BENCHMARKING SAFETY PERFORMANCE OF CONSTRUCTION PROJECTS: A DATA ENVELOPMENT ANALYSIS APPROACH

Saeideh Fallah-Fini, Industrial and Manufacturing Engineering Department, California State Polytechnic University, Pomona, CA 91768, 909-869-4087, sfallahfini@csupomona.edu
Jesus M. de la Garza, Virginia Tech, Center for Highway Asset Management Programs, Via Department of Civil and Environmental Engineering, Blacksburg, VA, USA, 540-23- 5789, chema@vt.edu

ABSTRACT

Worker safety is a significant concern in the construction industry. This paper utilizes data envelopment analysis (DEA) to evaluate performance of construction projects with respect to their level of implementation of the Zero Accident Techniques (ZAT) safety best practice. The proposed approach is then applied on empirical data provided by the Construction Industry Institute on 59 construction projects. Given the level of ZAT implementation in each project, our method quantifies the level of improvement that can be made in preventing incidents in construction projects. We also propose considering the inherent heterogeneity among construction projects while benchmarking their safety performance.

INTRODUCTION

Background

The Construction Industry Institute (CII) is an organization of companies who all share the objective of performing or assisting in research to benefit the productivity and safety of the industry. There have been many efforts by CII to capture the causes of project successes and failures in cost growth, schedule growth and safety performance using parametric methods. Employees, contractors, designers, owners and construction management firms are all affected by safety. Because of the moral obligation to employees, as well as the extreme financial cost of injuries, creating the safest possible workplace is of utmost importance. The current state of CII research on the effects of their Best Practices on project performance lies in parametric analysis with regressed trend lines. Figure 1 shows validation done by CII on the effects of the Zero Accidents Techniques (ZAT) best practice implementation on the Recordable Incident Rate (RIR).

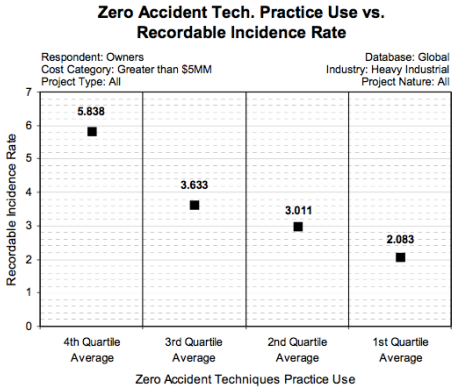

Figure 1. Recordable Incident Rate vs. Zero Accident Techniques Practice Use - Owners, Heavy Industry [1]

The result is an imposed shape or trend line on the data to explain the behaviors such as those seen in Figure 1; as the ZAT best practice use increases, the RIR decreases. The objective of this paper is to present additional and/or new understanding regarding the degree of implementation of ZAT and its effect on safety outcomes in construction projects using a widely-used nonparametric approach called Data Envelopment Analysis (DEA) [2].

The Recordable Incident Rate (RIR)

The RIR is a widely accepted measure of the level of safety on a job site. The Bureau of Labor Statistics (BLS) provides comprehensive information to companies directing them to correctly calculate the RIR and also provides the equation [3]. Equation 1 is designed to represent the average number of incidents present for 100 full time workers in one year, or for every 200,000 working hours.

$$RIR = \frac{\text{Total \# of Recordable Incidents}}{\text{Project Total Works Hours}/200{,}000} \tag{1}$$

The Zero Accident Techniques (ZAT)

The ZAT best practice includes the following thirteen components. Each component of the ZAT has been assigned a weighting by a panel of experts at CII. 1) Plan Implementation – Was there a site-specific safety plan for this project?; 2) Safety Supervisor Commitment – What is the time commitment of the safety supervisor?; 3) Safety Workers – How many workers per safety person on average were on site?; 4) Safety Orientation – How extensive was the site-specific safety orientation for new contractor and subcontractor employees?; 5) Formal Safety Training - On average how much ongoing formal safety training did workers receive each month?; 6) Toolbox Meetings – On average, how often were safety toolbox meetings held?; 7) Safety Audits – How often were safety audits performed by corporate safety personnel?; 8) Pre-Employment Drug Screenings - To what extent were pre-employment substance abuse tests conducted for contractor employees?; 9) Drug Screening - How frequently were contractor employees randomly screened for alcohol and drugs?; 10) Near-Miss Investigations - How often were near-misses formally (i.e., written documentation) investigated?; 11) Safety Incentive Use - To what extent were safety incentives used that were based upon zero injury objectives?; 12) Safety Performance Criteria - to what extent was safety performance utilized as a criterion for contractor /subcontractor selection?; and 13) Risk Identification - To what extent were safety risks systematically identified in the pre-construction phases of this project?

Data Envelopment Analysis

DEA [4] is a “non-parametric” analysis technique that evaluates the relative efficiency of a set of similar decision-making units (DMUs) when a number of factors need to be considered. A DMU whose performance is being measured is basically an entity that uses a production process to transform a set of inputs into a set of outputs. The underlying production process is constrained by the ‘‘production possibility set’’, which is the set of all physically/technologically attainable combination of inputs and outputs. In efficiency analysis, we are interested in the upper boundary of the production possibility set which is called the efficient frontier. The frontier is defined as the set of best performing DMUs that generate the maximum output given a specific input level or use the minimum input level to produce a given output level. DEA uses linear programming to estimate the frontier and the efficiency scores corresponding to all DMUs. The efficiency scores show how efficient those DMUs have been in transforming inputs to outputs in comparison with the best performance suggested by the frontier.

On disadvantage of parametric methods is that they impose an explicit functional form and distribution assumption on the data. However, non-parametric techniques, like DEA, do not impose any assumptions about functional form. DEA allows "the data to speak for itself"; hence there is no need to regress the data in order to conform to a linear or non-linear relation. Moreover, the non-parametric technique of DEA does not take into account random error. Hence, it does not need to make any assumption about the underlying distribution of the error term. The drawback of this characteristic is that in the presence of statistical noise, the efficiency estimates obtained by DEA may be biased. Given the characteristics of safety practices in construction projects, their implementation, as well as their associated safety data, we believe it is reasonable to assume that implementation of safety practices (the process under analysis in this paper) is not largely characterized by stochastic elements. Thus, the performance scores obtained by non-parametric methods are reliable to a large extent.

THE MODEL

This paper focuses on the application of DEA to evaluating the performance of CII's ZAT. The DMUs in this paper are construction projects. DEA treats the construction process as a "black box" and is only concerned with the inputs and outputs associated with the implementation of ZAT. In order to reduce the number of inputs, all of the 13 separate elements that comprise the ZAT were combined into one aggregate index known as the Best Practice Implementation Score (BPIS). This score is one final number that represents the level of overall ZAT implementation that was conducted by the project. The method for calculating the BPIS was developed by CII and the same method and weightings were utilized in this study. For reasons that will be explained later, the output used is the inverse of the RIR.

Before any DEA analysis is performed, it is necessary to decide on the orientation of the DEA model and its return to scale. The only orientation of DEA models that follows traditional safety logic is an output-oriented model. An output-oriented DEA model used to assess safety would calculate the amount of improvement in the output, or safety performance that can be achieved using the same amount of input, or safety practice implementation. In this study we have an undesirable output, i.e., RIR; hence our analysis uses the inverse of the output, i.e., 1/RIR, which is maximized by minimizing the RIR. DEA assumes data to be isotonic, meaning that efficiency scores drop as inputs rise, and efficiency scores rise as outputs increase [5]. By using inverse of the RIR as the output variable to make sure that our data shows the isotonic behavior required in DEA analysis. However, the issue that arises here is that the output variable RIR can also take zero values (as shown in our dataset), meaning that some projects have not injuries. Consequently, the inverse of those zero values is meaningless. To address this issue, we can potentially add a positive value to all output variables. This change in the output variable would force us to use an input-oriented model, since an affine transformation of output data can be performed with no effect on the DEA efficiency scores if an input-oriented model is used [6]. However, the input-oriented perspective to reduce the ZAT implementation level while keeping the number of Recordable Incidents the same is not a perspective that is moral, or can result in proper policy recommendations. Given the nature of the problem context, an output-oriented model is more meaningful to show how much output (reduction of recordable incident rate) is possible given a BPIS. To address this issue, we decided to remove the projects with zero RIR from the dataset, since they are inherently effective projects. Consequently, we can use the inverse of RIR as the output variable along with an output-oriented DEA model that can help us measure further improvements that construction projects could have had in their safety results given the level of input, or BPIS, that they have used.

To estimate an appropriate non-parametric frontier, we also need to decide on the return to scale (VRS or CRS) of the DEA model. In this paper, the output variable that represents the number of injuries

(RIR) cannot be improved past zero incidents. Thus, a VRS frontier is needed, since a CRS frontier continues extending linearly without taking any boundary constraint into account [7]. Consequently, we use the ‘‘BCC model’’ of DEA, as introduced in Banker et al. (1984), to appropriately account for the VRS behavior.

MODEL IMPLEMENTTION AND ANALYSIS

Data

The data source that was used in the study reported herein is an excerpt of the database created by the Benchmarking and Metrics division of CII. CII has created a questionnaire of 550 questions pertaining to all aspects of project planning and execution, best practice implementations, and project outcomes. The database contains more than 1800 projects that have been added by CII member companies. For this study, we extracted 226 industrial projects from this database. Each project has corresponding information regarding project characteristics as well as the ZAT best practice implementation information. The diversity of the data is sufficient for this study; there is a reasonable spread of best practice use within the projects in the data set, which allowed for trends to be investigated across the axis of the best practice use index. Each project contains information on project type, location and various other characteristics. In addition to these fields, information is available pertaining to the implementation of the ZAT best practice. The data organization and cleaning step involved analyzing the database of 226 projects and filtering them down to the 59 projects that had complete information in the data fields required for this study. The first criterion that was applied during the filtering was that each project must have reported the number of recordable incidents; any projects with no answer for this field were removed. Project characteristics, such as Location, Major Classification, Project Delivery Method, etc., data was also required for this study. Since the number of work-hours is necessary to calculate the RIR, any project survey that did not provide it was unusable for this study and removed from the data set. Next, the ZAT data was checked for completeness. All projects in the obtained data had either all 13 ZAT questions complete or all 13 ZAT questions incomplete (blank). The projects that did not answer the ZAT portion of the questionnaire were removed from the dataset because they would be unusable in this study. At the completion of these criteria checks, there were 59 projects remaining in the data set for use in this study.

DEA Results and Discussion

The DEA-Solver software of [9] is used to run the BCC model. Table 1 summarizes the descriptive statistics of DEA results. The maximum efficiency score is 1.0, while the minimum efficiency score is 0.02. Out of 59 projects, only 7 of them are efficient (having an efficiency score of 1) in terms of performing the safety zero accident best practices, meaning that those projects have been able to get the most out of the resources and efforts they have spent for performing safety best practices.

Table 1: Summary Statistics for Efficiency Scores

Number of DMUs	59
Average Efficiency Score	0.28
Median Efficiency Score	0.14
Standard Deviation	0.30
Maximum Efficiency Score	1
Minimum Efficiency Score	0.02
Number of Efficient DMUs	7
Number of Inefficient DMUs	52

Table 2 shows the efficiency scores of all DMUs (projects). A major advantage of using DEA for performance measurement is to quantify the potential opportunities for possible efficiency improvements by comparing the efficiency of projects with the best practice (most efficient ones). This comparison provides each project with quantitative guidance for improving their output and moving to the efficient frontier. For example, in project #3 in Table 2, the efficiency score of 33% means that using the same input that project #3 has used (i.e., using the same level of implementation of safety best practices), the output of this project can be improved (increased) by 67%. Also, according to Table 1, the efficiency scores average is 0.28. This means that given the level of implementation of safety best practices in an average project, the output of an average project can be improved (increased) by 72%.

Table 2: Efficiency scores of construction projects

Project ID	Efficiency Score	Project ID	Efficiency Score	Project ID	Efficiency Score
1	0.167	20	0.141	40	0.237
2	0.138	21	0.353	41	0.166
3	0.337	22	0.066	42	0.125
4	0.276	23	0.076	43	0.030
5	0.284	24	0.112	44	0.106
6	0.035	25	0.023	45	0.211
7	0.093	26	0.040	46	0.028
8	0.026	27	0.261	47	0.084
9	0.055	28	0.026	48	1.000
10	0.201	29	1.000	49	0.446
11	0.035	30	0.140	50	0.207
12	0.136	31	0.471	51	1.000
13	1.000	32	0.187	52	1.000
14	0.080	33	0.047	53	1.000
15	0.468	34	1.000	54	0.770
16	0.217	35	0.069	55	0.226
17	0.499	36	0.436	56	0.028
18	0.116	37	0.013	57	0.520
19	0.074	38	0.070	58	0.592
20	0.141	39	0.115	59	0.068

Low values observed for the average and most importantly median of efficiency scores led to further analysis to explore the potential causes of such underperformance for most of the projects. Such analysis revealed that there are several sources of heterogeneity among the projects under analysis. In fact these projects can be classified into different categories based on characteristics such as *location* (Domestic, International), *their major classification* (Light Industrial, Heavy Industrial, Infrastructure, Buildings), *project delivery method* (Design-Build, Multiple Design-Build, CM at Risk, Traditional D-B-B, Parallel Primes), and also other *characteristic* (Grass Roots, Modernization, Addition, Brownfield or Co-Location). Each one of these characteristics and also combinations of them imposes some limitations/regulations on the operation and the environment in which the projects operate. In fact, in a preliminary classification, we looked at the average of efficiency scores of domestic and international projects obtained from our DEA run, and the obtained results were 0.21 and 0.57, respectively. The large difference between average efficiency scores of projects in each category suggests that there should be fundamental limitation associated with domestic projects preventing them to perform as good as international projects. We also looked at the average efficiency scores of heavy and light industrial projects and similar observation we obtained. This finding suggest that we need to perform further analysis regarding the limitations/regulations associated with each one of these characteristics and their potential effect on performance of construction projects with respect to their safety best practice. Thus, in order to have a fair comparison among construction projects, we need to take the presence of heterogeneity into account. This requires (1) classification of projects into homogeneous groups based on their characteristics mentioned above, and (2) evaluating and comparing performance of construction projects with respect to their level of implementation of ZAT inside each homogeneous group. By following this approach we will not evaluate projects against a benchmark that may not be attainable for

them (due to the fact that the projects that construct the benchmark may not necessarily have similar characteristics and operational environment as the project under analysis). To address this shortcoming in the next step of our work we are planning on developing the homogeneous groups of construction projects, and consequently comparing performance of each project with the ones that have similar characteristic.

CONCLUSION

This paper uses DEA analysis for examining performance of construction projects with respect to their level of implementation of safety best practices and their effects on preventing incidents. Our analysis enables us to quantify the potential opportunities for possible efficiency improvements by comparing the efficiency of projects with the best practice (most efficient projects). Further analysis of the results showed that there are some sources of heterogeneity among the projects under analysis which can potentially cause different operational environments for these projects by imposing different sets of limitations and regulations. As the extension of this work, we propose the application of techniques such as meta-frontier technique that allow evaluation and comparison of DMUs in presence of heterogeneity.

ACKNOWLEDGEMENTS

The Construction Industry Institute's Benchmarking and Metrics committee graciously provided all data used in this study. Without their cooperation and support, this study would not have been possible. The opinions and findings discussed are those of the authors and do not necessarily reflect the views of CII. We would like to acknowledge specifically Dr. Stephen Mulva and Dr. Jiukun Dai for being so responsive and helpful in providing information and assistance.

REFERENCES

[1] B&MCommittee, (2003). "Benchmarking & Metrics Value of Best Practices Report." Construction Industry Institute, Authin, Texas.

[2] Rogers, J.K., (2012). "Safety Benchmarking of Industrial Construction Projects Based on Zero Accidents Techniques." Master of Science Thesis, Department of Civil and Environmental Engineering, Virginia Tech.

[3] BLS, (2011). "Injuries, Illnesses, and Fatalities." Retrieved 12/1/2011, from http://www.bls.gov/iif/osheval.htm.

[4] Charnes, A., Cooper, W.W., Rhodes, E., (1978). "Measuring the efficiency of decision making units." European Journal of Operational Research, 2, pp. 429–444.

[5] Akviran, N.K., (2011). Handbook on Data Envelopment Analysis, Editors: William W. Cooper, Lawrence M. Seiford, Joe Zhu, 2nd Edition, Springer, p. 439

[6] Poster, J., (1996). "Translation Invariance in Data Envelopment Analysis: A Generalization." Annals of Operations Research, 66(2), p. 93-102.

[7] Rouse, P., Chiu, T., (2008). "Towards Optimal Life Cycle Management in a Road Maintenance Setting Using DEA." European Journal of Operational Research, Vol. 196, pp. 672–681.

[8] 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, Vol. 30, pp. 1078–1092.

[9] Cooper W, Seiford L, Tone K., (2000), "Data envelopment analysis: a comprehensive text with models, applications, references and DEAsolver software". Boston/Dordrecht/London: Kluwer Academic Publishers.