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Efficiency Measurement by the Grey DEA Approach

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ABSTRACT

Nowadays, in competitive environment, a fundamental factor that helps governmental and non-governmental organizations to achieve their goals is attention to efficiency and its continuous improvement, which is only possible through continuous Efficiency Evaluation. Data Envelopment Analysis (DEA) is a suitable method for Efficiency Evaluation in organizations. But one limitation of this method is that, totality of DMUs must be at least triple that of the total number of inputs and outputs, and in practice lack of attention to this point, causes a large number of units to be inappropriately placed on the efficient frontier. The units evaluated in this paper were oil refineries of I.R. Iran active in the years 2000-2005. In this paper, using Grey clustering, indices were divided into several categories and from each category an index was selected as representative of it. Grey clustering reduced the number of indicators so that DEA could evaluate an amount for efficiency of DMUs.

KEYWORDS: Efficiency, Performance Evaluation, Data Envelopment Analysis, Grey Clustering, Absolute Degree of Grey Incidence.

1. INTRODUCTION

One of the most important subjects in management is efficiency and effectiveness and in other words productivity and efforts to increase productivity present the biggest challenge to managers. In this regard and in order to measure efficiency, Data Envelopment Analysis was founded in 1978 and is currently as one of the most acceptable methods, not only to determine efficiency of an organization (decision making units), but also to help managers to recognize their organization in a more scientific and accurate way. During the past two decades, many articles have been published, reports written and various applications of this technique made in prestigious journals worldwide that give credence to the capability of this technique [11].

Improving the performance of an organization is the most important responsibility of many managers. Possible inspections and detailed analysis of DMUs to understand the production process and extract useful information are necessary in order to improve on their efficiency. Efficiency is the ability to produce the outputs or services with a minimum resource level required, that is, to do the job right. Fortunately, DEA provides feasible simple methods for managers and economists in order to high performance in their firms and organizations [6].Efficiency can be framed as both market efficiency and operating efficiency. Market efficiency is largely referred as information efficiency, and it is measured by the amount and speed with which information is incorporated into prices. Operating efficiency denotes whether a firm is cost minimizing (consuming less inputs for the same level of outputs) or profit maximizing (producing more outputs for the same amount of inputs) based on published accounting numbers [14].

One of the limitations of the DEA method is that, the totality of DMUs must beat least triple than the total number of inputs and outputs, and in practice lack of attention to this point causes a large number of units to be placed on the efficient frontier making their efficiency score be one.

When there is not required differentiation between the units under consideration then some of them may be placed on the efficient frontier, usually there are several methods that can be used in such cases, two of which are the Anderson - Patterson's method and the Cross-efficiency ranking method. However, this paper has used Grey clustering to divide indices into several categories and from each category; an index was selected as representative of it. Therefore, this technique reduced the number of indicators and made it more likely for DEA to differentiate between the various units under consideration.

Improving the performance of an organization is the most important responsibility of many managers. Therefore, Investigating Iran's oil refineries', as one of the most important industries in the country, efficiency is so important. This paper used Grey clustering, indices were divided into several Categories and from each category, and an index was select as representative of it. Grey Clustering reduced the number of indicators so that DEA could evaluate the efficiency of DMUs. Units evaluated in this paper were oil refineries of I.R. Iran that were active in 2000-2005that are Abadan oil refinery, Arak oil refinery, Isfahan oil refinery, Bandar-e-Abbas oil

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refinery, Tabriz oil refinery, Tehran oil refinery, Shiraz oil refinery, Kermanshah oil refinery and Lavan oil refinery. This paper is organized into six sections. In Section 2, we review some of the previous studies that relate to this paper. In Section 3, we clearly demonstrate how the indexes are chosen and describe the theoretical background of the study. In section 4, we describe the methodology of the study. In section 5, we are going to show the results of the study, and finally in section 6, we express the conclusion of the study.

2. LITERATURE REVIEW

The DEA model was first introduced in the late 1980s and since then it has been used for many studies that demonstrate the capability of this technique for efficiency evaluation, so it can be said this method has capability and credibility to evaluate the efficiency of units. During the past two decades, many articles and reports have been published in prestigious journals demonstrating various applications of this technique Presented below are some of the most recent articles in this field.

Bevilacqua and braglia (2002) described a new model for evaluating the (relative) environmental efficiency of the seven Agip Petroli oil refineries set up in Italy during a 4-year period (1993–96). In particular, environmental impact has been considered in terms of air emissions. The Data Enveloped Analysis technique proposed an objective benchmark. This multi-criteria technique made it possible to evaluate relative environmental efficiency considering six different types of emissions such as CO, CO2 and SO2and an annual quantity of oil processed.

Kulshreshtha and Parikh (2002) studied efficiency and productivity of coal mining in the Indian coal sector using detailed input and output data for underground and opencast coal mining for the period between 1985 and 1997. The non-parametric approach to data envelopment analysis (DEA) was adopted for performance analysis of different coal mining regions. Total factor productivity growth was analyzed using the Malmquist index by decomposing productivity change into efficiency and technical change. Results of the analysis did not conform to the prevailing notion of opencast (OC) mining demonstrating more productivity growth than underground mining in India. It was concluded that underground mines adopted more efficient operating practice to compensate for the lag in technical change. However, operational efficiency of opencast mines seems to have been overlooked in the process of increasing production through technological improvement in OC mining.

Asmild et al (2007) presented a framework where Data Envelopment Analysis (DEA) measured overall efficiency and showed how to apply this framework to assess effectiveness for more general behavioral goals.

Mohammadi (2007) extended the traditional ratio analysis to permit the incorporation of any number of dimensions of performance, using data envelopment analysis. That method produces measures of corporate efficiency together with a wealth of supporting information. This study was conducted on 27 pharmacy companies in a period 2 years (2003-2004).

Li et al (2009) investigated the relationship between allocated costs and a DEA efficiency score and developed a DEA-based approach to allocate fixed cost among various DMUs. An example of allocating advertising expenditure between a car manufacturer and its dealers was presented a demonstration of the method proposed in this paper.

Staub et al (2010) investigated cost, technical, and allocation efficiencies for Brazilian banks in the recent period of 2000–2007. They used Data Envelopment Analysis (DEA) to compute efficiency scores. It was concluded that state-owned banks were significantly more cost efficient than foreign, private domestic and private with foreign participation and they found no evidence of differences in economic efficiency due to type of activity and bank size.

Shi et al (2010) considered Chinese industrial energy efficiency evaluation and investigated the maximum energy-saving potential in 28 administrative regions in China by DEA. Results showed that industries in the eastern area had the best average energy efficiency for the period 2000–2006, followed by the central area. Furthermore, after comparing the industrial energy overall efficiency, pure technical efficiency (IEPTE) and scale efficiency of the 28 administrative regions examined, results showed that in most regions the two main reasons contributing to large amounts of wasted energy during industrial production processes were that the industrial structure of most regions still relied on massive use of energy in order to support the industrial-based economy and the IEPTE was too low. Based on these findings, this paper correspondingly proposes some policies to improve regional industrial energy efficiency.

Jahanshahloo et al (2011) proposed an interval previous DEA model that was formulated to obtain an efficiency interval consisting of evaluations from both optimistic and pessimistic viewpoints. The purpose expressed in that paper was to rank DMUs by ideal points (the points obtained by that method were called ideal points) for each DMU. Finally, researchers extend the proposed ranking model to interval data.

Sueyoshi and Goto (2011) discussed a new DEA approach to measure the unified (operational and environmental) efficiency of energy firms. The proposed approach incorporated not only output separation but also the input separation within a computational framework of DEA non-radial measurement. In this study, the proposed approach compares with other previous DEA approaches used for performance evaluation of energy firms. After methodological comparison, researchers applied the proposed approach to measure the unified efficiency of Japanese fossil fuel power generation.

Hanrui and Xun (2011) expressed Bootstrap as a statistical technique based on sampling with repetition on empirical data and relative estimators, which improved the precision of critical value and confidence interval, and overcame the inherent dependence on DEA results. The paper presented the DEA method based on bootstrap, to improve the reliability of DEA results.

Rasoulian et al (2012) have used DEA method and Malmquist index for ranking social security organization branches in Tehran. In this paper, the types of performance (technical efficiency, managerial effectiveness and efficiency of scale), and the returns to scale in each branch (output rising, falling, or stable) is ranked each of the branches.

Meibodi et al (2012) have been studied 40 power plants of Iran functioning between 2003 and 2007. Based on the results gathered through (DEA) method, and by utilizing Windeap software, the average eco-efficiency of these power plants was measured such results are indicated that the eco-efficiency of power plants of Iran within the specified period has declined.

3. Theoretical Background

In this research, all oil refineries of I.R.Iran were investigated that were active in 2000-2005. Data were gathered from the document centers of each oil refinery.

To gather data related to oil refineries, firstly some indicators were identified for efficiency evaluation. For effective efficiency evaluation by DEA, a researcher must choose suitable inputs and outputs. For this purpose, main factors were collected; they were identified as those that were the most important, by using available resources. Those resources were:

1. Development interviews

Two important early steps in setting indices or generally determining contents in a research are developmental interviews with people that have the necessary information this involves interviewing senior managers and influential people. This purpose was fulfilled by interviewing knowledgeable and up to date people from two groups:

i- Experts associated with universities, who had valuable information about these cases and had studied evaluating and efficiency before.

ii- Experts associated with the oil refining industry, who had valuable information about oil refining, quality and types of main products.

2. An organization's previous research

An organization's previous research could be a valuable resource for setting indexes.

3. Published benchmarks and indicators

This study used indicators of the oil ministry, presented for showing status of specific oil refineries and types of product.

4. Theories and scientific findings

Scientific and theoretical findings were used as a guideline to determine indicators, and in doing so they elevated the quality of the research. Some other research with a similar background as this research was also studied, and was used to confirm and determine some indicators.

Finally, using all the above-mentioned facilitators, nine indicators were identified which as representatives for other indicators and that could have a decisive role in calculating performances of oil refineries. These nine indicators consisted of two sections. The first section included three indicators, called inputs and the second section included six remaining indicators called outputs.

I-Inputs

Included raw and primary materials considered as inputs in refineries and in the process of producing. These inputs puts were as follows:

1. Food

Food consisted of petroleum and other materials that enter oil refineries for producing refinery products and outputs. Here, food is the amount of petroleum, liquefied gas and other additives that enter a refinery. The unit of measurement for food is cubic meter/day in all parts of this study.

2. Personnel

Personnel or human power included human labor (the people who work in refineries). In this study, same numbers of workers were considered for the purpose of research. The unit of measurement for personnel is each person/day in all parts of this study.

3. Energy

In this study energy is an average amount of energy consumption from sources such as fuel, water, electricity and compressed air that enter a refinery to produce oil products and to refine oil. The unit of measurement for energy consumption is million BTU/day in all parts of this study.

II. Outputs

Outputs consisted of products and materials made from inputs. The unit of measurement for all outputs are cubic meter /day. These products are as follows:

4. LPG
5. Gasoline
6. Kerosene
7. Gas oil
8. Fuel oil
9. Other products

3.1. DATA ENVELOPMENT ANALYSIS

DEA is a mathematical planning model that experimentally estimates production function or efficiency frontier for observed data, based on optimization using linear programming. This method is called DEA because it envelops all data. In addition to measuring performance, productivity growth can be calculated for every single firm using the Malmquist index whereby productivity changes can be divided into changes resulting from technology and changes resulting from performance. In addition, there is no need to determine type of function for estimating performance and efficiency [11].

In evaluating a determinant unit that used the DEA model, the main idea is this: when there are numbers of unit for evaluating, a virtual unit, which is a combination of other units, will produced, so that the input of a virtual unit will be the same as inputs of desired units. Then DEA will determine performance of a unit by considering outputs and it will declare inefficiency of units with fewer outputs. This kind of evaluation hasbecome known as input oriented evaluating. The purpose of input oriented evaluating is to maximize outputs. If outputs of a virtual unit are going to check with a unit's output then it will be an output-oriented evaluation. In other words, the purpose of output oriented evaluating is to minimize inputs [3].

There is another way to estimate efficiency of a unit, and that estimates efficiency only if a production function exists. However, the problem is that most of the time, it is impossible to obtain a production function. One of the strong points of the DEA model is its capability to estimate efficiency without a production function.

All input oriented and output oriented modes, BCC, CCR, and general models have one primal model and one secondary model or a dual model. Performance value of the primal model and the secondary model are equal and they are identical. The dual model could be considered as an alternative model for the primal model and is only available as a structure for facilitating the calculation. Solving secondary model problems using linear programming means there are fewer constraints for solving the problem than the first and as such needs fewer calculations than the first way[3].An additive DEA model (also known as a slack-based model) was used in this study to evaluate performance. This model placed optimizing inputs and outputs on the agenda simultaneously.

The additive model forms models itself; a primary form and a secondary form. The primary form is an envelope and the secondary form is multiple. The additive model (Which is also called slack-based model) was introduced by Charnes, Cooper, Golany, Seiford and Stutz in 1985. The general form of the primary issue is based on additive model as shown below[10].

$$Min\, Z_0 = -\sum_{r=1}^{s} S_r^+ - \sum_{i=1}^{m} S_i^-$$

St :

$$\sum_{j=1}^{n} \lambda_j y_{rj} - S_r^+ = y_{r0} \qquad (r = 1,2, \dots, s)$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} + S_i^- = x_{i0} \qquad (i = 1,2, \dots, m)$$

$$\sum \lambda_j = 1 \qquad (j = 1,2, \dots, n)$$

$$\lambda_j, S_r^+, S_i^- \geq 0$$

In addition, the general form of the secondary issue is as shown below.

$$Max\ y_0 = \sum_{r=1}^{s} y_{r0} u_r - \sum_{i=1}^{m} x_{i0} v_i + w$$

St :

$$\sum_{r=1}^{s} y_{rj} u_r - \sum_{i=1}^{m} x_{ij} v_i + w \leq 0 \qquad (j = 1,2,\ldots,n)$$

$$\sum_{r=1}^{s} u_r \geq 1 \qquad (r = 1,2,\ldots,s)$$

$$\sum_{i=1}^{m} v_i \geq 1 \qquad (i = 1,2,\ldots,m)$$

$$u_r, v_i \geq \varepsilon \quad , \quad w \text{free sign}$$

In an industry, if producers are capable of producing certain amounts of different products using minimum amounts of inputs, or producing maximum amount of products using certain amounts of inputs, other producers will also be efficient, if they function in the same way as these producers. In a DEA pattern, one efficient firm or several combined efficient firms are introduced to a deficient firm as a template or reference set. These combined firms (DMU) (combination of two or more firms)are known as a virtual efficient branch, because they will not necessarily actually exist in an industry [3].In the Primal and Dual aspects of a DEA Additive model, each DMU will be effective when the Objective Function Value is zero.

3.2. Grey Clustering

Grey clustering is a pattern that is based on matrices of grey incidence or whitenization weight function of a grey number and it is used for categorizing views or allocating views to pre-defined categories[9].Observations can be categorized using grey clustering. It can be done in two ways, one way is to use a cluster of grey incidences, and the other is to use a cluster of whitenization weight function of grey classes.

In order to simplify complex systems, a cluster of grey incidencesis used for putting similar factors in the same group. For this kind of categorizing, researchers must check factors for whether or not they have approximation to any other factors. In this case, a factor could be used as a representative of a category. However, a factor must be chosen in a way that it will not damage the information.

Cluster of whitenization weight function of grey classes is mostly used for finding out if a view belongs to a pre-defined category or not[9].Matrices of grey incidence have been used for categorizing indicators in this study. Absolute degree of grey relation (ε_{ij}) is used for doing this, this amount is obtained from a pair comparison, and using all done comparisons, an upper triangular matrix (A) will form, which is called an incidence matrix of characteristics.

An amount $\boldsymbol{r}$, is used for categorizing $\boldsymbol{r \in [0,1]}$ and $\boldsymbol{r > 0.5}$ and when $\boldsymbol{\varepsilon_{ij} \geq r}$ and $\boldsymbol{i \neq j}$ shows that $\boldsymbol{X_i}$ and $\boldsymbol{X_j}$ have some features that make them mostly behave like each other. $\boldsymbol{r}$is usually determined by the needs of a study and as $\boldsymbol{r}$is closer to one, more categories will be produced, and the number of indicators, which are placed on them will be fewer and vice versa.

For making the best use of this categorizing technique, this study has attempted to duplicate this categorizing; one time on the input indicators and another time on output indicators. The purpose of this study was to show the power of grey clustering in categorizing and also in reducing numbers of input and output indicators, so according to oil refining units, a DEA model would be able to calculate an amount of target function for all refineries.

There are five steps for categorizing input and output indicators[9].

First step: calculating zero starting point images for series.

The first number of each series is subtracted from the numbers of each series. It means that by using equation (1), if X_0 shows primary raw series, zero starting point ($x^{(0)}(k)$) could be calculated for under review indicators. It should be noted that if the purpose is categorizing input indicators, this step must have been performing on all of the input indicators (It is the same for output indicators).

$$x^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n))$$
$$x_i^0(k) = x^{(0)}(k) - x^{(0)}(1) \text{Equation (1)}$$
$$x_i^0 = (0, x_i^0(2), x_i^0(3), \ldots, x_i^0(n))$$

Second step: finding $|s_i|$ for each series.

For finding $|S_i|$ for each series using calculated zero as a starting point, relation equation 2 use:

$$|s_i| = \left|\left(\sum_{k=2}^{n-1} x_i^0(k)\right) + \frac{1}{2}x_i^0(n)\right| \text{ Equation (2)}$$

Third step: Finding |Si-Sj| for each pair of comparison.

In the third step, each series compares with other series as paired. Equation number 3 uses pair comparison between series:

$$|s_i - s_j| = \left|\left(\sum_{k=2}^{n-1} x_i^0(k) - x_j^0(k)\right) + \frac{1}{2}\left(x_i^0(n) - x_j^0(n)\right)\right| \text{ Equation (3)}$$

Fourth step: Calculating absolute degree of grey relation.

Relation number 4 uses calculating absolute degree of grey relation:

$$\varepsilon_{ij} = \frac{1 + |s_i| + |s_j|}{1 + |s_i| + |s_j| + |s_i - s_j|} \text{ Equation (4)}$$

Outcome resulted from this equation, presented in a top triangular matrix for indicators that were the targets of categorizing.

Fifth step: Determining r for categorizing.

In this step by considering the study requirements, r must be defined in a way that categorizes according to specified targets, and if $\boldsymbol{\varepsilon_{ij} \geq r}$, it could be said that these two indicators have almost similar features; therefore their corresponding indicators could be placed in a category.

4. METHODOLOGY

This research was based on an analytical - mathematics method. In the first part of this study, oil refineries' efficiency was evaluate by a DEA additive model without using Grey Clustering. And in the second part, the efficiency of oil refineries was evaluated by a DEA additive model with Grey Clustering. Grey Clustering was used to reduce the number of indexes (inputs and outputs) and then used the DEA additive model for efficiency evaluation. Efficiency evaluation in this paper used DEA Frontier Analyst software and Microsoft office Excel was used for calculation of Grey Clustering.

The study population consisted all of the oil refineries of Iranactive in 2000-2005. The following 9 oil refineries in Iran active in that range were Abadan oil refinery, Arak oil refinery, Isfahan oil refinery, Bandar-e-Abbas oil refinery, Tabriz oil refinery, Tehran oil refinery, Shiraz oil refinery, Kermanshah oil refinery and Lavan oil refinery.

5. RESULTS

The first part of this study (oil refineries efficiency evaluated bythe DEA additive model and without Grey Clustering), data of various indicators were entered the DEA additive model and efficiency was calculated by DEA Frontier Analyst software. Software outlet was obtained by entering information into the DEA additive model as shown in table (1). In this part due to the number of DMUs being equal to the total number of inputs and outputs, so it didn't matter which form of the DEA additive model was used (primal or dual)because numbers of constraints in both forms were the same.

Table1. DEA Results without Grey Clustering

	Y_0								
	Abadan	*Arak*	*Isfahan*	*Bandar-e-Abbas*	*Tabriz*	*Tehran*	*Shiraz*	*Kermanshah*	*Lavan*
Objective F. Value	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
Efficiency Status	*Efficient*	*Efficient*	*Efficient*	*Efficient*	*Efficient*	*Efficient*	*Efficient*	*Efficient*	*Efficient*

As table(1) shows, efficiency number obtained for all refineries (from all 9 refineries in DEA additive models), all of the refineries are on the efficient frontier, and therefore necessary separation and differentiation between refineries' performance didn't evaluate their performances.

Charnes, Cooper and Rhodes in creation of the DEA model, found an empirical relationship between number of units to be evaluated and numbers of inputs and outputs in a model. That empirical relationship is as follows[10]:

Number of units, which are being, evaluated (DMU)>3*(number of inputs+number of outputs)

Non-use of the above relationship placed most of the refining units on the efficient frontier. In other words, they got a-performance. Therefore, power of differentiation model is reduced[10]. In the first part, due to the low number of DMUs, all DMUs were placed on the efficient frontier. So in the second part, to reduce numbers of these factors (inputs and outputs) Grey Clustering was used.

In the second part, to make best use of this categorization this study tried to do this categorizing two times, one time on input indicators and another time on output indicators. The purpose of this study was to show the power of grey clustering to categorize and reduce numbers of input and output indicators. So according to oil refining units, the DEA model could calculate a Target function for all refineries.

As was expressed, there were five steps for clustering input and output indicators (factors). They were as follows [9].After using the above-mentioned steps on input and output series, an upper triangular matrix (correlation matrix indices)was obtain for input and output series. Results are as shown below in figures 1 and 2.

Numbers shown in the matrixes are indicative of an absolute degree of grey relation (ε_{ij}), that will determinethe rate of a relationship between two factors. According to the requirements of the study, ***r*** of inputs and outputs must be defined in a way that helps to categorize according to a specified target. In this study,***r*** was set as ***0.53*** for inputs and if $\boldsymbol{\varepsilon_{ij} \geq r}$, then it could be said that the two indicators had almost similar features. According to this procedure, the input matrix followings were bigger than ***0.53*** therefore their corresponding indicators could be place in a group.

$$\varepsilon_{12} = 0.57 \quad , \quad \varepsilon_{23} = 0.53$$

Figure1. Inputs upper triangular matrix

$$A = \begin{bmatrix} 1 & .57 & .52 \\ & 1 & .53 \\ & & 1 \end{bmatrix}$$

As showed in Figure 1,$X_2$is in the same row and column as X_1, and $X_3$is in the same row and column as X_2. Therefore, food indicators were below category for inputs indicators,.X_1 because of its higher value than the other two indicators, $X_1$was selected as representative of category. X_1 is the indicant for Food.

$\{X_1, X_2, X_3\}$

In addition, for outputs, according the matrix, ***r = 0.66*** for them and if $\boldsymbol{\varepsilon_{ij} \geq r}$, then it could be said that those two indicators had similar features and could be placed in the same category (cluster). According to this, followings were bigger than ***r=0.66*** therefore their corresponding indicators could be placed in one group.

$$\varepsilon_{13} = 0.89 \; , \varepsilon_{16} = 0.89 \; , \varepsilon_{23} = 0.68 \; , \varepsilon_{24} = 0.8 \; , \varepsilon_{25} = 0.66 \; , \varepsilon_{26} = 0.67$$
$$, \varepsilon_{36} = 0.99 \; , \varepsilon_{45} = 0.89$$

Figure2. Outputs upper triangular matrix

$$A = \begin{bmatrix} 1 & .64 & .89 & .58 & .55 & .89 \\ & 1 & .68 & .80 & .66 & .67 \\ & & 1 & .61 & .56 & .99 \\ & & & 1 & .77 & .61 \\ & & & & 1 & .56 \\ & & & & & 1 \end{bmatrix}$$

So X_3 and X_6 could be placed in the same row and column as X_1; X_3, X_4, $X_5$and X_6 could be placed in the same group as X_2; and X_5 could be placed in the same group as X_4, therefore outputs could be placed in one group. In addition,X_2, which was the indicator for gasoline was representative of the group because of its strategic importance.$X_2$was the indicant of Gasoline. So there was one input and one output and the total number of factors (inputs and outputs) was two.

In this part (second part) due to number of DMUs are not equal to total number of inputs and outputs, selecting primal model or dual model is an effective point that will effect on the number of constraint, so it will effect on the required time to calculate the answer. Due to number of DMUs is more than the total number of factors, if primal model be used, number of constraints is less than dual model, therefore primal model be used. As was said, each DMU will be effective when Objective Function Value is zero.

Numerical models of all refineries are similar to each other, but with the difference that right-hand side values are different. Input and output indicators that belonging to each refinery is located in the right-hand side of each refinery model.

The results of putting these models into the Frontier Analyst Software are as shown below in table (2).

Table 2. DEA Results after Grey Clustering

VRS Results		***Objective Function Value***	***Optimal Lambdas with Benchmarks***				
DMU No.	DMU Name						
1	***Abadan***	**-16495.30**	**0.807**	***Bandar-e-Abbas***		**0.193**	***Kermanshah***
2	***Arak***	**-20162.60**	**0.115**	***Bandar-e-Abbas***		**0.885**	***Kermanshah***
3	***Isfahan***	**-28779.61**	**0.808**	***Bandar-e-Abbas***		**0.192**	***Kermanshah***
4	***Bandar-e-Abbas***	**0**	**1.000**	***Bandar-e-Abbas***			
5	***Tabriz***	**-5110.64**	**0.220**	***Bandar-e-Abbas***		**0.780**	***Kermanshah***
6	***Tehran***	**-4013.59**	**0.762**	***Bandar-e-Abbas***		**0.238**	***Kermanshah***
7	***Shiraz***	**-3376.25**	**0.010**	***Bandar-e-Abbas***		**0.990**	***Kermanshah***
8	***Kermanshah***	**-3.71E-09**	**1.000**	***Kermanshah***			
9	***Lavan***	**-1039**	**1.000**	***Kermanshah***			

According to the outputs that provided by Software, that is as shown in table (2), it can be said 7 oil refinery is deficient, Kermanshah oil refinery is close to the efficient frontier and software output showed it as efficient oil refinery, even has been as a reference set for some refineries. Only Bandar-e-Abbas refinery is completely effective. For example, about the Abadan refinery, it can be say if this refinery can close 81% of their inputs and outputs to Bandar-e-Abbas refinery and 19% to Kermanshah oil refinery, it close to efficient frontier.

6. SUMMARY AND CONCLUDING REMARKS

Efficiency in general describes the extent to which time, effort, or cost is well used for the intended task or purpose. It is often used with the specific purpose of relaying the capability of a specific application of effort to produce a specific outcome effectively with a minimum amount or quantity of waste, expense, or unnecessary effort. "Efficiency" has widely varying meanings in different disciplines. Efficiency and productivity are subjects under consideration by every organization, especially in terms of the global competition inherent in most industries. So, by attention to efficiency and its continuous improvement is a fundamental factor that helps governmental and non-governmental organizations to achieve their goals. Therefore, improving the performance of an organization is the most important responsibility of many managers. DEA is one of the good methods for efficiency evaluation that managers could use. It helps researchers to identify the failures points of deficient DMUs and to think about the decision that they have to made for improving the efficiency of these DMUs.

DEA (Data Envelopment Analysis) is a capable and credible method of evaluation and many researchers have used this method in their researches. Nevertheless, one of limitation of the DEA method is that totality of DMUs must be at least triple that of the total number of inputs and outputs and in practice lack of attention to this point causes a large number of units to be placed on the efficient frontier, in other words, their efficiency score becomes one. Therefore, this study has used Grey Clustering in an attempt to reduce the number of factors (inputs and outputs). This Grey-DEA approach was done to be able to differentiate between DMUs (oil refineries).For evaluating some DMUs efficiency in the previous studies, if there were many indices, researchers needed to increase the number of units, that it was not possible in many cases. Grey clustering could be helpful for such situations and could help researchers for data reduction and categorizing the attributes.

According to the outputs, it can be said 7 oil refinery is deficient, Kermanshah oil refinery is close to the efficient frontier and software output showed it as efficient oil refinery, even has been as a reference set for some refineries. Only Bandar-e-Abbas refinery is completely effective. The results obtained from this study demonstrate the high capability of Grey Clustering to categorize factors and to reduce numbers of factors in a study. In addition, it can be said that by reducing number of factors, DEA is a capable and credible model for efficiency and productivity evaluation, and grey clustering is a powerful method for categorizing the attributes that could be useful for data reduction, even when there is small amount of data.

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