AN OPTIMIZATION APPROACH TO CHANGE MANAGEMENT IN ACADEMIC LIBRARIES WITH AN EMPIRICAL APPLICATION IN RIO DE JANEIRO, BRAZIL

Abstract.

This paper presents an optimization approach to change management in short and long run from an efficiency standpoint. The empirical illustration uses data from a sample of academic libraries pertaining to a federal university, but there will be no loss of generality if other kinds of information centers are considered. Firstly our three steps approach employs optimal scores computed from the estimation of selected Data Envelopment Analysis models to rank libraries and secondly to provide optimal allocative corrections; in the third step long run evaluation is accomplished by Markovian analysis. Even though independently developed from Wang and Huang (2007), our model can be seen as a simple extension thereof.

Keywords – Academic libraries. Long run performance. Efficiency analysis. DEA. Markov Chain.

INTRODUCTION

The prominent imperative for change management is to help organizations to improve performance over time. In other words, the change management imperative is building performance into the future. As a counterexample, however, in the recent past GM ignored established alerts - despite its well known planning bureaucracy - and continued to sell gasoline guzzlers to customers then unaware that prices could soar to levels such as in 2008. Although market prices may sometimes be determined by multiple causes shot up by multiple factors, change evaluation in the long run is required much more often and must be practiced much more comprehensively so that strategic foresight be effective in due time. In addition to strategize continuously and execute rapidly, organizations should be capable of monitoring future results in advance as an important step in change management. Contrary to current terms, how should it be possible to monitor future change?

In this paper we present an optimization approach to change management from an Efficiency Analysis standpoint. Our model has been developed independently from the Markov Chain approach by Wang and Huang (2007) but can be seen as a simple extension thereof. Even though the empirical illustration employs data from a sample of Decision Making Units (DMUs) pertaining to a public organization, there is no loss of generality if and when other kind of organizations are considered. Our approach combines in a simple way efficiency scores computed from the estimation of selected Data Envelopment Analysis (DEA) models and a long run evaluation provided by Markovian analysis.

The text is organized in five sections that include this introduction. The second section brings together some background ideas and results that helped found the paper. In the next section the methodological procedure is explained, followed by empirical findings in the fourth section. Conclusions, limitations and pending issues are presented to close the text.

BACKGROUND

The proposed approach relies essentially on the application of the so-called Efficiency Principle to assess organizational performance. Following the literature, “organization” may be taken quite broadly as meaning both public and private entities, and even nonprofit ones among the latter (Nunamaker, 1985; Fox, 2001; Vakkuri, 2003; Smith and Street, 2005; Afonso, Schuknecht and Tanzi, 2006,).

Data Envelopment Analysis (DEA)

The Efficiency Principle simply states that, when studying the production process in any organization, whenever a production unit uses the same resources but yields greater quantities of output than another unit, it should be considered “relatively more efficient” (i. e., relative to one another), no matter how formally the productivity problem is analyzed. Analogously it should be considered “relatively more efficient” if it uses fewer resources and yields the same output. From an analytical standpoint these properties correspond to evaluating an organizational unit in terms of its position *vis à vis* an adequately defined and computed “efficiency frontier”, that is, the *locus* of all “equally best productive combinations of inputs and outputs”. Once identified the frontier, the performance of a specific organization may be evaluated by assessing the relative position of its component units relatively to each other and to the frontier.

Although it may seem restrictive to anyone aiming at “comprehensively tackling” the complexities of organizational assessment, no doubt the Efficiency Principle states an idea that very few would agree to dispose of. In addition there is an established body of knowledge - Data Envelopment Analysis (DEA), a class of mathematical programming models – with a now long tradition (Emrouznejad, Parker and Tavares, 2008) of being applied to a broad range of situations involving the analysis of production frontiers in a multi-unit, multi-input and multi-output framework in such a way that usual parametric restrictions are absent. The so called nonparametric models of frontier adjustment, such as DEA, represent the efficiency frontier as the best observed practices, that is, as the maximum output obtained from an input bundle when considering all the empirically observed organizational units in the population studied.

Despite being applied under varied forms, DEA is always used to assess the efficiency of productive units (Decision Making Units - DMUs) employing multiple inputs to obtain multiple products (DE NEGRI, 2003). In applied work DEA has been used to evaluate several types of public organizations, such as industrial plants, bank branches, education systems, hospitals and military units or systems, all properly understood as types of "complex organizations”. This flexibility stems from the fact that a DEA model does not request the predefinition of a functional form for the production function, as it is the case in econometric regression approaches, also long employed in the case of public libraries (for instance, VITALIANO, 1997).

Among the characteristics of interest of the DEA model that are relevant for the assessment of public organizations - subject to operate under the restriction of a budget *a priori* limited – mention must be made of the possibility to include in the analysis several inputs and outputs estimated by different units of measurement. It is also worth mentioning that the direct use of any empirically available inputs and outputs eliminates the need to define or redefine either resource or performance "indicators" of any type such as can be frequently found in the literature.

Efficiency Analysis in the long run

In a seminal methodological paper Tulkens and Vanden Eeckaut (1995) describe and explain the main issues relating to the role of time in nonparametric efficiency analysis, especially in what concerns alternative ways to accommodate empirical information into reference production sets that will be submitted to efficiency computations. Although they do not explicitly mention the long run, their presentation suffices to establish a neat picture on each possible approach to panel data efficiency analysis.

Of particular interest here (see Table 1) is their classification (*Ibid*., p. 478-480) of the variety whereby the time dimension present in panels may be treated when investigating observed productive activity:

(a) the contemporaneous reference sets refer to the situation where each observed production set corresponding to each time period is considered; the number of such sets is then equal to the number of dates;

(b) the sequential reference set is obtained when all observations are sequentially taken to form it simultaneously from first to each future date in turn; note then that successive sequential reference subsets are nested;

(c) the intertemporal reference set is the last member of the previous class, meaning it includes all the observations made throughout the whole observation period; and

(d) window analysis (Klopp, 1985), a special case of (b), refers to any sequence of observed adjacent but non nested subsets and are called locally intertemporal by Tulkens and Vanden Eeckaut (1995, p. 481). According to them, even though window analysis may seem analogous to a sort of "averaging" over the time periods, the size of the window – and correspondingly that part of the past it leaves aside – doesn't seem to have more than *ad hoc* justification.

Since efficiency is generally based on a sample of bundles of inputs and outputs, when a given time period is considered it can be argued that, no matter how interesting their approaches, even recent authors have mostly treated the issue of dynamic adjustment as restricted to the observed time lag – as if they were in fact "opening that black box" of bundles (NEMOTO and GOTO, 2003; EMROUZNEJAD and THANASSOULIS, 2005; de MATEO, COELLI and O'DONNELL, 2006; ELLERO, FUNARI and MORETTI, 2008; TONE and TSUTSUI, 2008).

In contrast, Semenick Alam and Sickles (2000), Ahn, Good and Sickles (2000), and Wang and Huang (2007) are interested in directly tackling the long run into (in)efficiency analysis. The first two papers do this essentially by econometric techniques apt to specify a lag structure for the estimation of models of panel data in such a way that (long run) equilibrium may be discussed with appropriate techniques related to solving difference equations (e. g. cointegration analysis in nonparametric applications; see also the pioneering Sengupta, 1992).

The paper by Wang and Huang (2007) introduces two new models to examine long run efficiency analysis:

(a) a dynamic panel data model with a lagged dependent variable that happens to be endogenous with respect to both errors and the intercept in the equation to be estimated – so that conventional estimators are not enough and are conveniently replaced (p. 1306); this model allows to estimate the size of dynamic adjustment costs; and

(b) a two-state Markov Chain model leading to the estimation, for each DMU, of its efficiency status as specified in their equation (2.12) (p. 1307).

According to the authors "the Markov model is mainly designed to uncover a potential link between financial indicators and the flow between states" (p. 1307) and provides "valuable information (…) which renders opportunities to regulators and managers reallocating scarce supervisory resources" (*ibid.*). Specifically the Wang-Huang Markov model allows discussing long run evolution of the efficient status in two ways:

(i) first, for each DMU, in terms of equilibrium values of efficient status by dealing with the corresponding difference equation (2.12) (p. 1307);

(ii) second, for the set of DMUs, in aggregate (or "structural", see Sengupta, 1997) terms by considering the difference equation in (2.5) (p. 1306).

However they do not further pursue these ideas and do not compute any long run solution in any of those cases. In addition, although they have modeled and specified the probability of one-step temporal transition from efficient (resp. inefficient) to inefficient (resp. efficient) state, there seems to be no indications as to how those probabilities might be used to compute long run "structural" distributions of the DMUs among the two states ("efficient" or "inefficient").

Using results from finite ergodic Markov chains (Kemeny and Snell, 1982, p. 130-131), and assuming one (estimated) aggregate transition matrix is available, it is possible to compute the long run distribution of the "system" (the set of DMUs) between the two states. This is the purpose of this paper.

METHOD

Our proposed assessment procedure consists of three steps. The first two steps – involving the computation of efficiency scores and of operational plans in turn – are typically performed in the application of Data Envelopment Analysis to empirical data on DMU performance. The third, the novel one, incorporates the "structural" long run assessment of efficiency.

Data collection

We focus on Brazilian data collected from an integrated system of academic libraries pertaining to a traditional federal university in Rio de Janeiro. The empirical application will help illustrate the scope and flavor of the proposed approach. Time periods refer to 2000 – 2007. The case is summarized in Table 1 and follows the Tulkens and Vanden Eeckaut (1995) framework.

[PLEASE INSERT TABLE 1 AROUND HERE]

Our example is supported by a convenience sample of 37 library units, corresponding to some 90% of total population, that were selected for ease of access and overall data availability. Despite its particular location, as well as historical and size aspects implied, the federal university may be considered convenient for the empirical study. Data were collected from the libraries' centralized MIS and relate to three inputs (*number of employees*, *physical area* and *number of volumes*) and four outputs (*number of visits*, *of loans*, *of registers* and *of consultations*).

Efficiency Analysis

The efficiency of productive units has been calculated by means of a deterministic production frontier, whose construction process is implemented with the support of the formulation and solution of a linear programming problem. This procedure, known as Data Envelopment Analysis (DEA), was initially introduced in the literature by Charnes, Cooper and Rhodes (1978, 1981) and later modified by Banker, Charnes and Cooper (1984). The most important difference between those two models is the possibility of treatment of scale economies. The Banker, Charnes and Cooper model (BCC model), used in this study, allows to calculate a deterministic production frontier with variable scale yields. In addition, given the *a priori* restricted nature of public budgets, the output-oriented version was adopted. In this version the optimization problem to be solved is an output maximization problem such as

$$\text{Max}_{\mu,v}\ (\mu' y_i / v' x_i), \text{ subject to :}$$
$$\mu' y_i / v' xi = 1,$$
$$\mu' y_j / v' x_j \leq 0,\ j=1, 2, \ldots, N,$$
$$\mu, v \geq 0. \qquad (3.1)$$

The solution of the appropriate linear programming problem provides numerical scores for each DMU that characterize them with respect to efficiency status. For each inefficient DMU an operation plan is also provided that indicates (re)allocative targets for the DMU to reach efficiency. Finally scores will also be needed to compute the transitions between the two states along the time period for the whole set of DMUs.

Markovian Analysis

As soon as a transition matrix is available, first passage time and long run analysis are possible and will result from the computation of a fixed point for the transition matrix (Kemeny and Snell, p. 130-131). This fixed point is a probability vector containing the distribution of the "system" between the two states in the long run.

To get a transition matrix from empirical data about the temporal behavior of a "system" of states it suffices to use the *transition count* (Anderson and Goodman, 1957; Billingsley, 1961; Wang and Huang, 2007, p. 1306) corresponding to the proportion of units in a given state and then count the transition between each pair of states in the period.

In the present application there are six transition matrices (one for each pair out of seven years) and some combination must be defined. Since we do not follow the statistical approach applied by Wang and Huang (2007), some form of combination must be chosen and we use the following basic result (Kemeny and Snell, 1980, p.131): when the number of time steps grows indefinitely one has

$$\lim (1/n)(P + P^2 + \ldots + P^n) = [1 \ 1 \ 1 \quad 1]'\pi \qquad (3.2),$$

where n is the number of steps; $P^n = ((\, p_{ij}{}^{(n)}\,))$ is the nth power matrix, whose (i ; j) element represents the probability of transition from state i to state j after n steps; [1 1 ;…1]' is a column vector with all elements equal to 1, and π is a constant vector containing the long run equilibrium distribution between states whose components are nonnegative and sum to 1 (as any probability vector). Note that the matrix product in the right hand side of (3.2) is a square matrix of the same order as P and with all lines equal to π. The expression "long run equilibrium" is then adequate since π does not depend neither on time, nor on the initial state.

The first application of Markovian Analysis is performed by using the so-called fundamental matrix (Kemeny *et al.*, p. 405) associated to the combined transition matrix (e. g., the "finite mean" in the left hand side of (3.2)) and to its equilibrium vector to compute mean first passage time and mean recurrence time (*Ibid*., p. 411-414) for any state of the system. A possible link between the mean first passage time (from a given state to another, for example, "inefficient to efficient") and efficiency analysis stems from the fact that the time before the (mean) first passage into efficiency may suggest how urgent may be the changes indicated in the "operations plans" provided by efficiency analysis (corresponding to the second step in the proposed procedure). Analogously, the time before the first passage into inefficiency might signal to how alert managers must remain even when their initial (or present) position may be comfortable.

The second application of Markovian Analysis is also related to the "finite mean" in the left hand side of (3.2) since it provides a way to estimate a single matrix from the seven available and then to compute the long run equilibrium of the system that corresponds to such "averaging matrix". In this application the long run equilibrium may be interpreted as the (percent) distribution of units between states, since system transitions between states are defined as counts of units' transitions.

RESULTS

In this section findings are presented relating to the selected academic libraries. Comments follow the order of proposed steps – computed efficiency scores, operation plans and long run distribution.

First step – efficiency scores are computed and DMUs may be ranked accordingly

A sample profile for the 37 DMUs is given in Table 2 for the last year of the period of study. The basic results for any DEA analysis – namely, computed efficiency scores – appear in Table 3.

[PLEASE INSERT TABLE 2 AROUND HERE]

[PLEASE INSERT TABLE 3 AROUND HERE]

Since every efficient DMU has a score equal to 1, the 8 DMUs in that situation along 2000-2007 have been removed from Table 5, since by the very definition of efficiency there is no way to improve their productive performance. These DMUs present a quite robust performance and deserve attention no matter how “benchmark” is understood. Relatively inefficient DMUs receive a score less than 1. Note that some inefficient DMUs never visited the efficient frontier and are even far away of it; in that sense they also deserve managerial attention. Note also the case of unit number 5 – it has been efficient along the whole period except for one year. Why is that so? Should this situation be ascribed to measurement error or does it mean a real although negligible loss in performance? In terms of management action all these signals must likely be accompanied by an individual follow-up.

Second step: operation plans indicate optimal changes for each library along time

Operation plans are always produced as a typical result from a DEA solution and in this example they appear in a consolidated form in Table 4. In every individual matrix (not exhibited here) showing the allocative change for each (inefficient) library and each year, there are indications of resource decrease and output increase; this information is summarized in that table and deserves managerial attention. The same occurs as long as volume discards are concerned: they deserve special attention because collections may not be altered, as well as some individual titles (such as current textbooks or books of historical interest) should not be disposed of.

In any case, since there is evidence that inputs may be reduced alongside with output being increased, managers must keep alert and proactive as to take advantage from potential efficiency gains along time. Allocative changes such as those indicated in Table 4 (and much more so in individual worksheets) may also serve to compare recommended paths against observed actions in a yearly basis for each DMU and to that extent help evaluate individual performance.

Third step: first passages, mean recurrence and long run change

Again, efficiency scores from Table 3 provide data to compute, for the whole system of libraries, the transition matrix between two states - "efficient" and "inefficient". Given that we are working with contemporaneous reference sets (see Table 1), data for 2000-2007 allow to obtain seven one-year transition matrices, say P_1, P_2, … , P_6, P_7 . In order to apply the finite sum approach, we employ successive products of yearly transition matrices, instead of powers of the same (initial or otherwise chosen) transition matrix. Note that since the sum and product of two transition matrices is of the same nature, the interpretation of the final sum of products makes full sense. Therefore we can take the seven factor average matrix A defined as

$$A = [P1 + P1P2 + P1P2P3 + ... + P1P2P3\ldots P6P7] / 7$$

as a good candidate to be used when solving the fixed point problem, since it incorporates more information than each individual matrix, in addition to being a good picture of the successive one-step, two-step until seven-step transitions, in the spirit of equation (3.2).

Since there are only two states, it is very simple to compute the fundamental matrix. Therefore, according to Kemeny *et al.* (1959, p. 411), the mean first passage time from "inefficiency" to "efficiency" is approximately equal to 2 years and 4 months. This means that if a given unit is inefficient today and if no managerial action is taken, then on average it will take 28 months for the unit to become efficient. This delay may be compared to the time required for any improving measures to receive both adequate budget and implementation.

To obtain the (estimated) long run distribution of the system between the two states the fixed point equation $\pi A = \pi$ is solved to give:

$$\pi_E \text{ (percent efficient) } = 49{,}52\%; \; \pi_{NE} \text{ (percent inefficient) } = 50{,}48\% .$$

Note that these figures slightly differ from the mean (48,65%, equal to the median) of percents in the last line of Table 3. In this sense it can be argued that long run analysis seems to be of a different nature *vis-à-vis* the arithmetics of numerical individual scores. Remember that products of transition matrices bring into play all the transitory visits to the two states along time.

The fixed point π for the equation $\pi A = \pi$ also provides directly the mean recurrence time (Kemeny *et al.* 1959, p. 413) for the states of the system, that is, the mean time required before the system returns to a given state having started in that same state. The mean recurrence time is approximately equal to 2 years in both cases, so that the period of two years seems to be critical in the sense of monitoring the return of a state to itself. In the case of inefficiency it represents a sort of “safe mean time span” for managers to try to change the operating conditions facing inefficient units, Since the operation plans already point to “optimal changes” by unit, managers may evaluate for which units those changes would be feasible within (the next) two years. Note that on average an inefficient will return to inefficiency four months before it may reach efficiency for the first time, if no managerial action is taken.

SUMMARY AND CONCLUSION

Upon assuming the Efficiency Principle as a guideline to organizational evaluation, this paper presented a model for strategy assessment in the long run by combining two approaches – the DEA approach to efficiency analysis and the Markovian assumption that introduces a long run perspective.

We proceed in three steps. The first step is typical of DEA-based efficiency analysis since one or more DEA models (Estellita Lins and Angulo-Meza, 2000) are estimated to provide efficiency scores allowing to rank (Marinho, 2001) the sampled DMUs according to their relative efficiency. The second step is also typical in DEA applications and consists in identifying "optimal" quantitative (re)allocations that would signal to managers how they might, if wanted, lead inefficient DMUs toward the efficient frontier. These quantities might equally help to evaluate allocative gaps between optimal prescriptions and observed allocations. The third step introduces a very simple long run perspective. We assume that any DMU can be in either of two aggregate states – "efficient" or inefficient" – and that the set of DMUs is accordingly classified in either state according to the proportion of DMUs in each state. The Markovian assumption (Kemeny and Snell, 1972) of constant transition probabilities between states will then allow establishing a long run equilibrium distribution between states.

Findings have shown that the three step model uncovers quantitative aspects that may be of assistance to managers committed to efficiency in the short and long runs.

In the first two steps, typical DEA models provide both rankings and operation plans that not only help evaluate performance but also help inefficient productive units in their quest for efficiency.

In the third step we rely on Markov Chains for long run assessment. We first compute an aggregate measure of the distribution of the productive system (the "organization") between two states – efficient or inefficient. To the extent that individual DMUs are assigned to a "state" according to their performance and that transitions refer precisely to those states, our approach is aggregate in the sense that only systemic information remains; levels of efficiency scores relating to specific DMUs are in that sense voluntarily lost (WANG and HUANG, 2007, p. 1306). The other useful application of the Markovian approach provides better knowledge concerning the time delay required for efficency to be attained for the first time when a prescribed operation plan happens to be adopted, as well as about the time during which an undesired (inefficient) situation will persist if that adoption is postponed.

Future research - based on alternative ways of using scores to define “states” and on alternative ways of obtaining a transition matrix to start the process - is likely to provide better theoretical as well as empirical information that will allow for a better assessment of the proposed model. Some alternatives might be a simply “statistical” treatment (e. g., “above the mean” as in Wang and Huang, 2007, p. 1307) of what “good state” means or else the use of fuzzy concepts to help define that same idea of “good performance”.

Two remaining though important issues refer to (a) how to compute transitions when longer time series of scores are available and (b) how to deal with errors in measuring efficiency scores. Despite the fact that the first issue has been “solved” here with the hint of a mathematical result, a rigorous answer will surely need the help of econometric modeling, exactly the same way that seems necessary to explore and understand the effects of (statistical) errors. Both issues have been acknowledged throughout the text but still deserve further attention.

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Table 1 – Summary on case study

Case (DMUs)	Number of DMUs	Number of variables	Time Period	DEA condition satisfied *	TVE classification**	DEA model
University libraries	37	7	2000 -2007	Yes	Contemporaneous	BCC-O

Notes: -*: number of DMUs not less than two (three) times the number of variables.
-**: classification of (sample) observed subsets by Tulkens-Vanden Eeckaut (1995, p. 479-480).

Table 2 – Sample profile for university libraries in 2007

Variables	Min	Max	Mean	Standard deviation	Coefficient of Variation
Number Employees	1	33	8,41	8,06	95,83%
Total area (m2)	37	6000	865,16	1400,03	161,82%
Volumes	872	277134	35228,92	53343,38	151,42%
Visits	108	137385	20974,68	33970,98	161,96%
Registrations	0	5603	1043,38	1115,40	106,90%
Loans	0	30191	5116,03	6578,68	128,59%
Consultations	0	66638	8091,62	12228,71	151,13%
Service mix (number)	5	13	9,54	1,87	20%

Table 4 – Average operation plans : 2000 - 2007

Inputs	2000	2001	2002	2003	2004	2005	2006	2007
Employees (number)	- 1,44	- 1,15	- 0,76	- 1,29	- 0,93	- 1,18	- 0,61	- 0,81
Area (m2)	- 60,75	- 71,04 *	- 29,85	- 70,35	- 48,94	- 143,47	- 88,05	- 136,27
Volumes (number)	- 3064,48	- 3373,49	- 1880,71	- 4601,0	- 6447,08	- 651,77	- 4720,75	- 3153,65

Note * - this figure relates to a single library.

Table 3 – Efficiency scores* and yearly averages : 2000 – 2007

DMU	ESCORES _2000	SCORES 2001	SCORES 2002	SCORES 2003	SCORES 2004	SCORES 2005	SCORES 2006	SCORES 2007
1	1,000	0,841	1,000	1,000	0,605	0,811	0,680	1,000
2	0,571	1,000	1,000	1,000	0,965	0,943	1,000	1,000
3	0,305	0,936	0,845	0,661	0,542	0,846	0,775	0,574
4	0,989	0,960	0,769	0,783	0,829	1,000	1,000	1,000
5	1,000	1,000	1,000	1,000	1,000	0,947	1,000	1,000
6	1,000	0,696	0,742	0,494	0,584	0,757	0,548	0,650
7	1,000	0,731	0,870	0,452	0,353	0,127	0,466	0,624
8	0,941	1,000	0,471	0,559	0,782	0,650	0,626	1,000
10	0,620	0,895	0,712	0,974	0,619	0,740	1,000	0,679
11	0,528	0,660	1,000	0,779	0,727	1,000	0,847	0,646
12	0,404	0,590	0,287	1,000	1,000	1,000	1,000	1,000
17	1,000	1,000	0,627	1,000	1,000	1,000	0,336	0,370
18	0,604	0,815	0,696	1,000	1,000	1,000	0,807	1,000
19	1,000	1,000	1,000	1,000	1,000	0,959	1,000	0,921
20	0,600	1,000	0,867	0,779	0,743	0,498	0,543	0,560
21	0,401	0,302	0,396	0,109	0,138	0,371	0,145	0,115
22	1,000	1,000	0,507	0,654	0,337	1,000	0,842	0,121
24	0,391	0,501	0,492	0,387	0,395	0,931	0,319	0,320
25	0,733	0,690	0,840	0,329	0,307	0,482	0,640	0,506
26	0,838	1,000	0,467	0,683	0,236	0,562	0,384	0,863
27	0,334	0,412	0,410	0,407	0,358	0,223	0,496	0,241
28	0,892	0,574	1,000	1,000	1,000	1,000	1,000	0,945
30	1,000	0,442	1,000	0,555	0,972	1,000	1,000	0,820
31	0,071	0,064	0,055	0,143	0,185	0,020	0,010	0,017
32	0,450	0,781	0,928	0,873	0,870	1,000	1,000	1,000
34	0,562	1,000	1,000	1,000	1,000	1,000	1,000	1,000
35	1,000	0,793	1,000	0,665	0,757	0,354	1,000	1,000
36	0,107	0,202	0,196	0,172	0,113	0,353	0,401	0,381
37	0,359	1,000	1,000	1,000	0,892	1,000	1,000	1,000
Mean (n=37)	0,7486	0,8077	0,7886	0,7691	0,7381	0,7993	0,7801	0,7663
Percent efficient	45,96%	48,65%	48,65%	48,65%	40,54%	51,35%	54,05%	51,35%

Note. * - All DMUs with scores equal to 1 for the whole period have been excluded.