Engineering Management
Field Project

Data Envelopment Analysis: A Linear Programming Application to Measure the Relative Efficiencies of Internal Business Divisions

By

Laura Shockley, PE, AIA, LEED®BD+C

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Tom H. Bowlin

Tom Bowlin
Committee Chairperson

Marc Richardson
Committee Member

Ben Biller

Ben Biller
Committee Member

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Executive Summary

Data Envelopment Analysis (DEA) is a non-parametric linear programming model used to determine relative efficiencies of similar decision making units based on identical categories of input and output variables. This research applied DEA to the Internal Business Divisions (IBDs) of a fictitious Architecture / Engineering / Construction firm to illustrate how business managers can identify internal inefficiencies. An overview of the mathematical theory behind DEA and its model variations are presented, as well as the methods used to apply DEA to the company's IBDs. The fictitious company and its IBDs were defined based on industry standards. Then, financial and non-financial key performance indicators were identified and used as the input and output variables. The variable data was developed based on averages of top performing design firms in the industry, and the results were analyzed to determine which IBDs were underperforming and how. The specific results of the analysis were irrelevant due to the fact that the company and data were fictitious; however, the results were examined and interpreted to illustrate how DEA can be used as a tool to realize potential efficiency optimization within an existent company.

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Definitions

(Wintner, 2014) and (Burson, 2014)

Operating Profit Margin = Operating Profit / Net Revenue
A ratio used to measure a company's pricing strategy and operating efficiency. It is a measurement of what proportion of a company's revenue is left over after paying for variable costs of production such as wages, raw materials, etc.

Utilization Rate = Actual Output / Potential Output
A metric used to measure the rate at which potential output levels are being met or used. Displayed as a percentage, capacity utilization levels give insight into the overall slack that is in the economy or a firm at a given point in time. If a company is running at a 70% capacity utilization rate, it has room to increase production up to a 100% utilization rate without incurring the expensive costs of building a new plant or facility.

Overhead Rate = All Non-Labor Operating Expenses / Direct Labor Expenses
In managerial accounting, a cost added on to the direct costs of production in order to more accurately assess the profitability of each product. Overhead costs are all costs that are not directly related to the production of the good to be sold. These include administrative salaries, the costs of the building or machinery, commissions to salespeople, and many other items.

Break-Even Rate = 1 + (Overhead Rate / 100)
The break-even rate represents the actual cost of each person's employment. It's equal to the overhead rate plus each person's hourly salary, represented by the unit of 1.0.

Net Labor Multiplier = Net Labor Revenue / Direct Labor Expense
The net multiplier represents the actual revenue generated by the firm, expressed as a percentage (or multiple) of total direct labor. If the net multiplier is greater than the break-even rate, the firm is earning a profit. If it is less than the break-even rate, the firm is losing money.

Terms

DEA – Data Envelopment Analysis

DMU – Decision Making Unit

IBD – Internal Business Division (analogous to DMU)

KPI – Key Performance Indicator

CRS – Constant Returns to Scale

VRS – Variable Returns to Scale

CCR Model – Charnes, Cooper, Rhodes Model

BCC Model – Banker, Charnes, Cooper Model

SBM – Slacks-Based Measure

Chapter 1: Introduction

Managers are required to make a variety of decisions daily that affect their organization from the small project scale to the overall company scale. Many of these decisions are largely based on experience, company tradition, and/or a "gut feeling." Although these techniques may prove to be historically accurate or efficient, much research has been completed in recent years to provide *objective* mathematical models for managers to use as a means of analyzing and predicting decision outcomes. Such research is generally referred to as quantitative analysis. The mathematical models and tools developed from the research are being used in conjunction with (and sometimes even instead of) the traditional subjective approaches for making decisions.

1.1 Linear Programming Models

"Management science," "operations research," and "decisions science" are all terms that were coined to describe research developed using quantitative analysis approaches to management. The concepts originated during the World War II era, when the military created task forces consisting of engineers, mathematicians, and behavioral scientists to study strategic and tactical problems. When the war ended, the research shifted to the area of management (Anderson, 2008). Furthermore, the development of computers (which provided a means to manage large amounts of data) greatly increased the applicability and practical use of ideas developed by quantitative analysis. Today, a multitude of mathematical models and computer programs have been developed to provide tools for managers to make objective decisions – ones that may or may not be in line with the subjective decisions made in the past.

Linear programming is a segment of quantitative analysis that is used to develop optimization models which can be applied to business decisions to determine optimal (rather than just satisfactory) solutions. These models can be used to determine the best location for a new manufacturing facility, the optimal gasoline blend for an oil company, a manufacturer's minimal production and inventory costs, the maximum return on investment of a stock portfolio, and a variety of other solutions that managers seek to determine. The objective of linear programming models is to determine the maximum or minimum of some quantity of the problem statement. All liner programming models include an objective statement, definition of the decisions variables, and the decision constraints. The models can be as simple or complex as needed depending on the number of input variables and the problem constraints and are generally calculated using computer software.

1.2 Data Envelopment Analysis

One particular advanced linear programming model type is Data Envelopment Analysis (DEA). This type of model is used to measure the relative efficiency of operating units with the same goals and objectives, which are generally referred to as Decision Making Units, or DMUs. For example, a bank may want to compare the efficiencies of each of their branch offices in a particular region, a fast food chain may want to compare the efficiencies of several of its restaurants, or a manufacturing company may want to compare the efficiencies of different plant processes. The goal of this analysis is to determine which units are underperforming compared to all other units so that further analysis or corrective action can occur, if necessary.

DEA gathers all empirical data regarding the DMUs to create an "envelope" of information with an established "frontier" that represents the border of the most efficient combination of input and output data.

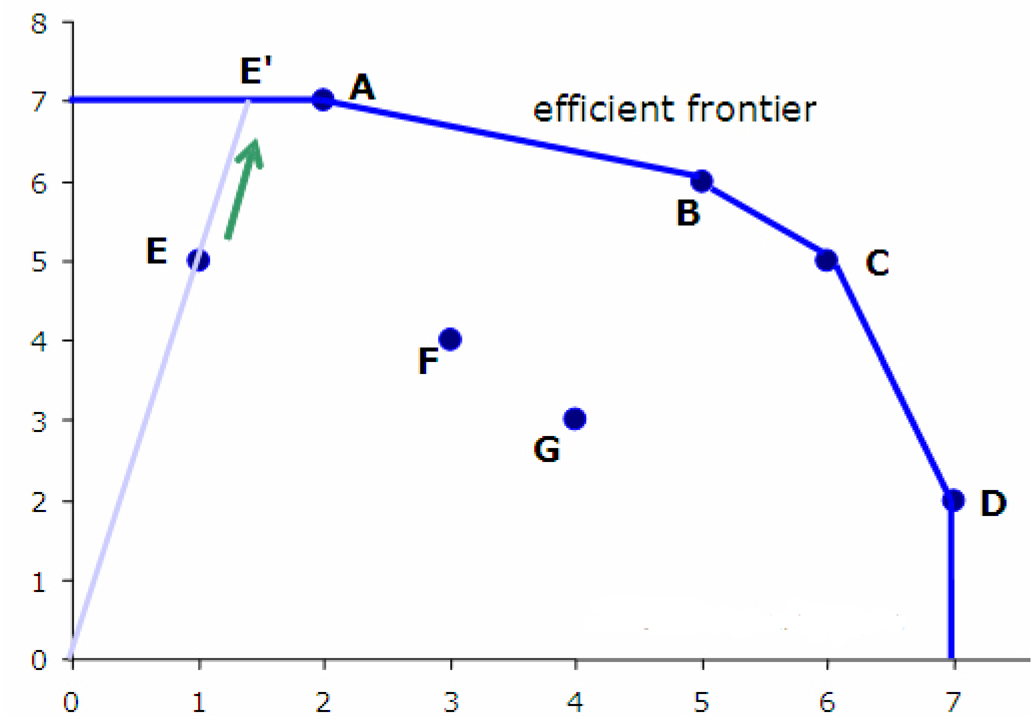

Figure 1: Efficiency Frontier

All DMUs are compared to this frontier to determine their relative efficiency to the best observed outcomes.

> "…DEA also identifies the sources and amounts of inefficiency in each input and output for every DMU. It also identifies the DMUs (located on the 'efficiency frontier') that entered actively in arriving at these results. These evaluating entities are all efficient DMUs and hence can serve as benchmarks en route to effecting improvements in future performances of the thus evaluated DMUs" (Cooper WW, Seiford LM, Tone K, 2006, *xx*).

1.3 Application of Data Envelopment Analysis

The research reported here applied DEA models to the Internal Business Divisions (IBDs) of a fictitious Architecture/Engineering/Construction firm (called XAEC) to determine the optimal areas where funds and resources should be spent in further research for improvements. The IBDs (which are analogous to DMUs) were selected based on the services they provided and the markets they served. Fourteen (14) IBDs were evaluated, each under separate management and each including employees from several offices nationally and globally:

- Architecture
- Aviation
- Business / Financial Services
- Construction / Design-Build
- Energy / Power
- Environmental
- Facilities
- Federal / Government
- Industrial
- Mining
- Oil & Gas
- Technology
- Transportation
- Water

The DEA models applied evaluated each IBD to determine which ones were performing efficiently and which ones were not.

DEA allowed efficiency to be defined in relative terms since the IBDs were compared to each other rather than an external benchmark. The best performing units based on empirical data (rather than theoretical) became the benchmarks themselves. Key Performance Indicators (KPIs) were used as metrics to define "best performance." The KPIs were both financial (quantitative) and non-financial (quantitative and qualitative). Each input and output variable was analyzed to determine its relationship to the KPIs and thus its relevance as a performance metric. The values of the input and output variables in each IBD are fictitious as is the firm to which the IBDs belong (XAEC); however, they reflect, as close as possible, current industry trends. The results are intended to reveal which DMUs are underperforming, by how much, and in what regards. They may also reveal relationships between variables that were not previously realized. The intent of the research is to show, by example, how DEA can be applied to IBDs of an actual Architecture / Engineering / Construction firm.

Chapter 2: Literature Review

In order for managers to determine if the linear programming model that they have developed is accurate and realistic, they need to understand the theory behind its development as well as the most current related literature.

2.1 Overview

DEA is a relatively new analytical tool; however, its research and application has wildly spread in recent years to incorporate several different activities in several different industries and across several different countries. Historically, some of the more popular applications have been in banking, health care, agriculture and farm, transportation, and education in order of the top five most number of publications produced from 2005-2009 (Liu JS, Lu LYY, Lu W-M, A, 2013). That is not to say that research has not been conducted elsewhere. In fact, in one of the more interesting applications, DEA was used to determine the best relocation city for the Japanese government when it decided to move from Tokyo in 2003 (Cooper WW, Seiford LM, Zhu J, 2004).

There are numerous literary sources of information available today, as the research and application of DEA has expanded exponentially since its inception. In fact, there is even research literature analyzing *the development of the research literature* over the years, including citation-based studies and application studies. The fact that DEA requires no prior assumptions regarding the definition of efficiency and that empirical data is generally readily available has contributed to its widespread growth, application, and acceptance.

2.2 Origins of DEA

The inception of Data Envelopment Analysis dates back as early as 1957 when a researcher named M.J. Farrell published an article entitled "The Measurement of Productive Efficiency" in the *Journal of the Royal Statistical Society*. Farrell postulated that, even though it would be natural for an efficiency production function to be developed by theoretical mathematics to establish benchmarks, the reality is that this function would become too complex to realistically incorporate all possible inputs and outputs. Furthermore, he speculated that the more complex the analysis, the more likely the function would become too idealistic and unobtainable. Therefore, he concentrated on the use of *empirical* data to estimate an efficiency production function in which to provide a best *observed* (rather than ideal) standard to use as a benchmark for comparisons of several firms (or units). This is the foundational concept of DEA (Farrell, 1957).

Farrell was also the first to observe that returns to scale must be considered in DEA efficiency production functions. The simplest assumption is the one of constant returns to scale (CRS). This is defined as a change in output that is proportionally equal to the change in input. In other words, if all inputs, say capital, labor, materials, etc., are doubled, then so will the outputs. However, returns to scale are rarely constant in reality.

> "The only practical method of dealing with this problem seems to be that of dividing the observation groups of roughly equal output, and applying the method to each of these groups separately, the assumption being that returns are constant within a group to a sufficient degree of approximation" (Farrell, 1957, 259).

Researchers will later expand on this notion and create ways of dealing with returns to scale in a more practical and realistic manner.

Even though Farrell introduced the foundational concepts of DEA, it is generally accepted among most literary sources that the modern concepts of DEA originated in 1978 with the seminal paper by Charnes, A; Cooper, WW; and Rhodes, E entitled “Measuring the efficiency of decision making units” (Cooper et al, 2006). Charnes et al. introduce the use of weighted sums of inputs and outputs to overcome the “index number problems” to which Farrell alluded. They also built upon Farrell’s single-output cases by developing a dual pair of linear programming equations that could handle multiple outputs and large data sets (Charnes et al., 1978). The development of these dual equations allowed for the determination of inefficiencies in each input and output for every DMU (Cooper et al., 2004). The use of weighted sums, combined with the use of linear programming, gave birth to the basic DEA model, the CCR Model, in which essentially all research has stemmed since.

2.3 Mathematical Model

As stated previously, all liner programming models include a definition of the decision variables, an objective statement, and the decision constraints. The CCR Model is mathematically expressed as follows:

<u>Definition of the Decision Variables</u>
j = the number of decisions making units (DMU) being compared
DMU_j = decisions making unit number j
$\boldsymbol{\Theta}$ = efficiency rating of the DMU being evaluated
y_{rj} = amount of output r produced by DMU j

x_{ij} = amount if input i used by DMU j
i = number of inputs used by the DMUs
r = number of outputs generated by the DMUs
u_r = coefficient or weight assigned to output r
v_i = coefficient or weights assigned to input i

<u>Objective Statement</u>

$$\text{Maximize } \theta = \frac{u_1 y_{1o} + u_2 y_{2o} + \ldots + u_r y_{ro}}{v_1 x_{1o} + v_2 x_{2o} + \ldots + v_m x_{mo}} = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}}$$

<u>Decision Constraints</u>
For all DMU$_j$:

$$\frac{u_1 y_{1j} + u_2 y_{2j} + \ldots + u_r y_{rj}}{v_1 x_{1j} + v_2 x_{2j} + \ldots + v_m x_{mj}} = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1$$

$u_1, \ldots, u_s \geq 0$ and $v_1, \ldots, v_m \geq 0$, for all u,v

The objective is to find the set of coefficients (*u*'s and *v*'s) that will give the highest possible efficiency ratio of outputs to inputs for each DMU being evaluated. If θ is less than 100% for a given DMU, then it is considered inefficient, and there is potential that it can produce the same amount of output without any additional input. The first constraint states that no DMU can be more than 100% efficient. The second constraint states that no coefficient can be less than zero.

2.4 Returns of Scale

The CCR model is built on the assumption of constant returns of scale (CRS). However, as stated previously, CRS is rarely observed in reality. In other words, providing two times the amount of a particular input typically does not generate exactly two times the amount of a particular output. Therefore, in 1984, Banker, Charnes, and Cooper developed the BCC model which allows for variable returns of scale (VRS).

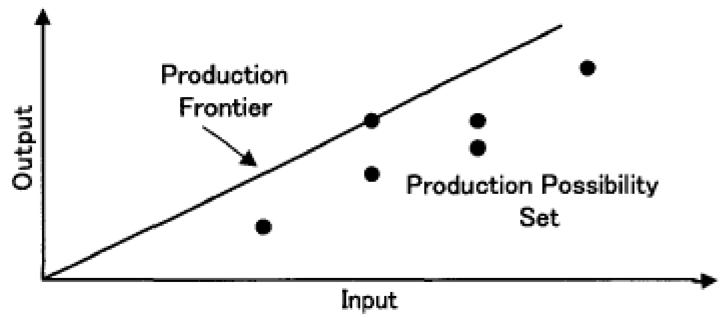

Figure 2: Production Frontier of the CCR Model

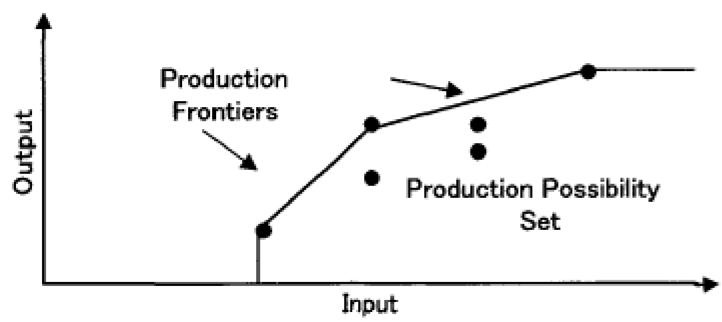

Figure 3: Production Frontier of the BCC Model

As observed in Figures 2 and 3 above, the CCR and BCC models have the same production possibility sets (observed efficiencies of DMUs); however, the BCC model has a piecewise linear and concave efficiency frontier possibility, which leads to variable returns to scale (Cooper WW, Seiford LM, Tone K, 2007). Following left to right across the x-axis, the returns of scale change from increasing to decreasing, with a constant return to scale at the points where the lines meet.

2.5 Model Extensions

The CCR and BCC models, however, ignore "slacks." Slacks are excess in inputs or shortfalls in outputs. In other words, a DMU has an input slack if it has an excess amount of resources needed to produce the outputs. An output slack would exist if a DMU has plenty of resources, yet isn't producing outputs as efficiently as it should. The CCR and BCC models can determine a DMU's ratio efficiency, but cannot identify its slacks. Therefore Charnes et al. developed the Additive Model in 1985, which deals directly with input excesses and output shortfalls. "Although this model can discriminate between efficient and inefficient DMUs by the existence of slacks, it has no means of gauging the depth of inefficiency, similar to the θ in the CCR model" (Cooper et al., 2007, 88). Up to this point, the DEA models developed could determine inefficiencies by either a) comparing their efficiency ratios with that of a frontier DMU or b) comparing the slacks of the DMUs. It wasn't until Tone introduced the Slacks-Based Measure (SBM) of efficiency in 1997, that the two measures were combined to provide a CCR-type θ efficiency ratio along with a scalar measure of slacks (Cooper et al., 2007).

DEA analysis can be approached in either radial or non-radial types of measures. The CCR and BCC models are radial, which ignore the non-radial input/output slacks. The Additive and SBM models are non-radial and ignore the radial characteristics of the inputs and outputs. Therefore unified framework models, or Hybrid models, have been developed to integrate both approaches (Cooper et al., 2007). DEA models continue to evolve today to meet the best fit for each application.

2.6 Growth in Research

A research study was conducted in 2012 that constructed a list of the top 20 DEA researchers, influential journals, and research growth trends. The study recognized Charnes, Cooper, and Rhodes's 1978 paper as the origin of the main path of research conducted. Below are two tables that identify the most influential researchers and influential journals on the topic of DEA according to their "g-indices."

g-index ranking	Authors	Years Active	Total no. of papers
1	Cooper, WW	1978-2009	82
2	Banker, RD	1980-2010	43
3	Charnes, A	1978-1997	42
4	Seiford, LM	1982-2009	42
5	Grosskopf, S	1983-2010	69

Table 1: Top 5 DEA Researchers According to their G-Index (Liu JS, Lu LYY, Lu W-M, B, 2013).

The g-index ranking is associated with the number of times an author has been cited in publications on the topic of DEA, with weights considered to the top rated articles that were cited.

g-index ranking	Journals	Years Active	No. of articles since 2000
1	European Journal of Operational Research	1978-2010	351
2	Management Science	1981-2008	11
3	Journal of Productivity Analysis	1991-2010	153
4	Journal of the Operational Research Society	1985-2010	145
5	Annals of Operations Research	1985-2010	46

Table 2: Top 5 Most Influential Journals in the DEA Field According to their G-Index (Liu et al., B, 2013).

Furthermore, the same research study created the following two figures that illustrate the growth trends in the topic:

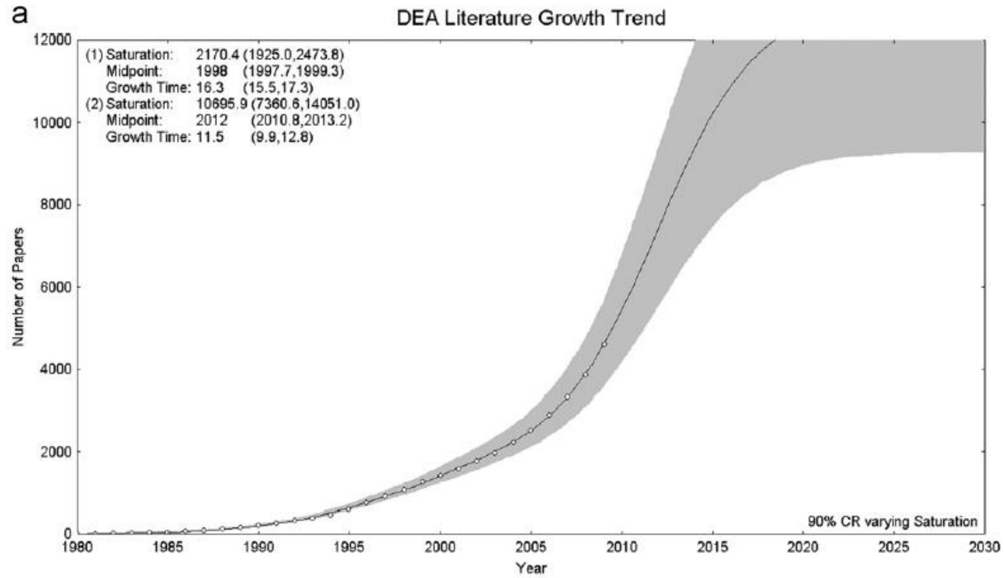

Figure 4: DEA Growth Curve, with the center line indicating the direct estimates, and the shaded boundaries representing the 90% confidence interval (Liu et al., A, 2013).

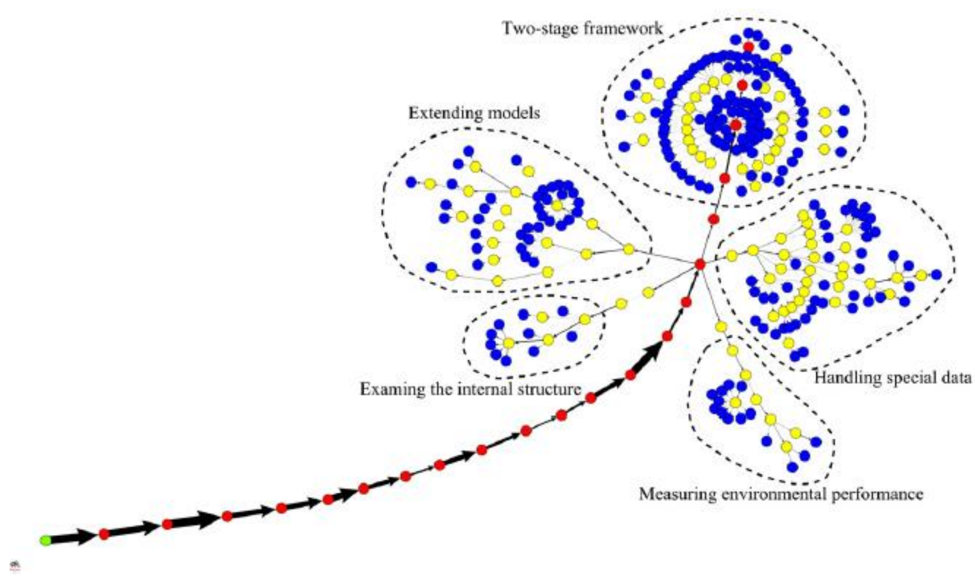

Figure 5: DEA Global Main Paths of DEA Development (Liu et al., A, 2013).

From Figure 4, it can be concluded that research and publications about DEA have grown exponentially. Figure 5 illustrates which sub-topics have grown the most, all stemming from Charnes et al. in 1978.

There have been several applications of DEA tools in making decisions or analyzing existing production including:

- traffic safety planning
- efficiency of water supply and sanitation projects
- priority ranking of public maintenance works
- target based planning for allocating government grants
- setting targets for electrical generation plants

By no means has the extent of DEA model variations and applications been exhausted within the literature review. A multitude of variations exist spanning several applications. Managers must understand the basic models and their variations and extensions in order to understand which is best fit for their decision application.

Chapter 3: Research Procedure

3.1 Company XAEC and its Internal Business Divisions

The first step in the research procedure was to define the fictitious company, XAEC, and its IBDs. It is assumed that XAEC is a publically owned and traded company comprised of 10,000 employees. The company headquarters are in Denver, CO, and the company has 25 branch offices nationally and internationally. Each branch office includes all IBDs, although some divisions are a larger percentage of the office (in number of employees) than others depending on the region. For example, the Texas branch office has a larger percentage of employees in the Oil & Gas division than the Florida branch office. It was assumed that XAEC performs on average with the top 25 design firms in the United States, and that the IBDs perform in accordance with the current industry trends.

The 14 IBDs were selected based on the highest frequency of markets served and services provided by the top 25 Design firms (by revenue) in 2013 according to Engineering New-Record. Refer to Appendix B for a matrix listing these firms along with the markets that the serve. From this matrix, the DMUs selected to be analyzed are as follows:

1. Architecture
2. Aviation
3. Business / Financial Services
4. Construction / Design-Build
5. Energy / Power
6. Environmental
7. Facilities
8. Federal / Government
9. Industrial
10. Mining
11. Oil & Gas
12. Technology

13. Transportation
14. Water

3.2 Model Selection

After the fictitious company and its DMUs were defined, the two most important next steps in applying DEA were to select 1) an appropriate model and 2) the inputs and outputs to be used. These two steps, although simple in theory, required some research and thought.

The first step, to select an appropriate model, proved difficult in the sense that little previous research has been generated regarding evaluation of general business divisions within a technical design/construction firm. Furthermore, research phrased as being geared towards "engineering applications" typically involved manufacturing process efficiencies rather than service or construction oriented efficiencies. In fact, the research that is most comparable to this application is in the banking industry, specifically in comparing efficiencies of bank branch offices. In particular, models were created to examine profitability by evaluating how well the branch office used its inputs (expenses) to generate outputs (revenues). "Based on the review of 68 DEA studies in bank branch analysis from 1997 to 2010, it was found that 46% use CCR assumption, 22% use BCC assumption, and 32% use both CCR and BCC assumptions" (Cooper et al., 2004, 343). The data used in these models were primarily financial and service related, which parallels the variables that indicate critical success factors in the A/E industry. This research will employ both the CCR and BCC models and compare the results.

3.3 Variable Quantity

The second step that had to be completed prior to beginning analysis was to determine what and how many input and output variables should be considered. As with linear regression analysis, if too many variables are used, it is likely that some will be highly correlated and may be eliminated without losing useful information (Luo Y, Bi G, Liang L, 2012). A general rule of thumb provided by (Cooper et al., 2007) suggested that the number of DMUs should be three times the number of inputs plus the number of outputs. In this analysis, there are 14 IBDs (or DMUs); therefore, per this rule, there should be approximately four to five total outputs and inputs.

If there is an insufficient number of DMUs in comparison to the number of preferred input and output variables, a technique called "window analysis" may be used. Window analysis evaluates DMUs over a given period of time. Each DMU (*n*) over each time period (*t*) is treated as a separate entity (DMU*nt*). For example, each IBD could be evaluated over the last five years resulting in a total of 70 DMUs, rather than just 14. Each IBD would be compared to itself over those five years in addition to being compared to all other IDPs over the same five years. The use of window analysis could potentially identify underlying economic trends, such as increasingly efficient recent years for the Oil & Gas division due to a boom in oil production which, in turn, increased work available within that division. Conversely, instead of using window analysis, subdivision within the IDPs themselves could be used to increase the number of DMUs (such as the Transmission subdivision within the Energy / Power IBD), and thus, the number of input and output variables according to the rule of thumb introduced previously.

3.4 Variable Quality

Perhaps determining *which* variables to include should occur prior to determining if the number of DMUs needs to be adjusted by applying the window analysis (or any other) technique. And that depends on what information business leaders deem as representative KPIs for their industry. According to several sources, the following are the top 10 financial KPIs for the Architectural / Engineering / Construction Industry:

1. Operating Profit Ratio
2. Utilization Rate
3. Overhead Rate
4. Break-Even Rate
5. Net Labor Multiplier
6. Total Payroll Multiplier
7. Aged Accounts Receivable
8. Profit-to-Earnings Ratio
9. Net Revenue per Employee
10. Backlog Volume

It is assumed that all top performing design firms already evaluate their key financial performance indicators with a dedicated and knowledgeable staff under the direction of a CFO. Comparing internal business units by these metrics is not a new concept, and industry standards can be easily researched. However, the value of DEA is the addition of *non-financial* KPIs within the analysis. These non-financial KPIs can be qualitative as well as quantitative. With the additional non-financial KPIs, an overall efficiency rating can be given which reveals the performance of a DMU beyond just the financial numbers. Furthermore, managers may be able to determine if there is a relationship between the financial and non-financial data. Some non-financial KPIs that an A/E/C firm may want to evaluate include:

1. Customer Satisfaction

2. Percent Repeat Customer Revenue
3. Employee Satisfaction
4. Employee Turnover Rate
5. OSHA Recordable Incidences
6. Lost Time due to Injury Rate

The DEA within this report will combine the financial and non-financial performance metrics to provide an objective efficiency rating of each DMU. The variables chosen to be evaluated in the analysis were based on the following key performance indicators:

1. Operating Profit Rate
2. Utilization Rate
3. Overhead Rate
4. Break-Even Rate
5. Net Labor Multiplier
6. Aged Accounts Receivable
7. Net Revenue per Employee
8. Customer Satisfaction
9. Employee Satisfaction
10. Employee Turnover Rate
11. OSHA Recordable Incidences

3.5 Input vs. Output Variables

Even though a list was generated to encompass the KPIs under consideration, the actual input and output variables were still yet to be determined. "In traditional application of DEA, it is assumed that the status of variables is provided with a priori. However, in the real world, there exists a kind of variable characterized as 'flexible', i.e., a variable that acts as an input and an output at the same time" (Luo et al., 2013, 1118). For example, should Employee Satisfaction be considered an input or an output variable? If there is high employee satisfaction, then profits may rise due to happy and efficient workers. That would indicate that the variable is an input, with profit being the output. However, perhaps the amount that the company invests in indirect expenses, say more desirable office furniture or better benefits, will raise employee satisfaction, thus implying that employee satisfaction is an output variable. One approach suggested is to determine if the variable adds or decreases value to the DMU's cash flow. If there is a positive influence on cash flow, then the variable can be considered an output variable. Otherwise, it should be considered an input variable (Luo et al., 2012). In the case of employee satisfaction, it is more likely that this value is affected more by the expenses accrued by the DMU rather than by employee satisfaction affecting profits. Thus, it should be considered as an output variable.

Another way to categorize variables as either input or output, especially if the variable is not financial and, therefore, does not fit well into the cash flow test, is to determine if the objective is to maximize or minimize the variable. For instance, if safety on the job site is of high concern for the company, minimizing the number of OSHA Recordable Incidences is of high priority. Therefore, this variable would be an input variable. In general, a company wants to maximize its outputs using as few inputs as possible.

Taking into consideration the key performance indicators, the general rule of thumb for the number of variables compared to the number of DMUs, and categorizing the variables as either input or output, the following variables were chosen for this research:

Inputs		Outputs	
1	Aged Accounts Receivable (Days)	1	Customer Satisfaction
2	OSHA Recordable Incidences	2	Net Labor Multiplier
3	Break-Even Rate	3	Utilization Rate
		4	Operating Profit Rate

Table 3: Input and Output Variables to be Used

These variables were chosen by eliminating correlated values as much as possible and by combining a good mix of financial and non-financial metrics. Fictitious Income Statements were generated for each IBD in order to calculate the values of some of the financial KPIs. These Income Statements can be found in Appendix A.

Chapter 4: Results

There are several options for free software available to download from the internet to compute DEA analysis, most of which have some limitations either by the number of DMUs you can input or the types of models available for calculation. There are also full software versions available for purchase. For the purposes of this research, a Microsoft Excel solver add-in called DEA Frontier and a Microsoft Access Database template called MaxDEA were used. Both have some limitations; however, they were sufficient for this analysis. The user input data taken from the income statements found in Appendix A and applied to the software to calculate the relative efficiencies of the DMUs are as follows:

Internal Business Division (IBD or DMU)	Aged Accounts Receivable	OSHA Recordable Incidences	Break-Even Rate	Customer Satisfaction	Net Labor Multiplier	Utilization Rate	Operating Profit Rate
Architecture	50	3	2.32	8.5	2.80	0.764	0.171
Aviation	50	3	2.27	7.5	2.80	0.764	0.189
Business / Financial Services	48	0	2.27	8.5	2.41	0.659	0.059
Construction / Design-Build	102	4	2.32	6.9	2.54	0.694	0.087
Energy / Power	50	2	2.32	7.5	2.63	0.719	0.119
Environmental	73	0	2.33	6.9	2.50	0.682	0.067
Facilities	56	3	2.36	7.5	2.52	0.689	0.065
Federal / Government	98	1	2.29	6.5	2.50	0.682	0.083
Industrial	50	4	2.27	8.4	2.72	0.742	0.164
Mining	60	2	2.35	8.5	2.50	0.682	0.059
Oil & Gas	88	2	2.43	8.5	2.86	0.780	0.149
Technology	75	1	2.25	8.0	2.43	0.664	0.075
Transportation	56	3	2.36	8.0	2.80	0.759	0.151
Water	56	2	2.36	8.9	2.63	0.717	0.102

Table 4: DEA Model User Input Data

4.1 Input-Oriented Constant Returns to Scale Model Results

The results using an Input-Oriented Constant Return of Scales model with DEA Frontier, provides the following efficiency ratings:

DMU No.	***DMU Name***	***Input-Oriented CRS Efficiency***
1	Architecture	1.00000
2	Aviation	1.00000
3	Business / Financial Services	1.00000
4	Construction / Design-Build	0.89029
5	Energy / Power	0.97385
6	Environmental	1.00000
7	Facilities	0.88442
8	Federal / Government	0.96842
9	Industrial	1.00000
10	Mining	0.95912
11	Oil & Gas	1.00000
12	Technology	0.96795
13	Transportation	0.97630
14	Water	1.00000

Table 5: Input-Oriented CRS Efficiency Results

From the results presented in Table 5, it can be concluded that DMUs 1, 2, 3, 6, 9, 11, and 14 are all along the efficiency frontier. In other words, these units are performing at full efficiency relative to all DMUs. Note that this does not mean that those DMUs are incapable of performing more efficiently theoretically, rather that they are the most efficient based on the empirical recorded data. The worst performing DMU is Facilities at an 88% rate.

The CRS model assumes that there is a linear relationship between the number of inputs required and the amount of outputs produced. Recall that a CRS model is analogous to the CCR model in that it neglects increasing and decreasing scales in input/output relationships.

4.2 Input-Oriented Variable Returns to Scale Model Results

If the VRS model analysis is used as opposed to the CRS model, the results show that, on average, all DMUs are more efficient:

DMU No.	***DMU Name***	***Input-Oriented VRS Efficiency***
1	Architecture	1.00000
2	Aviation	1.00000
3	Business / Financial Services	1.00000
4	Construction / Design-Build	0.97237
5	Energy / Power	0.98280
6	Environmental	1.00000
7	Facilities	0.96023
8	Federal / Government	0.98790
9	Industrial	1.00000
10	Mining	0.96819
11	Oil & Gas	1.00000
12	Technology	1.00000
13	Transportation	0.97712
14	Water	1.00000

Table 6: Input-Oriented VRS Efficiency Results

The VRS model is analogous to the BCC model in that it is based on the foundational algorithm; however, it adds a dimension of varying scales. Again, Facilities is the least efficient DMU, but only at 96% as opposed to 88% using the CRS model. The VRS model represents real world conditions more accurately as there is rarely a simple linear relationship between input and output data.

4.3 Input Slacks

Given that Facilities is the least efficient IBD, it is clear that management needs to focus resources on this DMU to determine how to increase its efficiency. One way to determine how to improve the efficiency of Facilities is to observe the DEA calculated slacks. The Input Slacks represent the amount of input that can be reduced without affecting the output. In other words, it represents the excess input waste that is not contributing to effective output.

		Input Slacks		
DMU No.	***DMU Name***	***Aged Accounts Receivable***	***OSHA Recordable Incidences***	***Break-Even Rate***
1	Architecture	0.00000	0.00000	0.00000
2	Aviation	0.00000	0.00000	0.00000
3	Business / Financial Services	0.00000	0.00000	0.00000
4	Construction / Design-Build	31.55000	2.30000	0.00000
5	Energy / Power	0.00000	0.25560	0.00000
6	Environmental	0.00000	0.00000	0.00000
7	Facilities	0.00000	1.86128	0.00000
8	Federal / Government	37.99695	0.00000	0.00000
9	Industrial	0.00000	0.00000	0.00000
10	Mining	9.16016	0.88901	0.00000
11	Oil & Gas	0.00000	0.00000	0.00000
12	Technology	0.00000	0.00000	0.00000
13	Transportation	0.91864	0.03136	0.00000
14	Water	0.00000	0.00000	0.00000

Table 7: Input-Oriented VRS Model Input Slacks

Focusing on Facilities alone, Table 7 shows that the number of OSHA Recordable Incidences can be reduce by nearly 1.86 without affecting Customer Satisfaction, the Net Labor Multiplier, Utilization Rate, or the Operating Profit Rate. However, solely focusing efforts on reducing the Incidences may not be feasible. Since there are a variety of inputs, and all of these inputs affect the outputs, it is more logical to reduce a *combination* of the inputs in order to operate along the efficiency frontier. Therefore, DEA Frontier calculates Target Values for management to works towards.

4.4 Input Target Values

Table 8 below shows the Target Values that each DMU can work towards to become as relatively efficient as the most efficient DMUs.

		Efficient Input Target		
DMU No.	***DMU Name***	***Aged Accounts Receivable***	***OSHA Recordable Incidences***	***Break-Even Rate***
1	Architecture	50.00000	3.00000	2.32000
2	Aviation	50.00000	3.00000	2.27000
3	Business / Financial Services	48.00000	0.00000	2.27000
4	Construction / Design-Build	67.63158	1.58947	2.25589
5	Energy / Power	49.14000	1.71000	2.28010
6	Environmental	73.00000	0.00000	2.33000
7	Facilities	53.77262	1.01940	2.26613
8	Federal / Government	58.81698	0.98790	2.26228
9	Industrial	50.00000	4.00000	2.27000
10	Mining	48.93099	1.04736	2.27524
11	Oil & Gas	88.00000	2.00000	2.43000
12	Technology	75.00000	1.00000	2.25000
13	Transportation	53.80000	2.90000	2.30600
14	Water	56.00000	2.00000	2.36000

Table 8: Input-Oriented VRS Model Efficiency Input Targets

Again, focusing on Facilities, the recorded vales for the inputs were 56, 3, and 2.36 respectively. If Facilities were to focus on reducing their values to match the ones highlighted in Table 8 without affecting their outputs, then it would be operating at 100% efficiency compared to all other DMUs. Therefore, DEA not only ranks DMUs in order of efficiency, it also can determine how and where management can focus efforts to increase a DMU's efficiency. Again, as previously emphasized, this includes not only financial criteria but *any* criteria that the company deems important to the success of its operations.

4.5 Output-Oriented Efficiencies

Thus far, only Input-oriented models have been presented. The objective of the input-oriented model is to minimize inputs without reducing the given outputs. Conversely, the output-oriented model attempts to maximize outputs without using more than the observed input variables (Tone, 2001).

DMU No.	DMU Name	*Input-Oriented* *VRS Efficiency*	*Output-Oriented* *VRS Efficiency*
1	Architecture	1.00000	1.00000
2	Aviation	1.00000	1.00000
3	Business / Financial Services	1.00000	1.00000
4	Construction / Design-Build	0.97237	0.90209
5	Energy / Power	0.98280	0.98489
6	Environmental	1.00000	1.00000
7	Facilities	0.96023	0.89879
8	Federal / Government	0.98790	0.97231
9	Industrial	1.00000	1.00000
10	Mining	0.96819	0.95985
11	Oil & Gas	1.00000	1.00000
12	Technology	1.00000	1.00000
13	Transportation	0.97712	0.99881
14	Water	1.00000	1.00000

Table 9: Input-Oriented & Output-Oriented VRS Model Efficiency Results

The efficiency results are slightly different for input- vs. output-oriented calculations due to the different objectives trying to be achieved. Concerning the Construction / Design-Build DMU, it can be determined from Table 9 that this DMU is much more efficient at minimizing the inputs needed to produce its outputs (97%) than it is at maximizing its outputs given its inputs (90%). In order for units 4, 5, 7, 8, 10, and 13 to operate as efficiently as the rest of the units, they would need to increase their outputs (without changing their inputs) per Table 10 below:

DMU No.	DMU Name	*Actual Customer Satisfaction*	*Target Customer Satisfaction*	*Actual Net Labor Multiplier*	*Target Net Labor Multiplier*	*Actual Utilization Rate*	*Target Utilization Rate*	*Actual Operating Profit Rate*	*Target Operating Profit Rate*
1	Architecture	8.5	8.5	2.80	2.80	0.764	0.764	0.171	0.171
2	Aviation	7.5	7.5	2.80	2.80	0.764	0.764	0.189	0.189
3	Business / Financial Services	8.5	8.5	2.41	2.41	0.659	0.659	0.059	0.059
4	Construction / Design-Build	6.9	7.8	2.54	2.82	0.694	0.769	0.087	0.176
5	Energy / Power	7.5	8.5	2.63	2.67	0.719	0.730	0.119	0.134
6	Environmental	6.9	6.9	2.50	2.50	0.682	0.682	0.067	0.067
7	Facilities	7.5	8.5	2.52	2.81	0.689	0.767	0.065	0.167
8	Federal / Government	6.5	7.6	2.50	2.57	0.682	0.702	0.083	0.105
9	Industrial	8.4	8.4	2.72	2.72	0.742	0.742	0.164	0.164
10	Mining	8.5	8.9	2.50	2.60	0.682	0.711	0.059	0.097
11	Oil & Gas	8.5	8.5	2.86	2.86	0.780	0.780	0.149	0.149
12	Technology	8.0	8.0	2.43	2.43	0.664	0.664	0.075	0.075
13	Transportation	8.0	8.0	2.80	2.81	0.759	0.767	0.151	0.176
14	Water	8.9	8.9	2.63	2.63	0.717	0.717	0.102	0.102

Table 10: Actual vs. Target Output Vales for Output-Oriented VRS Model

Table 10 indicates that the Mining IBD would need to increase its Customer Satisfaction, Net Labor Multiplier, Utilization Rate, and Operating Profit Rate by the highlighted vales to operate as efficiently as Environmental or Aviation. Again, in theory, a company would like to increase its Operating Profit Rate as much as possible and not just to meet the targets listed above; however, DEA deals with empirical data only. It can be concluded that the Aviation IBD utilizes its resources better than Mining. It's up to management to determine why and how.

4.6 Significance of DEA

Unlike the typical comparison of financial KPIs across IBDs or across branch offices, DEA offers a comprehensive overview which includes financial and non-financial criteria. With careful and constant analysis, a company may come to determine that certain performance criteria play a larger roll on an IBD's efficiency than anticipated. For example, employee satisfaction within a particular IBD may have a larger direct correlation to its break-even rate than previously realized. These trends may be noticed using DEA, yet they cannot be noticed using typical financial comparisons. If a trend is noticed, then management can determine which IBDs are performing well and apply the same management style or tools to the underperforming IBDs.

In addition to providing a comprehensive overview, DEA provides slack and target values. This gives management a clear direction of how and where an IBD is inefficient and what goals need to be set to bring it to the efficiency frontier. DEA offers a full and objective management tool to companies that track, analyze, and set goals for their operating units.

Chapter 5: Suggestions for Future Research

There are several areas of further research available on the topic of DEA. The information provided in this research is a broad overview of the main concepts. If a company was to decide to employ DEA tools to measure their IBD efficiencies, it is recommended that further research is completed.

There are several other DEA models that could be evaluated to determine which is best fit for a particular company and the purpose of the analysis; only the CCR and BCC models were used within this analysis. Unified Framework models or SBM measure of efficiency models may prove to be more applicable. Research of all of the available model types would be necessary to determine which one(s) should be applied.

Further research on which input and output variables to include would be beneficial. Depending on a company's goals, selecting the correct evaluation criteria is essential. This would require a thorough analysis of how financial and non-financial KPIs contribute to the efficiency of meeting the company goals. If more variables are desired in the calculations, then window analysis could be applied over a two to five year period as alluded to previously.

Also, more robust software could be used for the calculations, complete with graphs and the use of best fit model(s). Software for purchase provides a more comprehensive view of the results. Furthermore, there is a technique for graphically plotting multi-variable DEA results called Co-Plot, which wasn't presented within this report. "Co-Plot locates each decision making unit (DMU) in a two-dimensional space in which the location of each observation is determined by all variables simultaneously" (Adler N, Raveh A, 2008, 715). A Co-Plot graph visually looks like Figure 6 below.

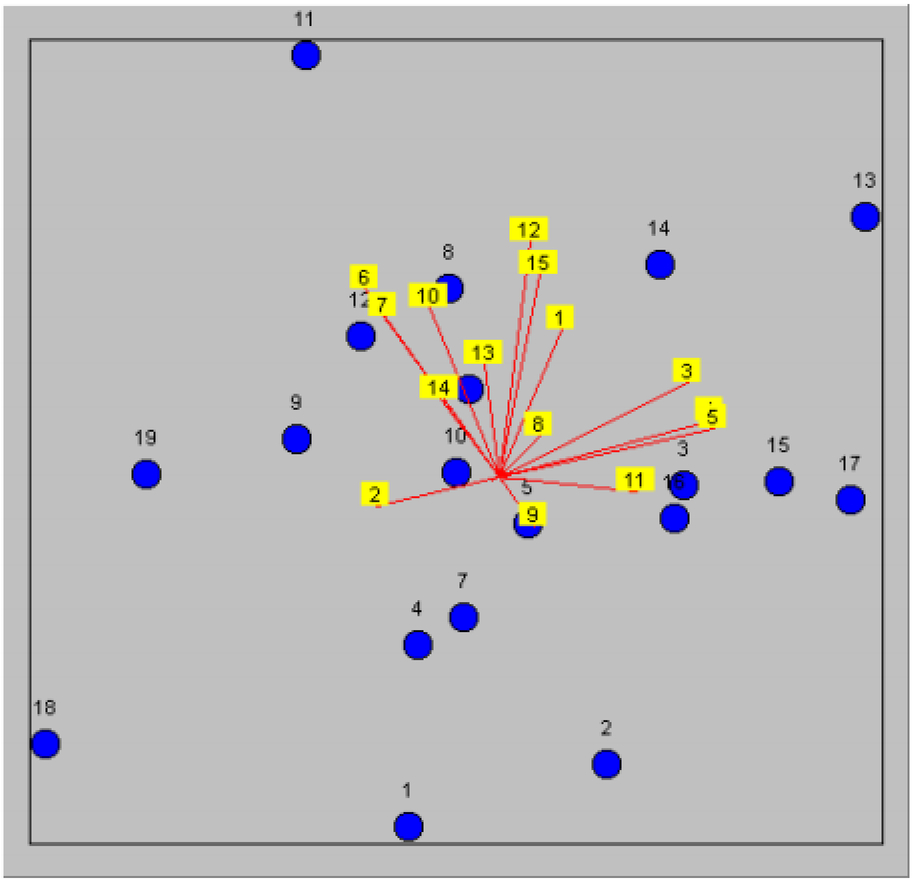

Figure 6: Example of a Co-Plot Graph

Further research on how Co-Plots are created and interoperated were beyond the scope of this document, but is certainly recommended for future research.

Finally, this research could be applied to an actual A/E/C firm using actual company data to capitalize on efficiency increase opportunities within its IBDs.

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Appendix A: Internal Business Division Data

Internal Business Division: Architecture

Employee Variables	**2013**
Number of Employees	542
Average Hourly Labor Rate / Employee	155
Yearly Billable Hours / Employee	1455
Income Statement	
Direct Expense Revenue	$48,893,820
Net (Labor) Revenue	$122,234,550
Total Revenue	$171,128,370
Direct Labor Expense	$43,685,200
Gross Profit	$78,549,350
Indirect Labor Expense	$27,084,824
Payroll-Related Labor Expense	$8,737,040
Other Indirect Expenses	$21,842,600
Operating Profit	$20,884,886
Key Financial Performance Indicators	
Operating Profit Rate	17.09%
Utilization Rate	76.42%
Overhead Rate	132%
Break-Even Rate	2.32
Net Labor Multiplier	2.80
Aged Accounts Receivable (Days)	50
Net Revenue per Employee	$225,525
Key Non-Financial Performance Indicators	
Customer Satisfaction	8.5
Employee Satisfaction	9.2
Employee Turnover Rate	5.0%
OSHA Recordable Incidences	3

Internal Business Division: Aviation

Employee Variables	2013
Ave. Number of Employees	456
Average Hourly Labor Rate / Employee	175
Yearly Billable Hours / Employee	1455
Income Statement	
Direct Expense Revenue	$44,121,420
Net (Labor) Revenue	$116,109,000
Total Revenue	$160,230,420
Direct Labor Expense	$41,496,000
Gross Profit	$74,613,000
Indirect Labor Expense	$23,652,720
Payroll-Related Labor Expense	$8,299,200
Other Indirect Expenses	$20,748,000
Operating Profit	$21,913,080
Key Financial Performance Indicators	
Operating Profit Rate	18.87%
Utilization Rate	76.42%
Overhead Rate	127%
Break-Even Rate	2.27
Net Labor Multiplier	2.80
Aged Accounts Receivable (Days)	50
Net Revenue per Employee	$254,625
Key Non-Financial Performance Indicators	
Customer Satisfaction	7.5
Employee Satisfaction	8.8
Employee Turnover Rate	7.2%
OSHA Recordable Incidences	3

Internal Business Division: Business / Financial Services

Employee Variables	2013
Ave. Number of Employees	122
Average Hourly Labor Rate / Employee	165
Yearly Billable Hours / Employee	1255
Income Statement	
Direct Expense Revenue	$13,136,838
Net (Labor) Revenue	$25,263,150
Total Revenue	$38,399,988
Direct Labor Expense	$10,467,600
Gross Profit	$14,795,550
Indirect Labor Expense	$5,966,532
Payroll-Related Labor Expense	$2,093,520
Other Indirect Expenses	$5,233,800
Operating Profit	$1,501,698
Key Financial Performance Indicators	
Operating Profit Rate	5.94%
Utilization Rate	65.91%
Overhead Rate	127%
Break-Even Rate	2.27
Net Labor Multiplier	2.41
Aged Accounts Receivable (Days)	48
Net Revenue per Employee	$207,075
Key Non-Financial Performance Indicators	
Customer Satisfaction	8.5
Employee Satisfaction	6.0
Employee Turnover Rate	2.0%
OSHA Recordable Incidences	0

Internal Business Division: Construction / Design-Build

Employee Variables	**2013**
Ave. Number of Employees	459
Average Hourly Labor Rate / Employee	175
Yearly Billable Hours / Employee	1321
Income Statement	
Direct Expense Revenue	$55,176,849
Net (Labor) Revenue	$106,109,325
Total Revenue	$161,286,174
Direct Labor Expense	$41,769,000
Gross Profit	$64,340,325
Indirect Labor Expense	$23,808,330
Payroll-Related Labor Expense	$8,353,800
Other Indirect Expenses	$22,972,950
Operating Profit	$9,205,245
Key Financial Performance Indicators	
Operating Profit Rate	8.68%
Utilization Rate	69.38%
Overhead Rate	132%
Break-Even Rate	2.32
Net Labor Multiplier	2.54
Aged Accounts Receivable (Days)	102
Net Revenue per Employee	$231,175
Key Non-Financial Performance Indicators	
Customer Satisfaction	6.9
Employee Satisfaction	8.5
Employee Turnover Rate	3.0%
OSHA Recordable Incidences	4

Internal Business Division: Energy / Power

Employee Variables	**2013**
Number of Employees	1335
Average Hourly Labor Rate / Employee	185
Yearly Billable Hours / Employee	1369
Income Statement	
Direct Expense Revenue	$135,243,510
Net (Labor) Revenue	$338,108,775
Total Revenue	$473,352,285
Direct Labor Expense	$128,427,000
Gross Profit	$209,681,775
Indirect Labor Expense	$79,624,740
Payroll-Related Labor Expense	$25,685,400
Other Indirect Expenses	$64,213,500
Operating Profit	$40,158,135
Key Financial Performance Indicators	
Operating Profit Rate	11.88%
Utilization Rate	71.90%
Overhead Rate	132%
Break-Even Rate	2.32
Net Labor Multiplier	2.63
Aged Accounts Receivable (Days)	50
Net Revenue per Employee	$253,265
Key Non-Financial Performance Indicators	
Customer Satisfaction	7.5
Employee Satisfaction	8.2
Employee Turnover Rate	4.9%
OSHA Recordable Incidences	2

Internal Business Division: Environmental

Employee Variables	2013
Ave. Number of Employees	645
Average Hourly Labor Rate / Employee	195
Yearly Billable Hours / Employee	1298
Income Statement	
Direct Expense Revenue	$73,465,178
Net (Labor) Revenue	$163,255,950
Total Revenue	$236,721,128
Direct Labor Expense	$65,403,000
Gross Profit	$97,852,950
Indirect Labor Expense	$41,203,890
Payroll-Related Labor Expense	$13,080,600
Other Indirect Expenses	$32,701,500
Operating Profit	$10,866,960
Key Financial Performance Indicators	
Operating Profit Rate	6.66%
Utilization Rate	68.17%
Overhead Rate	133%
Break-Even Rate	2.33
Net Labor Multiplier	2.50
Aged Accounts Receivable (Days)	73
Net Revenue per Employee	$253,110
Key Non-Financial Performance Indicators	
Customer Satisfaction	6.9
Employee Satisfaction	7.8
Employee Turnover Rate	8.3%
OSHA Recordable Incidences	0

Internal Business Division: Facilities

Employee Variables	2013
Ave. Number of Employees	1355
Average Hourly Labor Rate / Employee	175
Yearly Billable Hours / Employee	1312
Income Statement	
Direct Expense Revenue	$118,221,040
Net (Labor) Revenue	$311,108,000
Total Revenue	$429,329,040
Direct Labor Expense	$123,305,000
Gross Profit	$187,803,000
Indirect Labor Expense	$70,283,850
Payroll-Related Labor Expense	$24,661,000
Other Indirect Expenses	$72,749,950
Operating Profit	$20,108,200
Key Financial Performance Indicators	
Operating Profit Rate	6.46%
Utilization Rate	68.91%
Overhead Rate	136%
Break-Even Rate	2.36
Net Labor Multiplier	2.52
Aged Accounts Receivable (Days)	56
Net Revenue per Employee	$229,600
Key Non-Financial Performance Indicators	
Customer Satisfaction	7.5
Employee Satisfaction	8.8
Employee Turnover Rate	3.2%
OSHA Recordable Incidences	3

Internal Business Division: Federal / Government

Employee Variables	2013
Ave. Number of Employees	886
Average Hourly Labor Rate / Employee	170
Yearly Billable Hours / Employee	1299
Income Statement	
Direct Expense Revenue	$74,349,044
Net (Labor) Revenue	$195,655,380
Total Revenue	$270,004,424
Direct Labor Expense	$78,322,400
Gross Profit	$117,332,980
Indirect Labor Expense	$44,643,768
Payroll-Related Labor Expense	$15,664,480
Other Indirect Expenses	$40,727,648
Operating Profit	$16,297,084
Key Financial Performance Indicators	
Operating Profit Rate	8.33%
Utilization Rate	68.22%
Overhead Rate	129%
Break-Even Rate	2.29
Net Labor Multiplier	2.50
Aged Accounts Receivable (Days)	98
Net Revenue per Employee	$220,830
Key Non-Financial Performance Indicators	
Customer Satisfaction	6.5
Employee Satisfaction	8.2
Employee Turnover Rate	4.5%
OSHA Recordable Incidences	1

Internal Business Division: Industrial

Employee Variables	**2013**
Number of Employees	1345
Average Hourly Labor Rate / Employee	180
Yearly Billable Hours / Employee	1412
Income Statement	
Direct Expense Revenue	$136,738,080
Net (Labor) Revenue	$341,845,200
Total Revenue	$478,583,280
Direct Labor Expense	$125,892,000
Gross Profit	$215,953,200
Indirect Labor Expense	$65,463,840
Payroll-Related Labor Expense	$25,178,400
Other Indirect Expenses	$69,240,600
Operating Profit	$56,070,360
Key Financial Performance Indicators	
Operating Profit Rate	16.40%
Utilization Rate	74.16%
Overhead Rate	127%
Break-Even Rate	2.27
Net Labor Multiplier	2.72
Aged Accounts Receivable (Days)	50
Net Revenue per Employee	$254,160
Key Non-Financial Performance Indicators	
Customer Satisfaction	8.4
Employee Satisfaction	8.2
Employee Turnover Rate	4.2%
OSHA Recordable Incidences	4

Internal Business Division: Mining

Employee Variables	2013
Ave. Number of Employees	82
Average Hourly Labor Rate / Employee	160
Yearly Billable Hours / Employee	1298
Income Statement	
Direct Expense Revenue	$7,663,392
Net (Labor) Revenue	$17,029,760
Total Revenue	$24,693,152
Direct Labor Expense	$6,822,400
Gross Profit	$10,207,360
Indirect Labor Expense	$4,434,560
Payroll-Related Labor Expense	$1,364,480
Other Indirect Expenses	$3,411,200
Operating Profit	$997,120
Key Financial Performance Indicators	
Operating Profit Rate	5.86%
Utilization Rate	68.17%
Overhead Rate	135%
Break-Even Rate	2.35
Net Labor Multiplier	2.50
Aged Accounts Receivable (Days)	60
Net Revenue per Employee	$207,680
Key Non-Financial Performance Indicators	
Customer Satisfaction	8.5
Employee Satisfaction	9.0
Employee Turnover Rate	5.0%
OSHA Recordable Incidences	2

Internal Business Division: Oil & Gas

Employee Variables	**2013**
Ave. Number of Employees	1285
Average Hourly Labor Rate / Employee	195
Yearly Billable Hours / Employee	1485
Income Statement	
Direct Expense Revenue	$174,888,821
Net (Labor) Revenue	$372,103,875
Total Revenue	$546,992,696
Direct Labor Expense	$130,299,000
Gross Profit	$241,804,875
Indirect Labor Expense	$79,482,390
Payroll-Related Labor Expense	$26,059,800
Other Indirect Expenses	$80,785,380
Operating Profit	$55,477,305
Key Financial Performance Indicators	
Operating Profit Rate	14.91%
Utilization Rate	77.99%
Overhead Rate	143%
Break-Even Rate	2.43
Net Labor Multiplier	2.86
Aged Accounts Receivable (Days)	88
Net Revenue per Employee	$289,575
Key Non-Financial Performance Indicators	
Customer Satisfaction	8.5
Employee Satisfaction	8.9
Employee Turnover Rate	6.2%
OSHA Recordable Incidences	2

Internal Business Division: Technology

Employee Variables	2013
Ave. Number of Employees	121
Average Hourly Labor Rate / Employee	160
Yearly Billable Hours / Employee	1265
Income Statement	
Direct Expense Revenue	$11,020,680
Net (Labor) Revenue	$24,490,400
Total Revenue	$35,511,080
Direct Labor Expense	$10,067,200
Gross Profit	$14,423,200
Indirect Labor Expense	$5,536,960
Payroll-Related Labor Expense	$2,013,440
Other Indirect Expenses	$5,033,600
Operating Profit	$1,839,200
Key Financial Performance Indicators	
Operating Profit Rate	7.51%
Utilization Rate	66.44%
Overhead Rate	125%
Break-Even Rate	2.25
Net Labor Multiplier	2.43
Aged Accounts Receivable (Days)	75
Net Revenue per Employee	$202,400
Key Non-Financial Performance Indicators	
Customer Satisfaction	8
Employee Satisfaction	7.2
Employee Turnover Rate	10.0%
OSHA Recordable Incidences	1

Internal Business Division: Transportation

Employee Variables	2013
Ave. Number of Employees	725
Average Hourly Labor Rate / Employee	175
Yearly Billable Hours / Employee	1445
Income Statement	
Direct Expense Revenue	$69,667,063
Net (Labor) Revenue	$183,334,375
Total Revenue	$253,001,438
Direct Labor Expense	$65,975,000
Gross Profit	$117,359,375
Indirect Labor Expense	$37,605,750
Payroll-Related Labor Expense	$13,195,000
Other Indirect Expenses	$38,925,250
Operating Profit	$27,633,375
Key Financial Performance Indicators	
Operating Profit Rate	15.07%
Utilization Rate	75.89%
Overhead Rate	136%
Break-Even Rate	2.36
Net Labor Multiplier	2.78
Aged Accounts Receivable (Days)	56
Net Revenue per Employee	$252,875
Key Non-Financial Performance Indicators	
Customer Satisfaction	7.5
Employee Satisfaction	8.8
Employee Turnover Rate	3.2%
OSHA Recordable Incidences	3

Internal Business Division: Water

Employee Variables	**2013**
Ave. Number of Employees	642
Average Hourly Labor Rate / Employee	185
Yearly Billable Hours / Employee	1366
Income Statement	
Direct Expense Revenue	$61,651,132
Net (Labor) Revenue	$162,239,820
Total Revenue	$223,890,952
Direct Labor Expense	$61,760,400
Gross Profit	$100,479,420
Indirect Labor Expense	$35,203,428
Payroll-Related Labor Expense	$12,352,080
Other Indirect Expenses	$36,438,636
Operating Profit	$16,485,276
Key Financial Performance Indicators	
Operating Profit Rate	10.16%
Utilization Rate	71.74%
Overhead Rate	136%
Break-Even Rate	2.36
Net Labor Multiplier	2.63
Aged Accounts Receivable (Days)	56
Net Revenue per Employee	$252,710
Key Non-Financial Performance Indicators	
Customer Satisfaction	8.9
Employee Satisfaction	8.1
Employee Turnover Rate	6.7%
OSHA Recordable Incidences	2

Appendix B: Top 25 Design Firm Internal Business Divisions Matrix

2013 Rank	Firm	Firm Type*	Architecture	Aviation	Business / Financial Services	Construction / Design-Build	Energy / Power	Environmental	Facilities	Federal / Government	Industrial	Marine & Port Facilities	Mining	Nuclear	Oil & Gas	Planning	Technology	Transportation	Water / Wastewater
1	AECOM Technology Corp., Los Angeles, CA	EA	X	X	X	X	X	X	X	X	X	X	X		X	X	X	X	X
2	URS Corp., San Francisco, CA	AEC	X	X	X	X	X	X	X	X	X		X	X	X	X	X	X	X
3	Jacobs, Pasadena, CA	AEC	X	X	X	X	X	X	X	X	X		X		X	X	X	X	X
4	Fluor Corp., Irving, TX	EC		X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
5	CH2M HILL, Englewood, CO	AEC	X		X	X	X	X	X	X	X			X		X	X	X	X
6	AMEC, Tucker, GA	EC			X	X	X	X	X	X	X		X	X	X		X	X	X
7	Bechtel, San Francisco, CA	EC		X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	
8	Tetra Tech Inc., Pasadena, CA	E					X				X	X		X	X		X		X
9	KBR, Houston, TX	EC		X	X	X	X	X	X	X	X		X		X	X	X	X	X
10	Parsons Brinckerhoff, New York, NY	EA	X		X	X	X	X	X	X	X		X			X	X	X	X
11	HDR, Omaha, NE	EA	X	X	X	X	X	X	X	X	X		X		X	X	X	X	X
12	Arcadis U.S./RTKL, Highlands Ranch, CO	EA	X	X	X		X	X	X	X	X				X	X	X	X	X
13	The Shaw Group Inc., Baton Rouge, LA	EC			X	X	X	X	X	X	X	X			X	X		X	X
14	Black & Veatch, Overland Park, KS	EC		X	X	X	X	X	X	X	X		X		X	X	X	X	X
15	Parsons, Pasadena, CA	EC		X	X	X	X	X	X	X	X			X	X	X	X	X	X
16	WorleyParsons Group Inc., Bellaire, TX	EC			X		X	X	X	X	X	X	X	X	X	X	X	X	X
17	CB&I, The Woodlands, TX	EC			X	X	X	X	X	X	X	X			X	X		X	X
18	Wood Group Mustang, Houston, TX	EC			X	X	X	X	X		X	X			X	X	X		
19	MWH Global, Broomfield, CO	EC			X	X	X	X	X		X	X	X		X	X	X	X	X
20	Burns & McDonnell, Kansas City, MO	AEC	X	X	X	X	X	X	X	X	X		X	X	X		X	X	X
21	HNTB Cos., Kansas City, MO	EA	X	X		X			X	X						X	X	X	X
22	Gensler, San Francisco, CA	A	X	X	X	X			X	X						X	X		
23	CDM Smith, Cambridge, MA	EC			X	X	X	X	X		X		X	X		X	X	X	X
24	Stantec Inc., Irvine, CA	EAL	X	X			X		X	X	X		X		X	X		X	X
25	Louis Berger, Morristown, NJ	EAP	X	X	X	X	X	X	X	X						X	X	X	X

* A - Architecture; E - Engineering; C - Construction; L - Landscaping; P - Planning