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Efficiency Analysis of Oil Refineries Using DEA Window Analysis, Cluster Analysis, and Malmquist Productivity Index

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Abstract: Oil and gas refineries play a key role in the economies of countries by providing energy to various industrial sectors. A lack of an integrated efficiency analysis procedure, in many industries, could significantly impact the planning of sustainable industrial structures and operations. It also can influence company performance and competitiveness, and, eventually, negatively compromise the fuel supply process. All these problems taken together might negatively impact the environment and sustainable practices. Studies of efficiency in the oil industry can help to reduce its environmental and social impact and to achieve long-term green transition goals. In this work, the data envelopment analysis (DEA) method was used to present improvement goals for production units, based on efficiency indexes. Furthermore, the DEA window analysis model, integrated with the Malmquist index and cluster analysis, was used to evaluate efficiency and the factors that explain the differences between refineries in a number of timeframes. A numerical analysis was carried out with data collected from 12 Brazilian oil refineries between 2012 and 2020, using DEA window analysis, cluster analysis, and the Malmquist index.

Keywords: oil refineries; DEA window analysis; Malmquist productivity index; production efficiency analysis

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Citation: Oliveira, M.S.d.; Lizot, M.; Siqueira, H.; Afonso, P.; Trojan, F. Efficiency Analysis of Oil Refineries Using DEA Window Analysis, Cluster Analysis, and Malmquist Productivity Index. *Sustainability* **2023**, *15*, 13611. https://doi.org/10.3390/su151813611

Academic Editors: Francesco Nocera and Gerardo Maria Mauro

Received: 21 July 2023
Revised: 5 September 2023
Accepted: 7 September 2023
Published: 12 September 2023

1. Introduction

Refinery efficiency is extremely important in the oil and gas supply chain because petroleum products are needed by a diverse range of sectors as well as for industrial and commercial activities worldwide that depend on refined products [1]. Thus, an efficiency analysis of oil and gas refineries is also essential because it directly affects the building of projects and planning of operations, helping reduce their environmental impact and avoiding a lack of supplies. Managers need to know how efficiency levels change over time in order to plan sustainable building projects and to avoid losses of performance and problems with fuel supply.

According [2] improvements in the efficiency of the oil industry can reduce environmental and social impacts. It consequently helps countries that have oil-dependent economies to achieve goals regarding long-term green transition. In addition, good efficiency analysis allows managers to know how the refineries are being operated, compared to expected productivity goals. However, the current techniques used to evaluate oil and gas refinery efficiency are applied individually, without flexibility to analyze variables and scenarios for long-term planning.

Data Envelopment Analysis (DEA) is a technique commonly used to analyze efficiency; it helps in evaluating performance and in the promotion of benchmarking in this sector. Several studies have highlighted the importance and applicability of this technique [3–6]. The main advantage of the DEA model is that it reveals inefficiencies in production unit targets, initially identified by levels of inefficiency. Improving these targets can lead to corrective actions that in turn enable the elimination of the causes of inefficiency. Another aspect that can be exploited in this context is an analysis of technical inefficiency aspects, which shows how a given product could have its efficiency increased without the addition of new inputs or technologies, thus leading to an opportunity for low-cost improvement [6].

In this context, DEA window analysis (DEA-WA), which is derived from the DEA technique, can help to analyze the efficiency of refineries in different periods, associated with indicators that can influence the models, in order to know the differences in refinery structures between countries [7]. Also, a complete efficiency analysis on this topic should consider aspects of global structured buildings and relationships between refineries and their groupings.

Thus, this study analyzed the efficiency of 12 Brazilian oil refineries between 2012 and 2020 using DEA window analysis (DEA-WA), cluster analysis (CA), and the Malmquist index (MI), in order to demonstrate the advantages of the integrated use of these techniques, mainly to provide information for long-term production planning.

The research hypothesis of these experiments was related to the application of data envelopment window analysis, the Malmquist index, and cluster analysis in an output-oriented approach to enable the identification productivity and efficiency behaviors in different periods, incorporating an analysis of the technological progress of the units. Also, this study was expected to support the decision-making process for the sustainable management of refineries.

2. Literature Review

The models commonly used to evaluate efficiency, in general, are based on the DEA methodology, and its applications are related to existing DEA models, i.e., CCR [8] and BCC [9], which consider the constant return of scale (CRS) and variable return of scale (VRS), respectively. The majority of studies found in the literature and used to analyze efficiency in refineries have also used DEA, but they have applied it individually or to specific periods. They have provided just a partial or punctual view of efficiency analysis and may not show a complete analysis of this topic.

Some of these studies can be cited, such as that of [2] which analyzed the efficiency of nine oil refineries in Iran, using two-stage DEA-SBM (slacks-based measure) between 2011 and 2015. The results showed a low efficiency of the analyzed refineries and pointed to the necessity of production improvement through the acquisition of new technologies. The study of [6] evaluated the efficiency of twelve Indian oil refineries from 2011 to 2016 using input-oriented DEA-BCC and the Tobit model. In this study, no refinery was fully efficient, and just three refineries had efficiency rates over 95%. The factors pointed out as potential solutions were a feasibility of renewable energy sources and a reduction in the production of oil with high sulfur content.

According [1], was verified the operational performance of 696 units in oil and gas refineries from 2008 to 2017, divided into four global clusters (USA and Canada, Europe, Asia-Pacific and Africa and the Middle East), using an input-oriented DEA and DEA-DA (discriminant analysis). The results showed that the USA and Canada cluster outperformed the other three clusters and that this performance was close to the operations of American oil companies with vertical integration, increased profits, and low risks.

In the work of [10] was analyzed the environmental efficiency of 50 oil companies in the USA from 2012, separating them into independent and integrated companies. This approach contributed to verifying the corporate sustainability of companies, given that integrated companies outperformed independent companies in terms of corporate sustainability [11,12].

In the paper of [5] was proposed two efficiency measures (operational and environmental) for seven integrated oil companies and twenty-seven independent oil companies in the USA using the UEN (unified efficiency under natural disposability) method, which prioritizes environmental efficiency, and the UEM (unified efficiency under managerial disposability) method, which prioritizes operational efficiency, as well as the Kruskal–Wallis test for the two types of unified measures in the period between 2011 and 2015. The results showed that independent companies had a lower efficiency index when compared to integrated companies, since the latter operate around the world, needing to meet global environmental protection standards and measures. In the work of [13] was analyzed the efficiency of seven Indian oil refineries from 2010 to 2018 using DEA-BCC besides ordinary least squares (OLS), generalized least squares random effect (GLS), and the Tobit model to explain the determining factors in the variation of efficiency indexes. The results showed that two refineries were the most efficient in the analysis and that three variables could explain the variations in the indexes: refinery structure, utilization rate, and distillate yield.

In the study of [14] was created an index to analyze the environmental efficiency of ten Brazilian refineries using the DEA-CCR and BCC models. The inputs used were "percentage of idleness of the plant in operation" and "amount of water consumed", and the products were "refinery production volume" and "effluents generated, desirable and undesirable".

Although several authors have already used these techniques to analyze oil refineries or for other applications [3,15,16], and with these techniques only used for uninterrupted periods [17]. The way to improve these analyses is to integrate other technologies like the Malmquist index (MI) (Malmquist, 1953), which is used to analyze technological efficiency (catch-up effect) and progress (frontier shift effect). Thus, carrying out studies that include MI together with DEA will allow us to fill the gaps in both models.

In the study of [18] were applied DEA and the Malmquist index to assess the efficiency of seven Indian oil refineries between 1996 and 2011. Their study revealed that all refineries showed productivity improvements and that the effect of economic reforms on total factor productivity (TFP) was 8.6 per cent. In [19] was carried out an environmental and operational performance assessment combining DEA with the Malmquist index for the period from 2005 to 2009, considering 17 oil companies from different regions of the world. In general, these companies improved their environmental performance through ecotechnological progress and/or managerial innovation, but not operational performance, showing that one type of performance had no effect on the other.

In the paper of [17] was evaluated the technological innovation efficiency (TIE) of ten refinery plants of the Daqing Petroleum Company from 2012 to 2015 using an input-oriented DEA-BCC model and the Malmquist index. The results showed that the company had a high level of TIE and its TFP had fallen each year. Furthermore, it was found that technological progress decreased more than comprehensive technological efficiency, showing that the decline in TFP was mainly due to insufficient technological progress.

In [20] was found that, despite the growing number of publications involving DEA, there are few publications using this technique in the petroleum sector. Our literature review only found 33 publications in this area from 1992 to 2015.

This study used DEA-WA integrated with MI and cluster analysis, which offer the possibility of analyzing DMUs (decision-making units) in specific periods, unlike what happens with the models currently used. No study was found combining these two techniques to look at oil refineries. The development of the DEA-WA technique is attributed to [9], whose proposal aimed to analyze the variations of relative technical efficiency, considering each DMU over time, as a distinct unit. This technique allowed for the analysis of efficiency stability as well as of the sensitivity of technical efficiency scores and the efficiency trends of DMUs.

In [10] was studied the performance of the USA oil industry and analyzed independent companies using DEA-WA from an energy and environmental point of view, using three business implications. In the first one, under environmental disposability, the efficiency of oil companies showed an inability to reduce drilling and production operations. The second one showed pressure from regulations and stakeholders in relation to air pollution, with the growth rates of efficiency in relation to managerial disposability not showing great changes over time. The implications of business concerns were confirmed by regression analysis.

In addition, the grouping (or clusters) of refineries according to their efficiency indexes can improve the analysis and trend definitions for the sector. In the study of [21] was performed an analysis of the changing trends in total factor productivity (TFP), technical efficiency (TE), and technological progress (TP), based on eight clusters from China's oil and gas industry, measuring their capacity for technological innovation. Some findings were that TFP growth rates in three provinces (Heilongjiang, Gansu, and Shanxi) decreased significantly; the TFP growth rates in other provinces and regions increased for a long period of time, followed by a slight decrease in the last two cycles; in Heilongjiang, Gansu, and Shaanxi, where the growth rate of TFP decreased significantly, the efficiency index increased and the technical progress index decreased notably; and clusters based on mineral resources had to constantly work on technological innovation.

Brazilian Oil Refineries: Contextualization

According to data from the National Agency of Petroleum, Natural Gas and Biofuels (ANP), in 2020 Brazil was the highest-ranking oil producer in South America. The proven reserve of oil in the world reached the mark of 1.7 trillion barrels in 2020, with Brazil having a proven reserve of 11.9 billion barrels in that year. The Brazilian refining capacity represents 2.3% of the world capacity, with South America representing 6.2% of this total, as illustrated in Figure 1:

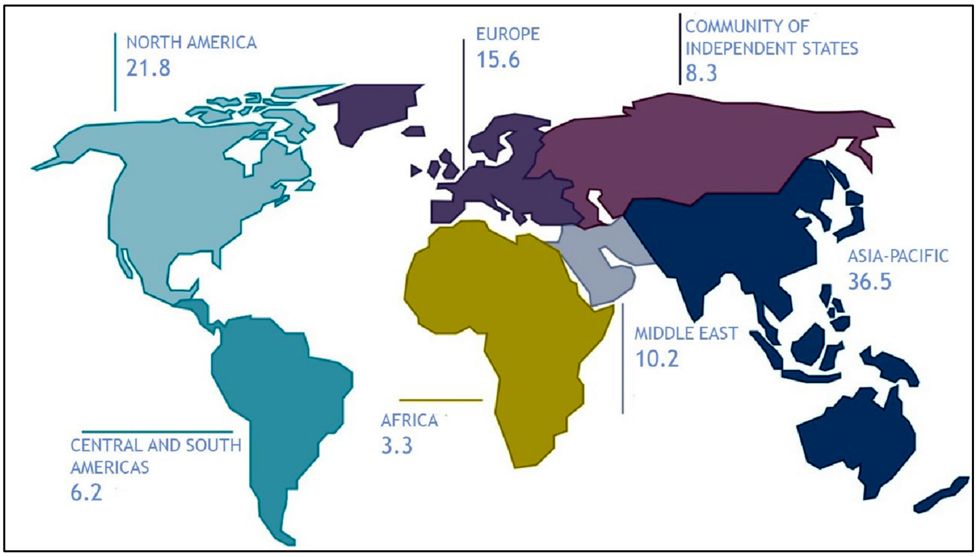

Figure 1. Oil-refining capacity in the world (million barrels/day) (adapted from ANP, 2021).

In Brazil, oil refineries are managed by Petrobras, the main Brazilian company in this field. According to the ANP statistical yearbook (2020), there are 18 oil refineries in Brazil with the capacity to process 2.4 million barrels/day, 13 of which are managed by Petrobras, which corresponds to 98% of the country's total refining capacity. One of these refineries, called Replan (SP), has the largest installed capacity, at 434 thousand barrels/day or 18% of the national capacity. Others, called Manguinhos (RJ), Riograndense (RS), Univen (SP), and Dax Oil (BA), are private refineries. The volume of oil produced in the world in 2020 fell by 6.9% compared to the previous year, representing a total of 88.4 million barrels/day. Brazil had a production of approximately 3 million barrels/day in 2020, occupying the ninth position in the world [22].

3. Materials and Methods

To define the efficiency index formulation, the following inputs were considered: area (km^2), production capacity (barrel/day), number of entry points, production units, oil storage capacity (m^3), and derivatives storage capacity (m^3). The product considered was production (barrel/day).

To perform the selection of variables, the Pearson correlation coefficient was calculated between all inputs and the product. After that, a model was defined representing the relationship between the product and inputs with the highest correlation coefficient. One new input was added at a time until average efficiency indicated an increase. Subsequently, a new model was defined considering inputs with the second-highest correlation coefficient. After that, the output and new inputs were added until average efficiency increased. The model was tested for all inputs whose correlation coefficient with the output was greater than 0.5. Finally, the model with the highest average efficiency was considered in the analysis. Efficiencies were calculated for the period from 2012 to 2020, using the DEA-WA model formulations, proposed by [23], as presented in equation (12). Subsequently, the values were used for the Malmquist index (MI) to evaluate technical efficiency and technological progress, based on the formulations proposed by [24] and expanded by [25] as a theoretical concept of production analysis, allowing for productivity measurement with variations over time and for evaluating changes in DMU efficiency.

In order to present the results of the Malmquist indexes, the refineries were organized into clusters, using the Ward linkage method and Euclidean distance. This procedure was performed based on a study by [26] which presented Ward's method (proposed by [27]) as a hierarchical cluster analysis procedure. With this method, production units were grouped and added to the analyzed variables. A summary of the applied methods is presented in Figure 2:

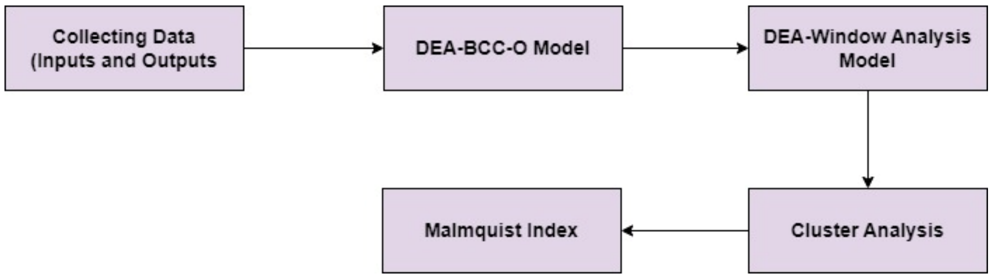

Figure 2. Summary of the integration of the methods.

3.1. DEA-Window Analysis Model (DEA-WA)

The purpose of window analysis is to evaluate the efficiency of DMUs over a period of time. In this model, efficiency is compared to each defined specific period of time (window analysis). It provides a deeper and more specific temporal analysis and can show variations in the efficiency of each DMU. These "time windows" are defined based on moving averages, wherein a new period is considered and the oldest one is removed.

In the work of [28] was stated that biased results can be generated if DMUs are compared in a single period of time. They may also require a more comprehensive efficiency analysis. Therefore, the use of the window analysis model can be promising in their case.

In [9] the authors were pioneers in the use of the window analysis technique. They analyzed variations in relative technical efficiency, which considered each DMU over time as a distinct unit. This technique allows for the analysis of efficiency stability and of the sensitivity of the technical and trending aspects of DMUs.

In the study of [29] was highlighted that window analysis does not consider the nature of technological progress or the ability of DMUs to increase their efficiency with the inputs, which is conventionally known as "frontier shift". Nor does it show relevant information on changes in productivity. So, it is necessary to integrate window analysis with another method.

An important measure to be considered is an understanding of the temporal evolution of DMUs as continuous, defined as "pairing". Thus, as MI incorporates this continuity concept, it can be considered as an extension of DEA-WA.

In [30] was claimed that this integration between DEA-WA and MI allows for the incorporation of the idea that there are changes in technology in the period being analyzed. This approach allows for a comparison between time-constrained, and therefore technologically similar, DMUs. The formulation of the DEA-WA model was proposed by Asmild et al. (2004) and is as follows:

Consider N DMUs $(n = 1, 2, \ldots, N)$ and T periods $(t = 1, 2, \ldots, T)$ using r outputs and s inputs. With that, the sample has $N \times T$ remarks, n observations in period t, DMU_t^n, a dimensional input vector r $x_t^n = \left(x_{1t}^n, x_{2t}^n, \ldots, x_{rt}^n\right)$, and a dimensional product vector s $y_t^n = \left(y_{1t}^n, y_{2t}^n, \ldots, y_{st}^n\right)$. The windows initialize in the instant k, $1 \le k \le T$ and when the window size is w $(1 \le w \le T - k)$, is denoted by k_w, and has $N \times w$ observations. The input matrix for this DEA-WA is described by Equation (1):

$$X_{k_w} = \left(x_k^1, x_k^2, \ldots, x_k^N, x_{k+1}^1, x_{k+1}^2, \ldots, x_{k+1}^N, \ldots, x_{k+w}^1, x_{k+w}^2, \ldots, x_{k+w}^N\right) \tag{1}$$

and the product matrix is denoted by Equation (2):

$$k_{t_w} = \left(y_k^1, y_k^2, \ldots, y_k^N, y_{k+1}^1, y_{k+1}^2, \ldots, y_{k+1}^N, \ldots, y_{k+w}^1, y_{k+w}^2, \ldots, y_{k+w}^N\right) \tag{2}$$

These inputs and outputs adapted to the BCC model [9] and to the model proposed by [28], generate the following formulation in (3):

$$\begin{array}{rl} & max\ \theta \\ \text{subject to}: & \\ & \theta' X_t - \lambda' X_{t_w} \ge 0 \\ & \lambda' Y_{t_w} - Y_t \ge 0 \\ & \sum\limits_{n=1}^{n} \lambda_n = 1 \\ & \lambda_n \ge 0\ (n = 1, 2, \ldots, N \times w) \\ & \lambda_n{}' \ge 1\ (n = 1, 2, \ldots, N \times w) \end{array} \tag{3}$$

The number of windows considered for this study was three (3), which was the number suggested by the original proponents of this technique [31]. And [28] stated that an output-oriented measure of technical efficiency of $k - th$ DMU, denoted by TE_k, can be computed by (4):

$$TE_k = \frac{1}{\theta_k} \tag{4}$$

3.2. Malmquist Index (MI)

The MI, initially proposed by [24] and expanded by [25], as a theoretical concept of production analysis, proposes a measure of productivity that varies over time and allows for the evaluation of changes in DMU efficiency. It was presented as an empirical index by [32], and is defined as a linear programming model based on DEA, according to [33], Equation (4):

$$M\left(x^t, y^t, x^{t+1}, y^{t+1}\right) = \left[\frac{D^t\left(x^{t+1}, y^{t+1}\right)}{D^t\left(x^t, y^t\right)} \cdot \frac{D^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D^{t+1}\left(x^t, y^t\right)}\right]^{\frac{1}{2}} \tag{5}$$

In Equation (4) y represents the output vector and x the input vector. $D^t\left(x^t, y^t\right)$ is defined as a function of distance results and M as the total change in productivity between period t and period $t + 1$.

MI scores allow for the decomposition of changes in total productivity factors into two terms, called changes in technical efficiency (catch-up effect) and technological progress (frontier shift effect). The first one is an important measure of the temporal evolution of DMUs.

The second one shows the evolution of the technical efficiency of production units and corresponds to a shift towards an efficient frontier (frontier shift effect), according to [30], Equation (5):

$$\mathrm{MI} = \mathrm{TE} \cdot \mathrm{TP} \tag{6}$$

where:

MI = Malmquist Index;
TE = Technical Efficiency;
TP = Technological Progress.

According to [30], the MI presents results such as MI > 1 showing progress, MI < 1 showing regression, or MI = 1 showing no change in the productivity of a given DMU in the period under analysis. The interpretation of the values of TE and TP is similar, namely TE > 1 shows progress in the relative efficiency from period t to period $t + 1$, TP > 1 shows progress in the technological frontier for the DMU from period t to period $t + 1$, TE < 1 and TP < 1 show setbacks, and TE = 1 and TP = 1 show that there was no change.

In [34] was highlighted that, with the calculation of the Malmquist index, it is possible to separate the frontier shift effect for all possible combinations of periods, including the next unobserved periods through forecast. This allows us to know the trends in the progress of technical efficiency, regression of efficiency, progress of frontier technology, and tendency to regress in frontier technology. This also allows operational decisions to be made before efficiency drops.

3.3. Cluster Analysis (CA)

Cluster analysis brings together different techniques designed to assess categorized alternative sets to analyze the similarities between alternatives or units, according to predefined criteria. In [35] was mentioned that one of the most used distances in cluster analysis is Euclidean distance, and that this distance between two cases (i and j) is the root of the squared sums of the difference between i and j for all variables ($v = 1, 2, \ldots, p$). Equation (6) presents the formulation:

$$d_{ij} = \sqrt{\sum_{v=1}^{p} (X_{iv} - X_{jv})^2} \tag{7}$$

where:

X_{iv} = the value of variable v of element i;
X_{jv} = the value of variable v of element j;
p is the number of variables.

In [26] was presented how Ward's method (proposed by [27]) is a hierarchical cluster analysis procedure. In this method, productive units are grouped by calculating the square sums between two groups and then added to the analyzed variables.

4. Results

The window analysis technique has gained prominence in the literature in recent years, and some authors have studied this technique, not always integrating it with the Malmquist index [28,36,37]. Thus, based on information from these studies, the efficiency index used in this study was defined in Equation (8):

$$\text{Efficiency Index} = \frac{Production\ (barrels/day)}{Access\ numbers + Annual\ Production\ capacity\ (barrels/day)} \tag{8}$$

In order to define the ideal efficiency index for this application, some average efficiency tests were carried out on all variables considered in the analysis. The highest average of the efficiency index was found by Equation (8), in which the variable "Number of entry points" represents the annual number of entry points to ensure an efficient flow of refinery production, considering terrestrial entry points and gas pipelines, among others. So, efficiency tends to decrease if the number of entry points is high. The variables were normalized from 0 to 100 for data standardization, where 0 represents the lowest value and 100 is the highest value.

Thus, this index was calculated using a DEA output-oriented BCC model in order to define data inputs for DEA-WA analysis. And then, the window analysis model was applied for the period between 2012 and 2020, considering seven specific window periods. This study collected data from the statistical yearbooks of the ANP (National Agency for Petroleum, Natural Gas and Biofuels) for 12 Brazilian oil refineries, named in Table 1 Column 1. The numerical results of this analysis are shown in Table 1.

The efficiency index averages calculated for the windows under analysis found the lowest efficiency (0.81) at Refap refinery (RS) and the highest efficiency (0.97) at Regap refinery (MG). Table 2 shows the average efficiency per year of each Brazilian refinery analyzed.

Table 1. Window analysis applied to Brazilian oil refineries.

Refineries	2012	2013	2014	2015	2016	2017	2018	2019	2020	Window Average
Replan (SP) Window 1	0.82	0.96	1.00							0.94
Window 2		0.89	0.93	1.00						
Window 3			0.93	1.00	0.97					
Window 4				1.00	0.97	0.93				
Window 5					1.00	0.95	0.81			
Window 6						1.00	0.85	0.83		
Window 7							1.00	0.97	0.86	
Rlam (BA) Window 1	0.97	0.89	0.88							0.90
Window 2		0.86	0.85	0.97						
Window 3			0.83	0.93	1.00					
Window 4				0.93	1.00	0.87				
Window 5					1.00	0.87	0.77			
Window 6						0.92	0.83	0.77		
Window 7							0.94	0.88	0.88	
Revap SP Window 1	1.00	0.99	1.00							0.96
Window 2		0.99	1.00	0.95						
Window 3			0.95	0.90	1.00					
Window 4				0.90	1.00	0.95				
Window 5					1.00	0.95	0.85			
Window 6						1.00	0.89	0.86		
Window 7							1.00	0.96	0.98	

Table 1. *Cont.*

Refineries	2012	2013	2014	2015	2016	2017	2018	2019	2020	Window Average
Reduc (RJ) Window 1	0.95	0.93	0.97							0.88
Window 2		0.87	0.91	0.98						
Window 3			0.91	0.97	0.95					
Window 4				0.97	0.95	0.77				
Window 5					0.96	0.78	0.76			
Window 6						0.82	0.80	0.73		
Window 7							0.89	0.82	0.88	
Repar (PR) Window 1	0.80	0.91	0.99							0.89
Window 2		0.86	0.93	0.91						
Window 3			0.92	0.90	0.95					
Window 4				0.90	0.95	0.89				
Window 5					0.95	0.90	0.77			
Window 6						0.96	0.82	0.78		
Window 7							0.90	0.86	0.92	
Refap (RS) Window 1	0.82	0.77	0.80							0.81
Window 2		0.74	0.77	0.98						
Window 3			0.76	0.96	0.93					
Window 4				0.96	0.93	0.78				
Window 5					0.93	0.78	0.67			
Window 6						0.82	0.71	0.65		
Window 7							0.79	0.72	0.71	
RPBC (SP) Window 1	0.97	0.92	0.95							0.93
Window 2		0.86	0.89	1.00						
Window 3			0.88	0.99	1.00					
Window 4				0.99	1.00	0.89				
Window 5					1.00	0.89	0.80			
Window 6						0.96	0.86	0.88		
Window 7							0.93	0.95	0.94	
Regap (MG) Window 1	1.00	0.91	1.00							0.97
Window 2		0.89	0.98	1.00						
Window 3			0.98	1.00	1.00					
Window 4				1.00	1.00	0.96				
Window 5					1.00	0.96	0.95			
Window 6						1.00	0.98	0.93		
Window 7							1.00	0.94	0.96	

Table 1. *Cont.*

Refineries	2012	2013	2014	2015	2016	2017	2018	2019	2020	Window Average
Recap (SP) Window 1	0.69	0.81	1.00							0.86
Window 2		0.78	0.96	0.97						
Window 3			0.95	0.95	0.97					
Window 4				0.95	0.97	0.61				
Window 5					0.97	0.61	0.82			
Window 6						0.67	0.89	0.83		
Window 7							0.96	0.89	0.88	
Reman (AM) Window 1	0.94	0.96	0.81							0.82
Window 2		0.94	0.79	0.85						
Window 3			0.78	0.84	0.90					
Window 4				0.84	0.90	0.76				
Window 5					0.92	0.79	0.69			
Window 6						0.84	0.74	0.69		
Window 7							0.75	0.70	0.71	
Riograndense RS Window 1	0.84	0.90	0.96							0.82
Window 2		0.86	0.91	0.89						
Window 3			0.88	0.87	0.74					
Window 4				0.87	0.74	0.54				
Window 5					0.74	0.54	0.77			
Window 6						0.62	0.88	0.92		
Window 7							0.93	0.97	0.96	
Lubnor (CE) Window 1	1.00	0.88	0.99							0.92
Window 2		0.83	0.93	1.00						
Window 3			0.88	0.94	1.00					
Window 4				0.94	1.00	0.83				
Window 5					1.00	0.84	0.81			
Window 6						1.00	0.96	0.82		
Window 7							1.00	0.85	0.90	

Table 2. Mean efficiency of Brazilian oil refineries per year.

Refineries	2012	2013	2014	2015	2016	2017	2018	2019	2020
Replan (SP)	0.82	0.92	0.95	1.00	0.98	0.96	0.89	0.90	0.86
Rlam (BA)	0.97	0.87	0.85	0.94	1.00	0.89	0.85	0.83	0.88
Revap (SP)	1.00	0.99	0.98	0.91	1.00	0.97	0.91	0.91	0.98
Reduc (RJ)	0.95	0.90	0.93	0.97	0.95	0.79	0.82	0.78	0.88
Repar (PR)	0.80	0.88	0.95	0.91	0.95	0.92	0.83	0.82	0.92
Refap (RS)	0.82	0.75	0.78	0.97	0.93	0.79	0.72	0.69	0.71
RPBC (SP)	0.97	0.89	0.91	0.99	1.00	0.91	0.87	0.91	0.94

Table 2. *Cont.*

Refineries	2012	2013	2014	2015	2016	2017	2018	2019	2020
Regap (MG)	1.00	0.90	0.99	1.00	1.00	0.97	0.98	0.93	0.96
Recap (SP)	0.69	0.79	0.97	0.96	0.97	0.63	0.89	0.86	0.88
Reman (AM)	0.94	0.95	0.79	0.85	0.90	0.79	0.73	0.69	0.71
Riograndense (RS)	0.84	0.88	0.92	0.87	0.74	0.57	0.86	0.95	0.96
Lubnor (CE)	1.00	0.85	0.93	0.96	1.00	0.89	0.92	0.84	0.90
Global average	0.90	0.88	0.91	0.94	0.95	0.84	0.85	0.84	0.88

The best efficiency average occurred in 2016, with an index of 0.95. The lowest average efficiency in the analyzed period was in 2020, with 0.88.

Riograndense (RS) refinery had the lowest efficiency index in the analysis, 0.57, in 2017. Other refineries with the lowest indexes were Recap (SP), with 0.63 and 0.69 in 2017 and 2020, respectively; Reman (AM), with 0.69 in 2019; and Refap (RS), with 0.69 in 2019. In 2013 and 2014 and in the period between 2017 and 2020, no refinery showed full efficiency, which can be explained by a higher level of competition at the national and/or international level and also by variations in the product considered for analysis, production (barrel/day). There were also variations in annual production capacity (barrel/day). Table 3 describes average efficiencies per window.

Table 3. Efficiency of Brazilian oil refineries per window.

Refineries	2012–2014	2013–2015	2014–2016	2015–2017	2016–2018	2017–2019	2018–2020
Regap (MG)	0.97	0.96	0.99	0.99	0.97	0.97	0.97
Revap (SP)	1.00	0.98	0.95	0.95	0.93	0.92	0.98
Replan (SP)	0.93	0.94	0.97	0.97	0.92	0.89	0.94
RPBC (SP)	0.95	0.92	0.96	0.96	0.90	0.90	0.94
Lubnor (CE)	0.96	0.92	0.94	0.92	0.88	0.93	0.92
Rlam (BA)	0.91	0.89	0.92	0.93	0.88	0.84	0.90
Repar (PR)	0.90	0.90	0.93	0.92	0.87	0.85	0.90
Reduc (RJ)	0.95	0.92	0.94	0.90	0.83	0.78	0.87
Recap (SP)	0.83	0.90	0.96	0.85	0.80	0.80	0.91
Riograndense (RS)	0.90	0.89	0.83	0.71	0.68	0.81	0.95
Reman (AM)	0.90	0.86	0.84	0.83	0.80	0.75	0.72
Refap (RS)	0.80	0.83	0.88	0.89	0.79	0.73	0.74
Average	0.91	0.91	0.93	0.90	0.86	0.85	0.89

The 2014–2016 window had the best average efficiency, 0.93, while the 2017–2019 window had the worst rate, 0.85. Only Revap (SP) refinery showed efficiency in its operations in the 2012–2014 window. In the other windows, no refinery was efficient. Riograndense (RS) refinery had the lowest efficiency rates, 0.68 in the 2016–2018 window and 0.71 in the fourth window, 2015–2017.

Two other refineries, along with Riograndense refinery (RS), had the lowest efficiency indexes in the windows: Reman (AM) refinery, with 0.72 in the 2018–2020 window and 0.75 in the 2017–2019 window, and Refap (SP) refinery, with 0.73 in the 2017–2019 window and 0.74 in the 2018–2020 window.

Considering the average efficiency data per year as input data for cluster analysis, the standard cluster technique of Euclidean distance was applied, which is expressed in Table 4.

According to [26] the creation of clusters can provide a grouping of refineries according to their average efficiency indexes per year without data distortion. However, despite the fact that the average indexes per year were considered, it was perceived that the clusters were organized according to the global average efficiency index. The first cluster, C1, brought together eight refineries that presented the best average efficiency rates, equal to or greater than 0.89 with an average of 0.92, which were Regap (MG), Revap (SP), RPBC (SP), Lubnor (CE), Replan (SP), Rlam (BA), Repar (PR), and Reduc (RJ).

Table 4. Cluster analysis based on average efficiency indexes, per year.

Cluster	Refineries	Average	Average per Cluster
C1	Regap (MG)	0.97	0.92
	Revap (SP)	0.96	
	RPBC (SP)	0.93	
	Lubnor (CE)	0.92	
	Replan (SP)	0.92	
	Rlam (BA)	0.90	
	Repar (PR)	0.89	
	Reduc (RJ)	0.89	
C2	Recap (SP)	0.85	0.85
	Riograndense (RS)	0.84	
C3	Reman (AM)	0.82	0.81
	Refap (RS)	0.80	

Cluster C2 contained two refineries with indexes of 0.84 and 0.85 and an average of 0.85, Recap (SP) and Riograndense (RS), while cluster C3 had two refineries with the worst average indexes, 0.80 and 0.82, and an average of 0.81, Reman (AM) and Refap (RS).

To verify the changes in productivity, a decomposition of the Malmquist index was calculated based on its two effects, matching (catch-up effect) and technological progress (frontier shift effect), besides the general Malmquist index, which allows for an analysis of total factor productivity [17]. The data referring to the pairing effect are presented in Table 5. A significant variation can be seen in the results presented. If the pairing results in an index greater than 1, it means that technical efficiency increased in period $t + 1$ in relation to period t. If this index is equal to 1, technical efficiency remained the same, and if it is less than 1, it worsened [28,38]. This index was equal to 1 in the case of Recap (SP), Revap (SP), Lubnor (CE), and Replan (SP) refineries, all belonging to the first cluster, which shows that there were no significant changes in their technical efficiency during the period.

Table 5. Effect of pairing efficiency of Brazilian oil refineries between 2012 and 2020.

Refineries	2012–2014	2013–2015	2014–2016	2015–2017	2016–2018	2017–2019	2018–2020	Average
Regap (MG)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Revap (SP)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
RPBC (SP)	0.98	1.07	1.05	0.96	0.93	1.05	1.05	1.01
Lubnor (CE)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Replan (SP)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Rlam (BA)	0.88	1.11	1.13	0.92	0.94	0.99	1.00	1.00
Repar (PR)	1.23	0.99	0.96	1.05	0.94	0.95	1.05	1.03
Reduc (RJ)	1.02	1.05	0.99	0.84	0.93	1.04	1.01	0.98
Average C1	1.01	1.03	1.02	0.97	0.97	1.00	1.01	1.00
Recap (SP)	1.43	1.14	0.97	0.69	0.99	1.40	0.96	1.08
Riograndense (RS)	1.12	0.92	0.77	0.69	1.26	1.62	1.08	1.06
Average C2	1.28	1.03	0.87	0.69	1.12	1.51	1.02	1.07
Reman (AM)	0.86	0.85	1.14	0.98	0.82	0.90	1.00	0.94
Refap (RS)	0.98	1.26	1.16	0.84	0.84	0.92	0.93	0.99
Average C3	0.92	1.06	1.15	0.91	0.83	0.91	0.97	0.96
Maximum	1.43	1.26	1.16	1.05	1.26	1.62	1.08	1.08
Minimum	0.86	0.85	0.77	0.69	0.82	0.90	0.93	0.94
Average/clusters	1.07	1.04	1.01	0.86	0.97	1.14	1.00	1.01
SD/clusters	0.14	0.01	0.08	0.14	0.09	0.26	0.01	0.10

Cluster C1 presented an average of very close to 1 in all analyzed periods, with values varying by 3% above or below this value. Cluster C2 showed significant variations in technical efficiency. Some periods showed strong declines in this index, while other periods showed a considerable improvement. At Riograndense refinery (RS), for example, there was an improvement in technical efficiency in the 2012–2014 and 2017–2019 periods. Cluster C3 also showed variation in the data, but in most periods, there was a drop in technical efficiency. It is worth noting that there was an improvement in the period 2014–2016 and a drop in the technical efficiency index, in both refineries, in another four periods.

Changes in the technical efficiency indexes, calculated through the pairing effect, are due to variations in the values of the product or inputs during the years 2012 to 2020.

The minimum value found in this analysis was 0.69, for refineries Recap (SP) and Riograndense (RS), in the period 2015–2017. Recap (SP) showed a 15% increase in production capacity in this period, but the considered product, production (barrel/day), did not increase considerably.

Riograndense refinery (RS) kept its inputs constant but showed a reduction of 37.5% in production (barrel/day), which determined a drop in efficiency index and a low value of the pairing effect.

The general averages between the clusters showed considerable variability in most periods, with a standard deviation of approximately 0.104. Analyzing the periods, there was a great variability between the averages of the clusters in 2012–2014, 2015–2017, and 2017–2019, with values of the standard deviation of, respectively, 0.14, 0.14 and 0.26. Data referring to technological progress (frontier shift effect), or frontier shift, are presented in Table 6.

Table 6. "Technological progress" effect of the Malmquist index decomposition of the efficiency of Brazilian oil refineries between 2012 and 2020.

Refineries	2012–2014	2013–2015	2014–2016	2015–2017	2016–2018	2017–2019	2018–2020	Average
Regap (MG)	1.00	1.12	1.03	0.97	0.95	0.93	0.96	0.99
Revap (SP)	1.00	0.95	1.06	1.06	0.85	0.86	0.98	0.97
RPBC (SP)	1.00	1.08	1.07	0.94	0.86	0.88	0.96	0.97
Lubnor (CE)	0.99	1.21	1.14	0.94	0.90	0.90	0.90	1.00
Replan (SP)	1.23	1.12	1.03	0.91	0.81	0.83	0.86	0.97
Rlam (BA)	1.03	1.02	1.06	1.01	0.82	0.85	0.94	0.96
Repar (PR)	1.00	1.07	1.06	0.94	0.85	0.86	0.97	0.97
Reduc (RJ)	1.00	1.07	1.06	0.94	0.85	0.86	0.98	0.97
Average C1	1.03	1.08	1.06	0.96	0.86	0.87	0.94	0.97
Recap (SP)	1.02	1.09	1.05	0.93	0.86	0.88	0.96	0.97
Riograndense(RS)	1.01	1.13	1.09	0.90	0.83	0.92	0.96	0.98
Average C2	1.01	1.11	1.07	0.92	0.84	0.90	0.96	0.97
Reman (AM)	1.00	1.07	1.00	0.92	0.92	0.91	0.95	0.97
Refap (RS)	1.00	1.05	1.06	0.98	0.86	0.86	0.97	0.97
Average C3	1.00	1.06	1.03	0.95	0.89	0.88	0.96	0.97
Maximum	1.23	1.21	1.14	1.06	0.95	0.93	0.98	1.00
Minimum	0.99	0.95	1.00	0.90	0.81	0.83	0.86	0.96
Average/clusters	1.02	1.08	1.05	0.94	0.86	0.89	0.95	0.97
SD/clusters	0.01	0.02	0.01	0.02	0.01	0.02	0.01	0.01

Subsection

Regarding technological progress (frontier shift effect), in product-oriented efficiency analysis models, if the index is greater than 1, the DMU shows technological progress, if it is equal to 1, there was no technological change, and if it is less than 1, it shows technological regression [17,30,38].

Overall, our results show that there was a technological regression in most periods. The mean and standard deviations between the cluster means were approximately 0.97

and 0.01, respectively. This shows homogeneity between these averages. There are also fewer significant technological changes when compared to changes in technical efficiency. The first three periods show an average greater than 1 among all clusters, which shows technological progress. Clusters 1, 2, and 3 are illustrated in Figures 3–5.

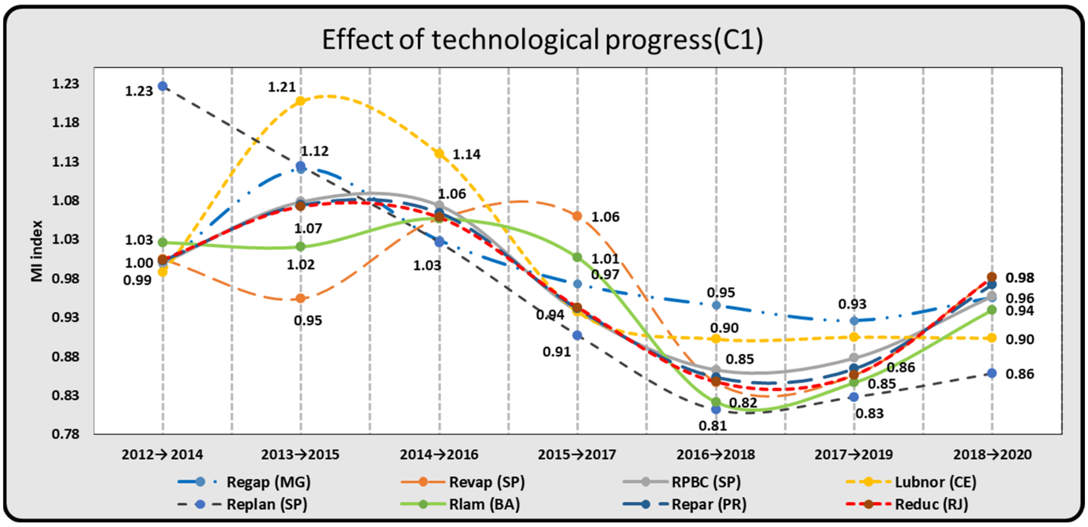

Figure 3. Effect of technological progress (cluster C1).

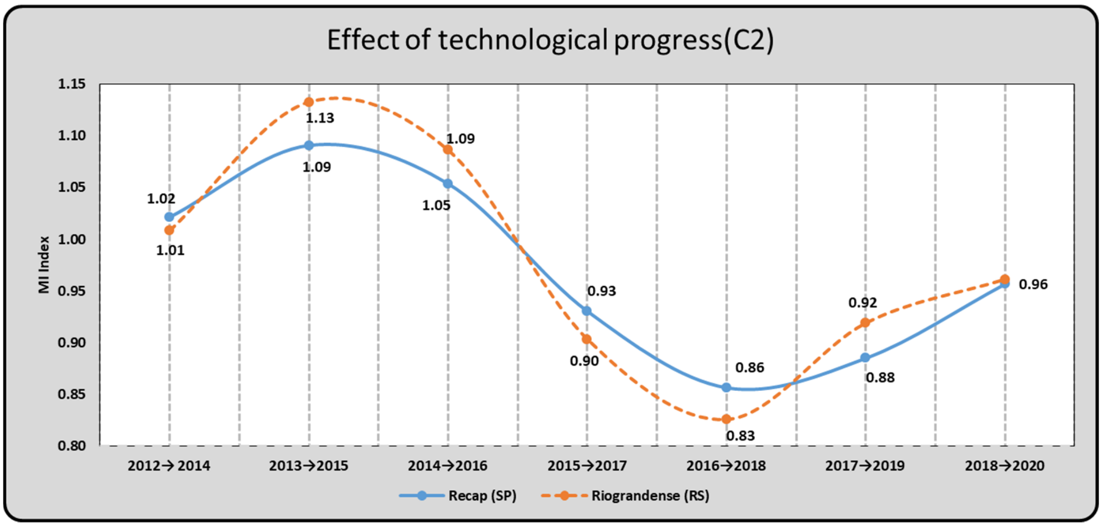

Figure 4. Effect of technological progress (cluster C2).

Replan refinery (SP) remained at a value close to 1, as did the other refineries. In the last five periods, average values among the clusters were lower than 1, indicating a technological regression. All refineries in the three clusters showed technological regression in the last three periods (from 2016–2018 to 2018–2020). The average for 2015–2017 was also less than 1, but there was variation in the values. Except for Lubnor (CE), all other refineries, on average, showed technological regression. The Malmquist index (MI), in its general form, shows changes in total factor productivity (TFP), which is the multiplication between the effects of technical efficiency and technological progress, as mentioned above. Table 7 presents the values of the Malmquist index, and Figures 6–8 illustrate this scenario in clusters 1, 2 and 3.

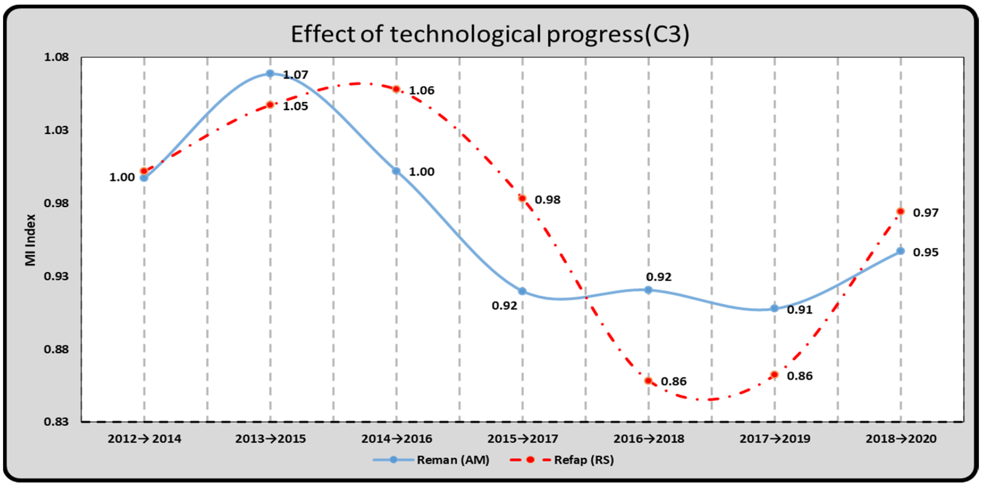

Figure 5. Effect of technological progress (cluster C3).

Table 7. Malmquist index of Brazilian oil refineries.

Refineries	2012–2014	2013–2015	2014–2016	2015–2017	2016–2018	2017–2019	2018–2020	Average
Regap (MG)	1.00	1.12	1.03	0.97	0.95	0.93	0.96	0.99
Revap (SP)	1.00	0.95	1.06	1.06	0.85	0.86	0.98	0.97
RPBC (SP)	0.98	1.16	1.13	0.90	0.80	0.92	1.01	0.98
Lubnor (CE)	0.99	1.21	1.14	0.94	0.90	0.90	0.90	1.00
Replan (SP)	1.23	1.12	1.03	0.91	0.81	0.83	0.86	0.97
Rlam (BA)	0.90	1.13	1.20	0.93	0.77	0.84	0.94	0.96
Repar (PR)	1.23	1.06	1.03	0.99	0.81	0.82	1.02	0.99
Reduc (RJ)	1.02	1.12	1.05	0.79	0.79	0.89	0.99	0.95
Average C1	1.04	1.11	1.08	0.94	0.83	0.87	0.96	0.98
Recap (SP)	1.46	1.24	1.02	0.64	0.85	1.24	0.92	1.05
Riograndense	1.13	1.04	0.83	0.63	1.04	1.48	1.04	1.03
Average C2	1.30	1.14	0.93	0.63	0.94	1.36	0.98	1.04
Reman (AM)	0.86	0.91	1.14	0.90	0.75	0.82	0.95	0.90
Refap (RS)	0.98	1.32	1.23	0.82	0.72	0.79	0.91	0.97
Average C3	0.92	1.12	1.19	0.86	0.74	0.81	0.93	0.94
Maximum	1.46	1.32	1.23	1.06	1.04	1.48	1.04	1.05
Minimum	0.86	0.91	0.83	0.63	0.72	0.79	0.86	0.90
Average/clusters	1.09	1.12	1.07	0.81	0.84	1.01	0.95	0.98

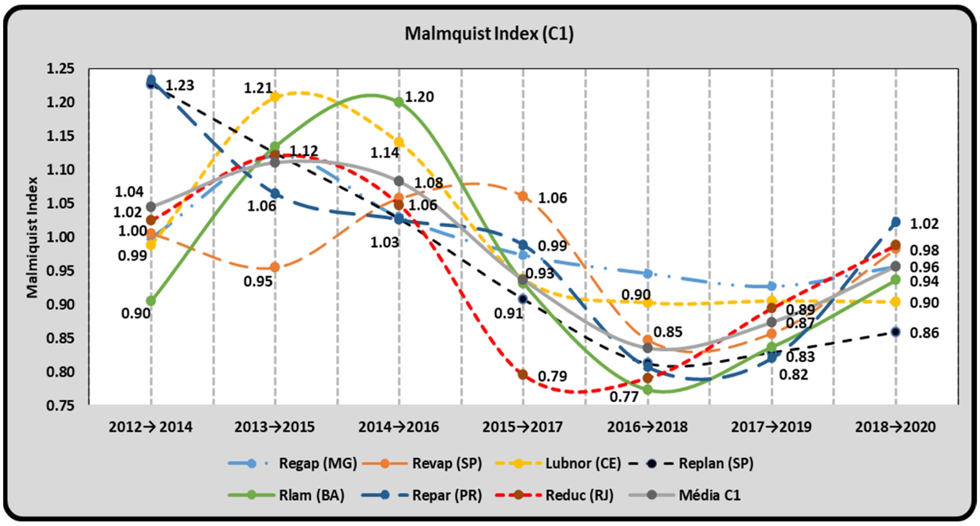

Figure 6. Malmquist index (cluster C1).

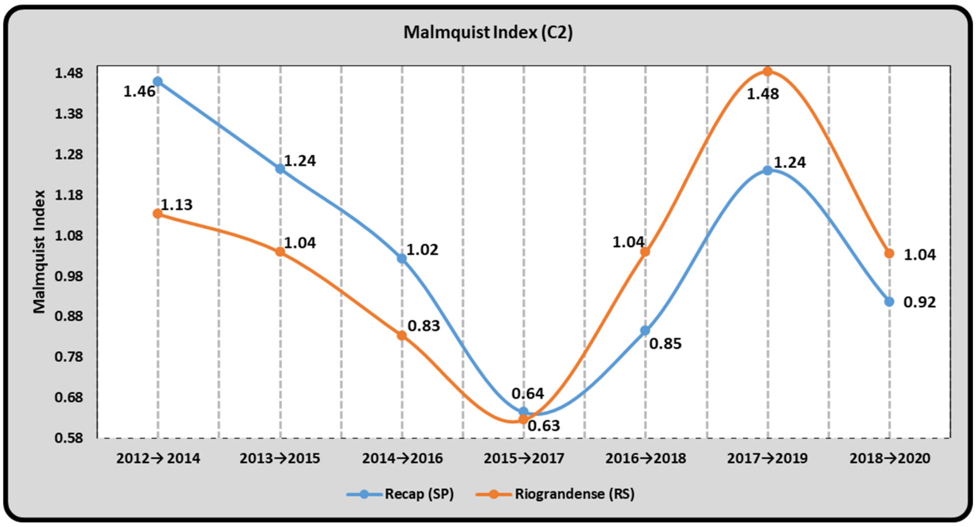

Figure 7. Malmquist index (cluster C2).

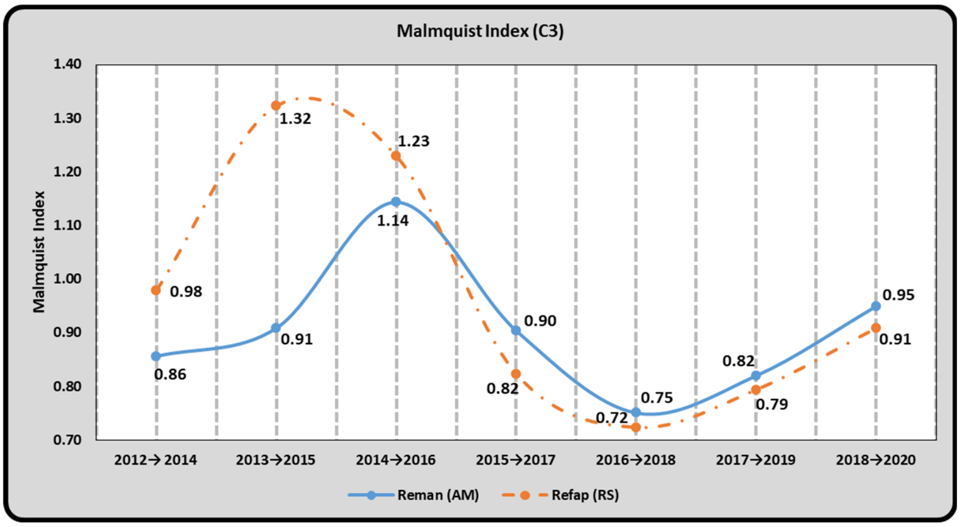

Figure 8. Malmquist index (cluster C3).

When the Malmquist index (MI) is MI > 1, it shows that productivity is improved, and with MI < 1, productivity is reduced, as presented by [18,30].

5. Discussion

The maximum improvement value in this productivity index occurred in Riograndense (RS) refinery, 1.48, in the period from 2017 to 2019, while the worst index was 0.63, in the same refinery in the period from 015 to 2017.

This sharp drop in productivity is because of the decrease in the product used in the analysis. Production decreased by approximately 4000 barrels/day in this period, while inputs remained constant.

There were significant variations in the values of total factor productivity between the refineries and between the analyzed periods, mainly because of the significant changes in technical efficiency, since technological changes presented little variation in their values. There was a fluctuation in the Malmquist index, showing that productivity varied in the analyzed period.

As for the predefined hypothesis and the findings expected from this study, it was possible to perceive that DEA-WA and the Malmquist index, when used concomitantly, can provide a clear view of the productivity and efficiency behaviors of every studied refinery and their technological changes in different periods. As for the other analysis, cluster analysis provided a global study scenario for the studied period 2012–2020. With this integrated analysis, it is possible to plan all potential decision-making and refinery management actions following our methodology.

Brazilian oil refineries play an important role in the production of oil and natural gas in Brazil, which is the largest oil-refining country in South America, with approximately 2734 million barrels/day. According [22], there are currently eighteen oil refineries in Brazil, thirteen of which are managed by Petrobras and five are managed by the private sector. In this study, 12 refineries were considered based on their size and foundation time.

The application of the DEA window analysis model to oil refineries enabled us to monitor the performance of refineries over several periods of time. In [28] was stated that comparing DMUs for a single period can generate biased results, and a more realistic efficiency analysis should be performed over a period of time. When a window efficiency analysis is performed on Brazilian oil refineries and none of them show efficiency throughout the entire period, it can be worrying for managers, since they are not achieving the maximum production possible with the inputs used. In order to compare different periods, the Malmquist general index and its decomposition into its two effects, matching and technological progress, were also verified. In most of the analyzed periods, there was variation between technical efficiency data, with gains and losses between periods in each refinery. Technological progress presented more discrete changes in values.

Environmental and social aspects were not considered in this analysis, because they would require subjective assessment from decision makers and specialists and the definition of relevant criteria to make their development more reliable. In reality, these aspects are relevant, but they must be developed and combined with a multicriteria analysis.

6. Final Remarks

Integrating data envelopment analysis, the Malmquist index, and cluster analysis enabled us to identify the refineries' productivity and efficiency behaviors in different periods and incorporate an analysis of the technological progress of the units.

To the best of our knowledge, the combination of these three techniques had not previously been applied to oil refineries, which opened the possibility of carrying out this study and contributing to the literature, in addition to presenting comparisons between Brazilian and international refineries.

This analysis contributes to the current research in different aspects, as it enables the use of the combination of these techniques for the analysis of productivity and efficiency and to support managers in their decision making.

It also opens up avenues to new developments that could involve multicriteria analyses with environmental, social, and economic aspects integrated into the efficiency aspect developed in this work. Knowledge of the performance of refineries by time periods in a given country is the first step to thinking about sustainable actions.

A refinery cannot have environmental responsibility without a minimum of efficiency in operations. Thus, this work provides an overview of efficiency in various time windows in order to promote a more robust analysis for future sustainable actions.

This study can significantly contribute to the theory in aspects related to efficiency calculation, showing a more viable way to determine operational efficiency in refineries and an initial analysis to help manage these enterprises.

The integration carried out can be highlighted as a practical contribution, since it separates unwanted periods or specific problems that occurred within these periods. It also groups refineries into clusters in order to know the best and worst performances in the studied periods. The measurement of the necessary technological changes is also evident with the determination of the Malmquist index.

Author Contributions: Conceptualization, M.S.d.O. and F.T.; methodology, M.S.d.O.; validation, M.S.d.O., M.L. and F.T.; formal analysis, H.S., F.T. and P.A.; investigation, M.S.d.O.; resources, M.L. and H.S.; data curation, M.S.d.O. and F.T.; writing—original draft preparation, M.S.d.O. and F.T.; writing—review and editing, H.S., F.T. and P.A.; visualization, M.L. and F.T.; supervision, H.S., F.T. and P.A.; project administration, F.T.; funding acquisition, H.S. and F.T. All authors have read and agreed to the published version of the manuscript.

Funding: The APC was funded in part by Universidade Tecnologica Federal do Parana, Brazil.

Conflicts of Interest: The authors declare no conflict of interest.

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