Assessment of Residential Sector Energy Consumption: Data Envelopment Analysis (DEA) Application

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Abstract

The objective of this study is in the assessment of residential sectors use of energy through a benchmarking methodology taking the years of consumption as the decision unit. It further assesses the effect of each of the independent variables responsible for each year's residential energy consumption known as sensitivity analysis. To achieve the following objectives, Data Envelopment Analysis (DEA) was employed. The study considered the United States residential sector data from 1984 to 2010, with residential population, gross domestic product, household size, median household income, cost of residential electricity, cost of residential natural gas and cost of residential heating oil as inputs while the energy consumed was the output. The study found out that the year 1996 proved the most efficient while gross domestic product proved important in the way energy needs to be consumed efficiently.

Keywords
Assessment; benchmarking; data envelopment analysis; residential sector; energy consumed

1. Introduction

The role of electricity in the lives of members of the modern society is regarded crucial (Liu et al., 2010). As reported by (ACEEE, 2014) (American Council for an Energy-Efficient Economy) in the publication 'International Energy Efficiency Scorecard', : 'countries can preserve their resources, address global warming, stabilize their economies, and reduce the costs of their economic outputs by using energy more efficiently – an eminently achievable goal.' Everyday activities require accessibility and use of energy serving as pre-requisite for fundamental needs (Sovacool et al., 2014). Human lives tend to improve drastically when energy is there to be consumed especially in various homes. The mind is enlightened, as well as activities are improved. Some may say disagree that this increase is to the detriments of the society. This is left to be debated on another platform. Increased energy use gives global emission rise concerns (Longo et al., 2015). Residential sector has not been an exception to this emission. Developing a systematic approach in the assessment of energy management of a building can increase its performance (Yu and Chan, 2012) especially in the way energy is consumed and ways of reducing greenhouse gas emissions. Evaluating the way energy could be efficiently used in guiding sustainable development has led to various propositions of energy demand management techniques for the past decade (Li and Tao, 2017). When it comes to evaluation, benchmarking approaches have been ideal.

Both simulation and data-driven techniques have been proved as benchmarking techniques, however, data-driven has the ability to evaluate a huge amount of multiple parameters (Wang et al., 2015). It can be said that among the challenges associated with benchmarking is the ability to deal with various parameters attributed to the objective performance (Wang et al., 2015). Data Envelopment Analysis (DEA) has successfully proven to be ideal in such circumstances. There are no prior functional assumptions required when DEA is employed as multiple inputs and outputs relationship is considered (Wang et al., 2015). DEA is a proven mathematical approach to measure the efficiency of a set of decision making units (DMU) using selected inputs and outputs (Ghyasi, 2017). DEA treats every entity of a homogenous nature as a Decision Making Unit (DMU). This study considers the years of operations as DMUs. DEA assumes the existence of DMU_1, DMU_2,…, DMU_S (s = 1, 2, …, n), with various kinds of inputs and outputs for each DMU (Xiaoli et al., 2014). There are two versions of operations of DEA – the Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS) (Wang et al., 2015). To determine efficiency evaluation using DEA, these versions of operations are required. These versions can be used based on either CCR (Charnes, Cooper and Rhodes) (Charnes et al., 1978) or BBC (Banker, Charnes and Cooper) (Banker et al., 1984) models.

There have been numerous energy studies that have benefitted using the various applications on DEA. In evaluating both generalized and special energy efficiency index of China's 34 thermal plants, (Song et al., 2015) made use of the CCR-DEA model. The study was successfully analyzed by considering coal, oil, water and electricity consumptions as inputs. Previous applications of DEA can be found in the studies of (Liu et al., 2010) and (Vanisky, 2006). (Liu et al., 2010) evaluated the operational performance using data envelopment analysis on Taiwan's thermal power plant. Their study considered the period between 2004 and 2006 and it was concluded that all power plants within the period of study operated efficiently. It also discovered that the heating value of total fuels was the most important factor among the considered variables. The electric power generation's efficiency was assessed in the United States by (Vanisky, 2006) using DEA, from 1991 to 2004. The study resulted in a stable efficiency in the range of 99 – 100% between 1994 and 2000. However, a sharp declination followed for the remaining years in the 94 – 95% range. Many other applications of DEA have been reviewed by (Song et al., 2012) for readers having interest.

The objective of this study is in the assessment of residential sectors use of energy through a benchmarking methodology taking the years of consumption as the decision unit. It further assesses the effect of each of the independent variables responsible for each year's residential energy consumption known as sensitivity analysis. Similar studies on the sensitivity analysis part of DEA are the studies of (Olanrewaju et al., 2012, Olanrewaju et al., 2014) and on the efficiency was (Olanrewaju et al., 2014). Another DEA efficiency application was in the study of (Lee, 2008). The study examined both environmental and management factors having effect on a building's electricity, annually. However, these studies only concentrated on industrial sectors and not on residential sector as is the objective of this paper.

(Patterson, 1996) advocated that energy is best estimated by a set of indicators. In this study, assessing the way energy in the residential sector can be best evaluated through the following inputs residential population, gross domestic product, household size, median household income, cost of residential electricity, cost of residential natural gas and cost of residential heating oil from the study of (Kiralashaki and Reisel, 2013).

2. Data and Methodology

2.1 Data

Data for this study was from the study of (Kiralashaki and Reisel, 2013) from 1984 – 2010. The combination of residential population, gross domestic product, household size, median household income, cost of residential electricity, cost of residential natural gas and cost of residential heating oil were defined as the inputs while the residential sector energy consumption was the output.

Table 1. Input and output data for United States Residential sector on energy consumption between 1984 and 2010 (Kiralashaki and Reisel, 2013).

Year	Resident population (thousand)	Gross Domestic Product (billion dollars)	Household size (persons)	Median household income (2010 dollars)	Cost of residential electricity (dollars per million Btu)	Cost of residential natural gas (dollars per million Btu)	Cost of residential heating oil (dollars per gallon)	Residential Sector energy consumption estimates (billion Btu)
1984	235825	3930.9	2.69	44802	20.169	5.719	7.571	15959563
1985	237924	4217.5	2.67	45640	20.129	5.517	7.056	16041334
1986	240133	4460.1	2.66	47256	19.842	5.169	5.5	15975109
1987	242289	4736.4	2.64	47848	19.221	4.73	5.097	16262213
1988	244499	5100.4	2.62	48216	18.531	4.494	4.955	17132613
1989	246819	5482.1	2.63	49076	18.081	4.412	5.233	17785725
1990	249623	5800.5	2.63	48423	17.558	4.308	5.864	16945297
1991	252981	5992.1	2.62	47032	17.301	4.145	5.394	17420310
1992	256514	6342.3	2.66	46646	17.15	4.072	4.8	17355685
1993	259919	6667.4	2.67	46419	16.875	4.147	4.546	18217687
1994	263126	7085.2	2.65	46937	16.572	4.203	4.301	18112431
1995	266278	7414.7	2.65	48408	16.154	3.872	4.102	18518963
1996	269394	7838.5	2.64	49112	15.616	3.937	4.545	19504218
1997	272647	8332.4	2.62	50123	15.394	4.21	4.421	18964947
1998	275854	8793.5	2.61	51944	14.852	4.05	3.769	18954918
1999	279040	9353.5	2.6	53252	14.355	3.906	3.791	19556929
2000	282172	9951.5	2.58	53164	14.024	4.392	5.489	20424794
2001	285082	10286.2	2.58	52005	14.199	5.284	5.089	20042076
2002	287804	10642.3	2.57	51398	13.75	4.279	4.525	20810265
2003	290326	11142.1	2.57	51353	13.89	5.086	5.31	21109915
2004	293046	11867.8	2.57	51174	13.886	5.547	5.909	21092623
2005	295753	12638.4	2.57	51739	14.181	6.326	7.576	21626073
2006	298593	13398.9	2.56	52124	15.119	6.625	8.459	20698278
2007	301580	14061.8	2.56	52823	15.054	6.143	9.014	21565031
2008	304375	14369.1	2.57	50939	15.328	6.282	10.78	21596245
2009	307007	14119	2.59	50599	15.724	5.521	8.019	21063265
2010	309349	14660.4	2.58	49445	15.511	5.106	9.252	22153450

2.2 DEA-Sensitivity and Efficiency Method

This study applied the input oriented model of the DEA. DEA involves three types of efficiencies – the Technical Efficiency, Pure Technical Efficiency and the Scale Efficiency. The CRS is applicable to technical efficiency (TE). VRS is applicable to pure technical efficiency (PTE) and the Scale Efficiency (SE) refers to the ratio of TE to PTE. CRS will be used as a sensitivity analysis to evaluate the impacts of each input on the energy consumed. This analysis give rise to seven models, comparing each models without a parameter among them. Regarding the DEA efficiencies, they portray how each year of energy consumption was (in)efficiently used. Equations governing the DEA efficiency approach is given in equation 1 and that of the sensitivity in equation 2 below:

$$\min \theta - \varepsilon \left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \right)$$

Subject to CRS

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{io}; i = 1...m$$
$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{r0}; r = 1...s \qquad (1)$$
$$\lambda_j \geq 0,\ j = 1,2...n$$

VRS add

$$\sum_{j=1}^{n} \lambda_j = 1$$

CRS

$$\min \theta - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right)$$

Subject to

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{io}; i \in I$$
$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_i^- = \theta x_{i0}; i \notin I \qquad (2)$$
$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro}; r = 1...s$$
$$\lambda_j \geq 0,\ j = 1,2...n$$

Where $\theta =$ measure of DMU's efficiency

$\varepsilon =$ infinitesimally positive numbers for all positive input and output coefficients

$s_i^- =$ non-negative slack variables for considered input constraints

$s_r^+ =$ non-negative slack variables for considered output constraints

$\lambda_j =$ the attached DMUs dual weights

$I =$ sets of specific inputs

As interpreted by (Tyagi et al., 2009), the best way of exercising DEA's strength is by leaving one of the input or output parameters out to see the effect on the operation's performance.

3. Results

Table 2 and Table 3 show the results for both the efficiency and sensitivity analysis simulation. Table 2 shows the efficiency operations of the DMUs from the simulated data. When the residential sector's energy consumption years were compared, the ones with efficiency lower than 100% are 1985, 1987, 1990, 1991, 1992, 1994, 1997, 2001, 2004, 2006, 2007, 2008 and 2009, with the least been 1990 with efficiency score of 0.94857. This confirms that when operational years are concerned, the year that operated less efficiently when compared to the others is the year 1990. Year 1996 has the highest number of peers with six different years wanting to emulate its ways of operation. The year with the most technical efficiency is 1996, while 1989, 1993, 2005 and 2010 are next in line with equal amount of peers the number of efficient years on the VRS scale is 1.6 times that of CRS. This illustrates that the inputs within these years were used successfully to obtain the respective output. All the technical efficient years correspond to the efficient scale efficiencies. Out of the 27 years recorded in this study, 13 years were recorded as inefficient. For Table 3, the best combination of inputs is the one without cost of residential electricity which has the highest mean of 0.98884 and the lowest standard deviation of 0.015819. This makes the cost of residential electricity less significant when all the inputs are combined for the use of electricity to be efficiently consumed in the residential sector. Without the gross domestic product, the combination of the remaining inputs gave the highest mean of 0.029284 which makes the gross domestic product very relevant when the way energy consumed is needed to be efficient.

Table 2. Operational efficiencies of the Residential DMUs

	CRS (TE)					VRS (PTE)							SE
DMU Name	Input-Oriented CRS Efficiency	Peer			Peer Count	Input-Oriented VRS Efficiency	Peer					Peer Count	Efficiency
1984	1.00000	Nil			1	1.00000	Nil					Nil	1.00000
1985	0.98682	1984	1988	1989	Nil	1.00000	Nil					Nil	0.98682
1986	1.00000	Nil			1	1.00000	Nil					Nil	1.00000
1987	0.99580	1986	1988		Nil	1.00000	Nil					Nil	0.99580
1988	1.00000	Nil			2	1.00000	Nil					1	1.00000
1989	1.00000	Nil			4	1.00000	Nil					Nil	1.00000
1990	0.94857	1989	1993	1996	Nil	1.00000	Nil					Nil	0.94857
1991	0.98653	1989	1993	1996	Nil	1.00000	Nil					1	0.98653
1992	0.97221	1989	1993	1996	Nil	1.00000	Nil					Nil	0.97221
1993	1.00000	Nil			4	1.00000	Nil					Nil	1.00000
1994	0.99014	1993	1995	1996	Nil	1.00000	Nil					1	0.99014
1995	1.00000	Nil			1	1.00000	Nil					Nil	1.00000
1996	1.00000	Nil			6	1.00000	Nil					1	1.00000
1997	0.96771	1996	1999	2002	Nil	0.99777	1991	1994	1996	1998	2002	Nil	0.96987
1998	1.00000	Nil			Nil	1.00000	Nil					1	1.00000
1999	1.00000	Nil			1	1.00000	Nil					Nil	1.00000
2000	1.00000	Nil			Nil	1.00000	Nil					Nil	1.00000
2001	0.97057	1996	2002	2003	Nil	0.99764	1988	2002				Nil	0.97286
2002	1.00000	Nil			2	1.00000	Nil					2	1.00000
2003	1.00000	Nil			3	1.00000	Nil					Nil	1.00000
2004	0.99849	2003	2005		Nil	1.00000	Nil					1	0.99849
2005	1.00000	Nil			4	1.00000	Nil					Nil	1.00000
2006	0.95454	2005	2010		Nil	1.00000	Nil					1	0.95454
2007	0.98966	2005	2010		Nil	1.00000	Nil					Nil	0.98966
2008	0.98464	2005	2010		Nil	1.00000	Nil					Nil	0.98464
2009	0.96055	2003	2010		Nil	0.99408	2004	2006	2010			Nil	0.96627
2010	1.00000	Nil			4	1.00000	Nil					1	1.00000

Table 2. Sensitivity analysis results

Without the following:	Statistical Measures	
	Mean	Standard Deviation
Resident population	0.98879	0.016105
Gross Domestic Product	0.96815	0.029284
Household size	0.98803	0.017064
Median household income	0.9882	0.016514
Cost of residential electricity	0.98884	0.015819
Cost of residential natural gas	0.98863	0.016349
Cost of residential heating oil	0.98415	0.017618

4. Conclusion

Benchmarking is very important to see how improvement could be implemented on areas where there is lack of attaining the objective set for a particular goal. This study considered data envelopment analysis in the best way to benchmark how residential sectors energy could be consumed. The United States data from 1984 to 2010 was used a s the case study. Apart from the way energy could be efficiently used, sensitivity analysis was also conducted by omitting one of the inputs in separate combinations of the remaining inputs.

From the result of the operational efficiencies, year 1996 proved very efficient as DMUs 1990, 1991, 1994, 1997 and 2001 would have being very efficient in the consumption of energy if only the way of operations in 1996 was emulated. Policies governing the year 1996 would also be advised to have been practiced in those years especially in the years 1997 and 2001 after experiencing the way 1996 performed. It has also been realized that the cost of residential electricity consumption should not be the focus when the remaining inputs are considered as without the cost of electricity, ways to minimize the energy consumed in the residential sector could be achieved. Gross domestic product on the other hand has proved to be important factor when considering the way our residential sector energy is consumed. It is assumed that the increase in a country's energy consumption there will be growth in the country's economy in essence the economy would increase. The misconception in this ideology is that if a lot of energy is consumed inefficiently it will also have a setback on the growth of the economy. The economy can only gain advantage if the way energy consumed is done efficiently.

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