Policy Implications on Industrial Energy Consumption: A DEA Sensitivity Approach

Oludolapo A. Olanrewaju
Department of Industrial Engineering
Tshwane University of Technology
Pretoria, South Africa

Adisa A. Jimoh
Department of Electrical Engineering
Tshwane University of Technology
Pretoria, South Africa

Pule A. Kholopane
Department of Industrial Engineering
University of Johannesburg
South Africa

Abstract

Energy consumption, a basic component of sustainable development can be improved with right policies in place. Most policies taken to reduce energy consumption contribute to sustainable development of a nation. In most cases, policies related to energy consumption are linked to various decision models. The question is how a decision model responds to policy formulation. DEA (Data Envelopment Analysis), a decision model was employed with the aid of sensitivity analysis on the various input factors that is responsible for industrial energy consumption and their combination thereof. Two case studies were observed in this research; the first is that of eleven South African industries and secondly, case study of a particular food industry. It was discovered that policies should be focused on intensity factor to realize the reduction of energy consumption. The results of the case studies successfully indicate how policies can be developed to improve the efficient consumption of energy. The sensitivity analysis conducted through statistical validation of the highest mean and lowest standard deviation proved activity and intensity factors to be responsible for the consumption of energy.

Keywords
Energy consumption, policy, DEA, Sensitivity analysis

1. Introduction
The enthusiasm of formulating and applying models to create policies in energy studies was enhanced by the world-wide awareness and concern on environmental issues in the 1980s (Zhou, P. et al. 2008). In a global context, it is essential to reduce environmental impact and consumption of natural resources (Henning, D. et al. 2006). No energy policy choices available are as attractive and necessary as energy efficiency and conservation. Unlike many other energy policy choices which involve long-term investments and technology development, increased emphasis on efficiency and conservation can deliver results in the short to medium term (Dernbach, J. 2007).
Most policies taken to reduce energy consumption contribute to sustainable development of a nation. In most cases, policies related to energy consumption are linked to various decision models. Policy implications for this study are concerned with the industrial policy and energy-conserving policy. Based on the findings with the two case-studies, it is suggested that the industrial sectors of a country need more aggressive energy-conservation policy to reduce its energy consumption. The case studies show that energy intensity is an informative and practical indicator. Energy-conservation policy can be improved by considering the information from the analysis of energy intensity. The energy intensity does provide some useful information (Yang, C.-J. 1999) for industrial policy makers. This study is for policy makers to reconsider industrial energy policies according to the findings of this study.

The industry's energy challenges are rooted in two facts: it consumes a lot of energy, and it continues to consume more. Unless there are new energy conservation policies or behavioral changes, there will continue to be a high industrial energy consumption rate. Thus, the crucial question: what policies and actions are the most effective, economically efficient, administratively feasible and politically acceptable? To be successful, industrial energy-efficiency policy must have clearly specified and measurable goals and an effective framework for implementing them (UNIDO 2011).

Analyzing the several factors leading to energy consumption and optimization by minimizing these factors and other input factors to energy consumption becomes necessary. Data Envelopment Analysis (DEA) has been applied to much energy related studies as an optimization tool to assess the possible energy saving potential. Hu and Kao (Hu, J.-L. and Kao, C.-H. 2007) found the energy-savings target using DEA for APEC economies without reducing their maximum potential gross domestic productions in each year. It was found that China had the largest energy-saving targets. Lieu et al., (Liu, C. H. et al. 2010) evaluated the thermal power plant operational performance in Taiwan using data envelopment analysis. The power plants studied achieved acceptable overall operational efficiencies during 2004-2006, and the combined cycle power plants were the most efficient among all plants. The performance of electricity generation plants in Turkey was analyzed and compared (Sarica, K. and Or, I. 2007) using DEA. Interesting conclusions regarding renewable power plants, thermal power plants investment performance and thermal power plants operational performance were drawn. Shi et al., (Shi, G.-M. et al. 2010) used DEA in their study to measure Chinese industrial energy efficiency and investigated the maximum energy-saving potential in 28 administrative regions in China, considering the issues of undesirable outputs and minimization of energy consumption. Based on their findings, they were able to propose some policies to improve regional industrial energy efficiency in China.

For a concrete industrial energy efficiency policy to be proposed, the causal variables (activity, structure and intensity) need to be assessed by performing a sensitivity analysis. The intention of this paper is to assess the relative operation of industries within two case studies of eleven South African industrial sectors and a particular food industry for efficient energy consumption. The other aim is to evaluate how efficiently the industries operate to identify efficient and inefficient industrial periods. Lastly, we apply sensitivity analysis to test the robustness of results and assess the operation of industries for different combination of the various factors responsible for energy consumption. Sensitivity analysis will allow us to answer the important question: Where is the need for innovative policy responses to the reduction of industrial energy consumption?

Changes in industrial energy consumption may be studied by quantifying the impacts of changes in the different factors: overall industrial activity (activity effect), activity mix (structure effect) and sectoral energy intensity (intensity effect) (Ang, B. W. 2005). This study empirically observes the industrial policy issue as to how to develop the industrial sector from the perspective of the combination of the variables that can lead to changes in energy consumption. The degree to which efficiency responds to these variables and/or combination thereof will give insight into strategies or ways to better manage energy consumption within an industry.

The next section introduces the sensitivity analysis. The application section discusses the total operation of the case studies based on the output, 'energy consumption'. It also explains the efficient utilization of input factors leading to the consumption of energy and robustness of the estimated efficiency scores to policy implications.

2. Sensitivity Analysis

There exist established parametric and non-parametric methods for measuring efficiency like operation. The parametric methods include ordinary least square method and stochastic frontier methods. The non-parametric methods include Data Envelopment Analysis and Free Disposal Hull methods. The difference between these methods is that the non-parametric methods do not require any functional form and work well with multiple inputs and outputs (Tyagi, P. et al. 2009).

There is increasing approval for the value of operation scenarios which can be used to direct management for the anticipated performance results of different policies (Athanassopoulos, A. D. et al. 1999). For this study, Data Envelopment Analysis (DEA) was employed to carry out our analyses.

In applications that involve flexible inputs like those involved for this study, input orientation model will be more appropriate. Based on the return to scale, there exists the constant returns to scale (CRS) and the variable returns to scale (VRS). 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. The mathematics behind the input oriented DEA is given below:

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

Subject to

CRS
$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{io}; i = 1,\ldots, m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro}; r = 1,\ldots, s$$

$$\lambda_j \geq 0 \quad j = 1,2\ldots, n$$

VRS Add
$$\sum_{j=1}^{n} \lambda_j = 1 \tag{1}$$

where θ is the measure of efficiency of DMU, the DMU in the set of $j = 1,2,\ldots n$ DMUs rated relative to the others; ε an infinitesimal positive number used to make both the input and output coefficients positive; s_i^- slack variables for input constraints, which are all constrained to be non-negative; s_r^+ slack variables for output constraints, which are all constrained to be non-negative; and λ_j the dual weight assigned to DMUs.
For sensitivity analysis, measure-specific DEA model was used. A way of testing the robustness of DEA results is conducting the analysis by omitting an input or output and then studying the results (Tyagi, P. et al. 2009). The mathematics behind it is given below

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

Subject to

CRS
$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{io;} i \in I;$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_i^- = \theta x_{io}; i \notin I;$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro}; r = 1,\ldots, s$$

$$\lambda_j \geq 0 \quad j = 1,2,\ldots, n. \tag{2}$$

Where I represents the sets of specific inputs respectively. For this study, the CRS approach was employed.

3. Applications

Data used was from the multiplicative decomposition results of a previous research. The data for case study 1 and 2 are given in Figures 1 and 2, where activity, structural and intensity are the input factors whereas the energy consumption is the output.

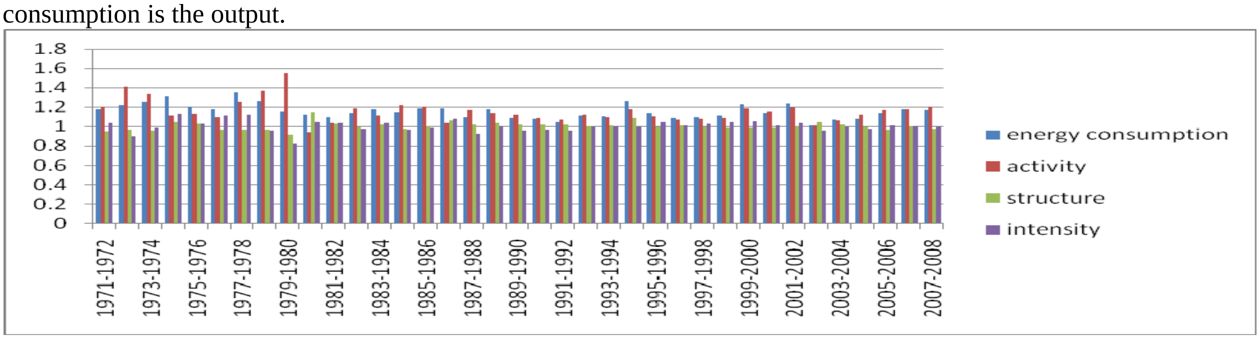

Figure 1: multiplicative decomposition for case study 1 showing the factors responsible for energy consumption in the South African industries

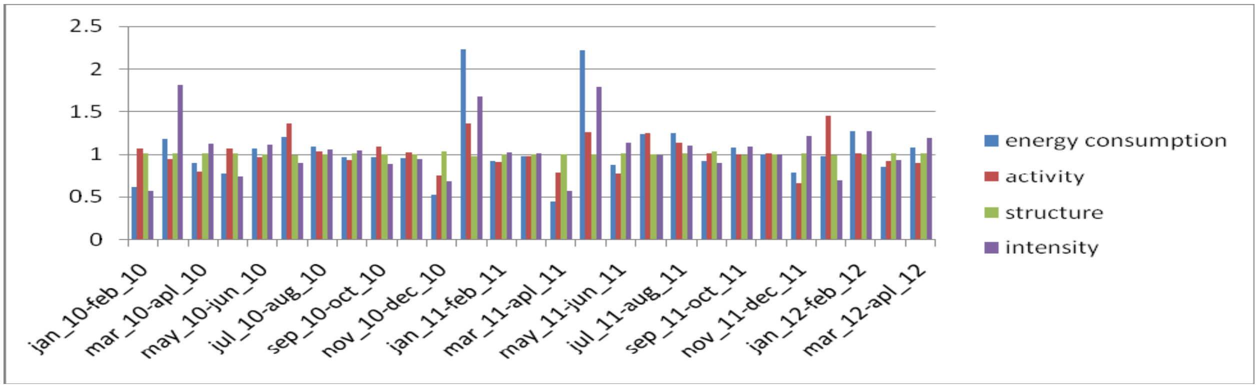

Figure 2: multiplicative decomposition for case study 2 showing the factors responsible for energy consumption in a food industry'X'

3.1 Case study 1: Assessment of the total operation for eleven South African industries

Industrial periods 1972-1973, 1973-1974, 1974-1975, 1975-1976, 1977-1978, 1978-1979, 1983-1984, 1985-1986, 1988-1989, 1994-1995, 1999-2000, 2001-2002, 2006-2007 and 2007-2008 scored lower than the average efficiency score. The lowest efficiency score (0.86978) is calculated for 1994-1995. This makes the total operation of 1994-1995 the weakest. 2002-2003 appears as a peer for maximum number of years, thus, it is the most technical efficient year. It is interesting to note that eight industrial years have VRS scores equal to one, four times more than the two efficient years of the CRS. This evidently explains that these years were able to convert their inputs into outputs efficiently, but the technical efficiencies of industrial years 1974-1975, 1976-1977, 1977-1978, 1980-1981, 1994-1995 and 1997-1998 are weak. The same technically efficient years have the values of their SE scores equal to one. This indicates that they operate at the best scale and there is no unfavorable impact of scale on their operation. 35 industrial years are recorded scale inefficient. These years are either absorbing too many inputs or too little relative to their optimality. The lowest SE is also calculated for 1994-1995. Table 1 depicts the results.

3.2 Case study 1: Sensitivity analysis for eleven South African industries

Model 1

Two inputs 'activity', 'structural' and the output 'energy consumption' have been considered in the first model. DEA has been carried out using CRS input oriented model. As a result of the analysis, it is observed that out of the 37 industrial years, 7 industrial years are efficient as they obtain CRS equal to one. The peers and their equivalent occurrence to other industrial years are 1972-1973 (0), 1974-1975 (29), 1977-1978 (230, 1978-1979 (1), 1979-1980 (7), and 1994-1995 (4). The highest peer counts of the industrial years signify the degree of its robustness in comparison with the other efficient industrial years. 1972-1973 is not a peer to any inefficient year; this makes it relatively inefficient considering 'activity' and 'structure' factors. We find that 1974-1975 has the highest peer count next to 1977-1978 and later 1980-1981. These industrial years are good examples for inefficient industrial years to imitate their operation practices to improve their utilization of 'energy consumption' without intensity factor in consideration.

For model 1, the inefficient industrial years and their equivalent percent reduction improvements for inputs 'activity' and 'structure' are 1971-1972 (10.05, 10.05)%, 1973-1974 (2.4, 2.4)%, 1975-1976 (8.64, 8.64)%, 1976-1977 (5.9, 5.9)%, 1981-1982 (10.11, 10.11)%, 1982-1983 (13.74, 13.74)%, 1983-1984 (9.13, 9.13)%, 1984-1985 (14, 14)%, 1985-1986 (10.9, 10.9)%, 1986-1987 (3.34, 3.34)%, 1987-1988 (16.47, 16.47)%, 1988-1989 (10.19, 10.19)%, 1989-1990 (16.23, 16.23)%, 1990-1991 (15.82, 15.82)%, 1991-1992 (17.46, 17.46)%, 1992-1993 (13.69, 13.69)%, 1993-1994 (13.62, 13.62)%, 1995-1996 (10.58, 10.58)%, 1996-1997 (13.51, 13.51)%, 1997-1998 (12.64, 12.64)%, 1998-1999 (11.48, 11.48)%, 1999-2000 (7.2, 7.2)%, 2000-2001 (12.35,12.35)%, 2001-2002 (6.67, 6.67)%, 2002-2003 (15.5, 15.5)%, 2003-2004 (14.75, 14.75)%, 2004-2005 (15.81, 15.81)%, 2005-2006 (12.53, 12.53)%, 2006-2007 (11.02, 11.02)%, 2007-2008 (12.13, 12.13)%.

Model 2

The second model excludes one input, 'structure'. By doing this, it was intended to examine the outcome of this change on efficiencies and to also appraise the ability of the industries in these years concerning energy consumption. The analysis shows the same years for model 1, 1972-1973, 1974-1975, 1977-1978, 1978-1979, 1979-

1980, 1980-1981 and 1994-1995. In spite of this, 1979-1980 is not a peer to any inefficient industrial year. This does not make the year relatively efficient considering the ‘activity’ and ‘intensity’ factors. All inefficient industrial years, except 1973-1974, 1975-1976, 1983-1984, 1985-1986, 1986-1987, 1988-1989, 1999-2000 and 2001-2001, obtained efficiency scores lower than the average efficiency score of 0.93150. The lowest efficiency score (0.87700) is calculated for 2002-2003. Thus, its operation is the weakest putting into consideration the absence of ‘structural’ input factor. The weakest industrial year has to reduce both its ‘activity’ and ‘intensity’ factors by 12.29% to reach the efficient frontier. Other inefficient industrial years and their equivalent percent reduction improvements for inputs ‘activity’ and ‘intensity’ are 1971-1972 (8.9, 8.9)%, 1973-1974 (1.76, 1.76)%, 1975-1976 (4.8, 4.8)%, 1976-1977 (8.59, 8.59)%, 1981-1982 (9.16, 9.16)%, 1982-1983 (8.8, 8.8)%, 1983-1984 (6.3, 6.3)%, 1984-1985 (8.4, 8.4)%, 1985-1986 (6.2, 6.2)%, 1986-1987 (3.3, 3.3)%, 1987-1988 (7.9, 7.9)%, 1988-1989 (5.6, 5.6)%, 1989-1990 (10.05, 10.05)%, 1990-1991 (10.3, 10.3)%, 1991-1992 (11.93, 11.93)%, 1992-1993 (10, 10)%, 1993-1994 (9.82, 9.82)%, 1995-1996 (8.94, 8.94)%, 1996-1997 (10.62, 10.62)%, 1997-1998 (10.91. 10.91)%, 1998-1999 (10.44, 10.44)%, 1999-2000 (5.49, 5.49)%, 2000-2001 (9.72, 9.72)%, 2001-2002 (4.11, 4.11)%, 2003-2004 (10.99, 10.99)%, 2004-2005 (11.52, 11.52)%, 2005-2006 (10.51, 10.51)%, 2006-2007 (7.2, 7.2)%, 2007-2008 (8.3, 8.3)%.

Table 1: Efficiency scores based on the total operation model for 11 industries in South Africa showing the technical efficiency, pure technical efficiency and scale efficiency

	CRS (TE)			VRS (PTE)			SE
DMU	**Efficiency**	**Peer**	**Peer Count**	**Efficiency**	**Peer**	**Peer Count**	**Efficiency**
1971-1972	0.96435	1979-1980, 2002-2003	Nil	0.98861	1976-1977, 1979-1980, 1997-1998	Nil	0.97546
1972-1973	0.93853	1979-1980, 2002-2003	Nil	0.97794	1974-1975, 1979-1980, 1980-1981, 1994-1995	Nil	0.9597
1973-1974	0.93006	1979-1980, 2002-2003	Nil	0.97826	1976-1977, 1977-1978, 1979-1980, 1980-1981	Nil	0.95072
1974-1975	0.90363	2002-2003	Nil	1	Nil	3	0.90363
1975-1976	0.91859	1979-1980, 2002-2003	Nil	0.97315	1976-1977, 1977-1978, 1979-1980, 1980-1981	Nil	0.94393
1976-1977	0.9926	2002-2003	Nil	1	Nil	24	0.9926
1977-1978	0.89521	1979-1980, 2002-2003	Nil	1	Nil	5	0.89521
1978-1979	0.92123	1979-1980, 2002-2003	Nil	0.97789	1974-1975, 1977-1978, 1979-1980, 1994-1995	Nil	0.94205
1979-1980	1	Nil	28	1	Nil	29	1
1980-1981	0.98395	2002-2003	Nil	1	Nil	19	0.98395
1981-1982	0.98871	2002-2003	Nil	0.99667	1976-1977, 1979-1980, 1980-1981, 2002-2003	Nil	0.99201
1982-1983	0.95858	1979-1980, 2002-2003	Nil	0.97578	1976-1977, 1979-1980, 1980-1981, 2002-2003	Nil	0.98237
1983-1984	0.93481	1979-1980, 2002-2003	Nil	0.9775	1976-1977, 1979-1980, 1980-1981, 2002-2003	Nil	0.95632
1984-1985	0.96465	1979-1980, 2002-2003	Nil	0.97724	1976-1977, 1979-1980, 1997-1998, 2002-2003	Nil	0.98711
1985-1986	0.93658	1979-1980, 2002-2003	Nil	0.96759	1976-1977,1979-1980, 1980-1981, 2002-2003	Nil	0.96795
1986-1987	0.95629	2002-2003	Nil	0.99222	1974-1975, 1976-1977, 1979-1980, 1980-1981	Nil	0.96378
1987-1988	0.96336	1979-1980, 2002-2003	Nil	0.97616	1979-1980, 1980-1981, 2002-2003	Nil	0.98688
1988-1989	0.92446	1979-1980, 2002-2003	Nil	0.96869	1976-1977, 1979-1980, 1980-1981, 2002-2003	Nil	0.95434
1989-1990	0.96776	1979-1980, 2002-2003	Nil	0.97991	1976-1977, 1979-1980, 1980-1981, 2002-2003	Nil	0.9876
1990-1991	0.97407	1979-1980, 2002-2003	Nil	0.98559	1976-1977, 1979-1980, 1980-1981, 2002-2003	Nil	0.98831
1991-1992	0.99124	1979-1980, 2002-2003	Nil	0.99326	1979-1980, 1997-1998, 2002-2003	Nil	0.99796
1992-1993	0.97078	1979-1980, 2002-2003	Nil	0.98486	1976-1977, 1979-1980, 1980-1981, 2002-2003	Nil	0.9857
1993-1994	0.96967	1979-1980, 2002-2003	Nil	0.98654	1976-1973, 1979-1980, 1980-1981,2002-2003	Nil	0.98289
1994-1995	0.86978	1979-1980, 2002-2003	Nil	1	Nil	2	0.86978
1995-1996	0.9626	1979-1980, 2002-2003	Nil	0.98846	1976-1977, 1979-1980, 1980-1981, 2002-2003	Nil	0.97383
1996-1997	0.98102	1979-1980, 2002-2003	Nil	0.99488	1976-1977, 1979-1980, 1997-1998, 2002-2003	Nil	0.98606
1997-1998	0.98641	2002-2003	Nil	1	Nil	9	0.98641
1998-1999	0.98432	2002-2003	Nil	0.99887	1976-1977, 1979-1980, 1997-1998, 2002-2003	Nil	0.98543
1999-2000	0.92962	1979-1980, 2002-2003	Nil	0.98057	1976-1977, 1977-1978, 1979-1980, 1980-1981	Nil	0.94804
2000-2001	0.96551	1979-1980, 2002-2003	Nil	0.98252	1976-1977, 1979-1980, 1997-1998, 2002-2003	Nil	0.98268
2001-2002	0.91624	1979-1980, 2002-2003	Nil	0.97756	1976-1977, 1977-1978, 1979-1980, 1980-1981	Nil	0.93727
2002-2003	1	Nil	35	1	Nil	20	1
2003-2004	0.98375	1979-1980, 2002-2003	Nil	0.99322	1976-1977, 1979-1980, 1997-1998, 2002-2003	Nil	0.9904
2004-2005	0.98462	1979-1980, 2002-2003	Nil	0.99232	1979-1980, 1997-1998, 2002-2003	Nil	0.99224
2005-2006	0.9734	1979-1980, 2002-2003	Nil	0.98986	1976-1977, 1979-1980, 1997-1998	Nil	0.98337
2006-2007	0.93845	1979-1980, 2002-2003	Nil	0.97135	1976-1977, 1979-1980, 1980-1981, 2002-2003	Nil	0.96612
2007-2008	0.95593	1979-1980, 2002-2003	Nil	0.97593	1976-1977, 1979-1980, 1980-1981, 2002-2003	Nil	0.9795

Model 3

In this model, we omit ‘activity’ parameter from the input parameters. The efficient industrial years for model 1 and model 2 remained for model 3. Peer industrial years and their equivalent peer counts are 1972-1973 (5), 1974-1975 (1), 1977-1978 (24), 1978-1979 (27), 1979-1980 (2), 1980-1981 (0), and 1994-1995 (28). Industrial year 1980-1981 is not present in the peer group. This peer analysis spots out that 1980-1981 is not a good operator for this model.

Table 2: Comparison of CRS efficiency scores of energy consumption based on different combination of input parameters (South African industries)

DMU	Model 1	Model 2	Model 3
1971-1972	0.89943	0.91093	0.90865
1972-1973	1(0)*	1(4)*	1(5)*
1973-1974	0.97577	0.98239	0.98613
1974-1975	1(29)*	1(24)*	1(1)*
1975-1976	0.91357	0.95158	0.93055
1976-1977	0.94007	0.91408	0.87444
1977-1978	1(23)*	1(8)*	1(24)*
1978-1979	1(1)*	1(3)*	1(27)*
1979-1980	1(1)*	1(0)*	1(2)*
1980-1981	1(7)*	1(2)*	1(0)*
1981-1982	0.89887	0.90833	0.84761
1982-1983	0.86255	0.91197	0.89874
1983-1984	0.90869	0.93688	0.90672
1984-1985	0.85970	0.91559	0.90411
1985-1986	0.89037	0.93710	0.93053
1986-1987	0.96658	0.96669	0.91905
1987-1988	0.83529	0.92051	0.89901
1988-1989	0.89808	0.94368	0.92301
1989-1990	0.83765	0.89945	0.87170
1990-1991	0.84173	0.89633	0.85447
1991-1992	0.82532	0.88065	0.83431
1992-1993	0.86305	0.89918	0.86937
1993-1994	0.86378	0.90173	0.86389
1994-1995	1(4)*	1(28)*	1(28)*
1995-1996	0.89419	0.91050	0.87510
1996-1997	0.86482	0.89372	0.84462
1997-1998	0.87350	0.89085	0.84535
1998-1999	0.88516	0.89551	0.85276
1999-2000	0.92798	0.94507	0.93428
2000-2001	0.87644	0.90271	0.88666
2001-2002	0.93323	0.95887	0.95329
2002-2003	0.84495	0.87700	0.80756
2003-2004	0.85240	0.89005	0.83976
2004-2005	0.84189	0.88480	0.85581
2005-2006	0.87463	0.89485	0.88228
2006-2007	0.88978	0.92781	0.91917
2007-2008	0.87861	0.91674	0.90894

3.3 Case study 2: Assessment of the total operation for food industry

Industrial dates apl_10-may_10, may_10-jun_10, jun_10-jul_10, jul_10-aug_10, aug_10-sep_10, sep_10-oct_10, oct_10-nov_10, dec_10-jan_11, feb_11-mar_11, apl_11-may_11, jun_11-jul_11, jul_11-aug_11, aug_11-sep_11, sep_11-oct_11, oct_11-nov_11, jan_12-feb_12 and mar_12-apl_12 scored lower than the average efficiency score. The lowest efficiency score (0.51917) is calculated for dec_10-jan_11. This makes the total operation of dec_10-jan_11the weakest. Mar_11-apl_11 appears as a peer for maximum number of years, thus, it is the most technical efficient year. Nine industrial years have VRS scores equal to one. This evidently explains that these years were able to convert their inputs into outputs efficiently, but the technical efficiencies of jan_10-feb_10, nov_10-dec_10, dec_10-jan_11, apl_11-may_11, aug_11-sep_11 and dec_11-jan_12 are weak. The same technically efficient periods have the values of their SE scores equal to one. This indicates that they operate at the best scale and there is no unfavorable impact of scale on their operation. The same technically inefficient periods are recorded scale inefficient. These periods are either absorbing too many inputs or too little relative to their optimality. The lowest SE is calculated for dec_10-jan_11. Table 3 depicts the results.

Table 3: Efficiency scores based on the total operation model for a particular food industry showing the technical efficiency, pure technical efficiency and scale efficiency

	CRS (TE)			VRS (PTE)			SE
DMU	**Efficiency**	**Peer**	**Peer Count**	**Efficiency**	**Peer**	**Peer Count**	**Efficiency**
Jan_10-feb_10	0.98493	mar_11-apl_11	Nil	1	Nil	14	0.98493
feb_10-mar_10	1	Nil	19	1	Nil	18	1
mar_10-apl_10	0.85075	feb_10-mar_10, mar_10-apl_10, nov_11-dec_11	Nil	0.85178	feb-10-mar_10, nov_10-dec_10, mar_11-apl_11, nov_11-dec_11	Nil	0.99879
apl_10-may_10	0.76759	mar_11-apl_11	Nil	0.90101	jan_10-feb_10, feb_10-mar_10, aug_11-sep_11, dec_11-jan_12	Nil	0.85192
may_10-jun_10	0.72873	feb_10-mar_10, mar_11-apl_11	Nil	0.77039	jan_10-feb_10, feb_10-mar_10, mar_11-apl_11	Nil	0.94592
jun_10-jul_10	0.63669	mar_11-apl_11	Nil	0.91153	feb_10-mar_10,apl_11-may_11, aug_11-sep_11, dec_11-jan_12	Nil	0.69848
jul_10-aug_10	0.70077	feb_10-mar_10, mar_11-apl_11	Nil	0.77628	jan_10-feb_10, feb_10-mar_10, dec_11-jan_12	Nil	0.90272
aug_10-sep_10	0.75849	feb_10-mar_10, mar_11-apl_11	Nil	0.79369	jan_10-feb_10, feb_10-mar_10, nov_10-dec_10, mar_11-apl_11	Nil	0.95565
sep_10-oct_10	0.6989	feb_10-mar_10, mar_11-apl_11	Nil	0.82506	jan_10-feb_10, feb_10-mar_10, dec_11-jan_12	Nil	0.847089
oct_10-nov_10	0.72476	feb_10-ma_10, mar_11-apl_11	Nil	0.80379	jan_10-feb_10, feb_10-mar_10,mar_11-apl_11	Nil	0.90167
nov_10-dec_10	0.97877	mar_11-apl_11, nov_11-dec_11	Nil	1	Nil	5	0.97877
dec_10-jan_11	0.51917	feb_10-mar_10, mar_11-apl_11	Nil	1	Nil	_	0.51917
jan_11-feb_11	0.77907	feb_10-mar_10, mar_11-apl_11	Nil	0.80485	jan_10-feb_10, feb_10-mar_10, mar_11-apl_11	Nil	0.96796
feb_11-mar_11	0.73558	feb_10-mar_10, mar_11-apl_11	Nil	0.79231	jan_10-feb_10, feb_10-mar_10, mar_11-apl_11	Nil	0.92839
mar_11-apl_11	1	Nil	24	1	Nil	12	1
apl_11-may_11	0.54288	feb_10-mar_10, mar_11-apl_11	Nil	1	Nil	2	0.54288
may_11-jun_11	0.86976	feb_10-mar_10, mar_11-apl_11, nov_11-dec_11	Nil	0.87061	feb_10-mar_10,nov_10-dec_10,mar_11-apl_11, nov_11-dec_11	Nil	0.99902
jun_11-jul_11	0.61593	feb_10-mar_10, mar_11-apl_11	Nil	0.90604	feb_10-mar_10, apl_11-may_11, aug_11-sep_11,dec_11-jan_12	Nil	0.6798
jul_11-aug_11	0.64172	feb_10-mar_10, mar_11-apl_11	Nil	0.80282	jan_10-feb_10, feb_10-mar_10, aug-11-sep_11, dec_11-jan_12	Nil	0.79933
aug_11-sep_11	0.72073	feb_10-mar_10, mar_11-apl_11	Nil	1	Nil	4	0.72073
sep_11-oct_11	0.71691	feb_10-mar_10, mar_11-apl_11	Nil	0.77398	jan_10-feb_10, feb_10-mar_10, mar_11-apl_11	Nil	0.92626
oct_11-nov_11	0.7238	feb_10-mar_10, mar_11-apl_11	Nil	0.79197	jan_10-feb_10, feb_10-mar_10, mar_11-apl_11	Nil	0.91391
nov_11-dec_11	1	Nil	3	1	Nil	2	1
dec_11-jan_12	0.83632	mar_11-apl_11	Nil	1	Nil	7	0.83632
jan_12-feb_12	0.68837	feb_10-mar_10, mar_11-apl_11	Nil	0.7323	jan_10-feb_10, feb_10-mar_10, dec_11-jan_12	Nil	0.94001
feb_12-mar_12	0.78584	feb_10-mar_10, mar_11-apl_11	Nil	0.83085	jan_10-feb_10, feb_10-mar_10, nov_10-dec_10, mar_11-apl_11	Nil	0.94582
mar_12-apl_12	0.753	feb_10-mar_10, mar_11-apl_11	Nil	0.77712	jan_10-feb_10, feb_10-mar_10, nov_10-dec_10, mar-11-dec_11	Nil	0.96896

3.4 Case study 2: Sensitivity analysis for food industry

Model 1

Two inputs 'activity', 'structural' and output 'energy consumption' are considered in the first model. DEA has been carried out using CRS input oriented model. As a result of the analysis, it is observed that out of the 27 DMUs (month-year), 4 DMUs are efficient as they obtain CRS equal to one. The peers and their equivalent occurrence to other industrial years are feb_10-mar_10 (22), dec_10-jan_10 (1), apl_11-may_11 (13) and dec_11-jan_12 (1). The highest peer counts of the industrial period signify the degree of its robustness in comparison with the others. We find that feb_10-mar_10 has the highest peer count next to apl_11-may_11. These DMUs are good examples for the inefficient DMUs to initiate their operation practices to improve their utilization of 'energy consumption' without 'intensity' factor in consideration.

For model 1, the inefficient DMUs and their equivalent percent reduction improvements for inputs 'activity' and 'structure' are jan_10-feb-10 (68.3, 68.5)%, mar_10-apl_10 (38.43, 48.12)%, apl_10-may_10 (59.36, 59.59)%, may_10-jun_10 (39.12, 39.12)%, jun_10-jul_10 (40.5, 41.7)%, jul_10-aug_10 (42.07, 42.07)%, aug_10-sep_10 (43.02, 43.02)%, sep_10-oct_10 (50.86, 50.90)%, oct_10-nov_10 (48.12, 48.12)%, nov_10-dec_10 (61.71, 70.45)%, jan_11-feb_11 (43.9, 46.3)%, feb_11-mar_11 (44.78, 44.78)%, mar_11-apl_11 (69.2, 74.1)%, may_11-jun_11 (38.33, 49.32)%, jun_11-jul_11 (44.37, 44.71)%, jul_11-aug_11 (38.68, 39.41)%, aug_11-sep_11 (49.11, 51.48)%, sep_11-oct_11 (40.49, 40.49)%, oct_11-nov_11 (45.41, 45.41)%, nov_11-dec_11 (34.12, 54.21)%, jan_12-feb_12 (30.6, 30.6)%, feb_12-mar_12 (49.18, 50.82)%, mar_12-apl_12 (34.3, 37.9).

Model 2

The second model excludes one input, 'structural'. By doing this, it intends to examine the outcome of this change on efficiencies and to also appraise the ability of the food industry in the month-year concerning the amount of energy consumed. The analysis shows the same DMUs as that of model 1 as the efficient DMUs. These are feb_10-mar_10, dec_10-jan_11, apl_11-may_11 and dec_11-jan_12. All inefficient DMUs, except apl_10-may_10, jun_10-jul_10, ep_10-oct_10, jun_11-jul_11, jul_11-aug_11, obtained efficiency scores lower than the average efficiency score of 0.77176. The lowest efficiency score (0.56642) is calculated for nov_10-dec_10. Thus, its operation is the weakest putting into consideration the absence of 'structural' input factor. The weakest DMU has to reduce both its 'activity' and 'intensity' factors by 43.35% to reach the efficient frontier. Other inefficient DMUs and their equivalent percent reduction improvements for inputs 'activity' and 'intensity' are jan_10-feb_10 (24.19, 24.19)%, mar_10-apl_10 (36.14, 36.14)%, apl_10-may_10 (22.46, 22.46)%, may_10-jun_10 (28.11, 28.11)%, jun_10-jul_10 (2.9, 2.9)%, jul_10-aug_10 (23.72, 23.72)%, aug_10-sep_10 (30.61, 30.61)%, sep_10-oct_10 (20.23, 20.23)%, oct_10-n0v_10 (24,9, 24.9)%, jan_11-feb_11 (32.57,32.57)%, feb_11-mar_11 (27.46, 27.46)%, mar_11-apl_11 (42.72, 42.72)%, may_11-jun_11 (36.49, 36.49)%, jun_11-jul_11 (9.0, 9.0)%, jul_11-aug_11 (15.93, 15.93)%, aug_11-sep_11 (24.0, 24.0)%, sep_11-oct_11 (26.27, 26.27)%, oct_11-nov_11 (25.77, 25.77), nov_11-dec_11 (33.75, 33.75)%, jan_12-feb_12 (23.9, 23.9)%, feb_12-mar_12 (31.8, 31.8)%, mar_12-apl_12 (29.45, 29.45)%.

Model 3

In this model, 'activity' parameter was omitted from the input parameters. The efficient DMUs for model 1 and model 2 remain for model 3. Peer DMUs and their equivalent peer counts are feb_10-mar_10 (0), dec_10-jan_11 (21), apl_11-may_11 (0) and dec_11-jan_12 (23). DMUs feb_10-mar_10 and apl_11-may_11 are not present in the peer groups. This peer analysis spots out that feb_10-mar_10 and apl_11-may_11 are not good operators for this model.

Table 4: Comparison of CRS efficiency scores of energy consumption based different combination of input parameters

DMU	Model 1	Model 2	Model 3
Jan_10-feb_10	0.31658	0.75806	0.7941
Feb_10-mar_10	1(22)*	1(2)*	1(0)*
Mar-10-apl_10	0.61565	0.63852	0.58560
Apl_10-may_10	0.40638	0.77539	0.75870
May_10-jun_10	0.60870	0.71882	0.70640
Jun_10-jul_10	0.59494	0.97090	0.96864
Jul_10-aug_10	0.57927	0.76276	0.75090
Aug_10-sep_10	0.56979	0.69381	0.67989
Sep_10-oct_10	0.49134	0.79762	0.78494
Oct_10-nov_10	0.51873	0.75004	0.73630
Nov_10-dec_10	0.38285	0.56642	0.54222
Dec_10-jan_11	1(1)*	1(21)*	1(21)*
Jan_11-feb_11	0.56004	0.67421	0.65956
Feb_11-mar_11	0.55218	0.72535	0.71177
Mar_11-apl_11	0.30739	0.57278	0.55399
Apl_11-may_11	1(13)*	1(5)*	1(0)*
May_11-jun_11	0.61661	0.63505	0.57089
Jun_11-jul_11	0.55628	0.90914	0.90331
Jul_11-aug_11	0.61312	0.84065	0.83226
Aug_11-sep_11	0.50886	0.75909	0.74538
Sep_11-oct_11	0.59504	0.73724	0.72496
Oct_11-nov_11	0.54586	0.74224	0.72897
Nov_11-dec_11	0.65877	0.66245	0.48448
Dec_11-jan_12	1(1)*	1(18)*	1(23)*
Jan_12-feb_12	0.69338	0.76000	0.74124
Feb_12-mar_12	0.50810	0.68148	0.66545
Mar_12-apl_12	0.65626	0.70541	0.66950

4. Policy Derivation

Outcomes from a diversity of models need to be deliberated by policy makers of developing countries in order to evaluate the dynamics of their decisions (Pandey, R. 2002). Otherwise, energy, which is a priceless exhaustible resource, will repeatedly be exhausted and give increase to severe environmental harms, such as air pollution and global warming gases (Bor, Y. J. 2008). The primary objective of this research has been to derive concrete policy for industrial energy consumption. For this purpose, these assessments were carried out for the above case studies, namely activity and structure input utilization assessment, activity and intensity input utilization assessment and structure and intensity input utilization assessment for the industrial periods of operation using 3 models. Sensitivity analysis was carried out on these 3 models using measure-specific DEA models. Among all models concerning the measure-specific DEA for case study 1, the highest mean (0.9315) and the lowest standard deviation (0.0411) are calculated for model 2. This indicates that ‘activity’ and ‘intensity’ combined together are better factors in energy consumption utilization without the ‘structural’ input. The lowest mean (0.90589) is calculated for model 1. This indicates that ‘intensity’ is an important factor in the efficient energy consumption utilization.

For case study 2, the highest mean (0.77175) and the lowest standard deviation (0.12989) are calculated for model 2. This implies that ‘activity’ and ‘intensity’ combined together are better factors in energy consumption utilization without the ‘structural’ input. The lowest mean (0.6094) is calculated for model 1. This indicates that ‘intensity’ is an important factor in the efficient energy consumption of food industry ‘X’. The results of these case studies imply that policies on how to reduce industrial energy intensity should be thoroughly revised.

The examination of International Energy Agency (IEA) demonstrates that considerable opportunities to enhance industrial energy efficiency exist. Much of this potential through policies can be captured for improving use and optimization of energy-efficient industrial equipment and systems, and promoting general efficiency through energy management (IEA 2011). To assist in reducing the industrial energy intensity, a mandatory energy efficiency policy in the industrial entities to employ certified energy managers and setting energy efficiency targets should be in place. So also, there is need for policy that should prevent old and inefficient equipment to be purchased and installed in the industries.

Policy assists technical efforts. The successful utilization of policy for energy efficiency development is based on how policy gives incentives for possible technical improvement, directly or indirectly, to industry sector (Tanaka, K. 2011). Energy efficiency is a path to ease the investment costs for increasing energy supply infrastructure in the presence of rigid financial limitations for many developing countries. Pressures from the environment also have its exerting influence (Peck, M. and Chipman, R. undated). An effective industrial energy efficiency primary policy is consistency, precision, obligation of industry in program design and realization, and, most importantly, permission for flexibility of industry response (McKane, A. et al. 2007).

5. Conclusion

The introduction of energy policies has been to reduce the intensity of energy. Various governments and stakeholders across the globe including South Africa has its department which responds to various energy challenges that has led to one or more energy policy development. A proper analysis of qualitative and quantitative models will assist in the development of policies needed for the abatement of energy consumption. This study successfully analyzed the operation of industrial sectors quantitatively through DEA models using different combinations of input variables. The primary objective is to analyze input parameter utilization assessment to obtain concrete policies for the industry. It successfully provided information about energy consumption factors. For both case studies, activity and intensity factors contribute most to the consumption of energy, with more focus on policies concentrating on the intensity factor if energy is to be reduced. Policy makers can utilize recommended deductions to improve the efficient consumption of energy. Policies and measures to save energy effectively in the industrial sector are important; it will go a long way in the efficient consumption of energy.

References

Ang, B. W. (2005). "The LMDI approach to decomposition analysis: a practical guide." Energy Policy 33: 867-871.

Athanassopoulos, A. D., N. Lambroukos and L. Seiford (1999). "Data envelopment scenario analysis for setting targets to electricity generating plants." European Journal of Operational Research 115: 413-428.

Bor, Y. J. (2008). "Consistent multi-level energy efficiency indicators and their policy implications" Energy Economics 30: 2401-2419.

Dernbach, J. (2007). "Stabilizing and Then Reducing U.S Energy Consumption: Legal and Policy Tools for Efficiency and Conservation."

Henning, D., S. Amiri and K. Holmgren (2006). "Modelling and optimisation of electricity, steam and district heating production for a local Swedish utility." European Journal of Operational Research 175: 1224-1247.

Hu, J.-L. and C.-H. Kao (2007). "Efficient energy-savings targets for APEC economies." Energy Policy 35: 373-382.

IEA (2011). 25 Energy Efficiency Policy Recommendations. 2011 Update.

Liu, C. H., S. J. Lin and C. Lewis (2010). "Evaluation of thermal power plant operational performance in Taiwan by data envelopment analysis." Energy Policy 38: 1049-1058.

McKane, A., L. Price and S. d. l. R. d. Can (2007). Policies for Promoting Industrial Energy Efficiency in Developing Countries and Transition Economies.

Pandey, R. (2002). "Energy policy modelling: agenda for developing countries." Energy Policy 30: 97-106.
Peck, M. and R. Chipman (undated). Industrial energy and material efficiency: what role for policies: 333-385.
Sarica, K. and I. Or (2007). "Efficiency assessment of Turkish power plants using data envelopment analysis." Energy 32: 1484-1499.
Shi, G.-M., J. Bi and J.-N. Wang (2010). "Chinese regional industrial energy efficiency evaluation based on a DEA model of fixing non-energy inputs." Energy Policy 38: 6172-6179.
Tanaka, K. (2011). "Review of policies and measures for energy efficiency in industry sector." Energy Policy 39: 6532-6550.
Tyagi, P., S. P. Yadav and S. P. Singh (2009). "Relative performance of academic departments using DEA with sensitivity analysis." Evaluation and Program Planning 32: 168-177.
UNIDO (2011). Industrial Development Report Industrial energy efficiency for sustainable wealth creation. Capturing environmental, economic and social dividends.
Yang, C.-J. (1999). Taiwan's Industrial Structural Change and its Implication on Energy Intensity, Massachusetts Institute of Technology. Master of Sience in Technology and Policy and Master of Science in Civil and Environmental Engineering.
Zhou, P., B. W. Ang and K. L. Poh (2008). "A survey of data envelopment analysis in energy and environmental studies." European Journal of Operational Research 189: 1-18.

Biography

Oludolapo A. Olanrewaju received the B.Sc degree in Electrical / Electronics Engineering and M.Sc in Industrial Engineering from the University of Ibadan (U.I), Nigeria, in 2005 and 2008 respectively, and the Ph.D degree from Tshwane University of Technology, Pretoria, in South Africa. He has published journal and conference papers. Dr Olanrewaju is a researcher in energy efficiency and artificial intelligent techniques.

Adisa A. Jimoh received the B.Eng. and M.Eng. degrees from Ahmadu Bello University (ABU), Zaria, Nigeria, in 1977 and 1980, respectively, and the Ph.D. degree from McMaster University, Hamilton, ON, Canada, in 1986. In 2001, he joined Tshwane University of Technology, Pretoria, South Africa, where is a Professor and the leader of the Energy and Industrial Power Systems research niche area. His research interests are in electric machines, drives, and power-electronics applications in power systems. Prof. Jimoh is a Registered Engineer in South Africa.

Pule A. Kholopane holds a Masters Degree in Industrial Engineering and Operations Management and several diplomas from different institutions, that is, Economics (Turin; Italy), Production Management (PMI), Communications (Wits), Industrial Relations (Wits) and Management (Wits). He obtained his PhD degree in Engineering Management from the University of Johannesburg. Dr. Kholopane is a researcher in the Quality and Operations management at the University of Johannesburg having presented papers at the Portland International Centre for Management of Engineering and Technology (PICMET) in the USA, the South African Institute of Industrial Engineering and (SAIIE) and the Association for Operations Management of Southern Africa.(SAPICS).