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Analysis of influencing factors of Chinese provincial carbon emissions based on projection pursuit model and Markov transfer matrix

Lei Wen and Linlin Huang
Department of Economics and Management,
North China Electric Power University Baoding Campus, Baoding, China

Abstract

Purpose – Climate change has aroused widespread concern around the world, which is one of the most complex challenges encountered by human beings. The underlying cause of climate change is the increase of carbon emissions. To reduce carbon emissions, the analysis of the factors affecting this type of emission is of practical significance.

Design/methodology/approach – This paper identified five factors affecting carbon emissions using the logarithmic mean Divisia index (LMDI) decomposition model (e.g. per capita carbon emissions, industrial structure, energy intensity, energy structure and per capita GDP). Besides, based on the projection pursuit method, this paper obtained the optimal projection directions of five influencing factors in 30 provinces (except for Tibet). Based on the data from 2000 to 2014, the authors predicted the optimal projection directions in the next six years under the Markov transfer matrix.

Findings – The results indicated that per capita GDP was the critical factor for reducing carbon emissions. The industrial structure and population intensified carbon emissions. The energy structure had seldom impacted on carbon emissions. The energy intensity obviously inhibited carbon emissions. The best optimal projection direction of each index in the next six years remained stable. Finally, this paper proposed the policy implications.

Originality/value – This paper provides an insight into the current state and the future changes in carbon emissions.

Keywords Carbon emissions, Influencing factors, LMDI, Markov transfer matrix, Projection pursuit model

Paper type Research paper

1. Introduction

Climate change has aroused widespread concern around the world, which poses one of the greatest challenges to human beings. Greenhouse gas emissions are not considered as simple environmental affairs but involve some fields associated with the political and economic interests. These even impact the survival, development and security of one

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country (Yao and Qin, 2012). China now undergoes the rapid growth of urbanization and industrialization (Tan, 2012). There will still be the vast pressure on energy saving and emission reduction in China due to the large population, rapid development and increasingly prominent contradictions between resources and environment. Accordingly, how to promote energy savings and reduce carbon emissions in China have become a focus. In recent years, carbon emissions have been broadly studied and researched.

Kapusuzoglu (2014) studied the impact of GDP on CO_2 emissions. He suggests that nearly 4 per cent of the world's future changes in CO_2 emissions are attributed to the changes in GDP with population density as an endogenous variable. Borhan and Ahmed (2012) built a simultaneous equation and assessed the relationship between the air pollution index and economic growth between 1996 and 2006 in Malaysia. Air pollution indicators consist of carbon monoxide (CO), sulfur dioxide (SO_2), nitrogen dioxide (NO_2), ozone (O_3), as well as particulate matter (PM_{10}). As these results suggest, the primary source of pollution in Malaysia originated from transport. From 1965 to 2010, GDP exports, energy consumption and CO_2 emissions in Thailand showed a two-way causal relationship. As the results suggest, energy consumption, exports or GDP resulted in CO_2 emissions (Anatasia, 2015).

Using co-integration and vector error correction models, Istaiteyeh (2016) found that per capita GDP consequently increased per capita electricity consumption. Katircioglu (2017) investigated the impact of oil price trends on CO_2 emissions in the traditional environmental Kuznets curve of Turkey's economy. As the results suggest, the rapid changes of oil prices negatively impacted carbon emissions. Kalayci and Koksal (2015) analyzed the impacts of China's air freight industry on CO_2 emissions from 1980 to 2011 using econometric models. Using the co-integration and vector error-correction modeling techniques, Ang (2007) examined the dynamic causal relationships between pollutant emissions, energy consumption and output for France. The results suggest that economic growth had a causal impact on the increase in energy use and pollution in the long run.

The logarithmic mean Divisia index (LMDI) method is used to decompose the factors affecting carbon emissions at the multi-regional level, which was verified by Ang *et al.* (2009). By using the LMDI method, carbon emission factors were decomposed into energy intensity, per capita GDP, energy consumption and population. The impact of these factors on carbon emissions was discussed (Vinuya *et al.*, 2010; Wang, 2012). The impact of energy intensity, energy structure and output proportion on carbon emissions was analyzed by Xu *et al.* (2016). The carbon intensity factors in China's industrial sector was decomposed as energy intensity, emission coefficient and structure. As the results suggest, energy intensity was the critical factor for inhibiting carbon emissions. Carbon intensity was improved by the emission coefficient, while the structure effect did not significantly impact carbon intensity (Liu *et al.*, 2015). The drivers of carbon emissions were decomposed into industrial structure, energy intensity, etc. using the LMDI method, and the impact of these factors on carbon emissions in Beijing were explored (Wu *et al.*, 2014).

Using the fuzzy clustering algorithm, Xia *et al.* (2011) investigated an integrative assessment on the Chinese industry from 2002 to 2007, classified the industrial sectors into five types and summarized the major characteristics of each type. Industries in Tianjin fell into four types, and the features of "emission-efficiency" were analyzed by conducting cluster analysis (Shao *et al.*, 2014). Yue and Zhu (2010) divided the carbon emission types of 30 provinces, except for Tibet, into four regions in accordance with two indicators (i.e. the emission and discharge efficiency) using the cluster analysis method. Based on a projection pursuit model, carbon emissions in China from 1996 to 2008 were studied (Yao and Qin, 2012). Based on the accelerated genetic algorithm and projection pursuit method, Zhang (2016) conducted cluster analysis of carbon emissions in each province in China, obtained the optimal projection direction that determined the degree of all factors and classified all regions in China into four types.

In recent years, the Markov prediction model has been used to predict the energy structure, as well as carbon emissions. Niu *et al.* (2012) came up with a method to calculate the transfer matrix, which was verified by the statistical data of energy consumption structure in a region. The research status and existing problems of carbon emissions in Jiangsu Province were analyzed by Zhu *et al.* (2015), and the Grey Markov prediction model was used to forecast carbon emissions from 2014 to 2020 in line with the data from 2002 to 2013. As the results suggest, carbon emissions in Jiangsu Province would reach nearly 334 million tons in 2020, and there would have been a rapid growth in carbon emissions in 2020. Huang and Shang (2015) built the traditional Grey Markov prediction model and improved the actual error of the initial prediction of the Grey Markov prediction. The improved new model was adopted to calculate carbon emissions in China. As the results suggest, the new model had higher accuracy and effectiveness in comparison with the traditional Grey Markov model.

In contrast to the wealth of studies primarily exploring the factors affecting carbon emissions in China, the contribution of each factor influencing carbon emissions and the prediction of these factors have been rarely discussed. To fill these gaps, we decomposed the factors affecting carbon emissions into per capita carbon emissions, industrial structure, energy intensity, energy structure and per capita GDP using the LMDI model, and the contributions of the five influencing factors to carbon emissions from 2001 to 2014 were studied based on the data of 2000. In line with the study of Shao *et al.* (2014), this paper chose 2000 year as the base year. Using the projection pursuit model, this paper investigated the optimal projection direction of each indicator from 2000 to 2014. The optimal projection direction can be well expressed as the influence degree of factor. Using the Markov transfer matrix, we predicted the weights of the five indexes in the next six years. By comparing the optimal projection direction and investigating carbon reduction ability and potential, this paper proposed the corresponding policy measures and suggestions.

2. Methodology

2.1 Carbon emission calculation method

In accordance with China's central types of energy consumption, this paper primarily studied eight types of energy (i.e. coal, coke, crude, gasoline, kerosene, diesel, fuel oil and natural gas). There are some limitations that standard coal consumption was obtained by multiplying the energy consumption based on the standard coal coefficient. Thus, this paper calculated the standard coal consumption based on the average net calorific values of all energy and the CO_2 emission factor. Given this, carbon emissions may be calculated as:

$$C = \sum_i E_i \times Q_i \times EF_i \times {}^{12}/_{44} \tag{2-1}$$

where, i denotes the type of energy consumed; C is the total carbon emissions; E_i is the total consumption of energy i; Q_i is the average net calorific value of energy i; and EF_i is the CO_2 emission factor.

2.2 Decomposition analysis

Using the LMDI method, this paper subdivided the change of carbon emissions in China into five factors (i.e. per capita carbon emissions, industrial structure, energy intensity, energy structure and per capita GDP) and analyzed the contribution and the rate of various factors to carbon emissions:

$$C = \sum_i \frac{C_i}{E_i} \times \frac{E_i}{E} \times \frac{E}{Y} \times \frac{Y}{P} \times P = \sum_i F_i S_i I_i RP \tag{2-2}$$

$$\frac{C}{P} = A = \sum_i F_i S_i I_i R \tag{2-3}$$

where, C_i denotes carbon emissions of energy i; E_i is the consumption of energy i; E is the total energy consumption; Y is GDP; P is the population; $\frac{C}{P}$ is per capita carbon emissions; $F_i = \frac{C_i}{E_i}$ is the carbon emissions intensity, i.e. the consumption of carbon per unit of energy i, which can be considered as a constant; $S_i = \frac{E_i}{E}$ is the energy structure; and $I = \frac{E}{Y}$ is the energy intensity, which was defined as the energy consumption of per unit of GDP. Because energy intensity is closely associated with the industrial structure, the impact of energy intensity on carbon emissions was measured by the industrial structure and energy intensity; $R = \frac{Y}{P}$ is per capita GDP representing the degree of economic development.

The change in carbon emissions from the base year to year T can be calculated as:

$$\Delta C = C^T - C^0 = \Delta F + \Delta S + \Delta I + \Delta R + \Delta P \tag{2-4}$$

where, ΔF, ΔS, ΔI, ΔR, ΔP are the contributions of carbon intensity, energy structure, energy intensity and industrial structure, per capita GDP and population, respectively. The decomposition equations may be calculated as follows:

$$\Delta F = \sum_i L\left(C^T, C^0\right) \ln\left(\frac{F_i^{\,T}}{F_i^0}\right) \tag{2-5}$$

$$\Delta S = \sum_i L\left(C^T, C^0\right) \ln\left(\frac{S_i^{\,T}}{S_i^0}\right) \tag{2-6}$$

$$\Delta I = \sum_i L\left(C^T, C^0\right) \ln\left(\frac{I_i^{\,T}}{I_i^0}\right) \tag{2-7}$$

$$\Delta R = \sum_i L\left(C^T, C^0\right) \ln\left(\frac{R_i^{\,T}}{R_i^0}\right) \tag{2-8}$$

$$\Delta P = \sum_i L\left(C^T, C^0\right) \ln\left(\frac{P_i^{\,T}}{P_i^0}\right) \tag{2-9}$$

where:

$$L\left(C^T, C^0\right) = \begin{cases} \left(C_i^{\,T} - C_i^0\right) / \left(\ln C_i^{\,T} - \ln C_i^0\right) & C_i^{\,T} \neq C_i^0 \\ C_i^{\,T} & C_i^{\,T} = C_i^0 \\ 0 & C_i^{\,T} = C_i^0 = 0 \end{cases} \tag{2-10}$$

And, the contribution rates of various factors may be calculated as follows:

$$r_F = \frac{\Delta F}{\Delta C} \times 100\%, r_S = \frac{\Delta S}{\Delta C} \times 100\%, r_I = \frac{\Delta I}{\Delta C} \times 100\%,$$
$$r_R = \frac{\Delta R}{\Delta C} \times 100\%, r_P = \frac{\Delta P}{\Delta C} \times 100\%$$

where r_F, r_S, r_I, r_R, r_P are the contribution rate of carbon intensity, energy structure, energy intensity and industrial structure, per capita GDP and population, respectively.

2.3 Projection pursuit

The projection pursuit model, proposed by Kruskal (1969), is a multi-data processing method projecting high-dimensional data into low-dimensional space under numerical optimization calculation, to find out the optimal projection reflecting the data structure characteristics. The model has no special requirements of data, and sample size can ignore the effects of variables not associated with the structure and features of the data, and can efficiently solve various practical problems (Kruskal, 1969). The specific steps are as follows:

- *Step 1*: Normalize the evaluation index. The normalization process is capable of eliminating the dimension of the index and unifying the range of the evaluation index.

  Normalize the forward indicator as:

$$x_{(i,j)} = \frac{x^*_{(i,j)} - x_{\min(j)}}{x_{\max(j)} - x_{\min(j)}} \tag{2-11}$$

  Normalize the negative indicator as:

$$x_{(i,j)} = \frac{x_{\max(i,j)} - x^*_{(i,j)}}{x_{\max(j)} - x_{\min(j)}} \tag{2-12}$$

  where, $\{x^*_{(i,j)} | i = 1, 2 \ldots n, j = 1, 2 \ldots p\}$, the sample set of each evaluation index, is the index j of sample i; n and p refer to the sample size and the number of indicators, respectively; $x_{\max(j)}$ and $x_{\min(j)}$ are the maximum and minimum values of the index j, respectively j; $x_{(i,j)}$ is the normalized sequence of indicators.

- *Step 2*: Construct a projection function $Q_{(a)}$. The p-dimensional data, $\{x^*_{(i,j)} | i = 1, 2 \ldots n, j = 1, 2 \ldots p\}$, is incorporated into $Z_{(i)}$, one-dimensional projection value with the projection direction $a = \{a_{(1)}, a_{(2)}, \ldots a_{(p)}\}$, the unit vector in the projection pursuit method.

  Where:

$$Z_{(i)} = \sum_{j=1}^{p} a_{(j)} x_{(i,j)}, i = 1, 2, \ldots, n \tag{2-13}$$

  When $Z_{(i)}$ is incorporated, the distribution of the projection value is as follows: the local projection point is as dense as possible; it is better to gather into several points; the whole projection point is scattered as much as possible. Accordingly, the projection function may be expressed as:

$$Q_{(a)} = S_z D_z \tag{2-14}$$

where:

$$S_z = \sqrt{\frac{\sum_{i=1}^{n} \left(Z_{(i)} - E_{(z)}\right)^2}{n-1}} \tag{2-15}$$

$$D_z = \sum_{i=1}^{n} \sum_{j=1}^{n} \left(R - r_{(i,j)}\right) \cdot u\left(R - r_{(i,j)}\right) \tag{2-16}$$

where:

$$r_{(i,j)} = |Z_{(i)} - Z_{(j)}| \tag{2-17}$$

$$u_{(t)} = \begin{cases} 1 & t \geq 0 \\ 0 & t < 0 \end{cases} \tag{2-18}$$

Here, S_z denotes the standard deviation of $Z_{(i)}$; D_z is the local density of $Z_{(i)}$; $E_{(z)}$ is the average of the sequence; R is the window radius of D_z; $r_{(i,j)}$ is the distance between the samples; $u_{(t)}$ is the unit step function.

- *Step 3*: Optimize the projection index function. When the sample set of each index is gained, the projection function varies only with the projection direction. Thus, the optimal projection direction may be calculated by solving the maximum problem of the projection function as follows:

$$\begin{aligned} &Max\colon Q_{(a)} = S_z D_z \\ &s.t. \sum_{j=1}^{p} a^2{}_{(j)} = 1 \end{aligned} \tag{2-19}$$

2.4 Markov transition matrix

The Markov transfer matrix, proposed by Russian mathematicians A. A. Markov at the beginning of the twentieth century, is a useful tool to predict the status of the future (Rabiner, 1990). By exploring the initial probabilities of different states and transition probabilities between states, it considers the time series as a stochastic process and determines the trend of the state change to predict the future (He, 2011). Specific steps are as follows:

- *Step 1*: Input experimental data and processing the data. A Markov chain with a set of states $\{s_1, s_2, \ldots s_n\}$ and the transfer matrix $A = (a_{ij})_{n\times n}$, where, $a_{ij} \geq 0$. The index j in t year is valued as $y_t(j)$, $j = 1, 2\ldots k$; $t = 1, 2, 3 \ldots n$; the index j in $t+1$ year is valued as $y_{t+1}(j)$, $j = 1, 2 \ldots k$; $t = 1, 2, 3 \ldots n$, where, $\sum_{j=1}^{k} a_{ij} = 1, i = 1, 2, \ldots n$.
- *Step 2*: Determine the Markov transfer matrix using the least squares method. According to the properties of Markov chain, $y_{t+1}(j) = \sum_{t=1}^{n} y_t(i)a_{ij}, (j = 1, 2, \ldots k)$ can be yielded. And, the transfer matrix A is yielded by solving the equation using the least squares method.
- *Step 3*: Predict the future state according to the Markov transfer matrix.

2.5 Data resources

The data for eight types of fuels in each province studied in this paper were collected from the *China Statistic Yearbook* and *China Energy Statistical Yearbook* from 2000 to 2014 (e.g. coal, coke, crude, gasoline, kerosene, diesel, fuel oil and natural gas). The carbon emissions were calculated by energy consumption, average net calorific value of energy and CO_2 emission factor, where the average net calorific of energy, and the CO_2 emission factor originated from the IPCC Guidelines for National Greenhouse Gas Inventories (2006). This paper selected five factors as influencing factors (i.e. per capita carbon emissions, energy intensity, industrial structure, energy structure and per capita GDP). Per capita carbon emissions were acquired by the total carbon emissions of each province divided by the total population of each province, in which the whole carbon emissions were gained by adding the carbon emissions of all types of energy, and the total population originated from *National Bureau of Statistics of China*. Because energy consumption is dominated by coal in various provinces, energy structure was acquired by the proportion of coal consumption to total consumption. Energy intensity was obtained by energy consumption divided by GDP, where GDP of each province came from *National Bureau of Statistics of China*. The industrial structure was obtained by sharing the added value of the secondary industry in the gross product, in which the added value of the secondary industry and the gross product originated from *National Bureau of Statistics of China*. Per capita GDP was acquired by GDP divided by the total population.

3. Results and discussion

3.1 Decomposition of carbon emissions factors

In total, 30 provinces in China were explored using the LMDI method. The contributions and rates of factors to the increase of carbon emissions in China are listed in Table I. The contribution values on carbon emissions of the provinces in China about five factors from 2000 to 2014 are listed in Table II. To more clearly compare the contribute values of the provinces, Table II was converted into Figures 1 to 5. The impact of five indicators was analyzed.

Table I suggests that, in the last 15 years, per capita GDP had the largest contribution to carbon emissions, taking up 67.42 per cent. The contribution of per capita GDP to carbon emissions had always been positive, showing an increase, and the growth was still fast in 2005. Due to the new normal of China's economy, the national economic slowdown policy, per capita GDP growth has been slowed down since 2011. The economic growth could directly affect carbon emissions. With the decline of per capita GDP growth, the total carbon emissions would decrease accordingly. Accordingly, new normal of China's economy contributes to carbon control.

Per capita GDP in all provinces is positive, as shown in Figure 1, suggesting that economic development accelerates the rise of carbon emissions in China. The contributions of per capita GDP in Hebei, Shanxi, Shandong, Inner Mongolia and Liaoning to national carbon emissions reached 18.19×10^8 *t*, 20.21×10^8 *t*, 22.26×10^8 *t*, 15.79×10^8 *t* and 16.79×10^8, taking up 7.03, 7.81, 8.60, 6.10 and 6.49 per cent, respectively. The industrial structure of these provinces is a typical energy-intensive structure. Chemistry, energy and steal industry are the economic foundation of these provinces.

The contributions of per capita GDP on Beijing, Ningxia and Hainan were just 3.58×10^8 *t*, 2.68×10^8 *t*, 0.58×10^8 *t*, taking up 1.39, 1.04 and 0.22 per cent, respectively. In Beijing, high-tech industries take up a relatively big proportion in industrial structure. Ningxia was a big agricultural province. In Hainan, tourism was the primary industry, and its

Table I. Contribution value and rate of carbon emissions factors

	Industrial structure		Energy structure		Energy intensity		Per capita GDP		Population	
Years	Value (10^4)	Rate (%)	Value (10^4)	Rate (%)	Value (10^4)	Rate (%)	Value (10^4)	Rate (%)	Value (10^4)	Rate (%)
2001	–0.07	–4.04	–0.0039	–0.21	–0.67	–36.56	1.08	59.05	0.0025	0.14
2002	–0.06	–1.59	0.0458	1.27	–0.99	–27.59	2.35	65.08	0.16	4.47
2003	0.43	6.62	0.21	3.21	–1.13	–17.38	4.44	68.54	0.28	4.25
2004	0.80	7.61	0.11	1.03	–1.72	–16.39	7.45	71.07	0.409	3.90
2005	1.35	4.37	0.19	0.62	–2.17	–7.01	26.78	86.52	0.46	1.48
2006	1.81	9.05	0.26	1.32	–3.29	–16.48	13.98	70.02	0.63	3.14
2007	1.93	7.37	0.34	1.32	–5.21	–19.92	17.86	68.33	0.80	3.06
2008	2.25	6.84	0.33	1.02	–7.81	–23.73	21.54	65.44	0.98	2.97
2009	1.92	5.41	0.13	0.38	–8.63	–24.28	23.69	66.68	1.16	3.26
2010	2.57	5.92	–0.04	–0.10	–10.95	–25.25	28.36	65.37	1.46	3.36
2011	2.91	5.57	0.22	0.43	–13.46	–25.81	33.92	65.05	1.64	3.15
2012	2.49	4.44	–0.01	–0.02	–15.27	–27.25	36.49	65.11	1.78	3.17
2013	1.67	2.84	–0.12	–0.21	–17.09	–28.99	38.17	64.74	1.896	3.22
2014	1.23	1.99	–0.42	–0.68	–18.44	–29.82	39.75	64.27	2.006	3.24
total	21.22	4.84	1.25	0.28	–106.83	–24.35	29.58	67.42	13.65	3.11

Table II. Contribution values on carbon emission of the provinces in China about five factors from 2000 to 2014

	Industrial structure		Energy structure		Energy intensity		Per capita GDP		Population	
Provinces	Value (10^4)	Rate (%)	Value (10^4)	Rate (%)	Value (10^4)	Rate (%)	Value (10^4)	Rate (%)	Value (10^4)	Rate (%)
Beijing	–1.04	–4.70	–0.88	–5.97	–3.82	–3.94	3.58	1.39	0.79	6.84
Tianjin	0.03	0.12	–0.11	–0.75	–3.32	–3.43	4.76	1.84	0.63	5.43
Hebei	0.54	2.43	–1.96	–13.27	–5.44	–5.62	18.19	7.03	0.77	6.69
Shanxi	2.31	10.46	–0.37	–2.53	–9.02	–9.32	20.21	7.81	0.896	7.75
Inner	2.397	10.84	–0.13	–0.88	–3.50	–3.62	15.79	6.10	0.196	1.69
Liao Ning	–0.102	–0.46	–0.93	–6.32	–8.79	–9.08	16.79	6.49	0.35	3.03
Jilin	0.93	4.21	0.24	1.62	–3.28	–3.38	6.58	2.54	–0.006	–0.05
Heilong Jiang	–1.24	–5.63	1.07	7.23	–4.42	–4.56	7.92	3.06	–0.067	–0.58
Shang Hai	–0.69	–3.12	–1.298	–8.78	–4.65	–4.80	5.396	2.09	1.73	14.95
Jiangsu	0.14	0.65	–0.006	–0.04	–6.24	–6.45	16.84	6.51	0.62	5.41
Zhe Jiang	–0.39	–1.77	0.052	0.35	–4.09	–4.22	9.86	3.81	0.81	6.97
Anhui	1.69	7.66	0.17	1.18	–4.04	–4.17	8.45	3.27	–0.11	–0.91
Fujian	0.42	1.92	0.17	1.17	–0.69	–0.72	4.18	1.62	0.16	1.38
Jiangxi	1.14	5.16	–0.02	–0.16	–1.97	–2.04	4.37	1.69	0.10	0.90
Shan Dong	1.14	5.17	1.13	7.62	–1.89	–1.95	22.26	8.60	0.76	6.54
Henan	1.70	7.71	0.30	2.04	–4.36	–4.50	14.49	5.60	–0.14	–1.18
Hubei	0.74	3.37	0.095	0.64	–3.49	–3.61	9.49	3.67	0.009	0.08
Hunan	0.80	3.64	0.65	4.39	–1.72	–1.78	6.91	2.67	–0.13	–1.14
Guang Dong	0.41	1.84	1.32	8.95	–6.32	–6.52	12.74	4.93	1.43	12.36
Guangxi	0.48	2.16	–0.59	–3.98	–1.09	–1.12	4.12	1.59	–0.11	–0.91
Hainan	0.07	0.33	–0.35	–2.40	0.11	0.11	0.58	0.22	–0.05	–0.48
Chong Qing	0.31	1.39	–0.31	–2.07	–2.19	–2.27	3.77	1.46	–0.09	–0.75
Sichuan	1.26	5.68	–0.78	–5.27	–2.49	–2.57	7.92	3.06	–0.27	–2.31
Guizhou	0.14	0.65	–0.15	–1.02	–3.14	–3.25	7.24	2.80	–0.296	–2.56
Yunnan	–0.03	–0.15	–0.45	–3.08	–0.41	–0.42	4.49	1.74	0.197	1.70
Shannxi	0.88	3.98	0.22	1.48	–1.52	–1.57	8.00	3.09	0.011	0.09
Gansu	0.31	1.42	0.24	1.66	–2.32	–2.39	4.51	1.74	–0.04	–0.33
Qinghai	0.06	0.29	–0.13	–0.87	–0.48	–0.49	0.92	0.35	–0.05	–0.43
Ningxia	0.195	0.88	0.06	0.43	–0.07	–0.07	2.68	1.04	0.12	1.06
Xinjiang	0.49	2.21	0.57	3.83	–1.94	–2.00	5.69	2.20	0.64	5.51

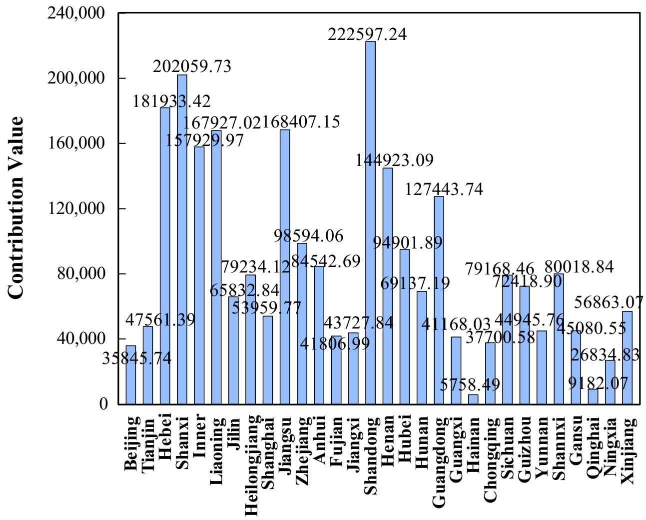

Figure 1.
Contribution values on carbon emissions of the provinces in China about per capita GDP from 2000 to 2014

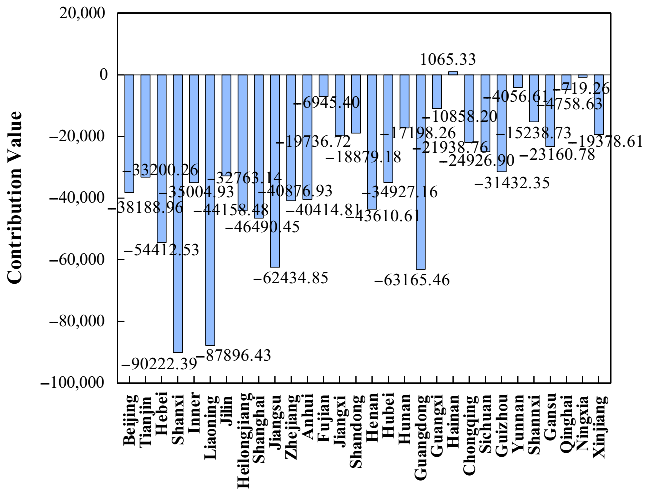

Figure 2.
Contribution values on carbon emission of the provinces in China about energy intensity from 2000 to 2014

development was driving the growth of the economy. Energy consumption in these provinces was small.

Energy intensity improvements efficiently alleviated the increasing of carbon emissions, as shown in Table I. From 2000 to 2014, the total of contribution value of energy intensity to carbon emissions change was –106.825 × 10^8 t, with the average contribution ratio of 24.35 per cent. The contribution of the energy intensity to carbon emissions had always been

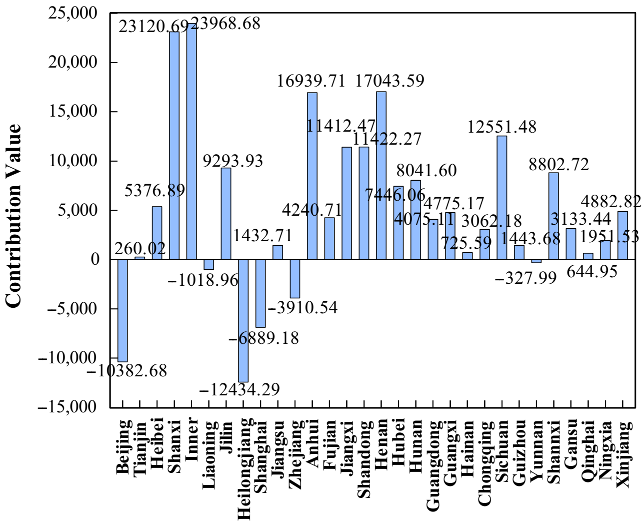

Figure 3.
Contribution values on carbon emission of the provinces in China about industrial structure from 2000 to 2014

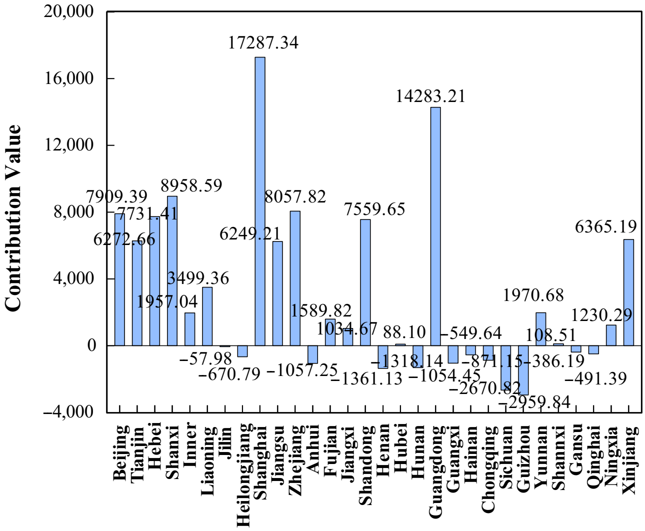

Figure 4.
Contribution values on carbon emission of the provinces in China about population from 2000 to 2014

negative, and the degree of that was getting bigger and bigger, suggesting that active control of energy intensity would inhibit carbon emissions.

As suggested in Table II and Figure 2, from 2000 to 2014, only the energy intensity effect value of Hainan province was positive, i.e. $0.11 \times 10^8\ t$, taking up 0.11 per cent. The energy intensity in Hainan province promoted carbon emissions.

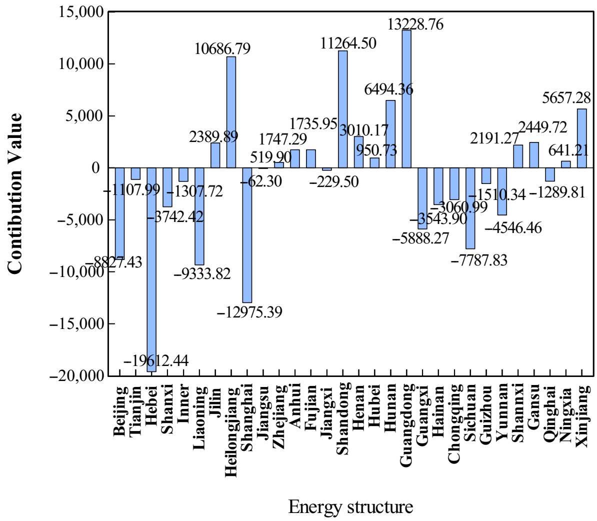

Figure 5.
Contribution values on carbon emission of the provinces in China about energy structure from 2000 to 2014

Besides, the energy intensity effect values of other provinces were negative. In Hebei, Shanxi, Liaoning, Jiangsu, Henan and Guangdong, the degree of inhibition was relatively large as $-5.44 \times 10^8\,t$, $-9.02 \times 10^8\,t$, $-8.79 \times 10^8\,t$, $-6.24 \times 10^8\,t$, $-4.36 \times 10^8\,t$, $-6.32 \times 10^8\,t$, respectively. These areas were energy-intensive regions. Improving energy efficiency would alleviate the increase of carbon emissions in China.

In Beijing, Jilin, Fujian, Jiangxi, Guangxi, Yunnan, Qinghai, Ningxia and Xinjiang, the degree of inhibition was small as $-3.82 \times 10^8\,t$, $-3.28 \times 10^8\,t$, $-0.69 \times 10^8\,t$, $-1.97 \times 10^8\,t$, $-1.09 \times 10^8\,t$, $-0.41 \times 10^8\,t$, $-0.48 \times 10^8\,t$, $-0.07 \times 10^8\,t$, $-1.94 \times 10^8\,t$, respectively. These areas were non-energy-intensive regions. Agriculture, high-tech industries and tourism were the focus of development. Energy intensity had less effect on carbon emissions. These areas had reduced the investment in primary energy consumption, and the energy structure had been reasonably improved and adjusted.

Table I shows that changes in the industrial structure around contributed to $21.22 \times 10^8\,t$, taking up 4.84 per cent, which caused the cumulative increase in carbon emissions. The contribution of the industrial structure to carbon emissions was changed from being negative to positive in 2003. From 2003 to 2010, the contribution rate of industrial structure for several years was relatively stable, suggesting the share of the secondary industry in the gross product increased increasingly faster. Yet after 2010, the contribution rate of industrial structure started to fall. China began to focus on industrial structure transformation and propel the supply-side structural reform.

The contribution of the industrial structure of Beijing, Liaoning, Heilongjiang, Shanghai, Yunnan and Zhejiang was negative, respectively $-1.04 \times 10^8\,t$, $-0.102 \times 10^8\,t$, $-1.24 \times 10^8\,t$, $-0.69 \times 10^8\,t$ and $-0.39 \times 10^8\,t$, as shown in Figure 3. The industrial structure of these areas hindered the increase in carbon emission. In Beijing, Shanghai and Zhejiang, rapid economic growth and sizable investment in science and technology helped to gain more considerable efforts to develop new energy. Besides, the vigorous development of the service industry led to a decline in the proportion of the second industry. In Yunnan, tourism was the primary industry, and its development was driving the growth of the economy. Energy consumption was small. Carbon emissions would be controlled. Otherwise, the contribution of the industrial structure in other energy-intensive provinces, such as Inner Mongolia and Shanxi, was positive and great, respectively 2.397×10^8 *t* and 2.31×10^8 t. In these areas, energy consumption was very high. Economic development would be driven by the secondary industry. The industrial structure of these provinces enormously expedited the changes in carbon emissions.

Table I shows that changes in population around contributed to 13.64×10^8 *t*, which caused the cumulative increase in carbon emissions, taking up 3.11 per cent. According to the National Bureau of Statistics of China, the population of the provinces has been growing from 2000 to 2014. According to the basic situation of China's vast population base and the "Two Children" policy, the trend would continue. The large population would undoubtedly bring the increase in consumption, probably leading to augment in carbon emissions.

From 2000 to 2014, the overall population effect was positive. Yet the population effect of Jilin, Heilongjiang, Anhui, Henan, Hunan, Guangxi, Hainan, Chongqing, Sichuan, Guizhou, Gansu and Qinghai was negative, respectively, -0.006×10^8 *t*, -0.067×10^8 *t*, -0.11×10^8 *t*, -0.14×10^8 *t*, -0.13×10^8 *t*, -0.11×10^8 *t*, -0.05×10^8 *t*, -0.09×10^8 *t*, -0.27×10^8 *t*, -0.296×10^8 *t*, -0.04×10^8 *t* and -0.05×10^8 *t*, as shown in Figure 4. This suggested that the population in these provinces hindered the increase in carbon emissions, while the population effect in other provinces increased carbon emissions. Thus, to efficiently deal with carbon emissions, the population of the provinces with the positive effect should be controlled and the people of the regions with adverse impact should be encouraged.

Table I shows that, in the last 15 years, the energy structure had little contribution to carbon emissions, with the average contribution ratio of only 0.28 per cent. The overall impact of energy structure adjustment on carbon emissions was small. Before 2007, the contribution of the energy structure to carbon emissions showed an increase and underwent an obvious growth in 2003. At this stage, the energy structure intensified carbon emissions, and the degree was rising. China boosted rapid economic development primarily through the heavy industry, which would cause the increase of carbon emissions. But, beginning in 2008, the energy structure effect has been declining in the whole. After 2012, the energy structure effect became negative. The energy structure hindered the increase of carbon emissions, and the degree was rising. At this time, China started to stress the energy structure adjustment. The optimization and upgrading of energy structure had effectively hindered the increase of carbon emissions.

From 2000 to 2014, the overall energy structure effect was positive. Yet, provinces with adverse energy structure effects are more than those with positive energy structure effect, as shown in Figure 5. That is to say, every province had gradually made energy structure adjustment and had some improvement. In Shandong, Henan shannxi and Gansu, the contribution of energy structure is positive as 1.13×10^8 *t*, 0.3×10^8 *t*, 0.22×10^8 *t* and 0.24×10^8 *t*, respectively. In these areas, reducing coal consumption and promoting the exploitation of new energy were the focus of development. China had the foundation for renewable energy sources and clean energy, such as wind power, geothermal and natural gas. The transformation of energy structure was achievable.

3.2 The optimal projection direction analysis

The optimal projection direction of carbon emissions indicators can be obtained using the projection pursuit method, as shown in Table III. The optimal projection direction could be

Years	Per capita carbon emissions	Energy intensity	Energy structure	Industrial structure	Per capita GDP
2000	0.5892	0.5559	0.4083	0.3819	0.1767
2001	0.5998	0.3557	0.6533	0.1041	0.2759
2002	0.6122	0.4000	0.2853	0.5573	0.2705
2003	0.5234	0.6652	0.5241	0.0886	0.0335
2004	0.5740	0.6412	0.5016	0.0682	0.0554
2005	0.5614	0.5334	0.5748	0.2593	0.0516
2006	0.3317	0.5043	0.7322	0.3089	0.0645
2007	0.7247	0.4481	0.1918	0.4704	0.1268
2008	0.4798	0.4460	0.6470	0.3878	0.0421
2009	0.5146	0.5179	0.4958	0.4677	0.0490
2010	0.4024	0.4576	0.6200	0.4927	0.0392
2011	0.5440	0.3237	0.6186	0.4154	0.2099
2012	0.4700	0.3320	0.6454	0.4972	0.0712
2013	0.3354	0.4600	0.5827	0.5781	0.0467
2014	0.3652	0.3854	0.6673	0.5152	0.0856

Table III.
The optimal projection direction of indicators

well described as the influence degree of various factor on carbon emissions. Taking each five-year plan as a stage, this paper analyzed the influence degree of various factor.

There is a difference in the influence degree of factors in various periods, as shown in Table III. In the period of "10^{th} Five-Year" plan, the optimal projection direction of per capita carbon emissions in each year was the largest as 0.5998, 0.6122, 0.5234, 0.5740 and 0.5614. Besides, the optimal projection direction value of energy intensity and energy structure were also large. It could be argued that per capita carbon emissions, energy structure and energy intensity had a significant impact on carbon emissions in China in these five years. China was in a crucial period of rapid development. All aspects were in a significant growth trend. Energy consumption had also increased significantly, in particular the coal consumption, contributing to the increase of carbon emissions.

The impact of per capita GDP on carbon emissions was relatively small as 0.2759, 0.2705, 0.0335, 0.0554 and 0.0516. In the tenth five-year plan, economic development was relatively fast, whereas GDP was still relatively low, which caused a little effect on carbon emissions. As industrial development was not very mature, the impact of industrial structure on carbon emissions was not obvious.

In the "11^{th} Five-Year" plan, except for 2007, the optimal projection directions of energy structure in 2006, 2008, 2009 and 2010 were relatively large, respectively, 0.7322, 0.6470, 0.4958, 0.6200, as shown in Table III. In these four years, energy structure was the primary factor affecting carbon emissions. Due to the Beijing Olympic Games, all over the country were reducing carbon emissions and controlling pollution, so the consumption of coal fell sharply. Energy structure had undergone huge changes, which had a significant impact on carbon reduction.

Besides, the optimal projection direction values of per capita carbon emissions and energy intensity were also large. Energy intensity would also drop significantly with the decline of high-polluted energy consumption. Thus, carbon emissions were affected by the change of energy intensity. The sustained growth of the population accelerated the increase of carbon emissions.

In the "12^{th} Five-Year" plan, the optimal projection direction of energy structure in each year was the largest as 0.6186, 0.6454, 0.5827, 0.6673, as shown in Table III. Besides, the optimal projection direction value of the industrial structure is also large. It could be argued that in these five years, energy structure and industrial structure had a crucial impact on carbon emissions in various provinces. The "12th Five-Year Plan" required to adjust the industrial structure, vigorously develop the service industry, reduce the development of primary energy and energetically develop clean energy and new energy. Energy structure and industrial structure have been optimized. Carbon emissions from the consumption of coal and the high-energy consumption industry had been significantly reduced.

Energy intensity and per capita GDP had little impact on carbon emissions. The pace of economic growth had been slowed down, but the total economy had been on the rise. Per capita GDP did not undergo obvious change, resulting in the little impact on carbon emissions. The impact of energy intensity on carbon emissions also was not large.

3.3 Prediction analysis

Based on the optimal projection direction of 2000 to 2014, the optimal projection direction prediction value of 2015 to 2020 was obtained using Markov transfer matrix, as listed in Table IV.

From the horizontal perspective, the optimal projection direction of each index in the six years from the largest to the smallest is energy structure, industrial structure, per capita carbon emissions, energy intensity, per capita GDP, as shown in Table IV. The trend of each index remains stable. Energy structure and industrial structure still will have the greatest impact on carbon emissions in the next few years. The exploitation and utilization of clean energy, as well as the development of the tertiary industry, turn out to be the developing trends of the present and the next few years. Carbon emissions will be directly controlled.

From the vertical view, the optimal projection direction of energy intensity has been risen steadily from 2015 to 2020 year, while the optimal projection direction of the industrial structure has been fallen. The optimal projection directions of the other three indexes are fluctuated, but roughly stable. By 2020, energy restructuring would be basically mature. Even in some economically backward and energy-intensive areas, industrial structure optimization and upgrading are also basically completed. The industrial reorganization has not been critical for the control of carbon emissions. As a result, the impact of the industrial structure on carbon emissions has been fallen from 2015 to 2020 year. With the continuous improvement of energy efficiency, energy intensity is, therefore, declining, which plays an important role in carbon emissions control.

4. Conclusions and policy implications

In this paper, carbon emissions from 2000 to 2014 in China were analyzed using the projection pursuit and Markov model. Through the LMDI decomposition model, several factors affecting carbon emission were identified, i.e. per capita carbon emissions,

Year	per capita carbon emission	Energy intensity	Energy structure	Industrial structure	per capita GDP
2015	0.4727	0.3968	0.5654	0.5364	0.1083
2016	0.4364	0.4262	0.6190	0.4870	0.0872
2017	0.4727	0.4237	0.5846	0.4946	0.1033
2018	0.4618	0.4320	0.6000	0.4798	0.0997
2019	0.4735	0.4321	0.5887	0.4811	0.1055
2020	0.4712	0.4354	0.5929	0.4753	0.1052

Table IV. The best projection direction prediction value in 2015-2020 industrial structure, energy intensity, energy structure and per capita GDP. Based on the projection pursuit method, the optimal projection directions of five influencing factors in 30 provinces (except for Tibet) were acquired, and the difference of the optimal projection direction of each element in 2003, 2008 and 2013 was studied. The weight of each index in the next five years was predicted, and the corresponding suggestions were proposed using the Markov transfer matrix according to the data from 2000 to 2014. Specific conclusions are as follows:

- Based on the LMDI decomposition model, five influencing factors were determined (e.g. per capita carbon emissions, industrial structure, energy intensity, energy structure and per capita GDP). Based on the 2000 year, the contribution rates of the five influencing factors to the carbon emissions in the period from 2001 to 2014 were analyzed. The contribution of per capita GDP to carbon emissions was the most prominent (Xu *et al.*, 2016); energy intensity has negative impact on carbon emissions, which is a crucial factor in the reduction of carbon emissions. The contribution of energy structure and industrial structure to carbon emissions was changed from negative to positive and increased generally. The decomposition results of this paper were consistent with the study of Shao *et al.* (2014) and Liu *et al.* (2015).
- The classification standards of 30 provinces (except for Tibet), the optimal projection direction of the five factors, were obtained using the projection pursuit model, reflecting the degree of various influencing factors on carbon emissions in different years. Given the national policy, the paper analyzed the change of the influence degree on carbon emissions of five indicators in three periods.
- The relative weight values of the five indexes in the next six years were predicted using the Markov transfer matrix according to the optimal projection direction of each index from 2000 to 2014. Moreover, the relative weight difference of the optimal projection direction was not significant and relatively stable.

Based on the noted findings, the policy of promoting energy savings and emission reduction in the process of economic development is continuously supposed to be improved and constructed. Specific recommendations are as follows:

- Improve energy structure and proactively develop renewable energy. Greater attempt should be made to vigorously adjust and improve the energy structure in various regions, especially Gansu, Heilongjiang and other provinces with relatively rich energy resources but backward economic progress. Green energy and clean energy should be vigorously developed and exploited to decrease the share of high-carbon energy consumption. Besides, it is necessary to vigorously facilitated building energy saving, encourage the use of energy-saving appliances and reduce the energy consumption of the unit production.
- Pay more attention to readjusting industrial structure of the provinces and autonomous regions. Tertiary industries (e.g. the tourism and services industry) should be vigorously developed. The government should adjust the industrial structure, making it gradually transfer from resource-intensive to intelligence-intensive. The disparity of economic development in China is prominent, so it is indispensable to formulate various industrial structure adjustment policies and measures for the actual situation of each province in China. For the provinces in the process of transferring from the primary industry to the secondary industry, they

should adhere to the road of sustainable development and prioritize the improvement of the technology level and the utilization of clean energy. For some of the more developed provinces, they should attach importance to developing high-tech industry, new energy industry and modern service industry. For the provinces prioritizing the traditional coal production or high-energy consuming heavy industry, the efficiency of existing technology should be proactively improved, and the clean industry should be actively facilitated.

- Reasonably control the coal production and improving energy efficiency. The government should limit the scale of high-energy-consuming production enterprises. The advanced technology should be introduced to increase the energy efficiency (e.g. coal moisture control). For the traditional coal production enterprises, the development of other renewable energy or green energy could be gradually improved, which would contribute to control carbon emissions.
- Establish an effective regional cooperation mechanism among the provinces in China (Renukappa *et al.*, 2013). For those provinces with low total CO_2 emissions and fast the deterioration, the government should stress its CO_2 emissions reduction based on the condition of CO_2 emissions reduction in the provinces. The establishment of CO_2 emissions accounting and comparison system is urgently required. Furthermore, relevant professionals are needed, and guide is required.

In general, this paper studied the factors affecting carbon emissions and acquired the current and future influence degree of various factors, which is of great significance to the low-carbon development in China. Due to the limitations of research experience and various conditions, the following aspects should be improved: first and foremost, carbon emission factors should be further refined. There are vast factors affecting carbon emission, and more accurate data should be collected to further analyze and discuss. Second, to predict the influence degree of each factor in the next few years, the selected data remain minimal, and the predicted results may have some limitations. Accordingly, the further study may make more in-depth and accurate predictions based on the index weight for more consecutive years.

References

Anatasia, V. (2015), “The causal relationship between GDP, exports, energy consumption, and CO_2 in Thailand and Malaysia”, *International Journal of Economic Perspectives*, Vol. 9 No. 4, pp. 37-48.

Ang, J.B. (2007), “CO_2, emissions, energy consumption, and output in France”, *Energy Policy*, Vol. 35 No. 10, pp. 4772-4778.

Ang, B.W., Huang, H.C. and Mu, A.R. (2009), “Properties and linkages of some index decomposition analysis methods”, *Energy Policy*, Vol. 37 No. 11, pp. 4624-4632.

Borhan, H.B. and Ahmed, E.M. (2012), “Simultaneous model of pollution and income in Malaysia”, *International Journal of Economic Perspectives*, Vol. 6 No. 1, pp. 50-73.

He, C.G. (2011), “The research and application of Markov model forecasting method”, Doctoral dissertation, Anhui University.

Huang, Y.S. and Shang, Y. (2015), “Prediction of the carbon emissions in China by improved grey Markov forecasting model”, *Journal of Chifeng University (NATURAL SCIENCE EDITION)*, No. 9, pp. 71-73.

Istaiteyeh, R.M.S. (2016), "Causality analysis between electricity consumption and real GDP: evidence from Jordan", *International Journal of Economic Perspectives*, Vol. 10 No. 4, pp. 526-540.

Kalayci, S. and Koksal, C. (2015), "The relationship between China's airway freight in terms of Carbon-Dioxide emission and export volume", *International Journal of Economic Perspectives*, Vol. 9 No. 4, pp. 60-68.

Kapusuzoglu, A. (2014), "Causality relationships between carbon dioxide emissions and economic growth: results from a multi-country study", *International Journal of Economic Perspectives*, Vol. 8 No. 2, pp. 5-15.

Katircioglu, S. (2017), "Investigating the role of oil prices in the conventional EKC model: evidence from Turkey", *Asian Economic and Financial Review*, Vol. 7 No. 5, pp. 498-508.

Kruskal, B. (1969), "Toward a practical method which helps uncover the structure of a set of multivariate observations by finding the linear transformation which optimizes a new index of condensation", *Statistical Computation*, pp. 427-440.

Liu, N., Ma, Z. and Kang, J. (2015), "Changes in carbon intensity in China's industrial sector: decomposition and attribution analysis", *Energy Policy*, Vol. 87, pp. 28-38.

Niu, D.X., Sun, W. and Zhao, L. (2012), "Markov energy structure prediction model based on transfer matrix recognition", *Journal of North China Electric Power University*, Vol. 3, pp. 59-61.

Rabiner, L. (1990), *A Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition*, Morgan Kaufmann Publishers Inc., pp. 267-296, available at: www.cs.ubc.ca/~murphyk/Bayes/rabiner.pdf

Renukappa, S., Akintoye, A. and Egbu Goulding, J. (2013), "Carbon emission reduction strategies in the UK industrial sectors: an empirical study", *International Journal of Climate Change Strategies and Management*, Vol. 5 No. 3, pp. 304-323, doi: 10.1108/IJCCSM-02-2012-0010.

Shao, C., Guan, Y., Wan, Z., Guo, C., Chu, C. and Ju, M. (2014), "Performance and decomposition analyse of carbon emissions from industrial energy consumption in Tianjin, China", *Journal of Cleaner Production*, Vol. 64 No. 2, pp. 590-601.

Tan, Z.R. (2012), *Study on the Efficiency and Factors of Carbon Emission in China's Provincial Regions*, Chongqing University.

Vinuya, F., DiFurio, F. and Sandoval, E. (2010), "A decomposition analysis of CO_2 emissions in the United States", *Applied Economics Letters*, Vol. 17 No. 10, pp. 925-931.

Wang, S. (2012), "Analysis on the influence factors of CO_2 emission in France – based on LMDI approach", *Advanced Materials Research*, Vol. 616-618 No. 1315, pp. 1537-1540.

Wu, Z., Shi, J. and Wang, S. (2014), "Analysis of the driving factors of carbon emissions in Beijing based on LMDI method", *Forum on Science and Technology in China*.

Xia, X.H., Huang, G.T., Chen, G.Q., Zhang, B., Chen, Z.M. and Yang, Q. (2011), "Energy security, efficiency and carbon emission of Chinese industry", *Energy Policy*, Vol. 39 No. 6, pp. 3520-3528.

Xu, S.C., He, Z.X., Long, R.Y., Chen, H., Han, H.M. and Zhang, W.W. (2016), "Comparative analysis of the regional contributions to carbon emissions in China", *Journal of Cleaner Production*, Vol. 127, pp. 406-417.

Yao, Y. and Qin, N.I. (2012), "Evaluation of carbon emission reduction in different regions based on projection pursuit classification model", *Operations Research and Management Science*.

Yue, R. and Zhu, Y. (2010), "Provincial cluster analysis on China's energy carbon emission from 1990 to 2007", *Technology Economics*, Vol. 3, pp. V3-81-V3-84.

Zhang, J.Y. (2016), *Cluster Analysis of Carbon Emissions of Different Provinces in China Based on Projection Pursuit Method*, North China Electric Power University.

Zhu, W., Tian, Z. and Yue, J.G. (2015), "Carbon emissions measurement and prediction of economic growth in Jiangsu province: based on the grey Markov model", *World Scientific Research and Development*, No. 4, pp. 399-403.

Further reading

Al-Amin, A.Q., Jaafar, A.H. and Siwar, C. (2010), "Climate change mitigation and policy concern for prioritization", *International Journal of Climate Change Strategies and Management*, Vol. 2 No. 4, pp. 418-425.

Li, J.S., Alsaed, A., Hayat, T. and Chen, G.Q. (2014), "Energy and carbon emission review for Macao's gaming industry", *Renewable and Sustainable Energy Reviews*, Vol. 29, pp. 744-753.

Soytas, U., Sari, R. and Ewing, B.T. (2007), "Energy consumption, income, and carbon emissions in the United States", *Ecological Economics*, Vol. 62 Nos 3/4, pp. 482-489.

Corresponding author
Lei Wen can be contacted at: wenlei0312@126.com

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