Benchmarking the Efficiency of
Government Warehouse Operations:
A Data Envelopment Analysis Approach

by

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ABSTRACT

The purpose of this research was to benchmark the performance of 18 Defense Logistics Agency (DLA) supply warehouses located within the contiguous United States using 22 months of historical data. This study used a mathematical programming tool, Data Envelopment Analysis (DEA), to measure the relative overall efficiency of the warehouses and to determine the sources of inefficiency where they exist.

DLA anticipates a reduced workload for each of the warehouses in the future, which translates into excess capacity and increased inefficiency for the system. With this methodology, DLA can intelligently target facilities for closure. The closure of facilities can result in potential savings of millions of tax dollars.

This study concluded that less automated warehouses are more efficient than warehouses with higher levels of automation, and that larger warehouses are more efficient than smaller warehouses.

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CHAPTER 1: INTRODUCTION TO THE STUDY

Introduction

Performance measurement has become an integral part of most business operations. Firms can choose to measure their performance either internally using historical data or externally with data collected from their industry peers. The literature refers to this practice as benchmarking. Camp (1989) defined benchmarking as the search for the best practices in the industry that lead to improved performance. Heizer and Render (1995) summarized benchmarking as a process that involves the selection of a demonstrated standard of performance that represents the absolute best performance of processes that are similar to one's own. According to Camp, benchmarking forces a firm to evaluate and compare its performance in various functions to similar functions in other firms. To be effective, the comparison must be of similar functions, but it is not necessary for the firms to be in exactly the same business.

Camp (1989) reported that the critical self-examination performed during the benchmarking process should aid companies in discovering their own inefficiencies and to establish realistic goals for improvement. Camp suggested a framework for the benchmarking process, which consists of five basic components: Planning, Analysis, Integration, Action, and Maturity. The first step in the benchmarking process is planning, which consists of identifying the process to be studied, determining the data required, and selecting the firms against which to compare. Analysis requires the company to collect the data from both internal and external sources and perform the comparison study. The integration step involves communicating the findings of the study to the management and for the management to establish goals for improvement. The action phase occurs with the implementation of the plans required to modify existing processes and achieve improved performance. The action phase must include a process for monitoring the process and modifying the action plans as required. The final stage of maturity requires the firm to recalibrate its benchmarks and to renew its quest for improvement.

During the initial phase of the benchmarking process, the firm must determine which type of benchmarking to perform. Camp (1989) described an outline of four distinct types of benchmarking that can be performed: (a) benchmarking against internal operations, (b) benchmarking against direct external competitors, (c) benchmarking against external functional best operations or industry leaders, and (d) generic process benchmarking.

According to Camp (1989) internal benchmarking studies are one of the most straightforward comparisons for a firm to perform. This methodology works especially well for large multidivision or multinational firms because the data and information required for an internal study should be available and confidentiality problems are less of a problem than when dealing with competitors.

Focus of the Study

The internal benchmarking approach is ideal for the subject of this study, the Defense Logistics Agency (DLA). DLA is a large federally funded combat support agency that manages more than 20 warehouses (in this study, the terms warehouse and depot are synonymous) and exists for the sole purpose of providing all forms of logistical support to every Federal agency. DLA ships requested materiel worldwide to customers on demand. DLA's primary customer is the United States Department of Defense (DoD), which includes support to the Army, Navy, Air Force, and Marine Corps. Simultaneously, DLA supplies many foreign nations with spare parts and other logistics items in fulfillment of various foreign military sales agreements.

DLA employs more than 40,000 people, manages more than 6 million different items, and has annual sales in excess of $9 billion. DLA has forward deployed forces in Bosnia, South Korea, Panama, Southwest Asia, and in virtually every state across the nation. The materiel managed by DLA runs the entire gamut of supplies from toilet seat covers to spare parts for NASA's space shuttle. DLA supplies its customers with anything and everything the federal civilian employee, soldier, sailor, airman, or Marine needs to perform assigned missions.

Statement of the Problem

An ongoing concern of the senior Defense Logistics Agency (DLA) management is differing performance among the warehouses it operates (R. Sample, personal communication, July, 1998). The problem for DLA is that few measures of efficiency exist that adequately gauge the efficiency of government management in its use of resources. This study focuses on addressing this problem for the DLA supply warehouses located within the continental United States.

Current Performance Evaluation Methodology

According to (R. Sample, personal communication, July, 1998), the current evaluation strategy for DLA warehouses is an aggregation of equally weighted variables reported on a monthly basis. The measures include *receipt processing, warehouse denial rate, issue processing,* and *locator accuracy*. *Receipt processing* measures the average number of days to receive, inspect, and store each item. *Receipt processing* is an aggregate measure comprised of three components, new procurements, customer returns, and materiel transfers. New procurements are all new materiel purchased by DLA and shipped from a manufacturer for storage at a warehouse. Customer returns constitute all materiel that is returned to DLA from its customers. This process is similar to returning merchandise to a mail order company like L. L. Bean. Materiel transfers is comprised of the materiel that is transferred from one warehouse to another. The second measure, *warehouse denial rate,* is a percentage measurement of items not on hand at the warehouse when requested.

The DLA *issue processing* metric measures the time warehouses take to issue materiel from on hand stock. The *issue processing* measurement is comprised of three types of issues: high-priority issues, routine issues, and issues for disposal. Collectively, the DLA warehouses process more than 27 million requests for materiel each year.

Locator accuracy is a proxy measure for the accuracy of the storage location data in the warehouse Management Information System (MIS). *Locator accuracy* is a percentage measure of the number of times that an employee goes to a location, specified by the MIS, and finds the requested item at the location.

According to (R. Sample, personal communication, July, 1998), DLA collects the aforementioned performance data to track performance trends of the warehouses. The warehouse performance is reported to the senior DLA leadership on a monthly basis. However, DLA does not use the data to evaluate the individual depot managers on their use or management of resources. Currently, DLA is lacking a formalized method for comparing and evaluating the performance of the depot managers.

Purpose of the Study

The purpose of this dissertation was twofold. First, the researcher created a warehouse model that highlights government warehouses that are the most efficient at using available resources. Second, a new methodology was developed for DLA to rank order the performance of the warehouse managers using a model that incorporates data currently collected by DLA.

The warehouse model focused on a very specific aspect of the benchmarking process, the analysis process. The analysis process is the performance of a comparison study using the internal benchmarking technique. To determine which DLA warehouse operations is the "best," the researcher looked for those warehouses that are the most efficient at using available resources to perform the tasks that are required of most government warehouses. The model focused at the warehouse manager level of decision making. While the study concentrated at the warehouse manager level of decision making, the results of the study are useful to both the warehouse manager and senior DLA managers. Similar to the 1995 Hollingsworth study, the researcher demonstrated that a mathematical programming model can be applied to highlight those organizations that are exceptional at performing the tasks under consideration.

Study Assumptions

The researcher made several assumptions about the warehouse operations. First, the requirements assigned to the manager were assumed to translate into the goals that must be achieved by the warehouse manager. The first assumption is related to the homogeneity of the warehouses in the study. Specifically, each assigned requirement is a goal for the warehouse and that the efforts of the warehouse will be directed towards achieving that goal. Additionally, the researcher assumed the warehouse manager has limited control over the amounts of resources available to support the mission of the warehouse. The warehouse manager's annual budget is established by DLA headquarters based upon the workload forecast generated by DLA headquarters. Once the budget is determined, the warehouse manager has limited discretion about how to spend the funds. Finally, the researcher assumed that the most efficient warehouses require fewer resources than less efficient warehouse per unit of output produced.

DEA Background

The researcher used a mathematical programming model to measure the efficiency of warehouses. The method, Data Envelopment Analysis (DEA) is a robust efficiency measurement technique initially designed for nonprofit organizations. DEA is the result of the doctoral work of Edwardo Rhodes, then a student at the Carnegie Mellon University's School of Urban and Public Affairs. Rhodes's dissertation work compared the performance of school districts that were participating in Program Follow Through, a federally funded assistance program for disadvantaged youth, with schools that were not participating. At the time, Rhodes faced the problem that no technique existed to measure the technical efficiency of organizations with multiple inputs and outputs, without the normal information on prices. The study resulted in the publication of the first paper introducing DEA in the *European Journal of Operations Research* in 1978 (Charnes, Cooper, Lewin, & Seiford, 1994).

The benefit of the DEA methodology lies in its ability to handle multiple inputs and outputs simultaneously and that the inputs and outputs do not have to be in the same units of measure. For example, it is common for DEA models to include variables in terms of hours, dollars, or even customer satisfaction indices.

Research Questions

This study used the following questions to help guide the researcher and to focus the study.

1. What insight can a mathematical programming model offer that is not provided by the current DLA evaluation methodology?

2. Which government warehouses are the most efficient in using available resources?

3. To what degree does model sensitivity affect the results of the DEA models?

4. In what way does the size of a warehouse affect the results of the DEA models?

5. What are the returns to scale for the individual government warehouses?

Study Significance

According to senior DLA management (Glisson, 1998), DLA is under constant pressure from all of its customers to lower its prices for the items it supplies. This pressure is especially intense from the DoD services. If DEA is able to identify inefficiencies in warehouse operations, increased savings are possible for DLA, enabling the organization to lower its prices. This result is meaningful because for the past several years senior DLA management has promised the armed services that it will reduce its prices. In turn, each service has allocated less and less future money for logistical support and channeled the expected savings into funding new weapons systems. Should DLA fail to deliver lower prices, new weapons systems might be jeopardized. Additionally, these savings will not only benefit DoD; they may ultimately translate into a lower tax burden for Federal taxpayers.

Warehouse Operations Overview

DLA operates geographically dispersed warehouses, which include both indoor and outdoor storage for materiel. Each warehouse has areas designated for receiving, storage, and shipping. The size of the area designated for each operation is a function of the scale of operations at the warehouse. All warehouse facilities have multiple storage buildings with an average of 18 million cubic feet of indoor storage space for each warehouse (www.dla.mil/public_info/distrib.htm, January 14, 1998). In addition to indoor storage, all warehouses have areas designated for outdoor storage (some with overhead cover similar to automobile carports).

The DLA warehouses employ fewer than 100 people at small facilities to more than 2,000 people at the large warehouses performing a variety of tasks in support of the warehouse mission. The majority of employees working in the warehouses are high school graduates with limited post high school education. Employee training requirements are managed with job specific on-the-job training programs at each warehouse. DLA enjoys a low employee turnover rate at the warehouse facilities, which minimizes the impact of new employees on overall warehouse efficiency.

Each warehouse receives materiel from three sources: new materiel from manufacturers, customer returns, and transfers from other warehouses. The bulk of receiving is new materiel followed by customer returns and redistributed materiel from other warehouses. Materiel received at a warehouse is first inspected and then placed in storage according to each item's characteristics. For example, large trucks are stored outdoors with no overhead cover, barrels of petroleum products are stored outdoors under overhead covers, and electronic components are stored indoors in small individually marked boxes.

When a warehouse receives an item request, a worker goes to the storage location, selects the correct number of items for the order, and delivers the part to the shipping area. The shipping area is responsible for packaging the materiel for shipment, addressing the item, and putting the item on a truck for delivery to the customer.

A challenge for DLA is a projected reduction in the receipt and issue workload for the future. The reduced workload is the result of ongoing DLA efforts to ship materiel directly from manufacturers to its customers. The purpose of shipping directly to customers is to leverage technology and to realize savings. The net result for DLA is reduced workload for its warehouses and lower costs for the customers (www.ddc.dla.mil/aboutddc/lrpiv.htm, January 25, 2000).

Organization of the Remainder of the Study

This chapter has laid the foundation for the remaining pages. The next chapter contains the review of relevant literature for this study. The third chapter establishes the research methodology employed to examine the efficiency of DLA warehouses. The fourth chapter presents the study results and answers to the research questions, and the final chapter presents the study conclusions and recommendations for further research.

CHAPTER 2: LITERATURE REVIEW

Introduction

This literature review was designed to be an explicit, systematic, and reproducible interpretation of the existing body of knowledge about the application of DEA for benchmarking the efficiency of government warehouse operations (Fink, 1998). The review will include a description of benchmarking and the DEA methodology.

Literature Search Methodology

The literature review concentrates on applicable works published in scholarly journals within the past 5 years. Additional scholarly material was not excluded if the author deemed it germane to the research topic. An example of a dated work included in the literature review for this study is the DEA seminal work of Charnes, Cooper, and Rhodes that appeared in the European Journal of Operational Research in 1978.

Benchmarking

The development and application of benchmarking techniques has proven a fruitful ground for companies to find new process savings and for the development of new processes that increase efficiency and effectiveness. Hollingsworth (1995) described the essence of benchmarking as setting a standard by which others are measured. Current electronic and traditional literature is replete with articles and case studies about benchmarking in nearly every field of endeavor. A quick search of the Internet using any web browser will reveal a large number of websites dedicated exclusively to benchmarking.

In the late 1970s, Robert Camp worked with Xerox to establish the first formal benchmarking process. This effort was very focused on specific product comparisons. The studies revealed that Xerox's Japanese competitors were selling copiers for the same price that Xerox was paying to manufacture the machines. Within 3 years of Xerox beginning its pioneering work in benchmarking, it was adopted as a corporate wide effort to focus on improved quality and as a means to reduce costs (Camp, 1989).

Since its beginnings, benchmarking has blossomed into a well-defined and refined process of examining the internal processes of a firm and then comparing those processes both internally and externally. This study focused on one segment of the benchmarking process, the comparison study, which is a component of the analysis benchmarking step.

Efficiency Measurement Concepts

Traditional measures of efficiency have examined efficiency from the following perspective (Charnes et al. 1994):

$$\text{Efficiency} = \frac{\text{Output}}{\text{Input}}$$

This ratio approach is limited in its ability to deal with different unit measures of inputs and outputs. In most instances, the inputs and outputs will require some type of transformation to standardize the units. To overcome the limitations of traditional techniques, analysts ordinarily convert all values into dollars or some other "common" unit. Unfortunately, this transformation frequently excludes important input and output measures that cannot be easily quantified or transformed. An example of such a measure might be customer satisfaction as an output measure. The analyst can survey the customers to determine their satisfaction with the firm but that satisfaction is difficult to quantify in terms of dollars.

Coelli, Prasada Rao, and Battese (1998) suggested that there are four principal efficiency measurement methods: (a) least-squares econometric production models (regression), (b) total factor productivity indices, (c) stochastic frontiers, and (d) data envelopment analysis. Each form of efficiency measurement has unique assumptions, strengths, and limitations and may be more appropriate depending upon the objectives of the researcher. The least-squares method is a parametric approach frequently applied to time series data. Least-squares implicitly assumes that all organizations are efficient. The least-squares method uses all of the available data to construct a single optimized equation that is assumed to apply equally to all observed entities. The limitation of this approach is that it results in a notional average entity score that all of the organizations are then compared against. Another drawback of this approach, and all other parametric techniques, is that a functional form must be specified (Coelli, Prasada Rao, & Battese, 1998). The functional form requires specific assumptions about the distribution of the error terms (e.g., independence and normally distributed) and other restrictions (Charnes, Cooper, Lewin, & Seiford, 1994). An additional limitation of the regression approach is its inherent inability to deal with multiple output or dependent variables (Bowlin, Charnes, Cooper, & Sherman, 1985). A further limitation of regression approaches to efficiency, when compared to

DEA, is the inability of regression to identify sources of and estimate the amount of inefficiency if it exists. This deficiency limits the ability of management to take corrective action, even when the dependent variable shows that inefficiency exists within the organization (Bowlin, 1998).

Total factor productivity (TFP) is an index defined as the ratio of outputs produced by an entity to inputs used. The index can be used to measure the performance of an entity over time (Salerian & Jomini, 1994). Like the least-squares method, TFP assumes that all organizations are efficient and that all organizations cost minimize and revenue maximize (Coelli et al., 1998). Another requirement of the TFP methodology is the specification of a production function for the entity under study (Schnorbus & Israilevich, 1987). The implicit TFP assumption of revenue maximization coupled with the assumption that all organizations are efficient makes the application of TFP to organizations without a profit motive difficult.

The stochastic frontier methodology shares some commonality with the least-squares technique. Both are parametric and assume that firms are cost minimization and profit maximization oriented. Stochastic frontier differs from least-squares by measuring the technical efficiency, economies of scale, and allocative efficiencies of the firms which least-squares does not (Coelli et al., 1998). Like the least-squares and TFP methodologies, the core assumptions of stochastic frontiers make it difficult to use in a government environment.

The strength of DEA for nonprofit organizations is its ability to handle simultaneous inputs and outputs measured in various units. Additionally, no a priori functional form is required as with other efficiency measurement techniques. One challenge of the DEA methodology is that the problem must be solved for every single organization under investigation. In large problems, this can be very computationally intensive. However, modern DEA specific software coupled with today's powerful computers has virtually eliminated this problem.

Bradley and Baron (as cited in Hollingsworth, 1995) developed an operating performance measure of efficiency that compared U.S. Postal Service mail processing centers. Bradley and Baron used the results to determine the specific characteristics of each center and which of the characteristics contributed to the overall efficiency of the center. The efficiency of each center was estimated using regression analysis with operating efficiency as the dependent variable. Iyengar, Lee, and Kota (as cited in Hollingsworth, 1995), developed a methodology for objectively evaluating various product designs that could potentially be converted to evaluate firms. The methodology decomposes the functions into the basic subfunctions, evaluates the performance of the subfunctions, and then reconstructs the functions into a composite score for an overall evaluation.

The limitations of traditional efficiency estimation tools force the researcher to look for a more powerful and flexible efficiency estimation tool. The tool that will adequately address DLA's problem is Data Envelopment Analysis. The robust characteristics of DEA should identify the efficient and inefficient warehouses and those characteristics that make warehouses inefficient.

Data Envelopment Analysis

Since the introduction of DEA in 1978, there have been very few studies of warehouse operations incorporating DEA in the methodology and a very limited examination of government warehouse operations. Each examination of government warehouses has included for-profit warehouses in the data set. To date, no work has been conducted that applies DEA to exclusively government warehouses.

With this gap in the literature identified, this literature review will review the seminal DEA model, review two variations of the seminal model, and report the findings of other studies that have applied DEA to warehousing efficiency measurement.

DEA is a relatively new nonparametric methodology for obtaining new information about a set of decision-making units (DMU). DMU is commonly used in the DEA literature to refer to the organizations under examination. DEA incorporates the extreme point technique of linear programming to optimize on each observation or DMU in a population. The result of the calculations is a piecewise linear frontier that is determined by the Pareto-efficient DMUs in the population.

CCR Model

The CCR model is named after its creators, Charnes, Cooper, and Rhodes. The model extended the earlier 1957 work of Farrell (as cited in (Charnes, Cooper, Lewin, & Seiford, 1994;; Epstein & Henderson, 1989) on estimating technical efficiency. The CCR model is a constant returns to scale model that offers an evaluation of the overall efficiency of a DMU and identifies both the sources and amounts of inefficiencies (Charnes et al., 1994).

The seminal model introduced by (Charnes et al., 1978), is designed to measure the efficiency of a DMU by obtaining the maximum value of a weighted ratio of outputs to weighted inputs subject to the constraint that the similar ratios for every DMU be less than or equal to unity. The basic CCR model is represented algebraically in a fractional programming form at equation 1.

Basic CCR Formulation

$$\text{Maximize:} \quad h_o = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}} \tag{1}$$

$$\text{Subject to:} \quad \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1$$

$v_i, u_r \geq \varepsilon > 0$, for $i = 1,\ldots,m$; $r = 1,\ldots,s$; $j = 1,\ldots,n$

o ≡ evaluated DMU
h_0 ≡ efficiency score of DMU_0
y_{rj} ≡ output r for DMU j
y_{r0} ≡ output r for the evaluated DMU
x_{ij} ≡ input i for DMU j
x_{i0} ≡ input i for the evaluated DMU
v_i ≡ variable weight for input i
u_r ≡ variable weight for output r
n ≡ total number of DMUs being evaluated
s ≡ total number of outputs
m ≡ total number of inputs
ε ≡ infinitesimally small constant to maintain positivity

This basic DEA model is designed to evaluate the relative performance of some DMU, designated as DMU_0, based upon the observed accomplishment of $j = 1,\ldots n$ DMUs including DMU_0. As previously described, the DMU is the entity responsible for converting inputs to outputs (W. F. Bowlin, personal communication, July, 1999).

The y_{rj}, $x_{ij} > 0$ elements of the model are constants that represent observed amounts of the r^{th} output and the i^{th} input of the j^{th} DMU which is referred to as DMU_j in the set of $j = 1,\ldots n$ organizations that utilize the $i = 1,\ldots,m$ inputs to produce $r = 1,\ldots,s$ outputs. Each of the $j = i,\ldots,n$ DMUs is evaluated individually and is designated as DMU_0 while it is evaluated. When DMU_0 is evaluated for efficiency, it rotates into the objective function and remains in the constraints. It then follows that the maximum optimum value for DMU_0 will be $\boldsymbol{h^*_o} \leq 1$ by virtue of the constraints (Charnes et al., 1994).

The $\varepsilon > 0$ constraint in equation 1 represents a non-Archimedean infinitesimally small constant that is smaller than any real number and positive. According to Bowlin (1999), the ε is handled by DEA software and does not require explicit specification. However, a common value for ε is 10^6 (W. F. Bowlin, personal communication, April, 2000).

Like traditional efficiency measures, the numerator in equation 1 designates a set of desired outputs, and the denominator represents the set of resources consumed to obtain the outputs. This ratio results in a scaler value resembling ratio forms frequently used in engineering and in other types of analyses. The h^*. value obtained from this ratio satisfies the constraint $1 \geq h^*_0 \geq 0$ and is interpreted by the analyst that an efficiency score of $h^*_0 = 1$ represents maximum efficiency for DMU_0. When $h^*_0 < 1$, the DMU_0 is less than efficient. The * indicates that the best possible value has been determined from solving the model. Additionally, the h^*_0 is unaffected by the models inputs and output units of measure (W. F. Bowlin, personal communication, July, 1999).

Another advantage of the DEA methodology is that no weights are required to be specified a priori to obtain the scalar measure of performance. The optimal values, u^*_r, v^*_i, are interpreted as the weights for the output and input variables in equation 1. The values for u^*_r, v^*_i are determined once the model is solved. The DEA literature refers to u^*_r, v^*_i as *virtual multipliers* which are interpreted in DEA so that they yield a virtual output, $Y_0 = \sum u^*_r y_{r0}$ (summed over $r = 1, \ldots, s$), and a virtual input, $X_0 = \sum v^*_i x_{i0}$ (summed over $i = 1, \ldots, m$), that enables the analyst to calculate the efficiency ratio $h_0 = Y_0/X_0$ (W. F. Bowlin, personal communication, July, 1999).

The CCR model is a linear, constant returns-to-scale envelopment surface. The CCR model formulation can be either input minimization or output maximization. The two forms provide different projections of inefficient DMUs onto the empirical efficient frontier. The user should choose a specific form depending upon how management intends to use the efficiency information. The output orientation focuses on maximal movement toward the efficiency frontier by proportional augmentation of outputs and the input orientation focuses on maximal movement toward the efficiency frontier through proportional reduction of inputs. The CCR model efficiency scores represent a measure of the distance to a point on the efficient frontier. An implicit assumption of the CCR model is that efficient production is theoretically possible at any point along the efficient frontier (Charnes et al., 1994).

The output maximization CCR model depicted in Figure 1 offers a visually descriptive explanation of DMU efficiency.

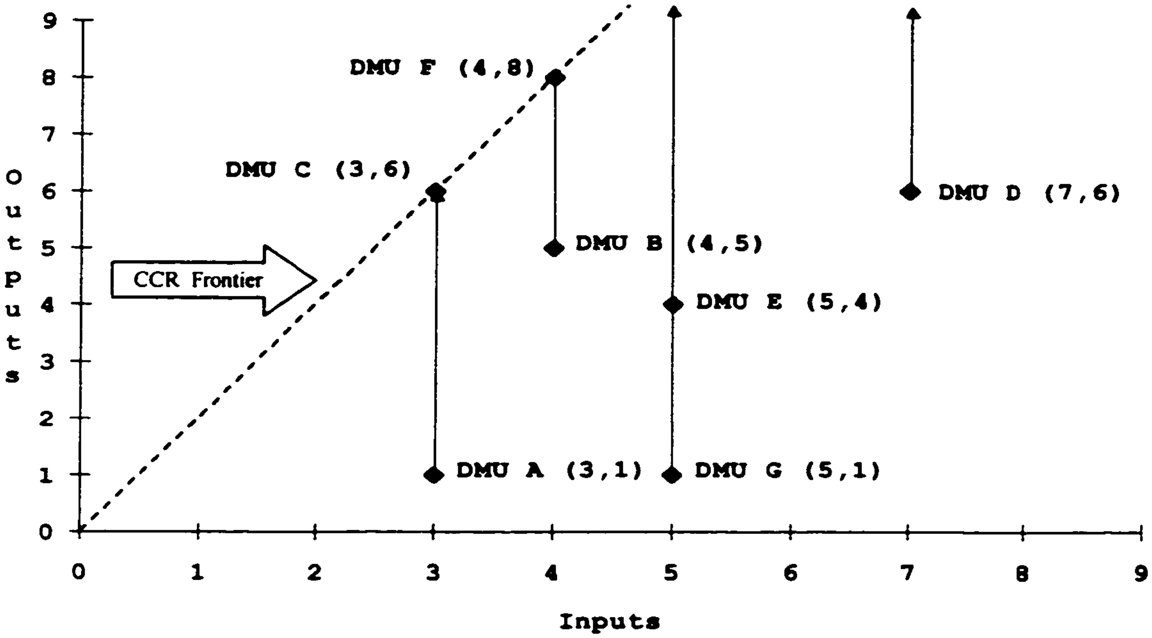

Figure 1. DEA output maximization graphical representation.

DMUs C and F are the only DMUs on the efficiency frontier. DMU A produces one unit of output using three units of input and is inefficient. If DMU A were efficient, it would produce six units of output given three units of input. It follows that since DMU A produces only one sixth of what it should if it were efficient, DMU A has an efficiency score of 1/6 or .1667 (Charnes et al., 1994). The output maximization CCR model is represented algebraically in linear programming form at equation 2.

CCR Output Maximization

$$\text{Maximize: } \sum_{r=1}^{s} u_r y_{r0}$$

$$\text{Subject to:} \qquad (2)$$

$$\sum_{i=1}^{m} v_i x_{i0} = 1$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0$$

v_i , u_r $\geq \varepsilon > 0$, for $i = 1,\ldots,m$; $r = 1,\ldots,s$; $j = 1,\ldots,n$

y_{rj} ≡ output r for DMU j
y_{r0} ≡ output r for the evaluated DMU
x_{ij} ≡ input i for DMU j
x_{i0} ≡ input i for the evaluated DMU
v_i ≡ variable weight for input i
u_r ≡ variable weight for output r
n ≡ total number of DMUs being evaluated
s ≡ total number of outputs
m ≡ total number of inputs
ε ≡ infinitesimally small constant to maintain positivity

The output maximization model enables management to ask the question "How much can we expect to produce without increasing inputs if all organizations are efficient?" Conversely, the input minimization CCR model will tell management "How much can we reduce inputs and still maintain the current level of output?" Management has the ability to discretely and empirically identify sources of inefficiency in their organization. With this knowledge, management has the ability to attack the inefficiency with confidence and increase their chances for achieving organizational improvement.

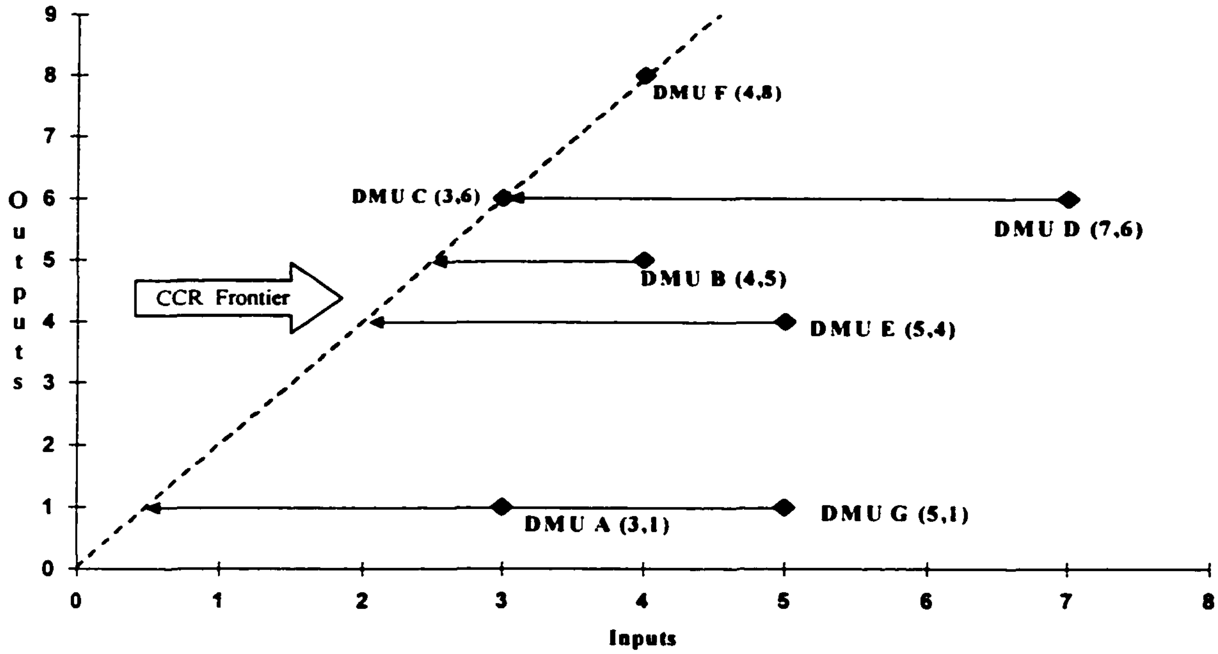

Figure 2. DEA input minimization graphical representation.

The input minimization CCR model is graphically portrayed at Figure 2. The input minimization CCR model focuses on moving the organizations to the efficiency frontier by proportionally reducing their inputs while maintaining their current level of output.

The input minimization CCR model depicted in Figure 2 offers a second graphic explanation of DMU efficiency. Once again, DMUs C and F are the only DMUs on the efficiency frontier. DMU B produces 5 units of output using 4 units of input and is inefficient. If DMU B were efficient, it would produce 5 units of output given 2.5 units of input. Since DMU B uses approximately one third more input than it would if it were efficient, DMU B has an efficiency score of 2.5/4 or .625 (Charnes et al., 1994). The input minimization CCR model is represented algebraically in linear programming form at Equation 3.

CCR Input Minimization

$$\text{Minimize:} \quad \Theta - \varepsilon\left[\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right]$$

Subject to: (3)

$$\Theta x_{i0} - \sum_{j=1}^{n} y_{rj}\lambda_j - s_i^- = 0$$

$$\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = y_{r0}$$

$\lambda_j, s_i^-, s_r^+ \geq 0$ for i = 1,…,m; r = 1,…,s; j = 1,…,n

0	≡ evaluated DMU
Θ	≡ intensity score of DMU_0
y_{rj}	≡ output r for DMU j
y_{r0}	≡ output r for the evaluated DMU
x_{ij}	≡ input i for DMU j
x_{i0}	≡ input i for the evaluated DMU
s_r^+	≡ slack output r for the evaluated DMU
s_i^-	≡ slack input i for the evaluated DMU
λ_j	≡ upper and lower limit for the evaluated DMU
n	≡ total number of DMUs being evaluated
s	≡ total number of outputs
m	≡ total number of inputs

Equations (2) and (3) constitute linear programs. For each DEA warehouse analysis, a separate linear program must be solved.

The CCR model is the seminal DEA model, which provides the foundation for the each new advance in DEA theory. The CCR model assumes that constant returns to scale are present but makes no a priori assumptions of the functional form for the system under examination. The second major advance in DEA theory was published in 1984 and is discussed in the next section.

BCC Model

Another version of DEA that is commonly referred to in the literature is the Banker, Charnes, and Cooper (BCC) model. Banker, Charnes, and Cooper first published their work in 1984. The fundamental difference between the BCC model and the CCR model lies is the difference in which each model measures the returns to scale. As previously noted, the CCR model assumes that each DMU operates in a constant returns to scale environment. The BCC model relaxes the constant returns to scale assumption and assumes that the DMUs are operating in a variable return to scale (VRS) environment (Bowlin, 1998; Banker, Charnes, & Cooper, 1984).

The VRS assumption is important because it allows the researcher to determine if the DMUs are operating in a decreasing returns to scale, increasing returns to scale or in a constant returns to scale environment. Returns to scale information can be useful to management when determining resource allocation. When a DMU is operating at constant returns to scale, increasing input by some multiple, say *k*, increases output by the same multiple. If the DMU is experiencing decreasing returns to scale, increasing input by a multiple *k* generates less than *k* times the original output level. It follows that when *k* times the current level of input yields more than *k* times the current level of output, the DMU is operating in an increasing returns to scale environment (Nicholson 1995).

Additionally, this assumption is useful when the user does not have perfect information about the system the DMUs are operating in or if the researcher knows that VRS are present. Thus, the BCC model is a more flexible model than the CCR model since it allows for variable returns to scale. Like the CCR model, the BCC model can have either an input minimization or an output maximization orientation. The BCC output maximization model represented algebraically at equation 4.

BCC Output Maximization

$$\text{Maximize: } \sum_{r=1}^{s} u_r y_{r0} - u_0$$

Subject to: (4)

$$\sum_{i=1}^{m} v_i x_{i0} = 1$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} - u_0 \leq 0$$

v_i , u_r $\geq \varepsilon > 0$, for $i = 1,\ldots,m$; $r = 1,\ldots,s$; $j = 1,\ldots,n$

y_{rj} ≡ output r for DMU j
y_{r0} ≡ output r for the evaluated DMU
x_{ij} ≡ input i for DMU j
x_{i0} ≡ input i for the evaluated DMU
v_i ≡ variable weight for input i
u_r ≡ variable weight for output r
u_0 ≡ returns to scale measurement for the evaluated DMU
n ≡ total number of DMUs being evaluated
s ≡ total number of outputs
m ≡ total number of inputs
ε ≡ infinitesimally small constant to maintain positivity

The difference between the CCR and the BCC model frontiers is best explained by use of the following graph.

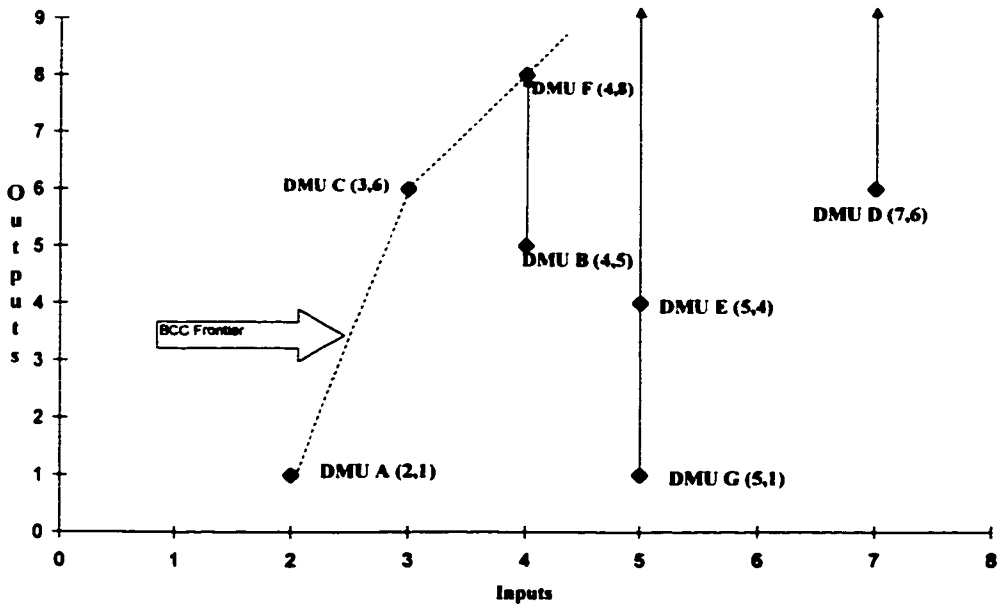

Figure 3. BCC output maximization graphical representation.

A comparison between Figures 1 and 3 show that the shape of the DEA efficiency frontiers is quite different. DMUs C and F are efficient in the CCR formulation; BCC includes DMU A as an efficient DMU. The CCR formulation originates the efficiency curve from the origin and assumes the constant returns to scale. The BCC efficiency frontier originates at DMU A and envelopes C and F. The mathematical formulation of the input minimization BCC model is:

BCC Input Minimization

Minimize: $$\Theta - \varepsilon\left[\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right]$$

Subject to: (5)

$$\Theta x_{i0} - \sum_{j=1}^{n} y_{rj}\lambda_j - s_i^- = 0$$

$$\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = y_{r0}$$

$$\sum \lambda_j = 1$$

$\lambda_j, s_i^-, s_r^+ \geq 0$ for i = 1,…,m; r = 1,…,s; j = 1,…,n

- $_0$ ≡ evaluated DMU
- Θ ≡ intensity score of DMU_0
- y_{rj} ≡ output r for DMU j
- y_{r0} ≡ output r for the evaluated DMU
- x_{ij} ≡ input i for DMU j
- x_{i0} ≡ input i for the evaluated DMU
- s_r^+ ≡ slack output r for the evaluated DMU
- s_i^- ≡ slack input i for the evaluated DMU
- λ_j ≡ upper and lower limit for the evaluated DMU
- n ≡ total number of DMUs being evaluated
- s ≡ total number of outputs
- m ≡ total number of inputs

The differences between the CCR model and the BCC model are subtle but important for understanding the environment that the DMUs operate in.

Other DEA Warehousing Applications

In 1994, Frazelle and Hackman surveyed 50 distribution centers (warehouses) that ranged in size from 50,000 to 500,000 square feet. The distribution centers were a mix of for-profit and government firms. Frazelle and Hackman used the data to develop a model to calculate a warehouse performance index (WPI). Frazelle and Hackman used the WPI to convert all of the individual warehouse data for their CCR DEA model.

The Frazelle and Hackman WPI model consisted of five variables, (input) *labor* and *equipment*, (output) *movement*, *storage*, and *accumulation*. *Labor* was proxied by counting the number of employees and multiplying by 2,000 to calculate work hours. *Equipment* was proxied by summing the average replacement costs associated with each of the materiel handling pieces of equipment at each facility. This included vehicles, small parts storage systems, and conveyor systems. The *movement* output was proxied by summing the annual broken case lines shipped, full case lines shipped, and annual pallet lines shipped. *Storage* was an index of the effort required to store the materiel in the warehouses. Frazelle and Hackman calculated the measure of *storage* by assuming that the distance traveled to complete activities is proportional to the square root of the area traveled. Frazelle and Hackman also assumed that 1 square foot was allocated to each broken case stock keeping unit (SKU) and that 25 square feet was allocated to each pallet location. The storage function is calculated using the formula at Figure 4 (Frazelle & Hackman, 1994):

$$S = \left(\frac{BCL}{TL}\right)\sqrt{\#\,BC} + \left(1 - \frac{BCL}{TL}\right)\left(\sqrt{25*\#\,PL} + \sqrt{FS}\right)$$

where:
BCL = broken case lines picked
TL = total lines picked
BC = broken case
PL = pallet locations
FS = available floor storage space

Figure 4. Frazelle and Hackman storage formula.

A limitation of the WPI model, stated by the authors, is that it is inappropriate to apply the model to operations that occupy more than one building or handle a wide variety of materiel. The study concluded that there are three key warehouse design variables in common with all of the warehouses studied. The three variables-workforce composition, warehouse size, and level of automation-were common links across the industry. Frazelle and Hackman concluded that there was no difference between the efficiency of union and nonunion warehouses. Additionally, Frazelle and Hackman were unable to determine an economy of scale size for the warehouses. In fact, they determined that the larger sized warehouses increased employee travel times and may have a detrimental effect on efficiency but could not state this conclusion definitively. Finally, Frazelle and Hackman were unable to determine if warehouse automation contributed to or detracted from efficiency.

In 1998, Frazelle and Hackman published a study with Griffin and Vlatsa that again used DEA to measure the efficiency of warehouse operations. The 1998 study included 57 different warehouse and distribution facilities that were all for-profit. The 1998 study built upon the 1984 study and examined many of the same factors. The Frazelle, Griffin, Hackman, and Vlatsa (1998) study focused on attempting to find an optimum level of materiel handling equipment, storage equipment, and facility size for a warehouse. The 1998 model differed from the 1994 model in that space, proxied by the square feet dedicated to receiving, storage, and shipping operations, was added as an input measure. The authors also attempted to specify more precisely the labor hours for the model. They asked the surveyed firms to categorize the hours and to exclude all hours not directly associated with warehouse functions. Frazelle and Hackman reported in their 1994 study that it was difficult, if not impossible, to measure all of the hours spent on warehouse operations. In the instances where head counts of personnel were provided, the authors multiplied the head count by 2,000 to estimate the number of hours. All of the other variables included in the study were proxied and estimated as in the previous study. The authors employed the CCR and BCC models in their analysis. The conclusion of this study was that union and nonunion warehouses were equally efficient, that smaller warehouses were more efficient than larger warehouses, and that warehouses using less automation were more efficient than more automated warehouses. One of the strengths of this study is that it demonstrated the application of both CCR and BCC to evaluate to warehouses. Additionally, the inclusion of the space variable as an input variable more accurately captured the activities of the warehouse. However, the results were limited in scope because government warehouses were not included in the study population. Additionally, this study failed to consider warehouse operations with multiple buildings.

Scope and Limitations

The current study was limited to evaluating the DLA warehouses located in the continental United States. The research examined data for the period of October 1997 to July 1999.

Summary

This literature review has placed the study within the context of benchmarking. The purpose of benchmarking is to review and measure a firm's internal processes. Those results are then compared to others to determine who the best performers are. The comparison can be done either internally or externally depending upon the objectives of the firm. Four benchmarking measurement methodologies were reviewed, highlighting strengths and weaknesses of each. Data envelopment analysis was shown to be a robust measurement tool capable of measuring the performance of similar organizations using multiple inputs and outputs. For this study, DEA is the appropriate tool for a variety reasons. DEA has proven effective in similar benchmarking efforts. However, previous studies included a either mix of for-profit and government warehouses in the same study population or focused exclusively on for-profit warehouse operations. Additionally, previous studies have excluded multiple building operations which this study includes.

This study focused exclusively on government warehouses to fill the gap in the existing literature. DEA allows the researcher to use multiple inputs and outputs when modeling the warehouse operations. DEA identified the efficient warehouses and the sources of inefficiency for the warehouses identified as inefficient. This study was designed to meet the need of senior DLA warehouse management for a method to discriminate between the performances of the warehouses.

CHAPTER 3: RESEARCH METHODOLOGY

Introduction

This research has applied Data Envelopment Analysis (DEA) to measure the effectiveness of the Defense Logistics Agency (DLA) management in their use of resources. This study provides a new metric for senior DLA management to measure the performance of warehouse managers. The literature review placed this issue within the existing DEA literature, described the various models, and the logic for choosing a specific model for this study. This chapter presents a detailed schema that includes a description of the methodology, study design, data source, data collection, and analysis.

Description of the Methodology

This study was designed to provide a new metric for assessing the performance of the management at government supply warehouses. The study was performed using a cross-sectional examination of monthly performance data for October 1997 - July 1999.

At the time the data were collected, DLA was under a congressional competitive review of its warehouse activities. This review made the warehouse performance data very sensitive, which resulted in only 22 months of data being made available for this study. This limitation forced the researcher to aggregate the data.

To address this problem, the quantitative research paradigm was used. A quantitative study approach is appropriate for this study since defined and measurable variables exist for the population of warehouses.

DEA Model Specification

Bowlin (1998) and Charnes et al. (1994) outlined several considerations for the researcher when developing and implementing DEA models. The *positivity property* requires that the DEA model formulation measures be positive (>0) for all of the input and output variables. Charnes, Cooper, and, Thrall (1991) showed that this requirement can be relaxed but according to Bowlin (1998) this relaxation technique is not normally employed.

The second property is the *isotonicity property*. Charnes, Cooper, Golany, Seiford, and Stutz (1985) showed that the relationship between the input and output measures must display the mathematical property of *isotonicity*. Charnes et al. (1985) described the mathematical term *isotone* as synonymous with the phrase *monotonically increasing*. Simply stated, this means that any increase in inputs should result in some output increase and no decrease in any output (Bowlin, 1998).

DMU Selection Criteria

One of the factors that researchers must consider when choosing the DMUs for inclusion in the study is the size of the comparison group. While no absolute minimum or maximum number of DMUs is required to conduct a DEA study, the literature agrees that there should be at least three times as many DMUs as the sum of input and output measures (Bowlin, 1998; Charnes et al., 1994). The disadvantage of smaller comparison groups is that an excessive number of DMUs might be evaluated as efficient (assigned a rating of 1) because of an inadequate degrees of freedom in solving the model (Bowlin, 1998; Charnes et al., 1994). The advantage of larger DMU populations is that more input and output measures may be included in the study thus increasing the likelihood that the model will capture all of the necessary measures.

Another consideration for selecting DMUs is that they must all be *homogeneous* in nature. This means that all of the DMUs under investigation must generally perform the same tasks with the same inputs and outputs in positive amounts. However, one disadvantage of a large study population is that the homogeneity of the study group can decrease due to external factors (W. F. Bowlin, personal communication, January, 2000).

Selection of DMUs

With consideration given to the previously specified guidelines, this study excluded 10 DLA operated warehouses located both overseas and within the continental United States. These depots were excluded for several reasons. The overseas warehouses in Japan, Korea, Germany, Saudi Arabia, and other locations each have local citizens as employees and are subject to local labor laws. These laws vary by country and are different from the labor practices of the United States. Additionally, three warehouses in the United States were not included in the study because they are scheduled for closure.

While each of the warehouses is slightly different in terms of size and layout, each warehouse performs the exact same core tasks of receiving materiel, storing materiel, and shipping materiel. Additionally, the warehouses have the required properties of isotonicity and homogeneity.

Variable Selection Criteria

The selection of input and output measures is a critical step in the model specification process. Several researchers (Bowlin, 1998; Crino, 1996; Norman & Stoker, 1991) have described methods for selecting measures. The literature agrees that whatever measures are selected, they must meet the following criteria. First, the measures must be comprehensive in scope, which is to cover the whole gamut of activities for the selected DMUs. To ensure that the measures are comprehensive in scope, management involvement in the selection process is essential (Bowlin, 1989). If the measures fail to capture all of the activities adequately, the usefulness of the model will be limited. Second, the measures must meet the isotonicity and positivity conditions previously described. Third, the measures must be measurable (but not necessarily all in the same units) and reported by the DMUs. Finally, Bowlin (1998) recommended selecting measures that are not easily manipulated by the DMU managers and that are familiar to the management concerned with evaluating and controlling the DMUs.

Selection of Variables

This study shares some commonality with previous studies (Frazelle, Griffin, Hackman, & Vlatsa, 1998; Frazelle & Hackman, 1994) in that it examined the three basic areas of warehouse operations *receiving*, *storing*, and *shipping* materiel. This study differs from previous work by measuring the relative efficiency for only government warehouse operations. Previous studies have included both for-profit and nonprofit warehouses in their studies. The previous approaches are flawed because the researcher believes that the DEA homogeneity requirement was violated. The difference between DMUs lies in the objectives for government operated warehouses and for-profit warehouse operations are not necessarily the same.

Bowlin (1998) recommend that when developing a DEA model of a system that there be three DMUs for each variable, either input or output. The ratio of DMUs to variables in this study exceeds this recommendation. Bowlin (1998) stated that the danger in having too few DMUs is that there will be a disproportionately large number of DMUs considered efficient if the three to one rule is violated since there will be an inadequate number of degrees of freedom.

This study included four inputs. Total cost of labor (TCL) measured in dollars by the cost of direct and indirect labor required by warehouses to perform their assigned missions. Total non-labor costs (TNLC), measured in dollars, is used to determine the impact of the noncore tasks performed at each depot. Core tasks are defined as the tasks performed in the receipt, storage, and issue of materiel from the depot. Noncore tasks like security police, administrative overhead, facility maintenance all require funding but do not directly contribute to the receipt and issue of materiel. Receipt processing (RP) is an aggregate measure in days of the time required to receive and store materiel at the warehouse. RP is comprised of three components, new procurements, customer returns, and materiel transfers. New procurements are all new materiel purchased by DLA and shipped from a manufacturer to a warehouse for storage. Customer returns constitute all materiel that is returned to the warehouse from its customers. The final element, materiel transfers, is comprised of the materiel that is transferred from one warehouse to another. Depreciation expense (DEP) is measured in dollars and is the result of the straight line accounting method for each warehouse. Depreciation expense is included in the model to serve as a proxy measurement for the capital investment at each depot. The output variable is the number of issues/line items shipped (LIS) measured as the count of orders issued/shipped to customers.

These measures were chosen for several reasons. First, the measures are quantifiable and cover each of the fundamental warehouse operations. Second, these variables meet the selection criteria specified and are comprehensive in scope. Third, DLA management is interested in these performance measures and tracks them on a monthly basis for all of the warehouses. Lastly, the researcher assumes that DLA management will accept a DEA model that incorporates measures that they are familiar with more readily than one that incorporates new measures.

DEA Models

The models used for this study were the CCR and BCC input minimization models found at equation 3 and depicted algebraically at equations 6 and 7. Given the forecast for reduced warehouse workload in the future, the minimization models are chosen because they allow senior DLA leaders to determine what minimum level of resourcing is required to enable the depots to maintain the current level of output.

CCR Input Minimization

$$\text{Minimize: } \Theta - \varepsilon\left[\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right]$$

Subject to: (6)

$$\Theta x_{i0} - \sum_{j=1}^{n} y_{rj}\lambda_j - s_i^- = 0$$

$$\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = y_{r0}$$

$\lambda_j, s_i^-, s_r^+ \geq 0$ for i = 1,…,m; r = 1,…,s; j = 1,…,n

BCC Input Minimization

$$\text{Minimize: } \Theta - \varepsilon\left[\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right]$$

Subject to: (7)

$$\Theta x_{i0} - \sum_{j=1}^{n} y_{rj}\lambda_j - s_i^- = 0$$

$$\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = y_{r0}$$

$$\sum \lambda_j = 1$$

$\lambda_j, s_i^-, s_r^+ \geq 0$ for i = 1,…,m; r = 1,…,s; j = 1,…,n

The purpose of using both the CCR and the BCC models was to allow the researcher to gain additional insight from the collected data about the efficiency of the depots. The researcher used the results of the two models to determine the scale efficiencies of each depot by dividing the CCR result by the BCC result of each depot.

Data Collection and Analysis

The Defense Logistics Agency collects and reports the data used in this study and made them available to the researcher (W. Stormer, personal communication, January, 1999). Prior to collecting the data, the researcher made several visits to warehouses included in the study to gain an understanding of warehouse operations. The site visits included extensive discussions with warehouse personnel that proved instrumental in formulating the model of warehouse operations.

The final inputs and output values for each warehouse is shown in Table 1. The next two chapters will explore methods for comparing the warehouses, determine their efficiencies, identify sources of inefficiency, and recommend area's for future research.

Table 1

Warehouse Input and Output Values

DMU	Total Labor Cost	Total Non-Labor Costs	Depreciation	Receipt Processing Days	Line Items Shipped
A	$24,566,463	$19,423,463	$1,881,354	19.70	301,323
B	$12,495,898	$12,807,757	$964,102	12.86	424,883
C	$13,161,975	$11,171,090	$416,236	23.87	259,126
D	$10,582,447	$11,477,174	$2,529,399	25.60	759,934
E	$32,434,708	$63,812,151	$6,751,858	5.30	1,105,756
F	$11,741,966	$8,618,466	$615,262	16.50	330,285
G	$32,883,536	$35,039,440	$3,004,092	17.20	1,534,658
H	$58,036,831	$34,615,487	$1,789,196	25.00	1,065,343
I	$13,788,382	$17,445,736	$2,247,453	17.10	1,239,186
J	$26,394,392	$11,380,554	$205,077	18.20	626,914
K	$52,153,417	$34,036,214	$5,509,085	15.20	2,129,413
L	$52,747,963	$32,379,651	$3,051,396	27.30	1,873,826
M	$10,770,964	$5,980,574	$813,385	7.92	424,640
N	$55,837,413	$47,918,418	$2,944,285	5.80	971,681
O	$47,421,059	$53,775,960	$7,414,641	8.20	1,754,439
P	$14,705,503	$56,173,190	$858,131	9.01	985,999
Q	$16,958,391	$15,842,420	$3,490,338	16.50	300,211
R	$47,107,026	$37,543,903	$10,860,291	19.90	1,368,786

Summary

This chapter has laid the foundation for the DEA methodology, selection of DMUs, and variables used in this study. The next chapter presents the results of the study and the answers to the study questions. The final chapter discusses areas for further research and implications of the study for DLA.

CHAPTER 4: RESULTS

Introduction

This chapter describes the analysis of the data collected from DLA using the DEA models developed in Chapter 3. In this chapter, the researcher will present the results of the analysis and answer the following research questions:

1. What insight can a mathematical programming model offer that is not provided by the current DLA evaluation methodology?

2. Which government warehouses are the most efficient in using available resources?

3. To what degree does model sensitivity affect the results of the DEA models?

4. In what way does the size of a warehouse affect the results of the DEA models?

5. What are the returns to scale for the individual government warehouses?

The first step the researcher used before attempting to answer each of the research questions was to plot the warehouse data. The warehouses were then categorized to provide the researcher with an additional means for comparison. The researcher used the output variable line items shipped to group the warehouses into three groups. Each warehouse was then considered either "small," "medium," or "large."

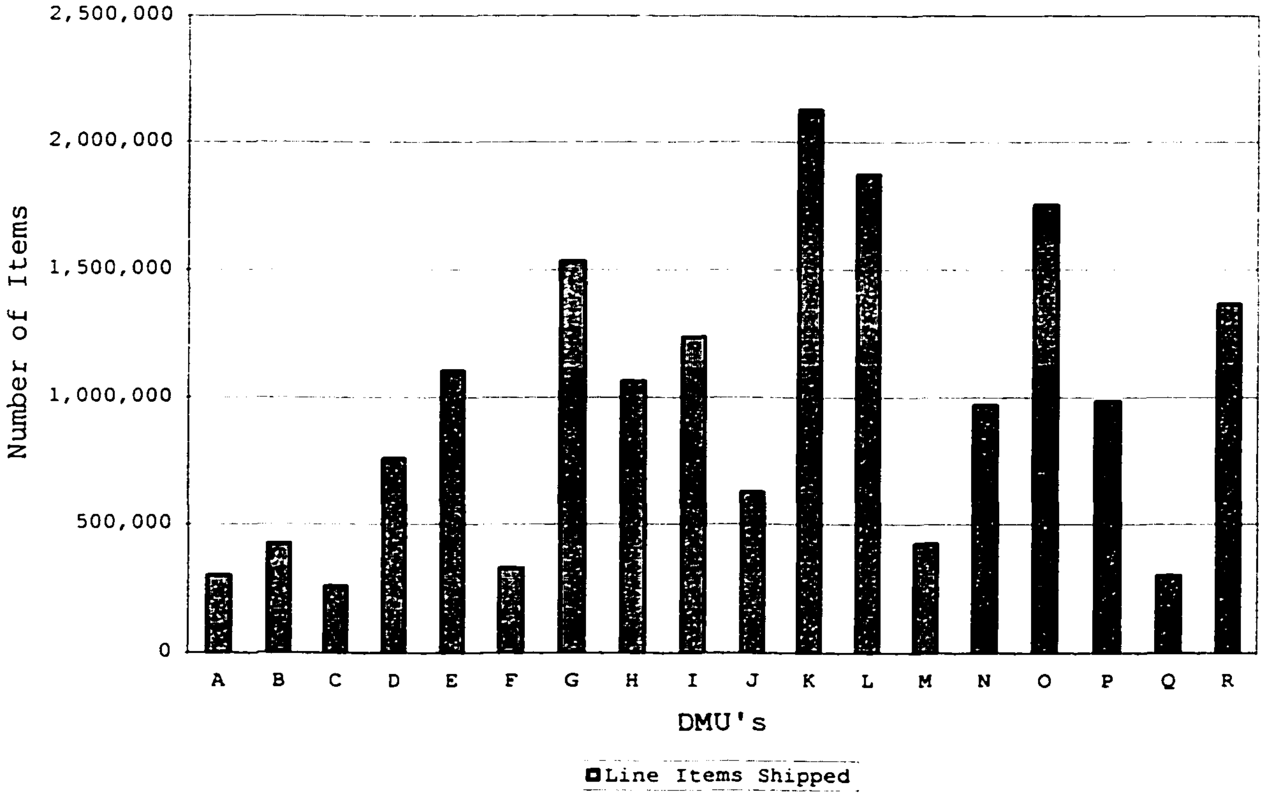

Figure 5. Line items shipped.

To group the depots into categories, small depots shipped fewer than 500,000 items, medium depots shipped between 500,001 and 1,200,000 items, and large depots shipped more than 1,200,001 items. For the purpose of this study, depots A, B, C, F, M, and Q are considered as small. Depots D, E, J, H, N, and P are considered as medium.

Finally, depots G, I, K, L, O, and R are considered as large. This relationship is more readily evident in Figure 6 where the number of line items shipped for each warehouse are arranged in ascending order.

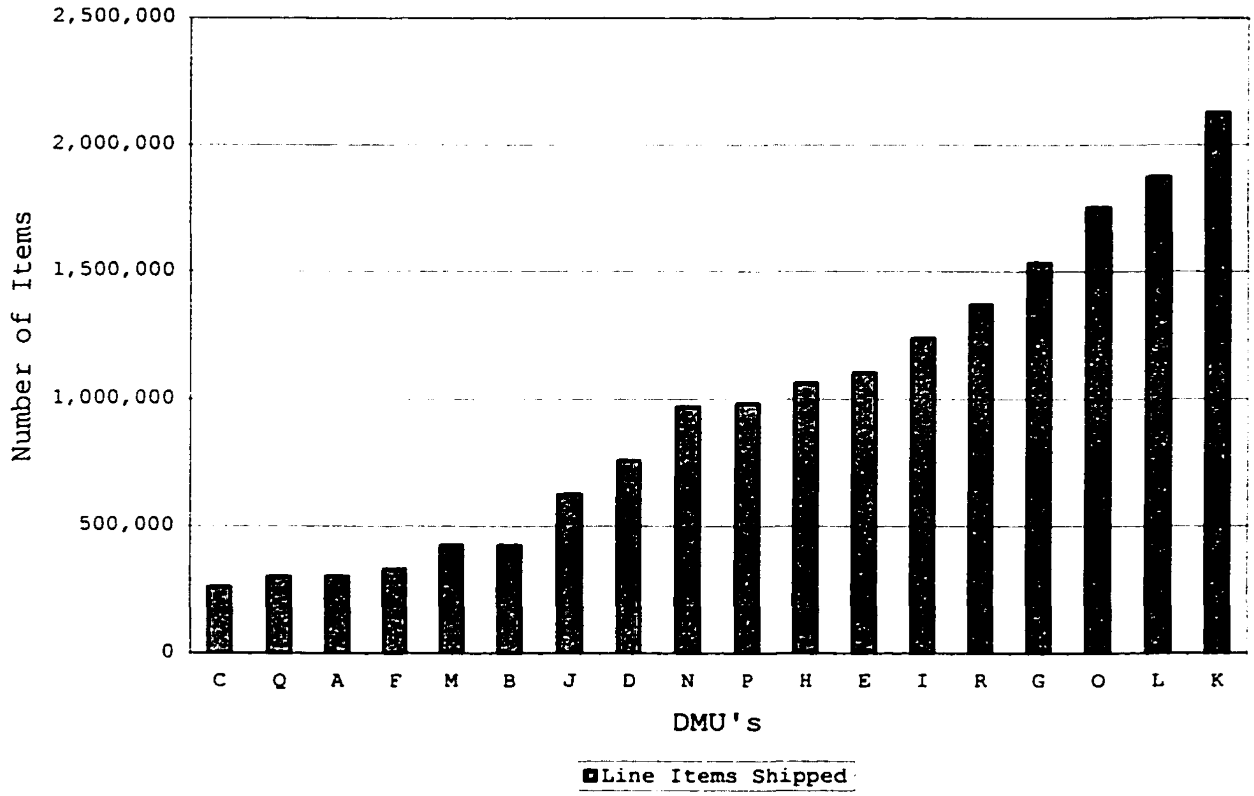

Figure 6. Line items shipped in ascending order.

Appendix A graphically depicts each of the input variables graphed against the efficiency results.

Model Insights

The first research question asks what insight can a mathematical programming model offer that is not provided by the current DLA evaluation methodology. Chapter 1 discussed the current DLA method for evaluating warehouse managers performance of assigned missions with available resources. In this chapter, the current DLA process is highlighted and new information that can gained by use of a mathematical model is presented.

According to (R. Sample, personal communication, July, 1998), the standard "evaluation" procedure is an aggregation of equally weighted variables reported on a monthly basis to the senior DLA leadership. The reported measures include *receipt processing, warehouse denial rate, issue processing,* and *locator accuracy*. DLA collects the data but does not use the data to rank or evaluate the individual depot managers on their ability to perform assigned missions or in their use of resources. DLA lacks a formalized method for comparing and evaluating the performance of the depot managers.

The mathematical model results enable senior DLA managers to identify where specific inefficiencies exist within the organization. The ability to identify inefficiency within the organization is a useful new tool for several reasons. Frequently, DLA is directed by the Department of Defense to reduce costs. Often times, the reduction cost areas and amounts are specifically mandated in the DoD directive to DLA. During the 1990s, labor costs were commonly the target for reductions. During the time the author worked for DLA, the personnel cost cuts were applied equally across all organizations regardless of impact upon the affected organization's mission. In some instances, organizations could absorb personnel reductions through normal attrition from the force. However, many times people were laid off. With this model, DLA can focus the reductions on less efficient warehouses and improve overall organizational efficiency. Additionally, this methodology can be extended to other DLA organizations to identify their efficiencies for the same purpose.

The DEA methodology enables DLA management to make empirical evaluations of the warehouse manager's performance that were previously unavailable. This process will assist senior DLA managers in making their assessments about how well depot commanders are performing their assigned missions when compared to their peers. The evaluation can be considered a fair and impartial one since DEA optimizes upon the strengths of each warehouse operation. The ability to distinguish between management performance will assist senior DLA leaders when making recommendations for promotions and incentive rewards. Thus, strong performers are rewarded and identified inefficiencies can receive the necessary attention from DLA leadership.

In addition to identifying inefficiencies due to labor, this methodology can be used to identify inefficiencies due to excess capacity or overhead. This information will be useful to the Department of Defense when making future recommendations to the U.S. Congress about which facilities to close. Closing inefficient facilities will increase overall system efficiency while at the same time saving substantial tax dollars.

Warehouse Efficiencies

Bowlin (1998) and Charnes et al. (1994) list several DEA specific software packages that are useful for determining which DMUs are efficient and inefficient. The researcher assumes that each of the DEA packages yields similar results for a given model and that each software package has the ability to solve both the CCR and BCC models. One package, Frontier Analyst is a user-friendly package that is currently used by DLA and was used for this study. In addition to Frontier Analyst, the researcher used one other DEA specific software program that estimated the returns to scale and scale efficiency for the DMUs, which Frontier Analyst does not. The program, Data Envelopment Analysis Program (DEAP) version 2.1 was downloaded from the Internet. DEAP generated the same efficiency scores as Frontier Analyst for the DMUs.

Using the data provided by DLA, the two DEA input minimization efficiency models specified in Chapter 3 were created with four inputs (Total Labor Cost, Total Non-Labor Cost, Depreciation, and Receipt Processing) and one output (Issues/Line Items Shipped) variables.

The second research question asks which government warehouses are the most efficient in using available resources. The CCR model results indicate seven out of eighteen warehouses are efficient, while the BCC model indicates that twelve out of eighteen warehouses are efficient. The difference between the CCR and BCC model results is that BCC indicates that five warehouses are technically efficient but scale inefficient (W. F. Bowlin, personal communication, April, 2000). Figure 7 provides an overview of the range of depot efficiency.

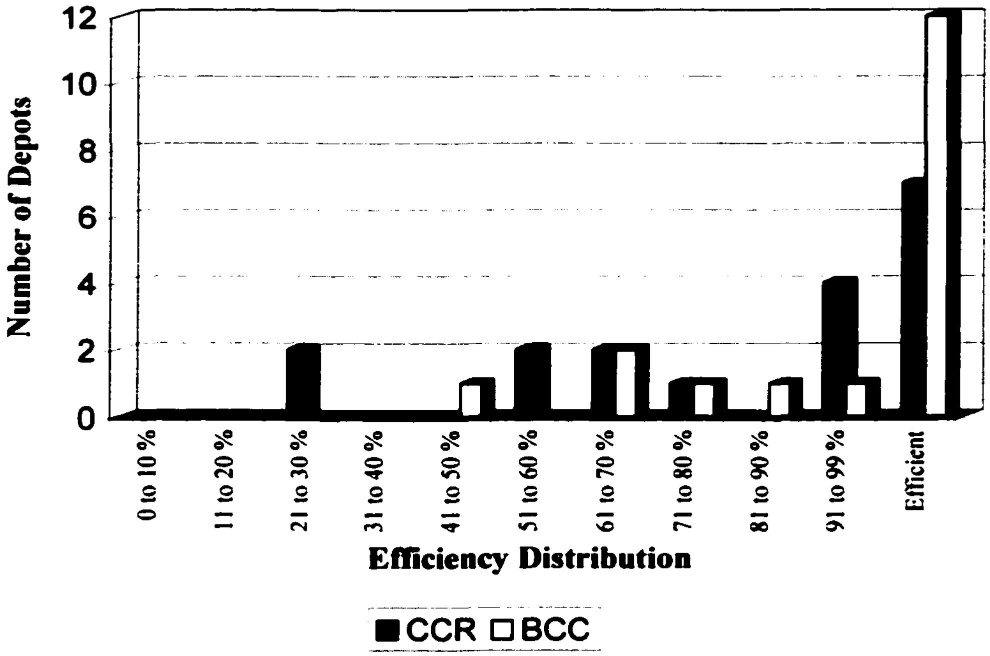

Figure 7. Efficiency results.

Using Frontier Analyst, the researcher calculated the efficiencies for the two DEA models shown at Figure 7. As can be seen, the CCR model described seven depots I, J, K, L, N, O, and P as efficient. The poorest performing warehouse was warehouse A with an efficiency rating of 24.70%. The next lowest efficiency rating was 26.68% for warehouse Q. The BCC model described twelve warehouses C, D, E, F, I, J, K, L, M, N, O, and P as efficient. The lowest efficiency rating using the BCC model was 43.84% for warehouse A. The next lowest efficiency rating was for warehouse Q at 63.35%. The efficiency percentage represents the efficiency score estimated for each DMU multiplied by 100.

Figure 8 depicts both the CCR and BCC efficiency scores for each of the warehouses graphed against the number of items shipped.

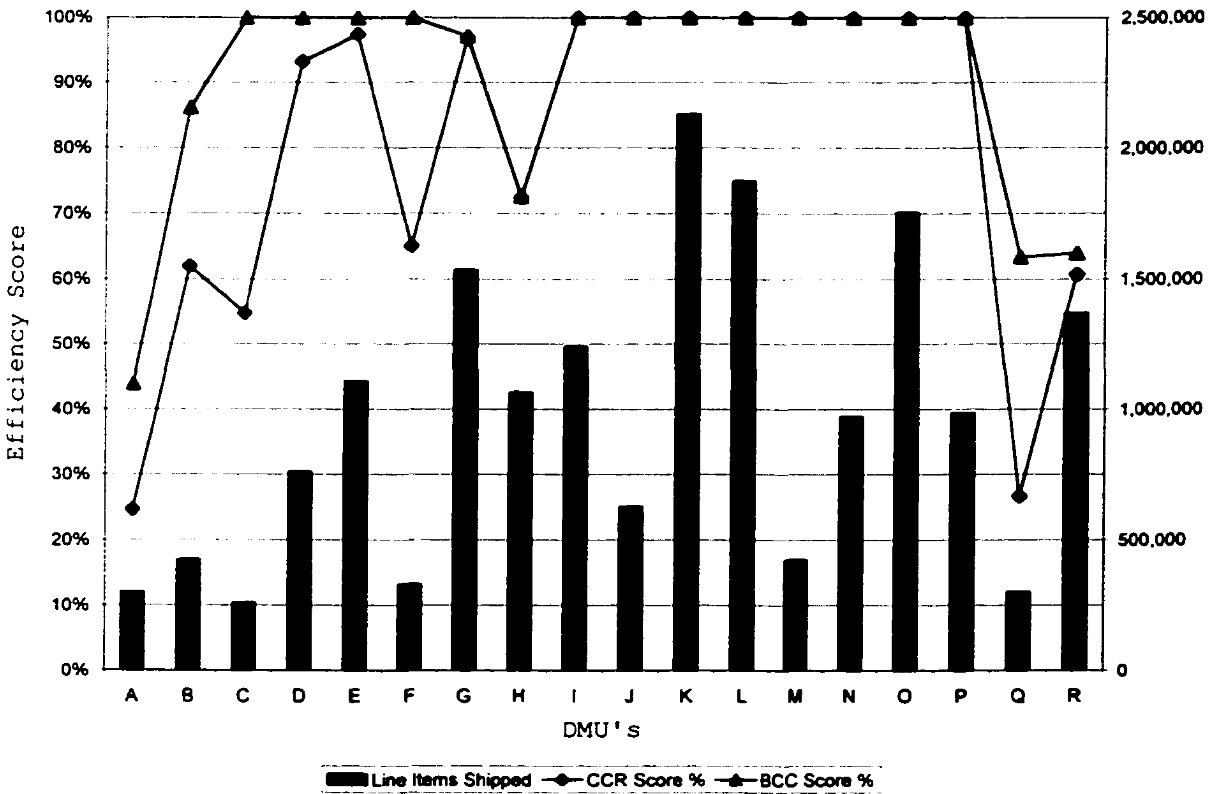

Figure 8. Line items shipped vs. efficiency scores.

The researcher determined that low efficiency scores (<75%) require additional investigation as to the roots of the inefficiency. The first step in the investigation was to check of the values used in the analysis. The researcher checked the data used for each model. This step is important because of DEA's inherent sensitivity to extreme values that might be the result of incorrect data values. An inspection of the data revealed that data were entered correctly. The second step of the investigation was to contact DLA to determine if the warehouses identified as inefficient were performing additional missions that required resources but did not contribute to shipping out materiel. The researcher discovered that many of the inefficient warehouses perform a maintenance and repair mission in addition to shipping materiel. This mission is a consolidated DoD program to repair and refurbish major end items, for example, aircraft, tanks, trucks, et cetera. A limitation of this study is that the data provided by DLA does not identify the amount of labor, non-labor, or depreciation attributable to the maintenance and repair mission. It is unclear if the maintenance mission accounts for some or all of the identified inefficiency.

As previously mentioned, a strength of DEA is that it identifies specific inefficiencies in DMUs and prescribes amounts or targets for the DMU to achieve to reach the efficiency frontier. The CCR model describes DMU A as

24.7% efficient and 43.84% BCC efficient. To achieve efficiency, DMU A would have to reduce its input consumption by the amounts listed in Table 2.

Table 2

Warehouse Inefficiency

Variable	Input Amount	CCR Target	CCR % Reduction	BCC Target	BCC % Reduction
TCL	$24,566,463	$6,067,372	-75.3	$10,769,713	-56.16
TNLC	$19,423,463	$4,797,165	-75.3	$6,017,037	-69.02
DEP	$1,881,354	$464,653	-75.3	$824,768	-56.16
RP	19.70 Days	4.9 Days	-75.3	8.0 Days	-59.20

Table 2 illustrates the benefit of DEA to decision makers. DEA establishes goals for the inefficient organizations and assists the decision makers in assessing the performance of their subordinate managers. A detailed list of the inefficiencies by warehouse is at Appendix B and C.

Model Sensitivity

The range of efficiency results suggests that the model results might be affected by which variables are included in the model. To test this hypothesis, additional models were developed that eliminated one input variable at a time to determine if the model differences are statistically significant. Various nonparametric statistical methods are suggested in the literature. Bowlin (1998), Banker (1996), Simar (1996), and Ahn, Charnes, and Cooper (1988), use various tests depending upon the assumptions that the researcher makes regarding the distribution of the DEA ratings. According to Bowlin (1998), two common assumptions used with DEA are that efficiency scores follow either an exponential or half-normal distribution.

The DEA efficiency results for this study were tested to determine what distribution they followed. The test was performed using BestFit version 2.0d. BestFit compares the data against 26 different probability distributions and measures the goodness of fit for the optimized function. BestFit identified the results of this study as best fitting the Beta distribution. This result is significant because many familiar statistical tests assume the test data are normally distributed (Aczel, 1996).

To test the sensitivity of the model, the Mann-Whitney U test was performed. According to Aczel (1996), the Mann-Whitney U test is a nonparametric test that is also referred to as the Wilcoxon rank sum test or simply the rank sum test. Previous studies (Ahn, Charnes, & Cooper, 1988; Siegle & Castellan, as cited in Banker, 1996) have applied the Mann-Whitney U test to determine if inefficiency differences exist between two groups of DMUs. This study extended this methodology to test the differences between models to determine the sensitivity of the models to the variables.

Aczel (1996) stated that the underlying Mann-Whitney U test assumptions require random samples from two populations of interest and that the samples are drawn independently. This study meets these assumptions since it is a survey of the government-managed warehouses and that all 18 warehouses are included in both models when compared.

For the sensitivity analysis, the base model will include the four input variables (TCL, TNLC, RP, and DEP) and one output variable (LIS). To determine if the model is variable sensitive, one variable was dropped, DEA scores calculated, and the models compared using the Mann-Whitney U test. The null hypothesis was that no difference will exist between the models while the alternative hypothesis is that the two models are not equal

$$H_0: m_1 = m_i$$

$$H_a: m_1 \neq m_i$$

where m_1 = base model
m_i = alternative models

To perform the Mann-Whitney U test, the DEA scores for two models are combined and rank ordered. Ties are assigned the average rank score for the observation. The ranks for the base model are then summed. For large populations (>10), like this study, the calculation of the Mann-Whitney U test is performed in four parts. The U statistic, mean, and standard deviation are initially calculated and then used to determine the final *z* value. For a two-tailed test, the null hypothesis is rejected if *z* is greater than or less than the value of the chosen α. For this test the researcher selected $\alpha = 0.05$, which dictates a critical value of $z = \pm 1.96$. The Mann-Whitney U test large sample equations are listed at equations 8-11.

The Mann-Whitney U statistic:

$$U = n_1 n_2 + \frac{n_1(n_1+1)}{2} - m_1 \qquad (8)$$

where n_1 = the sample size from population 1
n_2 = the sample size from population 2
m_1 = the sum of the sample ranks

The mean of the distribution of U:

$$E(U) = \frac{n_1 n_2}{2} \tag{9}$$

The standard deviation of U:

$$\sigma_U = \sqrt{\frac{n_1 n_2 (n_1 + n_2 + 1)}{12}} \tag{10}$$

The large sample test statistic:

$$z = \frac{U - E(U)}{\sigma_U} \tag{11}$$

The results of the Mann-Whitney U test are presented at Table 3. The critical value of z = ± 1.96.

Table 3

Mann-Whitney U Test Results

Model - Variables Included	z Value
CCR - TCL, TNL, DEP	-1.65
CCR - TCL, TNL, RP	-0.85
CCR - TCL, DEP, RP	-0.92
CCR - TNL, DEP, RP	0.02
BCC - TCL, TNL, DEP	-1.11
BCC - TCL, TNL, RP	0.32
BCC - TCL, DEP, RP	1.27
BCC - TNL ,DEP, RP	0.79

The result of the Mann-Whitney U tests was that the null hypothesis was not rejected for any of the models at the α = 0.05 level of significance. The CCR-TNL, DEP, RP model z value of 0.02 indicates that Total Cost of Labor has very little impact on the model. However, Total Cost of Labor can account for up to 70% of the expense associated with operating a warehouse, which makes removing it from the base model unacceptable.

Warehouse Size

Research Question 4 examines the impact of warehouse size on warehouse efficiency. Given that the different variables were not statistically sensitive, the researcher examined the relationship between warehouse size and efficiency. The researcher used the output variable line items shipped to categorize the 18 warehouses into warehouses considered either "small," "medium," or "large." Table 4 lists the warehouses and their efficiency scores by size.

Table 4

Warehouse Efficiency by Size

	DMU	Line Items Shipped	CCR Score %	BCC Score %
Small	A	301,323	24.70%	43.84%
Small	B	424,883	61.99%	86.18%
Small	C	259,126	54.79%	100.00%
Small	F	330,285	65.11%	100.00%
Small	M	424,640	99.96%	100.00%
Small	Q	300,211	26.68%	63.35%
Medium	J	626,914	100.00%	100.00%
Medium	D	759,934	93.22%	100.00%
Medium	E	1,105,756	97.48%	100.00%
Medium	H	1,065,343	72.50%	72.58%
Medium	N	971,681	100.00%	100.00%
Medium	P	985,999	100.00%	100.00%
Large	G	1,534,658	96.92%	97.07%
Large	I	1,239,186	100.00%	100.00%
Large	K	2,129,413	100.00%	100.00%
Large	L	1,873,826	100.00%	100.00%
Large	O	1,754,439	100.00%	100.00%
Large	R	1,368,786	60.73%	63.93%

To determine if differences exist between the different warehouse sizes, the warehouses were compared using the Mann-Whitney U test. As with the model comparisons, the null hypothesis was that no difference would exist between the depot sizes while the alternative hypothesis is that the depot size does affect efficiency.

The following schema was used to test the hypothesis for both the CCR and BCC models:

H_0: $m_S = m_M$ and H_0: $m_S = m_L$ and H_0: $m_M = m_L$
H_a: $m_S \neq m_M$ H_a: $m_S \neq m_L$ H_a: $m_M \neq m_L$

where m_S = Small depots
m_M = Medium depots
m_L = Large depots

For a two-tailed test, the null hypothesis is rejected if the *U* table lookup value is greater than or less than the value of the chosen $\alpha/2$. For this test the researcher used $\alpha = 0.05$. Unlike the previous model tests, the comparison between depot sizes required the Mann-Whitney U test for small sample formulations. The Mann-Whitney U small sample test equation is listed at equation 12.

The Mann-Whitney U statistic:

$$U = n_1 n_2 + \frac{n_1(n_1+1)}{2} - m_1 \tag{12}$$

The result of the CCR small vs. medium and small vs. large depots Mann-Whitney U test was to reject the null hypothesis at the $\alpha = 0.05$ level of significance. The null hypothesis was not rejected for the CCR medium vs. large depots or for any of the BCC comparisons at the $\alpha = 0.05$ level of significance. This result is not surprising since two thirds of the warehouses in the small category have the maintenance mission in addition to storing and shipping materiel and that the mean CCR result for small depots was 55.5% compared to medium depots 93.8% and large depots 92.9%. This result suggests that larger warehouses are more efficient than small warehouses.

This study result differs from the Frazelle and Hackman (1994) and the Frazelle et. al. (1998) results, which found small warehouses to be more efficient than large warehouses. This difference is undoubtedly due to the inclusion of a distance factor in those studies not included in this study and the maintenance mission performed by the small depots included in this study.

Returns to Scale

The final research question deals with estimating the returns to scale for each warehouse. This study considers three types of returns to scale the constant, increasing, and decreasing. Nicholson (1995) and Banker and Thrall (1992) describe constant returns to scale exist when an increase in inputs increases outputs by the same proportion. Increasing returns to scale exist when an increase in inputs increases outputs by a larger proportion of outputs. Alternatively, decreasing returns to scale are present when an increase in inputs results in a less than proportionate increase in outputs.

According to (W. F. Bowlin, personal communication, April, 2000), the CCR efficiency measure is an aggregate measure of both scale and technical efficiency. By contrast, the BCC efficiency measure only measures the technical efficiency of the DMU. The relationship between the two models can be described as BCC * scale efficiency (SE) = CCR. Thus, a DMU can be technically efficient and scale inefficient. Additionally, a DMU cannot be scale efficient and technically inefficient. Finally, because of the relationship between the two models, the CCR rating will always be less than or equal to the BCC rating.

To estimate the returns to scale for each warehouse, the scale efficiency score must be calculated. The scale efficiency score is the quotient of the CCR/BCC results for each DMU. If CCR/BCC = 1, then the DMU is considered scale efficient and operating at constant returns to scale. When the DMU scores are BCC = 100% and CCR = 100%, then CCR/BCC = SE = 1 and the DMU is both scale and technically efficient. When the quotient of the CCR/BCC < 1, the DMU is considered scale inefficient. For example: If BCC = 90% and the CCR = 80%, then CCR/BCC = SE = 0.889. The DMU is considered both technically and scale inefficient. When the DMU scores are BCC = 100% and CCR = 80%, then CCR/BCC = SE = 0.80. The DMU is technically efficient but scale inefficient. Unfortunately, the returns to scale for each DMU are unknown by the SE calculations alone (W. F. Bowlin, personal communication, April, 2000).

According to (W. F. Bowlin, personal communication, January, 2000; Banker and Thrall, 1992), the warehouse returns to scale are estimated by decomposing the BCC minimization formulation used in this study into technical efficiency and scale efficiency. The BCC minimization formulation uses lambda (λ) to measure scale efficiency. At optimality (*) the λ values are summed and evaluated. Specifically, when the $\sum_{j=1}^{n} \lambda_j^* = 1$ constraint is satisfied, the warehouse is operating at constant returns to scale. When $\sum_{j=1}^{n} \lambda_j^* > 1$ occurs, decreasing returns to scale exist for the warehouse. Increasing returns to scale exist when $\sum_{j=1}^{n} \lambda_j^* < 1$.

Table 5 presents the scale efficiency scores and returns to scale result.

Table 5

Returns to Scale Results

MINIMIZE INPUTS		
DMU	Scale Efficiency	Returns to Scale
A	.5634	Increasing
B	.7193	Increasing
C	.5479	Increasing
D	.9322	Increasing
E	.9748	Increasing
F	.6511	Increasing
G	.9985	Increasing
H	.9989	Increasing
I	1	Constant
J	1	Constant
K	1	Constant
L	1	Constant
M	.9996	Constant
N	1	Constant
O	1	Constant
P	1	Constant
Q	.4212	Increasing
R	.9499	Increasing

Summary

The SE result is important because it describes how close the warehouse is to operating at its optimal size. For example, Warehouse R need only reduce its inputs by approximately 5% after technical efficiency is achieved to become scale efficient. By contrast, Warehouse Q must reduce its input by approximately 48% after achieving technical efficiency to achieve its optimal scale efficient size.

The 10 warehouses operating at increasing returns to scale indicates where the warehouse is operating on the efficiency frontier. Additionally, increasing returns to scale indicates that an increase in input for those 10 warehouses will result in a greater than proportionate increase in outputs (Banker & Morey, 1986). The knowledge about which DMUs are operating at increasing or constant returns to scale will assist DLA decision makers about how to apply future resources (W. F. Bowlin, personal communication, January, 2000).

CHAPTER 5: CONCLUSION

Summary

Camp (1989) defined benchmarking as the search for the best practices in the industry that lead to improved performance. Heizer and Render (1995) summarized benchmarking as a process that involves the selection of a demonstrated standard of performance that represents the absolute best performance of processes that are similar to one's own. This process can be performed either internally or externally. This dissertation has focused on performing an internal benchmarking study of government warehouses. The researcher has shown how to construct a mathematical programming model to identify those warehouses that are the most efficient within that group.

The overall aim of this study was to develop a mathematical programming model that identified the warehouse managers who are the most efficient at using available resources. Additionally, a new methodology was developed for DLA to rank order the performance of the warehouse managers using a model that incorporates data currently collected by DLA.

The mathematical programming model focused on a very specific aspect of the benchmarking process, the analysis process. The model is focused at the warehouse manager level of decision making and assumes that the manager has little control over the requirements assigned to the warehouse. The requirements, materiel shipped, is an exogenous variable and serves as the independent variable for the model. The inputs labor, nonlabor, depreciation, and receipt processing are the dependent variables.

Similar to the 1995 Hollingsworth, the 1994 Frazelle and Hackman, and the 1998 Frazelle et al. studies, the researcher has demonstrated how a mathematical programming model can be applied to highlight those organizations that are exceptional at performing the tasks under consideration.

A weakness of those studies was that they included both for-profit and nonprofit warehouses in the same study population. This violates the homogeneity requirement for DEA analysis since warehouses in these two populations do not necessarily have the same objectives. An example of the differences can be found in this study. The majority of the inefficient warehouses identified in this study performed repair missions that required inputs that did not contribute to shipping materiel, an output measure in all of the aforementioned studies. This is a weakness in this study as well since the input amounts required for the maintenance mission are not known. The earlier studies found that small warehouses were more efficient than large warehouses. This study found that larger warehouses were more efficient than small warehouses. This difference could be attributable to the differences between for-profit and government warehouses but more likely is due to the maintenance mission.

This study has filled a void in the existing body of knowledge regarding the application of DEA in the efficiency measurement of government warehouse operations. This study has focused exclusively on government nonprofit warehouses, which had not been previously studied. However, a limitation of this study is that the small sample size limits the extent to which the results might be generalized to other government agencies.

Another benefit of the study is that it provides DLA a formalized method for comparing and evaluating the performance of the warehouse managers. The DEA methodology enables senior DLA management to make empirical evaluations about the warehouse manager's performance that were previously unavailable.

Another benefit of this methodology is the ability to identify specific inefficiencies within the organization. This information will be useful to DLA and the Department of Defense when making future recommendations to the U.S. Congress about which facilities to close. Closing inefficient facilities will increase overall system efficiency while at the same time saving substantial tax dollars.

Social Impact

DLA anticipates a reduced workload for each of the warehouses in the future. The reduction in workload translates into additional excess capacity and increased inefficiency for the system. With this methodology, DLA can intelligently target facilities for closure. The closure of facilities can result in potentially millions of tax dollars can be saved for the citizens of the Unites States. Those savings translate into quantifiable benefits for all citizens. The savings in warehouse operations are essential for the United States to maintain a flexible, technologically advanced, and effective 21st century defense (www.ddc.dla.mil/aboutddc/lrpiv.htm, January 25, 2000).

Conclusions and Recommendations

One area of future research would be to identify the amount of input required to support the maintenance mission at the small warehouses. If that data were separated out, it would allow a more compete comparison between the warehouses.

Another area for future research is the comparison of warehouse operations with other nonprofit warehouses. Other state and federal agencies have small warehouses that could be sampled and compared to DLA. While the other agencies, Red Cross, National Forest Service, and others have warehouses, they are generally much smaller in size and scale of operation than those of DLA. However, the size difference will not matter with a DEA analysis.

Frazelle et al. (1998), Hollingsworth (1995), and Frazelle and Hackman (1994) all found that small warehouses were the most efficient in their studies. This study found a different result but did not include for-profit warehouses, which were included in the other studies. Additional research must be done to determine if a profit motive makes smaller warehouses more efficient or if this phenomenon exists for another reason.

Finally, additional research is required to determine if a relationship exists between scale efficient size and returns to scale. The question that needs to be answered is if a DMU is scale inefficient and operating at the increasing returns to scale portion of the frontier, how much will output increase with an increase in inputs? Current literature only describes the scale efficiency and returns to scale concepts but does not explain how the information, once determined, can be applied by management.

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Appendix A: Efficiency Graphs

This appendix provides a graphical illustration of the variables used in this study compared to efficiency. As expected, given the minimization orientation of the models, the warehouses that use fewer inputs are generally more efficient. Figures A1 - A4 show each of the input variables.

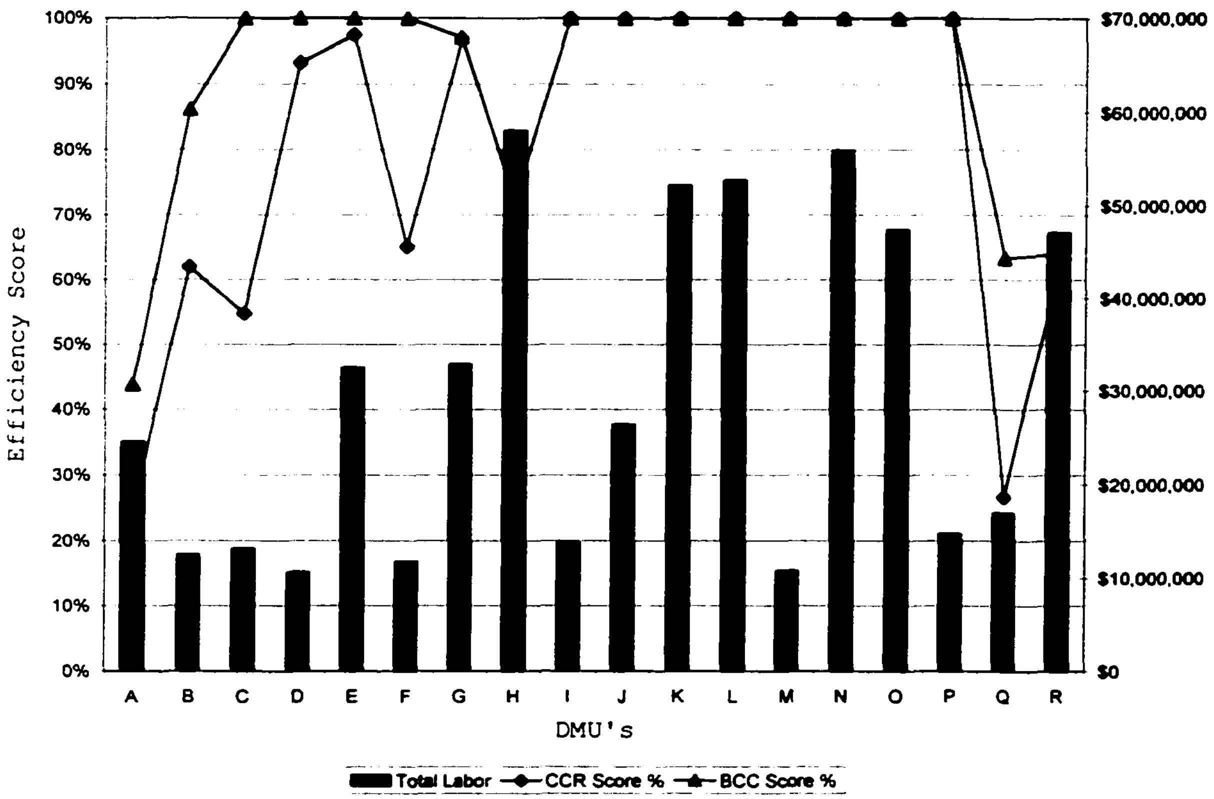

Figure A1. Total labor costs vs. efficiency scores.

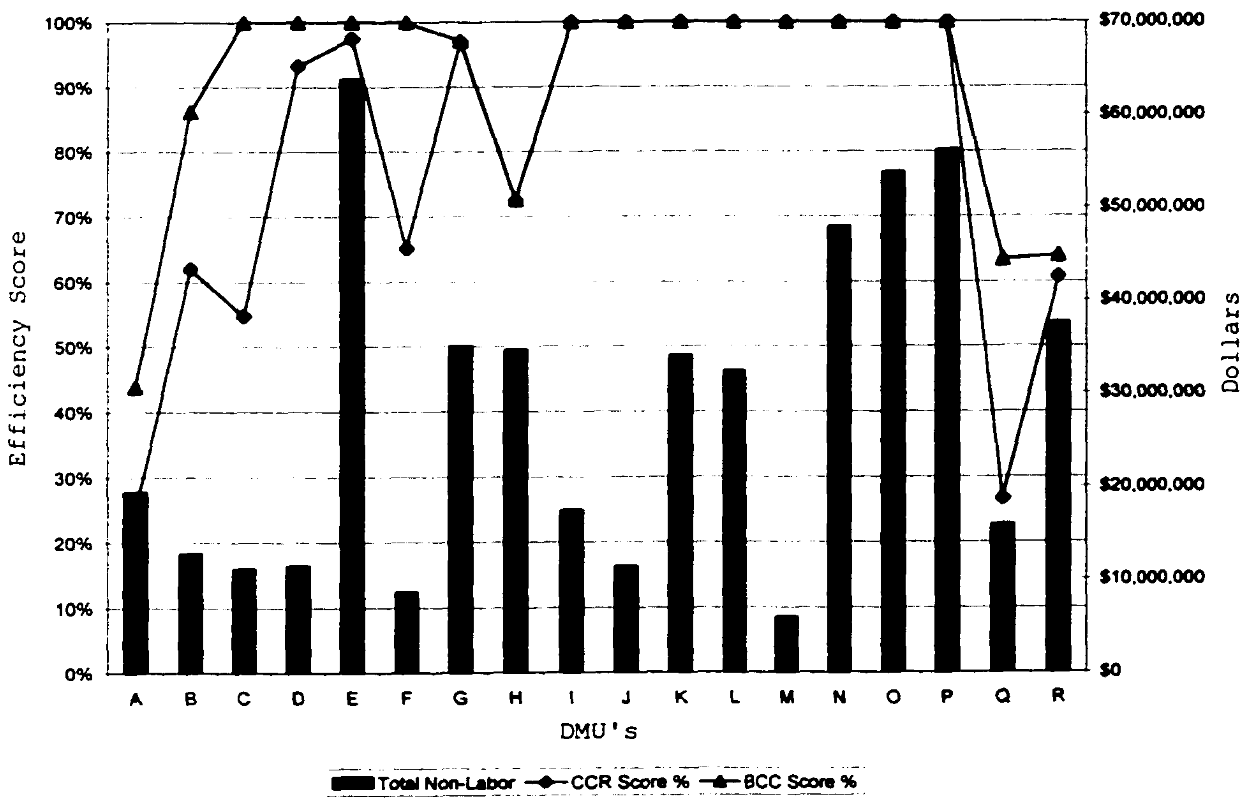

Figure A2. Total non-labor costs vs. efficiency scores.

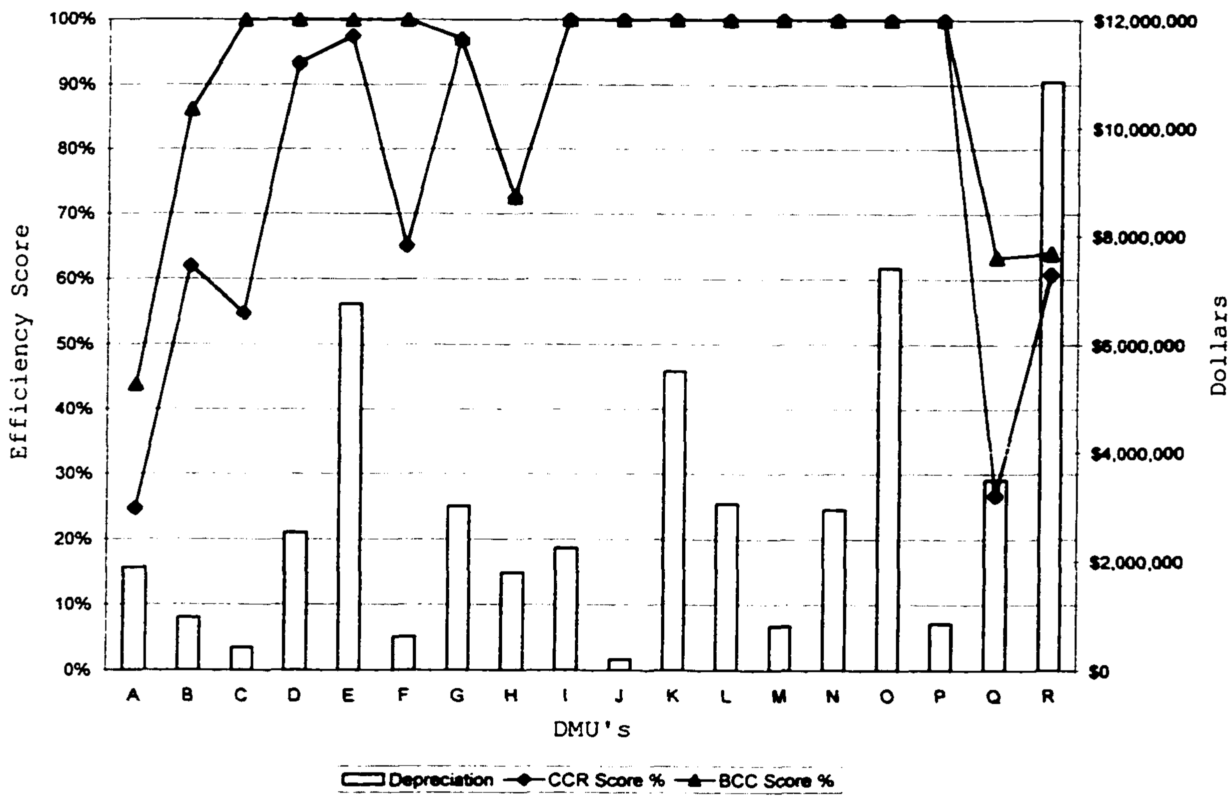

Figure A3. Depreciation vs. efficiency scores.

In this study, depreciation was included to serve as a proxy measurement of the automation at each warehouse. The efficiency result indicates that more automated warehouses are less efficient than less automated warehouses. This result supports the findings of Frazelle et al. (1998), Hollingsworth (1995), and Frazelle and Hackman (1994). Each of those studies found that less automated warehouses were more efficient than warehouses with greater automation.

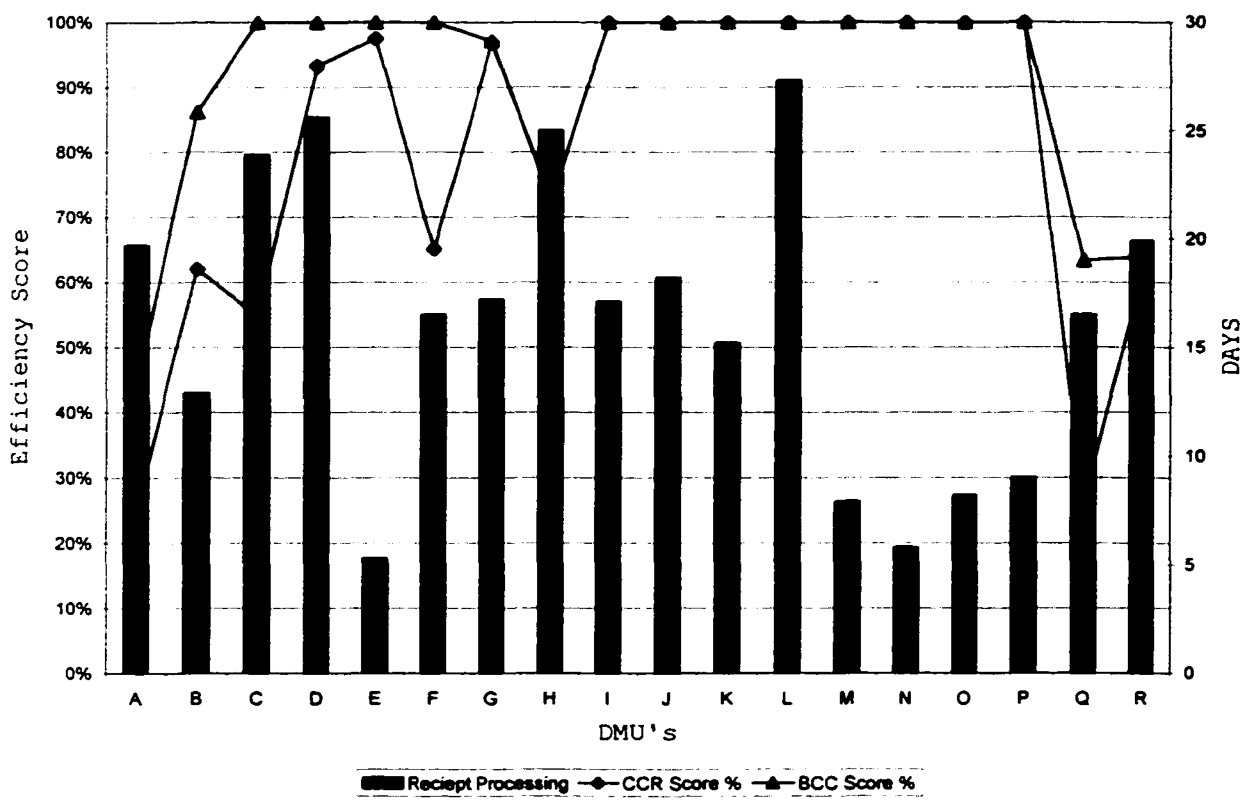

Figure A4. Receipt processing time vs. efficiency scores.

Appendix B: CCR Detailed Results

This appendix presents the detailed output results from Frontier Analyst for the CCR input minimization model. At the top of the page, the result lists the depot name and efficiency score. Next is the list of actual variable values used in the model, the new target value, and the percent increase or decrease required for each variable. Using Depot A as an example, the total labor used was $24,566,463. The new target value is $6,067,371.90, which represents a 75.3% reduction in labor costs. Since the model was input minimization the line items shipped value remains unchanged.

The peer contributions section is a by variable comparison the set of efficient units to which an inefficient unit has been most directly compared with when calculating its efficiency rating. It contains the efficient units that have the most similar input / output orientation to the inefficient unit and they should therefore provide examples of good operating practice for it to emulate.

Peer contributions describes extent of influence that the efficient warehouses have upon a given warehouse. Using Depot A as an example, the Depot I total labor value contribution is 32.11%. This indicates that Depot I exerted fairly significant influence over Depot A's efficiency rating. By contrast, Depot P is in the reference set that describes the overall efficiency of Depot A but has little significant influence. The level contribution to the efficiency of a DMU is a method for narrowing which peer DMU's to look for methods to improve efficiency.

The Input / Output Contribution section lists specific information about the weight that each input / output had in determining the DMU's efficiency. In the case of DMU A, the impact of total labor was negligible at 0.61%.

The Peer References is the set of efficient units to which an inefficient unit has been most directly compared with when calculating its efficiency rating. It is the same list as the peer contribution list but without the variables. The peer units are efficient units that have the most similar input / output orientation to the inefficient unit and they should provide examples of good operating practices for the inefficient DMU to emulate.

Depot A 24.70%

Potential Improvements

Variable	Actual	Target	Percent Change
Total Labor	24,566,463.0	6,067,371.9	-75.30%
Total Non-Labor	19,423,463.0	4,797,164.9	-75.30%
Depreciation	1,881,354.0	464,652.7	-75.30%
Receipt Processing	19.7	4.9	-75.30%
Line Items Shipped	301,323.0	301,323.0	0.00%

Peer Contributions

Peer	Variable	Contribution
Depot I	Total Labor	32.11%
Depot I	Total Non-Labor	51.39%
Depot I	Depreciation	68.35%
Depot I	Receipt Processing	49.66%
Depot I	Line Items Shipped	58.11%
Depot J	Total Labor	30.02%
Depot J	Total Non-Labor	16.37%
Depot J	Depreciation	3.05%
Depot J	Receipt Processing	25.82%
Depot J	Line Items Shipped	14.36%
Depot L	Total Labor	37.16%
Depot L	Total Non-Labor	28.85%
Depot L	Depreciation	28.07%
Depot L	Receipt Processing	23.99%
Depot L	Line Items Shipped	26.58%
Depot P	Total Labor	0.70%
Depot P	Total Non-Labor	3.39%
Depot P	Depreciation	0.53%
Depot P	Receipt Processing	0.54%
Depot P	Line Items Shipped	0.95%

Input / Output Contributions

Variable	Contribution	Input/Output
Total Labor	0.61%	Input
Total Non-Labor	14.40%	Input
Depreciation	44.46%	Input
Receipt Processing	40.54%	Input
Line Items Shipped	100.00%	Output

Peer References

DMU

Depot I, Depot J, Depot L, Depot P

Depot B 61.99%

Potential Improvements

Variable	Actual	Target	Percent Change
Total Labor	12,495,898.0	7,746,505.2	-38.01%
Total Non-Labor	12,807,757.0	7,939,834.0	-38.01%
Depreciation	964,102.0	597,669.8	-38.01%
Receipt Processing	12.9	7.1	-44.73%
Line Items Shipped	424,883.0	424,883.0	0.00%

Peer Contributions

Peer	Variable	Contribution
Depot I	Total Labor	42.39%
Depot I	Total Non-Labor	52.33%
Depot I	Depreciation	89.55%
Depot I	Receipt Processing	57.30%
Depot I	Line Items Shipped	69.46%
Depot J	Total Labor	50.52%
Depot J	Total Non-Labor	21.25%
Depot J	Depreciation	5.09%
Depot J	Receipt Processing	37.97%
Depot J	Line Items Shipped	21.88%
Depot P	Total Labor	7.09%
Depot P	Total Non-Labor	26.42%
Depot P	Depreciation	5.36%
Depot P	Receipt Processing	4.73%
Depot P	Line Items Shipped	8.67%

Input / Output Contributions

Variable	Contribution	Input/Output
Total Labor	32.32%	Input
Total Non-Labor	13.04%	Input
Depreciation	54.64%	Input
Receipt Processing	0.00%	Input
Line Items Shipped	100.00%	Output

Peer References

DMU

Depot I, Depot J, Depot P

Depot C 54.79%

Potential Improvements

Variable	Actual	Target	Percent Change
Total Labor	13,161,975.0	7,211,517.3	-45.21%
Total Non-Labor	11,171,090.0	6,120,700.7	-45.21%
Depreciation	416,236.0	228,058.0	-45.21%
Receipt Processing	23.9	5.4	-77.33%
Line Items Shipped	259,126.0	259,126.0	0.00%

Peer Contributions

Peer	Variable	Contribution
Depot I	Total Labor	12.34%
Depot I	Total Non-Labor	18.40%
Depot I	Depreciation	63.61%
Depot I	Receipt Processing	20.40%
Depot I	Line Items Shipped	30.87%
Depot J	Total Labor	78.37%
Depot J	Total Non-Labor	39.82%
Depot J	Depreciation	19.26%
Depot J	Receipt Processing	72.02%
Depot J	Line Items Shipped	51.81%
Depot P	Total Labor	9.28%
Depot P	Total Non-Labor	41.79%
Depot P	Depreciation	17.13%
Depot P	Receipt Processing	7.58%
Depot P	Line Items Shipped	17.33%

Input / Output Contributions

Variable	Contribution	Input/Output
Total Labor	49.33%	Input
Total Non-Labor	16.48%	Input
Depreciation	34.19%	Input
Receipt Processing	0.00%	Input
Line Items Shipped	100.00%	Output

Peer References

DMU

Depot I, Depot J, Depot P

Depot D 93.22%

Potential Improvements

Variable	Actual	Target	Percent Change
Total Labor	10,582,447.0	8,455,760.7	-20.10%
Total Non-Labor	11,477,174.0	10,698,642.2	-06.78%
Depreciation	2,529,399.0	1,378,256.3	-45.51%
Receipt Processing	25.6	10.5	-59.04%
Line Items Shipped	759,934.0	759,934.0	0.00%

Peer Contributions

Peer	Variable	Contribution
Depot I	Total Labor	100.00%
Depot I	Total Non-Labor	100.00%
Depot I	Depreciation	100.00%
Depot I	Receipt Processing	100.00%
Depot I	Line Items Shipped	100.00%

Input / Output Contributions

Variable	Contribution	Input/Output
Total Labor	0.00%	Input
Total Non-Labor	100.00%	Input
Depreciation	0.00%	Input
Receipt Processing	0.00%	Input
Line Items Shipped	100.00%	Output

Peer References

DMU

Depot I

Depot E 97.51%

Potential Improvements

Variable	Actual	Target	Percent Change
Total Labor	32,434,708.0	29,887,685.2	-07.85%
Total Non-Labor	63,812,151.0	33,892,937.0	-46.89%
Depreciation	6,751,858.0	4,673,165.5	-30.79%
Receipt Processing	5.3	5.2	-02.49%
Line Items Shipped	1,105,756.0	1,105,756.0	0.00%

Peer Contributions

Peer	Variable	Contribution
Depot O	Total Labor	100.00%
Depot O	Total Non-Labor	100.00%
Depot O	Depreciation	100.00%
Depot O	Receipt Processing	100.00%
Depot O	Line Items Shipped	100.00%

Input / Output Contributions

Variable	Contribution	Input/Output
Total Labor	0.00%	Input
Total Non-Labor	0.00%	Input
Depreciation	0.00%	Input
Receipt Processing	100.00%	Input
Line Items Shipped	100.00%	Output

Peer References

DMU

Depot O

Depot F 65.11%

Potential Improvements

Variable	Actual	Target	Percent Change
Total Labor	11,741,966.0	7,645,216.5	-34.89%
Total Non-Labor	8,618,466.0	5,611,499.7	-34.89%
Depreciation	615,262.0	400,598.3	-34.89%
Receipt Processing	16.5	6.4	-60.96%
Line Items Shipped	330,285.0	330,285.0	0.00%

Peer Contributions

Peer	Variable	Contribution
Depot I	Total Labor	28.09%
Depot I	Total Non-Labor	48.42%
Depot I	Depreciation	87.39%
Depot I	Receipt Processing	41.34%
Depot I	Line Items Shipped	58.44%
Depot J	Total Labor	69.89%
Depot J	Total Non-Labor	41.05%
Depot J	Depreciation	10.36%
Depot J	Receipt Processing	57.19%
Depot J	Line Items Shipped	38.42%
Depot P	Total Labor	2.02%
Depot P	Total Non-Labor	10.52%
Depot P	Depreciation	2.25%
Depot P	Receipt Processing	1.47%
Depot P	Line Items Shipped	3.14%

Input / Output Contributions

Variable	Contribution	Input/Output
Total Labor	41.03%	Input
Total Non-Labor	11.86%	Input
Depreciation	47.12%	Input
Receipt Processing	0.00%	Input
Line Items Shipped	100.00%	Output

Peer References

DMU

Depot I, Depot J, Depot P

Depot G 96.92%

Potential Improvements

Variable	Actual	Target	Percent Change
Total Labor	32,883,536.0	24,638,243.2	-25.07%
Total Non-Labor	35,039,440.0	33,959,298.1	-03.08%
Depreciation	3,004,092.0	2,911,486.5	-03.08%
Receipt Processing	17.2	16.7	-03.08%
Line Items Shipped	1,534,658.0	1,534,658.0	0.00%

Peer Contributions

Peer	Variable	Contribution
Depot I	Total Labor	35.14%
Depot I	Total Non-Labor	32.26%
Depot I	Depreciation	48.47%
Depot I	Receipt Processing	64.41%
Depot I	Line Items Shipped	50.70%
Depot K	Total Labor	48.75%
Depot K	Total Non-Labor	23.08%
Depot K	Depreciation	43.57%
Depot K	Receipt Processing	21.00%
Depot K	Line Items Shipped	31.95%
Depot P	Total Labor	16.12%
Depot P	Total Non-Labor	44.66%
Depot P	Depreciation	7.96%
Depot P	Receipt Processing	14.59%
Depot P	Line Items Shipped	17.35%

Input / Output Contributions

Variable	Contribution	Input/Output
Total Labor	0.00%	Input
Total Non-Labor	19.47%	Input
Depreciation	46.73%	Input
Receipt Processing	33.80%	Input
Line Items Shipped	100.00%	Output

Peer References

DMU

Depot I, Depot K, Depot P

Depot H 72.50%

Potential Improvements

Variable	Actual	Target	Percent Change
Total Labor	58,036,831.0	31,196,435.7	-46.25%
Total Non-Labor	34,615,487.0	25,095,712.4	-27.50%
Depreciation	1,789,196.0	1,297,140.4	-27.50%
Receipt Processing	25.0	18.1	-27.50%
Line Items Shipped	1,065,343.0	1,065,343.0	0.00%

Peer Contributions

Peer	Variable	Contribution
Depot J	Total Labor	32.57%
Depot J	Total Non-Labor	17.45%
Depot J	Depreciation	6.09%
Depot J	Receipt Processing	38.65%
Depot J	Line Items Shipped	22.65%
Depot L	Total Labor	59.63%
Depot L	Total Non-Labor	45.51%
Depot L	Depreciation	82.97%
Depot L	Receipt Processing	53.12%
Depot L	Line Items Shipped	62.04%
Depot P	Total Labor	7.80%
Depot P	Total Non-Labor	37.04%
Depot P	Depreciation	10.95%
Depot P	Receipt Processing	8.23%
Depot P	Line Items Shipped	15.32%

Input / Output Contributions

Variable	Contribution	Input/Output
Total Labor	0.00%	Input
Total Non-Labor	21.27%	Input
Depreciation	35.29%	Input
Receipt Processing	43.44%	Input
Line Items Shipped	100.00%	Output

Peer References

DMU

Depot J, Depot L, Depot P

Depot I 100.00%

Potential Improvements

Variable	Actual	Target	Percent Change
Total Labor	13,788,382.0	13,788,382.0	0.00%
Total Non-Labor	17,445,736.0	17,445,736.0	0.00%
Depreciation	2,247,453.0	2,247,453.0	0.00%
Receipt Processing	17.1	17.1	0.00%
Line Items Shipped	1,239,186.0	1,239,186.0	0.00%

Input / Output Contributions

Variable	Contribution	Input/Output
Total Labor	27.75%	Input
Total Non-Labor	4.42%	Input
Depreciation	0.00%	Input
Receipt Processing	67.83%	Input
Line Items Shipped	100.00%	Output

Depot J 100.00%

Potential Improvements

Variable	Actual	Target	Percent Change
Total Labor	26,394,392.0	26,394,392.0	0.00%
Total Non-Labor	11,380,554.0	11,380,554.0	0.00%
Depreciation	205,077.0	205,077.0	0.00%
Receipt Processing	18.2	18.2	0.00%
Line Items Shipped	626,914.0	626,914.0	0.00%

Input / Output Contributions

Variable	Contribution	Input/Output
Total Labor	0.00%	Input
Total Non-Labor	95.29%	Input
Depreciation	4.71%	Input
Receipt Processing	0.00%	Input
Line Items Shipped	100.00%	Output

Depot K 100.00%

Potential Improvements

Variable	Actual	Target	Percent Change
Total Labor	52,153,417.0	52,153,417.0	0.00%
Total Non-Labor	34,036,214.0	34,036,214.0	0.00%
Depreciation	5,509,085.0	5,509,085.0	0.00%
Receipt Processing	15.2	15.2	0.00%
Line Items Shipped	2,129,413.0	2,129,413.0	0.00%

Input / Output Contributions

Variable	Contribution	Input/Output
Total Labor	0.00%	Input
Total Non-Labor	27.34%	Input
Depreciation	0.00%	Input
Receipt Processing	72.66%	Input
Line Items Shipped	100.00%	Output

Depot L 100.00%

Potential Improvements

Variable	Actual	Target	Percent Change
Total Labor	52,747,963.0	52,747,963.0	0.00%
Total Non-Labor	32,379,651.0	32,379,651.0	0.00%
Depreciation	3,051,396.0	3,051,396.0	0.00%
Receipt Processing	27.3	27.3	0.00%
Line Items Shipped	1,873,826.0	1,873,826.0	0.00%

Input / Output Contributions

Variable	Contribution	Input/Output
Total Labor	0.00%	Input
Total Non-Labor	15.60%	Input
Depreciation	47.20%	Input
Receipt Processing	37.20%	Input
Line Items Shipped	100.00%	Output

Depot M 99.96%

Potential Improvements

Variable	Actual	Target	Percent Change
Total Labor	10,770,964.0	4,724,955.4	-56.13%
Total Non-Labor	5,980,574.0	5,978,244.9	-00.04%
Depreciation	813,385.0	770,149.5	-05.32%
Receipt Processing	7.9	5.9	-26.01%
Line Items Shipped	424,640.0	424,640.0	0.00%

Peer Contributions

Peer	Variable	Contribution
Depot I	Total Labor	100.00%
Depot I	Total Non-Labor	100.00%
Depot I	Depreciation	100.00%
Depot I	Receipt Processing	100.00%
Depot I	Line Items Shipped	100.00%

Input / Output Contributions

Variable	Contribution	Input/Output
Total Labor	0.00%	Input
Total Non-Labor	100.00%	Input
Depreciation	0.00%	Input
Receipt Processing	0.00%	Input
Line Items Shipped	100.00%	Output

Peer References

DMU
Depot I

Depot N 100.00%

Potential Improvements

Variable	Actual	Target	Percent Change
Total Labor	55,837,413.0	55,837,413.0	0.00%
Total Non-Labor	47,918,418.0	47,918,418.0	0.00%
Depreciation	2,944,285.0	2,944,285.0	0.00%
Receipt Processing	5.8	5.8	0.00%
Line Items Shipped	971,681.0	971,681.0	0.00%

Input / Output Contributions

Variable	Contribution	Input/Output
Total Labor	0.00%	Input
Total Non-Labor	0.00%	Input
Depreciation	35.47%	Input
Receipt Processing	64.53%	Input
Line Items Shipped	100.00%	Output

Depot O 100.00%

Potential Improvements

Variable	Actual	Target	Percent Change
Total Labor	47,421,059.0	47,421,059.0	0.00%
Total Non-Labor	53,775,960.0	53,775,960.0	0.00%
Depreciation	7,414,641.0	7,414,641.0	0.00%
Receipt Processing	8.2	8.2	0.00%
Line Items Shipped	1,754,439.0	1,754,439.0	0.00%

Input / Output Contributions

Variable	Contribution	Input/Output
Total Labor	0.00%	Input
Total Non-Labor	0.00%	Input
Depreciation	49.47%	Input
Receipt Processing	50.53%	Input
Line Items Shipped	100.00%	Output

Depot P 100.00%

Potential Improvements

Variable	Actual	Target	Percent Change
Total Labor	14,705,503.0	14,705,503.0	0.00%
Total Non-Labor	56,173,190.0	56,173,190.0	0.00%
Depreciation	858,131.0	858,131.0	0.00%
Receipt Processing	9.0	9.0	0.00%
Line Items Shipped	985,999.0	985,999.0	0.00%

Input / Output Contributions

Variable	Contribution	Input/Output
Total Labor	1.22%	Input
Total Non-Labor	0.00%	Input
Depreciation	10.88%	Input
Receipt Processing	87.90%	Input
Line Items Shipped	100.00%	Output

Depot Q 26.68%

Potential Improvements

Variable	Actual	Target	Percent Change
Total Labor	16,958,391.0	3,340,438.0	-80.30%
Total Non-Labor	15,842,420.0	4,226,485.7	-73.32%
Depreciation	3,490,338.0	544,478.5	-84.40%
Receipt Processing	16.5	4.1	-74.89%
Line Items Shipped	300,211.0	300,211.0	0.00%

Peer Contributions

Peer	Variable	Contribution
Depot I	Total Labor	100.00%
Depot I	Total Non-Labor	100.00%
Depot I	Depreciation	100.00%
Depot I	Receipt Processing	100.00%
Depot I	Line Items Shipped	100.00%

Input / Output Contributions

Variable	Contribution	Input/Output
Total Labor	0.00%	Input
Total Non-Labor	100.00%	Input
Depreciation	0.00%	Input
Receipt Processing	0.00%	Input
Line Items Shipped	100.00%	Output

Peer References

DMU
Depot I

Depot R 60.73%

Potential Improvements

Variable	Actual	Target	Percent Change
Total Labor	47,107,026.0	28,607,528.4	-39.27%
Total Non-Labor	37,543,903.0	22,799,959.2	-39.27%
Depreciation	10,860,291.0	3,425,930.0	-68.45%
Receipt Processing	19.9	12.1	-39.27%
Line Items Shipped	1,368,786.0	1,368,786.0	0.00%

Peer Contributions

Peer	Variable	Contribution
Depot I	Total Labor	15.15%
Depot I	Total Non-Labor	24.04%
Depot I	Depreciation	20.61%
Depot I	Receipt Processing	44.46%
Depot I	Line Items Shipped	28.45%
Depot K	Total Labor	74.14%
Depot K	Total Non-Labor	60.71%
Depot K	Depreciation	65.39%
Depot K	Receipt Processing	51.15%
Depot K	Line Items Shipped	63.27%

Input / Output Contributions

Variable	Contribution	Input/Output
Total Labor	49.86%	Input
Total Non-Labor	6.85%	Input
Depreciation	0.00%	Input
Receipt Processing	43.29%	Input
Line Items Shipped	100.00%	Output

Peer References

DMU

Depot I, Depot K

Appendix C: BCC Detailed Results

The interpretations of the BCC Frontier Analyst results are the same as for the CCR result in Appendix B and are not repeated here.

Depot A 43.84%

Potential Improvements

Variable	Actual	Target	Percent Change
Total Labor	24,566,463.0	10,769,713.4	-56.16%
Total Non-Labor	19,423,463.0	6,017,036.5	-69.02%
Depreciation	1,881,354.0	824,768.4	-56.16%
Receipt Processing	19.7	8.0	-59.20%
Line Items Shipped	301,323.0	301,323.0	41.66%

Peer Contributions

Peer	Variable	Contribution
Depot D	Total Labor	0.65%
Depot D	Total Non-Labor	1.27%
Depot D	Depreciation	2.03%
Depot D	Receipt Processing	2.11%
Depot D	Line Items Shipped	1.18%
Depot M	Total Labor	99.35%
Depot M	Total Non-Labor	98.73%
Depot M	Depreciation	97.97%
Depot M	Receipt Processing	97.89%
Depot M	Line Items Shipped	98.82%

Input / Output Contributions

Variable	Contribution	Input/Output
Total Labor	99.17%	Input
Total Non-Labor	0.00%	Input
Depreciation	0.83%	Input
Receipt Processing	0.00%	Input
Line Items Shipped	0.00%	Output

Peer References

DMU

Depot D, Depot M

Depot B 86.18%

Potential Improvements

Variable	Actual	Target	Percent Change
Total Labor	12,495,898.0	10,769,043.2	-13.82%
Total Non-Labor	12,807,757.0	6,036,577.8	-52.87%
Depreciation	964,102.0	830,869.1	-13.82%
Receipt Processing	12.9	8.1	-37.01%
Line Items Shipped	424,883.0	428,056.0	0.00%

Peer Contributions

Peer	Variable	Contribution
Depot D	Total Labor	1.00%
Depot D	Total Non-Labor	1.94%
Depot D	Depreciation	3.10%
Depot D	Receipt Processing	3.22%
Depot D	Line Items Shipped	1.81%
Depot M	Total Labor	99.00%
Depot M	Total Non-Labor	98.06%
Depot M	Depreciation	96.90%
Depot M	Receipt Processing	96.78%
Depot M	Line Items Shipped	98.19%

Input / Output Contributions

Variable	Contribution	Input/Output
Total Labor	99.16%	Input
Total Non-Labor	0.00%	Input
Depreciation	0.84%	Input
Receipt Processing	0.00%	Input
Line Items Shipped	0.00%	Output

Peer References

DMU

Depot D, Depot M

Depot C 100.00%

Potential Improvements

Variable	Actual	Target	Percent Change
Total Labor	13,161,975.0	13,161,975.0	0.00%
Total Non-Labor	11,171,090.0	11,171,090.0	0.00%
Depreciation	416,236.0	416,236.0	0.00%
Receipt Processing	23.9	23.9	0.00%
Line Items Shipped	259,126.0	259,126.0	0.00%

Input / Output Contributions

Variable	Contribution	Input/Output
Total Labor	33.54%	Input
Total Non-Labor	0.00%	Input
Depreciation	66.46%	Input
Receipt Processing	0.00%	Input
Line Items Shipped	0.00%	Output

Depot D 100.00%

Potential Improvements

Variable	Actual	Target	Percent Change
Total Labor	10,582,447.0	10,582,447.0	0.00%
Total Non-Labor	11,477,174.0	11,477,174.0	0.00%
Depreciation	2,529,399.0	2,529,399.0	0.00%
Receipt Processing	25.6	25.6	0.00%
Line Items Shipped	759,934.0	759,934.0	0.00%

Input / Output Contributions

Variable	Contribution	Input/Output
Total Labor	100.00%	Input
Total Non-Labor	0.00%	Input
Depreciation	0.00%	Input
Receipt Processing	0.00%	Input
Line Items Shipped	48.04%	Output

Depot E 100.00%

Potential Improvements

Variable	Actual	Target	Percent Change
Total Labor	32,434,708.0	32,434,708.0	0.00%
Total Non-Labor	63,812,151.0	63,812,151.0	0.00%
Depreciation	6,751,858.0	6,751,858.0	0.00%
Receipt Processing	5.3	5.3	0.00%
Line Items Shipped	1,105,756.0	1,105,756.0	0.00%

Input / Output Contributions

Variable	Contribution	Input/Output
Total Labor	0.00%	Input
Total Non-Labor	0.00%	Input
Depreciation	0.00%	Input
Receipt Processing	100.00%	Input
Line Items Shipped	0.00%	Output

Depot F 100.00%

Potential Improvements

Variable	Actual	Target	Percent Change
Total Labor	11,741,966.0	11,741,966.0	0.00%
Total Non-Labor	8,618,466.0	8,618,466.0	0.00%
Depreciation	615,262.0	615,262.0	0.00%
Receipt Processing	16.5	16.5	0.00%
Line Items Shipped	330,285.0	330,285.0	0.00%

Input / Output Contributions

Variable	Contribution	Input/Output
Total Labor	79.57%	Input
Total Non-Labor	0.00%	Input
Depreciation	20.43%	Input
Receipt Processing	0.00%	Input
Line Items Shipped	0.00%	Output

Depot G 97.07%

Potential Improvements

Variable	Actual	Target	Percent Change
Total Labor	32,883,536.0	31,676,850.8	-03.67%
Total Non-Labor	35,039,440.0	34,012,980.1	-02.93%
Depreciation	3,004,092.0	2,916,088.9	-02.93%
Receipt Processing	17.2	16.7	-02.93%
Line Items Shipped	1,534,658.0	1,534,658.0	0.00%

Peer Contributions

Peer	Variable	Contribution
Depot I	Total Labor	13.15%
Depot I	Total Non-Labor	15.50%
Depot I	Depreciation	23.29%
Depot I	Receipt Processing	30.95%
Depot I	Line Items Shipped	24.40%
Depot K	Total Labor	42.53%
Depot K	Total Non-Labor	25.85%
Depot K	Depreciation	48.80%
Depot K	Receipt Processing	23.51%
Depot K	Line Items Shipped	35.84%
Depot L	Total Labor	33.16%
Depot L	Total Non-Labor	18.96%
Depot L	Depreciation	20.84%
Depot L	Receipt Processing	32.56%
Depot L	Line Items Shipped	24.32%
Depot P	Total Labor	11.16%
Depot P	Total Non-Labor	39.69%
Depot P	Depreciation	7.07%
Depot P	Receipt Processing	12.97%
Depot P	Line Items Shipped	15.44%

Input / Output Contributions

Variable	Contribution	Input/Output
Total Labor	0.00%	Input
Total Non-Labor	19.33%	Input
Depreciation	47.45%	Input
Receipt Processing	33.22%	Input
Line Items Shipped	100.00%	Output

Peer References

DMU

Depot I, Depot K, Depot L, Depot P

Depot H 72.58%

Potential Improvements

Variable	Actual	Target	Percent Change
Total Labor	58,036,831.0	27,193,754.1	-53.14%
Total Non-Labor	34,615,487.0	25,124,353.5	-27.42%
Depreciation	1,789,196.0	1,298,620.8	-27.42%
Receipt Processing	25.0	18.1	-27.42%
Line Items Shipped	1,065,343.0	1,065,343.0	0.00%

Peer Contributions

Peer	Variable	Contribution
Depot I	Total Labor	9.72%
Depot I	Total Non-Labor	13.31%
Depot I	Depreciation	33.18%
Depot I	Receipt Processing	18.07%
Depot I	Line Items Shipped	22.30%
Depot J	Total Labor	40.67%
Depot J	Total Non-Labor	18.98%
Depot J	Depreciation	6.62%
Depot J	Receipt Processing	42.02%
Depot J	Line Items Shipped	24.66%
Depot L	Total Labor	39.60%
Depot L	Total Non-Labor	26.31%
Depot L	Depreciation	47.97%
Depot L	Receipt Processing	30.72%
Depot L	Line Items Shipped	35.91%
Depot P	Total Labor	10.01%
Depot P	Total Non-Labor	41.40%
Depot P	Depreciation	12.24%
Depot P	Receipt Processing	9.19%
Depot P	Line Items Shipped	17.14%

Input / Output Contributions

Variable	Contribution	Input/Output
Total Labor	0.00%	Input
Total Non-Labor	21.45%	Input
Depreciation	34.52%	Input
Receipt Processing	44.03%	Input
Line Items Shipped	98.82%	Output

Peer References

DMU

Depot I, Depot J, Depot L, Depot P

Depot I 100.00%

Potential Improvements

Variable	Actual	Target	Percent Change
Total Labor	13,788,382.0	13,788,382.0	0.00%
Total Non-Labor	17,445,736.0	17,445,736.0	0.00%
Depreciation	2,247,453.0	2,247,453.0	0.00%
Receipt Processing	17.1	17.1	0.00%
Line Items Shipped	1,239,186.0	1,239,186.0	0.00%

Input / Output Contributions

Variable	Contribution	Input/Output
Total Labor	0.00%	Input
Total Non-Labor	12.83%	Input
Depreciation	51.44%	Input
Receipt Processing	35.73%	Input
Line Items Shipped	98.99%	Output

Depot J 100.00%

Potential Improvements

Variable	Actual	Target	Percent Change
Total Labor	26,394,392.0	26,394,392.0	0.00%
Total Non-Labor	11,380,554.0	11,380,554.0	0.00%
Depreciation	205,077.0	205,077.0	0.00%
Receipt Processing	18.2	18.2	0.00%
Line Items Shipped	626,914.0	626,914.0	0.00%

Input / Output Contributions

Variable	Contribution	Input/Output
Total Labor	0.00%	Input
Total Non-Labor	16.38%	Input
Depreciation	9.19%	Input
Receipt Processing	74.43%	Input
Line Items Shipped	98.02%	Output

Depot K 100.00%

Potential Improvements

Variable	Actual	Target	Percent Change
Total Labor	52,153,417.0	52,153,417.0	0.00%
Total Non-Labor	34,036,214.0	34,036,214.0	0.00%
Depreciation	5,509,085.0	5,509,085.0	0.00%
Receipt Processing	15.2	15.2	0.00%
Line Items Shipped	2,129,413.0	2,129,413.0	0.00%

Input / Output Contributions

Variable	Contribution	Input/Output
Total Labor	0.00%	Input
Total Non-Labor	0.00%	Input
Depreciation	0.00%	Input
Receipt Processing	100.00%	Input
Line Items Shipped	261.52%	Output

Depot L 100.00%

Potential Improvements

Variable	Actual	Target	Percent Change
Total Labor	52,747,963.0	52,747,963.0	0.00%
Total Non-Labor	32,379,651.0	32,379,651.0	0.00%
Depreciation	3,051,396.0	3,051,396.0	0.00%
Receipt Processing	27.3	27.3	0.00%
Line Items Shipped	1,873,826.0	1,873,826.0	0.00%

Input / Output Contributions

Variable	Contribution	Input/Output
Total Labor	0.00%	Input
Total Non-Labor	0.00%	Input
Depreciation	100.00%	Input
Receipt Processing	0.00%	Input
Line Items Shipped	151.70%	Output

Depot M 100.00%

Potential Improvements

Variable	Actual	Target	Percent Change
Total Labor	10,770,964.0	10,770,964.0	0.00%
Total Non-Labor	5,980,574.0	5,980,574.0	0.00%
Depreciation	813,385.0	813,385.0	0.00%
Receipt Processing	7.9	7.9	0.00%
Line Items Shipped	424,640.0	424,640.0	0.00%

Input / Output Contributions

Variable	Contribution	Input/Output
Total Labor	0.00%	Input
Total Non-Labor	100.00%	Input
Depreciation	0.00%	Input
Receipt Processing	0.00%	Input
Line Items Shipped	99.94%	Output

Depot N 100.00%

Potential Improvements

Variable	Actual	Target	Percent Change
Total Labor	55,837,413.0	55,837,413.0	0.00%
Total Non-Labor	47,918,418.0	47,918,418.0	0.00%
Depreciation	2,944,285.0	2,944,285.0	0.00%
Receipt Processing	5.8	5.8	0.00%
Line Items Shipped	971,681.0	971,681.0	0.00%

Input / Output Contributions

Variable	Contribution	Input/Output
Total Labor	0.00%	Input
Total Non-Labor	0.00%	Input
Depreciation	42.32%	Input
Receipt Processing	57.68%	Input
Line Items Shipped	109.40%	Output

Depot O 100.00%

Potential Improvements

Variable	Actual	Target	Percent Change
Total Labor	47,421,059.0	47,421,059.0	0.00%
Total Non-Labor	53,775,960.0	53,775,960.0	0.00%
Depreciation	7,414,641.0	7,414,641.0	0.00%
Receipt Processing	8.2	8.2	0.00%
Line Items Shipped	1,754,439.0	1,754,439.0	0.00%

Input / Output Contributions

Variable	Contribution	Input/Output
Total Labor	0.00%	Input
Total Non-Labor	0.00%	Input
Depreciation	56.66%	Input
Receipt Processing	43.34%	Input
Line Items Shipped	104.99%	Output

Depot P 100.00%

Potential Improvements

Variable	Actual	Target	Percent Change
Total Labor	14,705,503.0	14,705,503.0	0.00%
Total Non-Labor	56,173,190.0	56,173,190.0	0.00%
Depreciation	858,131.0	858,131.0	0.00%
Receipt Processing	9.0	9.0	0.00%
Line Items Shipped	985,999.0	985,999.0	0.00%

Input / Output Contributions

Variable	Contribution	Input/Output
Total Labor	54.36%	Input
Total Non-Labor	0.00%	Input
Depreciation	0.00%	Input
Receipt Processing	45.64%	Input
Line Items Shipped	146.40%	Output

Depot Q 63.35%

Potential Improvements

Variable	Actual	Target	Percent Change
Total Labor	16,958,391.0	10,743,949.6	-36.65%
Total Non-Labor	15,842,420.0	6,768,234.6	-57.28%
Depreciation	3,490,338.0	1,059,289.1	-69.65%
Receipt Processing	16.5	10.5	-36.65%
Line Items Shipped	300,211.0	472,687.5	57.45%

Peer Contributions

Peer	Variable	Contribution
Depot D	Total Labor	14.11%
Depot D	Total Non-Labor	24.30%
Depot D	Depreciation	34.22%
Depot D	Receipt Processing	35.09%
Depot D	Line Items Shipped	23.04%
Depot M	Total Labor	85.89%
Depot M	Total Non-Labor	75.70%
Depot M	Depreciation	65.78%
Depot M	Receipt Processing	64.91%
Depot M	Line Items Shipped	76.96%

Input / Output Contributions

Variable	Contribution	Input/Output
Total Labor	98.97%	Input
Total Non-Labor	0.00%	Input
Depreciation	0.00%	Input
Receipt Processing	1.03%	Input
Line Items Shipped	0.00%	Output

Peer References

DMU

Depot D, Depot M

Depot R 63.93%

Potential Improvements

Variable	Actual	Target	Percent Change
Total Labor	47,107,026.0	30,115,412.0	-36.07%
Total Non-Labor	37,543,903.0	24,001,729.7	-36.07%
Depreciation	10,860,291.0	3,552,295.1	-67.29%
Receipt Processing	19.9	12.7	-36.07%
Line Items Shipped	1,368,786.0	1,368,786.0	0.00%

Peer Contributions

Peer	Variable	Contribution
Depot I	Total Labor	11.13%
Depot I	Total Non-Labor	17.67%
Depot I	Depreciation	15.38%
Depot I	Receipt Processing	32.67%
Depot I	Line Items Shipped	22.00%
Depot K	Total Labor	60.39%
Depot K	Total Non-Labor	49.45%
Depot K	Depreciation	54.08%
Depot K	Receipt Processing	41.67%
Depot K	Line Items Shipped	54.25%
Depot M	Total Labor	10.52%
Depot M	Total Non-Labor	7.33%
Depot M	Depreciation	6.74%
Depot M	Receipt Processing	18.31%
Depot M	Line Items Shipped	9.13%

Input / Output Contributions

Variable	Contribution	Input/Output
Total Labor	37.17%	Input
Total Non-Labor	14.14%	Input
Depreciation	0.00%	Input
Receipt Processing	48.69%	Input
Line Items Shipped	76.65%	Output

Peer References

DMU

Depot I, Depot K, Depot M

CURRICULUM VITAE

Randal Jay Zimmerman was born on August 6, 1963 in Mason City, Iowa to Ronald and Ingrid Zimmerman. He received his Bachelor of Science degree in Business Administration from Minnesota State University in August 1985.

After graduating from Minnesota State University, he has served in a variety of infantry leadership positions. While serving as a Company Commander, he commanded more than 600 soldiers and was personally responsible for their training, health, and welfare. He has made more than 150 parachute jumps from various aircraft.

He received his Master of Science degree in Mineral Economics from the Colorado School of Mines in May 1996. After graduating from the Colorado School of Mines, he specialized in operations research and helped to solve a number of challenging logistical problems for the Defense Logistics Agency. While serving at the Defense Logistics Agency, he co-founded the OffSite Travel Optimization Government Reinvention Laboratory sponsored by Vice-President Gore. The laboratory generated more than $1 million dollars of savings in its first year of operation.

His accomplishments include selection by Government Executive Magazine as the 1998 Travel Manager of the Year for his work on OffSite. In July 1998, he was selected as a Walden National Service Fellow for his service to the nation. He is active in several operations research professional organizations, Informs and the Military Operations Research Society.

He enjoys coaching his children's youth teams, both soccer and baseball, and enjoys playing softball, riding mountain bikes, and other outdoor activities.