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Evaluating the Performance of Cement Companies Operating in A Stock Exchange: An Application of an Improved Fuzzy Data Envelopment Analysis (FDEA) Model

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Abstract: *In the current study, we have introduced and developed the fuzzy Data Envelopment Analysisi (DEA) model in such a manner that it can be used for an evaluation that is more realistic and more practical. In the existing FDEA models, the model was solved by taking the optimistic and pessimistic approaches. The two approaches have various constraints to determine the performance of Decision Making Units (DMUs), which led to the adoption of different production frontiers for evaluation. If the production frontier is not unified and fixed, then the relation between the performances is meaningless. That is why we have attempted to solve this problem by using the same constraint set for each optimistic and pessimistic approach. In this article, first by using the same constraint set for the both approaches, we have gained a common production frontier, and then we have merged the optimistic and pessimistic models to create a new interval model. Finally, by using the α-cut method, we have turned it into a deterministic model. Then, by substituting variables in the model, the non-linear model was changed to a linear.*
We used the developed model to measure the performance of cement companies. The efficiency that was calculated from this model was represented by the intervals; therefore, we have used the Mini-Max Regret Approach (MRA) method for ranking these interval efficiencies, 11 companies with interval efficiency (1 1) have together got the first place. We use the Anderson-Peterson Approach (AP) approach to rank these 11 companies.

Keywords: Data Envelopment Analysis (DEA), Performance Evaluation, fuzzy logic (FL), α-cut, MRA

INTRODUCTION

The world competition and the ever-rising economic changes have led companies to find more efficient processes to handle their enterprise services (Hatami marbini A, et al., 2010).
The performance evaluations and rankings of decision-making units (DMUs), such as nations, business units, banks, hospitals and non-profit organizations, are becoming increasingly important. Performance is considered a continuous assessment of the units under evaluation. Ranking is a measure of the competitiveness that is the indication of the strength of the unit compared to its competitors. The competiveness of a country is derived from the performance of its bussiness. Performance evaluation and benchmarking are methods extensively utlized to determine the best actions as a tool of improving efficiency and increasing productivity. This highlights the importance of performance evaluation (Mohammad Nordin Hj, et al., 2012).

DEA originally introduced via Charnes, is a non-parametric approach for estimating and determining the comparative effectiveness of entities set, named DMUs, with the standard inputs and outputs. Samples involve school, library, hospital and, entire financial and social organizations, in which data are always multiplied in character (Guo P, et al., 2001). One of the priorities of DEA is that it allows each DMU compare itself with the other DMU. Due to its easy use, DEA was concentrated on via researchers in marketing and academic research (Hemati M, et al., 2012). The second benefit of utilizing DEA is that it doesn't need any hypothesis on the configuration of the frontier surface. Also, it offers no hypotheses regarding the internal process of a DMU (Wang, Y.M, et al., 2005).
The traditional DEA techniques need a precise determination of whole the input and output data. Nevertheless, the detected amounts of the data in real-world queries are sometimes vague (Hamidi.H, et al., 2012). This occurs especially when the DMU has failed or missing input and output, judgmental data, qualitative data, or when data could be predicted. Non-secure input and output or incorrect one can be represented as fuzzy numbers (Hatami-Marbini A, et al., 2011). So, for reaching sensible decisions that are more adaptive to the real world, it is necessary to apply FL as a means to enhance the ultimate purpose. Bellman and Zadeh have introduced the theory of decision-making in fuzzy environments. Various methods were developed in relation to the fuzzy data in DEA. For the first time, Sengupta carried out an investigation applying FL technique in the DEA and implemented the policy of fuzzy set approach to offer fuzziness in the cost function and the right-hand side vector of the traditional DEA. Chiang and Shiang proposed a technique that can give fuzzy performance evaluation for DMUs, via fuzzy observations (Rostami-Malkhalifeh M, et al., 2012).

The FL begins from a fuzzy set approach introduced via Zadeh. It has since discovered employment as a hypothesis of graded theories. It presents a logical structure that vague, conceptual phenomena could be rigorously analyzed. FL models are human experience in various fields. When they implemented to solve efficiency evaluation or forecast queries, FL uses the assistant of the expert knowledge and uses fuzzy arithmetic to generate fuzzy inference schemes. FL is a utilization of the fuzzy set approach, especially applied to deal with the processing of imprecise information via a varied membership function (Udoncy Olugu, et al., 2009).
The significant aim of the current research is to develope a novel interval DEA model that could concurrently overcome the weaknesses of before discussed and pattern imprecise data in a rational, simple and efficient manner. The interval DEA patterns would be proposed for interval data in comparision to the crisp one. The terminal effectiveness rank for per DMU would be described via an interval restricted via the optimal lower bound performance and the optimal upper bound performance of per DMU that we related to as interval performance. A mini-max regret-based method has been proposed to examine the interval capabilities of DMUs.

1. The proposed mothod

Suppose that there were n DMUs to be assessed. Per DMU uses different values of m various inputs to generate s various outputs. DMUj primarily uses values $Xj = \{x_{ij}\}$ of inputs $(i = 1,2,3\ldots, m-1, m)$ and genrates values $Yj = \{y_{rj}\}$ of outputs $(r = 1,2,3\ldots, s-1, s)$. We propose that all data and x_{rj} $(i = 1,2,3,\ldots, m-1, m;\ r = 1,2,3\ldots, s-1, s;\ j = 1,2,\ldots, n-1, n)$ cannot be properly enhanced since the uncertainty existence. They are justdetermined to lie throughout the bounds, expressed via the intervals $[x_{ij}^L, x_{ij}^U]$ and$[y_{rj}^L, y_{rj}^U]$, that $x_{ij}^L > 0$ and $y_{rj}^L > 0$.
The pair of LP models was proposed to produce the bounds of interval performance for per DMU to deal with such an uncertain condition.

$$Max\ E^{U}{}_{0} = \sum_{r=1}^{s} u_r\,(y^{U}{}_{ro})_{\alpha}$$
$$s.t. \qquad \sum_{i=1}^{m} v_i\,(x^{L}{}_{io})_{\alpha} = 1$$
$$\sum_{r=1}^{s} u_r\,(y^{U}{}_{ro})_{\alpha} - \sum_{i=1}^{m} v_i\,(x^{L}{}_{io})_{\alpha} \le 0$$
$$\sum_{r=1}^{s} u_r\,(y^{L}{}_{rj})_{\alpha} - \sum_{i=1}^{m} v_i\,(x^{U}{}_{ij})_{\alpha} \le 0 \quad j = 1,2,3 \ldots n-1, n$$
$$v_i \ge 0 \qquad i = 1,2,3, \ldots m-1, m$$
$$u_r \ge 0 \qquad r = 1,2, \ldots s-1, s \qquad (1)$$

$$Max\ E^{L}{}_{0} = \sum_{r=1}^{s} u_r\,(y^{L}{}_{ro})_{\alpha}$$
$$s.t. \qquad \sum_{i=1}^{m} v_i\,(x^{U}{}_{io})_{\alpha} = 1$$
$$\sum_{r=1}^{s} u_r\,(y^{L}{}_{ro})_{\alpha} - \sum_{i=1}^{m} v_i\,(x^{U}{}_{io})_{\alpha} \le 0$$
$$\sum_{r=1}^{s} u_r\,(y^{U}{}_{rj})_{\alpha} - \sum_{i=1}^{m} v_i\,(x^{L}{}_{ij})_{\alpha} \le 0 \quad j = 1,2,3, \ldots n-1, n$$
$$v_i \ge 0 \qquad i = 1,2,3, \ldots m-1, m$$
$$u_r \ge 0 \qquad r = 1,2,3 \ldots s-1, s \qquad (2)$$

where DMU_o is the DMU under evaluation; v_i and u_r are the weights related to the outputs and inputs; E_o^U and E_o^L are the optimal performances for DMU_o under the optimal condition and the most unsuffiencient condition.

Exactly following the over bounds of the DEA models, we might discover that the constraints utilized to evaluate the effectiveness of DMUs differ from one DMU to the other. Also, despite the constraints used to evaluate the bounds of the performance of the related DMU are distinct from each other. In instance, the constraints employed to evaluate the upper bound performance of DMU_o includs of the data $\{(x_{ijo}^L, y_{rjo}^U), (x_{ij}^U, y_{rj}^L)(j = 1,2, \ldots n-1, n; j \ne 0\,; i = 1,2, \ldots m-1, m\,; r = 1,2, \ldots s-1, s)\}$, whearse the constraints used to evaluate its lower bound effectivness is contained the dataset $\{(x_{ijo}^L, y_{rjo}^U), (x_{ij}^U, y_{rj}^L)(j = 1,2, \ldots n-1, n; j \ne 0\,; i = 1,2, \ldots m-1, m\,; r = 1,2, \ldots s-1, s)\}$. It is clear that these two data are distinct.

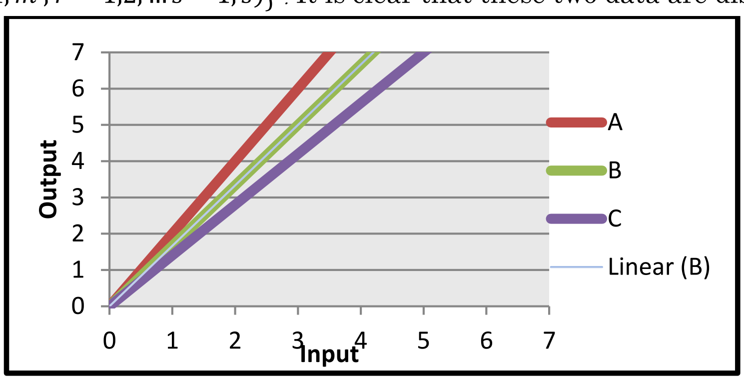

Fig. 1. Production frontiers utilized in 1 & 2 model

The obvious weakness associated with the application of various constraints to evaluate the effectivness of DMUs is that, different constraint make the comparision between the effectiveness complicated since various production frontiers were used in the procedure of performance determination. We consider a simple example of one dataset. Three DMUs—identified as A, B and C in Figure 1—utilize interval inputs (Guo P, et al., 2001; Hamidi.H, et al., 2012), (Hatami-Marbini A, et al., 2011; Hatami marbini A, et al., 2010) & (Hemati M, et al., 2012; Mohammad Nordin Hj, et al., 2012) to provide interval outputs (Guo P, et al., 2001; Hamidi.H, et al., 2012), (Hatami marbini A, et al., 2010; Hemati M, et al., 2012) & (Mohammad Nordin Hj, et al., 2012; Rostami-Malkhalifeh M, et al., 2012). When calculating the upper limit performance of DMUA, pattern (1) applies the data {(1,2),(4,4),(6,6)}, that makes the production frontier indicated via the radiate line OA1 in Figure 1. While determining the upper limit performance of DMUB, pattern (1) applies the data {(2,1),(3,5),(6,6)}, that provides the production frontier indicated via the radiate line OB1 in Figure 1. When calculating the upper limit performance of DMUC, model (1) uses the data {(2,1),(4,4),(5,7)}, that generates the production frontier indicated via the radiate line OC1. The production frontiers applied to calculate the lower limit performances of DMUA, DMUB & DMUC are the radiate lines OB1, OA1 & OC1 respectively. As the performance is measured as the rate of the real output to the max one on the production frontier, if they weren't set and united, the relations between the performances will become pointless.

Also, we believe DMUs could just have a single real production frontier. As per DMU has the probability of utilizing the minimum inputs to generate the greatest outputs, the actual production frontier should be created by the optimal production action state of per DMU. The actual and identified production frontier in Figure 1 is the discharge line OA1, that is created by the data {(1,2),(3,5),(5,7)} (Wang, Y.M, et al., 2005).

To prevent the application of various production frontiers to determine and examine the effectiveness of various DMUs, a novel interval DEA model would be proposed. The model are according to the interval estimation and ever utilize the same constraints that arrangements a unified and fixed production frontier, for whole DMUs further in order to the estimate lower and upper bound performances.

$$
\begin{aligned}
& Max\ E^U{}_0 = \sum_{r=1}^{s} u_r\,(y^U{}_{ro})_\alpha \\
& s.t. \quad \sum_{i=1}^{m} v_i\,(x^L{}_{io})_\alpha = 1 \\
& \qquad \sum_{r=1}^{s} u_r\,(y^U{}_{rj})_\alpha - \sum_{i=1}^{m} v_i\,(x^L{}_{ij})_\alpha \le 0 \quad j = 1,2,3,\dots n-1, n \\
& \qquad v_i \ge 0 \qquad i = 1,\dots,m \\
& \qquad u_r \ge 0 \qquad r = 1,\dots,s \qquad (3)
\end{aligned}
$$

$$
\begin{aligned}
& Max\ E^L{}_0 = \sum_{r=1}^{s} u_r\,(y^L{}_{ro})_\alpha \\
& s.t. \quad \sum_{i=1}^{m} v_i\,(x^U{}_{io})_\alpha = 1 \\
& \qquad \sum_{r=1}^{s} u_r\,(y^U{}_{rj})_\alpha - \sum_{i=1}^{m} v_i\,(x^L{}_{ij})_\alpha \le 0 \quad j = 1,2,\dots n-1, n \\
& \qquad v_i \ge 0 \qquad i = 1,2,\dots m-1, m \\
& \qquad u_r \ge 0 \qquad r = 1,2 \dots s-1, s \qquad (4)
\end{aligned}
$$

In the proposed model, instead of using ordinary numbers, we used interval numbers, so that it is reasonable that the calculated efficiency will be interval-based, too. In former models, we utilized to get upper and lower bounds of performance through two separate optimistic and pessimistic models, but in the proposed model, these two optimistic and pessimistic models are affricated into a single model. Therefore, in the following model, the efficiency will be interval-based.

$$
\begin{aligned}
& Max\ E_0 = \sum_{r=1}^{s} u_r \left[(y^U{}_{ro})_\alpha \quad (y^L{}_{ro})_\alpha \right] \\
& s.t. \quad \sum_{i=1}^{m} v_i \left[(x^L{}_{io})_\alpha \quad (x^U{}_{io})_\alpha \right] = 1 \\
& \sum_{r=1}^{s} u_r \left[(y^U{}_{rj})_\alpha \quad (y^L{}_{rj})_\alpha \right] - \sum_{i=1}^{m} v_i \left[(x^L{}_{ij})_\alpha \quad (x^U{}_{ij})_\alpha \right] \le 0 \qquad j = 1, \dots, n \\
& v_i \ge 0 \qquad i = 1,2 \dots m-1, m \\
& u_r \ge 0 \qquad r = 1,2 \dots s-1, s \qquad (5)
\end{aligned}
$$

$$\tilde{x}_{ij} = \left(x^1{}_{ij}, x^2{}_{ij}, x^3{}_{ij}, x^4{}_{ij} \right)$$

$$\tilde{y}_{rj} = \left(y^1{}_{rj}, y^2{}_{rj}, y^3{}_{rj}, y^4{}_{rj} \right)$$

$$
\begin{aligned}
& \left(x^L{}_{ij} \right)_\alpha = x^1{}_{ij} + \alpha\left(x^2{}_{ij} - x^1{}_{ij} \right), \quad \alpha \in [0,1], i = 1,2 \dots m-1, m; \\
& j = 1, \dots, n \\
& \left(x^U{}_{ij} \right)_\alpha = x^4{}_{ij} - \alpha\left(x^4{}_{ij} - x^3{}_{ij} \right), \quad \alpha \in [0,1], i = 1,2 \dots m-1, m; \\
& j = 1, \dots, n \\
& \left(y^L{}_{rj} \right)_\alpha = x^1{}_{rj} + \alpha\left(y^2{}_{rj} - y^1{}_{rj} \right), \quad \alpha \in [0,1], r = 1,2 \dots s-1, s; \\
& j = 1, \dots, n \\
& \left(y^U{}_{rj} \right)_\alpha = x^4{}_{rj} - \alpha\left(y^4{}_{rj} - y^3{}_{rj} \right), \quad \alpha \in [0,1], r = 1,2 \dots s-1, s; \\
& j = 1, \dots, n
\end{aligned}
$$

$$
\begin{aligned}
& Max\ E_0 = \sum_{r=1}^{s} u_r \left[y^4{}_{ro} - \alpha\left(y^4{}_{ro} - y^3{}_{ro} \right) \quad y^1{}_{ro} + \alpha\left(y^2{}_{ro} - y^1{}_{ro} \right) \right] \\
& s.t. \quad \sum_{i=1}^{m} v_i \left[x^1{}_{io} + \alpha(x^2{}_{io} - x^1{}_{io}) \quad x^4{}_{io} - \alpha(x^4{}_{io} - x^3{}_{io}) \right] = 1 \\
& \sum_{r=1}^{s} u_r \left[y^4{}_{rj} - \alpha\left(y^4{}_{rj} - y^3{}_{rj} \right) \quad y^1{}_{rj} + \alpha\left(y^2{}_{rj} - y^1{}_{rj} \right) \right] \\
& \quad - \sum_{i=1}^{m} v_i \left[x^1{}_{ij} + \alpha\left(x^2{}_{ij} - x^1{}_{ij} \right) \quad x^4{}_{ij} - \alpha\left(x^4{}_{ij} - x^3{}_{ij} \right) \right] \le 0 \\
& j = 1, \dots, n \\
& v_i \ge 0 \qquad i = 1,2 \dots m-1, m \\
& u_r \ge 0 \qquad r = 1,2 \dots s-1, s \qquad (6)
\end{aligned}
$$

As one can see above, after using the α-cut method to turn the new model from a fuzzy to a deterministic one, it became a nonlinear model—and the model has variables correlated to α, which generally makes the achievement of the global optimal solution impossible. It must also be solved for different α values, which lead to high volumes of calculation. On the other hand, there is no general rule for determining the values of α. And it could be lead to inconsistent ranks for one DMU. So, through variable substitution, we eliminate α from the new model and it becomes a linear model.

$$\acute{v}_i = v_i\alpha$$
$$i = 1,2 \dots m-1, m$$
$$\acute{u}_r = u_r\alpha$$
$$r = 1,2 \dots s-1, s$$
$$0 \le \acute{v}_i \le v_i$$
$$0 \le \acute{u}_r \le u_r$$

To overcome this shortcoming, we include Equations 5 and 6 in the model. The final model is as follows:

$$Max\ E_0 = \sum_{r=1}^{s}\left[u_r {y^4}_{ro} - \acute{u}_r\left({y^4}_{ro} - {y^3}_{ro}\right) \quad u_r\, {y^1}_{ro} + \acute{u}_r\left({y^2}_{ro} - {y^1}_{ro}\right)\right]$$
$$s.t.\ \sum_{i=1}^{m}\left[v_i {x^1}_{io} + \acute{v}_i({x^2}_{io} - {x^1}_{io}) \quad v_i {x^4}_{io} - \acute{v}_i({x^4}_{io} - {x^3}_{io})\right] = 1$$
$$\sum_{r=1}^{s}\left[u_r {y^4}_{rj} - \acute{u}_r\left({y^4}_{rj} - {y^3}_{rj}\right) \quad u_r {y^1}_{rj} + \acute{u}_r\left({y^2}_{rj} - {y^1}_{rj}\right)\right]$$
$$- \sum_{i=1}^{m}\left[v_i {x^1}_{ij} + \acute{v}_i\left({x^2}_{ij} - {x^1}_{ij}\right) \quad v_i {x^4}_{ij} - \acute{v}_i\left({x^4}_{ij} - {x^3}_{ij}\right)\right] \le 0$$
$$j = 1,2 \dots n-1, n$$
$$v_i \ge 0 \qquad i = 1,2 \dots m-1, m$$
$$u_r \ge 0 \qquad r = 1,2 \dots s-1, s$$
$$0 \le \acute{v}_i \le v_i$$
$$0 \le \acute{u}_r \le u_r \qquad (7)$$

The new model is linear. Because of that, we are able to achieve the global optimal solution. We can solve the model by operations research software like Lingo for each DMU, and the relative efficiency will be interval-based.

2. Results

In the current research, we used the developed interval DEA model to measure the interval efficiencies of cement factories operating in a stock exchange, and to evaluate the performance of these DMUs, we used the financial information of 30 of them during 2006–13.

Choosing the best set of inputs and outputs is one of the most important steps to measure the efficiency in the DEA approach. Because of that, with regard to experts' opinions and limited access to the data, we chose five input and five output variables, as in the following:

Table 1. The table of input and output variables

Output variables		Input variables	
Non-financial	Financial	Non-financial	Financial
Capacity	Quick Ratio	Human resources	Ratio of total debt to total assets
Capacity Utilization	ROA	Energy	The average of collection
	Inventory Turnover	Raw material	

1-3. Data analysis and findings of the research

The developed interval DEA patterns were developed to measure the bounds of the best comparative performance of per DMU via interval data that are distinctive from the interval determined via the best and the worst comparative performances of per DMU. We solved the new interval model by Lingo and the interval efficiency of each company is shown in Table 2. Eleven factories with (1 1) efficiency were known as efficient factories and the rest were inefficient.

2-3. Mini-max regret approach (MRA)

Here we present the MRA proposed via Wang. The method contains some interesting charachter and could be utilized to evaluate the effectivness intervals of DMUs even if they are equal-united though varying in widths. The method is considred as:

$Ai = [a_i^L, a_i^U] = (m(Ai), w(Ai))\ (i = 1, \ldots, n)$ is the effectivness intervals of n DMUs that $w(Ai) = \frac{1}{2}(a_i^R - a_i^L)$ $and\ m(Ai) = \frac{1}{2}(a_i^R + a_i^L)$ are their widths and midpoints respectively. Propose $Ai = [aLi, aUi]$ is selected as the optimal performance interval. Considere $b = max_{j\neq i}\{a_i^U\}$. Clearly, if $a_i^L < b$, the DM may suffer the performance loss (In addition named the opportunity loss) and makes regret. The Max efficiency loss which may be suffered is produced as

$$max(ri) = b - a_i^L = max_{j\neq i}\{a_i^U\} - a_i^L$$

If $a_i^L \geq b$, the DM would exactly suffer no efficiency loss and makes no regret. In this condition, his/her regret is expressed is equal to 0. By considering the aftermentioned two condition concurrently, we have:

$$max(r_i) = max\left[max_{j\neq i}(a_i^U) - a_i^L, 0\right].$$

Thus, the mini-max regret criterion will determine the performance interval providing the following situation as the optimal performance interval:

$$min_i\{max(r_i)\} = min_i\left\{max\left[max_{j\neq i}(a_i^U) - a_i^L, 0\right]\right\}$$

Let $Ai = [a_i^L, a_i^U] = (m(Ai), w(Ai))\ (i = 1, 2 \ldots n-1, n))$ be a collection of performance intervals. The most efficiency loss of per performance interval Ai is expressed as:

$$R(A_i) = max\left[max_{j\neq i}(a_i^U) - a_i^L, 0\right] = max\left[max_{j\neq i}\{m(Aj) + w(Aj)\} - \left(m(Ai) - w(Ai)\right), 0\right], i = 1, 2 \ldots n-1, n.$$

It is obvious that the performance interval by the smallest Max efficiency loss is the desired performance interval.

As the Max losses of efficiency are related numbers, these are defined via the Max performance between whole the other performance intervals. Hence, these could just be utilized to select the optimal performance interval between a collection of performance intervals. However, these cannot be utilized to rank them straight (Wang, Y.M, et al., 2005).

MRA was employed to measure of these 30 DMUs; the results are shown in Table 2:

Table 2. Interval efficiency and the rank of companies

DMU	interval performance	Rank	DMU	interval performance	Rank
2	(1 1)	1	10	(0.92 0.97)	6
6	(1 1)	1	1	(0.921 1)	7
7	(1 1)	1	4	(0.91 0.99)	8
11	(1 1)	1	24	(0.90 0.99)	9

14	(1 1)	1	27	(0.83 0.93)	10
19	(1 1)	1	5	(0.82 0.95)	11
21	(1 1)	1	8	(0.82 0.93)	12
22	(1 1)	1	28	(0.80 1)	13
23	(1 1)	1	13	(0.79 0.97)	14
26	(1 1)	1	17	(0.77 0.89)	15
29	(1 1)	1	9	(0.76 1)	16
25	(0.98 1)	2	20	(0.71 0.89)	17
12	(0.97 1)	3	3	(0.70 0.86)	18
30	(0.95 0.96)	4	16	(0.68 0.89)	19
15	(0.93 0.99)	5	18	(0.53 0.74)	20

As we can see, by using the RMA to compare and rank the factories, 11 of them obtained the first place at the same time since they achieved (1 1) score of efficiency, and so, we used the AP approach and the optimistic efficiency score to rank these 11 factories. In this approach, we eliminate the constraint corresponding to the unit under review because after eliminating the constraint, the efficiency will go much far than 1. The results are shown in Table 3:

Table 3. Ranking the efficient company

DMU	Score of efficiency	Rank
7	1.73	1
23	1.37	2
22	1.29	3
19	1.19	4
21	1.16	5
2	1.13	6
29	1.10	7
26	1.09	8
6	1.04	9
11	1.03	10
14	1.02	11

The final ranks of factories are shown in Table 4:

Table 4. Final ranks of companies

DMU	Rank	DMU	Rank
7	1	10	16
23	2	1	17
22	3	4	18
19	4	24	19
21	5	27	20
2	6	5	21
29	7	8	22
26	8	28	23
6	9	13	24
11	10	17	25
14	11	9	26
25	12	20	27

12	13	3	28
30	14	16	29
15	15	18	30

3. Conclusions

In the current research, we have proposed a novel interval DEA model by using the DEA approach and FL in order to relation with imprecise data like interval, ordinal preference, and fuzzy data. The main purpose behind developing this new model is to be able to evaluate the performance of DMUs without any interference from managers who want to show the efficiency as being higher than in reality. For overcoming this shortcoming, we eliminate α from the fuzzy model, so that the managers could not change the efficiency score through manipulation of the α-level, and with that, the model became a linear one. We used the proposed model to measure the effectivness of 30 cement factories operating in stock exchanges. A MRA is used to measure these 30 factories. As we saw by using the RMA to compare and rank the factories, 11 of them get the first place at the same time since they achieved (1 1) score of efficiency. So we used the AP approach and the optimistic efficiency score to rank these 11 factories.

Our new interval DEA model utilizes a unified and fixed production frontier as a benchmark to evaluate the effectiveness of whole DMUs that lead to reliability and accurately of the proposed model. The application of a unified and fixed production frontier further simplifies—to a large degree—the calculation of the effectiveness of those DMUs without any fuzziness since the α-level has no influence on their performances. There is no requirement to recomputing them for various α-levels.

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