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EVALUATION OF PLASTERING CREW PERFORMANCE IN BUILDING PROJECTS USING DATA ENVELOPMENT ANALYSIS

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Abstract. The research question addressed in this study was how the performance of construction crews working in a certain project or locality could be evaluated, ranked and improved. To develop and demonstrate the relevant framework, data envelopment analysis (DEA) was applied to establish the relative efficiency of plastering crews working in building projects located in different cities around Turkey. Data were collected from 40 crews of varying characteristics, and their technical efficiency scores were computed using the Banker, Charnes and Cooper (BCC) model, which is based on variable returns-to-scale (VRS). The model yields efficiency scores that range between 0 and 1, and a company or crew is considered efficient if its score is 1.0 (100%). Efficient and inefficient crews were identified and ranked on this basis in the study. Cross tabulation analyses were subsequently conducted to gain further insights into the relationships between the efficiency scores and input factors of numbers of skilled and unskilled laborers, daily labor unit costs, work hours, average age of crew members, total crew experience, plastering location, plastering technique, and plaster type. No discernible relationship could be identified between the efficiency scores and productivity outputs of the crews. It was found that plastering technique, plastering location, and total crew experience had a significant association with crew efficiency. Efficiency improvement strategies identified included training, hiring experienced plasterers, adopting more advanced plastering technology, implementing better jobsite management practices, and enhancing workers' knowledge, skills and attitude towards productivity and quality.

Keywords: plasterer crew efficiency, data envelopment analysis, BCC model, cross tabulation analysis, performance improvement.

JEL Classification: C67, C81, D24, L25.

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Introduction

Productivity of construction crews, based on the relationship between the input (work hours) and the resultant output (quantity produced) has been of keen interest to researchers and practitioners (Liou, Borcherding 1986; Zakeri *et al.* 1996; Fayek, Oduba 2005; Song, AbouRizk 2008). However, because this concept is relatively narrow, involving a single input and a single output, adopting a broader performance measure has been considered desirable. Data envelopment analysis (DEA) was introduced by Charnes *et al.* (1978) to accommodate multiple inputs and outputs, enabling the evaluation of the relative efficiencies of decision making units (DMU's) and their ranking based on this criterion.

The research described here was undertaken under the auspices of a larger investigation aimed at the identification and analysis of the factors affecting the productivity of work crews (masons, formwork carpenters, plasterers and painters) engaged in reinforced concrete building construction projects in Turkey. Artificial neural network methodologies, such as Feed Forward Neural Network (FFNN), Radial Basis Neural Network (RBNN), and Self Organizing Maps (SOM) were employed to model the relationship between the productivity output and selected input factors. The results of these studies have been disseminated in (Oral *et al.* 2008, 2012; Oral, E. L., Oral, M. 2010; Gerek *et al.* 2014). This paper extends this work into the use of DEA for evaluating the performance of the plastering crews in terms of both productivity and efficiency, and then supplementing the findings by applying cross tabulation analysis.

1. Literature review

The specific research question addressed relative to efficiency was how the performance of different plastering crews in a group of projects could be evaluated, ranked and improved. The DEA technique adopted for this purpose provides the ability to benchmark against competing and noncompeting entities, while also affording opportunities for devising efficiency improvements. Since its inception, many developments have been realized in the DEA domain, and the methodology has been applied to a wide range of fields, such as banking (Mukherjee *et al.* 2001), iron and steel industry (Ma *et al.* 2002), marketing (Donthu *et al.* 2005), manufacturing industry (Duzakın, E., Duzakın, H. 2007), agriculture and animal science (Chen *et al.* 2008; Chen 2012), education (Johnes, Yu 2008), transportation (Barros, Peypoch 2009; Erturk, Asık 2011), and energy technologies (Lee, W. S., Lee, K. P. 2009; Cristobal 2011).

DEA has also been recognized as a beneficial tool in the construction arena. Wang and Chau (2001) evaluated the factors affecting the technical efficiency ratios of construction firms in Hong Kong using DEA. Pilateris and McCabe (2003) analyzed various contractors' financial performance with this technique. McCabe *et al.* (2005) utilized DEA in contractor prequalification. Vitner *et al.* (2006) investigated the possibility of using the DEA approach for evaluating the performances of projects in a multi-project environment. El-Mashaleh (2010) proposed a DEA approach for guiding contractors in the bidding process. Xue *et al.* (2008) used the DEA-based Malmquist productivity index (MPI) as a support tool for measuring the productivity changes in the Chinese construction industry from 1997 to 2003. Oggioni *et al*. (2011) evaluated the eco-efficiency of cement in European (EU) and other countries. Tsolas (2012) evaluated the performance of nineteen construction firms listed on the Athens Exchange by applying DEA and regression analysis.

2. DEA fundamentals

DEA is a popular nonparametric method based on linear programming, and it performs a frontier analysis of inputs and outputs. The efficient frontier (Fig. 1) defines the maximum combinations of outputs that can be produced for a given set of inputs. Efficiency is defined by the success with which a DMU (e.g. an organization or entity) uses its resources to produce outputs of a given quality (Wu 2009).

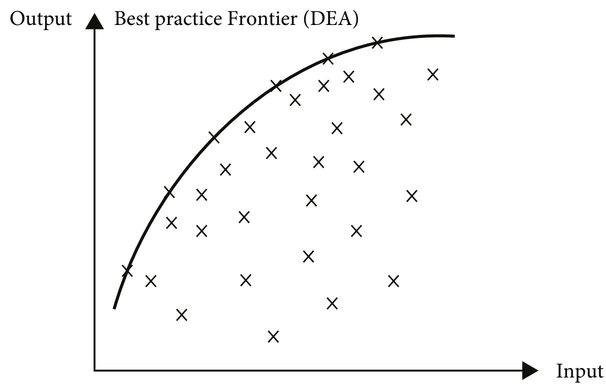

Fig. 1. Efficient frontier of DEA

The most common efficiency concept is technical efficiency, which is based on the conversion of physical inputs (e.g. services of employees and machines) into outputs relative to best practice. This implies that with current technology, there is no wasting of inputs in producing the given quantity of output. A DMU operating at the best practice level is given a score of one, which means it is 100 percent technically efficient. The score is computed as the ratio of the (radial) distance from the origin to the inefficient unit divided by the distance from the origin to the composite unit on the efficient frontier. So, DEA assigns an efficiency score of less than 100 percent to (relatively) inefficient units (Hussain, Jones 2001). Managerial practices and the scale or size of operations affect technical efficiency, which is based on engineering relationships but not on prices and costs (Wang, Chau 2001).

The concept was first introduced by Farrell (1957) and evolved over the years through the development of a number of DEA models. As discussed by Schubert (2011), the models can be categorized based on the economic concept of returns to scale, which is a term arising in the context of an entity's production function. It refers to changes in the output resulting from a proportional change in all inputs (where all inputs increase by a constant factor). If output increases by that same proportional change, then the model is constant returns to scale (CRS). If the output decreases or increases, respectively, by more or less than that proportional change, then the model becomes variable returns to scale (VRS). These two categories of models are shown in Figure 2, representing the first level of DEA model classification. The model can be input- or output-oriented for either category as shown in Figure 2.

The best known and widely used models are the *Charnes, Cooper, Rhodes model (CCR)* and the *Banker, Charnes, Cooper model (BCC)*, both of which can be input- or output-oriented. The CCR model, developed by Charnes *et al.* (1978), is widely used when a CRS relationship is assumed between inputs and outputs. It calculates the overall efficiency for each unit, where technical and scale efficiencies are aggregated into one value. The drawback with the CCR model is that it ignores the fact that different DMU's could be operating at different scales. To overcome this drawback, Banker *et al.* (1984) developed the VRS-based BCC model, which compares DMU's solely on the basis of technical efficiency (Kabnurkar 2001).

The basic aim of the DEA models is minimizing the use of inputs to produce a given level of output, or maximizing the level of output at given levels of inputs. With input-oriented DEA, the model is configured so as to determine how much the inputs could be reduced if the entity is operated efficiently in order to achieve the same output level. In contrast, with output-oriented DEA, given a set of inputs, the model is configured to determine the potential output, if the entity is operated efficiently along the best practice frontier.

Nonoriented additive and multiplicative models are also included in Figure 2. In these models, the output frontier and efficiencies may be determined without being conditional on input or output levels being held constant. The nonoriented DEA models share the common feature of maximizing slacks. As a consequence, the targets these models identify are the furthest from each DMU being assessed. Detailed descriptions of the nonoriented models are outside the scope of this paper, but they have been covered in depth by Portela *et al.* (2003).

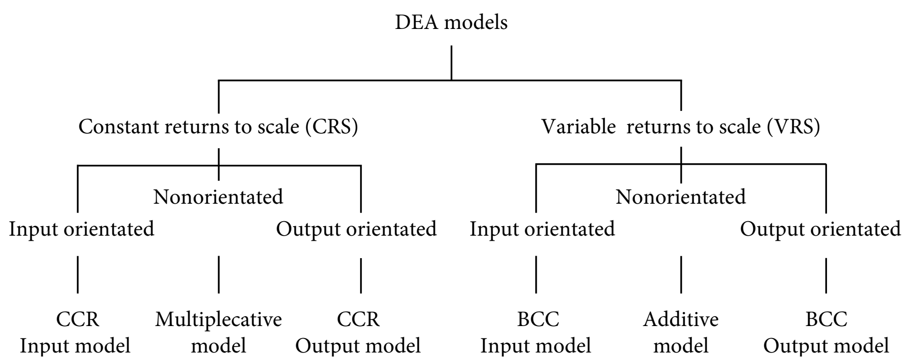

Fig. 2. DEA models

An input or output variable for a DEA model can be controllable or uncontrollable depending on whether the unit's management does or does not have control and ability to alter the level of use or production. Controllable variables are also referred to as "discretionary", while uncontrollable variables are termed "nondiscretionary" (Hussain, Jones 2001). It is important to identify the controllable variables in a DMU, because they are the ones that mainly offer possibilities for modifications in materials, processes, etc. to affect efficiency improvements.

All inputs and outputs have an impact on operational efficiency for all DMUs. According to Vincová (2005), efficiency can be based on ratios for the CCR model.

Let

p be the number of output measures;
m be the number of input measures;
k be the number of DMUs which are being evaluated with respect to one another;
y_{rk} be the value (≥0) of output measure $r(r = 1; \ldots ; p)$ for DMU $k(k = 1; \ldots ; n)$;
x_{ik} be the value (≥0) of input measure $i(i = 1; \ldots ; m)$ for DMU $k(1; \ldots ; n)$;
u_r be the weight (≥0) attached to output measure $r(r = 1; \ldots ; p)$ by DMU $k(k = 1; \ldots ; n)$;
v_i be the weight (≥0) attached to input measure $i(i = 1; \ldots ; m)$ by DMU $k(k = 1; \ldots ; n)$;
E_k be the (relative) efficiency of $k(k = 1; \ldots ; n)$ when evaluated using the weights; and
$\in$ be very small, a "non-Archimedean" number $(0 < e < \leq 1)$.

Then the input and output can be expressed in matrix form as:

$$x = [x_{ik}, i = 1; \ldots ; m, k = 1; \ldots; n];$$

$$y = [y_{rk}, r = 1; \ldots ; p, k = 1; \ldots ; n].$$

Then for a given DMU, the efficiency rate is given by:

$$\frac{\textit{weighted sum of outputs}}{\textit{weighted sum of inputs}} = \frac{\sum_{r=1}^{p} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}}.$$

It is important to note that DEA models derive input and output weights by means of an optimizing calculation. In this process, x and y values are data, and u and v become variables. Whereas an input minimization approach is used in the CCR model, outputs are maximized in the BCC model.

$$E_k = \mathrm{Max}\left(\sum_{r=1}^{p} u_r y_{rk}\right) \Big/ \left(\sum_{i=1}^{m} v_i x_{ik}\right);$$

$$v_i \geq \in \quad i = 1, \ldots, m;$$

$$u_r \geq \in \quad r = 1, \ldots, p.$$

The BCC model was incorporated in this study as described in the next section.

3. Research methodology and data analysis

Extensive data on various crews was collected in the larger project by using time study sheets, jobsite records, and questionnaires distributed to workers and supervisors. The crews studied were active in multi-story reinforced concrete residential construction projects in 10 different cities in north western, central, eastern and south eastern Turkey between the years 2006 and 2008. As mentioned, various nonparametric data analyses were performed using these data. It is important to note that the research on construction crew productivity reported in the literature cover a broad range of input factors, including material and equipment characteristics, worker skill levels, distractions and work stoppage due to a variety of reasons, and deficiencies in operations leading to waste of resources, rework, and consequent loss in productivity (Oral *et al.* 2008; Song, AbouRizk 2008). Overall, the input factors selected for our study were based on literature review, interviews with project managers, and practical constraints on data acquisition.

For the specific DEA study reported here, 40 plastering crews (and their data) were randomly selected and analyzed. Each plastering crew was treated as a DMU for the purposes of this study. In regard to the sample size to be selected for DEA, it is recommended that a minimum of twice the sum of inputs and outputs be taken as the number of DMUs to be analyzed (Maidamisa *et al.* 2012). The sample size of 40 plastering crews is based on a multiplier of 4.

Using the data subset for plasterers, crew productivity and technical efficiency values were computed for each crew using the BCC model and the DEA-Solver software (Cooper *et al.* 1999).The basis for selecting this VRS-based and output-oriented model was that it was concluded from observations on the collected data that increasing inputs (resources) for plastering crews would not necessarily result in a proportionate increase in the output (total amount of plastered surface).

The crew efficiency input factors included in the current study are listed in Table 1. These factors are grouped in three categories. *Laborer related factors* encompass the number of skilled laborers in the crew (SL), number of unskilled laborers (UL), average crew age (A), and total length of crew experience (E). The *contract-based factors* consist of daily unit cost of crew labor (UC) and total daily work hours (WH). Plastering location (PL), plastering type (PTP) and plastering technique (PT) make up the *technical factors*. Data types (continuous vs. categorical), and whether the factor is controllable or uncontrollable are also indicated in the table, and the ranges of values for the categorical variables are provided. Lastly, Table 1 includes the output variable, daily total production quantity (PQ), which is the total area of plastered surface completed by the crew. Additional input factors used in the broader study were birth place and education level of the crew members, distance commuted to jobsite, length of breaks during work hours, existence of direct supervision, quality of equipment and tools used in plastering, and job mix formula for the plaster mix. These factors were excluded from this effort to keep our scope to a manageable level, but they can be incorporated in future research endeavours.

Table 2 complements the data given in Table 1, showing the mean, standard deviation and range (minimum and maximum) for the continuous variables. The Pearson correlation analysis performed on pairs of these input factors yielded relatively low coefficients (below 0.5), so they were considered independent and mutually exclusive. Consequently, all of the input factors shown in Table 1 were included in the DEA study. It should be noted that product quality considerations were excluded from this study.

After completing the DEA calculations to determine the crew efficiencies and to rank them for benchmarking, cross tabulation analyses between the selected input factors and the output efficiency values were performed to supplement to the DEA results. Cross tabulation is a statistical technique utilizing joint frequency distribution of cases based on two or more categorical variables displayed on a contingency table. Chi-squared hypothesis testing follows this analysis to determine whether the variables are statistically dependent or if they are associated. Fisher's exact test is generally used for small samples (e.g. less than 5 observations in any cell), and is applied to 2 by 2 contingency tables (Ozdamar 2009). The SPSS software was employed for all analyses performed in this research.

Table 1. Crew efficiency input factors included in the study

Factors	Abbr.	Data type	Management control	Values
Input factors				
Laborer related factors				
No. of skilled laborers	SL	Cont.	Yes	See Table 2
No. of unskilled laborers	UL	Cont.	Yes	See Table 2
Average age of crew (yr)	A	Categ.	No	$18 < A < 30$ $30 \leq A \leq 35$ $35 > A > 44$
Total experience of crew (mo.)	E	Categ.	No	$1 \leq E \leq 120$ $121 \leq E \leq 202$ $203 \leq E \leq 300$
Contract-based factors				
Daily crew labor unit cost (€)	UC	Cont.	Yes	See Table 2
Daily total crew work hours (h)	WH	Cont.	Yes	See Table 2
Technical factors				
Plastering location	PL	Categ.	No	Interior Exterior Ceiling
Plaster type	PTP	Categ.	No	Roughcast Finish
Plastering technique	PT	Categ.	Yes	Spray Hand
Output factor				
Daily total production (m^2)	PQ	Cont.	No	See Table 2

Table 2. Descriptive statistics for the continuous variables

Factor	Mean	Std. deviation	Min.	Max.
SL	4.03	1.64	1	7
UL	2.25	1.10	1	5
UC	21.72	1.31	18.25	23.71
WH	49.50	15.84	24	80
PQ	48.68	19.28	16	90

4. Results and discussion

4.1. Data envelopment analysis

Table 3 shows the efficiency scores of the plastering crews (PC) determined by DEA and listed top down in ranking order. The PC numbers shown are identification numbers assigned to the crews in the database. The ranking is based on the efficiency scores, and for crews with 100% efficiency, on productivity outputs. The results show how each crew has performed in comparison to the rest of the crews. The first thirteen plastering crews listed in the table have the highest efficiency (100%), while the rest show lower values indicating inefficiency.

The overall correlation between efficiency and productivity was found to be moderately low (r = 0.498), which suggested that a discernable relationship or pattern would not be expected to exist between the efficiency and productivity values presented in Table 3. Along these lines, productivity is observed to vary between 1.30 and 0.74 m^2/hr among the crews with a constant efficiency score of 100 percent, while for the lower efficiency scores, a relatively higher efficiency score may correspond to a higher or lower productivity output. Comparing, for example, the efficiency scores and total productivity values of crews PC40 and PC19, one observes that efficiency is smaller for the latter crew while productivity is unchanged. Viewing the data for crews PC33 and PC12, it is noted that a small decrease in efficiency from the first to the second occurs with a significant drop in productivity. Then, an opposite tendency is evident in the case of crews PC3 and PC25, increased productivity yields a smaller efficiency score. Finally, comparing productivity values with the sample mean, one can observe that 100 percent efficient crews (e.g. PC31, PC37 and PC20) can even have below average productivity. This implies that the crews identified as efficient can be viewed as those which have made optimal use of their available resources.

The difference between the efficient frontier and daily total production for a given crew, expressed as a percentage of the efficient frontier value, is also shown in Table 3, which is an indication of (and termed as) the "potential improvement opportunity". These values are zero on the efficient frontier, and they increase as the daily total production becomes more distant from the frontier for the inefficient crews. The higher this ratio (percentage), the more is the magnitude of improvement needed to make up the difference between where a crew currently stands and the efficient frontier value that it may aspire to. Clearly, if the efficiency score of a crew is below 100 percent, there is room for operational improvement regardless of the productivity output.

Table 3. Efficiency scores and ranking of plastering crew performance

Plastering crew No.	Daily total production (m^2)	Daily total crew work hours (h)	Crew productivity (m^2/h)	Efficiency score	Efficient frontier (m^2)	Potential improvement opportunity (%)
PC17	39	30	1.30	100.00	39	–
PC14	32	25	1.28	100.00	32	–
PC8	30	24	1.25	100.00	30	–
PC13	50	40	1.25	100.00	50	–
PC36	64	55	1.16	100.00	64	–
PC22	38	35	1.09	100.00	38	–
PC6	80	75	1.07	100.00	80	–
PC11	50	50	1.00	100.00	50	–
PC27	40	40	1.00	100.00	40	–
PC34	80	80	1.00	100.00	80	–
PC31	48	50	0.96	100.00	48	–
PC37	64	70	0.91	100.00	64	–
PC20	48	65	0.74	100.00	48	–

Continued Table 3

Plastering crew No.	Daily total production (m^2)	Daily total crew work hours (h)	Crew productivity (m^2/h)	Efficiency score	Efficient frontier (m^2)	Potential improvement opportunity (%)
PC38	40	30	1.33	98.90	41.2	3
PC40	80	80	1.00	98.30	82.4	3
PC19	40	40	1.00	96.77	41.6	4
PC9	36	35	1.03	94.74	38.2	6
PC18	72	70	1.03	94.74	76.3	6
PC35	56	50	1.12	94.38	59.4	6
PC10	40	80	0.50	93.02	43.2	7
PC7	72	72	1.00	92.78	77.8	7
PC33	72	72	1.00	91.58	77.8	7
PC12	64	160	0.40	91.43	69.8	8
PC16	56	56	1.00	90.57	61.6	9
PC15	32	32	1.00	89.34	35.8	11
PC28	36	40	0.90	87.10	41.4	13
PC29	48	48	1.00	85.77	56.2	15
PC24	32	45	0.71	84.21	38.1	16
PC21	32	50	0.64	84.21	38.1	16
PC23	32	30	1.07	83.70	38.1	16
PC4	32	30	1.07	83.20	38.1	16
PC30	34	32	1.06	82.40	40.8	17
PC5	40	55	0.73	82.82	48.0	17
PC39	40	40	1.00	82.33	48.4	17
PC26	32	32	1.00	80.59	39.7	19
PC2	40	40	1.00	80.00	50.0	20
PC1	24	35	0.69	80.00	30.0	20
PC3	32	50	0.64	80.00	40.0	20
PC25	24	26	0.92	71.64	33.6	29
PC32	16	30	0.53	53.33	30.1	47
Mean value	45.43	49.98	0.96	90.72	49.46	14

Further comparisons are drawn in Table 4 between the efficient and inefficient crews based on the mean values of the crews' daily total production, the numbers of skilled and unskilled laborers in individual crews, the daily crew labor unit costs and daily total crew work hours. The data presented in the table indicate that the efficient crews, in comparison to the inefficient crews, have on the average, produced more quantity of total plastered area (TP) at a lower cost, while spending less time to complete their work. However, the data also shows that a plastering crew size of seven yields a higher efficiency than a crew size of six.

Table 4. Comparison of efficient and inefficient plastering crews

Factor	Efficient crews	Inefficient crews
TP (m^2)	51	42.74
SL	4	4
UL	3	2
UC (€)	21.45	21.85
WH (h)	49.15	50.37

4.2. Cross-tabulation analysis

Results from the cross tabulation analyses are presented in Tables 5 and 6 for groups of input factors related to plastering crew characteristics and plastering work characteristics, respectively. The contingency tables display information on the counts and percent frequencies of the values of the input variables (factors) for efficient and inefficient crews. The chi-square (or Fisher's exact test) values, degrees of freedom (df), and p statistics are also given in the tables. Overall, based on the p values, which came out to be below 0.05, it is determined that there are significant associations between the crew efficiency and total experience of plastering crew (E), plastering location (PL), and plastering technique (PT). On the other hand, the average age of plastering crew (A), plastering crew size (CS), plaster type (PTP) do not have significant associations with crew efficiency, having p values over 0.05 as listed in Tables 5 and 6.

According to the results in Table 5, the group of crews with longer experience (over 203 months or 16 years) appear to have produced higher efficiency scores than those with medium and shorter experience, which is plausible. It is evident in Table 6 that plastering crews working on the exterior walls and ceilings are particularly inefficient, while the crews plastering the interior walls and ceilings have comparable efficiencies. It is further observed in this table that crews performing spray plastering are less efficient than those who are using the traditional hand plastering technique. While the drop in efficiency in plastering the exterior of a building, as well as the ceiling, is expected because of the environmental factors and ergonomic difficulties, the apparent inefficiency of the mechanized spray plastering (as compared to manual hand plastering) is surprising. Inquiries on this matter to the plasterers revealed that spray technology was relatively new to most of them, and they indicated that they spent additional time for cleanup of the equipment after finishing their work each day. It is thought that experience gained with the technology should be expected to alleviate these inefficiencies. Further investigation into this matter revealed that when the top thirteen crews (having 100 percent efficiency) were compared to the bottom thirteen (with less than 85 percent efficiency scores), 36 percent of the efficient crews used spray plastering, while only 16 percent of the inefficient crews did the same. This suggests that use of spray technology will provide an advantage in closing the gap between efficient and inefficient crews.

Referring to Tables 5 and 6, it can be stated that the plastering crews analyzed, as a whole, tend to be relatively inefficient across all categories of age group, plaster type and crew size. In other words, there are no statistically significant differences in efficiency between the age groups of under 30, 30 to 35, and over 35; between roughcast and finish plaster types; and

Table 5. Contingency table for efficiency vs. plastering crew characteristics

Efficiency	Total experience of plastering crew (E)-month			Average age of plastering crew (A)			Plastering crew size (CS)	
	1 ≤ E ≤ 120	121 ≤ E ≤ 202	203 ≤ E ≤ 300	A < 30	30 ≤ A ≤ 35	A > 35	CS ≤ 6	CS > 6
	N(%)	N(%)	N(%)	N(%)	N(%)	N(%)	N(%)	N(%)
Efficient	2(22)	3(16)	8(67)	4(33)	5(33)	4(31)	6(26)	7(41)
Inefficient	7(78)	16(84)	4(33)	8(67)	10(67)	9(69)	17(74)	10(59)
Total	9(100)	19(100)	12(100)	12(100)	15(100)	13(100)	23(100)	17(100)

	Pearson chi-square								
	Value	df	p	Value	df	p	Value	df	p
	9.237	2	0.010	0.026	2	0.987	1.015	1	0.314

Table 6. Contingency table for efficiency vs. plastering work characteristics

Efficiency	Plastering Location (PL)			Plastering Technique (PT)		Plaster Type (PTP)	
	Interior	Exterior	Ceiling	Spray plastering	Hand plastering	Roughcast	Finish
	N(%)	N(%)	N(%)	N(%)	N(%)	N(%)	N(%)
Efficient	11(52)	1(11)	1(10)	1(5)	12(52)	9(38)	4(25)
Inefficient	10(48)	8(89)	9(90)	16(95)	11(48)	15(62)	12(75)
Total	21(100)	9(100)	10(100)	17(100)	23(100)	24(100)	16(100)

	Pearson chi-square			Fisher's exact test	Fisher's exact test
	Value	df	p	0.019	p
	7.968	2	0.019	0.002	0.503

between crew sizes of 6 and under and crew sizes exceeding 6. A separate analysis performed on whether a significant association existed between the distribution of the numbers of skilled and unskilled workers in a given crew and crew efficiency indicated that the ratio of skilled to unskilled workers did not have any effect on the outcome.

Of the three input variables that have been identified as having a significant relationship with the efficiency output, only the plaster technique is clearly controllable. Consequently, the efficiency of crews performing spray plastering can be improved by providing additional training on the use of technology, as well as on the procedures for equipment cleanup. Other factors that can have a positive impact on crew efficiency are employing more experienced plasterers, improving the jobsite management practices to achieve better utilization of resources (eliminating waste and rework), and enhancing workers' knowledge, skills and attitude towards productivity and quality through motivation, rewards, and further training.

Summary and conclusions

DEA analysis using the BCC model and cross tabulation were applied to evaluating the efficiency of plastering crews working in multi-storey reinforced concrete residential building projects. The crews were ranked based on their technical efficiency scores, and the efficiency and productivity values of the crews were examined, compared and contrasted. No discernible relationships could be identified between the crew efficiency scores and productivity outputs. It was observed that crews with higher productivity might exhibit lower efficiency and crews with lower productivity might have higher efficiency. Also, it was possible for the efficient crews, in comparison to inefficient crews, to produce more quantity of total plastered area at a lower cost, while taking less time to complete their work.

The relationships between efficiency and six crew input factors were investigated by cross tabulation analysis. It was found that total experience of the plastering crew, plastering location, and plastering technique had significant associations with crew efficiency, while average crew age, plastering crew size, and plaster type did not. It was determined that plastering crews working on exterior walls and ceilings were particularly inefficient, as well as the crews performing spray plastering rather than hand plastering. The latter was attributed to lack of experience with the spray technology. The more experienced crews (over 203 months, or 16 years) were more efficient than those with medium and short experience. It was observed that, overall, no statistically significant differences existed between the average age groups of under 30, 30 to 35, and over 35; between roughcast and finish plaster types; and between crew sizes of 6 and under 6 and crew sizes of over 6 with respect to crew efficiency.

Thirteen crews with 100 percent efficiency scores were identified as the "leaders" in performing plastering work. These crews can serve as a "benchmark" and can be adopted as models to which inefficient crews may adjust their practices in order to become efficient. When the top thirteen efficient crews were compared to the bottom thirteen inefficient crews for which the efficiency scores are less than 85, it was found that the efficient group used the spray plastering technique more extensively than the inefficient crews, underscoring the importance of technology in improving efficiency.

Based on the findings of this study, it can be stated that the DEA approach is well suited for performance evaluation of plastering crews. By conducting such an analysis periodically on construction crews, one would be able to quantitatively determine whether or not their performance is satisfactory, and is improving over time.

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References

Banker, R. D.; Charnes, A.; Cooper, W. W. 1984. Some models for the estimation of technical and scale inefficiencies in data envelopment analysis, *Management Science* 30(9): 1078–1092. http://dx.doi.org/10.1287/mnsc.30.9.1078

Barros, C. P.; Peypoch, N. 2009. An evaluation of European Airlines' operational performance, *International Journal of Production Economics* 122(2): 525–533. http://dx.doi.org/10.1016/j.ijpe.2009.04.016

Charnes, A.; Cooper, W. W.; Rhodes, E. 1978. Measuring the efficiency of decision making units, *European Journal of Operational Research* 2(6): 429–444. http://dx.doi.org/10.1016/0377-2217(78)90138-8

Chen, P. C. 2012. Measurement of technical efficiency in farrow-to-finish swine production using multi-activity network data envelopment analysis: evidence from Taiwan, *Journal of Productivity Analysis* 38(3): 319–331. http://dx.doi.org/10.1007/s11123-012-0267-1

Chen, P.; Yu, M.; Chang, C.; Hsu, S. 2008. Total factor productivity growth in China's agricultural sector, *China Economic Review* 19(4): 580–593. http://dx.doi.org/10.1016/j.chieco.2008.07.001

Cooper, W. W.; Park, K. S.; Pastor, J. T. 1999. RAM: a range adjusted measure of efficiency, *Journal of Productivity Analysis* 11(1): 5–42. http://dx.doi.org/10.1023/A:1007701304281

Cristóbal, J. R. S. 2011. A multi criteria data envelopment analysis model to evaluate the efficiency of the Renewable Energy technologies, *Renewable Energy* 36(10): 2742–2746. http://dx.doi.org/10.1016/j.renene.2011.03.008

Donthu, N.; Hershberger, E. K.; Osmonbekov, T. 2005. Benchmarking marketing productivity using data envelopment analysis, *Journal of Business Research* 58(11): 1474–1482. http://dx.doi.org/10.1016/j.jbusres.2004.05.007

Duzakın, E.; Duzakın, H. 2007. Measuring the performance of manufacturing firms with super slacks based model of data envelopment analysis: an application of 500 major industrial enterprises in Turkey, *European Journal of Operational Research* 182(3): 1412–1432. http://dx.doi.org/10.1016/j.ejor.2006.09.036

El-Mashaleh, M. S. 2010. Decision to bid or not to bid: a data envelopment analysis approach, *Canadian Journal of Civil Engineering* 37(1): 37–44. http://dx.doi.org/10.1139/L09-119

Erturk, M.; Asık, S. T. 2011. Efficiency analysis of Turkish natural gas distribution companies by using data envelopment analysis method, *Energy Policy* 39(3): 1426–1438. http://dx.doi.org/10.1016/j.enpol.2010.12.014

Farrell, M. J. 1957. The measurement of productive efficiency, *Journal of the Royal Statistical Society* 120(3): 253–281. http://dx.doi.org/10.2307/2343100

Fayek, A. R.; Oduba, A. 2005. Predicting industrial construction labor productivity using fuzzy expert systems, *Journal of Construction Engineering and Management* 131(8): 938–941. http://dx.doi.org/10.1061/(ASCE)0733-9364(2005)131:8(938)

Gerek, I. H.; Erdiş, E.; Mıstıkoğlu, G.; Usmen, M. 2014. Modeling masonry crew productivity using two artificial neural network techniques, *Journal of Civil Engineering and Management* 21(2): 231–238.

Hussain, A.; Jones, M. 2001. *An Introduction to Frontier Analyst: Frontier Analyst Workbook 1,* Banxia Software Ltd, Kendal, UK.

Johnes, J.; Yu, L. 2008. Measuring the research performance of Chinese higher education institutions using data envelopment analysis, *China Economic Review* 19(4): 679–696. http://dx.doi.org/10.1016/j.chieco.2008.08.004

Kabnurkar, A. 2001. *Mathematical modelling for data envelopment analysis with fuzzy restriction on weights.* MSc Dissertation, Industrial and Systems Engineering, Virginia Polytechnic Institute and State University, Falls church, Virginia.

Lee, W. S.; Lee, K. P. 2009. Benchmarking the performance of building energy management using data envelopment analysis, *Applied Thermal Engineering* 29(16): 3269–3273. http://dx.doi.org/10.1016/j.applthermaleng.2008.02.034

Liou, F.; Borcherding, J. D. 1986. Work sampling can predict unit rate productivity, *Journal of Construction Engineering and Management* 112(1): 90–103.

Ma, J.; Evans, D.; Fuller, R.; Stewart, D. 2002. Technical efficiency and productivity change of China's iron and steel industry, *International Journal of Production Economics* 76(3): 293–312. http://dx.doi.org/10.1016/S0925-5273(01)00195-5

Maidamisa, A. A.; Ahmad, R.; Ismail, A. A. M. 2012. A comparative analysis of window width selection technique in data envelopment analysis, *International Journal of Computer Applications* 41(5): 21–26.

McCabe, B.; Tran, V.; Ramani, J. 2005. Construction prequalification using data envelopment analysis, *Canadian Journal of Civil Engineering* 32(1): 183–193. http://dx.doi.org/10.1139/l04-073

Mukherjee, K.; Ray, S.; Miller, S. 2001. Productivity growth in large US commercial banks: the initial post-deregulation experience, *Journal of Banking and Finance* 25(5): 913–939. http://dx.doi.org/10.1016/S0378-4266(00)00103-5

Oggioni, G.; Riccardi, R.; Toninelli, R. 2011. Eco-efficiency of the world cement industry: a data envelopment analysis, *Energy Policy* 39(5): 2842–2854. http://dx.doi.org/10.1016/j.enpol.2011.02.057

Oral, E.; Oral, M.; Erdis, E.; Mistikoglu, G.; Ocal, E. 2008. *Man-hour/labor efficiency analysis and artificial neural network modeling in construction works*. 106M055 TUBITAK Project Final Report.

Oral, E. L.; Oral, M. 2010. Predicting construction crew productivity by using self organizing maps, *Automation in Construction* 19(6): 791–797. http://dx.doi.org/10.1016/j.autcon.2010.05.001

Oral, M.; Oral, E.; Aydın, A. 2012. Supervised vs. unsupervised learning for construction crew productivity prediction, *Automation in Construction* 22: 271–276. http://dx.doi.org/10.1016/j.autcon.2011.09.002

Ozdamar, K. 2009. *Paket Programlar ile İstatistiksel Veri Analizi.* 1. baskı, Kaan kitapevi. 421 p.

Pilateris, P.; McCabe, B. 2003. Contractor financial evaluation model (CFEM), *Canadian Journal of Civil Engineering* 30(3): 487–499. http://dx.doi.org/10.1139/l02-098

Portela, M. C. A. S.; Borges, P. C.; Thanassoulis, E. 2003. Finding closest targets in non-oriented DEA models: the case of convex and non-convex technologies, *Journal of Productivity Analysis* 19(2): 251–269. http://dx.doi.org/10.1023/A:1022813702387

Schubert, T. 2011. Are there scale economies in scientific production [online], [cited 26 June 2012]. Available from Internet: http://www.isi.fraunhofer.de/isimedia/docs/p/de/publikationen/tos_scale_economies_science.pdf

Song, L.; AbouRizk, S. M. 2008. Labor productivity modeling using historical data, *Journal of Construction Engineering and Management* 20(5): 786–794. http://dx.doi.org/10.1061/(ASCE)0733-9364(2008)134:10(786)

Tsolas, I. E. 2012. Modeling profitability and stock market performance of listed construction firms on the Athens Exchange: a two-stage DEA approach, *Construction Engineering and Management* 139(1): 111–119. http://dx.doi.org/10.1061/(ASCE)CO.1943-7862.0000559

Vincová, K. 2005. Using DEA models to measure efficiency, *Technical University Košice BIATEC* 13(8): 24–28.

Vitner, G.; Rozenes, S.; Spragget, S. 2006. Using data envelop analysis to compare project efficiency in a multi-project environment, *International Journal of Project Management* 24(4): 323–329. http://dx.doi.org/10.1016/j.ijproman.2005.09.004

Wang, Y. S.; Chau, K. W. 2001. An assessment of the technical efficiency of construction firms in Hong Kong, *International Journal of Construction Management* 1(1): 27–29. http://dx.doi.org/10.1080/15623599.2001.10773021

Wu, D. D. 2009. Performance evaluation: an integrated method using data envelopment analysis and fuzzy preference relations, *European Journal of Operational Research* 194(1): 227–235. http://dx.doi.org/10.1016/j.ejor.2007.10.009

Xue, X.; Shen, Q.; Wang, Y.; Lu, J. 2008. Measuring the productivity of the construction industry in China by using DEA-based Malmquist productivity indices, *Journal of Construction Engineering and Management* 134(1): 64–71. http://dx.doi.org/10.1061/(ASCE)0733-9364(2008)134:1(64)

Zakeri, M.; Olomolaiye, P. O.; Holt, G. D.; Harris, F. C. 1996. A survey of constraints on Iranian construction operatives' productivity, *Construction Management and Economics* 14(5): 417–426. http://dx.doi.org/10.1080/014461996373287

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