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Research Article

Eco-efficiency Evaluation in Cement Industries: DEA Malmquist Productivity Index Using Optimization Models

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Keywords

Data Envelopment Analysis,
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FDH model,
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Abstract

The cement industry faces many problems that contain reducing fossil fuel, lack of raw resources, continuously increasing requests for cement, rising ecological alarms connected with temperature change. Iranian cement companies, despite copious profits such as valuable mines, face many challenges. Difficulties such as ill use of the manufacturing capacity require investigating to this extent. The primary purpose of this study is to examine the Eco-efficiency determining factor in five different developing countries 22 cement companies over 2015-2019 with Data Envelopment Analysis (DEA). To find the superior model CCR-DEA (or Charnes, Cooper and Rhodes model), BBC-DEA (or Banker, Charnes and Cooper model) and additive DEA model for measuring the efficiency of decision processes are used. After applying the proposed model, the Malmquist Productivity Index (MPI) is computed to evaluate the productivity of companies over 2015-2019. Finally, the results indicate that FDH model has the most productive results during all periods compare with other suggested models since it has outstanding effects on both inputs and output.

1. Introduction

There are many papers recently used DEA, data mining and other optimization and machine learning approaches [1-12]. DEA has been commonly used for measuring energy and ecological efficiency and eco-efficiency since it was principally proposed by Charnes et al. [13]. It is a non-parametric frontier method where the effectiveness of a precise unit is designed by its distance from the highest performance training frontier shaped by the most exceptional performance entities inside the group. Correspondingly, FDH is a nonparametric method to measure the efficiency of DMUs. It relaxes the convexity hypothesis of the basic DEA models. While DEA model uses a linear programming problem, the FDH deals with a mixed integer programming problem. It has been implemented in different industries, including banking [14,15].

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The eco-efficiency creates with various insinuations. We designate eco-efficiency, effectively, in place of the volume to produce possessions or services by saving energy and capitals or by lessening waste and emissions.

The performance of the proposed approach provides us with a chance to recognize pattern recognition of the whole, DEA technique during the selected period (five years over 2015-2019). So, the significant concentration of the study is to respond to two preliminary questions. Secondly, among three proposed models (CCR, BCC and FDH) which model has the highest average productivity over average productivity over 5-year periods for 22 DMUs? Secondly, whether FDH proposed model has any corroboration impact on Eco-efficiency?

All the available companies' datasets are applied to three exclusive models, and their DMU's or cement companies efficiency is compared to find the unfamiliar trends in cement companies. A dataset for 22 companies with two inputs and two outputs is used. Malmquist Productivity Index in DEA with CCR, BCC, and FDH Models are applied to test and justify the alterations between companies. The use of DEA as a decision analysis tool is limitless in literature because DEA does not focus on finding a universal relationship for all unit's undervaluation in the sample. DEA authorities every group in the data to have its production function, and then it evaluates the efficiency of that single unit by comparing it to the effectiveness of the other units in the dataset. After running the three MPI models in DEA SOLVER with every group in the data, DEA categorizes all units into two productive (with one or more than one productivity scores) and unproductive (with less than one productivity scores) groups.

Zhang et al. [16], using the MPI, assessed the performance of events containing Co2 in the transportation industry in China. The investigation took place in several periods, showing that the performance of the Chinese transportation industry had fallen by 32.8 percentage. This declining performance was attributed to a low level of technology in the field Applying the DEA Slack Based Model (SBM) under the reflection of constant returns to scale and variable return to scale technologies, a composite index is considered from the efficiency scores of each model.

A common restriction discovers in the formerly supported DEA models in energy efficiency analysis relates to the lack of undesirable output in the production procedure. Energy consumption produces undesirable output, too, e.g., CO2 emissions in place of a by-product of cement. Therefore, the exclusion of undesirable output does not appear to deliver a broad scale of the production procedure. It is perceived that copious DEA are commonly utilized in different studies to compare, rank, and evaluate energy efficiency. Thus, a comprehensive comparison of several efficiencies delivers insight into the firm's performance. This comparison is of great significance to energy practitioners who desire to assess Eco-efficiency at a proper step of its progression. Thus, it can be beneficial for managers to have superior evaluating, remove unrelated data, and more effective processes.

2. Dataset Description

The standard data set, collected from international cement center covers five years (2015-2019), which is collected from 22 companies. Consequently, two inputs and two outputs which is 2015 to 2019, are presented in Table 1.

Table 1. The inputs and outputs for the 1ST DMUs

Period	**1st Input** (Energy Consumption (10TCE))	**1st Output** (Cement Production (1 ton))	**2nd Input** (Pollution Control Investment 1000RMB))	**2nd Output** (Waste Material Removed (100 kg))
2015	1063116	730865	8000	107237
2016	1425490	1216569	144000	289883
2017	1965650	1560395	144000	254899
2018	2539977	1861560	144000	264522
2019	2805942	2008740	144000	381952

Energy consumptions and pollution control investments in the companies are the first and the second inputs respectively. Cement production and waste material removed in companies are the first and the second outputs correspondingly.

3. Proposed Model

DMU j (j=1,. . . ,n): Cement companies

Xij (i= 1,. . . ,m): is the first input or energy consumption

Ncj (C= 1,. . . ,c) is the second input or pollution control investment

Yrj (r = 1,. . . ,s): is the first output or waste material removed

Mhj (H = 1,. . . ,h) is the second output or cement production

Figure 1 explains the proposed model.

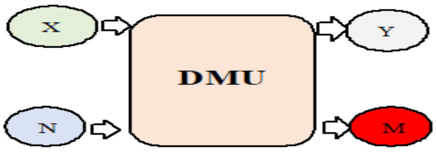

Figure 1. Two inputs and two outputs for the proposed model

4. Evaluation in Malmquist Productivity Index (MPI)

The MPI is considered to evaluate productivity growth relative to a reference technology. Two key issues are addressed in the computation of MPI growth. The first issue is the quantity of productivity change over the period. In contrast, the second is to decompose changes in productivity into what are generally denoted as a catching-up result or technical efficiency change (TEC) and a frontier shift result or technological change (TC). MPI assesses the total factor productivity change of a DMU between two periods. The idea of productivity usually referred to as labor productivity. This concept is related to TFP, defined as the product of efficiency change (catch-up) and technological change (frontier-shift). If TFP value is more than one, this indicates a positive TFP growth from period (t) to period (t+1). In contrast, a value of less than one indicates a decrease in TFP growth or performance relative to the previous year. The frontier obtained in the current (t) and future (t+1) periods are labeled. When inefficiency exists, the relative movement of any given DMU over time will, therefore, depend on both its position relative to the corresponding frontier (technical efficiency) and the position of the frontier itself (technical change), In fact: Malmquist Productivity Index

$$MPI = TEC \times TC \quad (1)$$

5. Result and Discussion

5.1. Result in MPI-FDH Model

The data covers in this study are five years from 2015 to 2019 for 22 local cement companies. The number of DMUs is N or 22, and the period is T or 5.

The average MPI-FDH for all cement companies over 2015-2019 are given in Table 2.

Table 2. Productivity measurement results based on MPI-FDH for 22 companies

Companies	MPI	Rank	Companies	MPI	Rank
1	1.103	5	12	1.035	13
2	1.064	10	13	1.063	9
3	1.138	4	14	0.917	20
4	1.072	7	15	1.020	16
5	0.903	21	16	1.021	15
6	0.957	19	17	1.436	1
7	1.066	8	18	0.975	18
8	1.224	2	19	1.038	12
9	1.056	11	20	1.144	3
10	1.023	14	21	1.076	6
11	0.879	22	22	0.976	17

The efficiency process of MPI-FDH for 22 companies is obtainable in Figure 2. The horizontal axis characterizes the number of cement companies, and the vertical axis describes the average efficiency scores. As shown in Figure 2 and Table 2, the 17th company has the highest efficiency score, and the 11th company has the lowest efficiency score. The efficiency amount of 5th, 6th, 11th, 14th, 18th, and 22nd companies decreased over the five years.

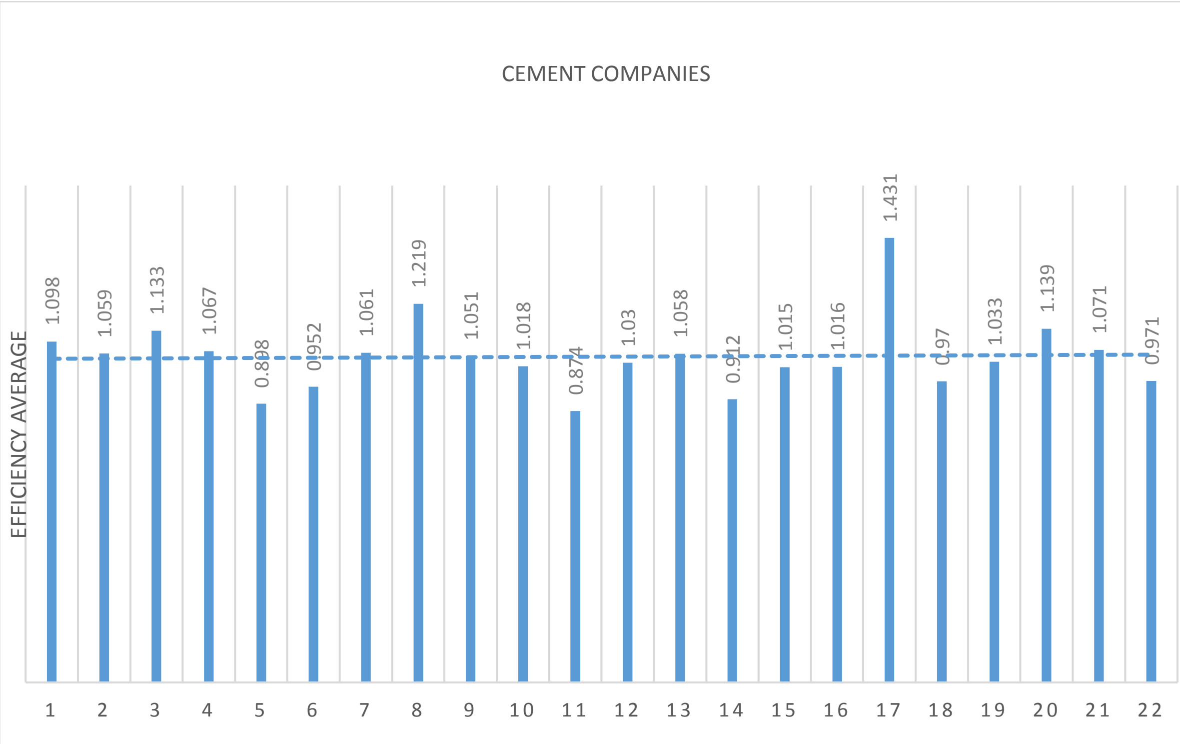

Figure 2. Average efficiency over 5-year periods for 22 DMUs

5.2 Result in MPI-CCR Model

The average MPI-CCR for all cement companies over 2015-2019 are given in Table 3.

The efficiency process of MPI-CCR for 22 companies is obtainable in Figure 3. The horizontal axis characterizes the number of cement companies, and the vertical axis describes the average efficiency scores. As shown in Figure 3 and Table 3, the 17th company has the highest efficiency score, and the 11th company has the lowest efficiency score. The efficiency amount of 5th, 6th, 11th, 14th, 18th, and 22nd companies decreased over the five years.

Table 3. Productivity measurement results based on MPI-CCR for 22 companies

Companies	MPI	Rank	Companies	MPI	Rank
1	1.095	5	12	1.026	13
2	1.054	10	13	1.055	9
3	1.131	4	14	0.909	20
4	1.064	7	15	1.012	16
5	0.894	21	16	1.013	15
6	0.950	19	17	1.428	1
7	1.059	8	18	0.966	18
8	1.216	2	19	1.030	12
9	1.049	11	20	1.136	3
10	1.015	14	21	1.067	6
11	0.871	22	22	0.968	17

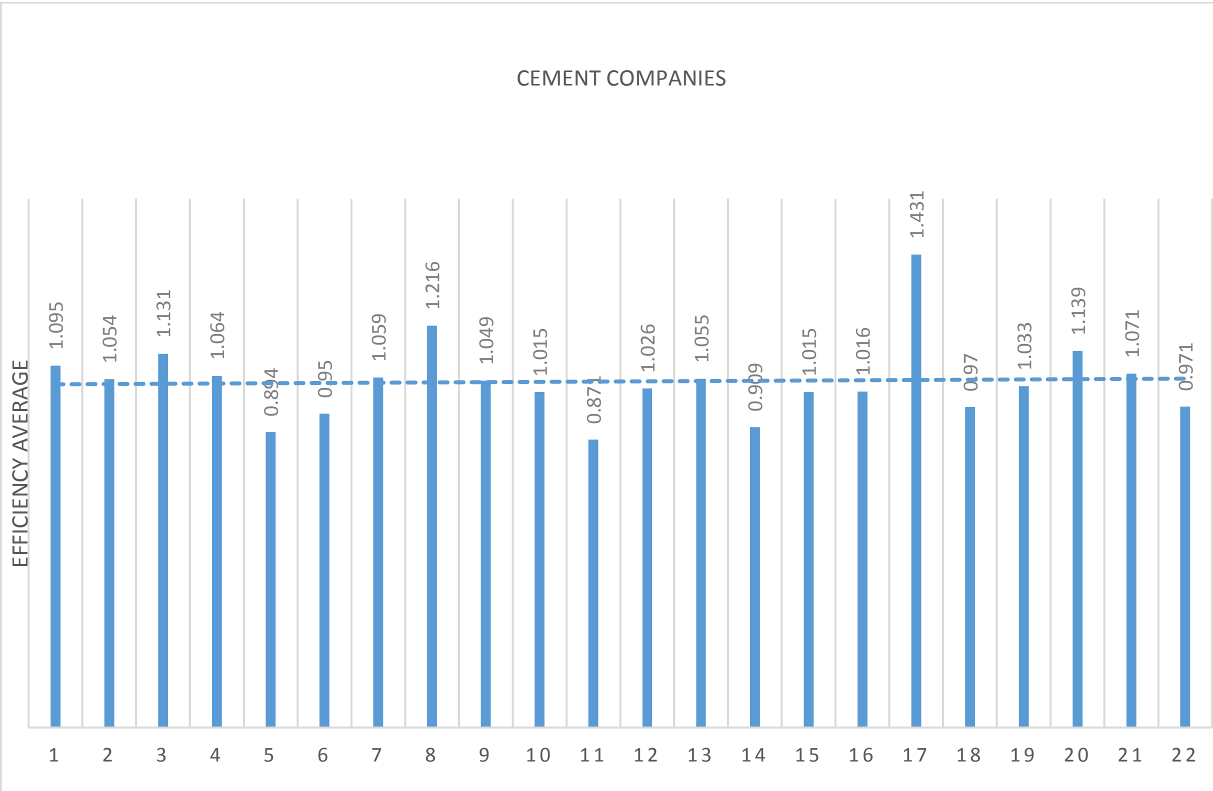

Figure 3. Average efficiency over 5-year periods for 22 DMUs

5.3. Result in MPI-BCC Model

The average MPI-BCC for all cement companies over 2015-2019 are given in Table 4.

Table 4. Productivity measurement results based on MPI-BCC for 22 companies

Companies	MPI	Rank	Companies	MPI	Rank
1	1.096	5	12	1.028	13
2	1.056	10	13	1.056	9
3	1.132	4	14	0.910	20
4	1.065	7	15	1.013	16
5	0.896	21	16	1.014	15
6	0.951	19	17	1.430	1
7	1.060	8	18	0.968	18
8	1.217	2	19	1.031	12
9	1.050	11	20	1.137	3
10	1.016	14	21	1.069	6
11	0.872	22	22	0.969	17

The efficiency process of MPI-BCC for 22 companies is obtainable in Figure 4. The horizontal axis characterizes the number of cement companies, and the vertical axis describes the average efficiency scores. As shown in Figure 4 and Table 4, the 17th company has the highest efficiency score, and the 11th company has the lowest efficiency score. The efficiency amount of 5th, 6th, 11th, 14th, 18th, and 22nd companies decreased over the five years.

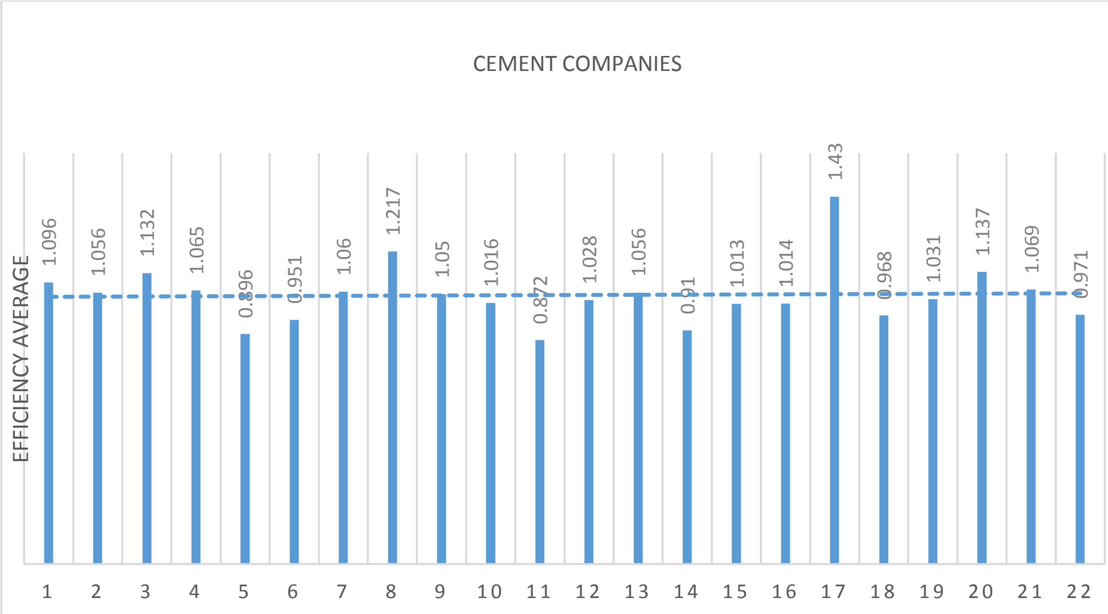

Figure 4. Average efficiency over 5-year periods for 22 DMUs

It can be concluded from Table 2, 3,4, and Figure 2, 3, 4:

- FDH, CCR and BCC models have the same ranking for all DMUs
- FDH model has the highest average efficiency score over 5-years period for 22 DMUs
- BCC model has the second average efficiency score over 5-years period for 22 DMUs
- CCR model has the third average efficiency score over 5-years period for 22 DMUs

FDH model is the best fit model for our evaluation. As we discussed earlier, one of the main advantages of FDH model is if a definite pair of input and output is producible, any pairs of more input and less output for the specific one is also producible. FDH model allows the free impossibility to construct the production possibility set.

6. Conclusion

Decreasing pollutant material investment, as well as energy consumption (inputs of the single proposed model) and increasing waste material removed as well as cement production (outputs of the unique proposed model) have a positive influence on profits, and efficiency of cement companies. The FDH model has a more strengthening impact on Eco-efficiency compare with other models such as CCR and BCC input-oriented and output-oriented. For the third question, the FDH model decreases the value of inputs and increases the value of outputs at the same time. Along with the results obtained from efficiency analysis, the managers of the 17th cement company have the highest efficiency in cement production centers during the five years. They should try to have better efficiency in the future. Consistent with the proposed approach, based on the geometric average, results, and predictions derived from the period in MPI can assist using a practical instrument for the general practitioner to compare the efficiency of uncertain cases and instruct accordingly effectively. Finally, FDH model with remarkable productivity difference received the highest score among another proposed model. For the future work, some other optimization and machine learning algorithms [17-30] will also be taken into account.

Conflict of Interest Statement

The authors declare no conflict of interest.

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