SAFETY BENCHMARKING OF INDUSTRIAL CONSTRUCTION PROJECTS BASED ON ZERO ACCIDENTS TECHNIQUES

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ABSTRACT

Safety is a continually significant issue in the construction industry. The Occupation Safety and Health Administration as well as individual construction companies are constantly working on verifying that their selected safety plans have a positive effect on reduction of workplace injuries. Worker safety is a large concern for both the workers and employers in construction and the government also attempts to impose effective regulations concerning minimum safety requirements.

There are many different methods for creating and implementing a safety plan, most notably the Construction Industry Institute's (CII) Zero Accidents Techniques (ZAT). This study will attempt to identify a relationship between the level of ZAT implementation and safety performance on industrial construction projects. This research also proposes that focusing efforts on certain ZAT elements over others will show different safety performance results.

There are three findings in this study that can be used to assist safety professionals in designing efficient construction safety plans. The first is a significant log-log relationship that is identified between the DEA efficiency scores and Recordable Incident Rate (RIR). There is also a significant difference in safety performance found between the Light Industrial and Heavy Industrial sectors. Lastly, regression is used to show that the pre-construction and worker selection ZAT components can predict a better safety performance.

DEDICATION

For my inspiring and soulful son, Kaiden. I sincerely hope that all of the sacrifices that you made for my education will be repaid to you with lessons of hard work, discipline, and dedication. This, and everything I do, is all for you.

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The Benchmarking and Metrics committee graciously provided all data used in this study. Without their cooperation and support, this study would not have been possible. I would like to acknowledge specifically Dr. Stephen Mulva and Dr. Jiukun Dai for being so responsive and helpful in providing the information and assistance I needed while on this academic endeavor.

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1. INTRODUCTION

1.1 OVERVIEW

The Construction Industry Institute (CII) is an organization of member companies who all share the objective of performing or assisting in research to benefit the productivity of the industry. There have been many efforts by CII in capturing the causes of project successes and failures in the areas of cost growth, schedule growth and safety performance using parametric methods. There has also been an attempt to combine the cost and schedule aspects into one performance index (B&MCommittee 2003). To date, there has been no non-parametric analysis on the impacts of safety implementation techniques on the overall performance of a project.

Safety is an element of construction that employees of contractors, owners and construction management firms are affected by. Because of the moral obligation to employees, as well as the extreme financial cost of incidents, creating the safest possible workplace is of utmost importance.

1.1.1 CONSTRUCTION INDUSTRY INSTITUTE (CII)

The framework for all of the improvements that CII has developed and implemented in the construction industry are the CII Best Practices. They are the metrics by which CII has been measuring the quality of construction projects and encouraging member companies to integrate into their corporate culture. There are 15 best practices, which CII has defined, refined, and validated as a result of implementation (B&MCommittee 2010). The 15 Best Practices are:

1. Alignment
2. Benchmarking and Metrics
3. Change Management
4. Constructability
5. Disputes Prevention & Resolution
6. Front End Planning
7. Implementation of CII Research
8. Lessons Learned
9. Materials Management
10. Partnering

11. Planning for Start-up
12. Project Risk Assessment
13. Quality Management
14. Team Building
15. Zero Accidents Techniques.

In 2003, the Benchmarking and Metrics division of CII compiled a report of all of their findings concerning the effect that implementation of the best practices had on the final project success (B&MCommittee 2003). This study showed the desire to investigate connections between the four main parameters of construction performance: cost, schedule, quality, and safety. The topic explored in this paper was to investigate whether projects utilizing a higher percentage of the Best Practices, as defined by CII, were more successful projects than those with lower percentage of Best Practice Implementation.

The current state of CII research on the effects the Best Practices have on project performance lie in parametric analysis with regressed trend lines. Figure 1 shows the previous validation that has been done on the effects of Zero Accidents Techniques implementation on the Recordable Incident Rate (RIR).

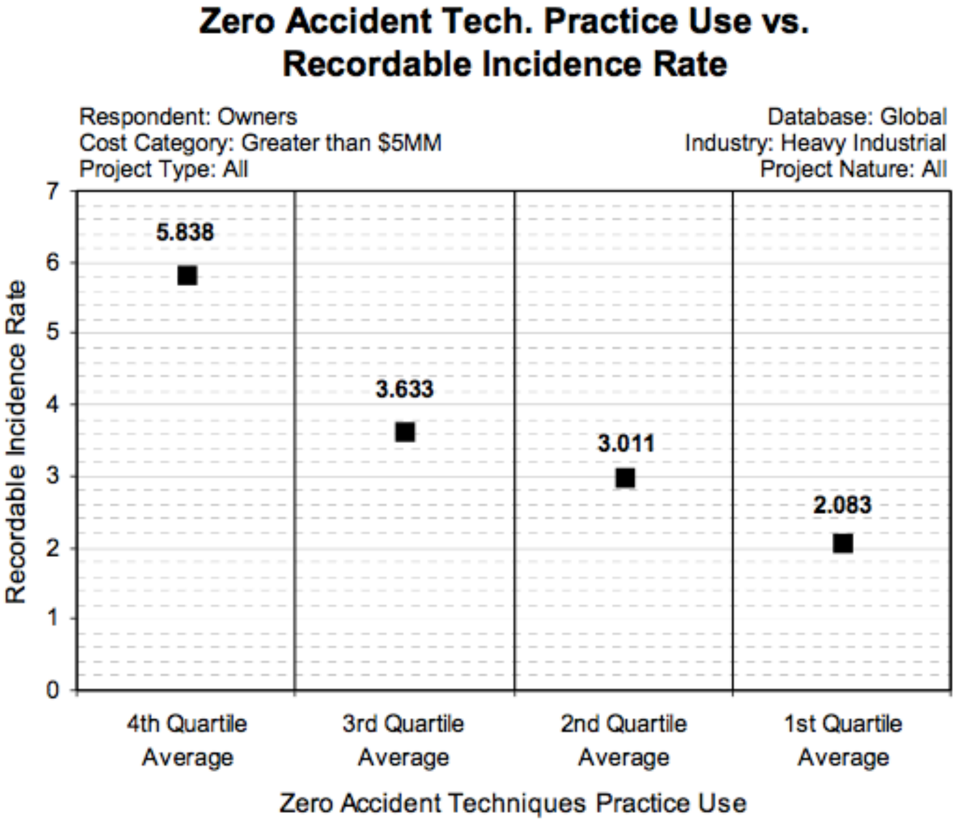


Figure 1: Recordable Incident Rate vs. Zero Accident Techniques Practice Use - Owners, Heavy Industry (B&MCommittee 2003).

There have been many different variations on this analysis, done with other best practices, cost performance, and schedule performance all using these parametric regression methods. The result from these methods is an imposed shape or trend line on the data to explain the behaviors such as the one seen in Figure 1. As the Zero Accidents Techniques Practice Use increases, the RIR decreases.

The current and historical state of the industry provides an environment in need of measurable improvements. The measurements of these improvements are what CII has displayed by various parametric methods showing the connection of one Best Practice to cost growth, schedule growth and safety performances individually.

CII has also attempted to combine the output factors of cost and schedule, via a single performance index (B&MCommittee 2003). The index was intended to represent the total project benefit. CII defined the performance index as the average of the cost growth and schedule growth. Quality and safety were not incorporated into this index.

1.1.2 DATA ENVELOPMENT ANALYSIS

Data Envelopment Analysis (DEA) is a “non-parametric“ analysis technique that results in a relative ranking of decision making units (DMUs). The DMUs in this scenario are construction projects. DEA is widely accepted in industrial engineering as a tool for performance measurement and evaluation, and can be applied similarly to a construction process.

This study will use DEA, a method that enables one to assess how efficiently a decision-making unit (DMU) uses input resources to generate a set of outputs relative to other units in the data set. DEA treats the construction process as a “black box”, or any generic production process, and is only concerned with the inputs and outputs of the process. Figure 2 shows a simplified schematic of the DEA model to illustrate that the project specific means and methods of construction are not considered directly; yet DEA can still compare one project against another.

Figure 2: Simplified Schematic of DEA Model

In the case of Figure 2, the process inputs are defined as any measurement that captures the resources that have gone into our measure of interest. In this case, the measure of interest will be the Zero Accidents Techniques Best Practice implementation. The construction process itself, and any happenings within, are isolated inside the “black box”. The outputs of a construction project are its successes at maintaining budget, schedule, quality, and safety goals. Safety goals are captured with outputs such as the Recordable Incident Rate (RIR), and the Days Away and Restricted Time (DART) Rate.

DEA assesses each DMU by maximizing the weights of inputs and outputs to show each DMU in its best light for comparison. This optimization of input to output ratios is based upon linear programming theory and principles and results in a depiction of how efficiently a DMU is utilizing its resources (Ozbek et al. 2009). The final result is an estimate of something called an efficient frontier that is comprised of the most efficient DMUs in the dataset. A frontier is the boundary between all input-output combinations that are technologically possible, and the area that is physically impossible. An efficient frontier is an estimation of this boundary using the available data. This frontier is then considered the target for all other DMUs within the group. In Figure 3 below, one example of an efficient frontier is shown and this frontier is constructed by connecting the DMUs that receive an efficiency score of one from a DEA analysis. This means that the DMUs on the frontier are producing maximum output with the available input, or they have used the minimum input for producing the output they have produced..

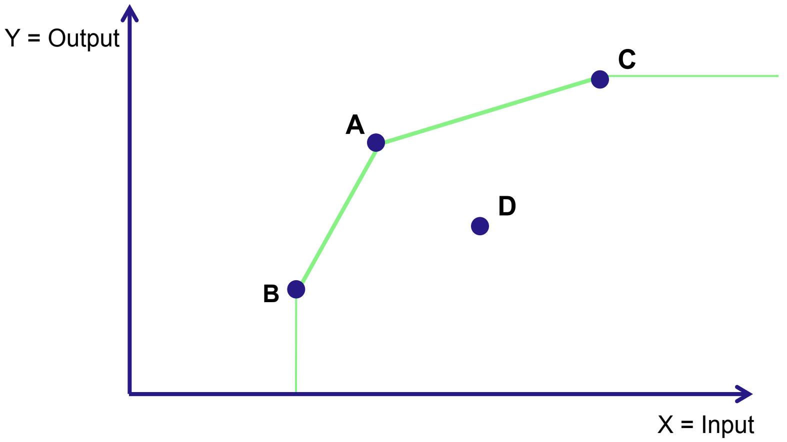


Figure 3: Illustration of a DEA Efficient Frontier with Variable Return to Scale (Triantis et al. 2010)

In the above example, DMUs A, B, and C are 100% efficient projects relative to the analyzed group, and DMU D would be considered inefficient. DMU D will be assigned a DEA efficiency score that is calculated as a percentage of the distance it lies away from the efficient frontier.

The performance measures and metrics used traditionally in the construction industry are important background to this study. A significant advantage of using DEA in this construction environment is that this non-parametric method allows the data to speak for itself. There is no need to regress the data in order to conform to a linear or non-linear shape. The DEA outputs are objective and, most importantly, require no human created weighting system to value the relative importance of the inputs or outputs.

1.2 PURPOSE, SCOPE AND OBJECTIVES

This section will discuss the specific purpose of this study to perform a safety analysis using DEA. This section will also define the scope of the project and the two specific objectives of this study. An outline of the components that make up each objective will also be found in this section.

1.2.1 PURPOSE

The purpose of this thesis study is to validate CII's Zero Accidents Techniques with respect to its ability to reduce injuries. This study will determine if DEA can be used to develop any understanding about the relationship between ZAT implementation and safety performance as measured by RIR and DART rates. This study will also determine if there are certain ZAT implementation strategies that will result in higher efficiency scores. That is, there are specific components, or combinations of ZAT components that will impact the safety performance of projects more than others.

1.2.2 SCOPE

The scope of this thesis is limited to analysis of CII's Zero Accidents Techniques Best Practice. The impact of implementing the Zero Accidents Techniques on the final safety statistics of a project will be explored as well as the specific components of the Zero Accidents Techniques. Safety statistics will be the Recordable Incident Rate and/or the Days Away and Restricted Time Rate in this study.

1.2.3 OBJECTIVES

There are two main objectives of this study. The first objective is a higher-level goal of investigating what type of understanding can be achieved of ZAT safety implementation using Data Envelopment Analysis. The second objective is to use regression in a more specific analysis of the different ways that the Zero Accidents Techniques can be implemented. These objectives, along with their specific components are defined in the following sections.

1.2.3.1 OBJECTIVE 1

The components that comprise Objective 1 are:

1. To identify sources of project heterogeneity with respect to safety performance.

2. To analyze the efficiency scores from DEA modeling and obtain an understanding of the relationship between ZAT implementation and safety performance.

1.2.3.2 OBJECTIVE 2

The components that comprise Objective 2 are:

1. To group the ZAT components according to common themes.

2. Compare regression results among these ZAT component groups to determine the group of ZAT components that shows the best safety performance.

1.3 THESIS ORGANIZATION

The overall organization of this study will be divided into two parts, those pertaining to Objective 1 and those parts pertaining to Objective 2.

This thesis will take on the following organizational structure. Chapter 2 will discuss the data used in detail. This will include the origin and amount of data as well as all fields that were considered for use in this analysis.

Chapter 3 will cover a literature review conducted on Data Envelopment Analysis and construction issues related to this study. This literature review will include topics on Data Envelopment Analysis, which create special considerations for this project. This chapter will also introduce any concepts of Data Envelopment Analysis that will affect the methodology choices.

Chapter 4 will cover the planned methodology for both objectives of this study. This chapter will consist of a chronological discussion of the process planned to achieve the goals of Objective 1, followed by a similar discussion of the plans to achieve the goals of Objective 2. For each objective, the procedures planed for data cleaning and data analysis will be included.

Chapter 5 will cover the execution of Objective 1 tasks. This chapter will contain any modifications to the planned methodologies in Chapter 4. Chapter 6 will contain information of the execution of objective 2 tasks, any modifications, and results.

Chapter 7 will discuss the results and conclusions from Objective 1. In this chapter the findings will be translated into recommendations for using DEA as a tool for safety analysis. Chapter 8 will discuss the results and conclusions from Objective 2. The findings from the analysis execution will be translated into recommendations for implementation of the Zero Accidents Techniques.

Chapter 9 is a chapter on limitations. This chapter will discuss any issues which arose in this study such as constrains in the methodology or available data. Chapter 10 will be a final discussion summarizing the main conclusions in this study. This chapter will include the importance and possible applications of each of the significant findings in this report. Chapter 11 will conclude the main content portion of this report with an overview of areas of future research. This chapter will discuss any issues that arose during this study, that were outside the scope of this project, which would provide a useful expansion upon this research.

2. DATA

The data source that will be used 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 the project planning and execution, each Best Practice, and project outcomes. There is a database of over 1800 projects that were completed by CII member companies. A representative from each of the 1800 projects has completed this 550-question survey and returned it to CII for inclusion in their Benchmarking and Metrics Database.

The number of samples in the obtained excerpt is 226. Each project has corresponding information regarding project characteristics as well as the ZAT BP implementation information. The excerpt of projects was a portion of the projects defined by CII as being “Large” projects. Large projects are defined by CII as any project having the following four criteria (Mulva 2012):

1. Total Installed Cost > 5million
2. Duration > 14 mo.
3. Site work hours > 100K
4. Full time PM resources required

The diversity of the data is sufficient for this proposed study. There is a reasonable spread of practice use within the projects in the data set, which allowed for trends to be investigated across the axis of the practice use index.

2.1 DATA FIELDS OF INTEREST

The full database contains 550 data fields for each project evaluated. For the purposes of a safety analysis, these data fields include all information on project defining characteristics and safety implementation information. The list of fields that are of importance to this study are:

Project Defining Characteristics:

1. Project ID
2. Company of Origin
3. Project Location (Country)
4. Major Classification (Light Industrial, Heavy Industrial, Infrastructure, Buildings)
5. Characteristic (Grass Roots, Modernization, Addition, Brownfield or Co-Location)

6. Project Delivery Method (Design-Build, Multiple Design-Build, Traditional D-B-B, Parallel Primes, Other)
7. Fast Tracked (yes, no)
8. Complexity (1-10)
9. Project Cost
10. Total Work Hours
11. Project Start Date
12. Project Completion Date

Zero Accident Technique Components:

1. Plan Implementation – Was there a site-specific safety plan for this project? (No, Yes)
2. Safety Supervisor Commitment – What is the time commitment of the safety supervisor? (None, Part-Time, Full-Time)
3. Safety Workers – How many workers per safety person on average were on site? (Over 200, 150-200, 70-150, 20-70, 1-20)
4. Safety Orientation – How extensive was the site-specific safety orientation for new contractor and subcontractor employees? (1/Not at all - 7/Extensive)
5. Formal Safety Training - On average how much ongoing formal safety training did workers receive each month? (None, <1hr/mo, 1-5hrs/mo, 5-8hrs/mo, >8 hrs/mo)
6. Toolbox Meetings – On average, how often were safety toolbox meetings held? (2+/day, Daily, Several/week, Weekly, Montly, None)
7. Safety Audits – How often were safety audits performed by corporate safety personnel? (Annually, Quarterly, Monthly, Biweekly, Weekly, Daily)
8. Pre-Employment Drug Screenings - To what extent were pre-employment substance abuse tests conducted for contractor employees? (Never, Occasionally, Usually, Always)
9. Drug Screening - How frequently were contractor employees randomly screened for alcohol and drugs? (Not at all, Once a year, Twice a year, Quarterly, Monthly)
10. Near-Miss Investigations - How often were near-misses formally (i.e., written documentation) investigated? (1/Never – 7/Always)
11. Safety Incentive Use - To what extent were safety incentives used that were based upon zero injury objectives? (1/Not at all – 7/Extensively)

12. Safety Performance Criteria - to what extent was safety performance utilized as a criterion for contractor /subcontractor selection? (1/Not at all – 7/Extensively)
13. Risk Identification - To what extent were safety risks systematically identified in the pre-construction phases of this project? (1/Not at all – 7/Extensively)

3. LITERATURE REVIEW

3.1 EXAMPLES OF DEA IN CONSTRUCTION APPLICATIONS

One example of DEA used in the construction domain is in a study which uses DEA to benchmark contracting companies based upon their construction as well as business performance (El-Mashaleh et al. 2007). The proposed models measure construction firm performance on a company-wide basis, foster trade-off analyses among various performance metrics, and tie the resources expended by construction firms to how well those firms perform overall. These DEA models also provide guidance for how specific company resources can be reallocated to improve overall company performance.

There are also other benchmarking platforms, such as icBench, to illustrate how the DEA technique can aggregate the multiple dimensions of company activity, evaluated by several key performance indicators (KPIs), into a single summary measure of performance (Horta et al. 2010). This method enables the obtaining of a ranking that reflects relative performance among the companies and defines targets for each company that take into account all aspects reflected in the KPIs considered. Horta et al. (2010) uses the DEA model of Cherchye et al. (2007), who developed the concept of "benefit of the doubt" indicators. The concept of "benefit of the doubt" indicators is one that has been lightly covered in the literature to date. This type of DEA model utilizing this indicator effectively aggregates several performance indicators (outputs) without considering the resources used for achieving those outputs explicitly as inputs (Cherchye et al. 2007). A "benefit of the doubt" weighting system is a flexible one that can adjust over time or type of DMU and eliminates the problem of a biased, human imposed weighting system on the inputs. This method adjusts the weighting system when aggregating inputs into one score, to give each DMU the "benefit of the doubt" and a maximized aggregate score. This is similar to the linear programming functions of DEA that maximize the weights of multiple inputs, but the benefit of the doubt maximizes the weights of these inputs prior to a DEA analysis to aggregate them into one cumulative DEA input. For the purposes of this study, CII has already developed an industry accepted weighting system to aggregate the ZAT components into a Best Practice Implementation Score and so this method will not be utilized in this study.

DEA can also be applied to the measurement of the relative efficiency of highway maintenance operations (Fallah-Fini et al. 2009, Ozbek 2007). In particular, Fallah-Fini discusses several methods for selection of controllable and uncontrollable factors that are appropriate for the evaluation of efficiency performance, and are an important part of DEA literature (Fallah-Fini et al. 2009). Three approaches are investigated to account for the impact of uncontrollable factors: Regression Analysis, Analytic Hierarchy

Process (AHP), and an environmental classification method. A regression model is used to identify correlations between input and output variables as the authors state, “regressing the output variable on the set of uncontrollable inputs indicates the importance of the uncontrollable factor” (Fallah-Fini et al. 2009, p.4). This technique allows a combination of all uncontrollable factors into one index (i.e. combining snowfall, temperature, and rainfall into one environmental harshness score).

There are other studies that use the Charnes–Cooper–Rhodes (CCR) model of DEA (Charnes et al. 1978) to benchmark safety performance of construction contractors (El-Mashaleh et al. 2007). These works in safety analysis using DEA provide some insight on how to make policy recommendations to inefficient companies. Using measurements in multiple different categories of accident severity, as the determination of safety efficiency, this study shows how DEA has been used for safety analysis. The input variable used was a measure of the contractor’s expenses on safety as a percentage of total revenues. These expenses include contractor’s annual cost of safety programs and salaries of safety personnel. The output variables used were number of accidents categorized from Type 1-5. Where they are categorized according to the following: Type 1: accidents that do not cause any disability and do not involve any lost work days; Type 2: accidents that do not cause any disability but involve lost work days; Type 3: accidents that cause temporary disability; Type 4: accidents that cause permanent partial disability; and Type 5: accidents that cause permanent full disability or fatality. Because the numbers of accidents are unfavorable, the reciprocals of these accident numbers were used.

Defining the DMU as either the project or the contracting company is a critical step in the DEA modeling. There is a strategy of looking at projects in a multi-project environment, where each project is a one-time non-repeated event (El-Mashaleh et al. 2007). Projects are evaluated by the earned value management system (EVMS) and the multidimensional control system (MPCS) methods. In this environment, it is usually necessary to reduce the number of outputs and inputs to increase the discriminating power of DEA. There are two rules of thumb that can be used when determining an appropriate number of DMU’s for a model. The first says that the number of DMU’s should be at least twice the product of the inputs and outputs. The second says that the number of DMU’s should be at least three times the sum of the inputs and outputs. Because this study uses the definition of a DMU as a single non-repeated event, these examples give some insight as how to create a DEA model for individual projects.

DEA can also be used to discriminate between contractors in the prequalification process. A Canadian study uses DEA as an improved contractor prequalification model as compared to typical weighted criteria assessment (McCabe 2005). A three-stage methodology is presented that is able to create Best Practice benchmarks (practical frontiers) for comparing contractors.

Regression analysis can be an effective tool to assess the impact of information technology (IT) on construction firm performance (El-Mashaleh 2006). The dependent variable for regression can be set as firm performance, and DEA analysis can be used to calculate this firm performance based on multiple input factors. This collection of multiple metrics for the independent variable enables a deeper analysis to be done of DEA results and to find statistically significant correlations between certain input parameters and efficiency.

There have been several previous applications of DEA to evaluate performance of contracting companies in the construction industry. El-Mashaleh (2007) showed that DEA could also be utilized to evaluate company performance by using an integrated entity such as a construction firm, where the firms' performance is evaluated. The inputs used in this process include project management expenses and safety expenses. Most of the company performance models use five metrics that have been determined to be the most critical indicators of industry success based on the consensus of the construction literature (El-Mashaleh et al. 2007). Measuring project success using the following performance outputs have proved to provide results combining business financial and project delivery success. These performance outputs include: schedule performance (percent of projects delivered on/ahead of time in past two fiscal years), cost performance (percent of projects delivered on/under budget in past two fiscal year), safety performance (OSHA recordable incident rate and experience modification rating, EMR), customer satisfaction (percent of repeat business customers), and profit (net profit after tax as a percentage of total sales). This research provides a foundation for the inputs and outputs that should be considered when evaluating performance in the construction industry. While this research was performed on a company level, we will apply a similar methodology to individual project performance.

Similar to El-Meshaleh's work, which defines a contracting company as a DMU, McCabe authored another piece of research in 2000 which applied DEA to the benchmarking of contracting companies (McCabe et al. 2000). In this study, many financial performance indicators are used to determine the business success of the contracting company. McCabe uses DEA in conjunction with a ratio analysis to provide the most well rounded results and conclusions possible. Because the DMUs in this study will be defined as construction projects, and not the construction company, these financial inputs and outputs are not applicable to this research.

3.2 IDIOSYNCRASIES OF DEA

When using DEA in any application, there are many nuances that can make a DEA model more representative of the reality of the situations that are being modeled. The works discussed in this section highlight some of the many different versions, or additional analyses to be used in conjunction with DEA.

Weight restrictions are one technique that has been developed to enhance the ability of DEA to better represent certain situations. Inserting weight restrictions in a DEA model will allow a user to create a model that is representative of a process where some inputs or outputs play a significantly larger role. Creating weight restrictions is done based on the value judgments expressed by domain experts (Cherchye et al. 2007). This concept is found in many works in the body of DEA literature. Weight restrictions can be applied to a DEA model if industry professionals agree that there should be more emphasis placed on certain aspects of the project evaluation. Generally, a DEA model will first be run without any restriction imposed on the variable weights. Then, the relative importance of the weights assessed by experts can be converted into constraints as ratios and added to the basic DEA model. McCabe (2005) used weight restrictions in a construction based DEA study, to allow industry professionals to restrict the weights of safety performance to a minimum value due to the importance of worker safety. The weights in this study will not be restricted using these weight restricting procedures, and will be allowed to be freely calculated by the linear programming theory on which DEA is based.

A common constraint, when creating a DEA model is ensuring that the appropriate number of DMUs is obtained with respect to the input and output variables. Methods to reduce redundancy among variables are another topic covered in the literature. Grouping algorithms to reduce the number of inputs and outputs while maintaining their essential information (Rozenes 2006) has proven to be an effective tool to reduce the variables required by a DEA model. The grouping algorithm developed by Rozenes in 2006 looks for similarities between the inputs and the outputs and a similarity correlation index was calculated between each pair of input and output from which groups of inputs and outputs are derived. Within each group a representative input and output is chosen using a quantitative criterion. This strategy can be used in conjunction with a model for reducing the number of outputs to support the discriminatory power of the DEA methodology. This second algorithm involves sequential DEA computations based on the same set of inputs. One rule of thumb that is commonly accepted is that the number of DMUs in a group must be three times the number of combined inputs and outputs. When the number of DMUs is limited due to the quality and abundance of the available data, appropriately reducing your variables is a valuable tool. There are 13 components of the ZAT that need to be combined in order to reduce the number of inputs to support the discriminatory power of DEA as discussed by Rozenes. However, CII has already developed an industry-accepted method to combine these 13 components into a Best Practice Implementation Score and this same methodology will be used in this study instead of applying a grouping algorithm to the input variables.

3.2.1 INPUT VS. OUTPUT ORIENTED MODELS

Once homogenous groups of projects are formed, each group can be analyzed using either an input-oriented perspective or an output-oriented perspective. In DEA, an input-oriented model calculates the level by which the inputs used by an organization can be reduced without altering the level of outputs produced by the organization. In other words, it minimizes the inputs while maintaining a constant output. This would be of interest to the construction project owner who wants to find out how to lower inputs such as budget or labor hours to maintain a certain standard, or level of outputs (facility size, cost growth, schedule growth, or safety performance).

The alternative approach is an output-oriented model that calculates the level by which the outputs produced by an organization can be increased without altering the level by which inputs are used. This perspective would be of value to a project contractor who receives a set budget and wants to know how to increase their performance in production quantities, cost growth, schedule growth, safety, and quality in order to improve profits or perhaps strengthen their reputation within the industry. In the context of safety, 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.

3.2.2 CONSTANT VS. VARIABLE RETURNS TO SCALE

There are two types of returns to scale that have been identified in DEA literature (Ozbek 2007). When a proportional increase in all input variables results in an equal proportional increase in the outputs, the variables are said to have a constant return to scale. Likewise, when a proportional increase in all input variables results in a larger or smaller proportional increase in the outputs, the variables are said to have a variable return to scale.

A DEA formula selection is based upon the variable or constant return to scale behavior of the DMUs. When a DMU is not operating under a constant return to scale, there are scale inefficiencies that must be accounted for. Because of the additional considerations that are required for variable returns to scale (VRS), the relationships between the inputs and outputs will need to be studied and, the appropriate method identified. In this study, the variable of safety performance cannot be improved past zero incidents; this output meets the criteria of variable returns to scale and a Baker Charnes Cooper (BCC) model will be used to appropriately account for this behavior.

4. METHODOLOGY

4.1 OBJECTIVE 1 METHODOLOGY

This section will cover the methodology that will be used in order to accomplish the necessary tasks corresponding to Objective 1. Objective 1 is a full analysis of the data to explore the ability of DEA to show a meaningful relationship between the level of ZAT implementation and the safety performance as measured by the Recordable Incident Rate (RIR) and Days Away and Restricted Time (DART) Rate.

4.1.1 DATA ORGANIZATION AND CLEANING

The first phase of this study is to acquire and investigate the available data. The accessible data will govern many of the decisions made during the design of the DEA model. Assessing the existing fields of data that have been collected by CII will help narrow down any vagueness in the selection of inputs and outputs. The main goal of a thorough analysis of data is to identify all fields that will be beneficial in capturing resources that a project has used in implementing the ZAT BP.

The CII questionnaire that the database is made from consists of 550 questions on all aspects of the construction project. These questionnaires are self reported and voluntarily submitted by CII member companies. The data that was requested for this study were only the fields pertaining to project characteristics and the Zero Accidents Techniques implementation of large projects. From this abbreviated list of project parameters, a shorter selection of those which will likely be used were separated by usefulness in:

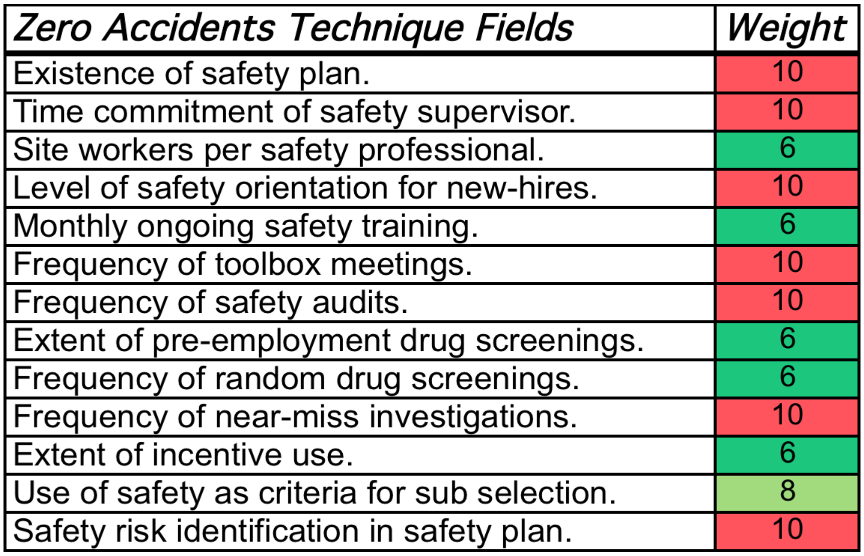
- Defining homogeneous groups
- Use as inputs
- Use as outputs

The inputs to be used in DEA analysis will be the Zero Accidents Techniques Best Practice implementation score. This is one value that represents the overall implementation level of the ZAT BP. The potential outputs are measures of safety performance, which are the Recordable Incident Rate (RIR) and the Days Away and Restricted Time (DART) Rate.

The individual components of the Zero Accident Technique will be combined into one normalized Best Practice Implementation Score (BPIS). The purpose of this step is to minimize the number of inputs to the DEA model to maintain the highest possible level of discrimination power. CII has already developed a procedure for combining the 13 ZAT components into one score and this same procedure will be utilized in this project.

Each component of the ZAT has been assigned a weighting by a panel of experts at CII. The sub-elements and their corresponding weightings are shown below in Table 1.

Table 1: CII Defined Weighting System for the 13 Components of the ZAT (B&MCommittee 2011).



Zero Accidents Technique Fields	*Weight*
Existence of safety plan.	10
Time commitment of safety supervisor.	10
Site workers per safety professional.	6
Level of safety orientation for new-hires.	10
Monthly ongoing safety training.	6
Frequency of toolbox meetings.	10
Frequency of safety audits.	10
Extent of pre-employment drug screenings.	6
Frequency of random drug screenings.	6
Frequency of near-miss investigations.	10
Extent of incentive use.	6
Use of safety as criteria for sub selection.	8
Safety risk identification in safety plan.	10

The ZAT BPIS is then calculated by multiplying the score for each component by the weighting for that category as shown in Table 1. Because the maximum total obtainable score is 108, the project totals are then divided by 10.8 to result in a score on a 1-10 scale that represents the intensity of Zero Accidents Techniques implementation. In the event that the data is missing for a certain ZAT sub-element, the average scores for that field from the project's company of origin will be used.

Calculating the ZAT BPIS begins with the survey responses exactly as the survey respondent enters them. An example of BPIS calculation will be shown by using an example project that has reported the following responses for each of the 13 ZAT fields. Table 2 shows a sample project and the responses that were returned for the ZAT questions. It was the responsibility of the respondent to take the qualitative or categorical answer to each question and use Table 3 to enter the corresponding number in the survey.

Table 2: Sample Project ZAT Survey Responses (B&MCommittee 2011).

Variable	Respndent Answer
plan_imp	2
sup_comm	3
workers	3
s_orient	5
s_formal	3
toolbox	2
audit	4
pre_abus	3
screen	4
near_miss	5
s_incent	5
s_perfor	7
risk_id	4

Table 3 shows the 13 ZAT fields, the corresponding name in the data set, and the possible responses that can be entered by the respondent.

Table 3: Questions Pertaining to the Zero Accidents Technique and Possible Responses (B&MCommittee 2011).

Zero Accidents Technique Portion of Questionnaire (13 Components)		
Question	**Variable Name**	**Possible Responses**
Was there a written site specific safety plan for this project?	plan_imp	1=no, 2=yes, 3=dk
Which of the following best describes the time commitment of the site safety supervisor for this project?	sup_comm	1=no site supe, 2=part time, 3=full time, 4=dk
Overall how many workers per safety person were typically (i.e., in terms of the average workforce) on site?	workers	1=over 200, 2=150-200, 3=70-150, 4=20-70, 5=1-20, 6=dk
How extensive was the job-specific safety orientation conducted for new contractor and subcontractor employees?	s_orient	1=not at all, 4=cursory, 7=extensive, 8=dk
On average how much ongoing formal safety training did workers receive each month?	s_formal	1=none, 2=less than 1hrmonth, 3=1-5hrs, 4=5-8hrs, 5=more than 8, 6=dk
On average, how often were safety toolbox meetings held?	toolbox	1=2+times, 2=daily, 3=several per week, 4=weekly, 5=monthly, 6=none, 7=dk
How often were safety audits performed by corporate safety personnel	audit	1=annually, 2=quarterly, 3=monthly, 4=biweekly, 5=weekly, 6=daily, 7=dk
To what extent were pre-employment substance abuse tests conducted for contractor employees?	pre_abus	1=never, 2=occasionally, 3=usually, 4=always, 5=dk
How frequently were contractor employees randomly screened for alcohol and drugs?	screen	1=not at all, 2=once a year, 3=twice per year, 4=quarterly, 5=monthly, 6=dk
How often were near-misses formally (i.e., written documentation) investigated?	near_miss	1=never, 4=usually, 7=always, 8=dk
To what extent were safety incentives used that were based upon zero injury objectives?	s_incent	1=not at all, 4=moderately, 7=extensively, 8=dk
To what extent was safety performance utilized as a criterion for contractor /subcontractor selection?	s_perfor	1=not at all, 4=moderately, 7=extensively, 8=dk
To what extent were safety risks systematically identified in the pre-construction phases of this project?	risk_id	1=not at all, 4=moderately, 7=extensively, 8=dk

Using the example project in Table 2, and the translation of Respondent Answers in Table 3, a score of 2 for the plan_imp variable means that there was a written site specific safety plan for this project. Note that for each question, one of the possible responses is "dk" which represents "don't know". This response is later adjusted in the data organization and cleaning process.

The direct responses from Table 2 are then translated to scores from 0 to1, which normalizes the responses of each of the 13 components onto a common scale. This translation is done according to a method defined by CII and included in the database provided for this project. Table 4 shows the translation for each of the 13 ZAT questions in the survey. For example, the sample project in Table 2, that answered "yes" for the "plan_imp" variable, "Was there a written site specific safety plan for the project?" entered the number 2 to represent that answer. Table 4 shows how that entry of a number two is translated to a score on a 0 to 1 scale. In this example, the sample project will receive a score of 1 for having a written site specific safety plan on the project. Note that there is no numerical value assigned to the "dk" or "don't know" responses in Table 3.

Table 4: Method of Translating Respondent Answers to Numerical Scores (B&MCommittee 2011).

CII Defined Variable Translation System

		No	Yes
1	plan_imp	0.00	1.00

		No site safety supervisor	Part time	Full time
2	sup_comm	0.00	0.50	1.00

		Over 200	150-200	70-150	20-70	1-20
3	workers	0.00	0.25	**0.50**	0.75	1.00

		1 - not at all	2	3	4 - Cursory Orientation	5	6	7 - Extensive Orientation
4	s_orient	0.00	0.17	0.33	0.50	0.67	0.83	1.00

		None	< 1 hrs/mo	1-5 hrs/mo	5-8 hrs/mo	>8 hrs/mo
5	s_formal	0.00	0.25	0.50	0.75	1.00

		2+/day	Daily	Several/wk	Weekly	Monthly	None
6	toolbox	1.00	0.80	0.60	0.40	0.20	0.00

		Annually	Quarterly	Monthly	Biweekly	Weekly	Daily
7	audit	0.00	0.20	0.40	0.60	0.80	1.00

		Never	Occasionally	Usually	Always
8	pre_abus	0.00	0.33	0.67	1.00

		Not at all	Once a year	Twice a year	Quarterly	Monthly
9	screen	0.00	0.25	0.50	0.75	1.00

		1 - Never	2	3	4 - Sometimes	5	6	7 - Always	None Occurred
10	near_miss	0.00	0.17	0.33	0.50	0.67	0.83	1.00	1.00

		1 - not at all	2	3	4 - Moderately	5	6	7 - Extensively
11	s_incent	0.00	0.17	0.33	0.50	0.67	0.83	1.00
12	s_perfor	0.00	0.17	0.33	0.50	0.67	0.83	1.00
13	risk_id	0.00	0.17	0.33	0.50	0.67	0.83	1.00

Now that the 13 scores from 0 to 1 have been obtained for the sample project they can be multiplied by the CII defined weights in Table 1. The shaded cells of Table 4 indicate the answers for the sample project. Using those values, and the weights for each component in Table 1, the math to calculate the BPIS of the sample project is shown in Table 5.

Table 5: Sample Calculation of BPIS for Sample Project in Table 2.

Component	Weight	Translated Project Response	Calculated Score
1	10	1.00	10.00
2	10	1.00	10.00
3	6	0.50	3.00
4	10	0.67	6.67
5	6	0.50	3.00
6	10	0.80	8.00
7	10	0.60	6.00
8	6	0.67	4.00
9	6	0.75	4.50
10	10	0.67	6.67
11	6	0.67	4.00
12	8	1.00	8.00
13	10	0.50	5.00
		TOTAL	**78.83**

Maximum Score of 108⇒ Divide total by 10.8 to scale to 1-10 point range

FINAL BPIS	**7.30**

This method of BPIS calculation as seen in Table 5 is the one used for all projects in the data set. The pre-defined, industry accepted weighting system and implementation score calculation greatly assists the process of variable reduction in this study. This one final BPIS value can be used as an input representative of all 13 components of the ZAT.

4.1.2 HETEROGENEITY ANALYSIS

Deciding on the framework of the DEA model is the next major milestone. Because of the wide array of member companies and types of projects, the heterogeneity in the projects will be an important consideration in this analysis. Projects that are compared against each other must be homogeneous in terms of the process. There will be many sources of heterogeneity among the projects contained in the CII database. The 7 fields from the General Info category of the project survey that will be used to find homogeneous groups of projects are:

1. Location (Domestic, International)
2. Major Classification (Light Industrial, Heavy Industrial, Infrastructure, Buildings)
3. Characteristic (Grass Roots, Modernization, Addition, Brownfield or Co-Location)
4. Project Delivery Method (Design-Build, Multiple Design-Build, Traditional D-B-B, Parallel Primes, Other)
5. Fast Tracked (yes, no)
6. Complexity (1-10)
7. Project Cost

The limitation to considering all sources of heterogeneity is the size of the final homogeneous groups. One limitation of DEA is that bias occurs when the groups of analysis contain an insufficient number of DMUs in relation to the number of input and output variables. When the data values are obtained and grouped, the sizes of the groups will be assessed. If there are groups that are deficient in the number of DMUs, some less significant forms of heterogeneity will have to be omitted.

The result of the clustering process will be a determination of which project characteristics show statistical differences in the safety performance and groups of projects that share characteristics that pertain to safety. Since the industry is so varied, this breakdown will produce more valuable information to owner and contracting companies.

The heterogeneity analysis will be a two-step process outlined below in the following sections.

4.1.2.1 DETERMINING PROJECT CHARACTERISTICS AFFECTING SAFETY PERFORMANCE

To test the level of influence each of the seven project characteristics has over the safety performance, a regression analysis will be used. This regression analysis will include the following data fields that classify project characteristics:

1. Location (Domestic, International)
2. Major Classification (Light Industrial, Heavy Industrial, Infrastructure, Buildings)
3. Characteristic (Grass Roots, Modernization, Addition, Brownfield or Co-Location)
4. Project Delivery Method (Design-Build, Multiple Design-Build, Traditional D-B-B, Parallel Primes, Other)
5. Fast Tracked (yes, no)
6. Complexity (1-10)
7. Project Cost

Figure 4 shows the frequency distribution of the Recordable Incidents from the CII data obtained for this thesis project.

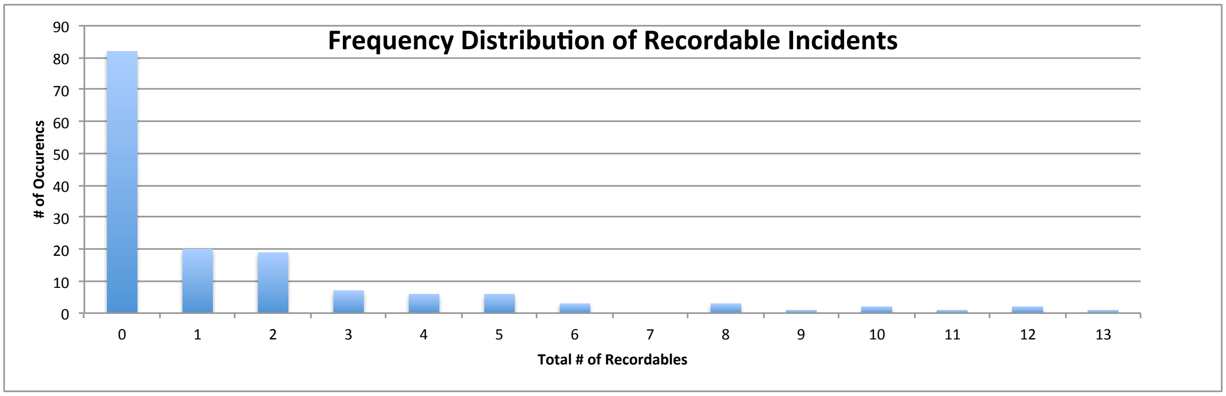


Figure 4: Frequency Distribution of Recordable Incidents.

The Recordable Incidents category has been analyzed and it has been determined that this frequency distribution most closely resemble a Zero Inflated Poisson's distribution. The distribution of this data is zero inflated because of the extreme number of times zero recordable incidents occurs. The shape of Figure 4 most closely resembles a natural log function with the exception of the abnormally high frequency of zero. Because the size of the column at zero is inflated relative to the other columns, it takes on the characteristics of a zero inflated function.

It can be seen in Figure 4 that the frequency of zero recordable incidents breaks the shape of the log function. The log-linear nature of the data, as well as the dependent variable occurring only in values of natural numbers lends itself to the Poisson distribution. Therefore, each of the project characteristics fields will be used as inputs against the total number of recordable incidents in a Zero Inflated Poisson's Distribution Regression model.

4.1.2.1.1 ZERO INFLATED POISSON REGRESSION

The Poisson (or log-linear) regression is chosen for this application because it is designed to be used when the dependent variable (total recordable incidents) consists of only natural, integer values (Cameron et al. 1998). The total number of recorded incidents is a “counted” variable because the only possible values are integers from 0 to infinity. The Poisson regression equation does normalize the total number of recordable incidents for the length of the project by defining the dependent variable in Equation 1 as the log(count/time). This is important so that longer projects are not penalized for having more time in which incidents can possibly occur. The full Poisson regression equation used for this heterogeneity analysis is:

Equation 1: Poisson Regression Equation

$$\log(\text{count}/\text{time}) = b_0 + b_1X_1 + \ldots + b_bX_n$$

Where,

count = number of total recordable incidents for the project

time = number of total work hours for the project

b = coefficient of independent variables

X = independent variables, or project characteristics

This regression analysis will be done on the largest group of data possible. Starting with the raw data, the projects will be selected which have all project characteristics and the total number of recordable incidents filled in fully. This will be the dataset used for the regression analysis in order to include the highest number of projects and obtain the most statistically acceptable results.

Any DEA, or regression analysis that will require the BPIS will require all 13 specific activities that combine to make the Zero Accidents Techniques to be completed in the data set. Therefore, after the homogeneous groupings have been created, the projects will be refined again to include only those with an acceptable amount of Zero Accidents Techniques data fully completed. An acceptable amount of ZAT data will be defined as any of the following options:

1. The survey respondent has completely filled in all 13 ZAT questions without the use of the "dk" (don't know) answer.
2. The survey respondent has filled in all 13 ZAT questions using the "dk" option and there are at least two other projects from the same company which have answered the fields containing a "dk" which can be averaged and used to replace any "dk" responses.

Any project that does not meet these two requirements for an acceptable level of ZAT information will be removed from the dataset for any DEA or regression analysis requiring use of the ZAT BPIS.

The Zero Inflated Poisson Regression analysis accounts for the extreme frequency of zero observations by separating the data into two groups, the data that falls under a normal Poisson function, and the data that lies outside of this normal Poisson function. In Figure 5, Frequency Distribution of Recordable Incidents, the frequency of incidents in the data is represented by the blue histogram, and the red line shows an estimate of a normal Poisson function fitted to this data. The data that falls outside of a normal Poisson function represents the additional zero observations, or the inflated zeroes.

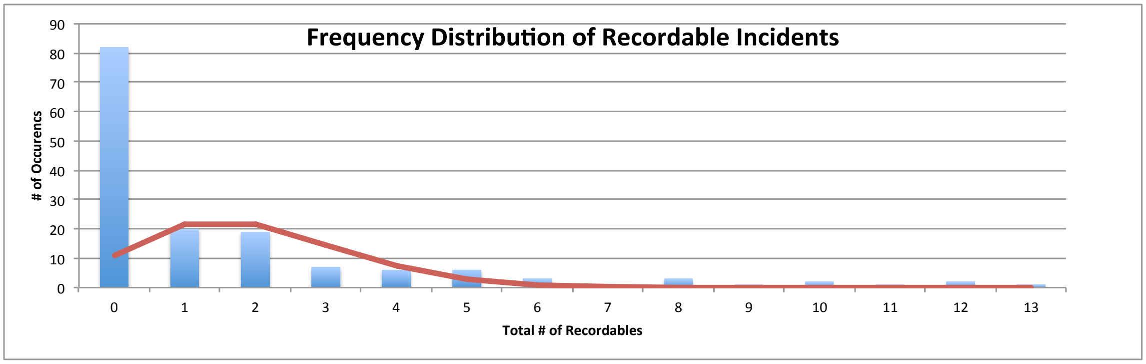


Figure 5: Frequency Distribution of Incident Data Compared to a Normal Poisson Function.

When performing a Zero Inflated Poisson regression, there are two components being calculated simultaneously. The first component is the regression equation for the data that is under the normal Poisson distribution function; the second is the regression equation for the data that is above the normal Poisson distribution function. These two equations are found simultaneously and changes in one equation affect the other. However, the resulting independent variables that are significant to each data grouping can be different. The results from a Zero Inflated Poisson regression analysis would include the variables that significantly impact the dependent variable for the group under the Poisson distribution and a separate list of variables that impact the dependent variable for the group above the Poisson distribution.

An indicator in Poisson regression models that can be used to compare one model against another is a Bayesian Information Criteria (BIC) score. Bayesian Information Criteria is a method of model selection were smaller values represent a better fit (Weakliem 1999). BIC was developed for use with log linear regression models (Raftery 1985) and therefore, is an appropriate criteria to use in selecting the best regression model when using a Zero Inflated Poisson regression model. The BIC is defined by an equation based upon the Bayes theorem.

Equation 2: Bayesian Information Critera

$$\mathrm{BIC} = \mathrm{n} \cdot \ln(\sigma_e^2) + k \cdot \ln(n)$$

Where,

n = the number of observations

k = the number of parameters included

σ_e^2 = the error variance

This BIC score can be used when there are multiple models that are tested. For example, if a researcher is unsure whether the inclusion of an additional variable will be beneficial or not, both models can be run and the BIC scores can then be compared. Whichever has a lower BIC score is a better fit for the data in use. This BIC score also adjusts itself according the size of the model, this means that a new variable must show a greater improvement to be determined beneficial to model with more variables than a model with fewer variables (Raftery 1985). This makes this BIC score a useful tool to use for models of any size and also allows a model with fewer variables to be compared to a model with a greater number of variables.

4.1.2.2 CLUSTERING PROJECTS BY DEFINED CHARACTERISTICS

When the results of the regression analysis have been obtained, the factors that show a statistically significant influence over the safety performance will be selected. These factors will then be used by a statistical software package, JMP, to cluster the projects accordingly. JMP uses a hierarchical process to take the smallest clusters, of one project, and combine them with other clusters until the desired number of groups is obtained. JMP assigns a “distance” between the values of each variable and then combines groups of projects having the least total “distance” between them. Once the homogeneous groups have been formed, they will be able to undergo a DEA analysis. This will return an efficiency score for each project based upon the BPIS, RIR and DART rates.

4.1.3 DEA MODEL DEVELOPMENT

Once the selection has been made of usable data and it has been organized appropriately as described in the Data Organization and Cleaning section, the DEA models must be properly defined to best represent the data and to achieve the desired objectives.

One constraint to be considered when choosing an input versus output-oriented model is whether your model needs to be translation invariant with respect to either the input values or the output values. A translation invariant model will be required when inputs or outputs contain zero values. This is specifically an area to be considered in this application, because the outputs to be used in the model are the inverse of RIR or DART, and RIR and DART rates of zero do exist in the data. Because the inverse cannot be taken of zero, a constant would have to be added to all values of RIR, requiring translation invariance. An input oriented model is translation invariant with respect to these zero RIR values if they are going to be included in the calculations. 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 domain, an output-oriented model will be used to show how much output (reduction of recordable incident rate) is possible given a BPIS level, however an output-oriented DEA model is not translation invariant with respect to the outputs. Therefore, the common solution of adding a constant to all output variables to alleviate the problem of zero values cannot be utilized in this situation. This means that all projects with a zero for Recordable Incident Rate will be removed from the dataset and can be considered an inherently effective project.

Given the nature of the domain, a variable return to scale (VRS) will be utilized in this application. Because the safety performance measure, RIR, cannot be improved infinitely, because a project can not have less than zero incidents, it satisfies the properties of a VRS. The form of DEA which models a variable return to scale is the Banker, Charnes, and Cooper (BCC) model. The output oriented version of the BCC model is formulated as:

Formulation 1: BCC DEA Model

$$\underset{\theta,\lambda_j,\forall j}{Max} \quad \theta + \left(\sum_{i=1}^{m} s_i^- + \sum_{k=1}^{s} s_k^+\right) \qquad (N4)$$

$$\begin{aligned} s.t. \quad & \sum_{j=1}^{n} \lambda_j y_{kj} = \theta y_{ko} + s_k^+ && k = 1,\dots,s \\ & \sum_{j=1}^{n} \lambda_j x_{ij} = x_{io} - s_i^- && i = 1,\dots,m \\ & \sum_{j=1}^{n} \lambda_j = 1 \\ & \lambda_j \geq 0 \end{aligned}$$

where

θ: The measure of output-oriented technical efficiency

λ: Positive scalars

n : The number of DMUs (j=1,…,n)

m : The number of inputs (i=1,…,m)

s : The number of outputs (k=1,…,s)

y_{kj} : Amount of output k produced by DMU_j

x_{ij} : Amount of input i used by DMU_j

s_i^- : input excesses by DMU_j (slack)

s_k^+ : output shortfalls by DMU_j (slack)

The DMU_O is called BCC-Efficient if the optimal solution (θ^*, λ^*, s^{-*}, s^{+*}) of model described in satisfies both:

(i) $\theta^*=1$

(ii) $s^{-*} = 0$, $s^{+*} = 0$ (zero slacks)

Otherwise, the DMU_O is called BCC-inefficient.

From this point forward in this study, all DEA models used and discussed will be of the output-oriented BCC form.

4.1.3.1 DEA MODEL DEFINITIONS

It has been determined that all DEA models in this study will be output-oriented, BCC models to comply with the issues discussed in the previous two sections. The inputs and outputs for each BCC output-oriented model will be defined in this section.

Models to achieve Objective 1 will be the following:

- **Model 1:** This model will test the efficiency of ZAT implementation on the Recordable Incident Rate
    - **Inputs:** Aggregate ZAT BPIS. The aggregate ZAT BPIS Score is used in place of the individual component scores to reduce the number of input variables, and therefore increase the discrimination power of DEA.
    - **Output:** 1/RIR
- **Model 2:** This model will test the efficiency of ZAT implementation on the Days Away and Restricted Time Rate.
    - **Inputs:** Aggregate ZAT BPIS.
    - **Output:** 1/DART Rate
- **Model 3:** This model will test the efficiency of ZAT implementation on total safety performance.
    - **Inputs:** Aggregate ZAT BPIS
    - **Outputs:** 1/RIR and 1/DART Rate

4.1.4 META-FRONTIER ANALYSIS

Models 1, 2 and 3 will be applied to homogeneous clusters of DMUs. Once these DEA models have been executed, the results will be a ranked order of the projects that have implemented the Zero Accidents Techniques. This will provide insight as to which of the projects has implemented this Best Practice in a way that has had the most positive overall impact on the project's safety performance. Additionally, mathematical relationships can potentially be identified between ZAT implementation, efficiency scores, and safety performance.

Homogeneous groups can and will be compared with one another under a Meta-Frontier analysis. The purpose of this second level of analysis is to compare one homogeneous grouping against another. The Meta-Frontier analysis provides a comparison between heterogeneous DMUs that will allow comparisons to be made among the different groups of large projects. It also allows for general conclusions to be made on the entire group of large projects as a whole. For example, Zero Accidents

Techniques implementation can be compared among all large industrial projects regardless of their delivery method, project nature or project cost. Viewing performance of different homogeneous project groups and comparing them to the overall performance of the projects in the data set can provide insight to inherent differences in types of construction projects in terms of safety implementation and performance.

A Meta-Frontier analysis is used to compare groups that are heterogeneous and to then investigate inherent differences among the groups (Fallah-Fini 2011). It is done by first analyzing each group and estimating an efficient frontier for each homogeneous cluster of DMUs. Next the DMUs are all pooled together and an estimate of a Meta-Frontier is calculated. Figure 6, Meta-Frontier for Two Group Frontiers, shows an example of two estimated group frontiers represented by 1-1' and 2-2'. These lines are the frontiers for two homogeneous groups producing the same output by using the same input. When the DMUs in both groups are pooled together, a Meta-Frontier represented by M-M' becomes the estimated frontier for the combination of both groups.

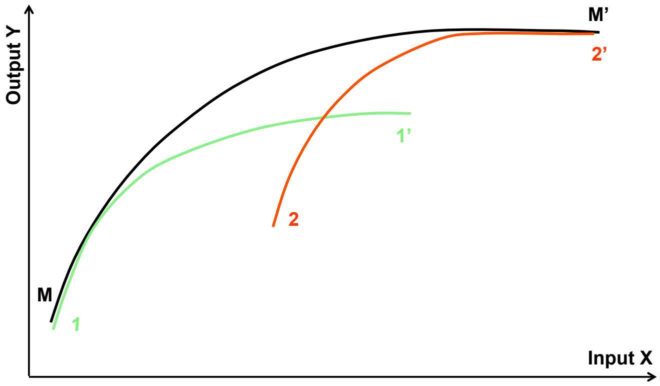


Figure 6: Meta-Frontier for Two Group Frontiers (Fallah-Fini 2011)

A Metatechnology Ratio (MTR) is then calculated by finding the ratio of the distance from a DMUs group frontier to the distance from the Meta-Frontier. This metatechnology ratio can be used to identify which homogeneous groups of DMUs are outperforming others or which homogenous groups seem to have some inherent differences to the other groups.

4.2 OBJECTIVE 2 METHODOLOGY

This section will outline the planned procedures to execute the tasks of Objective 2, which is to explore different aspects of the Zero Accidents Techniques and determine which components are larger driving factors in achieving good safety performance statistics. The variability among the implementation levels of each ZAT component provide good data to explore the different implementation strategies.

4.2.1 CLUSTERING ZAT COMPONENTS

The first task to complete objective 2 is to create groups of ZAT components to test. Investigating each component of the ZAT and identifying common themes or threads that connect the components to each other will determine which components will be grouped together. Making sub-categories of ZAT components that logically fall under a common heading will allow for an analysis of these ZAT sub-categories, and make result interpretations that apply to each sub-category of ZAT safety actions.

An example of a potential breakdown of the components is to divide the 13 components into the following three groups:

1. Initial Safety Plan
    - Existence of a written site specific safety plan
    - Number of safety professionals per site worker
    - Time commitment of safety professionals
    - Incentive use
    - Risk identification
2. Safety Maintenance
    - Extent of new employee safety orientation
    - Frequency of formal ongoing training
    - Frequency of toolbox meetings
    - Frequency of safety audits
    - Frequency of near-miss investigations
3. Worker Selection
    - Frequency of new hire drug testing
    - Frequency of random drug screenings
    - Use of safety as a criteria for contractor selection

In this scenario, the Initial Safety Plan group would contain components that are a part of the pre-construction planning phase; such as the number of safety professionals assigned to the project and the time commitment of these safety professionals.

4.2.2 CLUSTERING PROJECTS FOR DEA ANALYSIS

The projects must be organized into groups that can be entered into a DEA model. Because every project has implemented the same components of the ZAT, they are all homogeneous in this way. Every project will be included into each DEA model that focuses on one specific ZAT sub-category. Then, because every project will be included in the analysis of each sub-category, the changes in output that occur with the changes to the inputs can be compared, this will be discussed in more detail in Section 4.2.4 Meta-Frontier Analysis.

4.2.3 REGRESSION AND DEA MODELING

Regression analysis can be used to answer the question of Objective 2: Do some components of the ZAT impact safety performance more than others?

From Objective 1, the sources of heterogeneity with respect to safety performance have already been determined. Using these, as well as the scores from the three groups of ZAT components, regression analysis can be used to determine whether or not any of the ZAT component groups are statistically significant drivers, impacting the safety performance.

Objective 2 can be answered using a regression model with the following variables:

Dependent Variable:
    Recordable Incident Rate
Independent Variables:
    Location
    Major Classification
    Characteristic
    Project Cost
    ZAT Group 1 Score: Initial Safety Plan
    ZAT Group 2 Score: Safety Maintenance
    ZAT Group 3 Score: Worker Selection Score

Using this regression model, it will be determined whether or not the scores from any of the three ZAT groups are significantly impacting the Recordable Incident Rate in the presence of the other factors of heterogeneity as determined by Objective 1.

For verification and investigation, an experimental application of will be used. DEA software can be used to run all of the same data set of projects through the following DEA model in an attempt to verify the regression results.

Objective 2 DEA Model:

Inputs:

- ZAT Group 1 Score: Initial Safety Plan
- ZAT Group 2 Score: Safety Maintenance
- ZAT Group 3 Score: Worker Selection

Output:

- 1/RIR

The average weightings obtained for the inputs in this model could potentially be used to verify the results of the regression analysis. In this objective, the projects will not be separated into the previously defined homogeneous clusters, but run all together as a metagroup. The relative efficiency scores, therefore will not be used, nor will they provide an accurate analysis because of the mixed project group. This use of DEA is non-traditional and will only be used in an attempt to find a relationship between the average weightings assigned by the optimization algorithm and the regression results.

5. EXECUTION OF OBJECTIVE 1

This chapter will cover the actual progression of Objective 1 methodologies. Any changes that were found to be necessary will be covered in the following sections as well as the reasoning corresponding to such changes.

5.1 EXECUTION OF DATA ORGANIZATION AND CLEANING

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 to the data was that the projects must have completed the question on the number of recordable incidents that occurred on the project. Any projects with no answer for this field were removed.

Project characteristic data was also required for this study and all projects contained complete information for the data fields pertaining to the project characteristics with the exception of Total Work Hours. Any project that did not provide the total number of work hours on the project 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). These projects that did not answer the ZAT portion of the questionnaire were removed from the dataset as they would be unusable in this study. It should be noted that although all of the remaining projects have all 13 ZAT fields answered, an option for each one of the 13 ZAT questions is “Don’t Know”, which presents another challenge in creating usable data for this project. The solution to this issue will be discussed in further detail in the Best Practice Implementation Score Calculation section (5.1.2).

At the completion of these criteria checks, there were 59 projects remaining in the data set for use in this study.

5.1.1 RIR AND DART RATE CALCULATIONS

Now that the data set contains only the projects available for use in this study, all inputs and outputs that have been identified for potential use need to be calculated and available for the analysis. The

Recordable Incident Rate and Days Away and Restricted Time Rate are not present in the data, instead the total number of recordable incidents and the total number of DART cases are given.

RIR and DART rates are defined by the Occupational Safety and Health Administration (OSHA) and are used to track national data on workplace injuries (OSHA 2010). A recordable incident is any injury, regardless of severity, that is recorded in the project's safety log. A Days Away and Restricted Time case is any recordable incident that results in the victim requiring time away from their duties on the job. Any DART case is also a recordable incident, however not all recordable incidents result in a DART case.

The Bureau of Labor Statistics provides comprehensive information to companies directing them to correctly calculate their OSHA statistics and give the equations to find incident rates (Statistics 2011). The equations are designed to represent the average number of incidents present for 100 full time workers in one year, or for every 200,000 working hours.

Equation 3: Recordable Incident Rate

$$\text{RIR} = \frac{(\text{Total \# of Recordable Incidents} \cdot 200{,}000)}{\text{Project Total Work Hours}}$$

Equation 4: Days Away and Restricted Time Rate

$$\text{DART Rate} = \frac{(\text{Total \# of DART Cases} \cdot 200{,}000)}{\text{Project Total Work Hours}}$$

Using these OSHA defined equations; both incident rates are calculated for each project in the data set.

5.1.2 BEST PRACTICE IMPLEMENTATION SCORE CALCULATION

In order to reduce the number of inputs necessary in Objective 1, all of the 13 separate actions that comprise the ZAT will be combined into one aggregate Best Practice Implementation Score. 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.

Taking the survey responses from each of the 13 questions, and translating them to a scale of 0-1, with 0 being no implementation and 1 being the highest level of implementation of that specific action is the first step of calculating the Best Practice Implementation Score. If a project answered "Don't Know" for any of the 13 ZAT questions, the project was investigated to see if a company's average could be used in place of the "Don't Know" response. If the project was the only one from the company present in the data set, it was removed. If there were two or more projects from the same company present in the data, the company average was found for that response and inserted in place of the "Don't Know" response. There were no projects in the data set that had more than 3 "Don't Know" responses that required replacement with a company average.

Once all projects remaining in the data set had complete information for all 13 ZAT fields, the BPIS could be calculated. The scores in each field were multiplied by the weight assigned to the ZAT component by CII, and then all 13 scores were summed. The maximum possible value, or complete ZAT implementation would be a score of 108. To achieve a BPIS score on a 1-10 scale, the total values were all divided by 10.8.

5.2 EXECUTION OF HETEROGENEITY ANALYSIS

This section will discuss the process that was used in order to determine what factors make a construction project statistically different from another in terms of safety performance.

5.2.1 DATA PREPARATION

The heterogeneity analysis required information on project characteristics and the total number of recordable incidents the project had. Because the ZAT data did not pertain to this portion of the study, the original dataset was used. This allowed more projects to be used in the subsequent regression analysis that will give results with more validity. For the heterogeneity analysis, the original dataset was used; projects were removed that did not have complete information on project characteristics or recordable incidents. This left 158 projects for use in the heterogeneity analysis.

During review of possible sources of heterogeneity, it was determined that in addition to using the available data fields, other potential variables could be calculated and tested for heterogeneity effects. The first variable that was calculated from the data set was the project duration. The second variable that was calculated was worker density. The following are the nine project characteristics from the data set or additional calculated values that were tested as sources of heterogeneity:

1. Location (Domestic, International)
2. Major Classification (Light Industrial, Heavy Industrial, Infrastructure, Buildings)
3. Characteristic (Grass Roots, Modernization, Addition, Brownfield or Co-Location)

4. Project Delivery Method (Design-Build, Multiple Design-Build, CM at Risk, Traditional D-B-B, Parallel Primes, Other)
5. Fast Tracked (yes, no)
6. Complexity (1-10)
7. Project Cost
8. Project Duration = Project Completion Date – Project Start Date
9. Worker Density = Total Work Hours /(Project Duration * Project Cost)

However, in order to obtain the most meaningful regression results, some of the project characteristic options with a low number of occurrences had to be combined into other groups. For example, the Project Delivery Method category was reduced from a list of:

- Design-Build
- Multiple Design-Build
- CM at Risk
- Traditional D-B-B
- Parallel Primes
- Other

To an abbreviated list where the groups CM at Risk, and Multiple Design-Build were added to the "Other" category:

- Design-Build
- Traditional D-B-B
- Parallel Primes
- Other

The Major Classification category contained only one project in the Buildings group and one in the Infrastructure group, so these two projects were removed from the data set. Also, the country of location was translated into Domestic and International only, because each international country did not have enough projects to comprise an entire group.

5.2.2 REGRESSION ANALYSIS

Once the data was prepared for input to the regression analysis, the Zero Inflated Poisson Regression analysis was ready for execution. The initial regression model started with seven project characteristics that were potential sources of heterogeneity directly found in the data set. These seven characteristics that are found directly in the data and included in the first regression attempt are:

1. Location (Domestic, International)
2. Major Classification (Light Industrial, Heavy Industrial)
3. Characteristic (Grass Roots, Modernization, Addition, Brownfield or Co-Location)
4. Project Delivery Method (Design-Build, Traditional D-B-B, Parallel Primes, Other)
5. Fast Tracked (yes, no)
6. Complexity (1-10)
7. Project Cost

The results from this Zero Inflated Poisson Regression analysis using these seven independent variables and the dependent variable of Total Number of Recordable Incidents showed that there are four variables that are statistically significant drivers of the recordable incidents for the Normal Poisson Group. The results that are important in this application are the results for the Normal Poisson Group. The Inflated Zero group will include only projects with zero recordable incidents and as discussed during the development of the DEA models, these projects will be defined as inherently effective and removed.

Once all of the statistically insignificant variables have been removed, the final regression results are shown in Table 6 (see Appendix 1 for full results). Table 6 contains many different sections of results. The first portion "Model Information" states the data file used, the distribution and type of regression used and other characteristics of the regression model. The portion of Table 6 entitled, "Class Level Information" lists all of the independent variables and how many levels each variable contain. The next section "Criteria For Assessing Goodness of Fit" contains different measures of how well the regression equation fits the data; some of these measures will be used and discussed in future sections of this study. The "Analysis of Maximum Likelihood Parameter Estimates" section is the portion of Table 6 which contains the specific coefficient estimate and significance results for each independent variable. The "Estimate" column shows the coefficient the variable receives in the regression equation, and the "Pr>ChiSq" column is a measure of how statistically significant the variable is in the regression equation. A general rule is that the "Pr>ChiSq" column should have a value less than 0.05 to be considered statistically significant and remain included in the regression equation.

Table 6: SAS Software Results Output for Zero Inflated Poisson Regression Using Seven Variables

BIC (smaller is better)		692.4471	

Analysis Of Maximum Likelihood Parameter Estimates

Parameter		DF	Estimate	Standard Error	Wald 95% Confidence Limits		Wald Chi-Square	Pr > ChiSq
Intercept		0	0.0000	0.0000	0.0000	0.0000	.	.
country_r	**International**	1	-13.2823	0.2133	-13.7004	-12.8643	3877.89	<.0001
country_r	**United States**	1	-12.2530	0.1889	-12.6232	-11.8828	4207.97	<.0001
majorcls	**Heavy Industrial**	1	-0.7764	0.1022	-0.9767	-0.5761	57.71	<.0001
majorcls	**Light Industrial**	0	0.0000	0.0000	0.0000	0.0000	.	.
char	**Addition**	1	0.4864	0.1976	0.0992	0.8737	6.06	0.0138
char	**Brownfield or Co-location**	1	1.0830	0.2322	0.6278	1.5381	21.75	<.0001
char	**Grass Roots**	1	0.5556	0.1854	0.1922	0.9190	8.98	0.0027
char	**Modernization**	0	0.0000	0.0000	0.0000	0.0000	.	.
projectcost1		1	0.0007	0.0001	0.0006	0.0008	96.89	<.0001
Scale		0	1.0000	0.0000	1.0000	1.0000		

The results from this regression model are found in the "Analysis Of Maximum Likelihood Parameter Estimates" and "Analysis Of Maximum Likelihood Zero Inflation Parameter Estimates" sections of Table 6. The "Analysis Of Maximum Likelihood Parameter Estimates" portion of the table shows the results for the projects that lie under a normal Poisson function and the "Analysis Of Maximum Likelihood Zero Inflation Parameter Estimates" portion of the table shows the results for the projects that lie above a normal Poisson function. The remaining parameters in this regression model all contain a Chi Squared (shown as Pr>ChiSq in the column heading) value of less than 0.05, which defines the variable as statistically significant.

From the "Criteria for Assessing Goodness of Fit" section, the BIC of this initial model can be found and has a value of 692 and the significant variables that pertain to the data used in this study are:

- **Statistically Significant Variables to the Normal Poisson Group**
    - Project Location (Domestic, International)
    - Major Classification (Light Industrial, Heavy Industrial)
    - Characteristic (Grass Roots, Modernization, Addition, Brownfield or Co-Location)
    - Project Cost

The variables that were removed due to a lack of statistical significance are:

- **Statistically Insignificant Variables to the Normal Poisson Group**
    - Project Delivery Method (Design-Build, Traditional D-B-B, Parallel Primes, Other)
    - Fast Tracked (yes, no)
    - Complexity (1-10)
- **Statistically Insignificant Variables to the Inflated Zero Group**
    - Location (Domestic, International)
    - Major Classification (Light Industrial, Heavy Industrial)
    - Characteristic (Grass Roots, Modernization, Addition, Brownfield or Co-Location)
    - Fast Tracked (yes, no)
    - Complexity (1-10)
    - Project Cost

A second regression model was executed with the addition of two more independent variables. It was decided that the variables of project duration and worker density should be evaluated for any impact they will have on the recordable incidents in a project. A new regression analysis would be completed using the following independent variables:

1. Location (Domestic, International)
2. Major Classification (Light Industrial, Heavy Industrial)
3. Characteristic (Grass Roots, Modernization, Addition, Brownfield or Co-Location)
4. Project Delivery Method (Design-Build, Traditional D-B-B, Parallel Primes, Other)
5. Fast Tracked (yes, no)
6. Complexity (1-10)
7. Project Cost
8. **Project Duration**
9. **Worker Density**

It was immediately observed that the variable, Worker Density, had significant similarity with the dependent variable. Because the Total Work Hours is in the dependent variable as well as the Worker Density (an independent variable) equations, the Worker Density variable could not be properly analyzed using regression and was therefore removed from the analysis.

Now using the eight remaining project characteristics:

1. Location (Domestic, International)
2. Major Classification (Light Industrial, Heavy Industrial)
3. Characteristic (Grass Roots, Modernization, Addition, Brownfield or Co-Location)
4. Project Delivery Method (Design-Build, Traditional D-B-B, Parallel Primes, Other)
5. Fast Tracked (yes, no)
6. Complexity (1-10)
7. Project Cost
8. **Project Duration**

The Zero Inflated Poisson regression model was carried out. This was done by first including data for all eight characteristic variables for the 157 projects. (One project in the regression data set did not contain information required for the Project Duration variable and was removed from the data set originally containing 158). The least significant variables were removed, one at a time, until a final model was obtained.

With the insignificant variables removed, the final regression analysis results were obtained and pertinent values are shown in Table 7 (see Appendix 2 for full results).

Table 7: SAS Software Results Output for Zero Inflated Poisson Regression Using Eight Variables

BIC (smaller is better)		661.0695	

Algorithm converged.

Analysis Of Maximum Likelihood Parameter Estimates

Parameter		**DF**	**Estimate**	**Standard Error**	**Wald 95% Confidence Limits**		**Wald Chi-Square**	**Pr > ChiSq**
Intercept		1	-12.0220	0.1904	-12.3952	-11.6487	3984.82	<.0001
country_r	**International**	1	-1.2116	0.1095	-1.4263	-0.9969	122.35	<.0001
country_r	**United States**	0	0.0000	0.0000	0.0000	0.0000	.	.
majorcls	**Heavy Industrial**	1	-1.0795	0.1205	-1.3157	-0.8433	80.22	<.0001
majorcls	**Light Industrial**	0	0.0000	0.0000	0.0000	0.0000	.	.
char	**Addition**	1	0.4544	0.1963	0.0697	0.8390	5.36	0.0206
char	**Brownfield or Co-location**	1	1.2104	0.2329	0.7539	1.6670	27.00	<.0001
char	**Grass Roots**	1	0.6375	0.1839	0.2770	0.9979	12.01	0.0005
char	**Modernization**	0	0.0000	0.0000	0.0000	0.0000	.	.
projectcost1		1	0.0008	0.0001	0.0007	0.0010	112.86	<.0001
Scale		0	1.0000	0.0000	1.0000	1.0000		

The results from this regression model are found in the "Analysis Of Maximum Likelihood Parameter Estimates" and "Analysis Of Maximum Likelihood Zero Inflation Parameter Estimates" sections of Table 7. The "Analysis Of Maximum Likelihood Parameter Estimates" portion of the table shows the results for the projects that lie under a normal Poisson function and the "Analysis Of Maximum Likelihood Zero Inflation Parameter Estimates" portion of the table shows the results for the projects that lie above a normal Poisson function. The remaining parameters in this regression model all contain a Chi Squared (shown as Pr>ChiSq in the column heading) value of less than 0.05, which defines the variable as statistically significant.

From the "Criteria for Assessing Goodness of Fit" section, the BIC of this initial model can be found and has a value of 661 and the final results used for this heterogeneity analysis are:

- **Statistically Significant Variables to the Normal Poisson Group**
  - Project Location (Domestic, International)
  - Major Classification (Light Industrial, Heavy Industrial)
  - Characteristic (Grass Roots, Modernization, Addition, Brownfield or Co-Location)
  - Project Cost

The variables that were identified as statistically insignificant (having a ChiSq > 0.05) and removed from the regression model were:

- **Statistically Insignificant Variables to the Normal Poisson Group**
  - Project Delivery Method (Design-Build, Traditional D-B-B, Parallel Primes, Other)
  - Fast Tracked (yes, no)
  - Complexity (1-10)
  - Project Duration
- **Statistically Insignificant Variables to the Inflated Zero Group**
  - Location (Domestic, International)
  - Major Classification (Light Industrial, Heavy Industrial)
  - Characteristic (Grass Roots, Modernization, Addition, Brownfield or Co-Location)
  - Fast Tracked (yes, no)
  - Complexity (1-10)

- Project Cost
- Project Duration

The final step in determining the heterogeneity drivers is to conduct a practical and qualitative observation of the characteristics that were identified from the regression analysis. From a construction viewpoint, these four characteristics that were determined significant to the Normal Poisson group are:

1. Project Location (Domestic, International)
2. Major Classification (Light Industrial, Heavy Industrial)
3. Characteristic (Grass Roots, Modernization, Addition, Brownfield or Co-Location)
4. Project Cost

The four variables are logical characteristics that could create differences in project safety. All other project characteristics were also re-evaluated for re-inclusion based upon their logical significance to safety performance, but no other factors were deemed important enough to override the regression results.

The BIC of this second model, which included the project duration variable, has a BIC score of 661. Compared to the BIC of the first model (692), this second model better represents all of the factors impacting the total number of recordable incidents, and therefore these results will be utilized for the remainder of the study. In addition, the identical results in the Normal Poisson Group for the regression analyses both with and without the calculated variable, project duration, help to validate the results.

5.2.3 PROJECT CLUSTERING

With the sources of project heterogeneity determined, they can be used to effectively cluster the project into homogeneous groups. Note that all projects with zero recordable incidents have been removed from the data set and determined to be “inherently effective” projects, due to the constraints of an output oriented DEA model. An output oriented DEA model is only translation invariant with respect to the inputs and therefore can not be adjusted to handle outputs with a value of zero. The common method of adding a constant to all of the values (translation) can not be utilized for the outputs in an output-oriented model. This creates a problem with the output in this scenario (RIR) because it is undesirable and the inverse must be used. Because an output of 0 can not be inversed, and a constant can not be added in the output- oriented model, it must be removed from this study. Those four factors that influence the safety performance are again,

1. Project Location (Domestic, International)
2. Major Classification (Light Industrial, Heavy Industrial)

3. Characteristic (Grass Roots, Modernization, Addition, Brownfield or Co-Location)
4. Project Cost

A hierarchical clustering algorithm is now applied to the 59 projects in the dataset. The inputs are the four factors of heterogeneity listed above. The projects will then each begin in their own cluster and combined with another cluster that is the most similar with respect to the four input parameters. This process will continue until all data points are in one cluster. The user can then specify at which point (number of clusters) the data should be separated.

Using this hierarchical clustering algorithm, four different cluster scenarios were calculated:

1. 6 Clusters
2. 5 Clusters
3. 4 Clusters
4. 3 Clusters

These four different scenarios break up the 59 construction projects into 3-6 clusters. These different options were calculated to ensure that the ratio of DMU to input/output variables in DEA will meet all applicable criteria. When there are more clusters, each cluster will be more homogeneous within itself. The fewer clusters utilized, the more projects that will be present within each cluster, and this will increase the discrimination power of DEA but decrease the amount of homogeneity within the clusters. In order to be able to find the appropriate balance of accounting for the heterogeneity and allowing for maximum discrimination power to be presence, these four different clustering scenarios were calculated.

When the projects are clustered together in the four different scenarios, the breakdown of the number of projects in each group is shown in Figure 7.

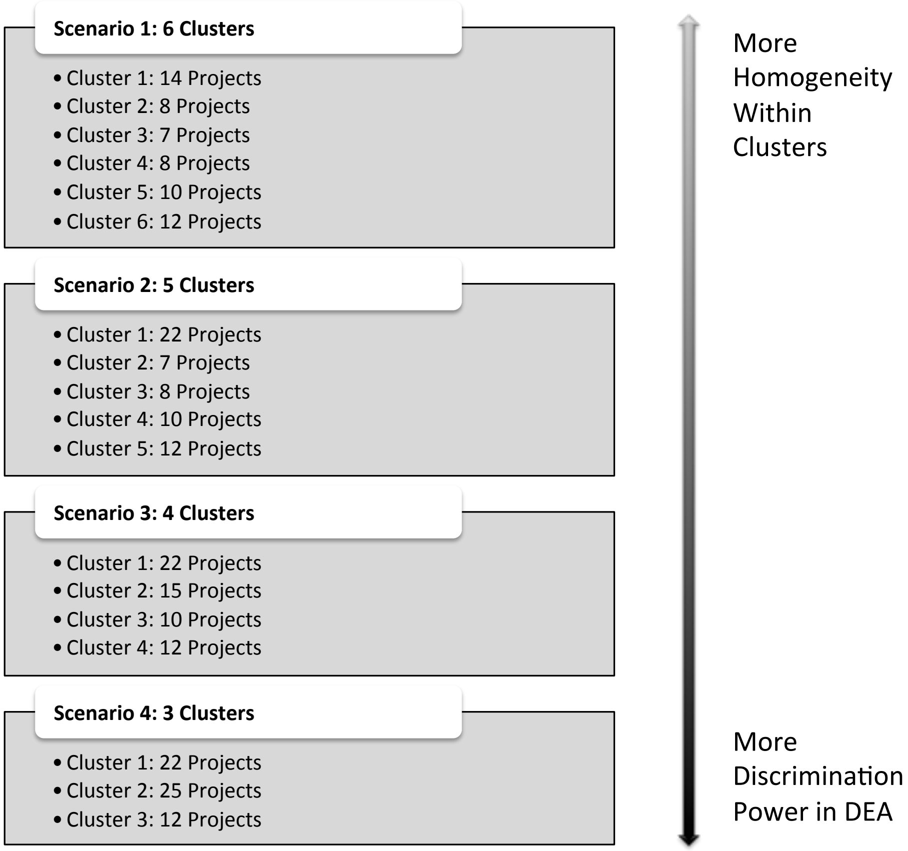


Figure 7: Clustering's Effect on Homogeneity and Discrimination Power

Using a qualitative analysis of the characteristics of the projects contained in each cluster as well as the criteria for number of DMUs required for the DEA models in this study, a clustering scenario is selected. The project groupings were searched for logical common threads, and the option of Scenario 3, 4 Clusters is selected for use in this study. Scenario 3 keeps a minimum of 10 projects in any cluster, which should provide an adequate amount of discrimination power but this will be mathematically tested in later sections of this study.

Taking a look at the descriptions of the characteristics in each cluster in Table 8, the characteristics of each cluster are shown. In Scenario 3, the project clusters are separated by location. The international cluster of projects contains both heavy and light industrial classifications in all scenarios. The domestic projects are clearly separated by light and heavy industrial projects. The heavy industrial cluster contains all domestic heavy industrial projects regardless of their characteristic while the domestic and light industrial projects are separated into two clusters. Dividing the grass roots projects from the modernization and addition projects is logical because of the nature of these types of construction. A grass roots project involved different elements of pre-construction preparation than revamping an existing unit.

Table 8: Characteristics of Project Clusters in Four Clustering Scenarios.

Scenario 1: 6 Clusters

Cluster	*# of Projects*	*Location*	*Major Classification*	*Characteristic*
1	14	Domestic	Heavy	Modernization Grass Roots Brownfield
2	8	Domestic	Heavy	Addition
3	7	Domestic	Light	Modernization
4	8	Domestic	Light	Addition
5	10	Domestic	Light	Grass Roots
6	12	International	Light Heavy	Modernization Grass Roots Addition

Scenario 2: 5 Clusters

Cluster	*# of Projects*	*Location*	*Major Classification*	*Characteristic*
1	22	Domestic	Heavy	Modernization Grass Roots Brownfield Addition
2	7	Domestic	Light	Modernization
3	8	Domestic	Light	Addition
4	10	Domestic	Light	Grass Roots
5	12	International	Light Heavy	Modernization Grass Roots Addition

Scenario 3: 4 Clusters

Cluster	*# of Projects*	*Location*	*Major Classification*	*Characteristic*
1	22	Domestic	Heavy	Modernization Grass Roots Brownfield Addition
2	15	Domestic	Light	Modernization Addition
3	10	Domestic	Light	Grass Roots
4	12	International	Light Heavy	Modernization Grass Roots Addition

Scenario 4: 3 Clusters

Cluster	*# of Projects*	*Location*	*Major Classification*	*Characteristic*
1	22	Domestic	Heavy	Modernization Grass Roots Brownfield Addition
2	25	Domestic	Light	Modernization Addition Grass Roots
3	12	International	Light Heavy	Modernization Grass Roots Addition

The similarities of projects within each of the four clusters of Scenario 3 are enough to logically justify the groupings while keeping 10 or more projects in each group for maximum discrimination power in DEA.

This clustering option keeps two general DEA rules of thumb valid. The first rule is to maintain a number of DMUs that is twice the product of inputs and outputs (Triantis et al. 2010). And the second rule is to maintain a number of DMUs that is three times the sum of inputs and outputs (Cooper et al. 1999). For the Objective 1 model that only utilized the Recordable Incident Rate (Model 1), there is only one input and one output. The following two equations will validate both rules for the four-cluster scenario, which has 10 DMUs in the smallest cluster.

Equation 5: Maintaining Discrimination Power 1

$$\#\text{ of DMUs} > 2\cdot(\#\text{ of inputs})\cdot(\#\text{ of outputs})$$

$$10 > 2\cdot 1\cdot 1 = 2 \qquad \text{TRUE}$$

and

Equation 6: Maintaining Discrimination Power 2

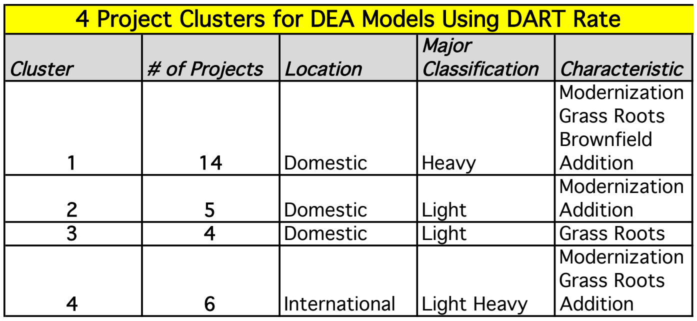
$$\#\text{ of DMUs} > 3\cdot(\#\text{ of inputs} + \#\text{ of outputs})$$

$$10 > 3\cdot(1+1) = 6 \qquad \text{TRUE}$$

While a larger number of DMUs in a cluster will always result in greater discrimination power when using DEA, the balance must be found between discrimination power and homogeneity. When both aspects are considered, and criteria are checked, the four-cluster scenario becomes the most desirable scenario for this study. The 4 cluster scenario is ultimately chosen for use in order to select the largest number of clusters (providing the most homogeneity) while still maintaining an acceptable level of discrimination power. Because it is unknown which divisions of project classification or characteristics will show different trends, it is important to keep the highest level of separation among them possible at this point in the research.

When considering Model 2 and Model 3 for Objective 1, the DART rate is used as an output. Because the DART rate is a subset of the Recordable Incident Rate, there are many more projects that have zero Days Away and Restricted Time cases than have zero Recordable Incidents. Because the output-oriented model cannot accommodate these zero values due its lack of translation invariance with respect to outputs, these projects must be removed from the data set. When the instances of the DART rate equaling zero are removed Table 9 shows the new cluster sizes and characteristics.

Table 9: Characteristics of the Four Clusters for Analyses Involving DART Rate.



4 Project Clusters for DEA Models Using DART Rate

Cluster	*# of Projects*	*Location*	*Major Classification*	*Characteristic*
1	14	Domestic	Heavy	Modernization Grass Roots Brownfield Addition
2	5	Domestic	Light	Modernization Addition
3	4	Domestic	Light	Grass Roots
4	6	International	Light Heavy	Modernization Grass Roots Addition

When the additional projects with zero for DART rate are removed, Cluster 3 is the smallest cluster with only four projects remaining.

Again, checking for an appropriate amount of discrimination power we use Equations 5 and 6. First, a test will be done for Model 3 (Input=BPIS, Outputs=1/RIR and 1/DART), which contains the highest number of input and output variables:

$4 > 2 \cdot 1 \cdot 2 = 4$ FALSE

and

$4 > 3 \cdot (1+2) = 9$ FALSE

Due to the inadequate amount of data remaining when the DART rate is used as an output, Model 3 cannot be used to obtain proper results. Model 2 (Input=BPIS, Output=1/DART) has a fewer number of input and output variables, and still a minimum cluster size of four projects, so Model 2 will also be tested to determine if a sufficient number of DMUs are available.

$4 > 2 \cdot 1 \cdot 1 = 2$ TRUE

and

$4 > 3 \cdot (1+1) = 6$ FALSE

Because the removal of projects with no DART cases drops the number of available DMUs below a level that maintains the suggested DMU to variable ratio levels, Model 2 also cannot be used to obtain reliable results. Therefore, Objective 1 conclusions will be based upon the results of Model 1 only.

5.3 EXECUTION OF DATA ENVELOPMENT ANALYSIS

Using the four project groupings previously defined by the heterogeneity analysis, the projects are able to undergo a Data Envelopment Analysis to determine the efficiency of the usage of safety inputs. The DEA analyses in Table 10 were executed.

Table 10: Objective 1 DEA Analyses of Model 1 Executed.

Objective 1 DEA Analyses of Model 1		
DMUs	Input	Output
Cluster 1	BPIS	1/RIR
Cluster 2	BPIS	1/RIR
Cluster 3	BPIS	1/RIR
Cluster 4	BPIS	1/RIR
Metagroup	BPIS	1/RIR

These Data Envelopment Analysis models were conducted as planned for the individual clusters as well as the Metagroup and the results will be discussed in Chapter 7 Results.

6. EXECUTION OF OBJECTIVE 2

This chapter will cover the actual progression of Objective 2 methodologies. Any changes that were found to be necessary will be covered in the following sections as well as the reasoning corresponding to such changes.

6.1 CLUSTERING ZAT COMPONENTS

Grouping each of the ZAT components is the first step in designing an experiment to test different aspects of the Zero Accidents Techniques. First, the components were studied to identify any commonalities among any of them. Looking at the 13 ZAT components, it was observed that multiple components pertain to the initial construction of the safety plan. Another common trait that five of the ZAT components share is the fact that they require upkeep throughout the entire construction phase. This makes safety maintenance a second logical category. The third grouping that the remaining components share was that they dictated how workers or subcontractors would be assessed for employment. Using these three traits as criteria four grouping, the final groupings are shown in Figure 8.

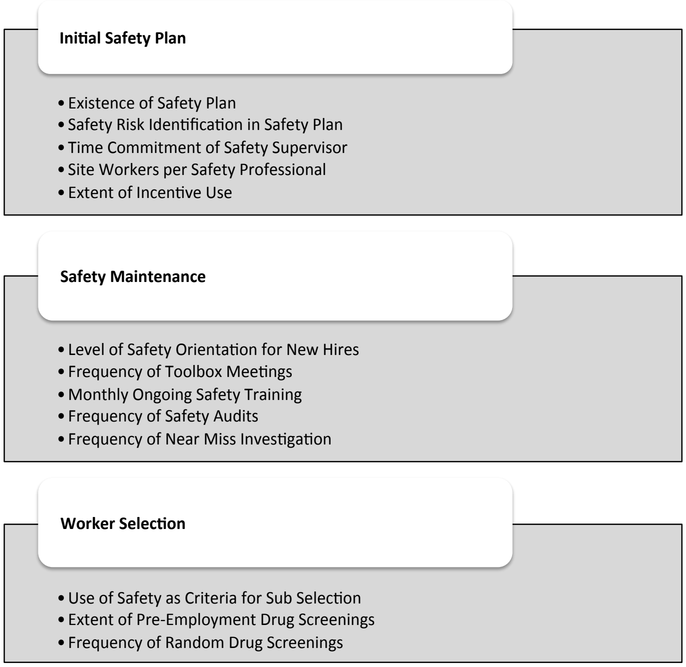


Figure 8: Final Grouping of the ZAT Components

The first group, the Initial Safety Plan, consists of all of the components that involve a definition prior to execution of the construction project. The second group, Safety Maintenance, contains all of the ZAT components that require periodical updating throughout the execution of the project. The third group, Worker Selection contains the components that attempt to select the highest quality workers to employ.

6.2 DATA PREPARATION

The process of data preparation for Objective 2 is much less intensive than the preparation required for Objective 1. The dataset that will be used is the same dataset at that used for Objective 1 before the clustering procedure; in other words, all of the 59 projects from Objective 1 are used together in one group.

Now that the three groups of ZAT components have been defined, a score for each group is calculated for each of the 59 projects in the data set. The following three fields are added to the dataset for Objective 2:

1. ZAT Group 1Score: Initial Safety Plan
2. ZAT Group 2 Score: Safety Maintenance
3. ZAT Group 3 Score: Worker Selection

The component scores that have been translated to a 0 to 1 scale during the process of calculating the BPIS will be used for the calculation of these three additional data fields. The five components included in ZAT Group 1: Initial Safety Plan are:

1. Existence of Safety Plan (0-1)
2. Safety Risk Identification in Safety Plan (0-1)
3. Time Commitment of Safety Supervisor (0-1)
4. Site Workers Per Safety Professional (0-1)
5. Extent of Incentive Use (0-1)

These five scores will be summed (for a maximum possible score of 5.0) to make the ZAT Group 1 Score. Because the purpose of this objective is to use statistical methods to determine if one group of ZAT components has more effect on the overall safety performance than others, the CII defined weightings will not be used. Imposing the weightings on these components would cause the results to be skewed towards the CII weighting system, and this objective desires to independently determine the most important factors of the ZAT. The same process will be used for ZAT Groups 2 and 3. Referring to Figure 8 and noting the number of components in each group, ZAT Group 2 Score will have a maximum possible score of 5.0 because there are five components in this group. ZAT Group 3 Score will have a maximum possible score of 3.0 because this group contains three ZAT components. Using these three ZAT Scores as inputs and the undesirable output of RIR, the DEA model used is shown in Figure 9.

Figure 9: Objective 2 DEA Model

The group of 59 DMUs must be checked against the proposed DEA model for an acceptable number of DMUs with respect to the proposed inputs and outputs. This check is important to ensure an appropriate level of discrimination power. Using Equation 5 and 6, the Objective 2 DEA model will be tested.

The Objective 2 DEA Model uses only 1/RIR as an output and the three ZAT Group Scores as inputs. The projects are not separated by heterogeneity in Objective 2, as they were in Objective 1. This means that there are some inherent differences between the groups of projects that are not being considered. The relative efficiency scores that DEA will output will be lacking the distinction of the heterogeneity. The relative efficiency scores are not needed for Objective 2, and only the average weightings that DEA assigns to each of the input variables, and therefore all 59 projects can be run together and the relative efficiency scores will not be misinterpreted because they will not be used in this study. Checking the Objective 2 DEA Model against Equations 5 and 6 gives:

$59 > 2 \cdot 3 \cdot 1 = 6$ TRUE

and

$59 > 3 \cdot (3+1) = 12$ TRUE

Both criteria for Model 1 hold true, and therefore this model can be run and will have an appropriate level of discrimination power to utilize the results.

6.3 EXECUTION OF REGRESSION ANALYSIS

The regression analysis was conducted on the 59 projects in the dataset. The distribution of the response variable (total number of recordable incidents) is shown below in Figure 10.

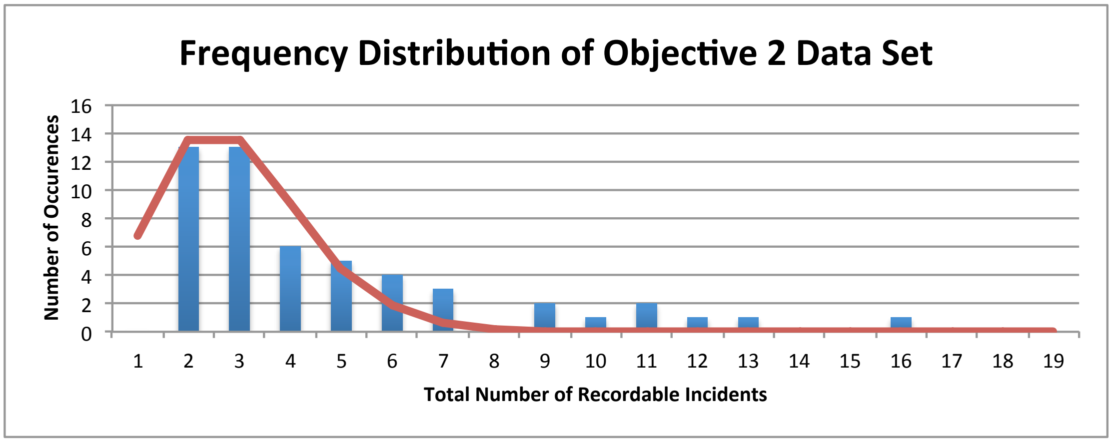


Figure 10: Frequency Distribution of the 59 Data Points in the Objective 2 Data Set.

The distribution of the data most closely resembles a Poisson distribution. A Poisson function has been fitted to the data in red on Figure 10. Because this dataset had already been cleaned of the "inherently effective" projects, which are the projects that had zero recordable incidents, the distribution is a normal Poisson, and not the Zero Inflated Poisson as used for the heterogeneity analysis of Objective 1.

A Poisson regression analysis was conducted using the following variables:

Dependent Response Variable:

1. Total Number of Recordable Incidents

Independent Variables:

1. ZAT Group 1 Score
2. ZAT Group 2 Score
3. ZAT Group 3 Score
4. Location
5. Major Classification
6. Characteristic
7. Project Cost

The independent variables that are insignificant are removed from the regression model, one at a time. When the remaining variables are significant or borderline significant using a significance criterion of $p\text{-value} < 0.05$ the final regression equation will be reached.

6.4 EXECUTION OF DATA ENVELOPMENT ANALYSIS

All 59 DMUs in the data set were included in the following DEA model:

- Input:
    - ZAT Group 1 Score
    - ZAT Group 2 Score
    - ZAT Group 3 Score
- Output:
    - 1/RIR

7. OBJECTIVE 1 RESULTS AND CONCLUSIONS

This chapter will discuss the results that were returned from the DEA analyses in Objective 1 as well as any conclusions that can be made from these results. The results chapter will be broken down to separate the results for the individual group analyses and Meta-Frontier analyses. The results sections will contain only the data regarding the DEA efficiency scores and any observations that can be made about this data. The conclusions sections will investigate trends found throughout the results sections and possible interpretations of these trends. The conclusions sections will also include any possible recommendations for safety improvements based upon the results of the DEA analyses.

7.1 OBJECTIVE 1 RESULTS

7.1.1 MODEL 1 GROUP RESULTS

This section will specifically cover the results from the DEA analysis of each cluster for Objective 1. The following sections will contain the efficiency scores obtained from the DEA analysis and a breakdown of the relationships between efficiency scores, inputs and outputs. Observing any relationships, or trends between the efficiency and either the input or the output will provide insight to the overall association of the efficiency scores to safety implementation and performance.

7.1.1.1 CLUSTER 1 RESULTS

The first cluster contains DMUs that consist entirely of Heavy Industrial projects. These Heavy Industrial projects are domestic and on the high end of the project cost range. The results of the DEA analysis are shown in Table 11.

Table 11: Cluster 1 DEA Results Table

Rank	DMU	Score
1	C8878-1693	1
2	C8189-2588	0.999643
3	O8496-8839	0.504623
4	C8927-6453	0.5
5	O8996-1824	0.377046
6	C8222-4439	0.325403
7	C8194-4139	0.306399
8	O8448-5127	0.223921
9	C8629-4799	0.212673
10	C8133-8458	0.181403
11	O8936-1335	0.150727
12	C8134-3983	0.147368
13	C8789-7530	0.144737
14	O8800-2009	0.123947
15	C8385-4404	9.75E-02
16	C8913-1125	8.38E-02
17	O8907-7435	7.89E-02
18	O9258-6364	6.57E-02
19	C8482-1942	5.86E-02
20	C8317-7585	3.77E-02
21	C8786-6958	3.58E-02
22	C8429-6775	2.90E-02

Cluster 1 contains one efficient DMU and one other DMU that is nearly efficient (within 0.1%). The two top ranked DMU's have BPISs of 7.6 and 5.8. The Recordable Incident Rate was less than 2 for the top two DMUs, however they were not the two DMUs with the lowest RIR in the cluster. Looking at the relationship between the efficiency scores and the RIR (output) in Figure 11, the trend of the data does show a negative correlation. Therefore as the RIR increases, the DEA efficiency scores are decreasing. This is a logical relationship that was expected from the Data.

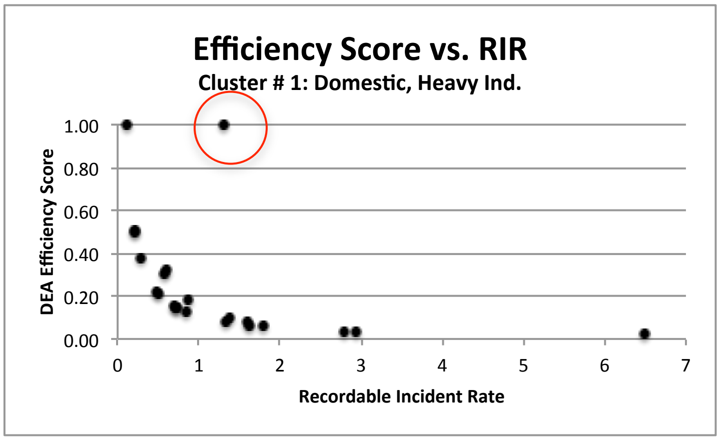


Figure 11: Graphical View of the Relationship Between DEA Efficiency Scores and the Recordable Incident Rate for Cluster #1.

The data in Figure 11 is taking on a logarithmic shape with the exception of the second ranked DMU that is circled in red. The subsequent groups will be checked for any similarities in this data behavior.

The efficient frontier of Cluster 1 is shown in Figure 12. The maximum output is 9.5 and the minimum input used is 7.6 in this cluster. Because the cluster has only one fully efficient project, the frontier takes on a rectangular shape.

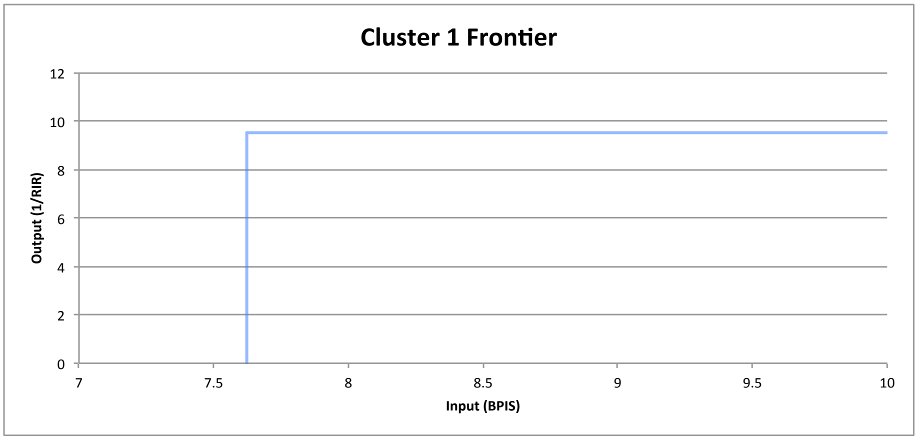


Figure 12: Estimated Frontier of Cluster 1

The results of Cluster 1's efficient frontier do not provide much insight standing alone, but will become more informative when investigated relative the frontiers of the other three clusters.

7.1.1.2 CLUSTER 2 RESULTS

The second cluster of DMUs contained projects that consist entirely of Light Industrial projects. These Light Industrial projects are also all domestic projects with a modernization or addition characteristic. The results and the efficiency scores for the projects in Cluster 2 are shown in Table 12.

Table 12: Cluster 2 DEA Results Table

Rank	DMU	Score
1	O9950-356	1
2	O9346-389	0.999727
3	O8846-953	0.999438
4	O8648-914	0.997563
5	O8839-500	0.848446
6	O8774-895	0.567251
7	O9123-710	0.51261
8	O8906-408	0.454592
9	O8358-124	0.323109
10	O8256-186	0.215721
11	O9222-666	0.135902
12	O9721-636	8.28E-02
13	O8811-468	7.10E-02
14	O8420-600	6.57E-02
15	O9986-742	3.69E-02

Cluster 2 contains one efficient DMU and three others that are nearly efficient (within 0.25%). From Figure 13, the top four ranked DMUs had BPISs ranging from 5.3 to 7.2. DMUs 2-4 appear to be "logical outliers" in Figure 13 and are circled in red. These three potential "logical outliers" have Recordable Incident Rates ranging from 2.9 to 4.5. While these data points may not be true outliers by statistically significant definitions, they lie outside of safety performance logic. It would be expected that any DMU having an RIR as high as 4.5 wouldn't be considered a desirable target for other DMU's to aim for.

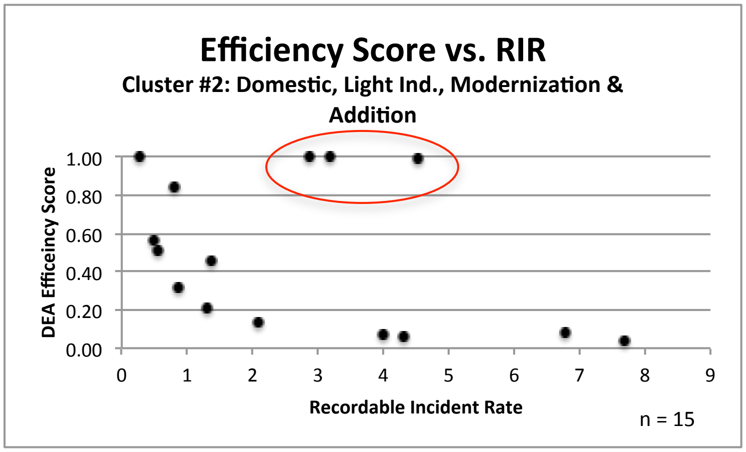


Figure 13: Graphical View of the Relationship Between DEA Efficiency Scores and the Recordable Incident Rate for Cluster #2.

The efficient frontier for Cluster 2 is shown in Figure 14, below. Just as was seen in Cluster 1, there is only one fully efficient DMU in Cluster 2, which means that the estimated frontier will consist of only two lines in a rectangular shape.

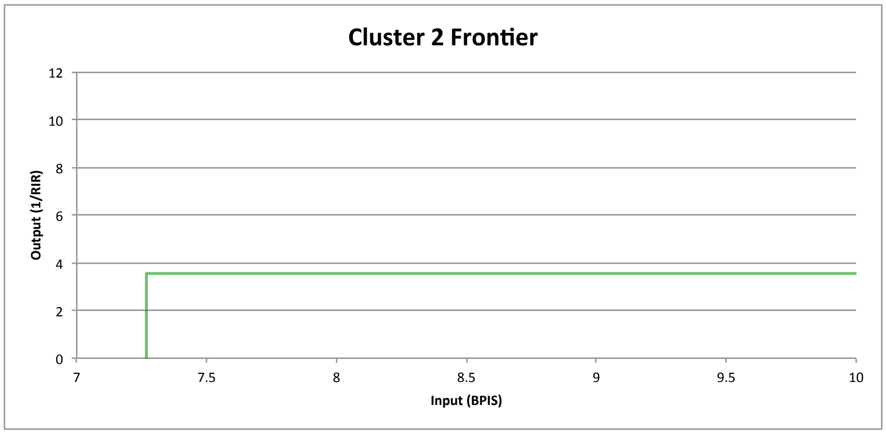


Figure 14: Estimated Efficient Frontier of Cluster 2.

The area under the frontier of Cluster 2 is significantly smaller than the area under the frontier of Cluster 1. The maximum output for Cluster 2 is 3.5 and 7.2 is the minimum input used to achieve the maximum output level. Compared to Cluster 1, which had a maximum output of 9.5, this group seems to be relatively underperforming compared to Cluster 1.

7.1.1.3 CLUSTER 3 RESULTS

The third cluster of DMUs contained projects that consist entirely of Light Industrial, domestic, grass roots projects. The first six ranked DMUs in Cluster 3 are within 0.01 of 100% efficient and only the first one is fully efficient. It would be expected that Cluster 3 would return a higher number of efficient projects because it contained the lowest number of DMUs and therefore will have the least discrimination power among the clusters. The results from the DEA analysis are shown below, in Table 13.

Table 13: Cluster 3 DEA Results Table.

Rank	DMU	Score
1	O8564-362	1
2	O9264-280	0.999876
3	O9160-805	0.999696
4	O8747-525	0.999529
5	O9861-156	0.999036
6	O8959-376	0.998003
7	O8591-611	0.884918
8	O8555-931	0.627166
9	C8692-438	0.398003
10	O9305-518	0.151985

Figure 15 shows somewhat of a logarithmic trend with the exception of DMUs 2-6, circled in red, that appear to be “logical outliers” from the logarithmic trend, and are lacking a logical reasoning for their nearly efficient scores. For example, a project with a RIR of almost nine, would not want to be used in application as a target model for other projects, regardless of its level of ZAT implementation.

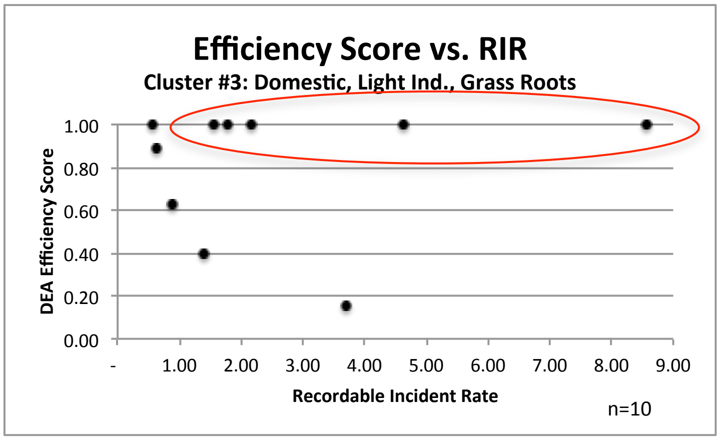


Figure 15: Graphical View of the Relationship Between DEA Efficiency Scores and the Recordable Incident Rate for Cluster #3.

The efficient frontier of Cluster 3 is shown in Figure 16, below. Again, a data set containing only one fully efficient DMU results in a rectangular shape. The maximum output of Cluster 3 is 1.8, and 7.8 is the minimum input used to achieve the maximum output in this cluster.

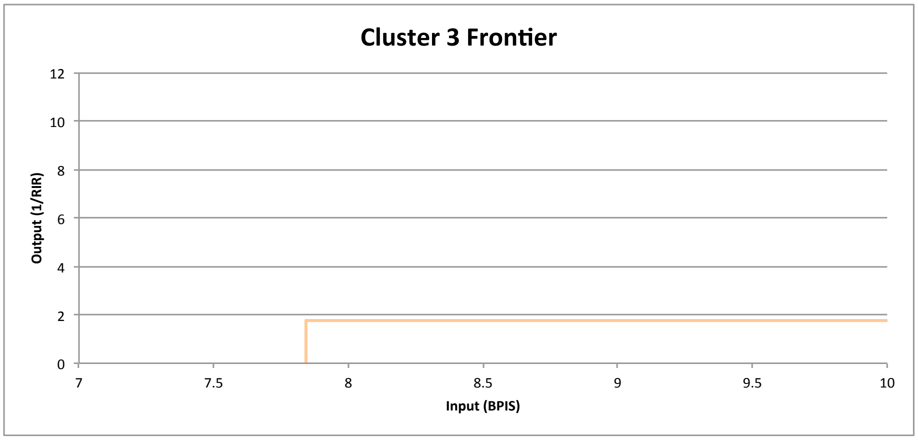


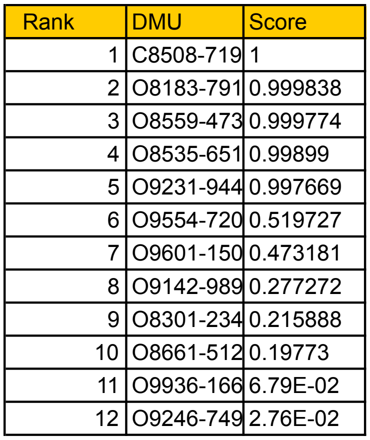
Figure 16: Estimated Efficient Frontier of Cluster 3.

Comparing the frontier of Cluster 3 to the frontiers of Cluster 1 and Cluster 2, it seems to be underperforming with respect to Cluster 1 and is similar to the frontier of Cluster 2.

7.1.1.4 CLUSTER 4 RESULTS

The fourth cluster of projects consists of entirely international projects. There is a mix of heavy and light industrial for the major classification, as well as a mix of project characteristic. The data for Cluster 4 has the most variance from the logarithmic trend shown in the first three clusters. This could be due to the fact that the common thread of Cluster 4 was the international location of them all, and the other defining characteristics were widely spread. Also international projects, by their nature, are coming from many different countries as opposed to the "Domestic" location which all come from one single country with the same safety laws and regulations. The results obtained from the DEA analysis are shown in Table 14.

Table 14: Cluster 4 DEA Results Table.



Rank	DMU	Score
1	C8508-719	1
2	O8183-791	0.999838
3	O8559-473	0.999774
4	O8535-651	0.99899
5	O9231-944	0.997669
6	O9554-720	0.519727
7	O9601-150	0.473181
8	O9142-989	0.277272
9	O8301-234	0.215888
10	O8661-512	0.19773
11	O9936-166	6.79E-02
12	O9246-749	2.76E-02

Cluster 4 contains one fully efficient project and four others that are nearly efficient (within 0.25%). DMUs 2-4 are circled in red and appear to be logical outliers when looking at Figure 17. The same logarithmic trend is still noticed in the relationship between the efficiency scores and the Recordable Incident Rate, however not as strongly as the first three clusters. The overall negative correlation between the Recordable Incident Rate and the DEA efficiency score can still be observed in Figure 17.

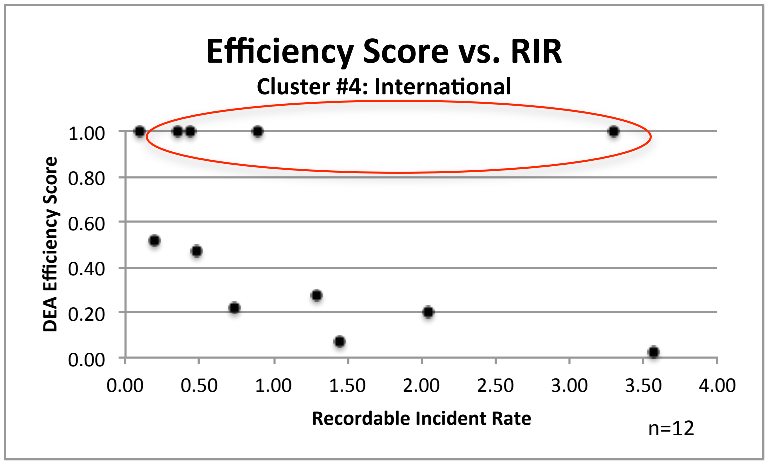


Figure 17: Graphical View of the Relationship Between DEA Efficiency Scores and the Recordable Incident Rate for Cluster #4.

The estimated frontier of Cluster 4 is shown in Figure 18, below. One fully efficient DMU results in a rectangular shaped frontier. The maximum output achieved by Cluster 4 is 10.1, and 8.1 is the minimum input used to achieve this maximum output.

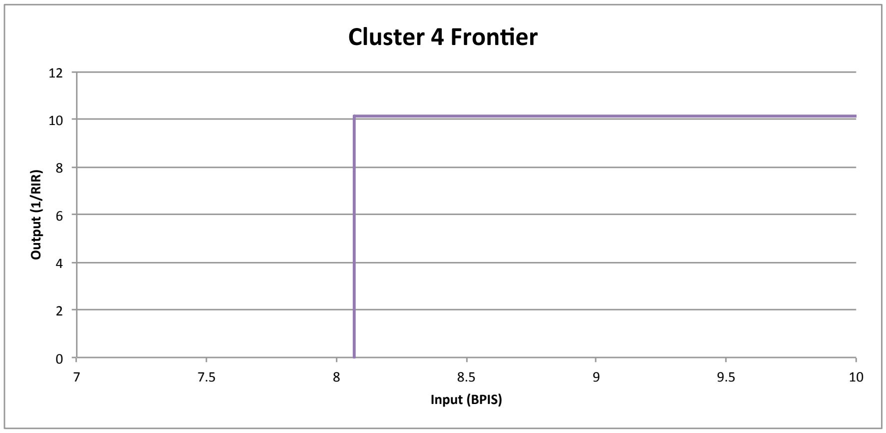


Figure 18: Estimated Efficient Frontier of Cluster 4.

The frontier of Cluster 4 has the highest maximum output of all of the clusters. While this group of projects is achieving the best safety performance it is also utilizing the highest amount of input (ZAT implementation) than any other cluster. That means that this cluster implemented the highest levels of the ZAT and also achieved the best safety performance.

7.1.2 META-FRONTIER RESULTS

This section will specifically cover the results from the Meta-Frontier analysis conducted by combining all four clusters in Objective 1. The efficiency scores returned for the Meta-Frontier analysis contain four 100% efficient DMUs, one originating in the first cluster and one originating in the fourth cluster.

To summarize the four clusters that will combine into the metagroup for the Meta-Frontier analysis, Table 15 shows the efficiency scores and MTRs for all of the projects in the dataset.

Table 15.: Efficiency Scores and MTRs of All DMUs

DMU	*Cluster*	*Group Efficiency Score*	*Metagroup Efficiency Score*	*MTR*
1	1	0.084	0.080	0.954
2	1	0.213	0.201	0.943
3	1	0.059	0.055	0.937
4	1	0.147	0.138	0.937
5	1	0.145	0.136	0.937
6	1	0.038	0.035	0.937
7	1	0.224	0.217	0.970
8	1	0.124	0.116	0.937
9	1	0.377	0.353	0.937
10	1	0.079	0.074	0.937
11	1	1.000	1.000	1.000
12	1	0.505	0.499	0.989
13	1	0.066	0.066	0.997
14	1	0.151	0.141	0.937
15	1	0.029	0.026	0.880
16	1	0.500	0.468	0.937
17	1	0.325	0.284	0.872
18	1	0.036	0.035	0.977
19	1	0.098	0.093	0.953
20	1	0.306	0.276	0.899
21	1	0.181	0.167	0.923
22	1	1.000	0.337	0.338
23	2	0.216	0.076	0.352
24	2	0.455	0.213	0.467
25	2	0.513	0.187	0.364
26	2	0.136	0.047	0.348
27	2	0.037	0.013	0.362
28	2	0.848	0.401	0.473
29	2	0.071	0.026	0.364
30	2	0.567	0.247	0.436
31	2	0.323	0.112	0.348
32	2	1.000	0.436	0.436
33	2	0.083	0.038	0.461
34	2	1.000	0.999	1.000
35	2	0.066	0.023	0.348
36	2	0.999	0.145	0.145
37	2	0.998	0.041	0.041
38	3	1.000	0.125	0.125
39	3	1.000	0.211	0.211
40	3	0.998	0.030	0.030
41	3	0.398	0.070	0.176
42	3	1.000	0.237	0.237
43	3	0.152	0.028	0.182
44	3	1.000	0.106	0.106
45	3	0.999	0.084	0.084
46	3	0.627	0.115	0.184
47	3	0.885	0.166	0.188
48	4	0.277	0.249	0.898
49	4	0.198	0.179	0.906
50	4	0.216	0.187	0.865
51	4	0.473	0.415	0.876
52	4	1.000	1.000	1.000
53	4	0.999	0.999	1.000
54	4	1.000	1.000	1.000
55	4	1.000	1.000	1.000
56	4	0.028	0.028	1.000
57	4	0.520	0.520	1.000
58	4	0.998	0.226	0.227
59	4	0.068	0.068	1.000

The metatechnology ratios for the Meta-Frontier analysis contain nine DMUs with a ratio of 100%, one of them originating in the first cluster, one originating in the second cluster and seven of them originating in the fourth cluster. This information begins to direct attention to the fourth cluster to investigate the reasoning why it is performing more efficiently than the other clusters. The average metatechnology ratios for the four clusters are:

- **Cluster 1** = 0.915
- **Cluster 2** = 0.396
- **Cluster 3** = 0.152
- **Cluster 4** = 0.898

These average metatechnology ratios represent how close the group frontier is to the Meta-Frontier. Cluster 1 and Cluster 4 compose the majority of the Meta-Frontier because their average metatechnology ratios are close to one. All of the DMUs with a metatechnology ratio of 1 come from Cluster 1 and Cluster 4 with the exception of one DMU from Cluster 2 lying on the Meta-Frontier.

Combining Figures 12, 14, 16, and 18 forms Figure 19 and it shows the estimated construction of the Meta-Frontier using estimates of each group frontier. The estimates were created using only the projects from each group that had an efficiency score of exactly one. There are other projects that had efficiency scores of very nearly one, as seen in the individual group results that appear to be efficient. For the purposes of estimating the frontiers to compare to the Meta-Frontier, using the 100.0% efficient projects creates an appropriate visual representation. The frontiers for Cluster 1 and Cluster 4 are clearly the most similar to the Meta-Frontier and the one project lying on the Meta-Frontier from Cluster 2 can be seen where the Cluster 2 frontier pushes the Meta-Frontier out further to the left.

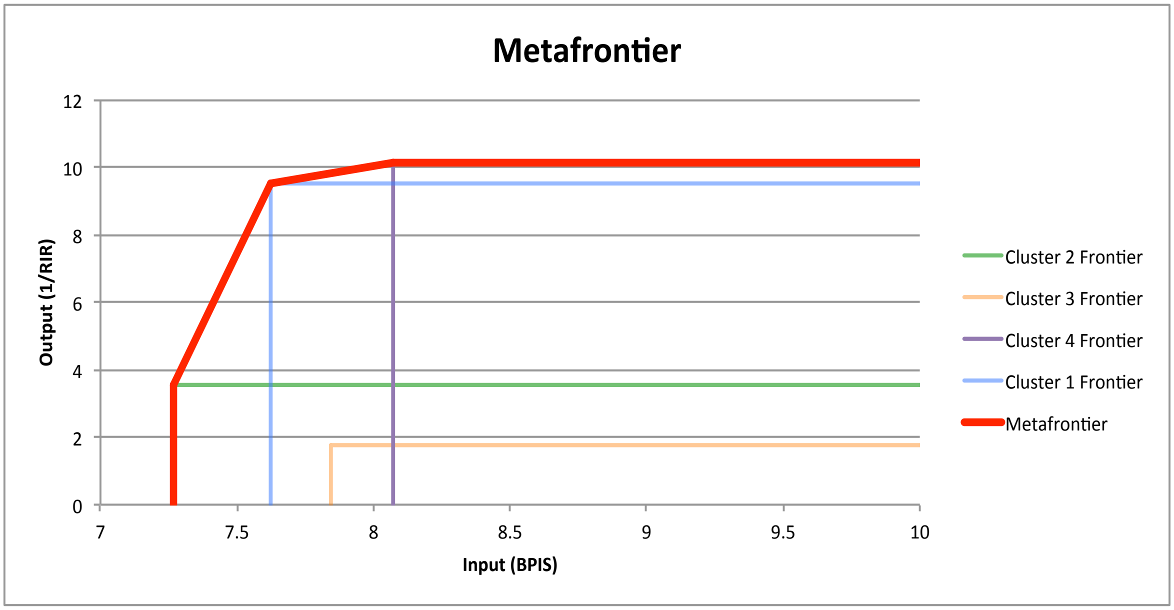


Figure 19: Estimated Construction of the Group Frontiers and Meta-Frontier.

The significant differences in the metatechnology ratios of the clusters indicate that there are some significant differences between the clusters' safety implementation and performances. Clusters 1 and 4 should be investigated for any reasons that they are outperforming other groups in safety efficiency. Cluster 3 especially is underperforming significantly compared to the other groups.

7.2 OBJECTIVE 1 CONCLUSIONS

The following sections will contain an analysis of the results from Objective 1. The conclusions will explore data trends found in the results as well as any interpretations of trends and policy recommendations based upon the DEA results.

7.2.1 RECORDABLE INCIDENT RATE DATA TRENDS

Each of the group results for all four clusters of data seem to take on a logarithmic shape, with the exception of the "logical outliers" that have received efficient, or nearly efficient scores. Removing all "logical outliers" or, efficient projects from the data with the exception of the efficient project with the lowest Recordable Incident Rate will show a more uniform trend.

When the "logical outliers" are removed, Cluster 1 is fitted with a power, or log-log regression line, and the fit is very significant. It should be noted that the data point that was removed as a "logical outlier" from Cluster 1 did not have an efficiency score of 1 but an efficiency score of 0.9996. The only DMU with an efficiency score of truly one was not an illogical data point. Figure 20 shows the data with a fitted trend line and an R^2, or goodness of fit value of 0.953, which is extremely significant on a scale of 0 to 1.

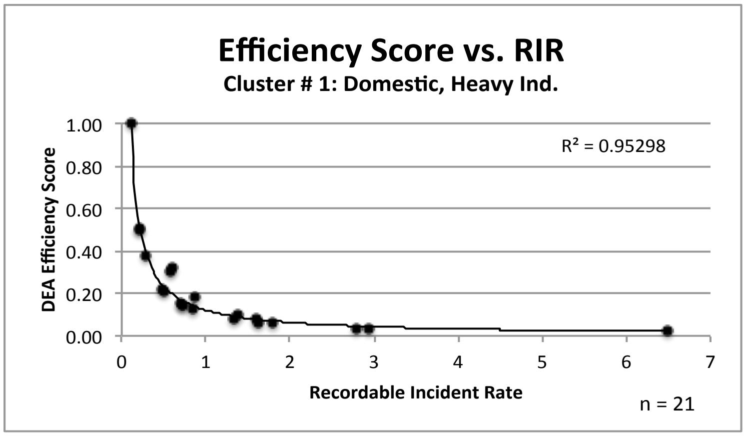


Figure 20: Cluster 1 Group Results Fitted to a Log-Log Trend Line.

When the other clusters are fitted with a log-log trend line in the same way after the "logical outliers are removed. Similar results are found. Figures 21-23 show the remaining groups, using the same method of "logical outlier" removal and with the fitted trend lines and the corresponding R^2 values.

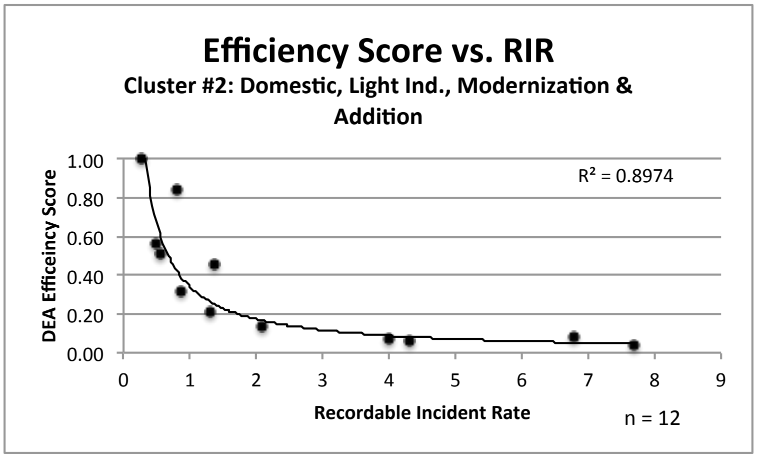


Figure 21: Cluster 2 Group Results Fitted to a Log-Log Trend Line.

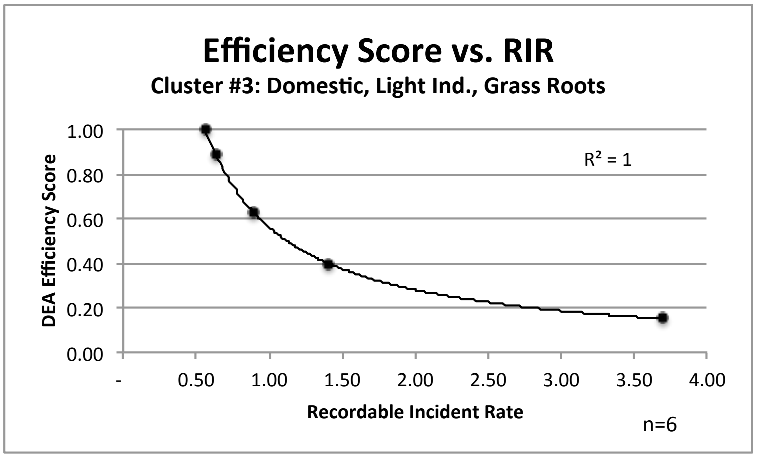


Figure 22: Cluster 3 Group Results Fitted to a Log-Log Trend Line.

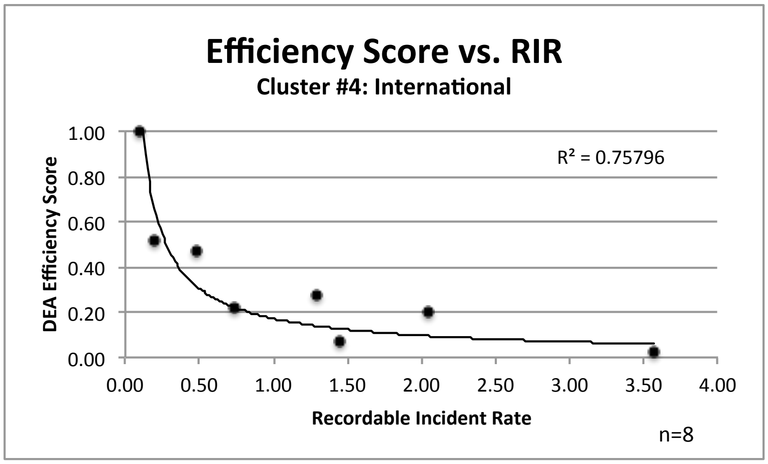


Figure 23: Cluster 4 Group Results Fitted to a Log-Log Trend Line.

Each of the remaining three project clusters show the same data trends to a very statistically significant degree. In each case, the "logical outliers" were projects who achieved efficiency scores ranging from 0.9976 to 0.9998, and never being a truly efficient project with a score of one. Once these "logical outliers" were removed, the goodness of fit of a log-log regression line ranged from 0.75 to 1. These are all very significant scores, indicating that this data does, in fact, take on the behaviors of a log-log function.

Using the metagroup for this same log-log analysis will provide a more general trend line equation applicable to industrial construction projects. Figure 24 shows the relationship the meatagroup has to a log-log function with four "logical outliers" removed.

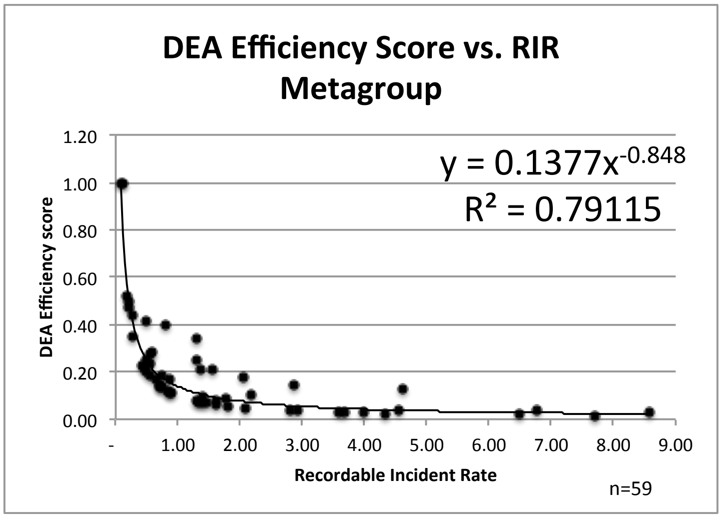


Figure 24: Metagroup Results Fitted to a Log-Log Trend Line.

The same log-log relationship is still holding true, but with more variance. This additional variance is to be expected since the data points are no longer totally homogenous. However, even without the separation of projects for heterogeneity, the goodness of fit of the log-log trend line is still statistically significant.

Combining the log-log trend lines for all for clusters onto one graph can provide insight to any similarities and differences in the shape and behaviors of the different clusters. Figure 25 shows the trend lines from Figures 20-24 superimposed onto one graph.

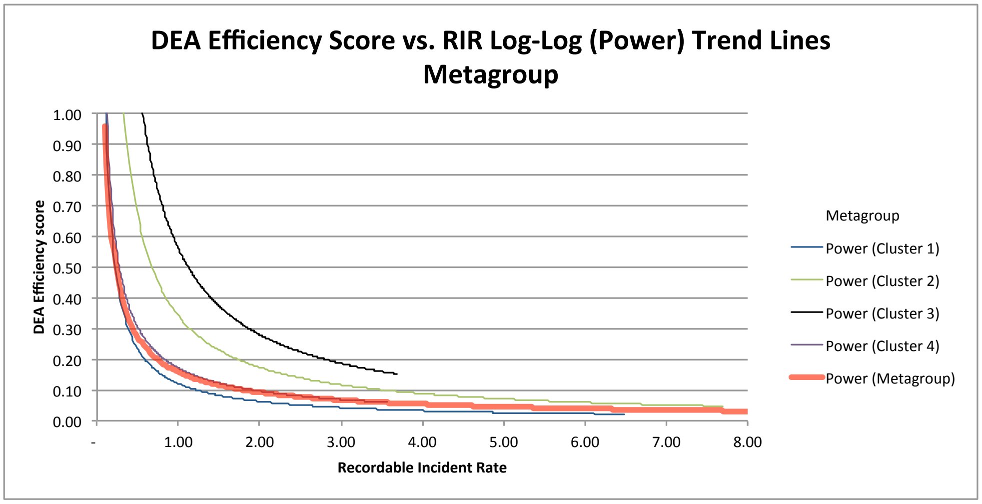


Figure 25: Comparison of Trend Lines for All Four Clusters.

The observation made from a comparison of the trend lines is that the trend line with the largest radial distance to the origin, corresponds to the cluster with the lowest average metatechnology ratio and the trend line with the smallest radial distance to the origin corresponds to the cluster with the highest average metatechnology ratio. The more efficient the group performs, the steeper the slope of the trend line will be on the 0 to 1 range.

This mathematical relationship indicates that there is a meaningful relationship between DEA efficiency scores and Recordable Incident Rates taking on the form of a log-log function. This could result in a useful tool to allow industry safety professionals to create hypothetical situations with a target RIR, and creating hypothetical DEA models with different BPIS inputs to achieve the corresponding target efficiency score. For example, if an industrial contracting company desires to achieve an RIR of 0.5 on all of their projects (all types of characteristic, locations, cost ranges etc.) Figure 24 can be used to find the corresponding DEA Efficiency score to an RIR of 0.5, which would be 0.25. The safety analyst can then determine the BPIS input that will result in an efficiency score of 0.25 using the equation in

Figure 24 for the trend line. This BPIS score can also be adjusted by putting more emphasis on some components over others, or based upon the individual company's safety practices. Additionally, if the type, location, cost and project characteristics are known, the more specific group graphs can be used in this same way.

7.2.2 SAFETY PERFORMANCE CONCLUSIONS

From the results of the Meta-Frontier analysis, Clusters 1 and 4 are shown to perform more efficiently relative to Clusters 2 and 3. Recalling the individual frontiers with respect to the Meta-Frontier as well as the descriptions of each cluster, Figure 26 shows each of the estimated efficient frontiers and Table 16 shows a breakdown of the characteristics of each cluster.

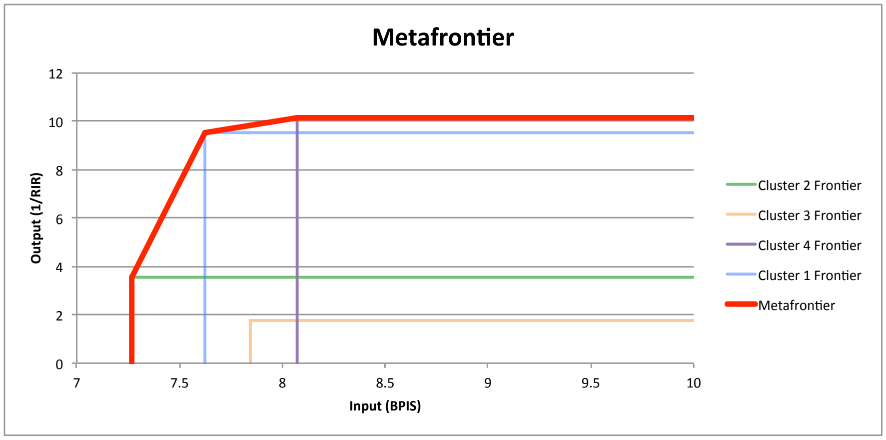


Figure 26: Estimated Cluster Frontiers and Meta-Frontier.

Table 16: Description of Characteristics of Each Cluster.

Scenario 3: 4 Clusters				
Cluster	*# of Projects*	*Location*	*Major Classification*	*Characteristic*
1	22	Domestic	Heavy	Modernization Grass Roots Brownfield Addition
2	15	Domestic	Light	Modernization Addition
3	10	Domestic	Light	Grass Roots
4	12	International	Light Heavy	Modernization Grass Roots Addition

Focusing attention on Clusters 1, 2 and 3, an interesting relationship can be seen among the Domestic & Light Industrial projects and the Domestic & Heavy Industrial projects. Clusters 1, 2 and 3 encompass all of the Domestic projects, and they are all classified as either Heavy or Light Industrial. Clusters 2 and 3 make up the entire Light Industrial sector of projects and they have very similar efficient frontiers. Cluster 1 contains all projects with a Heavy Industrial classification and has the highest MTR out of the four clusters.

The similarity of the two Light Industrial efficient frontiers can be quantified by comparing the MTRs for the two clusters (2 and 3) with respect to the MTR of the Heavy Industrial cluster (1):

- **Cluster 1** = 0.915
- **Cluster 2** = 0.396
- **Cluster 3** = 0.152

On the 0 to 1 scale, the difference between the MTRs of the two Light Industrial clusters, Cluster 2 and Cluster 3 is 24%, but more importantly, Cluster 3 is completely enveloped by Cluster 2. This envelopment of Cluster 3 means that it can be thought of as a subset of Cluster 2.

Each of these three clusters has a minimum ZAT BPIS on the range of 7.3 to 7.8 points. This difference of 0.5 on a scale of 0 to 10 is not significant. This represents only a 5% difference in BPIS implementation. Because all of the Heavy and Light Industrial projects are implementing the BPIS is approximately the same range, the difference in the safety performance is due to the inherent differences in the Light and Heavy Industrial construction procedures, regulations or culture and not the level of implementation.

Because the frontier of Cluster 3 lies completely within the frontier of Cluster 2, which are both Light Industrial clusters, Cluster 2 can be used to represent the Light Industrial classification of projects. Table 17 shows the difference in the MTRs and the maximum achieved safety performance for the two classifications of construction projects.

Table 17: Comparison of Safety Performance of Light and Heavy Industrial Projects.

Classification	*MTR*	*Maximum 1/RIR*
Heavy Industrial	0.915	9.5
Light Industrial	0.396	3.5

The maximum safety performance (measured by 1/RIR) achieved by any cluster in this study is 10.1. This makes the difference in safety performance between the Light and Heavy Industrial groups of 6, a 60% difference in safety performance the Heavy Industrial group has over the Light Industrial group. There are clearly some inherent differences in the safety culture, the safety implementation, construction procedures or applicable safety regulations between the Light and Heavy Industrial sectors.

8. OBJECTIVE 2 RESULTS AND CONCLUSIONS

This chapter will discuss the results that were returned from the regression and DEA analyses in Objective 2 as well as any conclusions that can be made from these results. The results chapter will be broken down to separate the results for the regression analysis and the DEA analysis. The results sections will contain only the data regarding the regression results and DEA weighting results and any observations that can be made about this data. The conclusions sections will investigate trends found throughout the results sections and possible interpretations of these trends. The conclusions sections will also include any possible recommendations for safety improvements based upon the results of the regression and DEA analyses.

8.1 OBJECTIVE 2 RESULTS

8.1.1 POISSON REGRESSION RESULTS

The first regression equation to be considered included the all of the potential variables discussed in the methodology:

Dependent Response Variable:

1. Total Number of Recordable Incidents

Independent Variables:

1. ZAT Group 1 Score
2. ZAT Group 2 Score
3. ZAT Group 3 Score
4. Location
5. Major Classification
6. Characteristic
7. Project Cost

Each of the variables used in this regression equation, as well as all Objective 2 analyses use the variables, after translated to a 0-1 scale, but without weights. Because the purpose of Objective 2 is to tests the relative significance of the ZAT components, the pre-developed CII weightings will not be used for this part of the study. The results obtained from the regression analysis pertinent values are shown in Table 18, below (see Appendix 3 for full results).

Table 18: Regression Results Including All Variables.

Full Log Likelihood		-171.8168	
AIC (smaller is better)		363.6337	
AICC (smaller is better)		368.2170	
BIC (smaller is better)		384.4090	

Algorithm converged.

Analysis Of Maximum Likelihood Parameter Estimates

Parameter		**DF**	**Estimate**	**Standard Error**	**Wald 95% Confidence Limits**		**Wald Chi-Square**	**Pr > ChiSq**
Intercept		1	-11.2024	0.6178	-12.4133	-9.9915	328.77	<.0001
G1_Sum		1	-0.2829	0.1177	-0.5135	-0.0523	5.78	0.0162
G2_Sum		1	0.2107	0.1107	-0.0064	0.4277	3.62	0.0571
G3_Sum		1	-0.5728	0.1171	-0.8022	-0.3433	23.94	<.0001

LR Statistics For Type 3 Analysis

Source	DF	Chi-Square	Pr > ChiSq
G1_Sum	1	5.58	0.0182
G2_Sum	1	3.64	0.0564
G3_Sum	1	23.18	<.0001
Bin_location	1	32.81	<.0001
majorcls	1	2.74	0.0981
char	3	22.53	<.0001
cost	1	88.74	<.0001

The BIC can be found in the "Criteria For Assessing Goodness of Fit" section of Table 18 and is 384. This is a smaller BIC score than found in either of the regression analyses from Objective 1. The smaller BIC obtained in this Objective 2 regression model indicates that the addition of the ZAT Scores has created a better representation of all impacting factors to safety performance and has improved the accuracy of the results.

The next observation resulting from this regression output comes from the portion of Table 18 titled, "LR Statistics for Type 3 Analysis". In this portion of the table an aggregate Chi Squared value is shown for each independent variable combining the significance of all levels of the variable. Because of the nature of the results that were obtained in this regression analysis, an alpha, or cutoff level for the Chi Squared value will be 0.1. It is shown here that all variables meet the Pr>ChiSq cutoff level of 0.1, meaning that they are all significant using a 90% confidence interval and used as an indicator to predict the recordable incidents.

The characteristic variable, Major Classification (Light Industrial and Heavy Industrial) is denoted by the abbreviation "majorcls" in the results table. This variable was determined in Objective 1 to be a significant factor showing inherent differences in the two groups. In the regression analysis, the Chi Squared value of 0.098 is very close to the cutoff level of 0.1 and so will be tested for it's significance in the regression equation.

A regression model without the Major Classification (majorcls) and the goodness of fit values are shown below in Table 19 (see Appendix 4 for full results) and the BIC can then be compared to the regression model including this variable from Table 18.

Table 19: Regression Results Omitting Major Classification.

Full Log Likelihood		-173.1850	
AIC (smaller is better)		364.3699	
AICC (smaller is better)		368.0434	
BIC (smaller is better)		383.0678	

The BIC score of the first model from Table 18, which includes Major Classification, is 384 and the BIC score for the second model from Table 19, which omits Major Classification, is 383. These two BIC scores are very close and it is not justifiable to select a model by these close BIC scores alone. A hypothesis test can be conducted to help determine which regression model is the best fit. This hypothesis test is based on the principle that:

-2(Full Log Likelihood of Model 1 – Model 2) should follow a chi-squared distribution

The values for the Full Log Likelihood can be found in the Criteria For Assessing Goodness of Fit portion of the table and are:

Model 1 Full Log Likelihood = -173.18

Model 2 Full Log Likelihood = -171.82

The hypotheses for this test will be:

H_0: Model 1 without the Major Classification variable is the best fit for the data

-2(Full Log Likelihood of Model 1 – Model 2) > $\text{ChiSq}_{\alpha = 0.1,\, df = 1}$

H_1: Model 2 with the Major Classification variable is the best fit for the data

-2(Full Log Likelihood of Model 1 – Model 2) < $\text{ChiSq}_{\alpha = 0.1,\ df = 1}$

The test statistics for the hypothesis test will be:

-2(Full Log Likelihood of Model 1 – Model 2) = -2(-173.18 + 171.82) = <u>2.7364</u>

Referring to a chi-squared table with DF = 1 and $\alpha = 0.1$ → <u>2.71</u>

Because the test statistic is greater than the value obtained from the chi-squared table (2.7364>2.71) we can reject H1 and conclude that the model is best with the Major Classification variable.

This result from the hypothesis test corresponds with the BIC score comparison of the models with and without the Major Classification variable. Therefore the regression model that includes the Major Classification variable is the best fit for the data and corresponds with the significant differences observed in Objective one between the Light and Heavy Industrial groups' safety performance.

Another important aspect of the regression results is the estimate of the parameter coefficient. Returning to Table 18, the results that were determined by the hypothesis test to be the most representative of the data, this value can be found in the Analysis Of Maximum Likelihood Parameter Estimates portion of the table under the heading "Estimate". The estimates of the parameter coefficient for the ZAT Groups from Table 18 are:

1. ZAT Group 1 Coefficient = -0.2829
2. ZAT Group 2 Coefficient = 0.2107
3. ZAT Group 3 Coefficient = -0.5728

These coefficients indicate the direction and magnitude of the relationship they hold with the dependent variable. The coefficient for ZAT Group 1 indicated that for every unit the ZAT Group 1 score increases, the rate of recordable incidents will decrease by 0.2829 units. Recalling that the depended response variable in a Poisson regression analysis is a form of an incident rate (not the OSHA defined Recordable Incident Rate) and is equal to:

ln(Number of Recordable Incident/Total Work Hours)

Group 3 ZAT Score is found to be very significant and therefore is the largest driving factor among the groups of ZAT components because the magnitude of the coefficient is the largest. The ZAT

Group 1 Score also has a negative coefficient, which indicates that a higher ZAT Group 1 Score will result in a lower Recordable Incident Rate.

The coefficient estimate for ZAT Group 2 is positive which seems illogical from a safety standpoint. The coefficient for Group 2 indicates that for every point the ZAT Group 2 Score increases, the Recordable Incident Rate will increase by 0.2107 points. To test this regression coefficient for validity, the ZAT Group 1 Score will be combined with the ZAT Group 3 Score in an attempt to isolate ZAT Group 2 and test for any complex co-linearity issues between the 3 ZAT Groups. When ZAT Groups 1 and 3 are combined and a regression analysis is conducted, Table 20 shows the pertinent result values (see Appendix 5 for full results).

Table 20: Regression Results to Isolate ZAT Group 2.

Analysis Of Maximum Likelihood Parameter Estimates								
Parameter		**DF**	**Estimate**	**Standard Error**	**Wald 95% Confidence Limits**		**Wald Chi-Square**	**Pr > ChiSq**
Intercept		1	-10.8292	0.5755	-11.9572	-9.7012	354.04	<.0001
G13		1	-0.4256	0.0730	-0.5687	-0.2826	34.00	<.0001
G2_Sum		1	0.2312	0.1111	0.0134	0.4489	4.33	0.0375

Table 20 shows the coefficient estimate for ZAT Group 2 is 0.2312. This coefficient is still positive and has a similar magnitude to the results from Table 19. It can be statistically concluded that it is, in fact, appropriate for this variable to have a positive coefficient.

8.1.2 DEA ANALYSIS RESULTS

The DEA analysis was used to obtain the average weightings used by the DMU optimization that DEA calculates. The projects were not grouped according to sources of heterogeneity and therefore the efficient frontier and relative efficiency scores are not going to provide meaningful insight. The desired results from this analysis are the average weightings used for each of the three ZAT Group Scores. These can show which of the variables were given the most emphasis on average to calculate maximum efficiency scores.

The results from the DEA analysis are shown below, in Table 21.

Table 21: Efficiency Scores and Weights Applied to Each ZAT Group.

No.	Score	V(1) G1 Sum	V(2) G2 Sum	V(3) G3 Sum
1	0.104909	5.406128383	0	5.866499806
2	0.212673	0	1.412028152	0
3	5.49E-02	2.521278905	0	2.747285693
4	0.145252	0.456309524	0	0
5	0.137086	0.464606061	0	0
6	3.58E-02	0	7.136731101	0
7	0.355004	0	3.8350451	0
8	0.132667	2.006214673	0	2.927362114
9	0.403572	0.659508374	0	0.962319663
10	0.082152	0	0	5.383397778
11	1	0.285714286	0	0
12	0.743696	0	1.80607005	0
13	7.31E-02	5.46923729	0	5.934982899
14	0.151485	0	0	2.81969592
15	3.08E-02	21.78981717	0	23.64537968
16	0.468496	0	0	0
17	0.5073	0	4.873125673	0
18	4.11E-02	0	17.16613237	4.825223046
19	0.095089	2.870352092	2.09988829	5.016111293
20	0.413495	0	4.610808641	0
21	0.252276	0	7.021880438	0
22	0.999787	0	8.434618665	1.839425883
23	9.49E-02	3.105922123	0	4.531996935
24	0.821469	4.635069798	0	5.029779937
25	0.289719	0	3.229305339	0.907724478
26	4.73E-02	0	0	0
27	1.76E-02	0	7.425490265	31.50359352
28	0.629584	2.431161121	1.295282918	3.057538363
29	0.034956	0	7.759050355	15.30338596
30	0.392356	0	4.244101217	0.376438219
31	0.140296	0	0	3.544165109
32	0.602333	0.95310178	0	1.034265376
33	0.998419	26.80303263	12.82694193	35.20430926
34	0.999769	15.2851872	0	0
35	2.28E-02	0	0	0
36	0.9994	0	24.25200696	2.151075538
37	0.042715	16.33516515	7.624319052	17.88525236
38	0.998771	33.73155749	0	16.27892547
39	0.999686	7.974885278	0	6.121477069
40	0.990389	130.8225478	172.9392177	6.042243647
41	7.00E-02	0.899765258	0	0
42	0.301876	1.324239675	0	1.932260344
43	3.70E-02	0	21.52671715	6.050938527
44	0.999478	13.46087729	0	8.587334131
45	0.145443	25.55737527	0	7.541440525
46	0.151889	0	0.862807848	3.660572805
47	0.217132	0.284274636	0.915042639	2.54149433
48	0.999761	6.006712718	0	5.043156612
49	0.304969	0	3.237337592	10.57249738
50	0.366406	0	0.707189549	3.00034224
51	1	5.62E-03	0	1.955020518
52	1	0	1.40284629	4.581415533
53	0.999323	11.87440851	5.542293465	13.00120267
54	1	0.13842556	0	0.150833992
55	1	0	0.336931829	1.429476441
56	5.17E-02	0	0	14.41981548
57	0.519727	0.12123396	0	0
58	0.227034	0.283422181	0	0
59	6.79E-02	0.928304687	0	0
	AVERAGE	5.845617954	5.669884924	5.006909433

The averages of the weights used by DEA's optimization process for each variable are shown at the bottom of Table 15 and give the ZAT Groups the following ranking:

1. ZAT Group 1 (G1_Sum): Average weight = 5.85
2. ZAT Group 2 (G2_Sum): Average weight = 5.67
3. ZAT Group 3 (G3_Sum): Average weight = 5.01

These results are not showing any significant differences based upon the weights assigned to the three ZAT variables using DEA.

8.2 OBJECTIVE 2 CONCLUSIONS

Before drawing any conclusions from Objective 2, a brief comparison of the projects in this study (having RIR>0) will be done with those projects that were removed (RIR=0). Using an ANOVA test, the two groups can be compared to look for any significant differences in the means between the two groups. This will give some insight into whether or not the "inherently effective" group of projects are implementing the G1, G2, or G3 components differently than the sample group used in the regression and DEA analyses.

Looking at the three LS means plots in Figure 27 from an ANOVA analysis, the flat lines show little to no difference in the group averages for the G1, G2 and G3 scores.

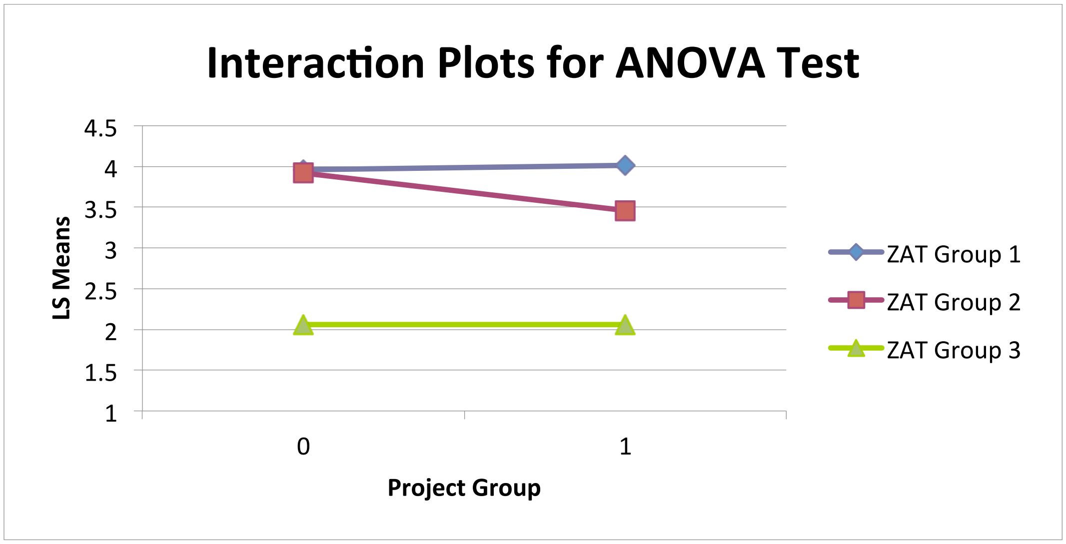
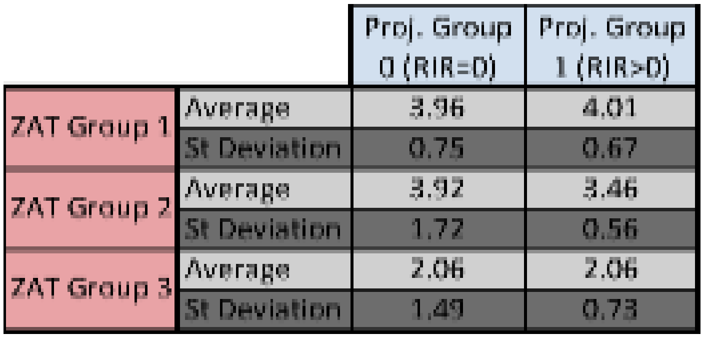


Figure 27: LS Means Plot for ZAT Group Scores for the RIR=0 and RIR>0 Groups.

The nearly flat lines in each of the three LS means plots above indicate that there are no significant differences in the average score between the two groups (see Appendix 6 for full ANOVA results output and confidence intervals). In addition, the average scores in each group along with the standard deviations are shown below, in Table 22.

Table 22: ZAT Group Scores Comparison against Project Groups.



		Proj. Group 0 (RIR=0)	Proj. Group 1 (RIR>0)
ZAT Group 1	Average	3.96	4.01
	St Deviation	0.75	0.67
ZAT Group 2	Average	3.92	3.46
	St Deviation	1.72	0.56
ZAT Group 3	Average	2.06	2.06
	St Deviation	1.49	0.73

This similarity between the implementation of G1, G2 and G3 scores is important to the conclusions in this study because it says that the analysis done on the RIR>0 group is representative of all projects regardless of their inherently inefficient nature.

The conclusions that can be drawn from both the regression and DEA analysis of Objective 2 are that it is likely that some of the ZAT Groups are more able to impact the safety performance of construction projects than others. In the regression analysis of Objective 2, the ZAT Group 3 showed the most significance to the regression equation as well as having a negative coefficient with the greatest magnitude. The ZAT Group 3 is the Worker Selection group and includes the following components:

ZAT Group 3 – Significant

1. Pre-Employment Drug Abuse Testing: To what extent were pre-employment substance abuse tests conducted for contractor employees?
2. Drug Screenings: How frequently were contractor employees randomly screened for alcohol and drugs?
3. Safety as Selection Criteria: To what extent was safety performance utilized as a criterion for contractor/subcontractor selection?

The data suggests that when these three ZAT components are implemented more thoroughly, the recordable incident rate will decrease. This implies that the safety reputation of a subcontractor is a good indicator of future safety performance.

The ZAT Group 2 showed statistical significance in the regression analysis but was also showing that an increased implementation worsened safety performance. The ZAT Group 2 is the Safety Maintenance group and includes actions that need to be continually repeated throughout a construction project. The ZAT components that are included in Group 2 are:

ZAT Group 2 – Inconclusive

1. Near Miss Investigation: How often were near misses formally (i.e. written documentation) investigated?
2. Formal Training: On average, how much ongoing formal safety training did workers receive each month?
3. Toolbox Meetings: On average, how often were safety toolbox meetings held?
4. Safety Audits: How often were safety audits performed by corporate safety personnel?
5. Safety Orientation: How extensive was the job-specific safety orientation conducted for new contractor and subcontractor employees?

This aspect of safety maintenance is showing to be a significant impacting factor of determining the Recordable Incident Rate on construction projects, however the data shows a positive correlation to safety performance for reasons that are beyond the scope of this study.

The ZAT Group 1 is the group of ZAT components related to developing a site-specific safety plan. This group showed a strong statistical significance in the regression analysis and was assigned the highest average weighting by the DEA analysis. The ZAT Group 1 also has a negative coefficient in the regression model indicating that an increased implementation of Group 1 components results in an improvement in safety performance. The ZAT Group 1 consists of the following components:

ZAT Group 1 – Significant

1. Safety Plan Implementation: Was there a site-specific safety plan for the project?
2. Safety Supervisor Commitment: What best describes the time commitment of the site safety supervisor for this project?
3. Workers Per Safety Supervisor: Overall how many workers per safety person were typically (i.e. in terms of the average workforce) on the project?
4. Risk Identification: To what extent were safety risks systematically identified in the pre-construction phases of this project?

5. Incentive Use: To what extent were safety incentives used that were based upon zero injury objectives?

All of these pre-construction safety-planning activities and the worker selection process found in ZAT Groups 1 and 3 are the most significant actions correlating to an improvement of safety performance on a project. This shows the importance of pre-construction planning and making safety a key consideration during this time. These results also indicate that past safety performance of contractors can be used to predict future safety performance. This could be due to the fact safety is often a part of a company's deep-rooted company culture or not, and it is not a fluctuating priority.

9. LIMITATIONS

This chapter will discuss any elements of this study that could be considered limitations to achieving a completely accurate analysis.

9.1 METHOD OF REPLACING "DON'T KNOW" RESPONSES IN DATA

During the calculation of the Best Practice Implementation Score (BPIS) a method had to be developed to account for instances in which the respondent answered with "Don't Know" or "DK" response. Because this situation occurred too frequently to remove all projects containing a DK response, a method of using company averages was utilized to help retain the most possible data for this study. When a DK response was given by a project that was executed by a company with two or more projects in the data set, the company average for the data field was used to replace the DK response.

While cleaning the data to replace the DK responses, it was noticed that there did not seem to be common scores for ZAT components by projects within the same company. The ZAT implementation showed significant variances among projects from the same company. This means that this use of the company average may not be an entirely representative way of replacing the DK responses with the most likely value. Because no alternative was developed to account for the DK responses, the company averages were used in this study.

9.2 ZAT DATA TRANSLATION

One of the steps in the BPIS calculation is to translate the survey respondent answers for each ZAT field to a 0-1 scale. The survey responses are on various types of scales, commonly 1-7 with each number representing a categorical variable. When these responses are translated to a 0-1 scale, they are done so in equal increments. For example, the ZAT field measuring the time commitment of the safety supervisor on the job site has three possible responses: No Safety Supervisor, Part-Time, and Full-Time. These three responses are then translated to the 0-1 scale:

- No Safety Supervisor = 0
- Part-Time = 0.5
- Full Time = 1.0

This translated score indicated that a full-time safety supervisor is 0.5 points better than having a part-time safety supervisor. Also, that having a part-time safety supervisor is 0.5 points better than having no safety supervisor. These increments between the options are equal. In reality, it is likely that the increment between having no safety supervisor at all and having a part-time safety supervisor could be much greater than the increment between a part-time and a full-time safety supervisor. Each ZAT component is scored in this same way, with equal increments between possible responses. This could be a potential limitation in the BPIS being an accurate measure of the efficacy of ZAT implementation.

The BIPS calculation is a score developed by the Construction Industry Institute (CII) and has already been accepted by industry. For this reason, this study aimed to remain consistent with CII measurement techniques and translations.

9.3 ZAT COMPONENT CLUSTERING

In Objective 2, the ZAT components were clustered into three groups for analysis. These groups are the Initial Safety Plan, Safety Maintenance, and Worker Selection groups. This clustering was done by a qualitative analysis of common traits among the ZAT components. While the groups each do have one or more common threads running through all of the ZAT components included in the group, without a mathematical analysis to justify these groups, there could be potential limitations to the developed groups.

One analysis that could help to justify the ZAT clustering would be a factor analysis. This would give a mathematical justification for a grouping scenario.

9.4 TIMESPAN OF PROJECT DATA

The data used in the entirety of this study consists of questionnaires returned to CII regarding projects completed anywhere from 1977 to 2010. The timespan of this project presents a research challenge because of the subjective nature of many of the safety questions. The construction safety culture has evolved over the past 40 years, and this may impact the ranking that managers would give a project's safety performance. The subjective questions in the Zero Accidents portion of the questionnaire are:

1. To what extent were safety incentives used that were based upon zero injury objectives?
2. To what extent was safety performance utilized as a criterion for contractor/subcontractor selection?
3. To what extent were safety risks systematically identified in the pre-construction phases of this project?
4. How extensive was the job-specific orientation conducted for new contractor and subcontractor employees?

These four (out of 13) ZAT questions are answered on a 0-7 scale (0=not at all, 7=extensively) and have no numerical measurement of the frequency or level of implementation. Because the emphasis on safety has changed so much over the 33-year time span these projects were completed, an “extensive” implementation of safety orientations or safety incentives could potentially mean very different things in different years. This issue should be acknowledged as a limitation of this study.

10. FINAL DISCUSSION

10.1 OBJECTIVE 1: RIR TO EFFICIENCY SCORE RELATIONSHIP

In Objective 1, it was observed from each of the four clusters as well as the metagroup, that there was a strong mathematical relationship between the RIR and the DEA Efficiency scores. There is a very significant log-log relationship between the two variables, RIR and DEA Efficiency. This mathematical relationship could be utilized by safety professionals to predict the level of RIR for a given BPIS. This type of prediction analysis can allow safety professionals to adjust the planned ZAT implementation levels pre-construction to obtain the desired safety performance.

10.2 OBJECTIVE 1: LIGHT VS. HEAVY INDUSTRIAL

The second significant observation that was made from Objective 1 was the major differences in safety performance between the Light Industrial, and the Heavy Industrial groups. The Heavy Industrial group showed less recordable incidents than the Light industrial group overall. Referring back to the Metafrontier analysis of Objective 1, the differences between these two groups were seen in the frontiers of Figure 28.

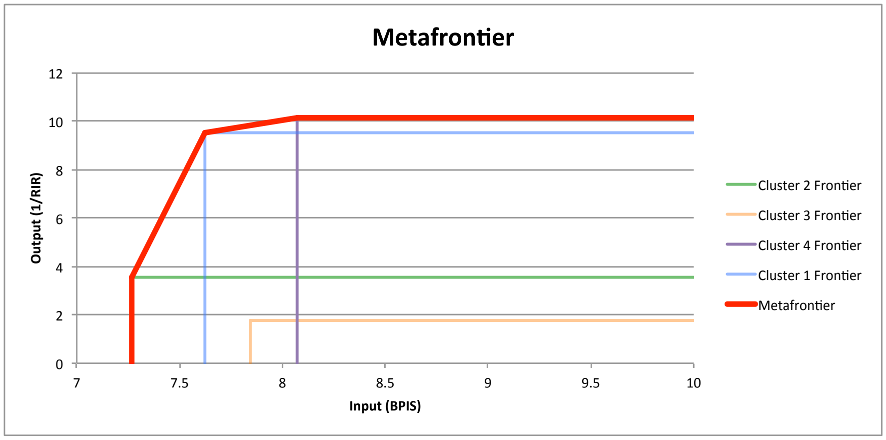


Figure 28: Estimated Frontiers and Metafrontier of Objective 1 Clusters and Metagroup.

Recalling that Cluster 1 represents the Heavy Industrial Group and Clusters 2 & 3 represent the Light Industrial group, the extreme difference in output levels is visible in Figure 28. Because of this difference in safety performance, safety professionals should investigate the differences in safety practices in order to detect the practices that are working well for the Heavy Industrial sector that can be applied in Light Industrial applications. In other words, the Light Industrial sector can use the Heavy Industrial sector to model their safety practices after, where applicable.

Speculating the reasoning for this inherent difference between these two types of projects is beyond the scope of this study.

10.3 OBJECTIVE 2: SIGNIFICANT ZAT GROUPS

The conclusions from Objective 2 were that the following ZAT components showed to improve the safety performance, as measured by Recordable Incident Rate:

1. Safety Plan Implementation: Was there a site-specific safety plan for the project?
2. Safety Supervisor Commitment: What best describes the time commitment of the site safety supervisor for this project?
3. Workers Per Safety Supervisor: Overall how many workers per safety person were typically (i.e. in terms of the average workforce) on the project?
4. Risk Identification: To what extent were safety risks systematically identified in the pre-construction phases of this project?
5. Incentive Use: To what extent were safety incentives used that were based upon zero injury objectives?
6. Pre-Employment Drug Abuse Testing: To what extent were pre-employment substance abuse tests conducted for contractor employees?
7. Drug Screenings: How frequently were contractor employees randomly screened for alcohol and drugs?
8. Safety as Selection Criteria: To what extent was safety performance utilized as a criterion for contractor/subcontractor selection?

These ZAT components came from Group 1: Initial Safety Plan and Group 3: Worker Selection. It can be noted that worker selection is also a group of safety actions that take place pre-construction also. This means that all of the safety planning processes are more significant in creating a project with better safety performance than attempting to implement safety actions after construction has started. This should be noted by safety professionals to exhibit the importance of making safety a priority from early in the planning stages of a project.

11. FUTURE RESEARCH

The availability for future research paths consists of a similar analysis of the other CII Best Practices. Using Data Envelopment Analysis to validate the importance and benefits of implementing any of the other Best Practices are all options for additional research projects. Benchmarking any of CII's best practices would provide an excellent opportunity for research. Only parametric analysis has been conducted by CII to date and therefore any additional views of the efficacy of their Best Practices can provide additional validation and incentive to owners or contractors to integrate these Best Practices into their company culture. Using an alternative method of analysis to verify the efficacy of the Best Practices can support the claims that these practices are measurably improving construction performance.

Using additional inputs and outputs to research the impact that a Best Practice has on the overall project performance (cost, schedule and safety performances) is another viable research topic that could be conducted with more detailed data. One of the advantages of DEA over other methods of analysis is its ability to utilize multiple inputs and multiple outputs. With additional data, or for Best Practices other than the ZAT, more input and output variables could be utilized to create a more inclusive analysis. With additional data points, the RIR and DART Rate could be used simultaneously as outputs for a more comprehensive view of safety performance. In addition, the individual ZAT components could be explored for use as inputs in a scenario where there are a sufficient number of DMU's to maintain discrimination power.

In addition to analyzing the impacts the different component groups have on project safety performance, a financial aspect could also be added. Using cost data on the implementation costs of each component, DEA could be used to find the most economical implementation strategy to obtain a certain level of safety performance. An analysis of economic efficiency could be very useful to both owners and contractors in assisting decision makers with the best money allocation strategies.

An alternative method in Objective 2 could provide a research opportunity. The ZAT component clusters were grouped using a qualitative analysis in this study. A factor analysis could be used to find any statistical similarities in the ZAT components and a comparison of the clusters using this factor analysis and the qualitative analysis could provide an additional perspective. A factor analysis could provide some statistical evidence that certain ZAT components have a tendency to be implemented together and therefore share common traits or required resources.

In this study, there were many categorical variables that were used in Data Envelopment Analysis. There are many pieces of literature that discuss how to deal with categorical variables within DEA. These alternative methods could be explored and applied to the variables used in this study for validation or a different perspective.

The variable of project cost was used in this study and was determined to be a source of heterogeneity among projects. This variable can be considered debatably significant until further investigation is done. Inspecting how the cost (or size) of a project translates into safety behavior can provide yet another opportunity for research in this field. It can be suggested that projects having a higher cost will have more formal safety procedures due to the increased allowance for overhead expenses but this speculation was outside the scope of this study.

Taking a look at the difference in safety performance between the Light and Heavy Industrial groups is another opportunity. There is a very large gap in the Recordable Incident Rate that was achieved within these two sectors. Also, an investigation of the difference in the levels of safety performance between the Light and Heavy Industrial groups as found in this study. The specific safety cultures and regulations that are applied to the Light versus the Heavy Industrial construction projects could provide insight to practices that play a role in the relative safety success of the Heavy Industrial group or relative safety shortcomings of the Light Industrial group.

In light of the conclusions from Objective 1, which show a strong difference between the light and heavy industrial sectors, an area of future research could be to explore different project cluster scenarios. Clusters 2 and 3 in Objective 1 both contained Light Industrial projects, and the frontiers were enveloped by one another. This indicates that these two clusters could justifiably be combined to achieve more discrimination power and refined DEA results.

Considering the limitation of the timespan of projects used in this study, another area of future research could relate to the evolution of safety practices over time. Studying the effects of the timespan of projects, and the perceived differences in safety implementation could provide more accuracy to this research topic. Creating an adjustment factor for self reported safety responses according to year of project execution would be a very useful tool. Being able to adjust safety responses would allow for older data to be retained in safety studies to create larger data sets and allow for more reliable statistical analyses.

One of the largest constraints of this study was the inability to use any project that had zero recordable incidents. Because construction data is so valuable, and difficult to find completed for many projects, discarding such a large number of data points is a serious concern. Future research to remedy the issues of data not complying with the translation invariance rules in DEA would be a true contribution. This area of future research could involve either developing a way to process the data that would allow it to be utilized in DEA, or exploring alternative outputs. One possible alternative output to the inverse of the RIR would be the time between recordable incidents. This time between events variable has been utilized in research and is accepted as an effective way to monitor rare occurring events. Another potential output to explore in place of RIR would be First-Aid cases or Near Misses, these are both additional measures of different types of safety incidents which can occur in construction settings.

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13. APPENDICES

13.1 APPENDIX 1: OBJECTIVE 1 REGRESSION RESULTS USING SEVEN VARIABLES

The SAS System

The GENMOD Procedure

Model Information		
Data Set	WORK.POISSONREG	
Distribution	Zero Inflated Poisson	
Link Function	Log	
Dependent Variable	recinj	recinj
Offset Variable	ln_offset	

Number of Observations Read	162
Number of Observations Used	158

Missing Values	4

Class Level Information		
Class	**Levels**	**Values**
country_r	2	International United States
majorcls	2	Heavy Industrial Light Industrial
char	4	Addition Brownfield or Co-location Grass Roots Modernization
pdcs	4	Design-Build Other Parallel Primes Traditional D-B-B
typical	2	Not Typical Typical

Criteria For Assessing Goodness Of Fit			
Criterion	**DF**	**Value**	**Value/DF**
Deviance		636.7585	
Scaled Deviance		636.7585	
Pearson Chi-Square	147	306.8708	2.0876
Scaled Pearson X2	147	306.8708	2.0876
Log Likelihood		961.0383	
Full Log Likelihood		-318.3793	
AIC (smaller is better)		658.7585	
AICC (smaller is better)		660.5667	
BIC (smaller is better)		692.4471	

Algorithm converged.

Analysis Of Maximum Likelihood Parameter Estimates								
Parameter		**DF**	**Estimate**	**Standard Error**	**Wald 95% Confidence Limits**		**Wald Chi-Square**	**Pr > ChiSq**
Intercept		0	0.0000	0.0000	0.0000	0.0000	.	.
country_r	**International**	1	-13.2823	0.2133	-13.7004	-12.8643	3877.89	<.0001
country_r	**United States**	1	-12.2530	0.1889	-12.6232	-11.8828	4207.97	<.0001
majorcls	**Heavy Industrial**	1	-0.7764	0.1022	-0.9767	-0.5761	57.71	<.0001
majorcls	**Light Industrial**	0	0.0000	0.0000	0.0000	0.0000	.	.

Analysis Of Maximum Likelihood Parameter Estimates

Parameter		DF	Estimate	Standard Error	Wald 95% Confidence Limits		Wald Chi-Square	Pr > ChiSq
char	**Addition**	1	0.4864	0.1976	0.0992	0.8737	6.06	0.0138
char	**Brownfield or Co-location**	1	1.0830	0.2322	0.6278	1.5381	21.75	<.0001
char	**Grass Roots**	1	0.5556	0.1854	0.1922	0.9190	8.98	0.0027
char	**Modernization**	0	0.0000	0.0000	0.0000	0.0000	.	.
projectcost1		1	0.0007	0.0001	0.0006	0.0008	96.89	<.0001
Scale		0	1.0000	0.0000	1.0000	1.0000		

Note: The scale parameter was held fixed.

Analysis Of Maximum Likelihood Zero Inflation Parameter Estimates

Parameter		DF	Estimate	Standard Error	Wald 95% Confidence Limits		Wald Chi-Square	Pr > ChiSq
Intercept		1	-22.0266	0.7771	-23.5496	-20.5036	803.51	<.0001
pdcs	**Design-Build**	1	20.1722	0.9427	18.3245	22.0199	457.86	<.0001
pdcs	**Other**	1	21.7013	0.9268	19.8847	23.5179	548.22	<.0001
pdcs	**Parallel Primes**	0	20.4004	0.0000	20.4004	20.4004	.	.
pdcs	**Traditional D-B-**	0	0.0000	0.0000	0.0000	0.0000	.	.

Lagrange Multiplier Statistics

Parameter	**Chi-Square**	**Pr > ChiSq**
Intercept	.	.

13.2 APPENDIX 2: OBJECTIVE 1 REGRESSION RESULTS USING EIGHT VARIABLES

The SAS System

The GENMOD Procedure

Model Information		
Data Set	JENNI.POISSONREG	
Distribution	Zero Inflated Poisson	
Link Function	Log	
Dependent Variable	recinj	recinj
Offset Variable	ln_offset	

Number of Observations Read	157
Number of Observations Used	154
Missing Values	3

Class Level Information		
Class	**Levels**	**Values**
country_r	2	International United States
majorcls	2	Heavy Industrial Light Industrial
char	4	Addition Brownfield or Co-location Grass Roots Modernization
pdcs	4	Design-Build Other Parallel Primes Traditional D-B-B
typical	2	Not Typical Typical

Criteria For Assessing Goodness Of Fit

Criterion	DF	Value	Value/DF
Deviance		605.6630	
Scaled Deviance		605.6630	
Pearson Chi-Square	143	277.5969	1.9412
Scaled Pearson X2	143	277.5969	1.9412
Log Likelihood		915.3244	
Full Log Likelihood		-302.8315	
AIC (smaller is better)		627.6630	
AICC (smaller is better)		629.5221	
BIC (smaller is better)		661.0695	

Algorithm converged.

Analysis Of Maximum Likelihood Parameter Estimates

Parameter		DF	Estimate	Standard Error	Wald 95% Confidence Limits		Wald Chi-Square	Pr > ChiSq
Intercept		1	-12.0220	0.1904	-12.3952	-11.6487	3984.82	<.0001
country_r	**International**	1	-1.2116	0.1095	-1.4263	-0.9969	122.35	<.0001
country_r	**United States**	0	0.0000	0.0000	0.0000	0.0000	.	.
majorcls	**Heavy Industrial**	1	-1.0795	0.1205	-1.3157	-0.8433	80.22	<.0001
majorcls	**Light Industrial**	0	0.0000	0.0000	0.0000	0.0000	.	.
char	**Addition**	1	0.4544	0.1963	0.0697	0.8390	5.36	0.0206

Analysis Of Maximum Likelihood Parameter Estimates								
Parameter		**DF**	**Estimate**	**Standard Error**	**Wald 95% Confidence Limits**		**Wald Chi-Square**	**Pr > ChiSq**
char	**Brownfield or Co-location**	1	1.2104	0.2329	0.7539	1.6670	27.00	<.0001
char	**Grass Roots**	1	0.6375	0.1839	0.2770	0.9979	12.01	0.0005
char	**Modernization**	0	0.0000	0.0000	0.0000	0.0000	.	.
projectcost1		1	0.0008	0.0001	0.0007	0.0010	112.86	<.0001
Scale		0	1.0000	0.0000	1.0000	1.0000		

Note: The scale parameter was held fixed.

Analysis Of Maximum Likelihood Zero Inflation Parameter Estimates								
Parameter		**DF**	**Estimate**	**Standard Error**	**Wald 95% Confidence Limits**		**Wald Chi-Square**	**Pr > ChiSq**
Intercept		1	-20.1274	0.7523	-21.6018	-18.6530	715.84	<.0001
pdcs	**Design-Build**	1	18.3337	0.9145	16.5412	20.1261	401.89	<.0001
pdcs	**Other**	1	19.7943	0.9203	17.9906	21.5981	462.60	<.0001
pdcs	**Parallel Primes**	0	18.5639	0.0000	18.5639	18.5639	.	.
pdcs	**Traditional D-B-**	0	0.0000	0.0000	0.0000	0.0000	.	.

13.3 APPENDIX 3: OBJECTIVE 2 REGRESSION WITH ALL VARIABLES

The SAS System

The GENMOD Procedure

Model Information		
Data Set	JENNI.G123_OFFSET_ALL	
Distribution	Poisson	
Link Function	Log	
Dependent Variable	recinj	recinj
Offset Variable	ln_offset	

Number of Observations Read	59
Number of Observations Used	59

Class Level Information		
Class	**Levels**	**Values**
Bin_location	2	Domestic International
majorcls	2	Heavy Industrial Light Industrial
char	4	Addition Brownfield or Co-location Grass Roots Modernization

Criteria For Assessing Goodness Of Fit			
Criterion	**DF**	**Value**	**Value/DF**
Deviance	49	154.3195	3.1494
Scaled Deviance	49	154.3195	3.1494
Pearson Chi-Square	49	214.5445	4.3785
Scaled Pearson X2	49	214.5445	4.3785

Criteria For Assessing Goodness Of Fit			
Criterion	**DF**	**Value**	**Value/DF**
Log Likelihood		913.9723	
Full Log Likelihood		-171.8168	
AIC (smaller is better)		363.6337	
AICC (smaller is better)		368.2170	
BIC (smaller is better)		384.4090	

Algorithm converged.

Analysis Of Maximum Likelihood Parameter Estimates								
Parameter		**DF**	**Estimate**	**Standard Error**	**Wald 95% Confidence Limits**		**Wald Chi-Square**	**Pr > ChiSq**
Intercept		1	-11.2024	0.6178	-12.4133	-9.9915	328.77	<.0001
G1_Sum		1	-0.2829	0.1177	-0.5135	-0.0523	5.78	0.0162
G2_Sum		1	0.2107	0.1107	-0.0064	0.4277	3.62	0.0571
G3_Sum		1	-0.5728	0.1171	-0.8022	-0.3433	23.94	<.0001
Bin_location	**Domestic**	1	0.8045	0.1456	0.5191	1.0898	30.53	<.0001
Bin_location	**International**	0	0.0000	0.0000	0.0000	0.0000	.	.
majorcls	**Heavy Industrial**	1	-0.2568	0.1550	-0.5606	0.0470	2.74	0.0976
majorcls	**Light**	0	0.0000	0.0000	0.0000	0.0000	.	.

Analysis Of Maximum Likelihood Parameter Estimates								
Parameter		**DF**	**Estimate**	**Standard Error**	**Wald 95% Confidence Limits**		**Wald Chi-Square**	**Pr > ChiSq**
	Industrial							
char	**Addition**	1	-0.0549	0.2193	-0.4847	0.3748	0.06	0.8022
char	**Brownfield or Co-location**	1	0.5283	0.2408	0.0563	1.0002	4.81	0.0282
char	**Grass Roots**	1	-0.3603	0.1981	-0.7486	0.0280	3.31	0.0690
char	**Modernization**	0	0.0000	0.0000	0.0000	0.0000	.	.
cost		1	0.0009	0.0001	0.0007	0.0010	87.33	<.0001
Scale		0	1.0000	0.0000	1.0000	1.0000		

Note: The scale parameter was held fixed.

LR Statistics For Type 3 Analysis			
Source	**DF**	**Chi-Square**	**Pr > ChiSq**
G1_Sum	1	5.58	0.0182
G2_Sum	1	3.64	0.0564
G3_Sum	1	23.18	<.0001
Bin_location	1	32.81	<.0001
majorcls	1	2.74	0.0981
char	3	22.53	<.0001
cost	1	88.74	<.0001

13.4 APPENDIX 4: OBJECTIVE 2 MAJOR CLASSIFICATION OMITTING MAJOR CLASSIFICATION

The SAS System

The GENMOD Procedure

Model Information		
Data Set	JENNI.G123_OFFSET_ALL	
Distribution	Poisson	
Link Function	Log	
Dependent Variable	recinj	recinj
Offset Variable	ln_offset	

Number of Observations Read	59
Number of Observations Used	59

Class Level Information		
Class	**Levels**	**Values**
Bin_location	2	Domestic International
majorcls	2	Heavy Industrial Light Industrial
char	4	Addition Brownfield or Co-location Grass Roots Modernization

Criteria For Assessing Goodness Of Fit			
Criterion	**DF**	**Value**	**Value/DF**
Deviance	50	157.0558	3.1411
Scaled Deviance	50	157.0558	3.1411
Pearson Chi-Square	50	235.7843	4.7157

Criteria For Assessing Goodness Of Fit			
Criterion	**DF**	**Value**	**Value/DF**
Scaled Pearson X2	50	235.7843	4.7157
Log Likelihood		912.6042	
Full Log Likelihood		-173.1850	
AIC (smaller is better)		364.3699	
AICC (smaller is better)		368.0434	
BIC (smaller is better)		383.0678	

Algorithm converged.

Analysis Of Maximum Likelihood Parameter Estimates								
Parameter		**DF**	**Estimate**	**Standard Error**	**Wald 95% Confidence Limits**		**Wald Chi-Square**	**Pr > ChiSq**
Intercept		1	-11.0395	0.6245	-12.2636	-9.8154	312.44	<.0001
G1_Sum		1	-0.2762	0.1221	-0.5156	-0.0368	5.11	0.0237
G2_Sum		1	0.1849	0.1090	-0.0287	0.3986	2.88	0.0898
G3_Sum		1	-0.6996	0.0877	-0.8715	-0.5277	63.64	<.0001
Bin_location	**Domestic**	1	0.8177	0.1506	0.5225	1.1129	29.47	<.0001
Bin_location	**International**	0	0.0000	0.0000	0.0000	0.0000	.	.
char	**Addition**	1	-0.0820	0.2213	-0.5156	0.3517	0.14	0.7111

Analysis Of Maximum Likelihood Parameter Estimates								
Parameter		**DF**	**Estimate**	**Standard Error**	**Wald 95% Confidence Limits**		**Wald Chi-Square**	**Pr > ChiSq**
char	**Brownfield or Co-location**	1	0.5009	0.2409	0.0287	0.9732	4.32	0.0376
char	**Grass Roots**	1	-0.3854	0.1994	-0.7762	0.0053	3.74	0.0532
char	**Modernization**	0	0.0000	0.0000	0.0000	0.0000	.	.
cost		1	0.0009	0.0001	0.0007	0.0011	96.33	<.0001
Scale		0	1.0000	0.0000	1.0000	1.0000		

Note: The scale parameter was held fixed.

LR Statistics For Type 3 Analysis			
Source	**DF**	**Chi-Square**	**Pr > ChiSq**
G1_Sum	1	4.97	0.0258
G2_Sum	1	2.89	0.0893
G3_Sum	1	58.93	<.0001
Bin_location	1	31.88	<.0001
char	3	22.39	<.0001
cost	1	96.77	<.0001

13.5 APPENDIX 5: OBJECTIVE 2 REGRESSION FOR ZAT GROUP 2 ISOLATION

The SAS System

The GENMOD Procedure

Model Information		
Data Set	JENNI.G123_OFFSET_ALL	
Distribution	Poisson	
Link Function	Log	
Dependent Variable	recinj	recinj
Offset Variable	ln_offset	

Number of Observations Read	59
Number of Observations Used	59

Class Level Information		
Class	**Levels**	**Values**
Bin_location	2	Domestic International
majorcls	2	Heavy Industrial Light Industrial
char	4	Addition Brownfield or Co-location Grass Roots Modernization

Criteria For Assessing Goodness Of Fit			
Criterion	**DF**	**Value**	**Value/DF**
Deviance	50	156.8370	3.1367
Scaled Deviance	50	156.8370	3.1367
Pearson Chi-Square	50	220.8912	4.4178
Scaled Pearson X2	50	220.8912	4.4178

Criteria For Assessing Goodness Of Fit			
Criterion	**DF**	**Value**	**Value/DF**
Log Likelihood		912.7136	
Full Log Likelihood		-173.0756	
AIC (smaller is better)		364.1511	
AICC (smaller is better)		367.8246	
BIC (smaller is better)		382.8490	

Algorithm converged.

Analysis Of Maximum Likelihood Parameter Estimates								
Parameter		**DF**	**Estimate**	**Standard Error**	**Wald 95% Confidence Limits**		**Wald Chi-Square**	**Pr > ChiSq**
Intercept		1	-10.8292	0.5755	-11.9572	-9.7012	354.04	<.0001
G13		1	-0.4256	0.0730	-0.5687	-0.2826	34.00	<.0001
G2_Sum		1	0.2312	0.1111	0.0134	0.4489	4.33	0.0375
Bin_location	**Domestic**	1	0.6781	0.1192	0.4444	0.9118	32.35	<.0001
Bin_location	**International**	0	0.0000	0.0000	0.0000	0.0000	.	.
majorcls	**Heavy Industrial**	1	-0.3625	0.1413	-0.6394	-0.0856	6.58	0.0103
majorcls	**Light Industrial**	0	0.0000	0.0000	0.0000	0.0000	.	.
char	**Addition**	1	-0.0682	0.2182	-0.4959	0.3596	0.10	0.7547

Analysis Of Maximum Likelihood Parameter Estimates								
Parameter		**DF**	**Estimate**	**Standard Error**	**Wald 95% Confidence Limits**		**Wald Chi-Square**	**Pr > ChiSq**
char	**Brownfield or Co-location**	1	0.4798	0.2388	0.0118	0.9479	4.04	0.0445
char	**Grass Roots**	1	-0.4123	0.1946	-0.7937	-0.0308	4.49	0.0341
char	**Modernization**	0	0.0000	0.0000	0.0000	0.0000	.	.
cost		1	0.0008	0.0001	0.0006	0.0010	87.57	<.0001
Scale		0	1.0000	0.0000	1.0000	1.0000		

Note: The scale parameter was held fixed.

LR Statistics For Type 3 Analysis			
Source	**DF**	**Chi-Square**	**Pr > ChiSq**
G13	1	35.21	<.0001
G2_Sum	1	4.33	0.0374
Bin_location	1	33.53	<.0001
majorcls	1	6.44	0.0112
char	3	24.32	<.0001
cost	1	87.47	<.0001

13.6 APPENDIX 6: ANOVA RESULTS OUTPUT FROM JMP VERSION 9

Least Squares Fit

Response G1 Score

Whole Model

Analysis of Variance

Source	**DF**	**Sum of Squares**	**Mean Square**	**F Ratio**
Model	1	0.053822	0.053822	0.1100
Error	90	44.055808	0.489509	**Prob > F**
C. Total	91	44.109630		0.7410

Effect Tests

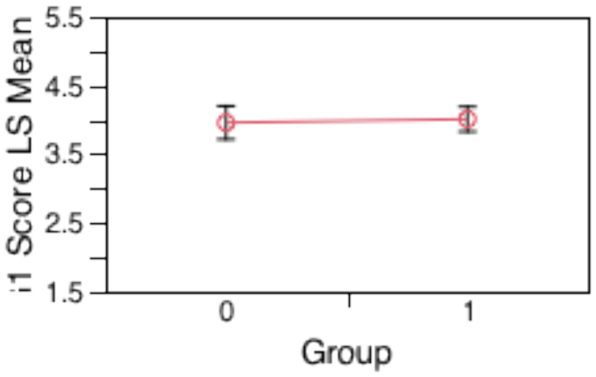
Source	**Nparm**	**DF**	**Sum of Squares**	**F Ratio**	**Prob > F**
Group	1	1	0.05382185	0.1100	0.7410

Group

Least Squares Means Table

Level	**Least Sq Mean**	**Std Error**	**Lower 95%**	**Upper 95%**	**Mean**
0	3.9596970	0.12179329	3.7177333	4.2016606	3.95970
1	4.0101271	0.09108656	3.8291678	4.1910865	4.01013

LS Means Plot



Response G2 Score

Whole Model

Analysis of Variance

Source	**DF**	**Sum of Squares**	**Mean Square**	**F Ratio**
Model	1	4.49167	4.49167	3.5654
Error	90	113.38290	1.25981	**Prob > F**
C. Total	91	117.87458		0.0622

Effect Tests

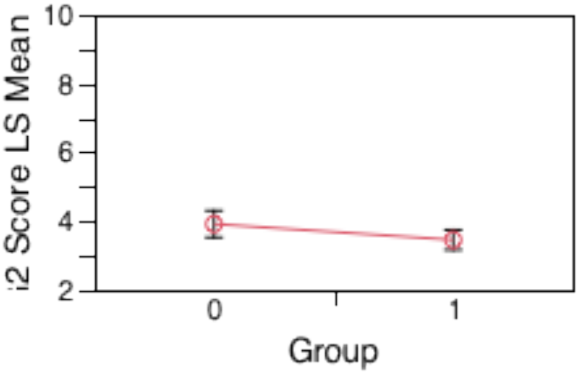
Source	**Nparm**	**DF**	**Sum of Squares**	**F Ratio**	**Prob > F**
Group	1	1	4.4916746	3.5654	0.0622

Group

Least Squares Means Table

Level	**Least Sq Mean**	**Std Error**	**Lower 95%**	**Upper 95%**	**Mean**
0	3.9221212	0.19538695	3.5339509	4.3102915	3.92212
1	3.4614245	0.14612567	3.1711204	3.7517287	3.46142

LS Means Plot



Response G3 Score

Whole Model

Analysis of Variance

Source	**DF**	**Sum of Squares**	**Mean Square**	**F Ratio**
Model	1	0.00034	0.00034	0.0003
Error	90	102.32878	1.13699	**Prob > F**
C. Total	91	102.32913		0.9862

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Group	1	1	0.00034396	0.0003	0.9862

Group

Least Squares Means Table

Level	Least Sq Mean	Std Error	Lower 95%	Upper 95%	Mean
0	2.0600000	0.18561825	1.6912369	2.4287631	2.06000
1	2.0559685	0.13881987	1.7801786	2.3317584	2.05597

LS Means Plot