Effects of Operational Activities on World Energy Consumption: Data Envelopment Analysis Application

Oludolapo Akanni Olanrewaju
dlp4all@yahoo.co.uk, OludolapoO@dut.ac.za
Industrial Engineering Department
Faculty of Engineering and the Built Environment, Durban University of Technology,
South Africa

Abstract

The global stage has a lot to achieve by simply having energy at its beck and call. However, its unavailability could only mean its inefficient use when available. The objective of this study is to determine how various operations with population and gross domestic product (GDP) as resources affect global energy consumption. These operations include overall, technical and scale efficiencies. Data Envelopment Analysis (DEA) technique was used to carry out this study applying it to the world energy consumption from 1995 to 2009. Out of the 15-year period, six years were reported as overall efficient, three years were discovered technical efficient and three years as scale efficient. Indications from this study reiterates for policies to be formulated that are globally favorable and not biased to any continent or country.

Keywords

DEA, GDP, Global Energy Consumption, Policies, Population.

Introduction

The global stage has a lot to achieve by simply having energy at its beck and call. However, its unavailability could only mean its inefficient use when available. The world government has observed the continuous increase in energy demand (Bilga et al., 2016). The concerns regarding the environment is majorly focused on the consumption of energy primarily as demand in energy increases. Among those environmental concerns are air pollution, acid rain and climate change (Peng et al., 2013, Seow et al., 2016). Energy-related CO2 emission has been recorded to have an estimate worldwide increase from 31.2 billion metric tons to 45.3 billion metric tons between 2010 and 2040 (EIA, 2013). The recent growth in the global economy has been possible through the sacrifices made by energy resources and the environment. These sacrifices have resulted to energy resource exhaustion and environmental ruin (Chen et al., 2017). The impact of human activities on the environment together with the continuous decrease in energy resources have justified the attention of the universe towards sustainable development (Naji et al., 2016). Every challenge associated with energy saving and the protection of the environment are huge (Allouhi et al., 2015b). For a change to occur, the supply and demand of energy would need drastic adjustments (Allouhi et al., 2015a). These adjustments will include energy users being efficient. A careful understanding of energy consumption and conservation's pattern as well as awareness form efficient policies and the changes in lifestyle are also required (Hara et al., 2015).

The objective of this study is to apply efficiency technique to determine how various operations involving population and GDP affected the global consumption of energy between 1995 and 2009. A non-parametric technique that has achieved credit in its application to determine how consumption of energy could be efficient is data envelopment analysis (DEA). Energy efficiency can be defined as 'measure for the amount of energy used per unit of activity'. In logical sense, energy efficiency can be influenced by the technical energy efficiency, that is, the energy consumed by buildings, equipment or processes under constant operating conditions as well as the operation of buildings, equipment and processes. The pure technical efficiency and scale efficiency also play a part in the total efficiency possible.

Among the literature studied in the application of DEA to determine how efficiency could be obtained during energy consumption include but not limited to (Liu et al., 2010) (Song et al., 2015) (Shi et al., 2010) (Khoshnevisan et al., 2013). In evaluating the operational performance of a thermal power plant, (Liu et al., 2010) applied DEA in such a case in Taiwan. Their study considered 12 plants (DMUs) between 2004 and 2006 under three inputs – installed capacity, electricity used and heating value of total fuels whereas the net electricity produced is the output. Both CCR and BBC models of DEA were applied. Among the 12 plants, only 4 were recorded CCR efficient, and 7 BCC efficient. However, when it comes to the operational performance, all CCR efficient plants are at their best operational performance and 4 of the BCC. (Song et al., 2015) focused on coal-fired power units in China. DEA was employed in the country's energy evaluation using the input-output CCR and BCC model. The energy efficiencies evaluated were generalized and special energy efficiencies. The generalized was based on coal, oil, water and auxiliary consumptions whereas special was only based on two inputs – coal and auxiliary consumption. The special efficiency resulted in 2 efficient power units by CCR and 8 efficient units by BBC out of the 34 power units. Focusing on the generalized energy efficiency however resulted in 7 efficient power units by CCR and 15 efficient units by BCC. The generalized energy efficiencies are more than that of the special energy efficiencies.

In proposing policies on how to improve China's industries, (Shi et al., 2010) employed DEA model on fixing the industries non-energy inputs. five factors were considered in three inputs and two outputs – desirable and undesirable. The inputs are yearly data of the investment on industries fixed assets, energy consumed by industries and industrial labor. Industries added value as desirable output and industries waste gas volume from the burning of fuel as undesirable output. 28 regions in China were considered as DMUs within the period of 2000 and 2006. These regions are divided into east, central and west. With the east totaling 10 regions, central eight regions and west 10 regions. Of the 28 regions, only Guangdong reported technical efficiency, pure technical efficiency as well as scale efficiency representing the east. In the improvement of energy efficiency and reduction of greenhouse gas emitted in wheat production, (Khoshnevisan et al., 2013) applied DEA in their approach. Their study was carried out for the simple reason of being able to differentiate between efficient and inefficient farmers as well as in the calculation of the amount of inefficient consumption of energy. The results of their study reported 0.82 as technically efficient and 0.99 s pure technical efficient. Should the performance increase, it was deduced that 2075.8 MJ ha^{-1} of energy inputs can be saved should the inefficient farmers improve to the maximum. The remaining part of this paper is structured as follows, next section details the data and methodology followed by the results section. The last section concludes the study.

Data and Methodology

Data

Data for this study was obtained from Handbook of Energy and Economic Statistics in Japan, 2012 Edition. The world refers to North America, Latin America, Europe – OECD Europe and Non-OECD Europe, Africa, Middle East, Asia, Oceania, OECD-34 and Non-OECD plus International bunkers. GDP was calculated on exchange rates of C.Y. 2000.

Table 1. Data for study

Years	Population (Million Person)	GDP (Billion $US)	Energy (Mtoe)
1995	5661	27364	8449
1996	5740	28300	8683
1997	5820	29346	8754
1998	5899	30034	8800
1999	5978	31014	9007
2000	6056	32346	9192
2001	6133	32877	9226
2002	6209	33536	9436
2003	6284	34447	9769
2004	6358	35856	10287
2005	6433	37140	10561
2006	6508	38642	10855
2007	6584	40175	11111

2008	6660	40784	11318
2009	6737	39975	11186

Methodology – Data Envelopment Analysis

DEA has earlier mentioned has gained recognition in the efficiency study, benchmarking decision making units (DMUs) to achieve better performance. This study applies DEA to achieve its objective. With an application that requires inputs' flexibility similar to those employed for the present study, input orientation model will be more adequate. Based on the return to scale, there exists the constant returns to scale (CRS) and the variable returns to scale (VRS). In DEA, efficiency is defined in three different forms, namely, technical efficiency (TE), pure technical efficiency (PTE) and scale efficiency (SE) (Qasemi-Kordkheili and Nabavi-Pelesaraei, 2014). The CRS refers to the technical efficiency (TE) whereas the VRS refers to the pure technical efficiency (PTE) which measures the efficiency without scale efficiency (SE). The SE is the ratio of TE to PTE (Olanrewaju et al., 2014). TE is defined to be present when evidence shows that it is possible to improve some input or output without worsening some other input or output (Charnes et al., 1978). Also, technical efficiency under VRS or PTE relates to the ability to use given sources and SE refers to exploit scale economies by operating at a point where the production frontier exhibits CRS (Banker et al., 1984). Charnes-Cooper-Rhodes (CCR) model of DEA was considered for this study. The objective of the input model is to minimize the inputs as it satisfies at least the given output (Liu et al., 2010). Each efficiency score achieved through the application of the input-oriented model for the inefficient years (DMU) handle the possible potential of residential energy consumption that could be conserved. The equation governing the CCR model is given below (William et al., 2007).

$$Max\ \frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{i=1}^{m} v_i x_{i0}}$$

$$\frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{i=1}^{m} v_i x_{i0}} \le 1,\ j = 1,\dots,n,$$

Such that $v_i \ge 0, i = 1,\dots,m,$ (1)

$$u_r \ge 0, r = 1,\dots,s,$$

With $y_{r0,} r = 1,\dots,s$ representing the number of outputs and the $x_{i0}, i = 1,\dots,m$ representing the number of inputs for each of $j = 1,\dots,n,$ DMUs and $j = 0$ signifies the DMU_j for evaluation. u_r represents the output weight while v_i represents the input weight. Since equation (1) is a linear fractional programming problem, it was converted to ordinary linear programming problem. This brings new variables $\mu_r = \beta u_r, v_i = \beta v_i$ and obtains the ordinary linear programming problem below which gives the same optimal value with equation (1) (William et al., 2007).

$$Max\ \ w_0 = \sum_{r=1}^{s} \mu_r y_{r0}$$

$$\begin{aligned}
& s.t. \sum_{r=1}^{s} v_i x_{i0} = 1, \\
& -\sum_{i=1}^{m} v_i x_{ij} + \sum_{r=1}^{s} \mu_r y_{rj} \le 0,\ j,\dots,n, \\
& v_i \ge 0, i = 1,\dots,m, \\
& \mu_r \ge 0, r = 1,\dots,s.
\end{aligned} \tag{2}$$

The dual form of the problem gives an "envelopment model" as written below

$$Min \ \theta_0$$

$$\text{Such that} \quad \begin{aligned} & \sum_{j=1}^{n} x_{ij}\lambda_i \le x_{i0}\theta_0, i = 1,...,m, \\ & \sum_{j}^{n} y_{rj}\lambda_j \ge y_{r0}, r = 1,...,s, \\ & \lambda_j \ge 0, \ j = 1,...,n. \end{aligned} \tag{3}$$

The solution to the problem is by deciding to choose $\theta_0, \lambda_j = 1$ for the $DMU_j = DMU_0$ for evaluation and the remaining $\lambda_j = 0$. In addition, the solution has a lower boundary with max $y_{r0,} r = 1,...,s,$ and the $\lambda_j \ge 0$ constraints. The optimum value of θ_0 is set so that, through the dual theorem of linear programming, model (1) has a set solution with $\omega_0^* = \theta_0^*$ with "*" indicating optimal value (William et al., 2007).

Results

With Technical Efficiency, years 1998, 1999, 2000, 2001, 2002 and 2003 scored lower than 0.98334, whereas for Pure Technical Efficiency, 1998 to 2003 are all lower than the average of 0.98872. The lowest efficiency score is in 2001 (0.952) for Technical Efficiency and for Pure Technical Efficiency, the lowest share is between 2001 and 2002. The most technical efficient for CRS include 1996 and 2008 with 12 number of peers that can be made efficient should 1996 and 2008 be emulated. With VRS, 1996 is the most efficient having nine peers to have it emulated to become efficient next to 2007 having just 7 peer counts. The amount of efficient VRS is twice that of the CRS. This indicates that for VRS, lesser inputs are required for the same amount of outputs compared to that of CRS which is evident from the Table 2 below. The technical efficiencies are not efficient in the years 2005 and 2007.

The technical efficient years are equal with the scale efficient years indicating that every operation leading to the consumption of energy in these years are at their best scale without unfavorable scale in their operations. Of the 15 years, 12 recorded close to becoming scale efficient. The times of global energy consumption in these years either absorbed lots of inputs or very less close to ideal amount expected. Indication of the result suggest more than half of the efficient years of global energy consumption have been inefficient. This has continuously led to the shortage of its supply to the global needs.

Table 2: Efficiency results

	CRS(TE)			**VRS (PTE)**			**SE**
DMU	**Efficiency**	**Peer**	**Peer Count**	**Efficiency**	**Peer**	**Peer Count**	**Efficiency**
1995	1	Nil	Nil	1	Nil	Nil	1
1996	1	Nil	12	1	Nil	9	1
1997	0.9829	1996, 2008	Nil	0.9904	1996, 2007	Nil	0.9923
1998	0.97	1996, 2008	Nil	0.9799	1996, 2007	Nil	0.9898
1999	0.9701	1996, 2008	Nil	0.979	1996, 2007	Nil	0.9909
2000	0.9624	1996, 2008	Nil	0.977	1996, 2007	Nil	0.9851
2001	0.952	1996, 2008	Nil	0.9666	1996, 2007	Nil	0.9848
2002	0.9579	1996, 2008	Nil	0.9666	1996, 2007	Nil	0.991
2003	0.9722	1996, 2008	Nil	0.9736	1996, 2007, 2008	Nil	0.9985
2004	0.9964	1996, 2008	Nil	0.999	1996, 2005, 2009	Nil	0.9974

2005	0.9982	1996, 2008	Nil	1	Nil	2	0.9982
2006	0.9986	1996, 2008	Nil	0.9986	1996, 2005, 2008	Nil	0.9999
2007	0.995	1996, 2008	Nil	1	Nil	7	0.995
2008	1	Nil	12	1	Nil	2	1
2009	0.9944	1996, 2008	Nil	1	Nil	1	0.9944

Conclusion

This study proposes DEA to evaluate the global consumption of energy taking world population and GDP as the determinant factors. Demonstrating how activities affect energy consumption was well represented by the proposed model. From the results gathered, the following conclusions can be drawn. First, most of the global years of energy consumption are not efficient, and the world should adjust its activities in the form of human behavior, waste of resources and how production of goods are made to allow possible saving and conservation. Second, energy use has a great correlation with population and GDP, which is very fundamental to sustainability, hence policy makers should consider this as vital in formulating policies. The last but not least, energy use under different continents, countries have different policies governing their use. The better for the world should the various continents and countries come to an agreement with a universal policy that is not biased to one continent or country. This should not be ignored. There should be a framework exploring all possible scenarios of energy use pertinent to every continent. Future studies will involve breaking GDP into the various sectors as well as dividing the population to various classes i.e., working class and retired class, which will expose where resources are not used optimally leading to inefficient energy use.

Biography

Oludolapo Akanni Olanrewaju is a Senior Lecturer in the Department of Industrial Engineering at the Durban University of Technology, South Africa. He earned B.Sc. in Electrical Engineering and Masters in Industrial Engineering from the University of Ibadan and his doctorate from the Tshwane University of Technology, Pretoria, South Africa. He has published journal and conference papers. Dr. Olanrewaju's research interests include energy and greenhouse gas analysis and optimization.

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