USING DEA TECHNIQUE FOR ESTIMATING THE MANAGERIAL EFFICIENCY, IN THE REENGINEERING PROCESS, VRS VERSUS CRS CASE

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Abstract
This paper will consider DEA technique, comparing VRS and CRS. Significant results will be obtained, which can be used within the reengineering process. A number of pharmaceutical companies in Romania have been assumed at national level but also at the level of 6 zones/geographic regions, namely the region of Moldova, the Muntenia region, the Oltenia region, the Banat region, the Ardeal region and the city of Bucharest, being pharmaceutical companies on the territory of Romania's historical regions. Efficiency scores at the managers level are determined for each group of decision-making units for each region, with the complete set consisting of all 120 decision units of the sample. Applying the separate VRS model for each of the six subsets, the DMU management scores in each group were calculated. Thus, it has been deduced that the effect of the managerial reengineering process has been a successful one, also providing precious information for improving the future managerial activity

Keywords:
CRS model, Data Envelopment Analysis, Efficiency, VRS model

JEL Classification:
C61, C67, I15

Introduction

Productivity analysis is an important tool in decision-making and managerial control activities, providing valuable insights into corporate reengineering, but also to assess the use of inputs in the process of achieving the desired results.

In this context, *DEA* analysis is a nonparametric technique based on linear efficiency measurement matrices, using mathematical programming techniques, being an important management and decision-making tool at the firm level and also a good benchmark in the application of reengineering at the corporate level. This technique has been widely used with the research of (Charnes et al., 1978) and (Cooper et al., 2004), using the *DEA* method as an assessment technique.

Although the *DEA* models require accurate data, there are a few situations where inputs and outputs are uncertain in terms of the volatility and complexity of the data provided by the

analyzed reality, so a precise measurement is quite difficult. As a result, it will be required to address the *DEA* technique in circumstances of uncertain inputs and outputs.
The *DEA* technique is based on two basic model categories: *CRS*-based models (Charnes et al., 1978) and models based on *VRS*-variable return (Banker et al., 1984), this latter case associating the two possible situations, namely: increasing, respectively decreasing scale.
A *DMU* decision unit uses at least 2 types of input units to obtain an output unit. The *CRS* model, which assumes that *DMU*s operating at constant scale yields are effective, corresponds to an effective linear frontier that originates as in (fig. no.1). There are, however, many other situations for which the output will not be linear proportional to the input, which means that the optimum ratio between output and input, as the input increases, is not a constant one. In this case, the assumption that we have *CRS* should be relaxed, having in this case the assumption of *VRS* variable return, the effective frontier being in this case given by the set of points below the *CRS*, defined by the effective *DMU*s forming the border of technical efficiency.
The simple case of a discretionary input and output, as in (fig. no.1), is used to highlight four key concepts, namely: choosing representative inputs and outputs as a typology; the efficiency frontiers for *CRS* and *VRS*; *DEA* model concept oriented to input and output; how to choose the decision-maker set, *DMU*, to eliminate inefficient *DMUs*; and respectively the use of discretionary inputs.
In Fig. no.1, *A*, *B*, *C*, *D*, *E* and *F* represent the inputs and outputs for six *DMUs*.

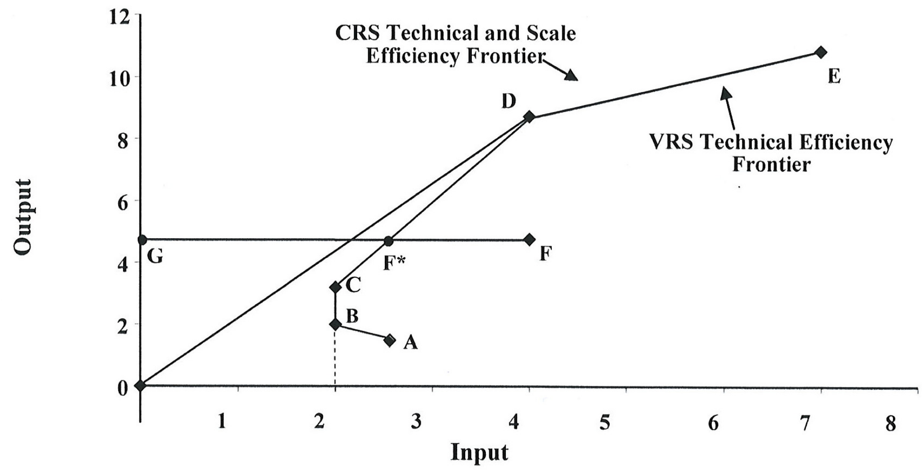

Fig. no. 1 Example of a DEA model
Source : Author's work

An input-oriented model aimes to produce the desired output in time, with the minimum of input quantities set. At the same time, in an input-oriented model, the goal is to produce over time the maximum outputs under the set conditions of input quantities.
As a result, in an input-oriented model, as assumed in (fig. no.1), the efficiency scores vary from zero to one, the 1-value being attributed to the efficient case. For a decision unit *k*, DMU_k, for $k = \overline{1,n}$, which at a given moment of time is inefficient, becomes efficient, in an input-oriented model, it is necessary to reduce input quantities while production remains constant. However, in (fig. no. 1), there is the exception that for the *B* decision unit, the

input is the same as for the *C* decision unit, namely two units. However, the output for the *C* decision unit, of three units, is greater than that of the *B* decision unit, which is two units. In this situation it is necessary that the *B* decision unit, without changing the input quantity, to increase the output quantity by one unit. Although the *B* decision unit has the optimum input level, it is not technically efficient. The same applies to any point on the dotted line that goes down to 2 in (fig. no.1).

As mentioned, the *VRS* effective border *DMU*s have efficiency scores equal to one. The technical efficiency score of the decision unit *F* is the ratio between the effective input quantity *F** and the effective input quantity given by *F*, which is: $\frac{GF^*}{GF} = \frac{2.8}{4.2} = 0.67$.

Therefore, taking into account the production scale of the F decision-making unit, if it would reduce the input quantity by 33%, it would be effective compared to other decision-making units.

Given that the decision unit F is technically inefficient, it is possible to identify which other decision-making units are effective in relation to it.

1. Stage of knowledge in the field

As a non-parametric method based on linear efficiency boundaries, using mathematical programming techniques, DEA (Mukherjee, 2008; Simar and Wilson,2000) allows the performance assessment of a set of decision making units (*DMU*) (Sun et al., 2013; Charnes et al., 1977), which assures a set of outputs using a set of inputs. The specificity of a decision-making unit (*DMU*) is that it manages the production process in the sense of making all inputs available and feasible from a technological point of view.

The developer of the *DEA* technique concept was (Farrell, 1957), who initiated the analysis from the fact that decision-makers (*DMU*s) can lead to a single type of output, using several types of inputs for this purpose, thus requiring evaluation performances of the analyzed system; this was followed by a variety of theoretical and applied research papers such as (Barra and Zotti, 2016; Woo et al., 2015; Wu et al., 2016; Tone, 2001).

The *DEA* technique can also be used to measure corporate efficiency, thus comparing the results to its level with other units, by converting a group of measurable inputs into a group of measurable outputs.

The underlying hypothesis, on which relies the measurement of effectiveness using the *DEA* technique, is the homogeneity of inputs and outputs, failure to realize this hypothesis would obviously affect the relevance of efficiency measurement across any set of *DMU*s.

Conceptualized and then developed by (Charnes et al., 1978), *DEA* technique was expanded and developed on a higher level by (Zhu and Lansink, 2010), using mathematical programming models, especially linear programming (Seiford and Thrall, 1990).

2. Used methodology-*DEA* enveloping techniques for estimating managerial efficiency in the reengineering process, *VRS* versus *CRS*

2.1. DEA model, VRS case

As a starting point, *n* decision making units will be considered (DMU_k , for $k = \overline{1,n}$), that are subject to assessment at a given moment, which, based on the consumption of different quantities of *m* inputs, each produce different quantities of *p* outputs, both inputs and outputs being assumed to be certainly known.

As a result, at the level of the *k* decision making unit, is consumed from the *i* input the r_{ik} > 0 quantity and it will be prduced the quantity y_{jk} > 0 from the *j* output.

Consequently, the linear programming problem associated with the *k* decision-making unit (DMU_k, for $k = \overline{1,n}$), has the following form:

$$\max_{\gamma_i, \lambda_j, \theta} \left\{ -\sum_{i=1}^{m} \gamma_i r_{ik} + \sum_{j=1}^{p} \lambda_j y_{jk} + \theta \right\}$$

$$-\sum_{i=1}^{m} \gamma_i r_{ik} + \sum_{j=1}^{p} \lambda_j y_{jk} + \theta \le 0 \text{, for } k = \overline{1,n} \qquad (1)$$

$$\gamma_i \ge 1 \text{, for } i = \overline{1,m}$$

$$\lambda_j \ge 1 \text{, for } j = \overline{1,p}$$

Coefficients of the mathematical programming problem (1) are: r_{ik} and y_{jk} (observed values for (DMU_k)) and the variables of the problem are: γ_i, λ_j and θ, also creating the achievable solution $(\gamma_i, \lambda_j, \theta)$.

2.2. DEA model, CRS case

Using the previous notations, the multipliers problem for the *k* decision making unit, (DMU_k, for $k = \overline{1,n}$), is written as follows:

$$\max_{\gamma_i, \lambda_j, \theta} \left\{ -\sum_{i=1}^{m} \gamma_i r_{ik} + \sum_{j=1}^{p} \lambda_j y_{jk} \right\}$$

$$-\sum_{i=1}^{m} \gamma_i r_{ik} + \sum_{j=1}^{p} \lambda_j y_{jk} \le 0 \text{, for } k = \overline{1,n} \qquad (2)$$

$$\gamma_i \ge 1 \text{, for } i = \overline{1,m}$$

$$\lambda_j \ge 1 \text{, for } j = \overline{1,p}$$

The optimal solution to the multiplier problem for the *k* decision unit, (DMU_k), is given by the γ^k vector (*m*- dimensional) and by the λ^k vector (p- dimensional).

For a constant yield scale enveloping surface, the k decision unit, (DMU_k, for $k = \overline{1,n}$), is effective if it is found on a hyperplane of the $-\gamma^k r + \lambda^k y = 0$ form, called supporting hyperplane, which defines a facet of the enveloping surface.

2.3. Managerial efficiency within the process of reengineering

In many management performance analysis situations, a subset of decision units can highlight discrepancies in the productivity level of the respective subset compared to the productivity level of decision units as a whole and which characterize an earlier situation, a situation that can be attributed either to technological disadvantages or due to organizational disadvantages compared to the previous situation.

This discrepancy can be measured by the managerial efficiency of the decision-making units (Cowie and Asenova, 1990). Noting with *TS* - the complete set of decision units DMU_k, for $k = \overline{1,n}$ and with *PS* - the subset of the less effective decision units, ie DMU_k, for certain specific values of *k*, with $k = \overline{1,n}$ (obtained by removing some points from *TS*), at

the corporate level (firm), decision makers can improve efficiency levels by improving technical efficiency, as rising yields on a scale can only be long-term achieved.
Fig. no. 2 shows the input-oriented efficiency frontier for the *VRS* models referring the two sets of data : *TS*, respectively *PS*. As a result, the *VRS-PS* border will be located most on the *VRS-TS* frontier, if not below it (in most cases), and the ratio of *HC* and *HG* distances for a decision unit DMU_k, for $k = \overline{1,n}$, represents the level of inefficiency attributed to the respective organizational structure (Cowie and Asenova, 1990).

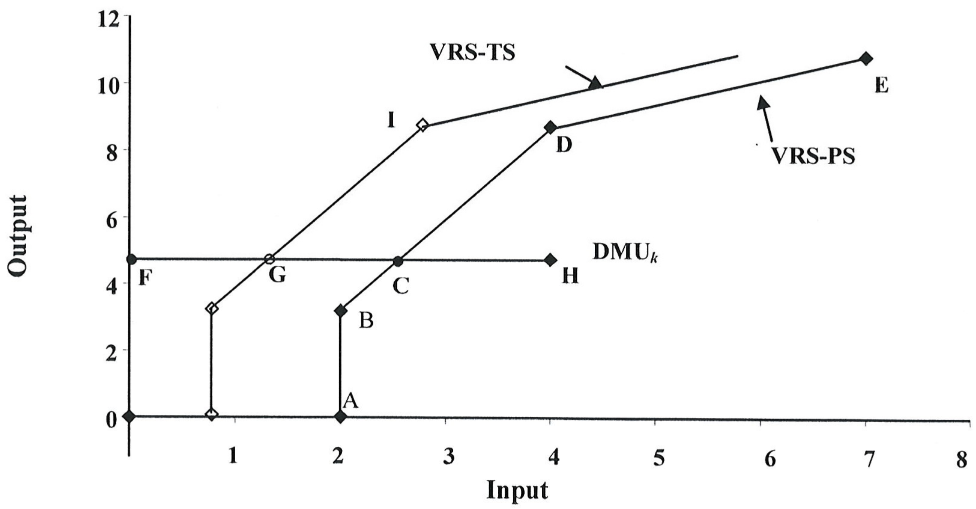

Fig.no 2. Estimating managerial efficiency within scale variable yields
Source : Author's work

In practice, the management efficiency of the decision units in the *PS* set is equal to the ratio of the technical efficiencies obtained with the *VRS* model, for the *TS* and *PS* sets, which means at the decision-making unit DMU_k we have:

$$\mu_k^{me} = \frac{\mu_k^{VRS-PS}}{\mu_k^{VRS-TS}}, \text{ for } k = \overline{1,n} \qquad (3)$$

The closer this ratio is to the 1 value, the higher of the subset of the PS units on the VRS-PS is more efficient from a managerial point of view, so the effect of the managerial reengineering process was successful.

3. Results and discussions-managerial efficiency analysis in the reengineering process

A total of 120 companies from the Romanian pharmaceutical industry were assumed at national level, which implies $k = \overline{1,120}$, so the *TS* set has 120 decision units, while there were created PS_k subsets at the level of each zone/ geographic region, thus $PS_{MO} = 21$ decision units at the level of Moldova region, $PS_{MU} = 25$ decision units at the level of Muntenia region, $PS_{OL} = 14$ decision units at the level of Oltenia region, $PS_{BA} = 12$ decision units at the level of Banat region, $PS_{AR} = 24$ decision units at the level of Ardeal region and $PS_B = 24$ decision units for the city of Bucharest, being pharmaceutical companies on the territory of Romania's historical zones/regions.

Efficiency scores at the managers level are determined for each group of decision-making units at regional level, with the complete *TS* set consisting of all 120 decision units of the sample. Applying the separate *VRS* model for each of the 6 subsets, the *DMU*'s managerial efficiency scores in each group are given by the relationship (3). The results are shown in table no. 1.

Table no.1 Managerial efficiency at the level of each region for the decision making units

	DMU_k	**Managerial Efficiency**		
		Minimum	Average	Maximum
Region MO	21	0.37	0.39	0.44
Region MU	25	0.44	0,51	0,57
Region OL	14	0.41	0.48	0.52
Region BA	12	0.52	0.57	0.62
Region AR	24	0.64	0.69	0.75
Region B	24	0.75	0.80	0.84
National	120	1	1	1

Source: Author's work

As a result, the *VRS-TS* and *VRS-PS* frontiers were drawn across the whole set and at the level of each historical zone/region of Romania, noting that in increasing order of the managerial efficiency, we have the regions Moldova, Oltenia, Muntenia, Banat, Ardeal and the city of Bucharest. This induces the fact that the reengineering process at the managerial level has been a successful one, while providing precious information regarding an improvement in the future managerial activity.

Each of the 6 regions, consisting of decision-making groups, must be treated separately when adopting modernization measures and comparative analysis (Post and Spronk, 1999; Novaes and Silveira, 2008). For example, some of the decision-making units in the Bucharest region show managerial performance closer to the unit, which means they can be projected at the efficient frontier in a benchmarking process. On the other hand, the companies in the region of Moldova, with the lowest efficiency scores, could be seen as having most of the issues to be remedied with regard to a future reengineering activity.

Conclusions

This work defined the efficiency at the level of the historical regions of Romania in terms of activity for a total of 120 companies in the Romanian pharmaceutical industry. Four components of efficiency, namely technical, scale efficiency, managerial efficiency and allocation efficiency, are highlighted, with emphasis being placed on managerial efficiency as a source of information for corporative/firm reengineering in the pharmaceutical field. At the same time, global productivity is defined at national level. In addition, the *DEA* technique as a measure of effectiveness in the pharmaceutical sector is presented through its basic models, which are the *DEA-VRS* model and the *DEA-CRS.*

The study on the efficacy of the Romanian pharmaceutical industry in the future can use the *DEA* to obtain the relative efficiency scores of the sample decision units. It can measure the technical efficiency of banks by assuming the uncertainty about the inputs and outputs that are part of the decision-maker elements.

Furthermore, the *DEA-VRS* model can be used to measure the efficiency score of each decision unit, using the same input and output variables, to investigate the causes of inefficiency. The purpose of this technique is to measure the source and level of inefficiency by decomposing the technical efficiency.

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