Nonlinear Multivariable Analysis of CO$_2$ Emissions in China

Hsiao-Tien Pao, Yi-Ying Li, Hsin-Chia Fu

Abstract—This paper addressed the impacts of energy consumption, economic growth, financial development, and population size on environmental degradation using grey relational analysis (GRA) for China, where foreign direct investment (FDI) inflows is the proxy variable for financial development. The more recent historical data during the period 2004–2011 are used, because the use of very old data for data analysis may not be suitable for rapidly developing countries. The results of the GRA indicate that the linkage effects of energy consumption–emissions and GDP–emissions are ranked first and second, respectively. These reveal that energy consumption and economic growth are strongly correlated with emissions. Higher economic growth requires more energy consumption and increasing environmental pollution. Likewise, more efficient energy use needs a higher level of economic development. Therefore, policies to improve energy efficiency and create a low-carbon economy can reduce emissions without hurting economic growth. The finding of FDI–emissions linkage is ranked third. This indicates that China do not apply weak environmental regulations to attract inward FDI. Furthermore, China's government in attracting inward FDI should strengthen environmental policy. The finding of population–emissions linkage effect is ranked fourth, implying that population size does not directly affect CO$_2$ emissions, even though China has the world's largest population, and Chinese people are very economical use of energy-related products. Overall, the energy conservation, improving efficiency, managing demand, and financial development, which aim at curtailing waste of energy, reducing both energy consumption and emissions, and without loss of the country's competitiveness, can be adopted for developing economies. The GRA is one of the best way to use a lower data to build a dynamic analysis model.

Keywords—Grey relational analysis, foreign direct investment, CO$_2$ emissions, China.

I. INTRODUCTION

THE increasing threat of global warming caused by greenhouse gases (GHG) emissions has been a major, world-wide, on-going concern during the last several decades. Climate changes influenced by GHG emissions have caused temperature increase of up to 2°C [1], while carbon dioxide (CO$_2$) was held responsible for 58.8% of the GHG emissions [2]. China is the world's biggest emitter of GHG, the second-largest global economy, and the world's most populous country; however, the per capita emissions are still significantly lower than that of the U.S., but approaching the average level of the E.U. countries [3], [4]. Fossil fuel production and combustion generates some 90% of China's total carbon emissions. Manufacturing and power generation are the major sectors contributing to China's carbon emissions [4]. China has promised to peak its CO$_2$ emissions by 2030 and cut them from coal power plants by 60% by 2020 during the world Paris Climate Conference (COP21) [5]. Therefore, the transformation of economic growth towards a lower dependency on fossil fuels and related GHG emissions is essential for the feasibility of a successful global climate strategy.

A dynamic link between the environment, resource use, and economic activity was found by Kolstad and Krautkraemer [6]. They argue that while resource use (especially energy sources) yields immediate economic benefits, its negative impact on the environment may be observed in the long run. Consequently, economic growth in excess of the carrying capacity of the environment is counterproductive and detrimental in the long run to human welfare. Although the majority of the studies are focused on economic development and environmental degradation, a lot of articles pointed out that another possible determinant of the environmental performance is financial development. Frankel and Romer [7] found that financial liberalization and development may attract FDI and higher degrees of R&D investments which in turn can speed up economic growth, and hence affect the dynamic of the environmental performance. Birdsall and Wheeler [8] and Frankel and Rose [9] indicated that the financial development provides developing countries with the motive and opportunity to use new technology, help them with clean and environment-friendly production, and consequently improve global environment at large and enhance regional development sustainability. Additionally, Jensen [10] and World Bank [11] asserted that though financial development may enhance economic growth, it may result in more industrial pollution and environmental degradation. Tamazian et al. [12] found that higher degree of economic and financial development decreases the environmental degradation. In this study, we employed FDI inflows as a measure of financial development.

Another issue of pollution is population, because people's usages of daily needs are increasing and they misuse it. It affects the earth as decreasing the nonrenewable resources. Environmentalists and economists increasingly agree that slowing the increase in population, especially in the face of rising per capita demand for natural resources, can reduce environmental pressures and have more time to improve living standards on a sustainable basis [13]. Moreover, Stern [14]

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presents a critical history of the environmental Kuznets curve (EKC). According to him the arguments of EKC do not stand firm on strong econometric footing. He pointed out that the major weaknesses associated with the econometric estimations namely, heteroskedasticity, omitted variables bias, and critical issues relating to cointegration analysis. Given these reasons and concerns, this study uses GRA to examine whether the economic development and financial development along with both energy consumption and population size tend to increase the environmental damage or not in China.

The grey system theory proposed by Deng [15] has been successfully applied in engineering prediction and control, social and economic system management, and environmental system decision making in recent years [16]-[19]. It has been proven to be useful for dealing with poor, incomplete and uncertain information. GRA is one of the major directions among the current applications of grey system theory. GRA can be used to effectively solve the complicated interrelationships among the multiple factors and variables through the optimization of grey relational grades [20]-[23]. Lin et al. [24] employ GRA to explore the inter-relationships among economy, energy and environment in Taiwan. GRA has been widely used due to its advantages of requiring low data items to build models.

This study is to explore the dynamic relationship between CO_2 emissions and the given four factors: Energy consumption, real GDP, FDI and population in China. Recent historical data during the period 2004-2011 are used, because China is in rapidly developing economies. Considering the recent year's data, GRA may be the best method using low data items to build dynamic analysis model. The remainder of this paper is organized as follows: Section II describes the methodology of GRA. Section III discusses the data used. Section IV discusses the empirical findings, and the last section summarizes and concludes the paper.

II. GREY RELATIONAL ANALYSIS

The main procedure of GRA is firstly translating the performance of all alternatives into a comparability sequence. This step is called grey relational generating. According to these sequences, a reference sequence is defined. Then, the grey relational coefficient between all comparability sequences and the reference sequence at a certain time point is calculated, which is also called the "point" relational grade. Finally, based on these grey relational coefficients, the grey relational grade between the reference sequence and every comparability sequences is calculated. The higher grey relational grade indicates that the compared sequence is the most similar to the reference sequence. The procedures of GRA are shown in Fig. 1 [25].

In this study, the calculations of GRA compare the geometric relationships between time series data in the relational space. If the relative variations between two factors, the compared series and the reference series, are basically consistent during their development process, then the grey relational grade is large and vice versa [26]. The details of GRA are presented below.

Denote the m series to be compared as

$$x_j = (x_j(1), x_j(2), \ldots, x_j(n))^T, \ j = 1, 2, \ldots, m, \quad (1)$$

where $x_j(k)$ is the yearly time series data and m is the number of factors. Translate the series using vector normalization to ensure that all of them are in the same order. The normalized series can be denoted as

$$x_j^* = (x_j^*(1), x_j^*(2), \ldots, x_j^*(n))^T, \ j = 1, 2, \ldots, m, \quad (2)$$

and let the reference series be x_1^*. The formula of vector normalization is defined as [27]:

$$x_j^*(k) = x_j(k) \Big/ \sqrt{\sum_{i=1}^{n} x_j^2(i) \Big/ n}, \ k = 1, 2, \ldots, n, \ \text{and} \quad (3)$$
$$j = 1, 2, \ldots, m,$$

The grey relational coefficient between the compared series, x_j^*, and the reference series, x_1^*, for the kth-year, is defined as

$$\zeta_{1j}(k) = \frac{\Delta_{\min} + \rho\Delta_{\max}}{\Delta_{1j}(k) + \rho\Delta_{\max}}, \ j=2, \ldots m, \ k=1,2, \ldots n \quad (4)$$

where

$$\Delta_{1j}(k) = \left| x_1^*(k) - x_j^*(k) \right|. \quad (5)$$

$\Delta_{1j}(k)$ represents the absolute difference between x_j^* and x_1^* at kth time point; $\Delta_{\min} = \min_j \left\{ \min_k \Delta_{1j}(k) \right\}$ and $\Delta_{\max} = \max_j \left\{ \max_k \Delta_{1j}(k) \right\}$ are the minimum and maximum distances for all factors in all series. ρ is the distinguishing coefficient which is defined in the range $0 \le \rho \le 1$ and typically $\rho = 0.5$. Then, the grey relational grade (GRG) can be calculated as

$$\gamma_{1j} = \sum_{k=1}^{n} \omega_k \zeta_{1j}(k) \ \text{for} \ j = 1, 2, \ldots, m, \quad (6)$$

where γ_{1j} is the grey relational grade between x_j^* and x_1^*. ω_k is the weight of kth- year and usually depends on decision makers' judgment or the structure of the proposed problem. In addition, $\sum_{k=1}^{n} \omega_k = 1$. In this study, both equal weight and unequal weight on each of the grey relational coefficient time series value are used. The equal weight grey relational grade can be denoted as

$$\gamma_{1j} = \frac{1}{n} \sum_{k=1}^{n} \zeta_{1j}(k) \ \text{for} \ j = 1, 2, \ldots, m. \quad (7)$$

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Because $\zeta_{1j}(k)$ is the time series value, the following exponential smoothing method weights the time series data unequally and more recent observations are weighted more heavily than more remote observations. It can be denoted as

$$\gamma_{1j} = \sum_{k=1}^{n} w_k \zeta_{1j}(k) \text{ for } j = 1, 2, \ldots, m, \qquad (8)$$

where

$$w_k = \alpha(1-\alpha)^{k-1} \text{ and } \alpha = (n-k+1)/[n(n+1)/2].$$

The value of α can be calculated using formula of rank sum weight. The γ_{1j} represents the level of correlation between the reference series and j-th comparability series.
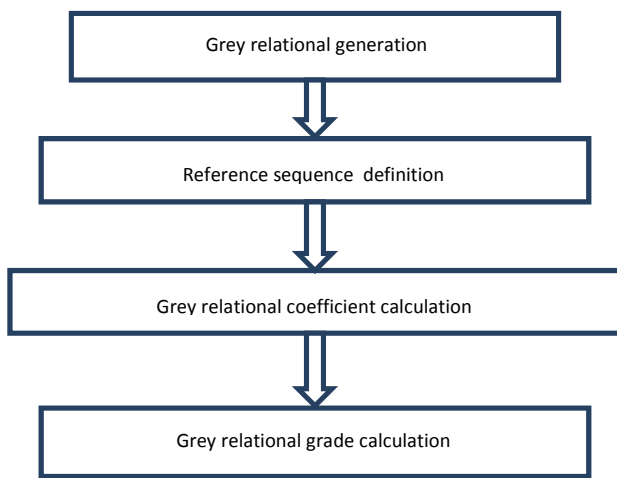

Fig. 1 Procedure of GRA

III. DATA

The focus of this study is to explore the relationship between CO_2 emissions and the given four factors: energy consumption, real GDP, FDI, and population in China. The annual data of emissions and energy consumption are obtained from Energy Information Administration (EIA), and real GDP, FDI net inflows and population are obtained from the World Bank Development Indicators (WDI) from 2004 to 2011. CO_2 emissions in metric tons of carbon dioxide are measured from the consumption and flaring of fossil fuels. Real GDP is measured in US dollars at 2005 prices. Energy consumption is measured in BTU (British thermal unit). FDI net inflows in current US\$ Billion are the value of inward direct investment made by non-resident investors in the reporting economy. The summary statistics associated with the five variables for China and the world in Table I show that the 7-year average (2004-2011) of emissions and energy consumption for China respectively accounted for about 21.14% and 16.45% of the average of the world, while average of real GDP only accounted for about 6.12% of the average of the world. One of the main reasons is the 7-year average of population accounted for about 19.66% of the 7-year average of the world. Table II

shows the compound annual growth rates (CAGRs) between 2004 and 2011 for each variable in China and in the world. The CAGRs of 8.48%, 8.67%, 11.02%, and 24.01% respectively in China's emissions, energy consumption, real GDP, and FDI are higher than the world, while the CAGR of population in China is lower than the world. All of these observations demonstrate that China should aim to develop a high-efficiency and low-carbon economy.

IV. EMPIRICAL RESULTS

Based on the original data, the GRA procedure is as:

Step1. Normalize the original values. The application of GRA uses vector normalization (3) for five time series: CO_2 emissions (x_1), energy consumption (x_2), real GDP (x_3), FDI (x_4) and population (x_5), where emissions are the reference sequence. The entire results of grey relational generating are shown in Table III.

Step2. Calculate the distance between the reference sequence x_1^* and the compared sequence x_j^*; $j = 2, \ldots m$ using (5).

Step3. Calculate the grey relational coefficient between the reference series and jth compared series. After calculating $\Delta_{1j}, \Delta_{max}$ and Δ_{min}, all grey relational coefficients can be calculated by (4). The entire results of grey relational coefficient are shown in Table IV.

Step4. Calculate the grey relational grade. After calculating the entire grey relational coefficients $\zeta_{1j}(k)$, the grey relational grade can be then calculated using both equal weight (7) and unequal weight (8) on each time series $\zeta_{1j}(k)$ ($k = 1, 2, \ldots, 8$) for four factors. The grey relational grade γ_{1E}, γ_{1G}, γ_{1F} and γ_{1P} represent the level of correlation between emissions and each of the four factors, including energy consumption, input, FDI and population. The entire results of grey relational grade (GRG) are shown in Table V.

In addition, this research also analyzes the impact on the results of GRA using both equal weight and unequal weight when the distinguishing coefficient set at 0.1, 0.3, 0.5, 0.7 and 0.9, respectively for each country. Results are shown in Table V and Fig. 2. The figures demonstrate that the impact of both the distinguishing coefficient and weighting form on the result of GRA is very small. For each country, no matter what both the distinguishing coefficient is and the weighting form is, the rank order of γ_{1E}, γ_{1G}, γ_{1F} and γ_{1P} is always the same.

V. DISCUSSION AND CONCLUSIONS

While most empirical studies have focused on the effects of economic growth on environmental performance, this paper also addressed the impact of both financial development and population size on environmental degradation, where FDI inflows is the proxy variable for financial development. Population is another issue of pollution, because people's usages of daily needs are increasing and they misuse it. It affects the earth as decreasing the nonrenewable resources. Hence, we examine China to show whether or not higher

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degrees of economic, financial development and population size lead to higher CO_2 emissions in developing economies. The more recent historical data during the period 2004–2011 are used, because China is rapidly developing countries. Taking the recent year's data into account, GRA may be the best method using low data items to build dynamic analysis model.

TABLE I
SUMMARY STATISTICS, 2004-2011

	CO_2 emissions (Million Metric Tons)		Energy use (Quadrillion Btu)		Real GDP (constant 2005 US$ Billion)		FDI (current US$ Billion)		Population (Millions)	
	Mean	S.D.	Mean	S.D	Mean	S.D.	Mean	S.D.	Mean	S.D.
China	6211.88	1178.80	78.88	15.39	3072.42	773.18	160.26	71.54	1320.81	0.02
World	29391.00	1672.13	479.61	25.95	50226.41	2893.38	1870.58	702.33	6719.14	0.20
China share	21.14%		16.45%		6.12%		8.57%		19.66%	

TABLE II
AVERAGE GROWTH RATES FROM 2004 TO 2011 (%)

	CO_2	Energy	GDP	FDI	Population
China	8.48	8.67	11.02	24.01	0.52
World	2.54	2.38	2.54	17.40	1.23

TABLE III
VECTOR NORMALIZATION VALUE ON THE FIVE FACTORS FOR CHINA

	CO_2	Energy	GDP	FDI	Population
2004	0.2159	0.2199	0.2434	0.1860	0.3450
2005	0.2250	0.2324	0.2636	0.2143	0.3475
2006	0.2626	0.2657	0.2876	0.2389	0.3509
2007	0.3085	0.3095	0.3164	0.2281	0.3529
2008	0.3859	0.3807	0.3483	0.2661	0.3549
2009	0.4180	0.4129	0.3845	0.3833	0.3569
2010	0.4408	0.4407	0.4291	0.3783	0.3590
2011	0.4697	0.4707	0.4849	0.6705	0.3611

TABLE IV
GREY RELATIONAL COEFFICIENT BETWEEN CO_2 EMISSIONS AND EACH OF THE FOUR FACTORS

	Energy	GDP	FDI	Popu.
2000	0.9623	0.7856	0.7708	0.4378
2001	0.9321	0.7228	0.9041	0.4507
2002	0.9711	0.8012	0.8092	0.5324
2003	0.9908	0.9280	0.5555	0.6939
2004	0.9510	0.7279	0.4562	0.7643
2005	0.9523	0.7504	0.7437	0.6220
2006	1.0000	0.8963	0.6165	0.5513
2007	0.9906	0.8691	0.3335	0.4807

This study evaluated four factors, including energy consumption, real GDP, FDI and population, all of which affected the CO_2 emissions using GRA. The results of the GRA indicate that the linkage effect (γ_{1E}) between energy consumption and emissions is ranked first. It reveals that energy consumption is strongly correlated with emissions in each country. The energy intensity in 2011 is 24708 Btu/USD, which is higher than 9905 Btu/USD, the average global energy intensity [28]. High energy intensity reflects low efficiency of energy use for industry, commercial, and household sectors, and indicates that there is high energy saving potentials. Therefore, in order to enhance energy efficiency and reduce emissions, a range of policies can be adopted. The policies may include the development of energy infrastructure, reduction of transmission and distribution losses, and the introduction of a variety of tariff reforms to control energy demand and energy-saving supply costs without affecting the end-use benefits. These policies will not harm economic growth in China.

The linkage effect (γ_{1G}) between output and emissions is ranked second. Such results reveal that economic growth is closely related to environmental pollution, with higher economic growth requiring more energy consumption and increasing environmental pollution. Consequently, China should aim to maintain stability and continuity economic policies to achieve appropriate economic growth and sustainable development.

The linkage effect (γ_{1F}) between FDI and emissions is ranked third. Table II shows the 7-year CAGRs of FDI and GDP in 2011 are the first and second high among the five factors. Therefore, China's government in attracting inward FDI and enhancing economic growth, but also should make environmental protection policy. The population–emissions linkage effect (γ_{1p}) is ranked fourth. It reveals that China is more economical use of energy-related products Overall, for China, the energy conservation, improving efficiency, managing demand and financial development can be adopted to reduce CO_2 emissions and without loss of the country's competitiveness.

The findings of energy–economic–finance–population and environment nexus and GRA method can also be used to provide insight to other developing economies.

TABLE V
THE RESULTS OF GRA FOR CO_2 EMISSIONS

	Equal weights				Unequal weights			
ρ	Energy	GDP	FDI	Popu.	Energy	GDP	FDI	Popu.
0.1	0.8683	0.4831	0.3204	0.2213	0.7306	0.3941	0.3357	0.1755
0.3	0.9495	0.7235	0.5447	0.4462	0.8139	0.6086	0.5372	0.3624
0.5	0.9688	0.8102	0.6487	0.5666	0.8337	0.6883	0.6216	0.4663
0.7	0.9774	0.8553	0.7117	0.6430	0.8426	0.7302	0.6700	0.5338
0.9	0.9823	0.8831	0.7546	0.6962	0.8477	0.7561	0.7019	0.5815

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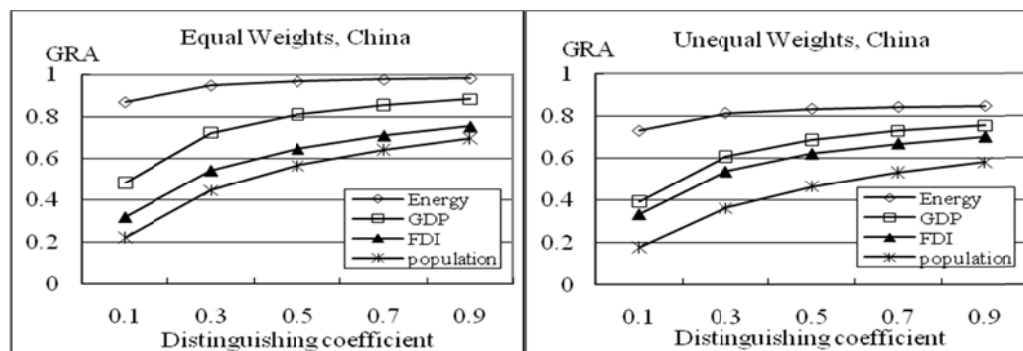International Journal of Environmental and Ecological Engineering
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Fig. 2 The impact of distinguishing coefficient on the results of GRA

REFERENCES

[1] Miomir J, Ljiljana K, Aleksandra D, and Vladimir K. The Impact of Agro-Economic Factors on GHG Emissions: Evidence from European Developing and Advanced Economies. Sustainability 2015, 7, 16290-16310.

[2] World Bank, Growth and CO_2 emissions: how do different countries fare, Environment Department, Washington, D.C., 2007.

[3] B. Chen, Where does China rank in the world? China Business review, 2015.

[4] Z. Liu, China's carbon emissions report 2015, Harvard Kennedy School.

[5] COP21, China has promised to cut emissions from its coal power plants by 60% by 2020, 2015.

[6] C.D. Kolstad, J.A. Krautkraemer, Natural resource use and the environment. In: A.V. Kneese, J.L. Sweeney, (Eds.), Handbook of Natural Resource and Energy Economics 3 1993, pp.1219-1265.

[7] J. Frankel, D. Romer, Does trade cause growth?, Am. Econ. Rev. 89, 1999, 379-399.

[8] N. Birdsall, D. Wheeler, Trade policy and industrial pollution in Latin America: where are the pollution havens?, J. Environ. Dev. 2, 1993, 137-149.

[9] J. Frankel, A. Rose, An estimate of the effect of common currencies on trade and income, Q. J. Econ. 117, 2002, 437-466.

[10] V. Jensen, The pollution haven hypothesis and the industrial flight hypothesis: some perspectives on theory and empirics, Working Paper 1996.

[11] World Bank, Is globalization causing a 'race to the bottom' in environmental standard? PREM economic policy group and development economics group, Washington, D.C., 2000.

[12] A. Tamazian, J.P. Chousa, K.C. Vadlamannati, Does higher economic and financial development lead to environmental degradation: evidence from BRIC countries, Energy Policy. 37, 2009, 246-253.

[13] D. Hinrichsen and B. Robey, Population and the Environment: The Global Challenge. Actionbioscience, 2000.

[14] D.I. Stern, The rise and fall of the environmental Kuznets curve, World Dev. 32, 2004, 1419-1439.

[15] J.L. Deng, Control problems of grey systems, Syst. Control Lett. 5, 1982, 288-294.

[16] G.H. Huang, B.W. Baetz, G.G. Patry, Grey dynamic programming for waste-management planning under uncertainty, J. Urban. Plann. Dev. 120, 1994, 132-156.

[17] G.H. Huang, B.W. Baetz, G.G. Patry, A grey hop, skip and jump approach: generating alternatives for expansion planning of waste management facilities. Can. J. Civ. Eng.. 23, 1996, 1207-1219.

[18] Y.Y. Yin, G.H. Huang, K.W. Hipel, Fuzzy relation analysis for multicriteria water resources management, J. Water Resour. Plann. Manag. 125, 1999, 41-47.

[19] J.S. Yeomans, G.H. Huang, An evolutionary grey, hop, skip, and jump approach: generating alternative policies for the expansion of waste management facilities, J. Environ. Inform. 1, 2003, 37-51.

[20] Z. Wang, L. Zhu, J.H. Wu, Grey relational analysis of correlation of errors in measurement, J. Grey Syst. 8, 1996, 73-78.

[21] F. Zhu, M. Yi, L. Ma, J. Du, The grey relational analysis of the dielectric constant and others, J. Grey Syst. 8, 1996, 287-290.

[22] X. Tan, Y. Yang, J. Deng, Grey relational analysis factors in hypertensive with cardiac insufficiency, J. Grey Syst. 10, 1998, 75-80.

[23] I.J. Lu, S.J. Lin, C. Lewis, Grey relation analysis of motor vehicular energy consumption in Taiwan, Energy Policy 36, 2008, 2556-2561.

[24] S.J. Lin, I.J. Lu, C. Lewis, Grey relation performance correlations among economics, energy use and carbon dioxide emission in Taiwan, Energy Policy 35, 2007, 1948-1955.

[25] Y. Kuo, T. Yang, G.W. Huang, The use of grey relational analysis in solving multiple attribute decision-making problems, Computers & industrial engineering 55, 2008, 80-93.

[26] C.T. Ho, Measuring bank operations performance: an approach based on grey relation analysis, J. Oper. Res. Soc. 57, 2006, 337-349.

[27] H. T. Pao, Y.Y. Li, and H.C. Fu, Intelligent data analysis and modeling for the determinants of carbon dioxide emissions. Advances in Environmental Development, Geomatics Engineering and Tourism, 2014, 26-30.

[28] EIA (Energy Information Administrator), Statistical review of world energy. Energy Information Administrator, US Department of Energy, 2009.