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DEA IN THE COMPARISON OF PERFORMANCES IN LOADING PETROLEUM DERIVATIVES

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Abstract
This paper develops indicators to assess the performance of crude oil derivate terminals. The performance evaluations consider differences related to operational uniformity, speed, capacity satisfaction, loading precision and productivity. Due to its ability to handle multiple inputs and outputs, Data Envelopment Analysis (DEA) is employed and is found to be especially suitable to compare such performances. As there are important differences between many of the units under study, the scores resulting from DEA are submitted to Wilcoxon-Mann-Whitney non-parametric test to verify the existence of significant differences due to different production volumes. The test results validated the use of a unique analysis for all units.

Keywords: *Data Envelopment Analysis, Performance measurement, Wilcoxon-Mann-Whitney statistical test.*

1. Introduction

Creating competitive advantage by high performance in logistics requires the integration of advanced measurement systems. The activities in the area of loading petroleum derivatives, being operated internally in warehouse facilities, often lack efficiency indicators. Notwithstanding, such activities are a part of the supply chain on which measurements become fundamental, both to reduce operational costs and to enhance the quality of the services provided. The starting point for managing and controlling supply chains is the accurate assessment of operational performance of the various components that constitute the integrated logistics. Good metrics and consistent measurement systems provided at the right time enable the logistics management to implement corrective actions to achieve better results.

Within the concept of integrated logistics are the activities of customer orders handling, warehouse and inventory management, dispatch of products and transportation. These activities constitute a system (Lambert, 1993) on which it is fundamental correctly evaluating the costs at every point of the chain. Thus, information systems in Logistics must start by precisely designing the ideal operational performance inside each of the various functional areas. The next step is to determine the costs to achieve such performances at minimum total cost. This means that the performance indicators at each link of the chain must drive to renounce sometimes to minimum local costs in an activity as transporting, inventory or any other, to assure minimum global costs.

In this article we study the activity of dispatch of petroleum derivatives, as gasoline, diesel, kerosene, fuels oils, etc., accomplished by trucks loading in two kinds of terminals: large terminals, where the products arrive through different pipelines directly from the refineries, and small terminals, where other arrival modes are employed.

The initial objective is to create indicators to identify levels at which the establishments are operating, in terms of the distribution of the loaded volumes along the day, of the involved costs and the quality of services provided. In a second stage, these indicators are used to build scores of relative performance of the diverse operational facilities. DEA (Cooper et al., 2000) enables ranking the operational facilities (Decision Making Units) according to its efficiency.

Although no functional form is assumed in the construction of the DEA frontier, guaranteeing a suitable specification of the model is a concern in the applications of DEA that is taken into account in the development of this article. A procedure to choose the most appropriate DEA model employing the Test of Wilcoxon-Mann-Whitney is developed.

Additionally, for the inefficient units, the factors that contributed negatively to their efficiency score are identified, as well as the units (benchmarks or peers groups) that serve as a positive reference are pointed. The objective of this is to create means to identify points in the units that may permit management to develop actions to improve the internal processes. These actions may depend on particular features of the units that may or may not be among those considered in the model here adjusted.

2. Identification of the objectives

The logistics activities should be viewed as a continuous process along which performances should be under permanent monitoring. In the present case, of the dispatch of products, we can expect that variations in the operations exist. But if some attributers are above or below certain levels, this may threaten the quality of service provided to customers or considerably raise operational costs. The purpose of the performance indicators is, essentially, to provide information especially about when the variability exceeds acceptable levels.

The operation of facilities answering for the shipment of oil derivatives in trucks has a large variation along days of the week and daily shifts. This variation may affect the quality of the services provided to customers. The service may present high concentrations at determined moments of the day, generating loading congestion and higher operational time. Moreover, to face such peak moments it is needed to contract an amount of manpower that becomes invariably idle for the rest of the day. By identifying these service peaks enables the management, for instance, to establish agreements with customers propitiating a more linear attendance during the period. In general such agreements may be dealt without any loss for the business.

Another important aspect is the daily operational schedule of the unit. Operating off the normal way raises costs. Nevertheless, this may be accomplished whenever there is some attractive financial return.

In this article, we are interested on analyzing the relations between loaded volumes and operational resources employed. The evaluation system must attribute a good performance evaluation to the establishment that operates linearly, following its income-producing schedules, with high precision in the shipment operations, high productivity and, besides, with an adequate percentage of use of the assets assigned for the process, not losing of sight that such performance scores must be coherent to observed financial results.

The operational units evaluated operate under similar conditions, in the shipment routines (which are standardized), as well as in the available equipment made available for their operations. This makes possible to develop consistent evaluation of their performances. They are partially automated, possessing a terminal operation system in charge of almost the totality of the information employed in the computation of the performance indicators.

3. Selection of Indicators

The first step in the application of DEA is to identify the set of indicators that signal performance levels, measuring either consumed resources or conditions that affect operation (inputs) or products and/or services generated or other measurable benefits created (outputs) in the units under evaluation. As observed in Section 2, the factors measured must contribute to explain existing differences in the units regarding the linear form of the daily movement, the operation according to schedules with the most reduced costs, the productivity levels, the precision of the operation and the use of the capacity installed in the unit. Indicators of these attributes are described below.

3.1. Measures of Output

3.1.1. Volume of loaded cargo (VOL)

This measure of output is the total volume of the product loaded and dispatched in the considered period. Unit: volume in 1.000 m3.

3.1.2. Precision of the loaded volume (PRE)

The fuel gauge must converge to the mark (called arrow) of the truck of the transporter regarding the specified loaded volume. In case that this does not occur, the mark at the vehicle must prevail. Handling eventual divergences provokes insecurity to the business and delay in the operation. As a measure of precision, the number of shipments without divergences of volume, divided by the total volume of shipment loaded is here employed. Unit: Percentage

3.2. Measures of Input

3.2.1. Average shipment time (TMC)

This indicator is the average time of permanence of the vehicle in the establishment. It is not considered in this indicator the last centile, that means, that 1% of movements that remained more time in the patio. The vehicles with time very high must not belong to this concept, because they represent shipments that had presented problems out of the routine of loading. Unit: minutes.

3.2.2. Capacity of loading (CAP)

This represents the capacity of outflow installed in the establishment for a period of 1 hour. With this indicator we search to estimate the fixed assets for the unit. Unit: m3/h

3.2.3. Coefficient of variation of the distribution load (CVA)

This measures the dispersion of the distribution of loaded volume for interval of time of 1 hour, in the daylight period, more precisely, from 6h to 18h. It is given by the standard deviation of the distribution divided by the average loaded per hour. Unit: adimensional.

3.2.4. Cost of overtime for loaded volume out weekday (HEX)

This aims at measuring the amount of operations of the establishment out of normal work schedule. The cost of overtime divide by the loaded total volume between 6h and 18h measures it. Unit: R$/m3.

3.3. Indicators values

Table 1 presents data regarding these indicators for 19 terminals. The direct analysis of Table 1 is difficult since, invariably, the units with a better behavior with respect to some factors present a worse performance with respect to others. Moreover, the indicators by themselves are not significant. Its importance is enhanced when they relative comparisons between the diverse units are carried through.

In this sense, the application of the methodology of DEA is suitable, because it makes possible to handle jointly several inputs and outputs, deriving global results for the relative efficiency of each unit under comparison. DEA theoretical foundations are briefly described in the next section. It has is its objective identifying units with values of the indictors analyzed below standard provided by the values observed in the more efficient ones.

Table 1: Indicators used for evaluation of DEA efficiency

Units	*Outputs*		*Inputs*			
	VOL	**PRE**	**TMC**	**CAP**	**CVA**	**HEX**
DMU1	84.320	0,65	52	800	0,22	0,39
DMU2	72.740	0,56	48	850	0,25	0,54
DMU3	23.700	0,35	79	350	0,36	0,45
DMU4	4.120	0,80	16	50	0,38	0,12
DMU5	30.623	0,46	60	200	0,43	0,60
DMU6	29.097	0,33	59	300	0,43	0,50
DMU7	22.194	0,69	73	180	0,44	0,44
DMU8	121.623	0,82	50	1000	1,95	0,45
DMU9	7.990	0,89	15	60	0,75	0,14
DMU10	6.597	0,88	18	60	0,75	0,16
DMU11	7.934	0,87	26	60	0,76	0,18
DMU12	7.806	0,84	87	60	0,84	0,20
DMU13	55.678	0,66	48	600	0,31	0,34
DMU14	21.987	0,63	32	300	0,43	0,56
DMU15	37.998	0,75	62	600	0,68	0,98
DMU16	18.022	0,82	47	500	0,55	0,60
DMU17	78.734	0,64	28	700	0,31	0,43
DMU18	88.547	0,78	39	850	0,39	0,63
DMU19	23.678	0,81	41	450	0,45	0,35

4. Evaluation of relative efficiency of terminals by DEA

4.1. Choice of DEA model

DEA was developed by Charnes et al. (1978) to determine the efficiency of productive units. This methodology estimates the relative efficiency of comparable production units. It has been widely used in applications in the most varied areas as education, health, finance, military field, etc.

One of the crucial points in the application of this methodology is the choice, amongst the diverse variants of existing models, of that specification more suitable to the problem in question. To avoid a poor specification, the analyst must, after the determination of the relevant factors, select the adequate approach. One possible choice is between assuming constant returns to scale (CRS or CCR, from Charnes, Cooper and Rhodes, 1978) or variable returns to scale (VRS or BCC, from Banker, Charnes and Cooper, 1984). Besides return of scale, the analyst must choose the type of orientation as: maximizing results generated (orientation to outputs) or minimizing resources employed (orientation to inputs).

The factors (inputs and outputs) identified in the previous section are resultant of discussions with specialists of the operational area, each of them dealing with the points described in section 1 as important features to be considered in identifying units with good performance. As for the choice of the initial model for our study, the CCR model was chosen, assuming constant returns of scale. This hypothesis will be tested and validated in Section 5 by application of the Wilcoxon-Mann-Whitney test. Unlike the BCC model, the CCR model leads to identical efficiency scores, independent of the orientation chosen (inputs or outputs). On the present study, the criterion adopted for the choice of the orientation input is that it is easier to conceive management action on those factors chosen as inputs.

The formulation of the CCR model with orientation to the minimization of inputs (CCR-I) solves, for each DMU, the problem of linear programming (PPL) presented in (1), in which it is assumed existence of *n* units (DMUs) to be evaluated, with *m* inputs and *s* outputs. For the analysis of the *oth DMU*, x_{ik} is the i*th* input for the k*th* unit, ν_i (i = 1, 2, …, *m*) the weight assigned to the i*th* input and u_j (j = 1, 2,…, *s*) the weight assigned to j*th* output.

Formulation (1) is known as the optimization model of multipliers and its dual as the envelopment model (2). In this second formulation, $\lambda\kappa$ denotes the contribution of the *kth* DMU in the formation of the target to be attained by the *oth* DMU o. In the models (1) and (2) the decision model ho represents the efficiency of the DMU o.

Primal (Multipliers Model) (1)

$$\text{Max } h_o = \sum_{j=1}^{s} u_j y_{jo}$$

subject to

$$\sum_{i=1}^{m} v_i x_{ik} = 1, \quad k = 1,...,n$$

$$\sum_{j=1}^{s} u_j y_{jk} - \sum_{i=1}^{m} v_i x_{ik} \le 0, \quad k = 1,...,n$$

$$u_j \text{ e } v_i \ge 0 \quad \forall\, j,i$$

Dual (Envelopment Model) (2)

$$
\begin{aligned}
&\text{Min } h_o \\
&\text{subject to} \\
&h_o x_{io} - \sum_{k=1}^{n} x_{ik}\lambda_k \geq 0, \quad i = 1,\ldots,m \\
&- y_{jo} + \sum_{k=1}^{n} x_{jk}\lambda_k \geq 0, \quad j = 1,\ldots s \\
&\lambda_k \geq 0, \quad \forall\, k
\end{aligned}
$$

4.2. Results of Application of the CCR-I Model

Tables 2 and 3 bring the results of application of the CCR-I model for the case in study. These results were obtained with the use of software SIAD (Angle et al., 2003). Table 2 shows the efficiency scores for the DMU under analysis and the references for the projection of the DMU inefficient on the efficiency border. Table 3 shows the improvements that the inefficient units must promote to reach the efficiency.

The efficiency scores presented in Table 2 for the inefficient units do not have to be used as a criterion to rank these units unless their benchmarks are the same. More appropriately, they point the degree of deficiency in relation to its corresponding reference. Thus, for example, DMU 7 is 94.94% efficient comparatively to its reference set (DMU 4, 5 and 17), while DMU 3 is 57.41% efficient in relation to the same references. This indicates that DMU 7 and DMU 10 can diminish its inputs without, diminishing their outputs. The efficiency score for an inefficient unit represents, in proportional terms, the maximum decrease that can uniformly be cut in all its inputs without causing reduction in output (Vassiloglou and Giokas, 1990).

Table 2: DEA Scores and Peer Groups

DMU	Efficiency (%)	Peer Group
DMU1	100,00	---

DMU17	100,00	---
DMU4 *	100,00	---
DMU5 *	100,00	---
DMU8	100,00	---
DMU9 *	100,00	---
DMU11 *	98,59	DMU5, DMU9
DMU12 *	97,00	DMU5, DMU9
DMU10 *	96,10	DMU4, DMU9
DMU7 *	94,94	DMU4, DMU5, DMU17
DMU18	93,72	DMU1, DMU4, DMU17
DMU13	87,98	DMU1, DMU4, DMU8, DMU17
DMU2	85,07	DMU1, DMU17
DMU19 *	77,73	DMU1,DMU4
DMU6 *	72,70	DMU5, DMU6, DMU17
DMU14 *	68,71	DMU1, DMU4, DMU17
DMU16 *	65,00	DMU1, DMU4
DMU3 *	57,41	DMU4, DMU5, DMU17
DMU15 *	56,05	DMU4, DMU5, DMU17

(*) Units with dispatch volumes below 50.000 m^3

Table 3: Potential Improvements for the Inefficient DMUs

DMU	**Potential Improvement (%)**			
	Inputs			
	TMC	**CAP**	**CVA**	**HEX**
DMU2	15	20	15	35
DMU3	75	43	43	51
DMU6	41	27	27	27
DMU7	49	4	4	17
DMU10	12	4	18	15
DMU11	43	1	4	23
DMU12	83	3	16	31
DMU13	27	13	13	13
DMU14	45	31	31	69
DMU15	57	44	44	69
DMU16	35	35	35	62
DMU18	9	6	6	23
DMU19	23	22	22	32

In our study, the analysis of results can identify several new opportunities for gain for the company (Table 3). Some units identified with poor use of their assets may become units with high potential for sales of warehouse services. Excessive concentration of movement in certain hours of the day can suggest changes in the loading schedule, through negotiation with customers, which will lead to a better level of service.

For example, while DMU14 is highly concentrated in its inefficiency HEX variable, indicating the need to a better management of problems related to overtime, for another side, to DMU03 a considerable deficiency in the variable TMC on the average time of loading (see Table 3), signals to the manager that there are problems in the loading courtyard. These reviews and course corrections must be a continuous process in the company, to increase their productivity.

Table 4 presents the weights obtained for the input oriented CCR multipliers model. These weights are unique for the inefficient DMUs and one of the best solutions for efficient DMUs, since for these the DEA linear program has multiple optimal solutions. These results were also obtained using the software SIAD. Some analysis can be made of inefficient DMUs. For instance, the variable TMC received a zero weight in 12 of the inefficient DMU (in a total of 13). This shows that these DMU have low performance on this variable and this is evidence that managerial actions must be taken to investigate the causes of low performance. The behavior was similar to the variable HEX (11 weights zero). Additionally, the DMU 10, 11 and 12 gave the total weight of the inputs to the variable CAP and almost total weight of the outputs for PRE, which shows that these DMU underprivileged other variables to calculate the efficiency index.

A correct interpretation of the results obtained using DEA requires a full discussion of the information in Tables 2, 3 and 4 with experts who have information of existing routines in terminals and databases, as well as representatives of the commercial area to ensure that possible management actions will not affect the level of customer service.

These discussions help to understand the differences in the efficiency scores, because, in many instances, management is able to identify the causes of results by the DEA.

Table 4. Multipliers

DMU	Weights					
	TMC	CAP	CVA	HEX	VOL	PRE
DMU1	0,00000	0,00135	0,17623	0,82242	1,00000	0,00000
DMU2	0,00491	0,00000	0,99509	0,00000	1,00000	0,00000
DMU3	0,00000	0,00266	0,99734	0,00000	0,00005	0,99995
DMU4	0,00000	0,01831	0,98169	0,00000	0,00011	0,99989
DMU5	0,00000	1,00000	0,00000	0,00000	1,00000	0,00000
DMU6	0,00000	0,00521	0,32577	0,66902	1,00000	0,00000
DMU7	0,00000	0,00266	0,99734	0,00000	0,00005	0,99995
DMU8	0,55450	0,44550	0,00000	0,00000	1,00000	0,00000
DMU9	0,56371	0,43629	0,00000	0,00000	0,00087	0,99913
DMU10	0,00000	1,00000	0,00000	0,00000	0,00002	0,99998
DMU11	0,00000	1,00000	0,00000	0,00000	0,00055	0,99945
DMU12	0,00000	1,00000	0,00000	0,00000	0,00055	0,99945
DMU13	0,00000	0,00121	0,15246	0,84633	0,00005	0,99995
DMU14	0,00000	0,00168	0,99832	0,00000	0,00004	0,99996
DMU15	0,00000	0,00266	0,99734	0,00000	0,00004	0,99996
DMU16	0,00000	0,00012	0,99988	0,00000	0,00000	1,00000
DMU17	0,03228	0,02515	0,94258	0,00000	1,00000	0,00000
DMU18	0,00000	0,00170	0,99830	0,00000	0,00004	0,99996
DMU19	0,00000	0,00012	0,99988	0,00000	0,00000	1,00000

5. Evaluation of influence of size of Terminal on relative efficiency

Tables 2, 3 and 4 show the relative performance, the benchmarks and the potential improvements to the units under study, assuming that they operate similarly. An important question to be investigated and that often appears in the context of DEA is the identification of possible differences in performance due to belonging to particular categories or groups of DMU. Even when the DMUs exhibit a high degree of homogeneity, one can find groups with certain characteristics that affect the performance of the group as a whole. The ability to differentiate managerial inefficiencies of inefficiencies resulting from exogenous and operational characteristics is an important point when you wish to evaluate management. For instance, in Table 2, many units reporting total load with less than 50,000 m3 (marked with *) show an inferior performance.

As noted in column VOL of Table 1, considerable differences exist in the dimensions among the operational units. They may be classified into two groups: large and small operational units. Thus, it is interesting to statistically test whether the efficiencies found are influenced by the size of the facility (scale of operation). If such influence is positive, a gain in efficiency can be related to variable returns to scale. The result of such a test validates whether or not CCR model should have been used, as this model assumes absence of gain of efficiency due to scale.

Due to the nonparametric feature of DEA, no probability distribution can be attributed to the vector of efficiency scores found. A non-parametric statistical test, like the Wilcoxon-Mann-Whitney, is suitable to this context. This test provides a basis for deciding whether two samples belong to the same population. It is based on the sum of positions of observed values arranged in ascending order (Cooper et al., 2000, Hettmansperger and McKean, 1998). Formally, the test is described below.

Consider the two samples *A* and *B*, where $A = \{a_1, a_2, ..., a_m\}$ e $B = \{b_1, b_2, ..., b_n\}$, ordered increasingly in a unique sample $C = \{y_{(1)}, y_{(2)}, ..., y_{(m+n)}\}$. The test statistics W is a function of the sum *P* of the ranks of the *y* that represent elements of A. W is a random variable defined in terms of *P* by

$$W = mn + \frac{m(m+1)}{2} - P \qquad (3)$$

If the hypothesis *Ho* of equal populations (the two samples are from the same population) is true, then to *m* e *n* above 8, *W has*, for practical purposes, a normal distribution with mean and variance given respectively by

$$E(W) = \frac{mn}{2} \qquad (4)$$

$$Var(W) = \frac{mn(m+n+1)}{12} \qquad (5)$$

This may be rephrased as in Cooper et alii (2000) by saying that T, given by

$$T = \frac{W - \frac{mn}{2}}{\sqrt{\frac{mn(m+n+1)}{12}}} \qquad (6)$$

has an asymptotically Normal distribution of zero mean and variance 1 (N (0, 1)).

In our case, the category *A* is formed by the establishments with less than 50,000 m3 of shipped volumes. The sum of the positions of the elements of *A* in the ranking of efficiencies (Table 2), has a value *P* = 142, with *m* = 13 e *n* = 6. Applying equations (3), (4) and (5) we find the values given in (7), (8) and (9).

$$W = 13.6 + \frac{13(13+1)}{2} - 142 = 27 \qquad (7)$$

$$E(W) = \frac{13.6}{2} = 39 \qquad (8) \qquad\qquad Var(W) = \frac{13.6(13+6+1)}{12} = 130 \qquad (9)$$

Consequently, the value for T given by equation (6) is $T = -0{,}09$. This value is employed to test the null hypothesis, of both groups belonging to the same population. At the significance level of 5%, the hypothesis is accepted if $T \le T_{\alpha/2}$ or $T \ge -T_{\alpha/2}$, where $T_{\alpha/2}$ is the 1-$\alpha/2$ percentile of the normal standard distribution.

For α = 0,05, $T_{0,025}$ = 1,96. Since $-1{,}96 \le T \le 1{,}96$, the hypothesis that the two categories belong to the same population is accepted. From this analysis we infer that the scale does not interfere in the efficiency of DMU and thus the CCR model of constant returns to scale, appears as the most appropriate

6. Conclusion

This article presents a variant of constant returns to scale DEA methodology to evaluate the performance of terminals for oil products. Initially a list of factors relevant to a routine evaluation of such establishments is raised. Theses factors influence the quality of service provided to the customers or serve as parameters to assess productivity.

The DEA methodology, aimed to assess efficiency of organizations where traditional techniques fail or can not be applied due to theoretical restrictions, reveals its usefulness in this case. For each unit identified as inefficient, it is diagnosed where potential improvements can be achieved by increasing output and a reference set to be used as benchmark is determined. Thus, for example, looking at Table 3 we see that DMU14 has its inefficiency highly concentrated in the variable HEX, indicating possibilities of managerial actions in negotiations with customers to decrease overtime expenditures.

An important complementary feature of the analysis developed is the use of the statistical test of Wilcoxon-MannWhitney. It allowed concluding by the absence of statistically significant difference in the operation of units operating on a large scale against those smaller, indicating that the CCR model is appropriate.

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