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Potential reductions in global gas flaring for determining the optimal sizing of gas-to-wire (GTW) process: An inverse DEA approach

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Abstract

Gas flaring in the petroleum industry has a negative environmental impact and is a source of greenhouse gas (GHG) emissions. This raise concerns such that sustainability must be incorporated into the design of supply chains for the petroleum industry. In this study, we extended the inverse data envelopment analysis (DEA) model for estimating potential reductions in gas flaring at the national level for the Nigerian petroleum industry. These potential reductions when monetized, are equivalent to potential revenue and potential energy savings. In addition to the extended inverse DEA model, we developed an algorithm to determine the level of commitment of the industry to the zero-routine flaring initiative co-launched by the World Bank. Initial results in 2011, revealed that the Nigerian petroleum industry was inefficient relative to other oil producing nations, indicating that there is ample room for reduction in gas flaring at the current production levels. Application of our algorithm also revealed that the Nigerian petroleum industry is not able to adopt the zero-routine flaring initiative with the current technology, infrastructure, and labor force. We recommend that the Nigerian government should invest in better technology and a more highly skilled labor force, on par with those of the benchmarks identified by our extended inverse DEA model.

Keywords: Gas flaring; sustainability; zero-routine flaring; inverse DEA; petroleum industry

1. Introduction

Gas flaring refers to process of burning gas naturally dissolved in crude oil during production. The global rise in demand for oil over the last few decades is responsible for the increase in the associated gas flaring. As a source of greenhouse gas (GHG) emissions, the environmental impact of gas flaring can never be overemphasized. In terms of economic loss, the global economy loses billions of dollars annually to gas flaring, and every major oil producing nation, including Africa's largest oil producer, Nigeria, contributes a significant amount to this loss. (Ismail and Umukoro, 2012). According to Aregbe (2017), the Nigerian National Petroleum Corporation (NNPC) claimed Nigeria flared an estimated 12,602,480 million ft^3 of natural gas in a fifteen year period from 1996 to 2010, an amount equal to $12{,}967 \times 10^{12}$ BTU loss in energy that can be utilized for power generation or domestic use. The continual emissions of large volumes of carbon dioxide and GHG during the gas flaring process is quite alarming and calls for proper monitoring (Mousavi et al., 2020). Unsurprisingly, GHG emissions and the negative impact on both the environment and climate is increasingly gaining the attention of researchers, climate change advocates and environmentalists (Anomohanran, 2011).

We now highlight the common cause of gas flaring in the petroleum industry, particularly in developing nations. During the oil extraction process, large volumes of gas are naturally dissolved in petroleum, commonly referred to as associated gas, and must be separated before the crude oil refining process can take place. In this connection, there are three separation techniques: channeling and converting the associated gas for marketed production or power generation via turbines, reinjection into underground reservoirs for yielding more crude oil, and burning excess associated gas (i.e. gas flaring). The availability of state-of-art drilling technology has allowed the first two techniques to become common practice in developed nations. However, the unavailability of the appropriate technology, coupled with the fact that gas flaring is the cheapest separation technique, makes gas flaring a common practice in most oil-producing developing nations (Worila, 2002). In the recent past, offshore engineers have often claimed that gas flaring is a reliable safety measure for hazardous field operations, like in equipment failures and unexpected fluctuations in flowline conditions, but the fact remains that many oil producing nations capitalize on this reason by continuous flaring beyond safety levels. We must carefully distinguish between routine flaring and safety and maintenance flaring. Both terms cannot be used interchangeably. Routine flaring is the burning of unwanted associated gas mainly due to the absence of proper technology and amenable geology for reinjection and marketing purposes. On the other hand, safety and maintenance flaring are sometimes inevitable and are needed to reduce operational risks. In other words, routine flaring does not include safety and maintenance flaring. One cannot fault an oil producer for flaring gas based on safety or maintenance reasons.

To promote global gas flaring reduction, the World Bank collaborated with the Norwegian Government in August 2002 by launching the Global Gas Flaring Reduction (GGFR) initiative at a summit held in Johannesburg. The primary aim of the GGFR is to support governments of oil producing nations in their endeavors to reduce gas flaring (World Bank, 2004). The GGFR was a much-needed initiative or policy for regulating gas flaring in the petroleum industry because of the increasing emphasis on global warming and climate change. The World Bank estimates 140 billion cubic meters of global gas is flared annually, and this is equivalent to about 750 billion kWh of power, which is more than Africa's annual consumption of electricity.

Further commitment to gas flaring was demonstrated in 2015, when the World Bank also collaborated with the United Nations (UN), and launched the Zero Routine Flaring by 2030 initiative. This initiative is to eliminate routine flaring no later than 2030 and has been endorsed by several oil companies, national governments, and development institutions. For example, Occidental was the first U.S. oil and gas company to endorse the initiative. On November 6, 2019 Saudi Aramco made an official announcement that they would be joining this initiative after maintaining their gas flaring reduction of less than 1% of total natural gas production for the first half of 2019. More recently, the International Energy Agency's (IEA) 2019 report also stipulates that operators should start developing strategies for the conservation of associated gas for new oil fields, and eliminate, if possible, routine flaring on existing oil fields by 2030.

Despite the launch of both initiatives, there was a significant rise in global gas flaring in 2018. The reasons are clear. The boost in American shale oil production coupled with political unrest in Syria, Yemen and Venezuela all contributed to the 3% rise (i.e. 145 billion cubic meters) in global gas flaring in 2018, an amount equivalent to the combined gas consumption in Central and South America (Bamji, 2019). While some oil producing nations give plausible reasons for annual gas flaring, such as safety and maintenance flaring, it is hard to determine or quantify the exact amount of flared gas that goes to waste annually. It all boils down to a very basic question: 'At current production levels of crude oil, what is the potential reduction of wasted gas? 'The effective implementation of the GGFR is highly dependent on the answer to this basic question. Secondly, in addition to gas flaring data captured by satellite, it is imperative to determine the level of commitment of national governments to the Zero Routine Flaring by 2030 initiative. In other words, we rephrase this as another question: 'Can an oil-producing nation adopt the Zero Routine Flaring initiative in any given production year assuming its production processes are efficient?' Our extension of the inverse DEA model to include negative inputs and a developed algorithm is a first step for finding solutions to both questions.

This paper contributes to the literature by developing a mathematical framework that consists of an inverse DEA model and an algorithm for effective implementation of the gas flaring reduction initiatives co-launched by the World Bank in 2002 and 2015. Our extended inverse DEA model can determine the potential reduction of the annual flared gas for an inefficient oil-producing nation. By applying our model to members of the Organization of the Petroleum Exporting Countries (OPEC), we find the inefficient oil producing nations have the capability to reduce a significant amount of flared gas at the current production level of inputs and outputs. The governments of such nations must realize they can reduce gas flaring with or without investment in better technology and skilled labor. We also applied our algorithm to determine the level of commitment of inefficient producers to the zero routine flaring initiative, and we find the aim can be achieved before 2030 with standard processes and investment in better technology.

We review the literature related to DEA and inverse DEA in section 2 and then introduce the development of extended inverse DEA model with negative input and a new algorithm in section 3. In section 4, we apply our extended model and algorithm to selected OPEC member nations and discuss the results. We conclude with suggestions for further research in section 5.

2. Literature review

A dominant and vital component of the energy sector is the petroleum industry. Despite the global fall in oil prices due to surplus oil, the ongoing COVID-19 pandemic, emphasis on climate change/global warming, production of electric and hybrid vehicles, and promising research in renewable energy sources, the industry is still important to mankind. It continues to be the mainstay of the economy in some oil producing nations, providing billions of dollars in annual revenue, and most importantly, it currently preserves industrial civilization. However, this industry continues to generate huge amounts of environmental waste such as in oil spills, gas flaring and in drilling.

There is no doubt that the global fall in oil prices is a significant blow to any oil exporting nation due to reduced oil revenue. This partly leads to consecutive current account balance deficits in some OPEC member nations like Nigeria. A good strategy to counteract the decline in oil revenue would be to convert a proportion of flared or wasted natural gas to marketed production of natural gas. This strategy, also known as gas flare commercialization, is a potential source of revenue for any oil producing nation, provided such nation is focused on the environmental waste management associated with gas flaring. In this connection, one might conclude that sustainability must be incorporated into the design of the supply chains for the petroleum industry.

Several studies have applied DEA and inverse DEA for improving environmental sustainability in the energy sector. In the first part of this review, we consider relevant works on DEA and those of inverse DEA in the second part.

2.1 DEA for Performance Evaluation

In the face of global competition, performance evaluation is crucial to any production or service work system. The performance of a work system is often defined as the degree to which inputs are well utilized to give outputs. Performance evaluation and efficiency are often used interchangeably because efficiency is a technical measure of outputs against inputs. The multi-dimensional nature of the attributes of a system makes aggregate performance evaluation cumbersome and inappropriate, and this calls for evaluating the relative efficiencies of homogenous systems (Chen 2010).

DEA is a benchmarking tool for evaluating the efficiency of a homogenous group of producers or service providers and its underlying principle is linear programming. By homogenous, we imply that all producers use same inputs to generate the same outputs. Conventionally, each producer or service provider is referred to as a decision-making unit (DMU). We now consider recent and relevant works on environmental efficiency using DEA.

Sueyoshi and Wang (2014) used DEA to assess the sustainability of the supply chains of petroleum firms in the United States. Their results indicated that integrated firms were more efficient than independent firms because of their large supply chains linking upstream and downstream activities. Molinos-Senante et al., (2014) evaluated the overall efficiency of wastewater treatment plants (WWTPs) using DEA, placing much emphasis on the reduction of greenhouse gas (GHG) emissions. Their results show that 15 out of 60 WWTPs used in the analysis were efficient, and the mean performance index of the sample was less than unity indicating the potential for reduction in GHG emissions (i.e. estimated to be 30 % of the current emission level of GHG). Wu et al., (2015) used a parallel DEA model to evaluate the efficiency of passenger and freight transportation subsystems in China. Riccardi et al., (2012) applied DEA and the directional distance function in evaluating the global cement industry, considering carbon dioxide emissions as an undesirable output. From their results, countries utilizing alternative raw materials and other sources of fuels were deemed efficient by the DEA model.

Wu et al., (2016) used the DEA model to evaluate the efficiency of a hybrid production and pollution treatment system. Efficiency rankings from their results closely depict the environmental status of the eight regions under evaluation. Moutinho et al., (2017) used DEA to estimate the economic efficiency of 26 European countries over a 12-year period (2001 – 2012), including the impacts of environmental tax revenue, transport, and energy taxes on lower and higher eco-efficient countries.

2.2 Inverse DEA: The Reverse Process of DEA

The inverse DEA is an inverse optimization technique and considered as the reverse process of the conventional DEA. The DEA model computes the efficiency score of a DMU, but the inverse DEA model uses a predetermined efficiency score of a DMU to compute the optimal variations in input and output data. We briefly discuss the relevant literature on the pioneering and recent works on inverse DEA.

The first inverse DEA model was developed by (Wei et al., 2000). With the aid of the included examples in their work, their model solved inverse problems in real life. Yan et al., (2002) extended the inverse DEA model to solve resource allocation problems. Within the last two decades, the inverse DEA model has been extended and modified to address inverse optimization problems in real life.

Gattouffi et al., (2014) applied the inverse DEA model for bank mergers. Lim (2016) developed an inverse DEA model for setting product goals in the development of vehicle engines. The overall results suggest that the inverse DEA model can act as a prescriptive tool for setting product goals. Hassanzadeh et al., (2018) used inverse DEA models for assessing the sustainability of 20 European countries. Emrouznejad et al., (2018) applied the inverse DEA in allocating CO_2 emissions for selected sectors in Chinese manufacturing industries. Their results identify three stages: CO_2 total emissions reduction, allocation to two-digit industries and further allocation to provinces. More recently, Wegener and Amin (2018) developed a novel inverse DEA model for minimizing GHG emissions in 23 oil companies in the U.S and Canada.

To the best of our knowledge, none of these works addressed the issue of routine gas flaring in the petroleum industry from the perspective of modeling and estimating potential flaring reductions. This leaves a significant gap in literature which is filled by our paper.

x_{ij}:

3. Methodology

In this section, we introduce the directional distance DEA model as the base optimization model for our mathematical framework. We then explain the proposed inverse DEA model of Wegener and Amin (2018) for optimizing undesirable output(s). The following nomenclature is adopted in this paper.

$General\ Parameters$:

n: number of decision-making units (DMUs)

t: number of inefficient decision-making units (DMUs)

m: number of inputs of each DMU

s: number of good outputs of each DMU

q: number of bad outputs of each DMU

$Data\ Parameters$:

x_{ij}: ith input of DMU_j $(j = 1, \dots, n)$

y_{rj}^{g}: rth good output of DMU_j $(j = 1, \dots, n)$

y_{pj}^{b}: pth bad output of DMU$_j$ ($j = 1, \dots, n$)

$\hat{y}_r^{g}$: desired production quantity of rth good output by inefficient DMUs

$Decision\ Variables$:

θ_k: inefficiency score of DMU$_k$ ($k = 1, \dots, n$)

λ_j: weight assigned to DMU$_j$ ($j = 1, \dots, n$)

α_{ik}: change in ith input of DMU$_k$ ($k = 1, \dots, t$)

β_{rk}: change in rth good output of DMU$_k$ ($k = 1, \dots, t$)

γ_{pk}: change in pth bad output of DMU$_k$ ($k = 1, \dots, t$)

γ_{pk}^{max}: maximum change in pth bad output of DMU$_k$ ($k = 1, \dots, t$)

3.1 The Directional Distance DEA by Chung et al., (1997)

A special type of DEA model classifies outputs into two types – good and bad outputs. While the conventional DEA introduced by Charnes et al., (1978) ignored bad outputs, the directional distance DEA model proposes a reduction of bad outputs for the purpose of waste management. It can minimize all forms of waste in production processes. Few works have used this model for environmental waste management. For this reason, we employ the directional distance DEA model as our reference model for this research.

To determine the inefficiency of score of DMU-k ($k = 1, \dots, n$), Chung et al., (1997) formulated the directional distance DEA model (1) as follows:

$$\theta_k^* = \max \theta$$

$$s.t.$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{ik} \qquad i = 1, \dots, m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj}^{g} \geq (1+\theta) y_{rk}^{g} \qquad r = 1, \dots, s$$

$$\sum_{j=1}^{n} \lambda_j y_{pj}^b = (1-\theta) y_{pk}^b \qquad p = 1, \dots, q$$

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

$$\lambda_j \geq 0 \qquad j = 1, \dots, n \tag{1}$$

When $\theta_k^* = 0$, DMU-k is regarded as an efficient unit with a score of 1, i.e. the relationship between inefficiency and efficiency is expressed as:

Efficiency,$\varepsilon_k = (1-\theta_k^*)/(1+\theta_k^*)$.

Note that index k refers only to the DMU under evaluation while j is the general index for other DMUs. The directional distance DEA model offers dual benefits because it can reduce undesirable output(s) while increasing desirable output(s).

3.2 Inverse DEA Model by Wegener and Amin (2018)

Suppose α_{ik} is the change in ith input to yield a corresponding change β_{rk} in rth good output with associated change γ_{pk} in pth bad output, then the objective is to minimize the associated changes γ_{pk} in all bad outputs.

With the aid of the defined notations, Wegener and Amin (2018) proposed the following inverse DEA model

$$\min \gamma = (\gamma_{11}, \dots, \gamma_{q1}, \dots, \gamma_{1t}, \dots, \gamma_{qt})$$

$s.t.$

$$\sum_{j\epsilon F} \lambda_j^k x_{ij} + \sum_{l\epsilon G} \hat{\lambda}_l^k (\alpha_{il} + x_{il}) - (\alpha_{ik} + x_{ik}) \leq 0 \qquad \forall k \in S,\ i = 1, \dots, m$$

$$\sum_{j\epsilon F} \lambda_j^k y_{rj}^g + \sum_{l\epsilon G} \hat{\lambda}_l^k (\theta_{rl} + y_{rl}^g) - (1+\hat{\theta}_k) \times (\beta_{rk} + y_{rk}^g) \geq 0 \qquad \forall k \in S,\ r = 1, \dots, s$$

$$\sum_{j\epsilon F} \lambda_j^k y_{pj}^b + \sum_{l\epsilon G} \hat{\lambda}_l^k (\gamma_{pl} + y_{pl}^b) - (1-\hat{\theta}_k) \times (\gamma_{pk} + y_{pk}^b) = 0 \qquad \forall k \in S,\ p = 1, \dots, q$$

$$\sum_{j\epsilon F} \lambda_j^k + \sum_{l\epsilon G} \hat{\lambda}_l^k = 1 \qquad \forall k \in S$$

$$\sum_{k\epsilon S} \beta_{rk} = \hat{y}_r^g \qquad r = 1, \ldots, s$$

$$\alpha_{ik} \geq 0, \beta_{rk} \geq 0, \gamma_{pk} \geq 0 \;\; \forall k \in S,\; i = 1, \ldots, m \;\; r = 1, \ldots, s \;\; p = 1, \ldots, q$$

$$\lambda_j^k \geq 0, \hat{\lambda}_l^k \geq 0 \;\; \forall k, l \in G,\; \forall j \in F \tag{2}$$

where S is a convex set consisting of two subsets F and G and there are t DMUs in S. By definition of convexity, any DMU-k in S is a convex combination of efficient units in subset F having weights $\lambda_j^k \geq 0 \;\; j \in F$ and inefficient units in subset G having weights $\hat{\lambda}_l^k \geq 0 \;\; l \in G$. To preserve the efficiency score of DMU-k, one must set $\hat{\theta}_k \leq \theta_k^*$

By considering no change in frontier movement (refer to the proof in Wegener and Amin (2018)) after production and for a single undesirable output, they simplified the model as expressed below

$$\min \gamma = (\gamma_1 + \gamma_2 +, \ldots + \gamma_t)$$

$$s.t.$$

$$\sum_{j\epsilon F} \lambda_j^k x_{ij} - (\alpha_{ik} + x_{ik}) \leq 0 \qquad \forall k \in S,\; i = 1, \ldots, m$$

$$\sum_{j\epsilon F} \lambda_j^k y_{rj}^g - \left(1 + \hat{\theta}_k\right) \times \left(\beta_{rk} + y_{rk}^g\right) \geq 0 \qquad \forall k \in S,\; r = 1, \ldots, s$$

$$\sum_{j\epsilon F} \lambda_j^k y_{pj}^b - \left(1 - \hat{\theta}_k\right) \times \left(\gamma_{pk} + y_{pk}^b\right) = 0 \qquad \forall k \in S,\; p = 1, \ldots, q$$

$$\sum_{j\epsilon F} \lambda_j^k = 1 \qquad \forall k \in S$$

$$\sum_{k\epsilon S} \beta_{rk} = \hat{y}_r^g \qquad r = 1, \ldots, s$$

$$\alpha_{ik} \geq 0, \beta_{rk} \geq 0, \gamma_{pk} \geq 0 \ \ \forall k \in S, \ i = 1, \dots, m \ \ r = 1, \dots, s \ \ p = 1, \dots, q$$
$$\lambda_j^k \geq 0, \hat{\lambda}_l^k \geq 0 \ \ \forall k, l \in G, \ \ \forall j \in F \qquad (3)$$

3.3 Proposed Inverse DEA Modelling for Gas Flare Reduction

In this section, we extend the inverse DEA model (3) by Wegener and Amin (2018) to gas flare reduction in the petroleum industry. It is imperative to state here that model (3) only minimizes the undesirable output (i.e. greenhouse gas emission) while increasing the production rate. However, our methodology focuses on maintaining the production rate while reducing the undesirable output (i.e. gas flaring) in accordance with the two global gas flare reduction (GGFR) initiatives. In this connection, we pose two research questions:

- *At current production levels of inputs and outputs and with the current technology and workforce, what is the potential reduction in gas flaring during the production process of crude oil?*
- *Can the petroleum industry adopt the Zero Routine Flaring Initiative in any given production year?*

To address the first research question, we initially set the changes in input and good output, $\alpha_{ik} = \beta_{rk} = 0$, and γ_{pk} becomes a reduction or negative change in volume of flared gas. We incorporate these changes into model (3) for a feasible extension. Routine gas flaring is the only bad output considered for this research, this implies index $p = 1$ and change in bad output p of DMU$_k$, $\gamma_{pk} = \gamma_{1k}$ ($\forall k = 1, \dots, t$). The larger the potential reductions in gas flaring, the greater the potential savings in energy and revenue, coupled with less environmental impact. Hence, the objective here is to maximize the potential reductions, as shown in the following model

$$\max \gamma = (\gamma_1 + \gamma_2 +, \dots + \gamma_t)$$
$$s.t.$$
$$\sum_{j \in F} \lambda_j^k x_{ij} - x_{ik} \leq 0 \qquad \forall k \in S, \ \ i = 1, \dots, m$$

$$\sum_{j \in F} \lambda_j^k y_{rj}^g - \left(1 + \hat{\theta}_k\right) \times y_{rk}^g \geq 0 \qquad \forall k \in S, \ \ r = 1, \dots, s$$

$$\sum_{j \in F} \lambda_j^k y_{pj}^b - \left(1 - \hat{\theta}_k\right) \times \left(y_{pk}^b - \gamma_{pk}\right) = 0 \qquad \forall k \in S, \ p = 1, \dots, q$$

$$\sum_{j \epsilon F} \lambda_j^k = 1 \qquad \forall k \in S$$

$$\gamma_{pk} \leq y_{pk}^b$$

$$\alpha_{ik} \geq 0, \beta_{rk} \geq 0, \gamma_{pk} \geq 0 \;\; \forall k \in S,\; i = 1, \dots, m \;\; r = 1, \dots, s \;\; p = 1, \dots, q$$

$$\lambda_j^k \geq 0, \hat{\lambda}_l^k \geq 0 \;\; \forall k, l \in G,\; \forall j \in F \qquad (4)$$

The additional constraint $\gamma_{pk} \leq y_{pk}^b$ implies the potential reduction of an undesirable or bad output can not exceed its actual quantity. Model (4) is an extension of model (3) but it partially answers the first research question because of the possibility of modelling negative inputs.

A basic assumption of the classical DEA model is that inputs and outputs are positive. For this research, an input takes both positive and negative values. This implies model (4) must be further extended to accommodate negative inputs.

3.3.1 Modelling Negative Inputs

Consider a special case of $i = 2$ inputs and j DMUs:

$\lambda_j^k x_{1j} + \lambda_j^k x_{2j} - x_{ik} \leq 0$ ………..constraint 1 of model (4)

$\lambda_j^k x_{1j} + \lambda_j^k x_{2j} \leq x_{ik}$. Suppose x_{1j} is a positive input and x_{2j} is a negative input such that the expression becomes:

$\lambda_j^k x_{1j} - \lambda_j^k x_{2j} \leq x_{ik}$ …………… (i)

The inequality (i) can be represented by a combination of two different inequalities:

$\lambda_j^k x_{1j} \leq x_{ik}$ ………………. (ii)

$-\lambda_j^k x_{2j} \leq 0$ ……………… (iii) multiply by (-1)

This is equivalent to: $\lambda_j^k x_{1j} \leq x_{ik}$ ……………… (iv)

$\lambda_j^k x_{2j} \geq 0$ ……………… (v)

Define positive input $x_{1j} = x_{ij}^+$ and negative input $x_{2j} = x_{2j}^-$, and we have

$\lambda_j^k x_{1j}^+ \leq x_{ik}$ ……………… (vi)

$$\lambda_j^k x_{2j}^- \geq 0 \quad \ldots\ldots\ldots\ldots\ldots \text{(vii)}$$

We generalize all positive and negative inputs as follows:

$$\lambda_j^k x_{ij}^+ \leq x_{ik} \quad \ldots\ldots\ldots\ldots\ldots\ldots \text{(vi)}$$

$$\lambda_j^k x_{ij}^- \geq 0 \quad \ldots\ldots\ldots\ldots\ldots \text{(vii)}$$

Constraint 1 of model (4) can now be expressed as:

$$\sum_{j\in F} \lambda_j^k x_{ij}^+ \leq x_{ik} \text{ (positive inputs)} \ldots\ldots\ldots\ldots \text{(ix)}$$

$$\sum_{j\in F} \lambda_j^k x_{ij}^- \geq 0 \quad \text{(negative inputs)} \ldots\ldots\ldots\ldots \text{(x)}$$

Using this representation of negative inputs, and for a single producer and only one bad output we modify model (4) to give an extended model (5)

$$\max \gamma^* = \gamma_{pk}$$

$$s.t.$$

$$\sum_{j \epsilon F} \lambda_j^k x_{ij}^+ \leq x_{ik} \qquad \forall k \in S,\ \ i = 1, \ldots, m$$

$$\sum_{j \epsilon F} \lambda_j^k\, x_{ij}^- \geq 0 \qquad \forall k \in S,\ \ i = 1, \ldots, m$$

$$\sum_{j \epsilon F} \lambda_j^k y_{rj}^g - \left(1 + \hat{\theta}_k\right) \times y_{rk}^g \geq 0 \qquad \forall k \in S,\ \ r = 1, \ldots, s$$

$$\sum_{j \epsilon F} \lambda_j^k y_{pj}^b - \left(1 - \hat{\theta}_k\right) \times \left(y_{pk}^b - \gamma_{pk}\right) = 0 \qquad \forall k \in S,\ p = 1, \ldots, q$$

$$\sum_{j\epsilon F} \lambda_j^k = 1 \qquad\qquad\qquad\qquad \forall k \in S$$

$$\gamma_{pk} \leq y_{pk}^b$$

$$\alpha_{ik} \geq 0, \beta_{rk} \geq 0, \gamma_{pk} \geq 0 \;\; \forall k \in S,\; i = 1, \ldots, m \;\; r = 1, \ldots, s \;\; p = 1, \ldots, q$$

$$\lambda_j^k \geq 0, \hat{\lambda}_l^k \geq 0 \;\; \forall k, l \in G,\; \forall j \in F \qquad (5)$$

To retain the efficiency score of DMU-k from model (1), we select $\hat{\theta}_k < \theta_k^*$ (to be specific, we set $\hat{\theta}_k$ to two decimals without approximation). The value of γ^* in model (5) is the potential reduction in gas flaring for any given production year and the answer to our first research question. If $\gamma^* = 0$, it implies the current level of gas flared is a minimum and cannot be reduced. There exists a relationship between γ^* and $\hat{\theta}_k$ which leads to a theorem and proof. LINGO 18 solver is employed for solving all proposed models in this study.

THEOREM

The maximum potential reduction occurs at zero inefficiency i.e. when $\hat{\theta}_k = 0,\; y_{pk}^b = \gamma_{pk}^{max}$

Proof

In model (5) F denotes the subset of efficient producers that created the efficiency frontier of model (1) and need no further improvement. In constraints 3 and 4 of model (5), the terms $\sum_{j\epsilon F} \lambda_j^k y_{rj}^g$ and $\sum_{j\epsilon F} \lambda_j^k y_{pj}^b$ only apply to efficient producers in F, while the terms $(1 + \hat{\theta}_k) \times y_{rk}^g$ and $(1 - \hat{\theta}_k) \times (y_{pk}^b - \gamma_{pk})$ only apply to the inefficient DMU-k that needs improvement. At zero inefficiency, DMU-k will be considered efficient and added to set F. This implies from constraint 4 that no further improvement in gas flaring reduction is needed for DMU-k and we have that:

$$(1 - \hat{\theta}_k) \times (y_{pk}^b - \gamma_{pk}) = 0$$

When $\hat{\theta}_k = 0$, $y_{pk}^b - \gamma_{pk} = 0$

$y_{pk}^b = \gamma_{pk} = \gamma_{pk}^{max}$ and this completes the proof.

We also demonstrate this theorem by sensitivity analysis in subsequent sections. In the next section, we develop an algorithm based on the application of model (1), model (5) and the stated theorem as a framework for implementing the zero routine flaring initiative.

3.3.2 The Zero Routine Flaring Initiative

Introduced by the World Bank in 2015, this initiative brings together governments of oil producing nations, oil and energy companies for the purpose of eliminating routine gas flaring no later than 2030. While some industry experts claim there is a sufficient time frame for oil producing nations to standardize production processes and eliminate routine flaring, the recent spike in global gas flaring proves otherwise. This is partly due to the unavailability of the technical means for effective implementation of this initiative. Put simply, it is difficult to really determine the level of commitment of oil producing nations.

To determine if this initiative can be adopted by any petroleum industry, we state the following definitions and algorithm.

DEFINITION ONE: Through model (5) the maximum reduction of bad output γ_{pk}^{max} occurs at $\hat{\theta}_k = 0$ or $\varepsilon_k = 1$

DEFINITION TWO: Zero routine flaring initiative is adoptable, if and only if, $y_{pk}^{b} = \gamma_{pk}^{max}$.

ALGORITHM

Step 1: Through model (1) evaluate θ_k^* for each DMU_j $\forall j = 1,2, \dots, n$

Step 2: If $\theta_k^* = 0$ add DMU_j to set F and go to step 3; if $\theta_k^* > 0$ add DMU_j to set G and go to step 4

Step 3: For all $\mathrm{DMU}_j \in F$ If $j < n$ go to step 1; if $j = n$ go to step 5

Step 4: For all $\mathrm{DMU}_j \in G$ If $j < n$ go to step 1; if $j = n$ go to step 5

Step 5: Apply model (5) by combining all $\mathrm{DMU}_j \in F$ with each $\mathrm{DMU}_j \in G$ and go to step 6

Step 6: Through definition one, determine γ_{pk}^{max}

Step 7: Zero routine flaring initiative is adoptable through definition two

This algorithm provides the answer to the second research question because if the maximum reduction of bad output is equivalent to actual amount of bad output, we have a zero difference. Otherwise, an inefficient producer should invest more in better technology and more highly skilled workforce, coupled with standard practices.

3.4 Data Collection

The production data of the13 OPEC members in 2011 were obtained from the 2016 OPEC Annual Statistical Bulletin. It is also an open data source that can be downloaded from the official OPEC site. Data from the 2016 ASB publication covers a five–year period (i.e. 2011-2015). We chose OPEC member nations for this study because they supply a combined 43.5 percent of global crude oil and have 81.9 percent of the global oil reserves. Another reason is our case study, Nigeria, is a major OPEC member nation and still Africa's largest oil producer. It is imperative to determine how Nigeria performs relative to other OPEC members. In 2011, the Nigerian petroleum industry flared the highest volume of natural gas (i.e. 14270 million cubic metres, refer to Table 1). Hence, we base our analysis on the 2011 production year.

Table 1: Annual Gas Production in Nigeria (million cubic metres)

	2011	2012	2013	2014	2015	% change 15/14

Nigeria						
Gross production	84,004.0	84,846.0	79,626.0	86,325.2	85,223.2	–1.3
Marketed production	41,323.0	42,571.0	38,411.0	43,841.6	45,148.1	3.0
Flaring	14,270.0	13,182.0	12,112.0	10,736.8	9,687.3	–9.8
Reinjection	22,519.0	20,520.0	21,466.0	22,894.3	21,040.2	–8.1
Shrinkage	5,892.0	8,573.0	7,637.0	8,852.6	9,347.6	5.6

Source: 2016 OPEC Annual Statistical Bulletin (ASB)

3.4.1 Data Description

Inputs

The following inputs were chosen for this research because all producers provide annual data on each input to OPEC as part of the stipulated obligations for each member nation, and to ensure homogeneity of all producers (DMUs) in subsequent analysis

I. Current account balance

Knowing the current account balance of an oil producing nation is important when trying to figure out whether the producer is a net exporter or importer. A positive current account balance is a surplus, implying that the producer is a net exporter, while a negative current account is a deficit which implies the producer is a net importer. Both cases influence the production rate of crude oil in the long run. In this study, we denote surplus and deficit as positive and negative inputs, respectively.

II. Wells completed

This refers to number of oil wells developed and completed for exploration and production of crude oil.

III. Producing wells

Total number of completed oil wells (excluding oil wells that do not produce

economically) that continually yielded crude oil till end of production year (i.e. 31st December).

IV. Active rigs

Total number of operational oil rigs (including workover rigs) used in the production of crude oil as at the end of the production year. Active rigs and wells completed; both have a significant influence on the quantity of the refined petroleum outputs taking into consideration the refinery capacity of each producer. In other words, as more rigs are engaged and more wells are completed, the refinery capacity will be upgraded to accommodate more crude oil input.

V. Refinery capacity

This refers to the maximum number of barrels of crude oil that can be processed by the refinery to give refined petroleum products like gasoline, kerosene, distillates, residual fuels, and other miscellaneous products. Expressed in thousand barrels per calendar day (1000b/cd). This input determines the volume of refined products available for export and domestic use. Countries with large refinery capacity, like those of Saudi Arabia and Iran, generate significant revenue from exports of refined products in both the short and long run. Unfortunately, the converse holds for an oil giant like Nigeria with low refinery capacity and utilization. Currently, Nigeria has four functioning refineries – Kaduna Refining and Petrochemicals (KRPC) Limited, Port Harcourt Refining Company (PHRC), and Warri Refining and Petrochemicals Company (WRPC) and Niger Delta Petroleum Resources (NDPR), all contributing to a total refining capacity of 446 thousand barrels per day (Refer to Table 2) but the combined utilization of all three refineries was 8.67 percent in 2018. The old Port Harcourt refinery is not operational.

Table 2: Annual Domestic Refining Capacity Utilization in Nigeria (1000 b/cd)

		Kaduna Refining & Petrochemical Company	Port Harcourt Refining Company (New)	Port Harcourt Refining Company (Old)	Warri Refining & Petrochemical Company	Niger Delta Petroleum Resources	Total	Capacity Utilization, %
Designed Capacity, BPSD		110,000.00	150,000.00	60,000.00	125,000.00	1,000.00	446,000.00	
Crude Oil Processed, BPSD	2010	21,986.72	19,345.38	-	53,345.20	-	94,677.30	21.23
	2011	20896.79	31,853.02	-	49,731.41	222.03	102,703.25	23.03
	2012	31,981.86	24,530.97	-	34,868.71	557.45	91,938.99	20.61
	2013	32,452.43	44,937.47	-	20,925.04	185.18	98,500.12	22.09
	2014	12,160.39	23,557.15	-	24,049.59	503.71	60,270.84	13.51
	2015	3,297.36	9,274.21	-	8,337.64	714.66	21,623.87	4.85
	2016	10,310.69	32,669.98	-	14,746.13	605.43	58,332.23	13.08
	2017	16,597.23	6,998.94	-	14,775.66	696.90	39,068.73	8.67

* Old Port Harcourt Refinery was not operational during the period under review.

*NDPR commenced AGO production in May 2011.

Source: 2017 Nigerian Oil and Gas Industry Report by the Department of Petroleum Resources

Good Output

I. GDP per capita

This is computed as the GDP at current oil prices divided by the national population, expressed in US dollars per person. This economic output of OPEC member nations partly reflects the revenue or wealth earned from the export of crude oils and refined petroleum products per population size. For example, Qatar was an OPEC member nation from 1961 till the end of 2018 and is still considered the richest country in the world in terms of GDP per capita. Population is crucial to this study because the usage of production rates of crude oil or refined products could be misleading. Currently, Nigeria produces more crude than any other African oil producing nation, but had the lowest GDP per capita compared to Algeria, Angola, and Libya in 2011. This is due to the large population of Nigeria. Consequently, there is a dire need to improve the production efficiency and generate more revenue for the Nigerian economy with respect to its population size.

Bad Output

I. Routinely flared gas

Volume of routinely flared gas by each producer expressed in million standard cubic metres. Does not include safety or maintenance flaring.

NOTE

Observation of data obtained from the 2016 ASB revealed that some OPEC member nations recorded no data for flared gas. For example, Saudi Arabia and Iran recorded no data for flared gas in 2011. This must not be interpreted as the complete absence of gas flaring, in fact both nations flared gas, but the proportions can be attributed to safety or maintenance. Furthermore, Saudi Arabia is more committed to reduction in gas flaring than other OPEC member nations when one considers the nation's vast oil and gas reserves.

On this basis, we proceed with caution and consider two different scenarios for this study. In the first scenario, we exclude Saudi Arabia and Iran from our production possibility set (PPS) on the basis of no recorded flaring data. We then consider a second scenario where both nations are added to the PPS and we input zero entries for their flare data. The main difference is the first scenario involves only 11 members, without any assumptions, while the second involves all 13 members based on the assumption that

Saudi Arabia and Iran had zero routine flaring. We compare results of both cases in the next section.

4. Application, Results and Analysis

4.1 Application of the Models

We follow Wegener and Amin (2018) by applying our reference DEA model (1) in evaluating the efficiency of OPEC member nations. Through our proposed model (5), we calculate the potential reduction for any selected inefficient producer. We conclude each analysis by applying our algorithm to determine if such an inefficient producer can adopt the zero-routine initiative. For ease of proper analysis, all producers in alphabetical order are denoted as DMU-j where $j = 1,2, \dots, n$.

4.2 Results and Analysis

2011 Production Year (Scenario 1: Eleven OPEC members)

Table 3 presents the initial results including five inputs, one good output, one bad output, inefficiency (θ), and efficiency (ε) scores for each OPEC member nation. From Table 3, we observe six DMUs are inefficient i.e. DMU_1 (Algeria), DMU_4 (Indonesia), DMU_5 (Iraq), DMU_8 (Nigeria), DMU_{10} (United Arab Emirates), and DMU_{11} (Venezuela). Their efficiency scores are less than one. Hence, we denote the subsets of efficient and inefficient producers as F and G respectively, such that

$F = \{\mathrm{DMU}_2, \mathrm{DMU}_3, \mathrm{DMU}_6, \mathrm{DMU}_7, \mathrm{DMU}_9\}$, and

$G = \{\mathrm{DMU}_1, \mathrm{DMU}_4\ \mathrm{DMU}_5, \mathrm{DMU}_8, \mathrm{DMU}_{10}\mathrm{DMU}_{11}, \}$. We need to do a separate analysis for each inefficient DMU in G starting with our case study DMU_9 and then compute and compare the results of the other five DMUs.

Table 3: Data, inefficiency, and efficiency scores for 11 OPEC member nations

DMU	Current Account Balance (m US$)	Wells Comp.	Producing Wells	Active Rigs	Ref. Cap. (1000b/cd)	GDP per Capita (US$/person)	Rout. Flared Gas (million cu m)	Ineff (θ)	Eff. (ε)
1-Algeria	17770	249	2010	33	592	5453.5	3604	0.83	0.093
2-Angola	13085	112	1476	22	65	4666.95	7183	0	1.000

3-Ecuador	-402	207	3079	39	188.4	5193.04	539	0	1.000
4-Indonesia	1685	838	10423	80	1125	3121	2452	0.78	0.124
5-Iraq	26365	76	1695	59	810	5571.55	9612	0.91	0.047
6-Kuwait	65743	523	1798	32	936	41672	217	0	1.000
7-Libya	3173	76	609	55	380	5858	1302	0	1.000
8-Nigeria	10757	124	2116	38	445	2451.75	14270	0.91	0.047
9-Qatar	51906	29	517	6	283	97983.27	558	0	1.000
10-UAE	50948	266	1592	19	675	40819.31	982	0.55	0.290
11-Venezuela	16342	1050	14915	116	1872	10283.2	9284	0.94	0.031

Taking DMU_8 (Nigeria) as our case study, we apply model (5) to determine the potential reduction of gas flaring.

From solution report, the potential reduction in gas flaring for the Nigerian petroleum industry is $\gamma_8 = 382.9901$million cubic metres from a total flare of 14270 million cubic metres in 2011.

This is equivalent to $\gamma_8 = 382.9901 \times 35.3\ million\ cubic\ feet$

$$\gamma_8 = 13519.55 million\ cubic\ feet = \left(\frac{13519.55 million}{3.41}\right) kWh\ of\ energy$$

$$\gamma_8 = 3964.68 million\ kWh\ of\ energy$$

$$\gamma_8 = 13519.55 million\ cubic\ feet = 13519550\ thousand\ cubic\ feet$$

At US\$3.00 per thousand ft^3 of natural gas, the economic loss equals:

$$\gamma_8 = 13519550\ thousand\ cubic\ feet \times \$3.00 = \text{US\$40,558,650}$$

4.2.2 Application of Proposed Algorithm

Through steps 1 to 6, we obtain $\gamma_8^{max} = 13020.17$ million cubic meters. This is equivalent to 459612million cubic feet. The corresponding maximum savings in energy and revenue are $134{,}783.58 million\ kWh$ and US\$1.379 billion, respectively. From Table 3, the actual volume of routinely flared gas by DMU_8 is $y_8^b = 14270$ million cubic meters.

Now since $y_8^b > \gamma_8^{max}$, we conclude that the Nigerian petroleum industry could not adopt the initiative in 2011, assuming the industry is relatively efficient compared to the other OPEC member nations. However, the deviation from this initiative (i.e. $y_8^b - \gamma_8^{max}$ =1249.83 million cubic metres) suggests that a continual investment in better technology and skilled labor can achieve this goal within the decade.

4.2.3 Sensitivity Analysis

We find from sensitivity analysis that as the inefficiency measure of DMU_8 (i.e. $\theta_8 = 0.91$) decrease in steps of 0.1 the potential reductions, γ_8 increases. When $\theta_8 = 0$, γ_8 achieves a maximum value $\gamma_8^{max} = 13020.17$ million cubic metres from a total flare of 14270 million cubic metres in 2011. This implies an inverse relationship between θ and γ. Fig. 1 shows the measure of inefficiency is a function of the potential reductions.

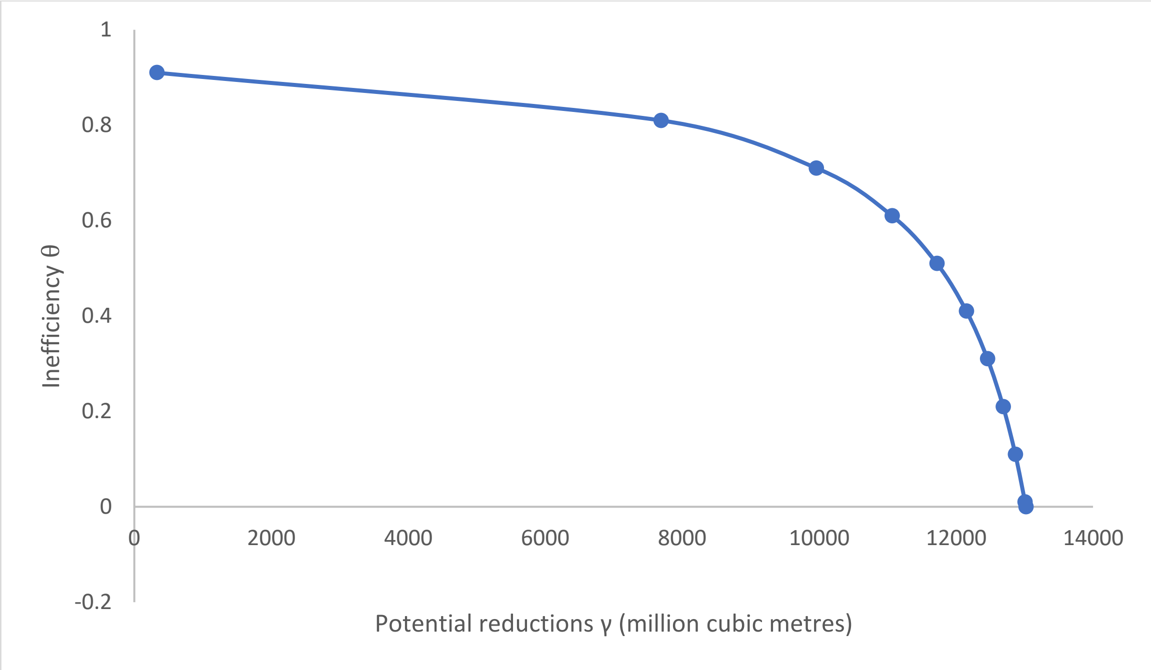

Fig 1: Effect of inefficiency on potential reductions in gas flaring for DMU_8(Nigeria)

The sensitivity analysis proved to be in accordance with our developed algorithm for the zero routine flaring initiative. Fig. 1 summarizes steps 1 to 6 of our algorithm, which, in fact, helps to determine the maximum potential reduction, γ_8^{max} for DMU_9.

4.2.4 Comparative Analysis

We need to apply our extended model and algorithm to $\mathrm{DMU}_1, \mathrm{DMU}_4, \mathrm{DMU}_5, \mathrm{DMU}_{10}$ and DMU_{11}, and compare their results with those of DMU_8. The aim is to validate our model and algorithm and to determine which DMU is more committed to the zero-routine initiative.

Table 4 presents the obtained results, including the computed deviations. Similarly, all five DMUs could not adopt the initiative in 2011. Consequently, we need to compute their deviations. In terms of least deviation, it is obvious from Table 4, that DMU_{10}(UAE) is most committed to the zero-routine initiative while DMU_8(Nigeria) least committed because it has the largest deviation. In order of least deviation, we rank them as follows:

$$\mathrm{DMU}_{10} > \mathrm{DMU}_{11} > \mathrm{DMU}_4 > \mathrm{DMU}_1 > \mathrm{DMU}_5 > \mathrm{DMU}_8$$

However, in terms of other yardsticks such as maximum potential revenue, maximum energy savings and maximum potential reductions, our case study, DMU_8 (Nigeria) outperformed the other five DMUs. This implies to a reasonable extent, that DMU_8 stands a far better chance of improvement with investment in improved technology that will place it on par with the other efficient DMUs. In this regard, the efficient DMUs of the subset F serve as the ideal benchmarks for DMU_8**.** Fig. 2 gives a perfect illustration of the scenarios involving maximum savings and makes the strong case that all inefficient DMUs have ample room for reduction in routine gas flaring. The maximum reductions are quite high compared to the other yardsticks. Also, the low deviations are indicators that the producers are on track to achieving the zero routine initiative provided further investments are made. Fig. 3 illustrates the potential improvements with current technology and workforce. Here the potential improvements refer to the case where producers are not willing to invest in better technology due to financial constraints or the unpredictability of global oil prices.

Table 4: Summary of results for inefficient DMUs (Scenario 1)

DMU	Potential Reduction γ $(m\ cu^3)$	Potential Energy Savings (MWh)	Potential Revenue $(m\ \$)$	Maximum Potential Reduction γ_k^{max} $(m\ cu^3)$	Maximum Energy Savings (MWh)	Maximum Potential Revenue $(m\ \$)$	Deviation $(y_k^b - \gamma_k^{max})$ $(m\ cu^3)$
1-Algeria	23.69	0.245	2.51	2995.35	31.00	317.20	608.65
4-Indonesia	39.51	0.409	4.18	1921.25	19.89	203.46	530.75
5-Iraq	658.56	6.817	69.74	8806.19	91.16	932.58	805.81
8-Nigeria	382.99	3.965	40.56	13020.20	134.78	1379	1249.83
10-UAE	16.63	0.172	1.76	547.58	5.67	57.99	434.42
11-Venezuela	1229.85	12.731	130.24	8825.04	91.36	934.57	458.96

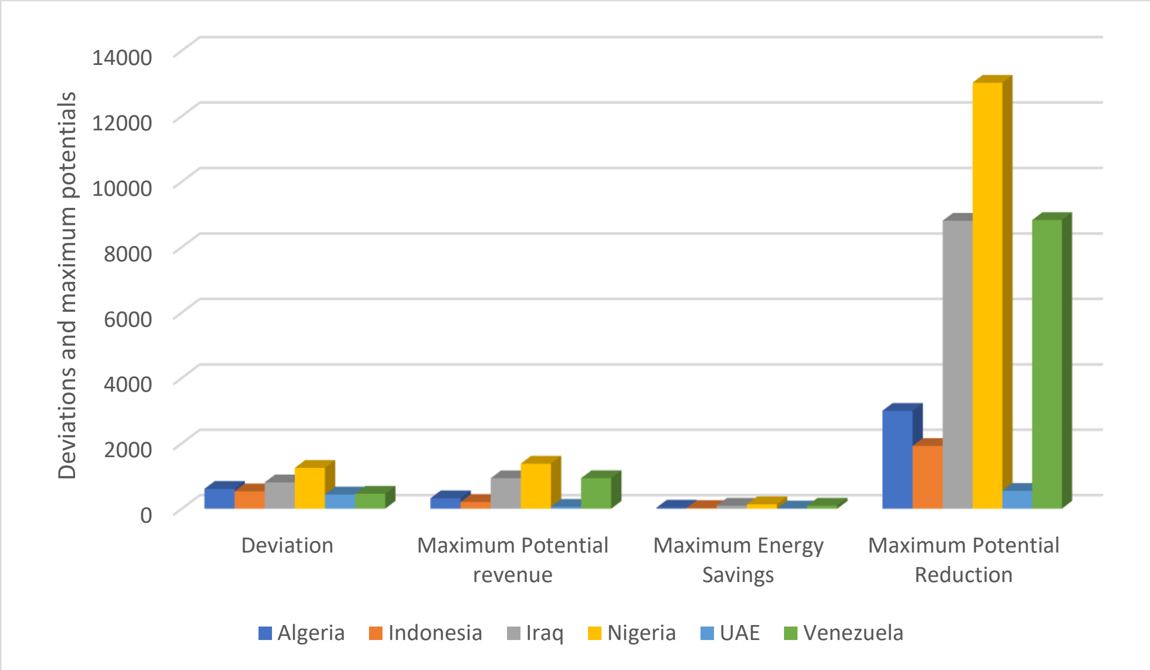

Fig 2: Deviations and Maximum Potential Improvements for inefficient producers

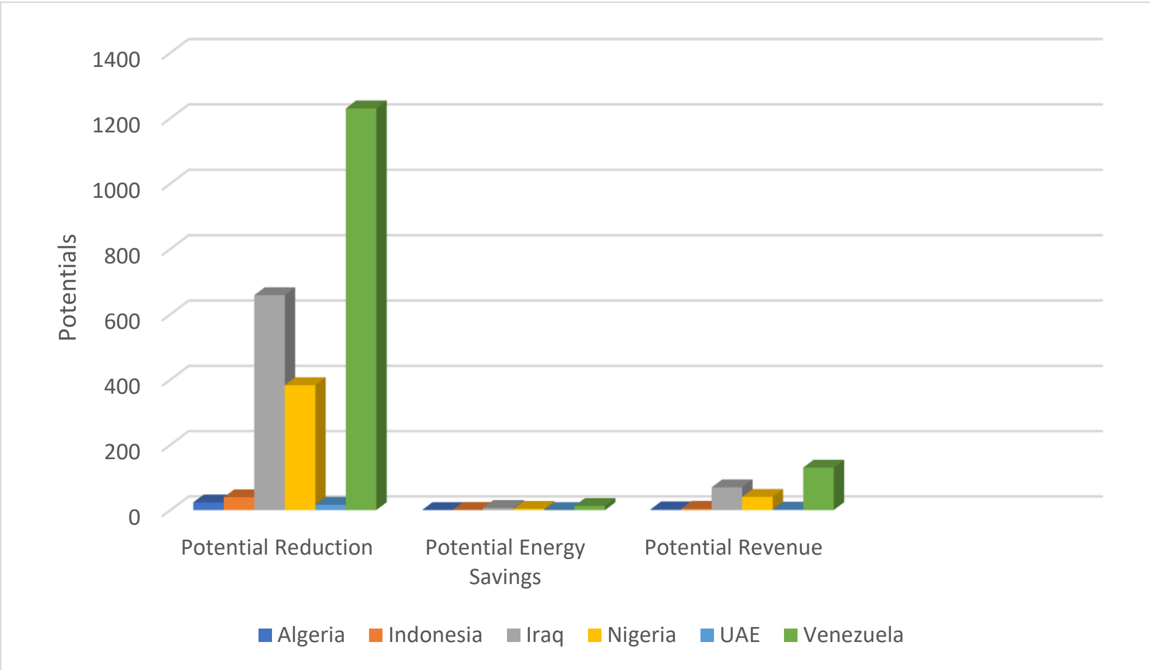

Fig 3: Potential Improvements for inefficient producers

To further support our claim that DMU inefficiency is a function of the potential reductions, we extend the sensitivity analysis to the other five inefficient DMUs. The results are presented in Figs. 4 to 8. In each case, the inefficiency score was decreased in similar steps of 0.1 and the maximum reduction occurred at zero inefficiency or when the DMU became efficient.

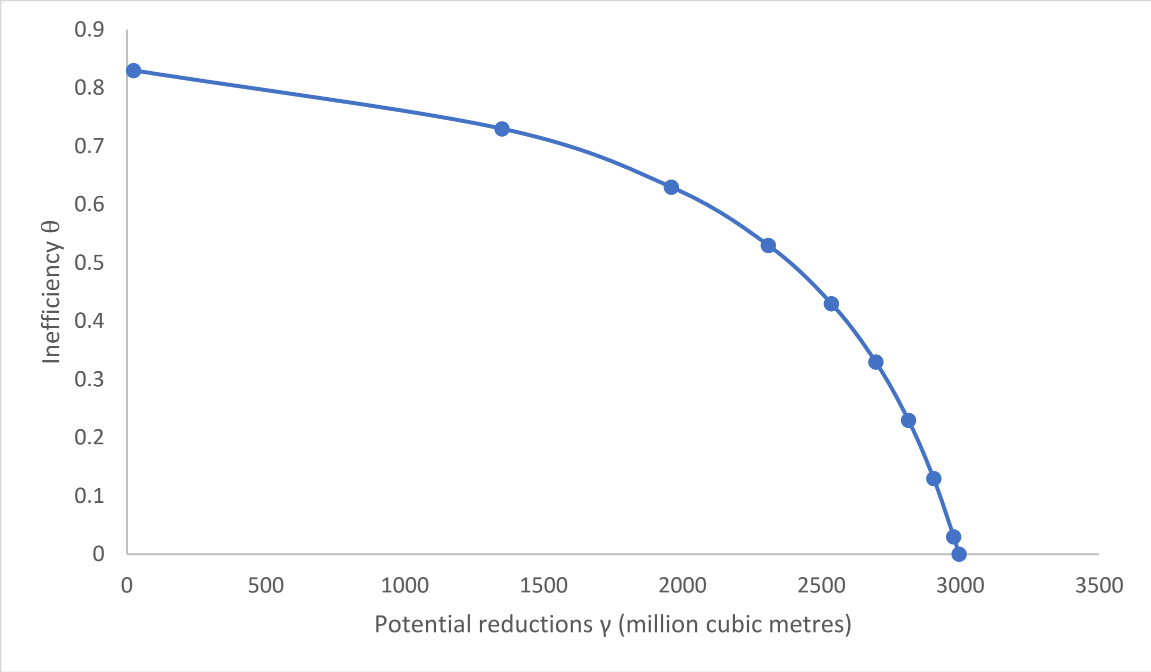

Fig 4: Effect of inefficiency on potential reductions in gas flaring for DMU_1(Algeria)

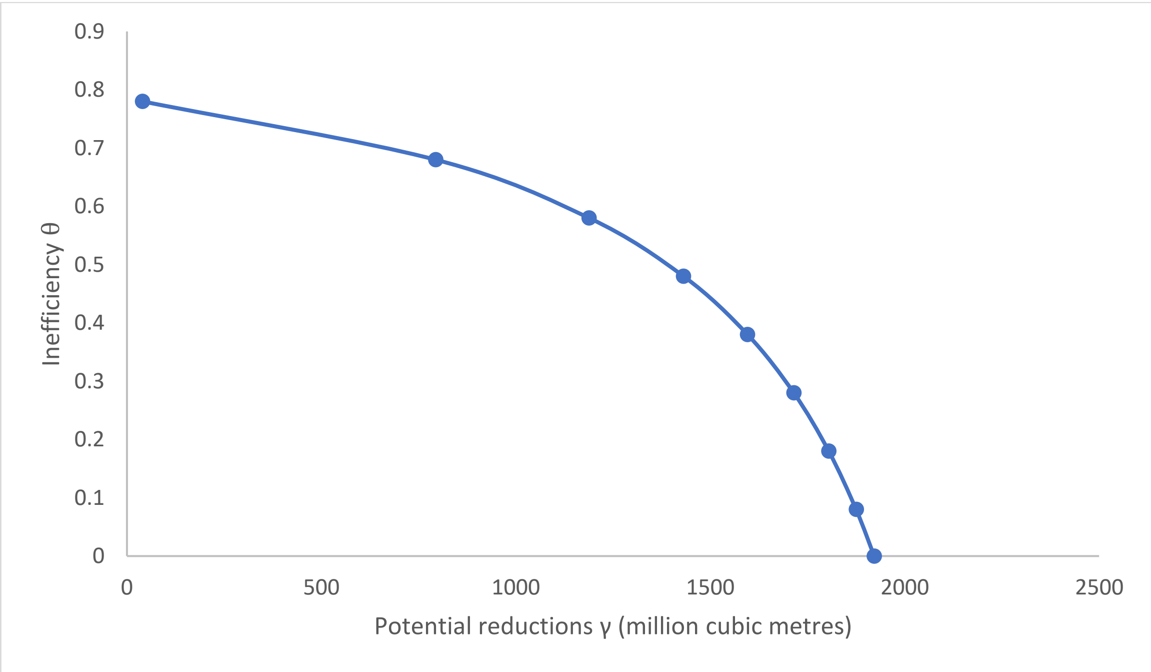

Fig 5: Effect of inefficiency on potential reductions in gas flaring for DMU_4 (Indonesia)

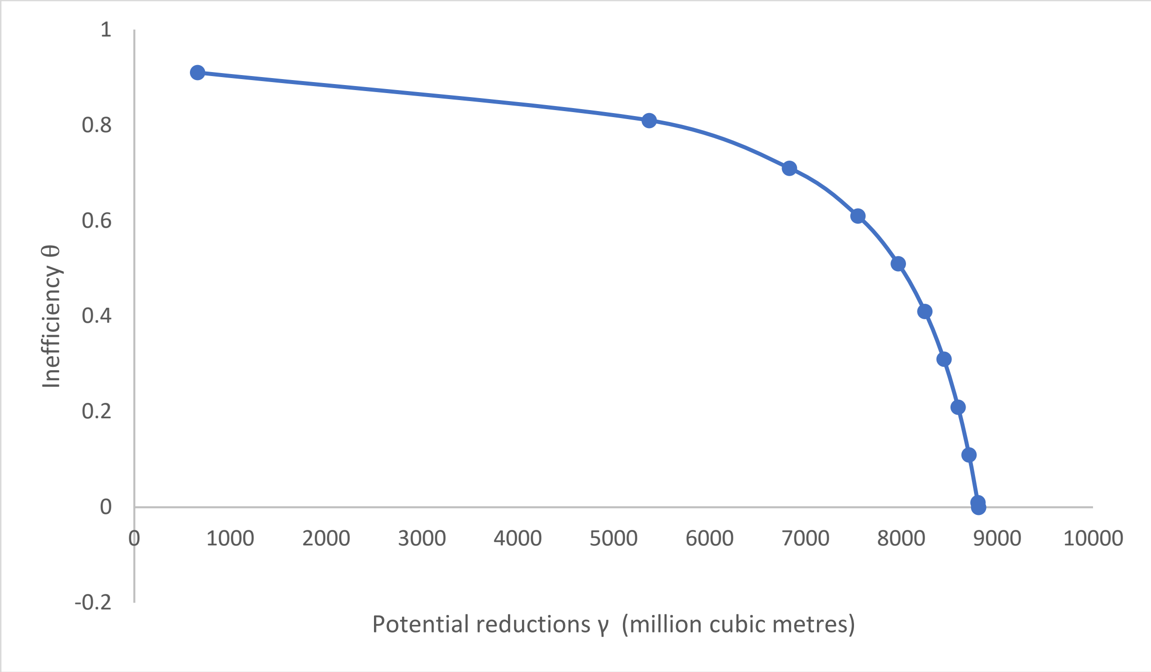

Fig 6: Effect of inefficiency on potential reductions in gas flaring for DMU_5 (Iraq)

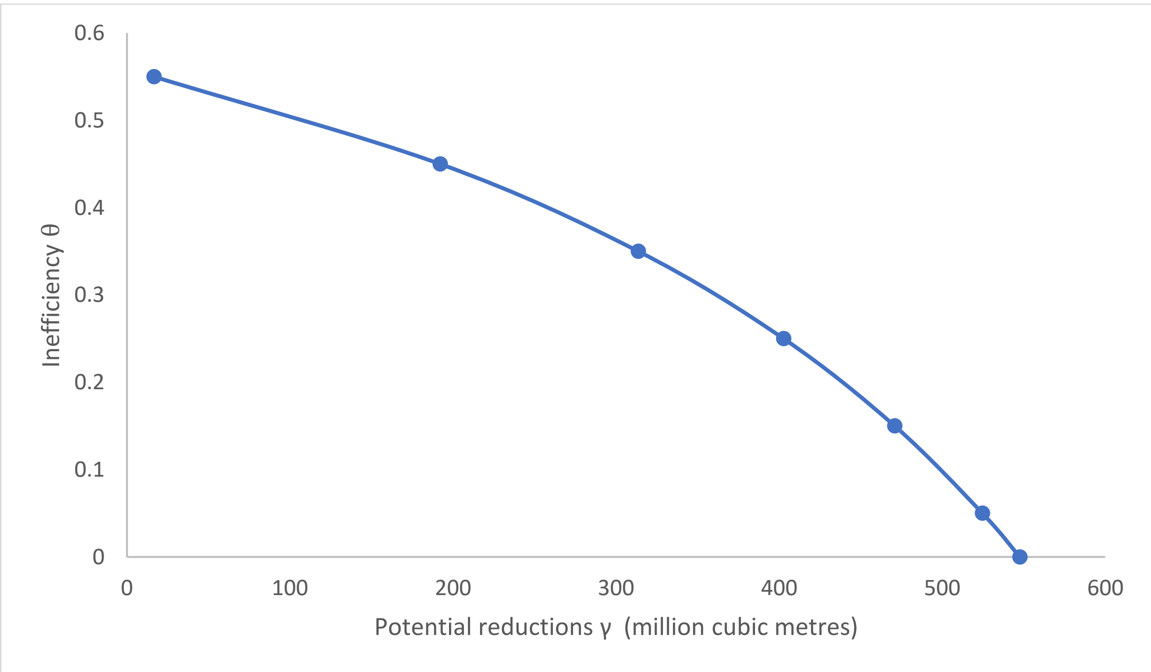

Fig 7: Effect of inefficiency on potential reductions in gas flaring for DMU_{10} (UAE)

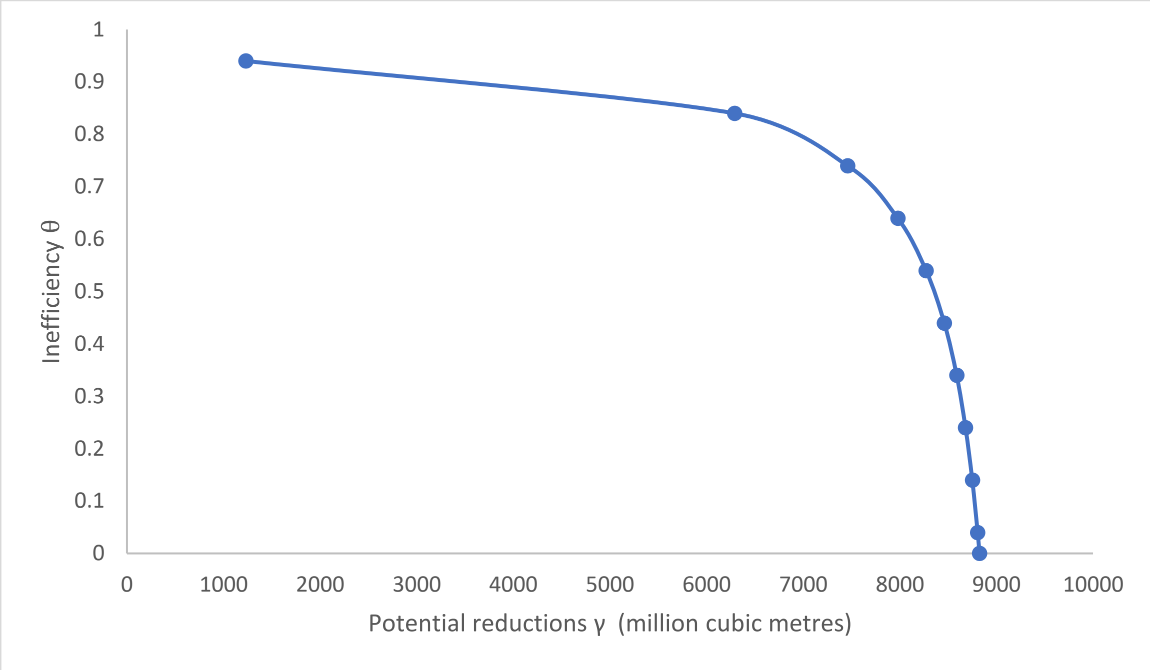

Fig 8: Effect of inefficiency on potential reductions in gas flaring for DMU_{11} (Venezuela)

2011 Production Year (Scenario 2: Thirteen OPEC members)

In this section, we consider all the 13 OPEC members by adding Saudi Arabia and Iran to the PPS. We assume that both members had zero routine flare for the 2011 production year. This makes them ideal benchmarks for the inefficient producers identified by the directional distance DEA model (1). Table 5 presents the initial results containing values of θ and ε for each producer. Once again, we have same number of inefficient DMUs, like Table 3, but two more efficient DMUs taking the number to seven. We define new subsets as follows:

$F = \{\mathrm{DMU}_2, \mathrm{DMU}_3, \mathrm{DMU}_5, \mathrm{DMU}_7, \mathrm{DMU}_8, \mathrm{DMU}_{10}, \mathrm{DMU}_{11}\}$, and

$G = \{\mathrm{DMU}_1, \mathrm{DMU}_4\ \mathrm{DMU}_6, \mathrm{DMU}_9, \mathrm{DMU}_{12}\mathrm{DMU}_{13}, \}$.

The values of θ and ε remain the same for the previous 11 members and we have same set of inefficient DMUs.

Table 5: Data, inefficiency, and efficiency scores for 13 OPEC member nations

DMU	Current Account Balance (m US$)	Wells Comp.	Producing Wells	Active Rigs	Ref. Cap. (1000b/cd)	GDP per Capita (US$/person)	Rout. Flared Gas (million cu m)	Ineff. (θ)	Eff. (ε)
1-Algeria	17770	249	2010	33	592	5453.5	3604	0.83	0.093
2-Angola	13085	112	1476	22	65	4666.95	7183	0	1.000
3-Ecuador	-402	207	3079	39	188.4	5193.04	539	0	1.000
4-Indonesia	1685	838	10423	80	1125	3121	2452	0.78	0.124
5-Iran	59364	204	2026	123	1715	7511.1	0	0	1.000
6-Iraq	26365	76	1695	59	810	5571.55	9612	0.91	0.047
7-Kuwait	65743	523	1798	32	936	41672	217	0	1.000
8-Libya	3173	76	609	55	380	5858	1302	0	1.000
9-Nigeria	10757	124	2116	38	445	2451.75	14270	0.91	0.047
10-Qatar	51906	29	517	6	283	97983.27	558	0	1.000
11-Saudi Arabia	158545	312	3245	121	2107	23594.13	0	0	1.000
12-UAE	50948	266	1592	19	675	40819.31	982	0.55	0.290
13-Venezuela	16342	1050	14915	116	1872	10283.2	9284	0.94	0.031

Table 6 summarizes the results. Except for DMU_4 (Indonesia) and DMU_{13} (Venezuela), the other four DMUs had same values of reductions and savings, like those of Table 4. With the addition of two new members to the PPS, we observe slight improvements in reductions and savings for DMU_4 and DMU_{13}. In order of least deviation, we define a new ranking:

$$\mathrm{DMU}_{13} > \mathrm{DMU}_{12} > \mathrm{DMU}_4 > \mathrm{DMU}_1 > \mathrm{DMU}_6 > \mathrm{DMU}_9$$

DMU_9(Nigeria) still better than all five in terms of maximum savings and potentials.

Table 6: Summary of results for inefficient DMUs (Scenario 2)

DMU	Potential Reduction γ $(m\ cu^3)$	Potential Energy Savings (MWh)	Potential Revenue $(m\ \$)$	Maximum Potential Reduction γ_k^{max} $(m\ cu^3)$	Maximum Energy Savings (MWh)	Maximum Potential Revenue $(m\ \$)$	Deviation $(y_k^b - \gamma_k^{max})$ $(m\ cu^3)$
1-Algeria	23.69	0.245	2.51	2995.35	31.00	317.20	608.65
4-Indonesia	64.26	0.665	6.81	1928.3	19.96	204.21	523.7
6-Iraq	658.56	6.817	69.74	8806.19	91.16	932.58	805.81
9-Nigeria	382.99	3.965	40.56	13020.20	134.78	1379	1249.83
12-UAE	16.63	0.172	1.76	547.58	5.67	57.99	434.42
13-Venezuela	1502.58	15.55	159.12	8869.33	91.81	939.26	414.67

For both scenarios, the 2011 reductions in gas flaring for the Nigerian petroleum industry are equal. We conclude our analysis by saying with the addition of efficient producers (i.e. Saudi Arabia and Iran) to the production possibility set, there are no better results for Nigeria. This implies our proposed model and algorithm yielded best results for our case study.

5.0 SUMMARY, MANAGERIAL INSIGHTS AND CONCLUSIONS

5.1 Summary

In our study, we extended the inverse DEA model and developed an algorithm for global gas flaring reductions. We applied our proposed model and algorithm to OPEC member nations and selected Nigeria as our case study. In doing so, we considered two different scenarios, eleven and thirteen member nations. The first scenario was without assumptions, while the second assumed that the added members had zero-routine flaring. Initial results identified efficient and inefficient nations. Algeria, Indonesia, Iraq, Nigeria, United Arab Emirates (UAE), and Venezuela were deemed inefficient in both cases. Reductions in gas flaring, savings in revenue and energy were computed using our proposed model and algorithm for all six nations. For Nigeria, the maximum reduction in gas flaring, maximum potential savings in energy and revenue were estimated to be 13020.20 million cubic meters, 134.78 MWh and US$ 1.379

billion, respectively in 2011. In addition, Nigeria had the highest estimates in maximum reductions and potentials.

In the second scenario, the production possibility set was expanded by the addition of Saudi Arabia and Iran, and both nations served as extremely efficient producers and benchmarks for the inefficient nations. The estimates remained the same for Algeria, Iraq, Nigeria, and United Arab Emirates. However, there were improvements for Indonesia and Venezuela.

From the obtained results, we also observed that inefficient member nations could reduce their annual gas flaring, with or without investment in better technology and a more highly skilled force. Application of our algorithm provided deviations, indicating the level of commitment of each nation to the zero-routine flaring initiative. UAE and Venezuela are more committed having the least deviation in the first and second scenarios, respectively. Nigeria is the least committed, having the largest deviations in both scenarios. We proved that the inefficiency estimated by the directional DEA model is a function of the potential reductions. The reductions are maximum with zero inefficiency.

5.2 Managerial Insights

The future challenges for crude oil make waste management an integral part of corporate long-term planning in the petroleum industry. Gas flaring is a huge waste in this industry and is regarded as an environmental hazard and a huge economic loss. Based on the results obtained in the previous section, we recommend the extended inverse DEA model for the Nigerian petroleum industry due to the following reasons:

I. Gas flare capture or reduction is a potential source of revenue when converted to marketed production of natural gas. Our model estimated the maximum revenue that can be obtained from flared gas to be US$ 1.379 billion in 2011. According to PricewaterhouseCoopers (PwC), Nigeria lost US$761 million worth of flared natural gas in 2018. Both amounts can be used to fund government projects like housing, renovation of roads and airports, and healthcare.

II. As an environmental hazard, gas flaring is responsible for some health problems within the oil producing regions of Nigeria. Respiratory illnesses, adverse skin disorders and heat burns are common, among other health problems. This has led some health experts to conclude that gas flaring is one of several factors responsible for the decline of average life expectancy to 53 in Nigeria. Another potential benefit of gas flare capture to society is reduced air pollution. This reduces health risks associated with gas flaring.

II. Erratic power supply is another huge problem in Nigeria and a cause of inflation. A major goal of the 2020 Nigerian Gas Flare Commercialization Programme (NGFCP) is the conversion of flared/wasted gas for power generation using turbines. However, technical knowledge of the right technology for such a conversion process is highly dependent on the gas flare volume captured during the production process. The volumes are the estimates determined in this study.

5.3 Conclusions and Future Research

Our extended inverse DEA model provided satisfactory results for a given set of homogenous DMUs. It allows reduction of the undesirable output at current production rates while retaining the efficiency of each DMU. Our model is the first to estimate the potential reductions in global gas flaring. However, there are two limitations we must state here. Firstly, as with all DEA models, the efficient units cannot be improved further. Our inverse DEA model imposes gas flare reduction on the inefficient units but lacks the capability of applying the same technique to the efficient units. This calls for further development or extension for improving the performance of the efficient units. A recurrent problem in DEA analysis is the ranking of efficient units. Several works in the literature have addressed this problem but none dealt with units having bad or undesirable outputs. Hence, there is a need to modify our inverse DEA model to fully rank efficient units with bad outputs.

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