

A hybrid DEA model for the measurement of the environmental performance

A. Hadi-Vencheh and N. Shayesteh Moghadam

Abstract—Data envelopment analysis (DEA) has gained great popularity in environmental performance measurement because it can provide a synthetic standardized environmental performance index when pollutants are suitably incorporated into the traditional DEA framework. Since some of the environmental performance indicators cannot be controlled by companies managers, it is necessary to develop the model in a way that it could be applied when discretionary and/or non-discretionary factors were involved. In this paper, we present a semi-radial DEA approach to measuring environmental performance, which consists of non-discretionary factors. The model, then, has been applied on a real case.

Keywords—Environmental performance, Efficiency, Non-discretionary variables, Data envelopment analysis.

I. INTRODUCTION

EVALUATION and assessment of companies' environmental performance have been the subject of intense scrutiny during the last few years [10], [15], [19]. Companies must have knowledge about the environmental performance in order to formulate adequate environmental policies, plans, and programs for their activities. Companies must also make commitments at the highest managerial level if environmental policies are to thrive throughout development projects [7], [11]. Although several qualitative and quantitative models have so far been developed in the field of environmental performance assessment, there are no comprehensive methods to assess such performance. Indeed, there is not even a common agreement over the definition of "superior performance" [6]. The major shortcoming of the qualitative models is that they could only succeed in presenting qualitative techniques or checklists and calculating a figure called "total score" as a measure of performance level [18]. There are two major shortcomings dealing with the quantitative models, particularly those developed based on the Data Envelopment Analysis (DEA) models [15], [16], [20]. The first shortcoming concerns the application of radial models which do not determine the effects of all inefficiency sources on the efficiency scale of the company under assessment. In other words, such models only consider θ as the efficiency measure while some of the inefficiencies relate to the slack variables (s^- , s^+) that their values do not affect the decrease of θ . The second shortcoming is due to considering all inputs/outputs as discretionary or controllable factors. However, in most real cases, there are some factors that cannot be changed or controlled by managerial efforts.

Therefore, the main objective of the present study is to propose

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a valid and appropriate model to assess the environmental performance. Since the proposed model possesses strong mathematical concepts and has been designed based on a linear programming problem (DEA), it undoubtedly removes the shortcomings of the qualitative models.

Data envelopment analysis (DEA) is currently a popular technique for analysing technical efficiency and it has been used in a number of applications. Standard DEA assumes that the assessed units (DMUs) are homogeneous, i.e. they perform the same tasks with similar objectives, consume similar inputs and produce similar outputs, and operate in similar operational environments. Often the assumption of homogeneous environments is violated and factors that describe the differences in the environments need to be included in the analysis. These factors, and other factors outside the control of the DMUs, are frequently called non-discretionary factors.

Standard DEA models, originally presented by Charnes et al. [4] and Banker et al. [2], do not take into account non-discretionary inputs and outputs. Thus, non-discretionary factors need to be excluded or treated as normal discretionary factors, which may lead to a biased view of efficiency. A number of different approaches have been developed to overcome this weakness.

Banker and Morey [3] provided the first of these DEA models by including the non-discretionary variables in the model and defining efficiency relative to the discretionary inputs only (in the input-oriented version). Ruggiero [12] provided an alternative model by relaxing the convexity constraint with respect to the non-discretionary variables and used simulation analysis to highlight the advantages of his model over the Banker and Morey model. A weakness of Ruggiero's model was the tendency to identify decision-making units (DMUs) as efficient by default as the number of exogenous factors increased. Ruggiero [13] extended this model to allow multiple non-discretionary inputs. This model requires three stages and uses regression analysis to develop an aggregate index capturing the influence of the non-discretionary factors.

Muñiz [8] provided an alternative three-stage model to control for the effect that non-controllable inputs have on production. Like the first stage in [13], this model considers only discretionary inputs and output in the first stage. This model, however, focuses not only on the radial measure of efficiency but also the remaining slacks that remain after equi-proportionate projection to the overall frontier. Moreover, by using only DEA methods, it has the advantage that there is no need to assume any functional form in any of the stages.

An alternative model, the handicapped DEA model, introduced by Yang and Paradi [17], balances the natural environmental

differences for the DMUs under examination, hence, it yields a fair and equitable comparison for DMUs with different cultural backgrounds. This model requires the definition of handicapping function that can compensate for the different environments in which the DMUs operate. The handicapping factor applied to each DMU, calculated from the handicapping function, can be either deterministic or stochastic. Following Yang and Paradi [17] Muñiz et al. [9] only consider the deterministic handicapping function. This factor is used to adjust the inputs and (or) outputs of the DMUs in the group being handicapped. More specifically, the DMUs in a disadvantaged environment will be compensated by reducing their inputs (or increasing their outputs) and the DMUs in a better environment will be penalized by increasing their inputs (or decreasing their outputs) in order to reach a stage where they can be compared as if they were all from the same culture.

The purpose of this paper is to introducing a hybrid model for efficiency evaluation in the presence of non-discretionary factors in DEA. In the next section, we present our model. In the third section, a numerical example is given to evaluate the proposed model and the last section concludes.

II. MODEL

Data envelopment analysis (DEA) was introduced by Charnes, Cooper and Rhodes [4]. DEA measures the relative efficiency of peer decision making units (DMUs) that have multiple inputs and outputs, and has been applied in a wide range of environmental performance measurement [20]. Suppose we have a set of n DMUs, each of which consumes m inputs to produce s outputs. Let $X \in \mathbb{R}_+^{m \times n}$ and $Y \in \mathbb{R}_+^{s \times n}$ be matrices containing the observed input and output for n DMUs. We denote by x_j (the j th column of X) the vector of inputs consumed by DMU $_j$, and by x_{ij} the quantity of input i consumed by DMU $_j$. A similar notation is used for outputs. Further assume that the slack variables $s_i^-, i = 1, \dots, m$, and $s_r^+, r = 1, \dots, s$ indicate the input excess and output shortfall, respectively, and $\lambda_j, j = 1, \dots, n$, is a non-negative value. Following the concept of slacks-based measure (SBM) of efficiency in DEA developed by Tone [14], to estimate the efficiency of a DMU $_o, o = 1, \dots, n$, we formulate the following fractional program:

$$\begin{aligned} \min \quad & \gamma_{SBM} = \frac{1 - \frac{1}{m} \sum_{i=1}^m \frac{s_i^-}{x_{io}}}{1 + \frac{1}{s} \sum_{r=1}^s \frac{s_r^+}{y_{ro}}} \\ \text{s.t.} \quad & \sum_{j=1}^n x_{ij} \lambda_j + s_i^- = x_{io} \quad i = 1, \dots, m \\ & \sum_{j=1}^n y_{rj} \lambda_j - s_r^+ = y_{ro} \quad r = 1, \dots, s \\ & \lambda_j, s_i^-, s_r^+ \geq 0 \quad \forall j, \forall i, \forall r \end{aligned} \quad (1)$$

It can be easily verified that $0 < \gamma_{SBM}^* \leq 1$ and satisfies the properties of units invariance and monotone. A large value of γ_{SBM}^* indicates that DMU $_o$ performs better in the aspect of performance. If there are no input excesses and no output

shortfalls in any optimal solution, i.e., $s_i^- = s_r^+ = 0$, then $\gamma_{SBM}^* = 1$ and the evaluated DMU is regarded as efficient.

It should be noted that γ_{SBM} in (1) is constituted by the arithmetic average of SR (slack ratio) of each input. It implies that (1) assumes a uniform weight ($1/m$) to all input factors. However, their relative importance is not always uniform. In fact, it may be more common to assume non-uniform weight for input factors. Thus, this study focuses on the weighted average of SR and introduces a modified SBM model, namely, the weighted SBM (WSBM) model. This model directly incorporates the non-uniform weight to input factors in the objective function instead of the uniform weight ($1/m$) for SR. The WSBM model can be applied to any case wherein the weights for inputs or outputs are known or can be supplied exogenously. The WSBM model that takes into account the weights of both input and output can be defined as follows:

$$\begin{aligned} \min \quad & \gamma_{WSBM} = \frac{1 - \frac{1}{m} \sum_{i=1}^m w_i^- \frac{s_i^-}{x_{io}}}{1 + \frac{1}{s} \sum_{r=1}^s w_r^+ \frac{s_r^+}{y_{ro}}} \\ \text{s.t.} \quad & \sum_{j=1}^n x_{ij} \lambda_j + s_i^- = x_{io} \quad i = 1, \dots, m \\ & \sum_{j=1}^n y_{rj} \lambda_j - s_r^+ = y_{ro} \quad r = 1, \dots, s \\ & \lambda_j, s_i^-, s_r^+ \geq 0 \quad \forall j, \forall i, \forall r, \end{aligned} \quad (2)$$

where w_i^- and w_r^+ are, respectively, the weights for input i and output r of DMU $_o$ given exogenously, and satisfy the normalizations $\sum_{i=1}^m w_i^- = 1$ and $\sum_{r=1}^s w_r^+ = 1$.

Now we decompose the input matrix X into the discretionary part, $X^D \in \mathbb{R}_+^{m_1 \times n}$, and non-discretionary part, $X^{ND} \in \mathbb{R}_+^{m_2 \times n}$, with $m_1 + m_2 = m$. Analogously, we decompose the output matrix Y into the discretionary part, $Y^D \in \mathbb{R}_+^{s_1 \times n}$, and non-discretionary part, $Y^{ND} \in \mathbb{R}_+^{s_2 \times n}$, with $s_1 + s_2 = s$.

In order to estimate the efficiency of DMU $_o$, we formulate the following hybrid WSBM fractional program.

$$\begin{aligned} \min \quad & \rho_{HWSBM} = \frac{1 - \frac{m_2}{m} (1-\theta) - \frac{1}{m} \sum_{i=1}^{m_1} w_i^- \frac{s_i^{D-}}{x_{io}^D}}{1 + \frac{s_2}{s} (\phi-1) + \frac{1}{s} \sum_{r=1}^{s_1} w_r^+ \frac{s_r^{D+}}{y_{ro}^D}} \\ \text{s.t.} \quad & \theta x_o^D = X^D \lambda + s^{D-} \\ & x_o^{ND} = X^{ND} \lambda + s^{ND-} \\ & \phi y_o^D = Y^D \lambda - s^{D+} \\ & y_o^{ND} = Y^{ND} \lambda - s^{ND+} \\ & \theta \leq 1, \phi \geq 1, \end{aligned} \quad (3)$$

where are slack variables are non-negative. Obviously, $\theta = 1, \phi = 1, \lambda_o = 1, \lambda_j = 0$ (for all $j \neq o$), with all slacks being zero is a feasible solution for the model (3). Model (3) is a fractional programming problem that could lead to some calculation difficulties. One can transform it into an equivalent linear programming problem by using the theory of Charnes-Cooper transformation [5]. Let

$$\frac{1}{p} = 1 + \frac{s_2}{s}(\phi - 1) + \frac{1}{s} \sum_{r=1}^{s_1} w_r^+ \frac{s_r^{D+}}{y_{ro}^D} \quad (4)$$

In this way, model (3) is changed to the following model:

$$\begin{aligned} \min \quad & \sigma = p - \frac{m_2}{m}(p - p\theta) - \frac{1}{m} \sum_{i=1}^{m_1} w_i^- \frac{ps_i^{D-}}{x_{io}^D} \\ \text{s.t.} \quad & p + \frac{s_2}{s}(p\phi - p) + \frac{1}{s} \sum_{r=1}^{s_1} w_r^+ \frac{ps_r^{D+}}{y_{ro}^D} = 1 \\ & \theta x_o^D = X^D \lambda + s^{D-} \\ & x_o^{ND} = X^{ND} \lambda + s^{ND-} \\ & \phi y_o^D = Y^D \lambda - s^{D+} \\ & y_o^{ND} = Y^{ND} \lambda - s^{ND+} \\ & \theta \leq 1, \phi \geq 1. \end{aligned} \quad (5)$$

The problem given above is a nonlinear programming problem since it contains the nonlinear terms $p\theta$ and ps_i^{D-} in the objective function and $p\phi$ and ps_r^{D+} in the constraint. Denote $\Theta = p\theta$, $S_i^{D-} = ps_i^{D-}$, $\Phi = p\phi$, $S_r^{D+} = ps_r^{D+}$ and $\Lambda = p\lambda$. Then (5) becomes the following linear program in Θ , S_i^{D-} , Φ , S_r^{D+} and Λ :

$$\begin{aligned} \min \quad & \sigma = p - \frac{m_2}{m}(p - \Theta) - \frac{1}{m} \sum_{i=1}^{m_1} w_i^- \frac{S_i^{D-}}{x_{io}^D} \\ \text{s.t.} \quad & p + \frac{s_2}{s}(\Phi - p) + \frac{1}{s} \sum_{r=1}^{s_1} w_r^+ \frac{S_r^{D+}}{y_{ro}^D} = 1 \\ & \Theta x_o^D = X^D \Lambda + S^{D-} \\ & px_o^{ND} = X^{ND} \Lambda + S^{ND-} \\ & \Phi y_o^D = Y^D \Lambda - S^{D+} \\ & py_o^{ND} = Y^{ND} \Lambda - S^{ND+} \\ & \Theta \leq p, \Phi \geq p. \end{aligned} \quad (6)$$

By solving (6), we can easily obtain the efficiency of each DMU with consideration of the input excess and output shortfall.

A. Oriented hybrid models

The input (output)-oriented hybrid model can be defined by neglecting the denominator (numerator) of the objective function (3). Thus, the input-oriented hybrid model is as follows:

$$\begin{aligned} \min \quad & \rho_{HWSBM-I} = 1 - \frac{m_2}{m}(1 - \theta) - \frac{1}{m} \sum_{i=1}^{m_1} w_i^- \frac{s_i^{D-}}{x_{io}^D} \\ \text{s.t.} \quad & \theta x_o^D = X^D \lambda + s^{D-} \\ & x_o^{ND} \geq X^{ND} \lambda \\ & y_o^D \leq Y^D \lambda \\ & y_o^{ND} \leq Y^{ND} \lambda \\ & \theta \leq 1, \lambda \geq \mathbf{0}, s^{D-} \geq \mathbf{0}. \end{aligned} \quad (7)$$

In a similar vein, we define the output oriented hybrid by neglecting the input side efficiencies as follows:

$$\begin{aligned} \min \quad & \rho_{HWSBM-O} = \frac{1}{1 + \frac{s_2}{s}(\phi - 1) + \frac{1}{s} \sum_{r=1}^{s_1} w_r^+ \frac{s_r^{D+}}{y_{ro}^D}} \\ \text{s.t.} \quad & x_o^D \geq X^D \lambda \\ & x_o^{ND} \geq X^{ND} \lambda \\ & \phi y_o^D = Y^D \lambda - s^{D+} \\ & y_o^{ND} \leq Y^{ND} \lambda \\ & \phi \geq 1, \lambda \geq \mathbf{0}, s^{D+} \geq \mathbf{0}. \end{aligned} \quad (8)$$

III. CASE STUDY

The case study of this research comprised the International and Iranian oil and gas upstream general contractors, which provide the Iranian oil and gas industries with special technical and engineering services ranging from seismic and geological survey and drilling and exploration to oil and gas production. In the present investigation, all general contractors (12) were subjected to analysis. Since the aim of the present study was to assess the environmental performance, it was required to incorporate managerial indicators. To do this, the contractors were asked to submit such indicators. In order to separate indicators into inputs and outputs, the views of contractors' top managers were taken into account. Each indicator comprised a number of components helping in accurate measurement and auditing of the indicator. Inputs and outputs and their relevant components are expatiated in the following.

Inputs:

x_1 : This indicator shows the number of years that the company has been working in the field of oil and gas. It is clear that the company background affects its performance in all aspects (i.e., the more the number of years that a company has been working in special fields is, the more each outputs level and consequently the more the efficiency value are expected to be). So this indicator is considered as a factor entering the system. Moreover, since this input cannot be changed by the administrative part of the company, it is considered as a non-discretionary input.

x_2 : This indicator expresses the company's training programs. Top-down commitments to environmental protection principles are not met unless appropriate training courses help employees better perceive the significance of environmental issues. Holding periodical workshops, preparing books and pamphlets, and presenting educational films are the components of training programs respected as one of the most important subelements of HSE. Similar to the first input, it is expected that an increase in the quality and quantity of training programs raises each output's level and consequently the efficiency value. So this indicator is considered as a factor entering the system. Moreover, as this input relates to the company's previous activities, it is considered as a non-discretionary input.

Outputs:

y_1 : This indicator presents the company's awareness of environmental laws, regulations, and standards in the field of oil and gas. A company expecting a high environmental performance should thoroughly be aware of and comply

with the relevant laws and standards. This output consists of such components as awareness of international and regional environmental conventions and agreements, awareness of national and local environmental laws and regulations, and awareness of current national and local environmental standards in the field of oil and gas.

y_2 : This indicator shows the company’s achievements of identifying adverse environmental impacts arising from its activities. Detecting all sources of environmental pollutants including atmospheric emissions, aqueous waste streams, solid wastes, noise pollution, etc. is one of the preliminary stages for developing any preventive measures and mitigation methods. This may help the company identify major and persistent environmental impacts and allow it to timely and financially allocate its resources to reduce, control, and eliminate those impacts. The company’s attention towards performing “environmental impact assessment” and preparing “environmental impact statement” before starting any project are also considered in this output.

y_3 : This indicator aims at environmental risk reduction measures considered as a part of risk assessment, which is one of the most important elements of HSE. Having reports on the past environmental incidents, studying and analyzing the factors involved in environmental incidents, developing “emergency response plan” and required actions in case of environmental incidents, the level of success in preventing environmental incidents and in reducing pollutants in the environment are considered as the components of this output.

y_4 : This indicator points out the company’s success in reduction of projects’ costs and expenses. Cost reduction has been the subject of interest for companies seeking a high performance. Some components such as the company’s success in employing “pollution prevention” (P2) techniques (i.e., preventing pollution at the source), recycling and reusing wastes, and applying “clean energy” technologies to reduce the need for fossil fuels and to decrease environmental pollution may result in reduction of projects’ costs and expenses usually within a long time.

To gather data, a checklist including inputs and outputs and their relevant components was designed. Then, a professional audit group including environmental, HSE, and management experts teamed up to audit the environmental performance in each company and finally to measure and determine the score of each indicator through the checklist. Table 1 show the inputs and outputs for each company (DMU). As mentioned before, each indicator comprised a number of components helping in accurate measurement and auditing of the indicator. The average of components’ scores showed the final score of the related indicator. In Table 1, scores of x_2 and all outputs were accordingly calculated for all DMUs. In this research, the indicators were weighed according to the top managers’ views. The weight constraints inserted to the model is as follows: $w_1^+ = w_2^+ = w_3^+ = w_4^+ = 0.25$. Since, in this case study, all of the inputs are considered as non-discretionary factors, the correspondent constraints of discretionary inputs in model (3) do not exist hereafter. In other words, the combined (input- and output-oriented) model changes to the output-oriented model

(8). Subsequently, the objective function in model (8) changes to the following function:

$$\max \rho_{WSBM-O} = 1 + \frac{s_2}{s}(\phi - 1) + \frac{1}{s} \sum_{r=1}^{s_1} w_r^+ \frac{s_r^{D+}}{y_{ro}^D} \quad (9)$$

Moreover, the correspondent constraints of non-discretionary outputs in model (8) do not also exist hereafter because all outputs of the case study are supposed to be discretionary.

TABLE I MEASURES OF INPUTS AND OUTPUTS

DMU	1	2	3	4	5	6	7	8	9	10	11	12
x_1	20	20	20	2.5	20	20	2.5	2.5	8	20	13	20
x_2	10	8	10	7.6	5	8.6	10	1	4.6	1.8	6	8.3
y_1	9.3	9.6	9	10	7	9.3	10	10	7	7	8	10
y_2	9.4	9.8	9.2	10	7.4	9.4	9.8	5.8	4.2	6.3	6.4	9.8
y_3	9.8	9.8	9.2	10	9	9.8	9.8	10	9	4.1	3	9.2
y_4	9.6	8.3	9	6.6	7	8.3	10	6	4.6	3.3	5	8.6

A. Results

The efficiency scores obtained by applying our model are given in Table 2. This table shows optimal value of the slacks and the rank of each DMU, too. Though three of the companies (DMU₄, DMU₇ and DMU₈) are efficient it was required to differentiate and rank them in order to identify the “superior performance” or the “best-in-class” company. To do this, we used the AP model proposed by Andersen and Petersen [1] and the ranking results of 12 contractors are shown in the last column of Table 2. In the proposed model, each y_{ro} , $r = 1, 2, 3, 4$, can increase to $y_{ro} + s_r^+$ if its increase is possible among the other DMUs. For each y_{ro} , the optimal solution of s_r^+ would be $s_r^{+*} = 0$ or $s_r^{+*} > 0$. $s_r^{+*} = 0$ means that its correspondent output (y_{ro}), considering the inputs used and the other outputs produced by DMU_o, has gained the relative optimal value in comparison with the other DMUs and this implies that more production of this output is not expected. $s_r^{+*} > 0$ means that its correspondent output (y_{ro}), considering the inputs used and the other outputs produced by DMU_o, has been less produced and this implies that more production of this output is expected. In other words, y_{ro} should increase to $y_{ro} + s_r^{+*}$, hence the increase value of y_{ro} is s_r^{+*} . For example, consider DMU₁ and the fourth output which is “reduction of projects’ costs and expenses.” As shown in Table 2, $s_4^{+*} = 1.737$ for this output of DMU₁. In other words, DMU₁ has not efficiently met the expectation of reducing projects’ costs and expenses. As we said before the increase of y_{41} is 11.337. In this way, DMU₁ would become efficient in the fourth output. As we see from Table 2 the values of s_1^{+*} and s_3^{+*} are greater than s_2^{+*} and s_4^{+*} for each DMU (except efficient DMUs). Due to this point, some contractors’ managers have not paid more attention towards outputs 1 and 3, i.e., such contractors have not efficiently met the expectations of these two outputs. Therefore, it is suggested that managers of other companies and contractors, working in the same field as the case study contractors, take account of outputs 1 and 3 and provide appropriate grounds to achieve their expectations at the primary stages of decision making. Finally, it is inferred from Table 2 that DMU₈ and DMU₁₁ achieved the highest and the weakest environmental performance, respectively.

TABLE II OBTAINED RESULTS FOR THE CASE STUDY

DMU	s_1^{+*}	s_2^{+*}	s_3^{+*}	s_4^{+*}	$\rho_{HWSBM-O}^*$	Rank
1	3.407	3.026	3.350	1.737	2.208	4
2	9.915	8.760	9.887	5.591	4.598	9
3	10.000	8.870	9.965	5.618	4.782	11
4	0.000	0.000	0.000	0.000	1.000	3
5	6.056	5.295	5.774	3.239	3.683	8
6	3.420	3.020	3.368	1.848	2.649	6
7	0.000	0.000	0.000	0.000	1.000	2
8	0.000	0.000	0.000	0.000	1.000	1
9	3.521	3.256	3.910	2.143	3.459	7
10	1.549	1.394	1.957	1.056	2.239	5
11	6.197	5.700	6.898	3.470	5.657	12
12	9.859	8.764	9.970	5.568	4.609	10

IV. CONCLUSION

Application of standard DEA models to analyze production technologies characterized by non-discretionary inputs is problematic. Early applications treated the non-discretionary inputs as discretionary, leading to improper frontier comparisons. The main objective of this paper was to develop a valid model possessing strong mathematical concepts for the environmental performance assessment. The proposed model, which removes the major shortcomings of the qualitative and quantitative models developed in this area, was designed on the basis of a mathematical method known as DEA. To sum up, the model is well defined since (1) its result is the optimal value of a linear programming problem and can easily be computed and interpreted, (2) it determines the specific criterion, bounded by 0 and 1, for measuring the relative efficiency and environmental performance of each company, (3) it determines the inefficiency sources and their values of inefficient companies, thus easily enabling companies to identify their weak points and root causes of inefficiency, (4) it can be applied when discretionary and/or non-discretionary factors are involved, and (5) it may help decision makers and authorities to accurately assess, rank, and compare contractors based on their environmental performance and choose the high-performing company.

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