strong policies and measures, and make every effort to reach peak carbon dioxide emissions by 2030 and realize the goal of carbon neutrality by 2060. “Peak Carbon Dioxide Emissions” refers to the gradual reduction of carbon dioxide emissions following the anticipated peak before 2030. “Carbon Neutrality” refers to that by 2060 China will suck away all carbon dioxide that humans have emitted by means of tree planting, afforestation, energy conservation and emission reduction. According to *Report on the Work of the Government* released in 2021, peak carbon dioxide emissions and carbon neutrality are clearly listed as one of the goals of government work in the coming years.

Economic development is inseparable from energy consumption. Combustion of energy sources inevitably discharges carbon dioxide. On the way to the goal of peak carbon dioxide emissions and carbon neutrality, the first and foremost issue for China to address is how to reduce carbon dioxide emissions while maintaining economic growth. In the document *Enhanced Actions on Climate Change: China*’*s Intended Nationally Determined Contributions*, it is proposed that by 2030, China’s carbon dioxide emissions per unit of GDP, i.e., Carbon Emission Intensity, will be reduced by 60%-65% compared to that in 2005 (hereinafter referred to as “Carbon Emission Reduction Targets by 2030”).

Because of rich reservation and relatively low mining cost, coal has been accounting for a high proportion in China’s total energy consumption. In 2020, coal still took up more than half of the total energy consumption (56.8%). As a type of eco-friendly and clean energy, natural gas has the advantages of high unit calorific value and low pollution compared with coal and other fossil fuels.

The carbon emission intensities of different types of fuel differ slightly in existing literature. As per data from China's carbon trading website[1], the carbon emission intensities of raw coal, coke and natural gas are 2.66, 2.94, and 1.62 (unit: kilogram of carbon dioxide per kilogram of standard coal[2]), respectively. In other words, among the three types of fuel, carbon dioxide emissions of raw coal and coke are 1.64 and 1.81 times, respectively, those of natural gas. According to Zhao et al. (2009), carbon emissions intensities of raw coal, coke and natural gas are 0.7559, 0.8550, and 0.4483 (unit: ton of carbon dioxide per ton of standard coal), respectively. Put differently, carbon dioxide emissions of raw coal and coke are 1.68 and 1.91 times, respectively, those of natural gas. A report from Hainan Green Finance Research Institute[3] indicates, "given the same amount of energy produced, carbon dioxide emissions of coal are about 1.5 and 2.2 times, respectively, those of petroleum and natural gas". According to Wu (2012), carbon emission intensities of raw coal, coke and natural gas are 2.7725, 3.1379, and 1.6442 (unit: ton of carbon dioxide per ton of standard coal), respectively. Carbon dioxide emissions of raw coal and coke are 1.69 and 1.91 times, respectively, those of natural gas. Generally speaking, given the same amount of energy produced, natural gas emits far less carbon dioxide than other fossil fuels.

Households use natural gas to heat buildings and water, to cook and even to fuel gas vehicles. The industrial sector uses natural gas as a fuel for process heating, in combined heat and power systems, as a raw material to produce chemicals, fertilizer, and hydrogen, and as plant fuel. It is not only a type of important energy source related to the national economy and people's livelihood, but also plays an important role in green transformation of China's economic development. *China Natural Gas Development Report 2021* points out that decreasing coal consumption, increasing gas consumption and developing new energy sources are important moves for China to realize its goal of peak carbon dioxide emissions and carbon neutrality.

1.2 Literature

In the context of global warming, "Low-carbon Economy", with low energy

---

[1] See: http://www.tanjiaoyi.com/article-3075-1.html

[2] With the unit calorific values, per kilogram of each type fuel first converts to the equvalent unit of standard coal.

[3] See: https://www.yicai.com/news/101132161.html

consumption and low pollution being at the core, has become a hot global issue; focused on carbon dioxide emissions are an increasing number of research papers both at home and abroad.

Hassan and Kouhy (2013) analyze the impact of the development of Nigeria's oil and gas industry on its carbon dioxide emission load from 1965 to 2009. Li et al. (2017) adopt Vector Autoregression Model (VAR) and Johansen Cointegration Test to examine the relationship between carbon dioxide release intensity and different consumption loads from various types of energy sources in the United States, and argue that the United States has succeeded in the reduction of carbon dioxide emission intensity due to the increase in the share of renewable energy consumption. Wang et al. (2016) use Least Squares Regression Method to analyze the influencing factors of carbon emission intensity from both national and local levels. Wei (2019) analyzes the relationship between carbon emission load and per capita GDP, total population and energy intensity based on Johansen Cointegration Test.

On the basis of analyzing the influencing factors of carbon dioxide emissions, many scholars are also interested in the prediction of carbon dioxide emissions. For example, Xie et al. (2020) use Influence Factor Decomposition Model to probe into the factors related to carbon emissions of Guangdong Province, China from 1995 to 2017, and make a prediction of the carbon dioxide emissions. The prediction results indicate that by 2030 per capita carbon dioxide emission in urban areas will exceed that in rural areas of Guangdong Province. Song (2011) selects six macroeconomic indicators from 1980 to 2009, i.e., Population, Urbanization Rate, Per Capita GDP, Proportion of Tertiary Industry in GDP, Energy Consumption Intensity and Coal Consumption Ratio, in an effort to build BP Neural Network Model to predict the future carbon emissions. The prediction of this model is highly accurate. Finally, it is concluded that a rapid increase in GDP will cause a substantial increase in carbon dioxide emission, and the future GDP growth should slow down in order to realize the goal of reducing carbon dioxide emission. Song (2011) fails to consider the consumption of clean energy, and the policy recommendations put forward are evidently biased.

In addition, some scholars carry out predictions to discuss whether Carbon Emission Reduction Targets by 2030, proposed by the Chinese Government, are feasible. For example, Zhang et al. (2017) use Dynamic Monte Carlo Simulation and Scenario Analysis to predict carbon emission, and argue that China can realize its voluntary Carbon Emission Reduction Targets by 2030.

As the Chinese government vigorously launches "Coal to Gas Conversion" Project, the replacement of coal by natural gas as the main energy source will become a future trend. Scholars choose different economic indicators from multiple perspectives, and seek after more accurate prediction models to predict the future gas demand. For example, Ma and Li (2010) refer to China's annual gas consumption data from 2001 to 2008, and use Grey Model to predict China's gas consumption and production from 2009 to 2020. Zheng et al. (2021) design a three-layer neural network based on China's GDP, residential electricity price, natural gas futures price and other data from 2009 to 2018, and establish different economic growth scenarios to predict China's gas demand from 2020 to 2030.

This paper focuses on the relationship among gas consumption, gas production, carbon dioxide emission, and GDP. Different scenarios of future gas consumption and production are hereby established, coupled with Johansen Cointegration Test and Neural Network Autoregression Model. In this way, this paper is intended to predict China's carbon dioxide emissions in the next ten years. Finally, detailed analysis is made on China's gas consumption, gas production, and the realization of Carbon Emission Reduction Targets by 2030.

The remainder of this paper is organized as follows. The next section describes the data involved in this study. Section 3 and section 4 present the analytical results with Johansen Cointegration Test and Neural Network Autoregression Model, respectively. The final section concludes.

2 Data Description

In this paper, four time series data refer to Carbon Dioxide Emission (unit: 1 million tons), Production of Natural Gas (unit: 10,000 tons of standard coal), Consumption of Natural Gas (unit: 10,000 tons of standard coal) and Gross Domestic Product (GDP, unit: RMB 100 million) from 2000 to 2020, respectively. Data about China's carbon emissions over these years are collected from official website of China Emission Accounts and Datasets[4]. Data about China's gas consumption and production and GDP over these years are collected from *China Statistical Year book 2020*[5].

[4] See: https://www.ceads.net.cn
[5] See: http://www.stats.gov.cn/tjsj/ndsj/2020/indexch.htm

2.1 Data Preprocessing

The changing trends of the four variables, i.e. Carbon Dioxide Emission, Gas Consumption, Gas Production, and GDP, are shown in Figure 1. It can be seen that these four time series demonstrate similar changing trends. The descriptive statistics of all variables are presented in Table 1.

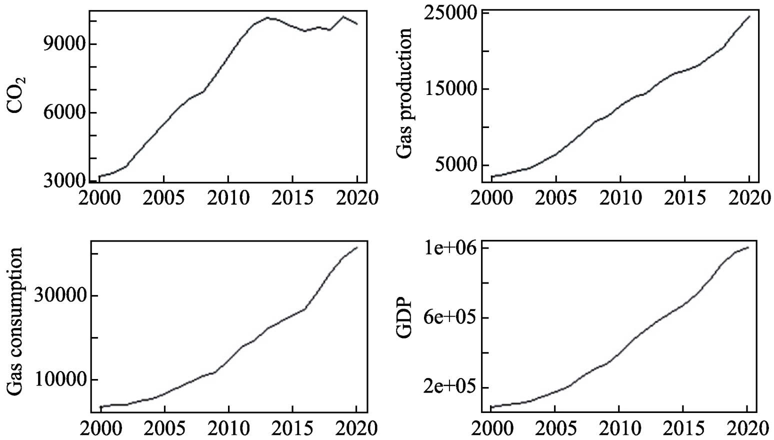

Figure 1 Trends of Carbon Dioxide Emission, Gas Production, Gas Consumption and GDP from 2000 to 2020

Table 1 Summary of Descriptive Statistics of All Variables

Descriptive statistics	Carbon dioxide emission	Gas production	Gas consumption	GDP
Minimum	3,214	3,603	3,233	100,280
Mean	7,551	12,591	17,383	468,618
Maximum	10,200	24,480	41,832	1,015,986
S.E.	2,548.749	6,503.646	12,427.37	307,275.6

Given that values and fluctuation ranges of these four variables differ, in order to stabilize the time series and avoid the disturbance from outliers, natural logarithms of these four variables are respectively taken. Carbon dioxide emission after logarithmic transformation is indicated as y_{1t}; gas production and gas consumption after logarithmic transformation are indicated as y_{2t} and y_{3t}, respectively; and GDP after logarithm transformation is indicated as y_{4t}, $t = 2000, 2001, ..., 2020$.

2.2 Unit Root Test

Unit Root Test is applied to test whether there is a unit root in the time series. The time series with unit root is deemed as non-stationary time series, while the regression of non-stationary time series gives rise to pseudo-regression phenomenon. In order to quantitatively judge whether the four variables are stationary time series, KPSS Unit Root Test Method (Kwiatkowski et al., 1992) is employed for stationarity test. For KPSS Unit Root Test, the original hypothesis is that series is stationary, and the alternative hypothesis is that series contains unit root. In other words, such series is non-stationary.

According to calculations, when significance levels are 10%, 5%, 2.5% and 1%, the corresponding critical values are 0.119, 0.146, 0.176 and 0.216, respectively. The values of KPSS test statistic for the above four series and the corresponding series after the first-order difference processing are given in Table 2.

Table 2 Values of KPSS Test Statistic (Original Series)

y_{1t}	y_{2t}	y_{3t}	y_{4t}
0.2039	0.1953	0.1844	0.1953

Table 3 Values of KPSS Test Statistic (Differenced Series)

Δy_{1t}	Δy_{2t}	Δy_{3t}	Δy_{4t}
0.0815	0.0937	0.1024	0.1426

KPSS Test is a one-sided and right-side test. When the value of KPSS test statistic is greater than the critical value, null hypothesis is rejected, and the series is considered non-stationary. At the significance level of 5%, series y_{1t} , y_{2t} , y_{3t} , y_{4t}∞ are all non-stationary. After the first-order difference processing, Δy_{1t} , Δy_{2t} , Δy_{3t} , Δy_{4t} are all stationary series. That is to say, four original series are all integrated of order one, which conforms to the premises of Vector Error Correction Model (VEC).

2.3 Selection for Optimal Order of Lag

Prior to Cointegration Test, it is necessary to determine the lag order p of VEC

Model. Equation of VEC Model (Pfaff, 2008) is given as:

$$\Delta \mathbf{y}_t = \mathbf{c} + \Pi \mathbf{y}_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta \mathbf{y}_{t-i} + \mathbf{u}_t, t = 1, 2, ..., T \quad (1)$$

where $\mathbf{u}_t = (u_{1,t}, u_{2,t}, u_{3,t}, u_{4,t})'$ indicates a white noise process to satisfy $E(\mathbf{u}_t) = 0$, and $E(\mathbf{u}_t \mathbf{u}_t') = \Sigma_u$. For $t \neq s$ in any case, $E(\mathbf{u}_t \mathbf{u}_s') = 0$. Covariance matrix $\sum_u$ is nonsingular. $\Delta \mathbf{y}_t = (\Delta y_{1,t}, \Delta y_{2,t}, \Delta y_{3,t}, \Delta y_{4,t})'$ is Random variable vector; $\mathbf{c} = (c_1, c_2, c_3, c_4)'$ indicates a constant vector; Π and $\Gamma_i, i = 1, 2, ..., p$ are matrixes of coefficients.

T indicates the sample size, K=4 indicates the number of variables, and the maximum order of lag in VAR Model is set to 3. That is to say, the maximum order of lag in VEC Model is set to 2. OLS Estimation is applied to calculate the following three information criteria:

Akaike information criterion: $AIC(p) = Ln\left|\hat{\Sigma}_u\right| + K^2 p \frac{2}{T}$ (2)

Hannan-Quinn criterion: $HQ(p) = Ln\left|\hat{\Sigma}_u\right| + K^2 p \frac{2Ln(Ln(T))}{T}$ (3)

Bayesian Information Criterion: $BIC(p) = Ln\left|\hat{\Sigma}_u\right| + K^2 p \frac{Ln(T)}{T}$ (4)

Calculation results are shown in Table 4.

Table 4 Selection for Optimal Lag Order of VAR

lag	1	2	3
AIC	−27.17	−27.81	−31.97*
HQ	−27.03	−27.56	−31.62*
BIC	−26.18	−26.03	−29.40*

The above four indicators all prove that the optimal order of lag in VAR Model is 3. Therefore, the optimal order of lag in VEC Model is 2.

3 Johansen Cointegration Test

3.1 Johansen Cointegration Test

Cointegration Test is designed to judge whether the linear combination of a set of non-stationary series presents a stable equilibrium relationship. Engle-Granger

Cointegration Test performs OLS Regression on two variables integrated of the same order. Unit root test is conducted for the obtained residual sequence. If the residual sequence passes unit root test, the series is considered stationary, and the two variables are considered cointegrated. Engle-Granger Cointegration Test can only find one cointegration relationship due to its own setting characteristics, and thus is unsuitable for a multi-cointegration system. Therefore, in this paper, Johansen Cointegration Test is performed for the purpose of analysis. Johansen Cointegration Test is a method of constructing the statistics for cointegration test through rank and characteristic root of Matrix $\prod$ in VEC Model (1, 2). Rank of Matrix $\prod$ is set as r :

(1) If $\prod$ is a full-rank matrix, i.e., $|\prod| \neq 0$ and $r = 4$, there is no cointegration relationship among the variables.

(2) If $0 < r < 4$, i.e., $|\prod| = 0$, cointegration relationship exists among the variables of $\mathbf{y}_t$. There are a total of r combinations in the form of stationary series.

(3) If $r = 0$, i.e., $|\prod| = 0$, there is no cointegration relationship among the variables of $\mathbf{y}_t$.

Johansen Cointegration Test examines the number of cointegration relationships in a circular manner:

$$H_{00} : r = 0 \quad vs \quad H_{10} : r > 0$$

$$H_{01} : r = 1 \quad vs \quad H_{11} : r > 1$$

$$H_{02} : r = 2 \quad vs \quad H_{12} : r > 2$$

$$H_{03} : r = 3 \quad vs \quad H_{13} : r > 3$$

Johansen (1988) puts forward Trace Statistic：

$$\lambda_{trace} = -T_s \sum\nolimits_{i=r+1}^{n} Ln(1 - \hat{\lambda}_i), r = 0,1,...,n-1 \tag{5}$$

where $\hat{\lambda}_i$ indicates the estimated value of the characteristic root of Matrix $\prod$, and T_s indicates the effective sample number.

The test statistics and critical values of Johansen Cointegration Test are presented in Table 5. When the value of trace statistic is greater than the critical value, the null hypothesis is rejected. At the significance level $\alpha = 5\%$, we come to the conclusion that $r = 3$. Therefore, there are three cointegration relationships between the variables of $\mathbf{y}_t$.

Table 5 Result of Johansen Cointegration Test

Null hypothesis	Value of Trace statistic	Critical value for $\alpha = 10\%$	Critical value for $\alpha = 5\%$	Critical value for $\alpha = 1\%$
$r = 0$	162.56	49.65	53.12	60.16
$r \leqslant 1$	73.67	32.00	34.91	41.07
$r \leqslant 2$	25.48	17.85	19.96	24.60
$r \leqslant 3$ *	8.48	7.52	9.24	12.97

3.2 Estimate of VEC Model Parameters

According to Granger Representation Theorem: If $0 < r < 4$ is true, Matrix $\prod$ can be broken down into two matrixes:

$$\Pi = \boldsymbol{\alpha}\boldsymbol{\beta}', \tag{6}$$

$$\Delta \mathbf{y}_t = \mathbf{c} + \boldsymbol{\alpha}\boldsymbol{\beta}'\mathbf{y}_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta \mathbf{y}_{t-i} + \mathbf{u}_t, t = 1, 2, ..., T \tag{7}$$

In this way, $\mathbf{z}_{t-1} = \boldsymbol{\beta}'\mathbf{y}_{t-1}$ keeps stationary. Cointegration vector describes the long-run equilibrium relationship between the variables. $\boldsymbol{\alpha}$ is called "Matrix of Speed of Adjustment Coefficients", while $\boldsymbol{\beta}$ is called "Cointegration Matrix". The cointegration matrix in the error correction term is obtained by means of Least Squares Estimation Method, as shown in Table 6.

Table 6 Matrix of Cointegration Vectors

	ect1	**ect2**	**ect3**
y1.l3	1	0	0
y2.l3	0	1	0
y3.l3	0	0	1
y4.l3	–0.627	–0.980	–1.077
constant	–0.750	3.452	4.293

Based on Table 6, three cointegration relationships are respectively given as:

Error Correction Equation 1: $y_{1,t-1} = 0.627 y_{4,t-1} + 0.750$ (8)

Error Correction Equation 2: $y_{2,t-1} = 0.980 y_{4,t-1} - 3.452$ (9)

Error Correction Equation 3: $y_{3,t-1} = 1.077 y_{4,t-1} - 4.293$ (10)

Under Error Correction Equation 1, every increase in GDP by 1% leads to an increase in carbon dioxide emission by 0.627%, and there is a positive long-run equilibrium relationship between carbon dioxide emission and GDP. Under Error Correction Equation 2, every increase in GDP by 1% leads to an increase in natural gas production by 0.98%, and there is a positive long-run equilibrium relationship between gas production and GDP. Under Error Correction Equation 3, every increase in GDP by 1% leads to an increase in natural gas consumption by 1.077%, and there is also a positive equilibrium relationship between gas consumption and GDP.

China's economic growth is inseparable from the consumption of natural gas energy. Therefore, the relationship between GDP and gas consumption and production is in line with intuition. The increase in GDP is accompanied by the consumption of energy sources, which inevitably causes carbon dioxide discharges. The correlation between GDP and carbon dioxide emission as estimated by error correlation model is generally a linear relationship, which does not take further substitution of natural gas for other fossil fuels into account. Thus the relationship between GDP and carbon dioxide emission, as shown in Cointegration Equation 1, should not be directly used to predict China's total carbon dioxide emissions in the future. In the following section, we will highlight three natural gas demand scenarios by integrating the substitution of natural gas for coal. Under different scenarios, neural network autoregression model is used to predict China's carbon dioxide emission in the next ten years.

4 Prediction through Neural Network Autoregression Model

Neural network model is very popular in the field of machine learning due to its super self-learning ability. Inspiration for artificial neural network originates from the operation mode of the central nervous system in human brain. The operation of the neural network model generally depends on the training set with a large sample size so that better parameter estimation can be obtained through the training set. There are two essential elements in the design of a set of neural networks, i.e., input and output layers. A complex neural network can contain multiple Hidden Layers between the input layer and the output layer. Each layer of the neural network contains multiple neurons simultaneously. The neural network model can automatically fit complex non-linear relationships, without the need for distribution hypothesis of variables.

Neural Network Autoregression Model (NNAR), also abbreviated as NNAR (p,

k) Model, is such a feed forward single hidden layer neural network that takes the *p*-order lag term of the series and other variables together as the inputs. The number of hidden layer neurons is *k*, and the output indicates the series of prediction value. The parameters of weights and bias in NNAR (p, k) Model are learned from sample data. In this paper, lag item order of NNAR (p, k) Model is set to be consistent with the lag order of VAR Model (p=3), and the number of hidden layer neurons is expressed as k=1.

Three scenarios for China's gas consumption and gas production in the next ten years are established as follows:

Scenario 1: Hindered by COVID-19 Pandemic, China's economy will continue to grow at a low rate in the future. The demand for natural gas and the gap between gas supply and demand will widen slowly.

Scenario 2: In the *Report on the Work of the Government,* China's economic growth rate for 2021 is targeted at 6%. Therefore, Scenario 2 is so established that China's economy will gradually recover from the adverse impacts of COVID-19 Pandemic. The future economic growth rate will rebound to the pre-COVID-19 level. Gas consumption will steadily rise, and the gap between supply and demand will further broaden.

Scenario 3: China has completely got rid of COVID-19. China's economy will show a trend of high-rate growth in the future. Gas consumption will grow rapidly, and the gap between supply and demand will keep increasing.

Above all, three simulation scenarios corresponding to low rate, medium rate and high rate of China's economic growth (Li, 2018; Zheng, 2021; Johansson, 2012), are shown in Table 7. Then the preset GDP value is imported into Error Correction Equation 2 and Error Correction Equation 3 to calculate the gas consumption and gas production in the future. Finally, the third-order lag term of carbon dioxide emission and the gas consumption and gas production in the future are adopted as the inputs. Neural Network Autoregression Model is used to predict the future carbon dioxide emission.

Prediction results are presented in Tables 8-10. Column 1 indicates the year; Column 2 indicates predicted gas production; Column 3 indicates predicted gas consumption; Column 4 indicates the gap between gas consumption and gas production; Column 5 indicates the predicted GDP; and Column 6 indicates the decrease rate of carbon emission intensity compared to that in 2005.

Table 7 Scenario Settings of China's GDP

Scenario	Item	2021	2024	2027	2030
Scenario 1 (low rate)	Growth rate/%	3	3	3	3
	GDP/RMB100 million	1,055,610	1,183,995	1,327,996	1,489,510
Scenario 2 (medium rate)	Growth rate/%	6	5.7	5.4	5.1
	GDP/RMB100 million	1,095,233	1,357,190	1,663,084	2,016,288
Scenario 3 (high rate)	Growth rate/%	6.8	6.9	6.5	6.3
	GDP/RMB100 million	1,105,799	1,430,860	1,825,097	2,311,252

Note: In this table, "GDP" refers to nominal GDP; "growth rate" refers to the actual GDP growth rate; GDP Index adopts the data released by the National Bureau of Statistics, with the data in Year of 1978=100.

(1) Scenario of China's Economic Development at a Low Rate

China's GDP is assumed to increase at an average annual growth rate of 3% in the next ten years. By 2030, gas consumption will increase by 64.2% while gas production will increase by 45.1% compared to 2020. The gap between gas consumption and gas production will reach 252.9144 million tons of standard coal, accounting for 41.6% of the total consumption.

By 2030, carbon emission intensity will be 59.20% lower than that in 2005. Therefore, in case China's economy fails to shake off the adverse impacts of COVID-19 and continuously grows at a low rate, gas consumption will witness a slow growth, and it will be difficult for China to realize the Carbon Emission Reduction Targets by 2030.

Table 8 Prediction Result of Scenario 1

Year	Gas production	Gas consumption	Gap	GDP	Percent (%)
2021	25,342.46	41,964.97	16,622.51	1,055,610	46.77
2024	27,315.88	45,569.77	18,253.88	1,139,553	49.82
2027	31,735.71	53,734.92	21,999.21	1,327,996	55.42
2030	35,513.86	60,805.30	25,291.44	1,489,510	59.20

(2) Scenario of China's Economic Development at a Medium Rate

China's GDP growth rate is assumed to be 6% in 2021, and the average annual GDP growth rate is assumed to be 5.7% during 2021-2024, 5.4% during

2024-2027 and 5.1% during 2027-2030.

In other words, China's economy will maintain a medium-rate growth in the future as the country gets over the adverse impacts of COVID-19. Total gas consumption and production will further increase. By 2030, the gap of domestic gas supply and demand will reach 364.6796 million tons of standard coal, accounting for 43.3% of total consumption.

Under this Scenario, by 2030, carbon emission intensity will be 67.62% lower than that in 2005, and it will be possible for China to realize the Carbon Emission Reduction Targets by 2030.

Table 9 Prediction Result of Scenario 2

Year	Gas production	Gas consumption	Gap	GDP	Percent (%)
2021	26,274.34	43,663.88	17,389.54	1,095,233	48.03
2024	32,419.28	55,008.25	22,588.97	1,357,190	55.99
2027	39,565.02	68,469.70	28,904.68	1,663,084	62.41
2030	47,783.38	84,251.34	36,467.96	2,016,288	67.62

(3) Scenario of China's Economic Development at a High Rate

China's GDP growth rate is assumed to be 6.8% in 2021, and the average annual GDP growth rate is assumed to be 6.9% during 2021-2024, 6.5% during 2024-2027, and 6.3% during 2027-2030.

In the future, China's economy will completely get rid of the adverse impacts of COVID-19, and boast great development momentum. The country will maintain a rapid GDP growth, and gas consumption will increase sharply. By 2030, gas consumption will reach 975.9718 million tons of standard coal, and natural gas import will account for 44% of the total consumption.

Under this Scenario, by 2030, carbon emission intensity will be 70.79% lower than that in 2005. The Carbon Emission Reduction Targets by 2030 will be overfulfilled.

Table 10 Prediction Result of Scenario 3

Year	Gas production	Gas consumption	Gap	GDP	Percent (%)
2021	26,522.73	44,117.74	17,595.00	1,105,799	48.23
2024	34,142.92	58,230.69	24,087.77	1,430,860	57.62
2027	43,338.67	75,679.57	32,340.90	1,825,097	64.92
2030	54,624.28	97,597.18	42,972.90	2,311,252	70.79

The neural network autoregression model differs from the error correlation model in integrating further substitution of natural gas for other fossil fuels. When a medium or high rate of GDP growth is reached (i.e. scenarios 2 and 3), both natural gas production and consumption grow much faster than the GDP growth due to more substitution of natural gas for other types of fossil fuel; when GDP grows slowly (i.e. scenario 1), both natural gas production and consumption grow as fast as the GDP growth and the proportion of each type of energy production and consumption would maintain. In other words, a medium or high rate of GDP growth requires much greater inputs of natural gas production/consumption. It is therefore not difficult to conclude that China's Carbon Emission Reduction Targets for 2030 can be achieved in the cases where medium and high-rate GDP growth maintains along with more substitution of natural gas for other types of fossil fuel.

5 Conclusions and Recommendations

On the way to the goal of peak carbon dioxide emissions and carbon neutrality, the first and foremost issue for China is to reduce carbon dioxide emissions while maintaining economic growth. There is no contradiction between economic growth and carbon emission reduction. If fossil energy (such as coal and petroleum) is replaced by clean energy (such as natural gas) and renewable energy (such as hydro energy, wind energy and solar power), economic growth can be sustained while carbon dioxide emissions are reduced. This is win-win situation toward transiting to the road of low carbon economic development.

In China, most technologies related to renewable energy are still at the initial stage of development. Renewable energy industry is an emerging industry in China. At present, small size of manufacturers, relatively low profitability, shortage of funds and absence of effective financing mechanisms pose major obstacles to the development and industrialization of renewable energy (Li, 2004). At this stage, it is impractical to popularize the use of renewable energy. Therefore, natural gas serves as the most important energy source required to develop low-carbon economy.

In this paper, four economic variables (Carbon Dioxide Emission, Natural Gas Consumption, Natural Gas Production, and GDP) are selected. Firstly, based on the analysis under Johansen Cointegration Test and Error Vector Correction

Model, three cointegration relationships are found, i.e., the long-run equilibrium between natural gas consumption and GDP, the long-run equilibrium between natural gas production and GDP, and the long-run equilibrium between carbon dioxide emission and GDP. Secondly, three scenarios of the future natural gas consumption and production are established. With the help of neural network autoregression model, carbon dioxide emissions under different scenarios are predicted. Neural network model has strong self-learning ability and can fit complex nonlinear relationships in a satisfactory manner.

Finally, conclusions are drawn as follows: Scenario 1: China's economy will grow at a low rate. Gas consumption and gas production will increase slowly. It will be difficult to realize the Carbon Emission Reduction Targets by 2030. Scenario 2: China's economy will maintain a medium-rate growth. Gas consumption and production will further increase. It is possible to realize the Carbon Emission Reduction Targets by 2030. Scenario 3: China's economy will maintain a high-rate growth. Gas consumption will increase rapidly. The Carbon Emission Reduction Targets by 2030 will be overfulfilled. It is worth noting that under all scenarios, the increase in gas production will be outpaced by the increase in gas consumption, and the gap between natural gas supply and demand will gradually broaden. It is necessary to guard against energy security issues concerning natural gas.

In *China Natural Gas Development Report 2021*, it is pointed out that during the "13th Five-Year Plan" Period, China has made major discoveries in natural gas explorations in such provinces as Inner Mongolia, Shaanxi, Sichuan and Xinjiang. Several new large-scale gas fields have been discovered, including two large gas areas with proved reserves of over one trillion cubic meters. This will help alleviate the problem of broadening gaps in the natural gas supply and demand in the future. In the future, China should vigorously publicize the substitution effect of natural gas and other types of clean energy on the coal, open new horizons for the joint development of natural gas and new energy, and adjust the energy consumption structure.

Forest plants, as the largest carbon pool in terrestrial ecosystems, can absorb carbon dioxide in the air and lower the concentration of green house gases. Therefore, while adjusting the energy consumption structure, China should also make efforts to absorb the emitted carbon dioxide by planting trees, afforesting and protecting the balance of the ecosystem, providing guarantee for achieving the goal of carbon neutrality around 2060.

References

Anderson R G, Hoffman D L, Rasche R H (2002). A vector error-correction forecasting model of the US economy. Journal of Macroeconomics, 24(4):569–598

Cao J, Zhu B, Zhao J (曹建海, 朱波, 赵锦辉) (2005). Positive analysis of the relationship between economic growth and public investment and private investment: A vector error correction model (公共投资, 私人投资与经济增长关系的实证研究——一个向量误差修正模型). Journal of Hebei University of Economics and Trade (河北经贸大学学报), 26(2): 1–7

Chai Z, Liu C (柴正猛, 刘彩云) (2016). The impaction of Yunnan province fiscal expenditure on private investment—Based on VECM model (云南省财政支出对私人投资的影响——基于 VECM 模型 的实证研究). Special Zone Economy (特区经济), (8): 106–107

Dong F, Long R, Li Z, Dai Y (2016). Analysis of carbon emission intensity, urbanization and energy mix: evidence from China. Natural Hazards, 82(2): 1375–1391

Dong F, Yu B, Hadachin T, Dai Y, Wang Y, Zhang S, Long R (2018). Drivers of carbon emission intensity change in China. Resources, Conservation and Recycling, 129: 187–201

Hassan A, Kouhy R (2013). Gas flaring in Nigeria: Analysis of changes in its consequent carbon emission and reporting. Accounting Forum, 37(2): 124–134 https://doi.org/10.1016/j.accfor.2013.04.004

Johansen S (1988). Statistical analysis of cointegration vectors. Journal of Economic Dynamics and Control, 12(2–3): 231–254

Johansson Å, Guillemette Y, Murtin F, Turner D, Nicoletti G, de la Maisonneuve C, Bousquet G, Spinelli F (2012). Looking to 2060: Long-term global growth prospects. OECD Economic Policy Papers, No. 3

Kwiatkowski D, Phillips P C, Schmidt P, Shin Y (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root?. Journal of Econometrics, 54(1–3): 159–178

Li B, Qi Z, Ding R (李标, 齐子豪, 丁任重) (2018). Estimation and prediction of China's potential GDP growth in the process of reform (改革进程中的中国潜在 GDP 增长率:估计及预测): Modern Economic Science (当代经济科学), 40(6): 1–13

Li J, Wang Z, Liang Z, Shi J (李俊峰,王仲颖,梁志鹏,时景丽) (2004). Strategy scenarios of China's future renewable energy exploitation (我国未来可再生能源开发利用的战略思考). Energy of China (中国能源), 26(3): 4–10

Li R, Su M (2017). The role of natural gas and renewable energy in curbing carbon emission: case study of the United States. Sustainability, 9(4): 600

Ma Y, Li Y (2010). Analysis of the supply-demand status of China's natural gas to 2020.

Petroleum Science, 7(1): 132–135

Maysami R C, Koh T S (2000). A vector error correction model of the Singapore stock market. International Review of Economics & Finance, 9(1):79–96

Pfaff B (2008). Analysis of Integrated and Cointegrated Time Series with R. Springer, Science & Business Media.

Sims C A (1980). Macroeconomics and reality. Econometrica, 48(1): 1–48

Song J, Zhang Y (宋杰鲲,张宇) (2011). Scene prediction of China’s carbon emissions based on BP neural network (基于 BP 神经网络的我国碳排放情景预测). Science Technology and Engineering (科学技术与工程), 11(17): 4108–4111

Tian Z, Wang Z (田志华, 王忠) (2013). The Dynamic relationship between environmental pollution and economic growth in Guangdong province: An empirical analysis based on vector error correction model (广东省环境污染与经济增长的动态关系——基于向量误差修正模型的实证研究). Journal of Guangdong University of Business Studies (广东商学院学报), 28(6): 4–10

Wang Z, Zhang B, Liu T (2016). Empirical analysis on the factors influencing national and regional carbon intensity in China. Renewable and Sustainable Energy Reviews, 55: 34–42

Wei X (魏厦) (2019). Analysis of the influencing factors of China’s carbon emissions—Empirical research based on vector error correction model (中国碳排放影响因素分析——基于向量误差修正模型的实证研究). The World of Survey and Research (调研世界), (3): 60–65

Wooldridge J M (2015). Introductory Econometrics: A Modern Approach (6 edition). Cengage Learning.

Wu G（吴国华）(2012). Calculation and analysis of carbon dioxide emissions from fossil energy consumption: Evidence from Jinan（化石能源消费的二氧化碳排放量计算与分析——以济南市为例）. Theory Journal (理论学刊)，(3)：61–65

Xie Z, Gao X, Yuan W, Fang J, Jiang Z (2020). Decomposition and prediction of direct residential carbon emission indicators in Guangdong province of China. Ecological Indicators, Volume 115 https://doi.org/10.1016/j.ecolind.2020.106344

Zhang H, Hou H, Sun Y (张海玲, 侯晖, 孙翊) (2017). Quantitative analysis and prediction of international Brent crude oil price based on VARM and VECM (基于 VARM 和 VECM 的 Brent 油价定量分析与预测). Journal of Mathematics in Practice and Theory (数学的实践与认识), 47(12): 7–20

Zhang S (张肃) (2016). Evaluation of technology input and output relationship in China based on the vector error correction model (基于向量误差修正模型的我国科技投入, 产出关系评价). Journal of Zhongyuan Institute of Technology (中原工学院学报), 27(2): 88–92

Zhang X, Zhao X, Jiang Z, Shao S (2017). How to achieve the 2030 CO2 emission-reduction targets for China’s industrial sector: retrospective decomposition and prospective trajectories. Global Environmental Change, 44: 83–97

Zhao M, Zhang W, Yu L (赵敏, 张卫国, 俞立中) (2009). Carbon emissions from energy consumption in Shanghai city (上海市能源消费碳排放分析). Research of Environmental

Sciences (环境科学研究), 22(8): 984–989

Zeng P, Wang M, Wu Z (曾品固, 王敏, 吴中华) (2019). Has the rise of China's electronic sports industry promoted technological innovation and the development of cultural creativity?—Analysis based on VECM model (我国电竞产业的兴起推动技术创新和文化创意发展了吗?——基于 VECM 模型的分析). Western China (中国西部), (5): 76–86

Zhu Z S, Liao H, Cao H S, Wang L, Wei Y M, Yan J (2014). The differences of carbon intensity reduction rate across 89 countries in recent three decades. Applied Energy, 113: 808–815