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Technical Efficiency Analysis in Turkey's Mining and Quarrying Industry by Data Envelopment Analysis (DEA)

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Abstract

The main purpose of this study is to explain the methodology of Data Envelopment Analysis (DEA), which is a linear programming based non-parametric method to analyze the comparative efficiency of an operation. Two different output-oriented DEA models (Constant Return to Scale and Variable Return to Scale) are applied to a data set to investigate the Turkey's mining and quarrying industry's technical efficiency between the years of 2003-2017 and result are shown and interpreted.

In addition, possible improvements for the inefficient years to be considered as efficient are also given. The data used in this study is obtained from Turkish Statistical Institute's database and DEA applied via an online solver at (www.deaos.com). The input data that is used for the analysis was average salary of the workers and purchase of goods and services, while the only output was total production.

Keywords: Data Envelopment Analysis; Turkey's mining; Mine Environmental Performance; Mining activities; Turkey's mining

Abbreviations: DEA: Data Envelopment Analysis; NPV: Net Present Value; MMEPI: Mixed Mine Environmental Performance Indicator; DMU: Decision Making Unit; CRS: Constant Return to Scale

Introduction

Economic sustainability of most of the developing countries around the world is highly related with their mining industries' efficiency. Production planning of a mining project consists of determination of yearly production rate and estimation of capital and operating costs procedures that will maximize the Net Present Value (NPV) of the project [1]. A mine is considered as efficient if the production is maximized with optimal use of inputs [2].

From a broad perspective, the inputs used in mining industry are capital which is invested on machinery and infrastructure and labors to produce minerals. The aim of this paper is determination of technical efficiency of Turkey's mining and quarrying industry by data envelopment analysis between the years 2003-2017 and interpretation of the results. In addition to showing the existing inefficiencies, the necessary arrangements to improve them are put forward. The input data were average salary of workers and purchase of good and services while the only output was annual production.

Literature Review

Tsolas I [3] has aimed to present some evidence regarding productive efficiency in Greek lignite mining is related with occupational safety. Technical efficiency is measured by basic DEA, and he used real output, labor, and fixed capital as inputs. In addition to that inputs the number of disabling injuries used as both input and negative output for different DEA models. They used National Statistical Service of Greece and the Ministry for Development's database and showed that using occupational data as input or output will give similar results in terms of efficiency scores. Kulshreshta M, Parikh JK [4] are used the nonparametric DEA to analyze the performance of different coal mining regions in India between the years 1985-1997.

Total factor productivity growth was analyzed using the Malmquist index by decomposing productivity change into efficiency and technical change. Their analyze show that open cast mining activities shown more productivity grown than underground mining activities. Technical progress seems to have been major driving factor for that growth. Fang H, et al. [5], attempted to compare the relative technical efficiency performance of listed coal mining companies in China and USA using CCR and BCC models in the advanced DEA linear program.

The result show that the level of relative efficiency in Chinese coal mining enterprises was much lower than American coal mining firms. They used different models according to the different inputs and outputs for the efficiency analyze. Tsolas IE [6], analyzed the performance of 15 ilinois strip coal mines which using publicly available data. He used a mixed mine environmental performance indicator (MMEPI) that is derived by means of a VRS DEA.

He used proxy capital (machine capacity), labor, seam characteristics as inputs and tons of produced coal as output. Akınloye O, et al. [7], analyzed the profit efficiency of 14 mining firms in South Africa over the 2003-2006 by SFA method. The estimated model shows the presence of SFA profit possibilities. Buys PW, et al. [8] developed a DEA model to estimate the relative scale efficiency of platinum mining companies' environmental performance.

They used greenhouse gas emissions, water usage and energy usage as inputs while using the platinum production, return on equity and return on assets as outputs of the model. Das A [9] compares the extraction efficiency of public and private mining firms in India by assessing their total factor productivity. The study reveals that TFP levels of private firms are significantly higher than that of public firms in metallic, non-metallic and coal mining sectors. She also stated that private participation in the mining industry may boost the overall productivity of the sector.

Yaşar Kasap and Fehmi Duman [10], used Malmquist total factor productivity index (MPI) to examine and compare the exported and imported primary energy resources and their use efficiency in Turkey between the years 2000-2009. Their model was output maximization with CRS. Their analyze determined a decrease of %5.4 in electrical energy production due to the inefficient use of indigenous resources and the current installed capacity. They also stated that the difference between the amount of usage of domestic and exported resources for the energy production is increasing. They used Turkey's gross electricity generation by share of primary energy resources (%) such as lignite, natural gas etc. and Turkey's installed capacity (MW) as inputs.

They used EÜAŞ's database for the analyze. Wysokinski M, et al. [11], compared the energy and economic efficiency of the mining and quarrying sector in European Countries by DEA. They used 22 DMU's for the year 2011 and used the number of hours worked by employers and energy consumption (TJ) as inputs while using the production value as output. They gave recommendations about the reasons of inefficiency. Debrath RM and Sebastian VJ [12] are evaluate the technical and scale efficiency of Indian steel manufacturing industries by DEA.

Annual income of the more than 50 DMU has used and VRS and CRS models applied to the output-oriented model. Their study presented that %45 of the steel manufacturing firms was both technically and scale inefficient. Ediger VŞ, et al. [13] analyzed the lignite production and overburden removal activities of TKI from a historical perspective. Malmquist efficiency index of TKI is investigated by principal component analysis and the historical development of the company between the years 1957-2010 was presented at their study.

They used the comprehensive data set of TKI for the first time and they created a mining efficiency index which can be used to analyze productivity in lignite mining activities. Budeba MD, et al. [1] described a model for estimating the technical efficiency of surface mines for coal supply to local and export. Application of model and evaluation is shown by using a simulated data. Their study proposes a predictive model for the efficiency of a new project.

Methodology

Data Envelopment Analysis

The terms efficiency and productivity can be used interchangeably assuming that, they state output-input ratio [14]. Farrell [15] introduced the "efficient production function" term in his "The Measurement of Productive Efficiency" study. This function was constructed from empirical data and was one of the most important contributions to the efficiency measurement field. Beccalli et al. stated that there are 2 types of technical efficiencies based on the orientation. Those are input-oriented and output-oriented technical efficiencies. A firm would be considered as efficient, either if it is cost minimizing (producing the same output with the less amount of inputs) or profit maximizing (producing more output with the same amount of inputs). Charnes, Cooper, and Rhodes [16] improved the Farrell's approach and proposed a model that was called as data envelopment analysis (DEA). In addition, they defined the decision-making unit (DMU) term which represents the unit (firms, countries etc.) whose efficiency score will be investigated. The purpose of DEA is identifying the efficient DMU and constructing the efficient production frontier (Figure 1).

DEA models, measures the relative efficiencies of the DMU's with respect to the other DMUs in the dataset. By doing so, the DMU data set can be divided in to two clusters as: efficient DMUs at the efficient frontier and inefficient DMUs lying below the frontier. The efficiency of a DMU is estimated as the ratio of weighted outputs to weighted inputs. Weights of DMUs is selected for efficiency score maximization. The maximum efficiency score is equal to 1 and the lower values shows the relative inefficiency of analyzed units.

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Where

s – quantity of outputs,

m – quantity of inputs,

u_r – weights denoting the significance of respective outputs,

v_i – weights denoting the significance of respective outputs,

y_{rj} – amount of output of r-th type (r =1..., R) in j-th object,

x_{ij} – amount of input of i-th type (n =1..., N) in j-th object; (j =1..., J).

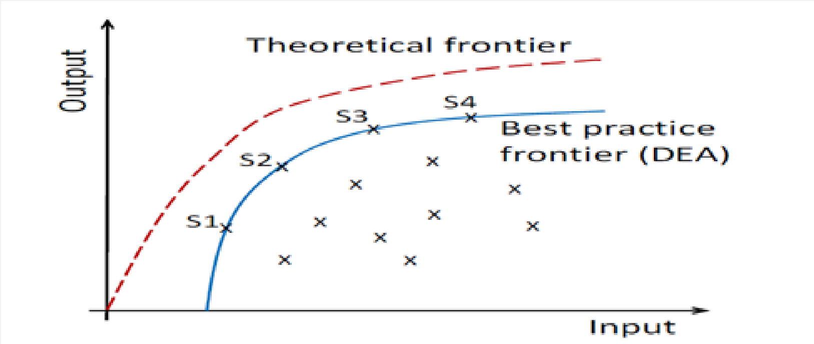

Figure 1: Basic concept of DEA [18].

The answer to the question "By how much can input quantities be proportionally reduced without changing the output quantities produced?" can be given by input oriented DEA model while the answer to the question "By how much can output quantities be proportionally expanded without altering the input quantities used?" can be given by output orientated model (DEA article). Moreover, as can be seen on Figure 2, DEA can be applied under the assumption of constant return to scale (CRS) and variable (increasing or decreasing) return to scale.

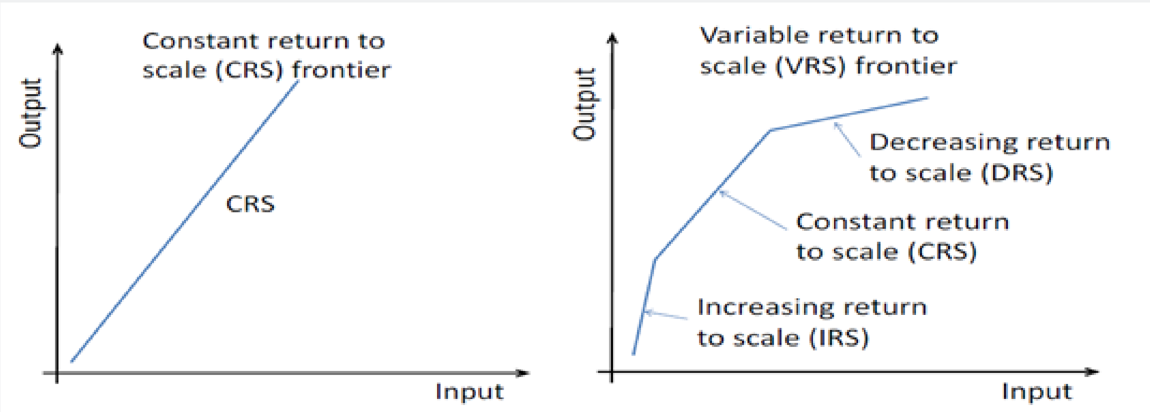

Figure 2: Visual representation of CRS and VRS frontiers [18].

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CRS assumption states that Equi proportionate increases in factor inputs yield an Equi proportionate increase in output. On the other hand, VRS assumption states that Equi proportionate increases in factor inputs yield a greater (or less) than Equi proportionate increase in output [17]. While the CCR model was formed under the assumption of CRS, the model (BCC) which assumes the VRS was developed by Banker, Charnes and Cooper [16].

Advantages and disadvantages of using CRS or VRS assumption on DEA is a frequent topic of debates in the academic literature (DEA article). The most important advantage of DEA model is that it allows the researchers to use multiple inputs and outputs with different units. However, the choice of appropriate variables is even more complicated than the choice of model specifications.

Data analysis and interpretation of the results

The data used for this study is obtained from Turkish Statistical Institute's database. The DEA is applied on www.DEAOS.com, which is an online software developed by DssBridge Decision Group Inc. for efficiency measurement purposes. Constant Return

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to Scale and Variable Return to Scale DEA models applied to the data set and efficiency scores are shared on Table 1. In addition, variation of the technical efficiency scores through the years 2003-2017 can be seen on Figure 3.

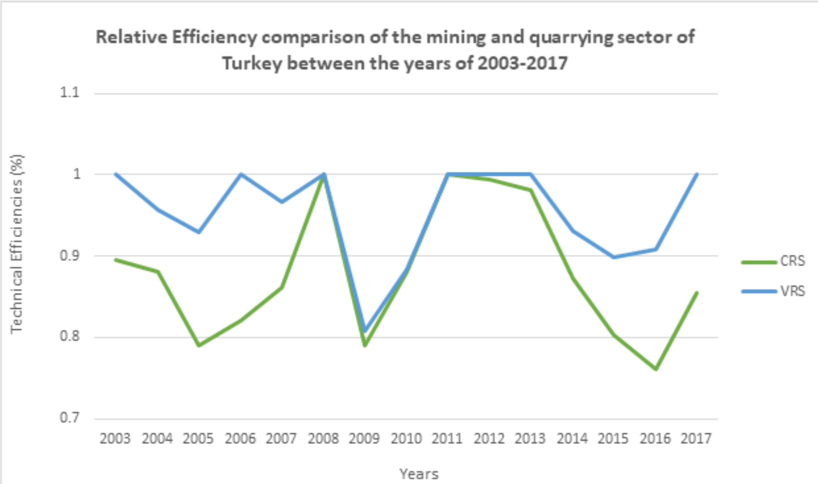

Figure 3: Relative Efficiency comparison of the mining and quarrying sector of Turkey between the years of 2003-2017.

Table 1: Technical efficiency scores of Turkey's mining and quarrying industry between years 2003-2017.

Years	CRS Model Efficiency Scores	With Respect to:	VRS Model Efficiency Scores	With Respect to:
2003	0.896	2008	1	-
2004	0.8805	2008	0.9562	2003-2006-2008
2005	0.7897	2008	0.9295	2003-2006-2008
2006	0.8204	2008-2011	1	-
2007	0.8621	2008-2011	0.967	2003-2006-2008
2008	1	-	1	-
2009	0.7896	2008-2011	0.8086	2008-2013
2010	0.8814	2008-2011	0.8837	2008-2011-2012
2011	1	-	1	-
2012	0.9941	2008-2011	1	-
2013	0.981	2008-2011	1	-
2014	0.8724	2008-2011	0.9305	2013-2017
2015	0.8033	2008-2011	0.8984	2013-2017
2016	0.7601	2008-2011	0.909	2013-2017
2017	0.8544	2008-2011	1	-

The model for DEA application is structured as:

$$\textit{Input}_1 + \textit{Input}_2 = \textit{Output}_1$$

Where:

$\textit{Input}_1$: Average salary of workers (Total Salary / Total # of Paid workers).

$\textit{Input}_2$: Purchase of good and services

$\textit{Output}_1$: Annual Production

The first observation that can be done by looking at the Figure 3. is that the efficiency scores obtained by VRS model are higher than that obtained by CRS model. The reason of this situation could be explained by the methodology of the DEA. The data space under the VRS frontier is smaller than data space under the CRS frontier (Figure 2) which results with higher efficiency scores.

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Also, the number of fully efficient operations according to the VRS model is higher than the CRS model. The most inefficient mining operation was conducted on 2009 according to the VRS model while on the other hand the most inefficient year in terms of mining operations was 2016 according to the CRS model (Figure 3). Possible improvements for the inefficient years to be considered as efficient can be seen on Table 2 and Table 3.

Table 2: Improvements for inefficient DMU's that obtained by output-oriented CRS model.

DMU(Years)	Average Salary	Purchase of Goods and Services	Production Value
2003	-51.94%	-	12%
2004	-37.55%	-	13%
2005	-17.17%	-	14%
2006	-	-	15%
2007	-	-	16%
2008	-	-	-
2009	-	-	27%
2010	-	-	13%
2011	-	-	-
2012	-	-	1%
2013	-	-	2%
2014	-	-	15%
2015	-	-	24%
2016	-	-	32%
2017	-	-	17%

Table 3: Improvements for inefficient DMU's that obtained by output oriented VRS model.

DMU(Years)	Average Salary	Purchase of Goods and Services	Production Value
2003	-	-	-
2004	-	-	4.58%
2005	-	-	7.59%
2006	-	-	-
2007	-	-	3.41%
2008	-3.75%	-	-
2009	-	-	23.67%
2010	-	-	13.16%
2011	-	-	-
2012	-	-	-
2013	-	-0.90%	-
2014	-8.86%	-	7.47%
2015	-17.70%	-	11.30%
2016	-	-	10%
2017	-	-	-

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As can be seen from Table 2, years 2008 and 2011 were only efficient years according to the CRS model, so that there are no improvements for those years. Because, the output-oriented DEA model used for analysis, the possible improvements for inefficient years are given as output maximization. Between 2003 and 2005, not only production value should be increased but also the average salary of the workers should be decreased too. For example, in 2005, average salary of the workers should be reduced by %17.17 while production value should be increased by %14. The most inefficient year was 2016 and the production value should have been increased by %32 for that year to be counted as fully efficient.

Different than the CRS model, the efficiency scores and number of fully efficient DMUs is higher according to the VRS model (Table 3). Reason of this situation is explained on Methodology section. When we look at the Table 1, the efficiency scores of the years 2012 and 2013 which were obtained by CRS model are very close to the 1 and they counted as fully efficient according to the VRS model. Years 2003, 2006, 2008, 2011, 2012, 2013 and 2017 counted as fully efficient according to the VRS model. The most inefficient year was 2009 and Production value should have been increased by %23.67 for that year to be counted as fully efficient (Table 3).

Conclusion

Economical sustainability of the high-cost mining investments has a great effect on the economic development of both enterprises and countries with mineral resources. Within this scope, the efficiency of this operations must be investigated in terms of optimal consumption of the inputs to produce maximum output. From a broad perspective, the inputs used in mining industry can be listed as capital, which is used for machinery and infrastructure, and labors for mineral production, while the main output is total production. In this study, average salary of the workers (total salary / # of paid workers) and purchase of good and services parameters are used as inputs and total production value is used as output.

The application of the DEA methodology to evaluate the efficiency of the mining and quarrying industry of Turkey between the years of 2003 and 2017 is presented and results are shown. Not only CRS model, but also VRS model is used for the analysis and the results are compared. Both models are applied as output-oriented models. The data used for evaluation is obtained from Turkish Statistical Institute's database. The analysis conducted on an online solver at www.deaos.com. The number of fully efficient operations and efficiency scores of DMU's obtained by VRS model was higher than that is obtained by CRS model (Figure 3). After the construction of the efficient frontier, the possible improvements for inefficient years are also given in this study (Table 2 & Table 3).

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