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Efficiency Evaluation in the Use of Natural Gas in Pre-Salt Petroleum Fields Using Data Envelopment Analysis (DEA) and Their Relation to CO_2 Contamination Level

Aline Karl Araujo* and Jacqueline Barbirato

LEPROD, Center of Science and Technology, Darcy Ribeiro State University of Northern of Rio de Janeiro, Rio de Janeiro, Brazil

Abstract
Verifying the existence of a direct relationship between the inefficient use of natural gas and the high levels of CO_2 contamination is indispensable. Therefore, in this study, the Data Envelopment Analysis (DEA) methodology to evaluate the efficiency in the use of natural gas from 11 pre-salt-producing fields was used. Both qualitative and quantitative data on the production of oil and natural gas, made available by the ANP, were analyzed. Afterwards, the Voador field was considered 100% efficient, while the least efficient fields were Búzios, Marlim, Sapinhoá, and Lula, respectively. This result confirmed the research hypothesis since Búzios, Sapinhoá, and Lula were expected to be among the least efficient fields, and they present the highest levels of CO_2 contamination. However, Marlim's great inefficiency highlights the fact that several other parameters greatly influence the best use of natural gas and should also be evaluated. Ultimately, the benchmarks identified in this study can help inefficient Decision Making Units (DMUs), as Marlim, in the search for techniques and production models that allow an improvement in the use of natural gas.

Key words: Natural gas, CO_2; Pre-salt, SIAD, Data Envelopment Analysis

Introduction
The pre-salt discovery is an important event for Brazil in the search for the status of self-sufficiency in oil and natural gas. Pre-salt oleo has a medium-density (about 28° API), low acidity and low sulfur content. Such features give it excellent quality and high commercial value [1]. Pre-salt gas is also considered to be of high quality (rich gas) since it has a wide variety of intermediate components (such as propane, butane, and others) that allow the extraction of more highly valued products. The downside is that the gas from some pre-salt reservoirs is contaminated with a large amount of carbon dioxide (CO_2).

The high concentration of CO_2 is an economic and technical challenge since the conventional separation technology is difficult to apply for reservoirs with high gas-oil ratio (GOR) and high contamination level.

The available technology occupies a lot of space in the production units; in addition, its application in the treatment of large volumes of contaminated gas is expensive. In addition, high levels of CO_2 impose critical technical challenges for the re-injection of natural gas, since they require equipment that is resistant to corrosion caused by the contaminant [2].

This study determined , among the most important pre-salt fields, those fields that their natural gas more efficiently could be used in the selected period. The most efficient fields can also be used as benchmarks for the other researchers who try to investigate their techniques and approaches and adapt them to their specific scenarios.

Data Envelopment Analysis (DEA) is widely used as a benchmarking tool for improving the performance of organizations in an industry or sector [3]. Despite its more than 30 years of existence, it continues to receive great attention in the academic environment [4]. Therefore, this methodology was chosen.

It is relevant to evaluate the efficiency of using natural gas in the pre-salt oil fields since the excellent oil quality may have become the preferred product of these fields. Also, a large amount of CO_2 present in some of them

**Corresponding author:* Aline Karl Araujo, LEPROD, Center of Science and Technology, Darcy Ribeiro State University of Northern of Rio de Janeiro, Rio de Janeiro, Brazil
E-mail addresses: jmrc@uenf.br
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may hamper the use of natural gas. Thus, the principal question which had to be answered was: “Is the CO_2 contamination level directly responsible for the inefficient use of natural gas in the pre-salt oil fields?”

Materials and Methods

Data Envelopment Analysis (DEA) was introduced by Charnes, Cooper, and Rhodes in 1978 [5]. One of the reasons for its popularity is its ability to handle situations involving multiple inputs and multiple outputs with multiple DMUs (Decision Making Units), in which the situations were difficult or impossible to be analyzed even by using other benchmarking methods [6].

There are two classic models of data envelopment analysis most widely used: the CCR model [5] that works with constant scale returns, and the BCC model [8] that considers production efficiency situations with variations of scale and does not assume proportionality between inputs and outputs. The present study has selected the CCR model because it is one of the DEA classic models, which is widely used, and it considers constant returns of scale. The model was oriented towards the maximization of outputs since it offered a higher value of profitable natural gas (desirable output) and a greater efficiency for the DMU.

In its mathematical formulation, it is considered that each DMU k is a production unit that uses n inputs x_{ik}, i= 1, ..., n, to produce m outputs y_{jk}, j= 1, ..., m, as seen in Equations 1 to

$$4.\min h_0 = \sum_{i=1}^{r} v_i x_{10} \quad (1)$$

Subjected to:

$$\sum_{j=1}^{s} u_j y_{j0} = 1 \quad (2)$$

$$\sum_{j=1}^{s} u_j y_{jk} - \sum_{i=1}^{r} v_i x_{ik} \le 0, \forall k \quad (3)$$

$$ujvi \ge 0 \forall j,i \quad (4)$$

where vi and uj are the input weights i, i= 1,...,r, and output weights j, j=1,..., s respectively, and h0 represents how many outputs must be multiplied, keeping the inputs constant, for the DMU0[1] to reach the efficient frontier.

A widespread problem in the DEA methodology is the low discrimination of DMUs by the classical models. To overcome this limitation, the inverted frontier [8], as well as the rule which was presented by Charnes et al. in 1978 [5], was used. In their rule, the total number of DMUs must be at least equal to twice the sum of inputs and outputs. According to Leta et al. in 2005 [10], an aggregate efficiency index must be calculated to order the DMUs. It is the arithmetic average between the efficiency relative to the original boundary and the inefficiency (= 1 - efficiency) relative to the inverted boundary. Where the following equation (Equation 1) is governed when the efficiency is calculated:

$$Eff_a = \frac{[Eff_s + (1 - Eff_i)]}{2} \quad (5)$$

1. DMU0: DMU that is under analysis at that particular moment.

2. ANP – Agência Nacional do Petróleo, Gás Natural e Biocombustíveis: federal government agency responsible for oil , natural gás and biofuel sector in Brazil.

Eff_a= aggregated efficiency
Eff_s= standard efficiency
Eff_i= inverted efficiency

The software SIAD (Sistema Integrado de Apoio a Decisão) [11,12] was selected to apply the methodology. The SIAD is a free software developed by Brazilian researchers. Moreover, it enables the use of the two classic DEA models, input and output orientation, inverted frontier, as well as some advanced features such as weight restriction and cross-evaluation.

In addition, the software itself provides information that allowed a sensibility analysis of the problem, such as the benchmarks for each inefficient DMU and the targets and slacks of each of them.

Eleven fields were selected from the greatest producers of the pre-salt according to ANP[1][2] [13]. The oil fields are called «Lula, Sapinhoá, Jubarte, Baleia Azul, Baleia Franca, Búzios, Marlim Leste, Caratinga, Barracuda, Voador, and Marlim.» These 11 oil fields represent 11 Decision Making Units (DMUs) in the DEA model. The number of selected fields is based on the available data and on the rule presented by Charnes et al. in 1978 [5] in which the total number of DMUs must be at least equal to twice the sum of inputs and outputs. The studied system consisted of one input and two outputs. The input was the total volume of the produced gas, and the two outputs represent the discarded volume of the produced gas (volume of flaring gas and injection for storage) and volume of the profitably produced gas (volume of gas for consumption, injected for secondary recovery and commercialized). The gas lift volume was not considered since, as soon as it is injected into the production column, it is produced again, and often this gas originates from outside the reservoir. In Table 1, the input and outputs are shown. ANP – Agência Nacional do Petróleo, Gás Natural e Biocombustíveis: federal government agency responsible for oil , natural gás and biofuel sector in Brazil.

According to Table 2, input and output 2 show a strong positive correlation, while input and output 1 do not show such a high correlation. This is because the inefficient use of natural gas is directly influenced by the level of CO_2 contamination. The results will demonstrate it.

Table 1 Inputs and Outputs.

Input	The total volume of gas produced
Output 1	The volume of discarded natural gas (volume of flared gas and (injection for storage
Output 2	The volume of produced gas that is profitable (volume of gas for consumption, injected for secondary recovery and commer-(cialized

Table 2: Pearson's correlation matrix.

	Output 1	Output 2
Input	0.62032	0.998373

Results And Discussion

From the 11 selected fields for the study, three of them present CO_2 contamination levels much higher than others. They are Lula (10-20%), Sapinhoá (15-20%) and Búzios (22-25%). If the research question was confirmed, these would be the fields with the lowest utilization of natural gas. To confirm this hypothesis, the production data provided by ANP2 [14] in the period from January to December 2016 were selected. Total gas production consists of the sum of associated and non-associated gas production (in Brazil, the gas produced is usually associated). The volume injected for storage is the volume of gas produced that has been stored in an already depleted reservoir. The flared gas volume represented the amount of natural gas sent for flaring.

The volume of gas for consumption represents the portion of natural gas that was used for the internal consumption of the platform. Moreover, the volume of gas injected for secondary recovery consists of the volume of gas re-injected into an underground reservoir to enhance oil recovery by increasing the pressure in the reservoir and the recovery factor.

Graphical analyses of production data provide an overview of the scenario found in these 11 oilfields. Figure 1 shows the total natural gas production of the fields. According to Figure 1 and in descending order of production, it is manifest that in 2016, Lula and Sapinhoá produced the largest volumes of natural gas, i.e. about 8.6 and 2.9 trillion m^3, respectively. Also, Jubarte and Marlim produced about 0.8 and 0.5 trillion m^3, respectively. On the other hand, Búzios and VOADOR produced the smallest yields, i.e. less than 0.1 trillion m^3 among the analyzed fields.

Figure 2 shows the volume of gas discarded per field in the selected period. While Figure 3 shows the profitable gas volume by each field in 2016. One important fact to note is that the Lula field, despite having a large discarded volume, also has the highest profitable volume, and it stands out in this aspect in comparison with the other fields. Thus, the large discarded volume may only be a consequence of production far superior to the others. It is considered in the Data Envelopment Analysis.

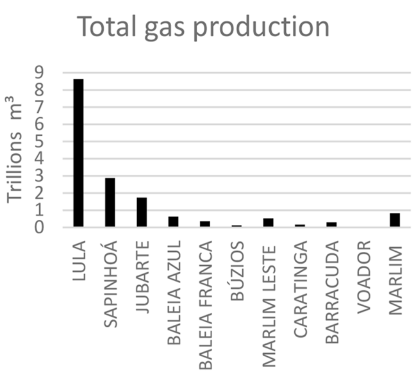

Fig 1 Total gas production per field in 2016.

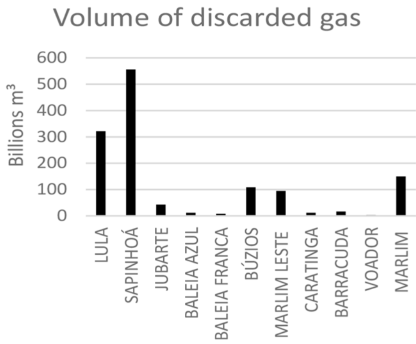

Fig 2 Volume of discarded gas per field in 2016.

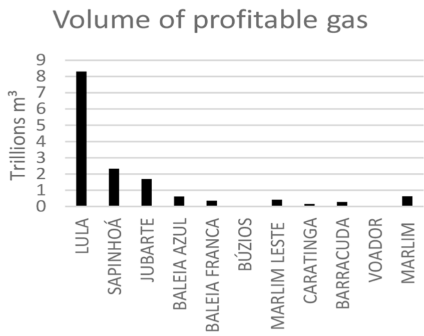

Fig 3 Volume of profitable gas per field in 2016.

To perform the DEA analysis, the average data of each field was launched in the SIAD software. Only two DMUs were 100% efficient , Baleia Azul and Voador. In addition to calculating each DMU efficiency, the DEA methodology allows a set of reference units to be used as benchmarking in improving the performance of less efficient units. These benchmarks indicate what needs to be changed in inputs or outputs and how to improve them to turn inefficient units into efficient ones [15].

Table 3 presents the benchmarks for each of the DMUs. The efficient frontier in the year 2016 is composed of the Baleia Azul and Voador fields. These fields are the benchmarks for the other inefficient DMUs. Except for the efficient ones and Búzios, all other DMUs had as the main benchmark of the Baleia Azul field.

Only the analysis of the standard efficient frontier is often not sufficient to assert with certainty the most efficient DMUs. Sometimes a DMU is very good in a feature where it performs well; however, it is very bad in the one in which its performance is not the best.

Table 3 Benchmarks for each DMU.

DMUs	Benchmarks	
Lula	Baleia Azul	---
Sapinhoá	Baleia Azul	
Jubarte	Baleia Azul	
Baleia Azul	Baleia Azul	
Baleia Franca	Baleia Azul	Voador
Búzios	Voador	Baleia Azul
Marlim Leste	Baleia Azul	
Caratinga	Baleia Azul	Voador
Barracuda	Baleia Azul	Voador
Voador	Voador	
Marlim	Baleia Azul	

The inverted frontier consists of a technique to increase the discrimination of the DMUs. Using this technique, the most efficient DMU becomes the one that can perform well at what is best, as reported by the classic efficiency level, without performing poorly at what is worse, as reported by the inverted efficiency level [10].

This technique has made it possible to determine the Voador field as the single 100% efficient DMU. The DMUs which are considered the least efficient were Búzios, Sapinhoá, and Marlim respectively. Figure 4 shows the results provided by the software with the inverted frontier application.

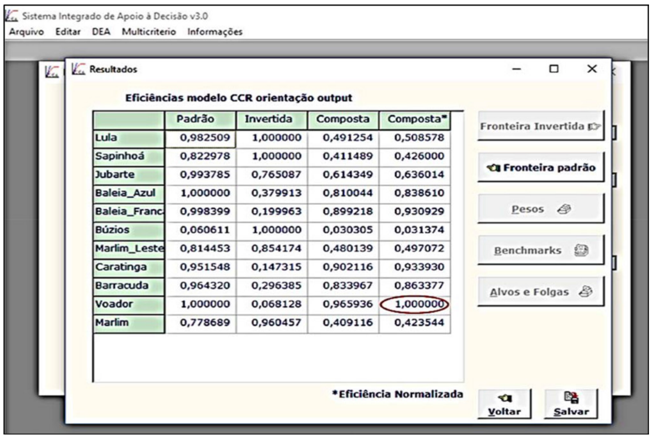

Fig 4 Inverted frontier application.

According to González-Araya and Estellita-Lins in 2002 [16] and González-Araya in 2003 [17], the efficient frontier has regions with different properties. Because the faces generated by efficient DMUs may or may not meet Pareto-Koopmans efficiency conditions. Moreover, faces that do not meet these conditions are called non-Pareto-Koopmans efficient regions or weakly efficient, and the radial projection of the inefficient DMUs in these regions presents non-zero slacks in inputs and outputs.

The targets represent the input or output values that the inefficient DMUs must have to reach the border, in other words, to become efficient. In the output orientation case, as in this study, the targets represent the output values, which inefficient DMUs should have to achieve efficiency. The higher the difference between the value of the output and the target value of a DMU is, the further it is from the border, and therefore, the less efficient it is. The targets and slacks are also provided by the software and presented in Tables 4 and 5.

Based on these results, it is possible to infer that the more efficient DMU and, therefore, the one that should serve as a parameter for the other DMUs was Voador. The Voador field, even producing only pre-salt fluids, is not among the fields with the highest levels of CO_2 contamination. This fact makes the exploitation of natural gas easier, and therefore, it was to be expected to be among the most efficient fields. The most relevant result for the research, however, is in the least efficient DMUs. This result will ratify or not the initial hypothesis that predicts a direct relationship between the high CO_2 contamination level and the inefficient use of natural gas.

Table 4 DMUs' targets and slacks.

DMUs	The volume of Profitable Gas (Mm³)	Slack (Mm³)	Target (Mm³)
Lula	8305497.7160	0	8453357.3000
Sapinhoá	2315438.9860	0	2813487.5000
Jubarte	1683942.9980	0	1694474.6000
Baleia Azul	611783.3979	0	611783.3979
Baleia Franca	347867.6498	0	348425.4700
Búzios	6777.2160	0	111922.9200
Marlim Leste	415376.8300	0	510007.1600
Caratinga	151632.7614	0	159353.8100
Barracuda	276394.5670	0	286621.1800
Voador	22216.1931	0	22216.1931
Marlim	628063.8378	0	806565.6100

Table 5 DMU's targets and slacks.

DMUs	1/Volume of Discarded Gas (Mm³)	Slack (Mm³)	Target (Mm³)
Lula	0.0000031100	0.001173	0.001176
Sapinhoá	0.0000018000	0.000389	0.000391
Jubarte	0.0000233092	0.000212	0.000236
Baleia Azul	0.00008510720	0.000000	0.0000851072
Baleia Franca	0.0001273510	0.000000	0.000128
Búzios	0.0000092100	0.000000	0.000152
Marlim Leste	0.0000105786	0.000058	0.000071
Caratin-ga	0.0000863913	0.000000	0.000091
Barracu-da	0.0000612981	0.000000	0.000064
Voador	0.0003682620	0.000000	0.000368262
Marlim	0.0000066700	0.000104	0.000112

By analyzing the standard frontier, the inverted frontier, and the targets, it is possible to identify the least efficient DMUs such as Búzios, Marlim, Sapinhoá, and Lula, respectively. This result confirms the research question since these fields present the highest levels of CO_2 contamination. However, the Marlim field appears as the second least efficient DMU, and the level of CO_2 contamination in this field is not the highest.

It is noteworthy that Búzios be a relatively new field and its production only be due to training tests and anticipated production systems where it is normal to have a higher intensity of gas flaring. Therefore, it can't be said that its inefficiency was due to its high level of contamination.

Conclusions

Lula, Sapinhoá, and Búzios were among the least efficient units, and it is strongly related to their high levels of CO_2 contamination. They have complex problems to be solved. However, it is probably temporary since technology has been advancing rapidly. Marlim appeared as the second least efficient DMU; however, it does not have one of the highest levels of contamination.

These results confirm the research hypothesis that the degree of CO_2 contamination is directly responsible for the inefficient use of natural gas in the pre-salt oil fields. However, Marlim's significant inefficiency highlights the fact that several other parameters such as shoreline distance, production unit capacity, field lifetime, the volume of gas produced, primary reservoir fluid, among others, greatly influence the best use of natural gas and should also be evaluated.

The Voador field was the benchmark identified in this study. It can help inefficient DMUs, such as Marlim, in the search for techniques and production models that allow an improvement in the use of natural gas, since it is a fluid of enormous abundance in the pre-salt and extremely versatile.

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Nomenclatures

DEA: Data envelopment analysis
DMUs: Decision Making Units
SIAD: Sistema Integrado de Apoio a Decisão

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