

THE INTERNATIONAL JOURNAL OF SCIENCE & TECHNOLEDGE

Framework for Natural Gas Performance Evaluation in Nigeria

Lolo Ojaraida

Ph.D. Scholar, Department of Petroleum Economics Emerald Energy Institute (EEI),
University of Port Harcourt, Nigeria

Iledare O. Omowumi

Professor, Louisiana State University Center for Energy Studies, USA

Ajienka Joseph

Professor, Department of Petroleum Engineering, University of Port Harcourt, Nigeria

Abstract:

For the purpose of proper economic planning, there is need for the gas industry in Nigeria to increase output by increasing its efficiency with given gas reserves. In this paper, a framework named the uncertain DEA plus is developed for the technical efficiency evaluation of the gas sector in Nigeria incorporating uncertainty in data from 2010 to 2018; since uncertainty is an intrinsic part of data. The framework is built on the uncertain DEA model with the inclusion of a correlation that assigns efficiency scores at different confidence levels based on the summation of slacks. The results of the analysis with natural gas reserves set as the input variable, gas production and gas utilized set as output variables shows that both gas production and gas utilization in Nigeria are still at a minimal stage; and drastic action in the form of policy formulation is urgently needed. The application of uncertain DEA plus for technical efficiency evaluation prior to policy enactment will give better policies and implementation strategies for increased gas production and gas utilization in Nigeria.

Keywords: *Uncertain DEA plus, Technical efficiency, framework, Uncertain DEA model, Natural gas, Natural gas reserves*

1. Introduction

The natural gas industry in Nigeria is of great interest due to the country's vast increasing natural gas reserves coupled with natural gas being the most dominant natural resource in the country. The current natural gas reserves of over 202 trillion cubic feet places Nigeria as the largest natural gas reserves holder in Africa. Ironically, little effort has been made in terms of gas development in Nigeria; most of the gases produced are produced incidentally in the course of oil production and are not profitably sold but simply flared due to gas infrastructural challenges. There are great opportunities in the gas sector that could bring about economic development and sustainable development of the sector thus, making the gas sector a focal point as regards the state of the national economy. It is therefore, pertinent to study the state of the gas sector in Nigeria with respect to its technical efficiency. This is because; there is need for every nation to know how a given industry can increase output by increasing its efficiency with limited or given resources for the purpose of economic planning.

Due to the limitation of resources at our disposal, and the necessity for resource management efficiency which in simple terms means lack of waste has always been a guiding part of all human activities (Kulik (2017)). This has brought about our inability to fulfill all needs concurrently and imposes making optimal decisions and economic choices to reduce waste to the barest minimum. Efficiency measures input versus output and is a very important principle in any business entity because every organization seeks to maximize her output with minimal input. As stated by Porcelli (2009), efficiency is an essential part of overall performance. Farrell (1957) was the first to present the measurement of efficiency; where he categorized efficiency measures into technical efficiency, allocative efficiency and economic efficiency. Page J.M. Jr. (1980) points out that low level of technical efficiency translates to poor economic performance. This implies that resources being well utilized without much waste (being efficient), will in turn, improve economic performance.

Data Envelopment Analysis (DEA) technique is a mathematical method where linear programming methods are applied to evaluate the efficiencies of sets of similar systems by looking at levels of input and output. The sets of comparable systems for efficiency evaluation are the Decision Making Units (DMUs). Charnes et al (1978) did an improvement on efficiency measurement, by developing the Data Envelopment Analysis (DEA) process where he presented the constant returns to scale model (CCR model). The variable return to scale model (VRS model) which introduces variability and an extension of the CCR model was developed by Banker et al (1984). Two orientations exist in calculating efficiencies as follows:

- Input Orientation: This has to do with minimizing inputs and keeping outputs fixed so as to have an efficient DMU. That is, avoiding wastes by producing as much output as possible as the input allows.
- Output Orientation: The output orientation approach maximizes outputs while keeping inputs fixed to have an efficient DMU. It has to do with avoiding wastes by using as little input as the output allows.

Several studies have been carried out with the use of DEA technique, but its use in the oil and gas sector is still at an infant stage. According to Paulo et al (2017), the use of DEA in the petroleum sector is rare with only forty three (43) publications where DEA was applied in the oil industry in twenty five (25) years. The study on the performance of four major oil and gas companies using Energy ratio analysis and DEA was done by Sanzhar et al (2015), while Stacy et al (2007) observed that the relative technical efficiencies of various National oil companies (NOCs) from a commercial point of view, are largely the result of government exercising control over the distribution of rents. Peter et al (2011) found that NOCs generally are less efficient than Shareholder-owned oil companies (SOCs). From the assessment of relative technical efficiency (RTE) of thirty two (32) active operators in Nigerian E&P using variable DEA model, Idowu et al (2018), discovered that there is declining trend in the operators' relative technical efficiencies (RTEs) from 2010 to 2016 in Nigeria. Ojaraida et al (2019) applied DEA technique to gas utilization in Nigeria and revealed that natural gas is not fully utilized in Nigeria; hence, economic growth in the country is negatively influenced.

The uncertainties which are intrinsic part of data used for performance evaluation cannot be ruled out. DEA technique is deterministic in nature because it does not incorporate data uncertainty and gives a single value efficiency score. This infers that the results obtained are sensitive to measurement errors and all deviations from the frontier are assumed to be attributed to inefficiency as stated by Huang et al, (2002). From the work of Lotfi et al (2009) it was proven that efficiency scores calculated from inaccurate data will also be inexact. Hence, the need for performance evaluation of the gas sector in Nigeria, using a framework or model which incorporates data uncertainty.

Different authors have established several ways of modeling data uncertainty in DEA, among which is the uncertain DEA model proposed by Meilin et al (2014) where uncertainty theory that deals with human uncertainty is applied to DEA in which input and output variables were considered uncertain. Uncertainty theory which is now a branch of axiomatic mathematics was first introduced by Liu (2007) and later refined by Liu (2010). The uncertain DEA model does not assign efficiency scores to DMUs, but rather tells if a particular DMU is efficient or not. This paper develops a framework known as the uncertain DEA plus that builds on the uncertain DEA model, incorporating a relationship between the summation of slacks and efficiency scores, to assign efficiency scores to each confidence level per DMU, and hence, gives a range of values of efficiency scores for each DMU. The framework is built on the components of python (a high-level programming language) libraries.

1.1. DEA Methodology

The DEA approach has both the constant return to scale model and the variable return to scale models as follows: Constant Returns to Scale model: The constant return to scale model also known as the CCR model maximizes output, and Charnes et al (1978) was the foremost presenter. It is given as:

$$\text{Max} \quad \frac{\sum_{y=1}^s V_y Y_{yp}}{\sum_{x=1}^m U_x X_{xp}} \quad \text{Equation 1}$$

$$\text{Subject to:} \quad \frac{\sum_{y=1}^s V_y Y_{yi}}{\sum_{x=1}^m U_x X_{xi}} \leq 1 \quad (\text{for all } i) \quad \text{Equation 2}$$

$$V_y, U_x \geq 0 \quad (\text{for all } y, x) \quad \text{Equation 3}$$

Where

$y = 1$ to s , s = number of output

$x = 1$ to m , m = number of input

y_{yi} = amount of output y produced by DMU i ,

x_{xi} = amount of input x utilized by DMU i ,

v_y = weight to be assigned to output y ,

u_x = weight to be assigned to input x .

1.1.1. Linear Model

The model can be transformed to a linear model by maximizing the numerator and setting the denominator as constant so that linear programming methods could be applied as follows:

$$\text{Max} \sum_{y=1}^s V_y Y_{yp} \quad \text{Equation 4}$$

$$\text{Subject to:} \quad \sum_{x=1}^m U_x X_{xp} = 1$$

$$\sum_{y=1}^s V_y Y_{yi} - \sum_{x=1}^m U_x X_{xi} \leq 0 \quad (\text{for all } i) \quad \text{Equation 5}$$

$$V_y, U_x \geq 0 \quad (\text{for all } y, x) \quad \text{Equation 6}$$

1.1.2. Dual Form

The dual form of the linear programming problem is another linear program derived from the original linear program. This is given as:

$$\text{Min } \theta \quad \text{Equation 7}$$

$$\sum_{x=1}^m X_{ix} \lambda_i \leq X_{io} \theta_0 \quad \text{for all } i \quad \text{Equation 8}$$

$$\text{Subject to:} \quad \sum_x Y_{rx} \lambda_x \geq Y_{ro}, \quad r=1, \dots, s \quad \text{Equation 9}$$

$$\lambda_x \geq 0, \quad x=1, \dots, n \quad \text{Equation 10}$$

The Variable Return to Scale model: The variable return to scale model which takes care of operational inconsistency is also known as the BCC model and was introduced by Banker et al, (1984). It is given as:

$$\text{Max } \sum_{y=1}^s V_y Y_{yp} + h_o \quad \text{Equation 11}$$

$$\text{Subject to: } \sum_{x=1}^m U_x X_{xp} = 1 \quad \text{Equation 12}$$

$$\sum_{y=1}^s V_y Y_{yi} - \sum_{x=1}^m U_x X_{xi} - h_o \leq 0 \quad \text{Equation 13}$$

$$V_y, U_x \geq 0 \text{ (for all } y, x)$$

For $h_o = 0$, it infers constant return to scale

$h_o \neq 0$, it infers variable return to scale. $h_o < 0$, infers increasing return to scale and $h_o > 0$, infers decreasing return to scale.

1.1.3. Uncertain DEA Methodology

The uncertain DEA model maximizes the total slacks in inputs and outputs subject to the constraints as proposed by Meilin et al (2014) and is given as follows:

$$\text{Max } \sum_{i=1}^p s_i^- + \sum_{j=1}^q s_j^+ \quad \text{Equation 14}$$

$$s. t: \sum_{k=1, k \neq 0}^n \lambda_k \vartheta_{ki}^{-1}(\alpha) + \lambda_0 \vartheta_{oi}^{-1}(1-\alpha) \leq \vartheta_{oi}^{-1}(1-\alpha) - s_i^-, \quad i = 1, 2, \dots \quad \text{Equation 15}$$

$$\sum_{k=1, k \neq 0}^n \lambda_k \psi_{kj}^{-1}(1-\alpha) + \lambda_0 \psi_{oj}^{-1}(\alpha) \geq \psi_{oj}^{-1}(\alpha) + s_j^+, \quad j = 1, 2, \dots, q \quad \text{Equation 16}$$

$$\sum_{k=1}^n \lambda_k = 1, \quad \text{Equation 17}$$

$$\lambda_k \geq 0, \quad k = 1, 2, \dots, n \quad \text{Equation 18}$$

$$s_i^- \geq 0, \quad i = 1, 2, \dots, p \quad \text{Equation 19}$$

$$s_j^+ \geq 0, \quad j = 1, 2, \dots, q \quad \text{Equation 20}$$

Where for a zigzag input variable $\mathfrak{E}(a, b, c)$,

$\vartheta^{-1}(\alpha)$ = inverse uncertainty distribution.

$$\begin{aligned} \vartheta^{-1}(\alpha) &= (1 - 2\alpha)a + 2\alpha b, & \text{for } \alpha \leq 0.5, \\ &= (2 - 2\alpha)b + (2\alpha - 1)c, & \text{for } \alpha > 0.5, \end{aligned}$$

For a zigzag output variable $\mathfrak{E}(a, b, c)$,

$\psi^{-1}(\alpha)$ = inverse uncertainty distribution.

$$\begin{aligned} \psi^{-1}(\alpha) &= (1 - 2\alpha)a + 2\alpha b, & \text{for } \alpha \leq 0.5, \\ &= (2 - 2\alpha)b + (2\alpha - 1)c, & \text{for } \alpha > 0.5, \end{aligned}$$

α = confidence level.

s_i^- = Input variable slacks

s_j^+ = Output variable slacks

The above crisp deterministic model is a linear programming model and, can be easily solved by any traditional methods. This uncertain DEA model has feasible solution and the optimal value $s_i^{-*} = s_j^{+*} = 0$ for all i, j .

DMU₀ is efficient at any confidence level when s_i^{-*} and s_j^{+*} are zero for $i = 1, 2, \dots, p$ and $j = 1, 2, \dots, q$ where s_i^{-*} and s_j^{+*} are optimal solutions of crisp uncertain DEA model. This definition is different from the normal efficiency definition since a degree of uncertainty is involved.

Input and output variables were transformed to zigzag variables denoted by $\mathfrak{E}(a, b, c)$. where a, b and c are the low case, base case, high case variable respectively with expert's assumed uncertainty range.

1.2. Uncertain DEA plus

The equivalent crisp uncertainty DEA model above was programmed using the Python.3.7 programming language (called the Uncertain DEA Plus) for the evaluation of DMUs with different α value (Expert's belief degree or confidence level) ranging from α of 0.1 to 0.9 in order to determine the efficient DMU at various confidence levels. DMUs with total input and output variable slacks equal to Zero (0) were termed efficient. DMUs whose total input and output variable slacks were closer to zero (0), are more efficient than DMUs whose total slack were farther away from zero.

Also included in the developed Uncertain DEA Plus is a correlation between the total slacks and efficiency scores which is based on the fact that at 0.5 confidence level, the efficiency derived from the uncertain DEA model is equivalent to efficiency scores from DEA model since it is the base case. The derived correlation is as follows:

$$\text{Efficiency} = - (1 * 10^{-5}) \sum(\text{slack}) + 1.001 \quad \text{Equation 21}$$

This correlation is used to generate efficiency scores for other α values.

2. Data Source for Analysis

The data source for this study is Nigerian National Petroleum Corporation (NNPC) annual statistical bulletin. The data includes annual natural gas reserves, annual gas production and annual gas utilized from 2010 to 2018.

3. Results and Discussion

3.1. DEA Results

The gas sector in Nigeria was evaluated in terms of technical efficiency with the annual gas reserves set as input variable, while the annual gas produced and annual gas utilized were set as the output variables. Output orientation with constant return to scale was utilized such that years with high gas production, high gas utilized and low gas reserves were termed efficient. Figure 1 with constant return to scale shows that only year 2015 is efficient. When output orientation with variable return to scale was utilized, it is seen that 2010, 2012, 2013 and 2015 were efficient, as shown in Figure 2; which proves that despite the huge natural gas resource in Nigeria, producing and utilizing the gas is still an issue.

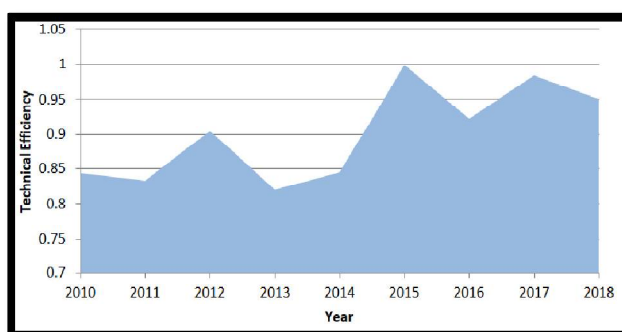


Figure 1: DEA Technical Efficiency with Constant Return to Scale

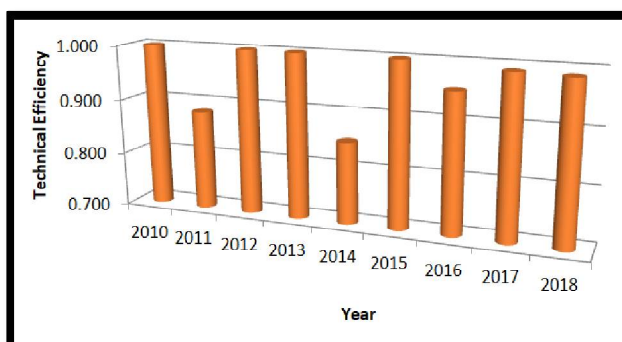


Figure 2: DEA Technical Efficiency with Variable Return to Scale

3.2. Uncertain DEA plus Results

Using the uncertain DEA plus program developed the efficiency results for nine (9) different confidence levels are shown in Table 1. With the incorporation of uncertainty, the technical efficiency for year 2010, could go as low as 70.8% and could go as high as 100%; while that of 2018 could go as low as 90.5% and as high as 93.2%. Having a range of values for efficiency scores from the uncertainty DEA plus instead of a deterministic single value from the DEA model, will help policy makers give better policies and implementation strategies. Table 2 shows the minimum, maximum, mean and standard deviation for each of the DMUs; while Figure 3 is a graph that displays a comparison of the DEA result and the Uncertain DEA plus result for each DMU.

DMU	$\alpha = 0.1$	$\alpha = 0.2$	$\alpha = 0.3$	$\alpha = 0.4$	$\alpha = 0.5$	$\alpha = 0.6$	$\alpha = 0.7$	$\alpha = 0.8$	$\alpha = 0.9$
2010	0.708	0.781	0.854	0.927	1.000	1.000	1.000	1.000	1.000
2011	0.973	0.973	0.972	0.972	0.970	0.896	0.823	0.749	0.676
2012	1.000	1.000	1.000	1.000	1.000	0.955	0.887	0.802	0.717
2013	1.000	1.000	1.000	1.000	1.000	0.939	0.863	0.782	0.709
2014	0.958	0.957	0.956	0.955	0.954	0.918	0.874	0.824	0.768
2015	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2016	0.934	0.933	0.931	0.930	0.929	0.916	0.901	0.884	0.865
2017	0.987	0.987	0.987	0.987	0.986	0.982	0.977	0.971	0.964
2018	0.932	0.931	0.929	0.928	0.926	0.922	0.917	0.911	0.905

Table 1: Uncertain DEA plus Result

DMU	Minimum	Mean	Maximum	Std Dev
-----	---------	------	---------	---------

2010	0.708	0.898	1.000	0.112
2011	0.676	0.868	0.973	0.114
2012	0.717	0.908	1.000	0.107
2013	0.709	0.900	1.000	0.111
2014	0.768	0.893	0.958	0.071
2015	1.000	1.000	1.000	0.000
2016	0.865	0.909	0.934	0.025
2017	0.964	0.979	0.987	0.009
2018	0.905	0.920	0.932	0.010

Table 2: Uncertain DEA plus Result Continued

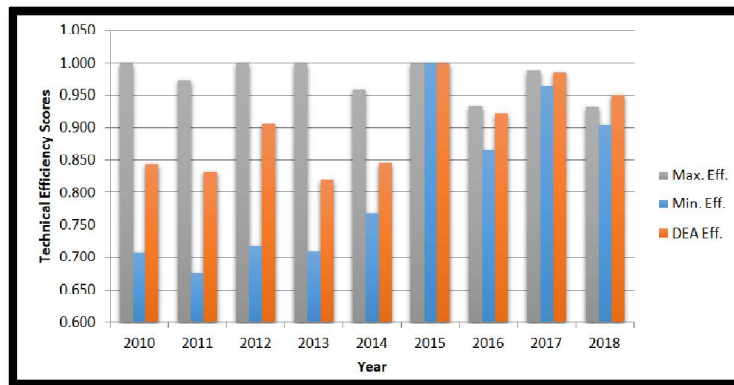


Figure 3: Comparison of DEA and Uncertain DEA plus Result

4. Conclusion and Recommendations

This paper develops a framework for evaluating the performance of the gas sector in Nigeria with the incorporation of data uncertainty, hence, addresses the limitation of the DEA model for performance evaluation. The framework is built on the uncertain DEA model but assigns efficiency scores to different confidence levels which give an improvement on the uncertain DEA model.

It is seen that despite the huge natural gas reserves in Nigeria, the country is still faced with challenges of gas production and gas utilization. Therefore, policies which will attract investors into the gas sector to boost gas production and eradicate gas flaring should be in place. Also, since efficiency is a significant part of overall performance, this framework for efficiency evaluation should be applied before policies which will bring about promotion of gas utilization and sustainable development of the gas industry are enacted.

5. Nomenclature

BCC	Banker, Charnes and Cooper
CCR	Charnes Cooper and Rhodes
CRS	Constant return to scale
DEA	Data Envelopment Analysis
DMU	Decision Making Unit
NNPC	Nigerian National Petroleum Corporation
NOC	National Oil Company
RTE	Relative Technical Efficiency
VRS	Variable returns to scale

6. References

- i. Banker R.D., Charnes A. and Cooper W.W. (1984); Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. *Management Science* Vol. 30, No. 9 (1984), pp. 1078 – 1092.
- ii. Charnes A., Cooper W. and Rhodes E. (1978); Measuring the Efficiency of Decision making units. *European Journal of operational Research*, 2: 429 - 444.
- iii. Farrell M.J. (1957); The Measurement of Productive Efficiency. *Journal of the Royal Statistical Society. Series A (General)*, Vol. 120, No. 3 (1957), pp. 253 – 290.
- iv. Huang T.H. and Wang M.H. (2002); Comparison of Economic Efficiency Estimation Methods: Parametric and non-parametric techniques. *The Manchester School* Vol. 70, No. 5, 682 – 709.
- v. Idowu A. J., Iledare O., Adeogun O. and Echendu J. C. (2018); Performance Assessment of Nigeria E&P Operators using Data Envelopment Analysis. SPE- 193455-MS: A Paper presented at the Nigerian Annual International Conference & Exhibition held in Lagos, Nigeria, 6th – 8th August, 2018.
- vi. Kulik J. (2017); Technical Efficiency and the methods of its measurement. *Ekonometria Econometrics* 3 (57), pp. 72 – 87.

- vii. Lotfi F.H., Firozja M. A. and Erfani V. (2009); Efficiency Measures in Data Envelopment Analysis with Fuzzy and Ordinal Data. *International Mathematical Forum*, 4, 2009. No. 20, 995 – 1006.
- viii. Liu B. (2007), *Uncertainty Theory*, Springer, Berlin, Germany, 2nd edition.
- ix. Liu B. (2010); *Uncertainty Theory: A branch of Mathematics for modeling Human Uncertainty*, Springer, Berlin, Germany.
- x. Meilin W., Linhan G., Rui K. and Yi Y. (2014); Data Envelopment Analysis with Uncertain Inputs and Outputs. *Journal of Applied Mathematics* volume 2014, Article ID 307108, 7 pages.
- xi. Ojaraida L., Iledare O. and Idowu A. (2019); Data Envelopment Analysis of Natural gas Utilization in Nigeria. SPE 198783-MS: A Paper presented at the Nigerian Annual International Conference & Exhibition held in Lagos, Nigeria, 5th – 7th August, 2019.
- xii. Page J.M. Jr. (1980); Technical Efficiency and Economic Performance: Some evidence from Ghana. *Oxford Economic Papers, New Series*, Vol. 32, No. 2 (1980), pp.319 – 339.
- xiii. Paulo R. C. B., Marcela M.V. and Mariana R.D. (2017); Comparative Analysis about the Application Methods of Data Envelopment Analysis (DEA) in the Oil Industry. *International Journal of Engineering Sciences and Research Technology*, 6(3), March, 2017.
- xiv. Peter R. H. and Kenneth B. M. (2011); Changes in Operational Efficiency of National Oil Companies. Porcelli F. (2009); Measurement of Technical Efficiency. A brief survey on parametric and non-parametric techniques.
- xv. Porcelli F. (2009); Measurement of Technical Efficiency. A brief survey on parametric and non-parametric techniques.
- xvi. Sanzhar I. and Nurgun K. Y. (2015); Performance Evaluation of Major Integrated Oil and Gas Companies. *International Journal of Economics, Commerce and Management*, Vol. iii, issue 6, June, 2015.
- xvii. Stacy L. E., Peter H. and Kenneth B. (2007); Empirical Evidence on the Operational Efficiency of National Oil Companies. The James A. Baker III for Public Policy Rice University.