Measuring and Evaluating Efficiency of a Glass Company Through Data Envelopment Analysis

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Abstract

Companies need to evaluate themselves on certain periods, both to investigate deviations from their plans and to determine if they are doing better or worse than their competitors. Efficiency evaluating is therefore vital for enterprises in modern era. In this study the efficiency of seven workshops, which are subsidiaries of the Turkish Glass Company located in İstanbul, were measured and evaluated by using a mathematical method named Data Envelopment Analysis (DEA). While labor, machinery, and raw material were taken as inputs, smooth glass and rough glass were treated as output for efficiency analysis in this research. DEA model is formed based on data obtained from seven workshops. The results presented in this study showed that four out of seven workshops are inefficient and they need some modification in terms of labor as the most potential improvements input factor.

Key words: Efficiency, Data Envelopment Analysis, Glass Company.
JEL Classification: M11, C61, L61.

Introduction

Performance evaluation is at the core of management activities (Schaffnit et al.,1997). Companies need to evaluate themselves on certain periods, both to investigate deviations from their plans and to determine if they are doing better or worse than their competitors. So, the idea that if it can not be measured, it can not be controlled must be the dominant strategy in modern companies. Also various departments, shops, services or people must be measured for efficiencies in order to fix their relative productivity. Consequently, efficiency evaluating is vital for enterprises in modern era.

Companies must make efficiency analysis to reach to accomplishment. There are many techniques to perform this analysis. Yolalan (1993) divided these techniques into three groups, namely ratio analysis, parametric methods, and nonparametric methods. In the first group of the techniques, productivity level is calculated by only one productivity dimension with each ratio. Such that it can result in different comments ranging from productivity to non-productivity. The second group of the techniques gathered "parametric" methods in which production function is assumed to be parametric. The parameters of the production function is estimated by various methods such as regression. The last group is "nonparametric" methods based on mathematical programming. The most useful technique among nonparametric methods is Data Envelopment Analysis (DEA) which has been used to measure efficiency in this study.

Even though efficiency and productivity are used in the same meaning generally, they were defined by Abbott (2005) differently. While efficiency can be described as being the degree to which resources are being used in an optimal fashion to produce outputs of a given quantity, productivity is a measure of the physical output produced from the use of a given quantity of inputs.

This study tries to explore what determines the efficient level of seven workshops. In order to reach this objective, a mathematical model named DEA is used. The study is organized as follows: Second section presents a brief overview of DEA. Current practices related DEA studies about manufacturing industry are discussed in the third section. Fourth section describes the methodology, sample and model. While fifth section presents the results of the analysis, sixth section gives some concluding remarks.

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Data Envelopment Analysis (DEA)

Data Envelopment Analysis (DEA), a new technique developed in operations research and management science over the last two decades, is a method for assessing the comparative efficiencies of decision making units by relating their output to their input levels (Sengupta, 1999; Thanassoulis and Allen, 1998). It defines the relative efficiency of the individual units known as decision making units (DMUs) each of which has a number of inputs used to produce several outputs. DEA easily handles multiple output production correspondences and also it is useful because provides a measure of relative producer performance that is independent of resource prices. Since DEA is not fully parametric, it is less sensitive to mis-specification of the production function (Ruggiero, 1998). As a result of these, DEA approach has become increasingly popular in the practice and research of efficiency analysis in the past few years (Yan et al., 2002).

DEA is a special application of linear programming based on frontier methodology as advanced by Charnes et al. (1978) named CCR and Banker et al. (1984) named BCC. The CCR model generalized the single output/input ratio efficiency measure for each DMU to multiple otputs/inputs situations by forming the ratio of a weighted sum of outputs to a weighted sum of inputs. The BCC model relaxed the constant returns to scale assumption of CCR model and made it possible to investigate whether the performance of each DMU was conducted in region of increasing, constant or decreasing returns to scale in multiple outputs and multiple inputs situations (Yun et al., 2004). The main characteristics of DEA are listed by Yun et al. (2004) as follows: (i) it can be applied to analyze multiple outputs and multiple inputs without preassigned weights, (ii) it can be used for measuring a relative efficiency based on the observed data without knowing information on the production function, and (iii) decision makers' preferences can be incorporated in DEA models.

Consider a number of DMUs, k=1,…..,n, each of which uses an amount (x_{ij}) of input, i=1,….,m, and produces an amount of output (y_{rj}), r=1,…..,s. The seminal paper by Charnes et al. (1978) formulated the DEA model as follows:

$$E_k = Max \frac{\sum_{r=1}^{s} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}}$$

Subject to $\dfrac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1$,

where (E_k) is the efficiency score of alternative *k*, (u_r) is the weight assigned to alternative *k* for maximizing criteria *y*, and (v_i) is the weight assigned to alternative *k* for minimizing criteria *x*. The basic formulation above can be transformed to a linear program and it is solved for each DMU:

$$E_k = Max \sum u_r y_{rk}$$

Subject to $\sum v_i x_{ik} = 1$

$$\sum u_r y_{rj} - \sum v_i x_{ij} \leq 0$$

$$u_r, v_i \geq \varepsilon \geq 0.$$

Using DEA in the Manufacturing Industry

Researchers interested in both service and manufacturing industry productivity have applied DEA to a variety of sectors. Moreover, DEA is used in service industry including finance (Basso and Funari, 2001; Cielen et al., 2004; Tone and Sahoo, 2005), education (Bradley et al., 2001; Fandel, 2005; Köksal and Nalçacı, 2006), health (Siddharthan et al., 2000; Athanassopoulos and Gounaris, 2001; Chen et al., 2005) mostly. However, this method is used in many studies on manufacturing industry too. Talluri et al. (1997) used a DEA model with three levels to propose a methodology for cell performance evaluation and improvement. Arcelus and Arozena (1999) examined the problem of measuring the evaluation of productivity changes over time and across the 14 countries included OECD's International Sectoral Data Base of two industries, manufacturing and service. Norway and the USA are best practice countries throughout the entire data set according to the geometric means of the sectoral productive efficiency scores and their corresponding coefficients of variation for each country during the 1970-1990, 1970-1980, 1980-1990 time periods. Furthermore, results of this study also suggest a higher degree of volatility in the service industry and there are more frontier countries than for manufacturing. Yan et al. (2002) proposed an inverse DEA model which can be used for a DMU to estimate its input/output levels when some or all of its input/output entities are revised, given its current DEA efficiency level and demonstrated how to apply the model to the case of a local home electrical appliance group company for its resource reallocation decision. Another study using DEA as the efficiency measurement tool was directed by Korhonen and Luptacik (2004) on 24 power plants in a European country. They presented two approaches which can be used for the estimation of eco-efficiency. The first approach was decomposed into two parts which are combined: (i) the problem of measuring technical efficiency (as the relation of the desirable ouputs to the inputs), and (ii) the problem of measuring ecological efficiency (as the relation of the desirable outputs to the undesirable outputs) separately. In the second approach, they treated pollutants as the inputs. They emphasized that both approaches leaded to similar results. However, the second approach provided a deeper insight into the causes of the eco-inefficiency. Sezen and Doğan (2005) used the DEA method to measure and evaluate the efficiencies of ship building and maintenance shops performing under one of the Turkish Navy Shipyards. Guan et al. (2006) attempted to find a systematic quantitative methodology to explore the relationship between technological innovation capability and competitiveness at enterprise level. As a result of DEA application on 182 industrial innovative firms in China, it was found that only 16% of the enterprises operate on the best-practice frontier and there are some inconsistencies between organizational innovation capability and competitiveness in many enterprises

Methodology

As it has been stated in the beginning of the study, we aimed to measure and evaluate the efficiency of seven workshops which are subsidiaries of a Turkish Glass Manufacturing Company. These workshops are located in Ümraniye, Hadımköy, Kartal, Bağcılar, İkitelli, Fatih in İstanbul and İzmit. This workshops are coded as 1, 2, 3, 4, 5, 6 and 7 in the following sections, respectively. The data has been obtained for each workshops by company document and interview with firm authors regarding 12-months period in 2005. Calculations about data can be seen in Appendix A.

DEA method is chosen to reach the aim of the survey. Appropriateness of company and data to DEA has been examined in this study in terms of many assumptions which cited by Dyson et al. (2001). One of them is *homogeneity assumptions* relating to the homogeneity of the units under assessment. In general the units are understood to be similar in a number of ways. Workshops in this study use similar manufacturing technologies and produce similar products by driving same inputs. A similar range of resources such as staff, raw materials and equipment are available to all units. All of the units are also operated by the same company. The second assumption according to Dyson et al. (2001) is about the *input/output set*. Workshops satisfy the second assumption because they cover the full range of resources used and they capture all activity levels and performance measure. The sets of factors are common to all units. The last assumption named as the *factor measurement* is on the measurement scales of the inputs and outputs. According to it, they should conform to ratio scales. Our study also supports the last assumption.

The Data

Three types of input and two types of output are choosen as candidates for the analysis performed in this study and are employed in the empirical study of glass workshops (Figure 1).

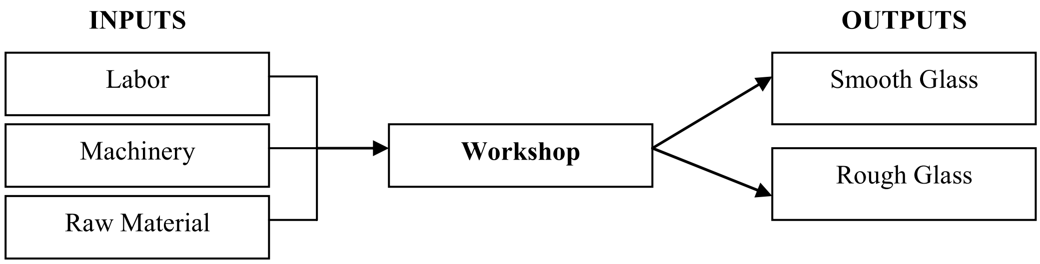

Fig. 1. The conceptual input-output framework

The inputs employed by each workshop are labor, machinery, and raw material. Labor is measured as the workforce in related periods in each workshop. It is obtained by multiplying the number of employees and the work duration. Similarly, machinery is measured as duration when band operation time in related periods in each workshop. Finally raw material is measured with order quantity in related periods for each workshop. Glass final products of a workshop are classified into two groups, namely smooth and rough glass and named as output items in the analysis. Both of them are measured as the final quantity. Information about each input and output for all workshops and their quantities are tabulated in Table 1 and Table 2, respectively.

Table 1

Information about inputs and outputs

Type	Variable	Measured as	Units	Controllable/ Uncontrollable
Input				
	Labor (L)	Number of employees * Work duration	Man-hour	Controllable
	Machinery (M)	Band operation time	Machine-hour	Controllable
	Raw Material (RM)	Order quantity	Tone	Controllable
Output				
	Smooth Glass (SG)	Production quantity	m^2	Controllable
	Rough Glass (RG)	Production quantity	m^2	Controllable

Table 2

Quantities of inputs and outputs for each workshop

Input/Output	Workshop (Decision Making Unit) Codes							Mean	SD
	1	2	3	4	5	6	7		
Labor	24.480	17.136	12.240	14.688	14.688	9.792	22.032	16.436	5.234
Machinery	7.344	4.896	2.448	2.448	4.896	2.448	4.896	4.196	1.850
Raw Material	15.000	10.000	8.000	5.000	9.000	4.000	10.000	8.714	3.638
Smooth Glass	40.000	22.000	12.000	10.000	21.000	11.000	22.000	19.714	10.436
Rough Glass	10.000	12.000	11.000	7.000	5.000	9.000	14.000	9.714	3.039

Results

Since the efficiencies of DMUs have been measured by above model, it is necessary to solve model seven-times for each DMU. The optimum value of objective function gives the efficiency score of interested DMU in the model. Any DMU whose efficiency score equals one is defined as “efficient”, otherwise “inefficient” (Bal and Örkcü, 2005). The model is run for each DMU by utilizing Frontier Analyst software program. The results of the analysis are discussed under headings of identifying efficient and inefficient workshops and determining realistic targets for inefficient workshops.

Identifying efficient and inefficient workshops

The results obtained from the data entered to DEA model are tabulated in Table 3. It can be seen from this table that three workshops, namely, Ümraniye (1), Fatih (6), and Kartal (3) have been running effectively. Hovewer, Workshop 1 is the most citest workshop as the peer group. So, it is the first rank. It can be said that Workshop 1 and Workshop 6 have been appeared in the most peer groups are the best workshops of the company. A peer group is a set of efficient units from which an inefficient unit’s inefficiency has been determined. For each inefficient unit the list of peer units is also determined and given in Table 3. The remaining four workshops which secured efficiency score less than one, are relatively inefficient.

Table 3

Efficient scores and reference groups

Efficient Rank	Workshop Code	Efficiency Score	Peer Group by Workshop Code	Peer Frequency
1	1	1.000	-	4
2	6	1.000	-	3
3	3	1.000	-	-
4	2	0.971	1 and 6	-
5	7	0.944	1 and 6	-
6	4	0.876	1 and 6	-
7	5	0.875	1	-

Determining realistic targets for inefficient workshops

Figure 2 shows the share of the various sources in the total input savings. It is evident from Figure 1 that the maximum contribution to the total input saving is about 46% from labor, followed by machine (28%), and raw material (23%). Thus, it needs some modification on labor as the most potential improvements factor. Similarly, Sezen and Doğan (2005) attained the missing labor as the most important factor. As it can be seen from Table 4, Workshop 2 should save machinery and raw material by 8.4% whereas Workshop 7 and Workshop 4 should save labor by 20%, 43.3%, respectively. Workshop 5 should save by machinery (21.2.%). From the perspective of improving outputs, the results suggest that need exists to increase the quantity of rough glass in Workshop 5. In terms of quantity of improvements, Workshop 2 should save the annual machinery capacity by 1.040 hours while Workshop 7 should reduce the annual labor from 22.032 to 17.625. However, Workshop 5 should improve its level of rough glass output as much as 5%.

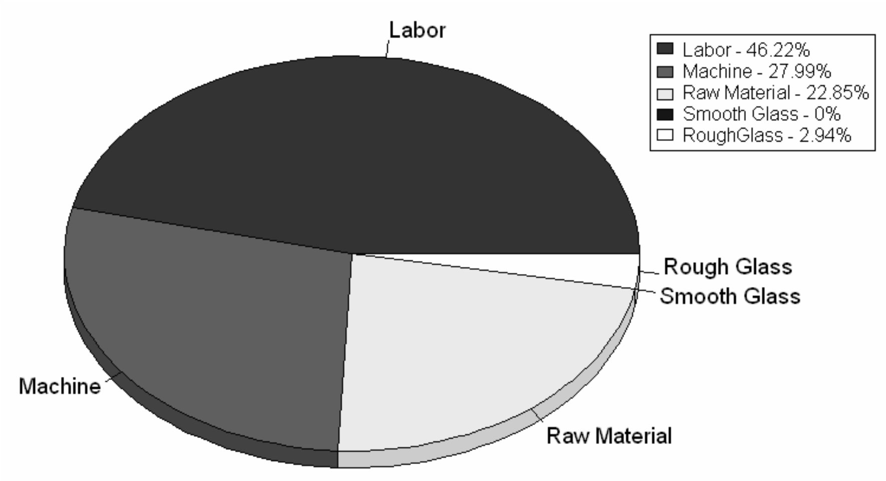

Fig. 2. Total potential improvements summary

Table 4

Targets and potential improvements for inefficient workshops

	Workshop 2			Workshop 7		
Input/Output	Actual	Target	Potential Improvements	Actual	Target	Potential Improvements
Labor	17.136	16.646	-490 (-2.9)	22.032	17.625	-4.407 (-20.0)
Machinery	4.896	4.485	-411 (-8.4)	4.896	4.622	-274 (-5.6)
Raw Material	10.000	9.160	-840 (-8.4)	10.000	9.440	-560 (-5.6)
Smooth Glass	22.000	22.000	0	22.000	22.000	0
Rough Glass	12.000	12.000	0	14.000	14.000	0
	Workshop 4			**Workshop 5**		
Input/Output	Actual	Target	Potential Improvements	Actual	Target	Potential Improvements
Labor	14.688	8.323	-6.365 (-43.3)	14.688	12.852	-1.836 (-12.5)
Machinery	2.448	2.144	-304 (-12.4)	4.896	3.856	-1.040 (-21.2)
Raw Material	5.000	4.380	-620 (-12.4)	9.000	7.875	-1.125 (12.5)
Smooth Glass	10.000	10.000	0	21.000	21.000	0
Rough Glass	7.000	7.000	0	5.000	5.250	250 (5.0)

Management can do so by weighting some factors more heavily than others. For example, Workshop 5 should save the annual machinery capacity while Workshop 4 should reduce the annual man-hour. Furthermore, some of the modification actions such as decreasing employees, multiple-shift operation, employee motivaiton, quality circles, and TQM implementations can be proposed for the related workshops.

Conclusion and Discussions

This study tried to explore the efficient level of seven manufacturing workshops by DEA and proposing to improve to workshops with low efficient score. DEA has the advantage over alternative (parametric) methods as it can be used in a multiple input and output production context. It is determined from the analysis that the efficiency scores of three out of the seven workshops are equal to "1". So they are defined as efficient workshops. The remaining four workshops should focus on inputs generally. It needs some modification on labor as the most potential improvements factor.

While the potential for DEA in manufacturing management is evident, there are a number of limitations. Regarding the pilot study presented here, the number of workshops was relatively small. This was the result of the limited number of workshops under the same organization. The other limitation is about input/output set. The other subject causing many limitations is about DEA method. For example, it is extremely sensitive to outliers, as these serve to influence the optimal frontier. Furthermore, DEA does not allow for an error structure and there is no goodness-of-fit information to test its result (Reynolds and Thompson, 2005).

Although this study has a few limitations, it can be a guidance for future research such as

1. the same study can be expanded on other glass companies to determine an average sector efficiency level and results should be compared by each company,
2. the same technique, DEA, can be carried out as multiperiod to compare workshops periodical.

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Appendix A. Calculations

The following are used in the analysis:

- ♦ Daily work duration for each workshop is 8 hours.
- ♦ Weekly work duration for each workshop is 6 days.
- ♦ Average annually work duration for each workshop is 51 weeks because of traditional holiday.
- ♦ Each of the production band can be run 8 hours per day.

Workshop 1 (Ümraniye)

Number of employees: 10

Daily labor = 10 man * 8 hours = 80 man-hour/day
Weekly labor = 80 man-hour/day * 6 day = 480 man-hour/week
Annual labor = 480 man-hour/week * 51 weeks = 24.480 man-hour

Number of production band: 3

Daily machinery capacity = 3 * 8 hours = 24 hours/day
Weekly machinery capacity = 24 hours/day * 6 day = 144 hours/week
Annual machinery capacity = 144 hours/week * 51 weeks = 7.344 hours

Workshop 2 (Hadımköy)

Number of employees: 7

Daily labor = 7 man * 8 hours = 56 man-hour/day
Weekly labor = 56 man-hour/day * 6 day = 336 man-hour/week
Annual labor = 336 man-hour/week * 51 weeks = 17.136 man-hour

Number of production band: 2

Daily machinery capacity = 2 * 8 hours = 16 hours/day
Weekly machinery capacity = 16 hours/day * 6 day = 96 hours/week
Annual machinery capacity = 96 hours/week * 51 weeks = 4.896 hours

Workshop 3 (Kartal)

Number of employees: 5

Daily labor = 5 man * 8 hours = 40 man-hour/day
Weekly labor = 40 man-hour/day * 6 day = 240 man-hour/week
Annual labor = 240 man-hour/week * 51 weeks = 12.240 man-hour

Number of production band: 1

Daily machinery capacity = 1 * 8 hours = 8 hours/day
Weekly machinery capacity = 8 hours/day * 6 day = 48 hours/week
Annual machinery capacity = 48 hours/week * 51 weeks = 2.448 hours

Workshop 4 (Bağcılar)

Number of employees: 6

Daily labor = 6 man * 8 hours = 48 man-hour/day
Weekly labor = 48 man-hour/day * 6 day = 288 man-hour/week
Annual labor = 288 man-hour/week * 51 weeks = 14.688 man-hour

Number of production band: 1

Daily machinery capacity = 1 * 8 hours = 8 hours/day
Weekly machinery capacity = 8 hours/day * 6 day = 48 hours/week
Annual machinery capacity = 48 hours/week * 51 weeks = 2.448 hours

Workshop 5 (İkitelli)

Number of employees: 6

Daily labor = 6 man * 8 hours = 48 man-hour/day
Weekly labor = 48 man-hour/day * 6 day = 288 man-hour/week
Annual labor = 288 man-hour/week * 51 weeks = 14.688 man-hour

Number of production band: 2

Daily machinery capacity = 2 * 8 hours = 16 hours/day
Weekly machinery capacity = 16 hours/day * 6 day = 96 hours/week
Annual machinery capacity = 96 hours/week * 51 weeks = 4.896 hours

Workshop 6 (Fatih)

Number of employees: 4

Daily labor = 4 man * 8 hours = 32 man-hour/day
Weekly labor = 32 man-hour/day * 6 day = 192 man-hour/week
Annual labor = 192 man-hour/week * 51 weeks = 9.792 man-hour

Number of production band: 1

Daily machinery capacity = 1 * 8 hours = 8 hours/day
Weekly machinery capacity = 8 hours/day * 6 day = 48 hours/week
Annual machinery capacity = 48 hours/week * 51 weeks = 2.448 hours

Workshop 7 (İzmit)

Number of employees: 9

Daily labor = 9 man * 8 hours = 72 man-hour/day
Weekly labor = 72 man-hour/day * 6 day = 432 man-hour/week
Annual labor = 432 man-hour/week * 51 weeks = 22.032 man-hour

Number of production band: 2

Daily machinery capacity = 2 * 8 hours = 16 hours/day
Weekly machinery capacity = 16 hours/day * 6 day = 96 hours/week
Annual machinery capacity = 96 hours/week * 51 weeks = 4.896 hours