

The Measurement and Empirical  
Evaluation of Quality and Productivity  
for Manufacturing Processes

by

Robert J. McNelis, Jr.

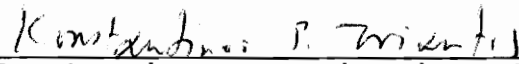
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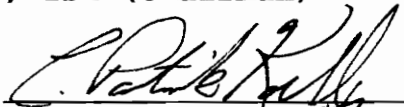
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**ABSTRACT**

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Evaluation of Quality and Productivity  
for Manufacturing Processes**

by

**Robert J. McNelis, Jr.**

**Chairman: Konstantinos P. Triantis**

**Department: Industrial and Systems Engineering**

This research investigates the conceptual relationships among quality costs, productivity, and quality proposed by Garvin, Juran, and Feigenbaum. It provides an empirical evaluation of these relationships by applying a specific linear programming approach, namely, Data Envelopment Analysis (DEA), to various production specifications developed for a linerboard manufacturing case study. The research investigates the changes in the efficiency values when various models derived from these quality, productivity, and cost specifications are evaluated. The use of DEA as a method to support the modeling of these relationships is also discussed. The I.D.E.A.S. software program developed by Ali is used to implement DEA in the research.

## DEDICATION

To my wife, Amy, for her endless patience and support, and to our daughter, Bridget, whose enthusiasm for life has been an encouragement.

## ACKNOWLEDGEMENTS

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My thanks also to Dr. Iqbal Ali of University of Massachusetts-Amherst, Department of General Business and Finance, for the I.D.E.A.S. software used in this research. His assistance in providing updated versions of the software, drafts of instruction manuals, and various working papers on I.D.E.A.S. were greatly appreciated.

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## CHAPTER 1. OVERVIEW

### 1.1. Introduction

Organizations are undergoing a shift in the perception of quality from "a narrowly focused, inspection-based activity to a multifaceted, prevention-based discipline" [Hart(1992), p.88]. Quality improvement was once considered possible only with costly increases in labor and capital expenditures, thus sacrificing productivity gains, increasing production costs, and ultimately reducing profits. In its expanded definition, however, quality improvement has become the key to increased profitability, productivity, and market share, and reduced cost.

The concept of strategic quality management is anchored in this new approach to quality. It asserts that business plans should no longer be structured to target profitability improvements through the short-term "fixes" of raising prices or cutting costs. Rather, "quality goals can and should be the cornerstone of the business plan" [Hart(1992), p.124]. The approach further contends that quality is a battle ground and that organizations need to consider quality improvement as an opportunity to obtain a major competitive advantage in the marketplace.

Widespread acceptance of strategic quality management concepts and therefore the resulting conclusion that quality



should be the primary goal of any organization, however, has been hampered by a shortage of organizational performance modeling research providing overwhelming empirical evidence to support claims of a positive relationship between quality, productivity, and cost reduction<sup>(1)</sup>. The motivation of this research is to: (1) present empirical evidence supporting some of these assertions by evaluating various models having quality, productivity, and cost specifications for an identified case study, and (2) propose an effective tool that can be used to assist organizations in modeling and improving these performance measures.

## **1.2. Research Goals and Objectives**

There are two primary goals of this research. The first is to develop cost, production, and quality specifications that will facilitate the study of the relationships among cost, productivity, and quality in the short run<sup>(2)</sup>. The second is to empirically evaluate these specifications for a proposed case study using a specific linear programming approach, namely, Data Envelopment Analysis [Charnes, Cooper, Rhodes (1978)]. The specific objectives of this research are as follows:

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1. One of the fundamental weaknesses of the quality management paradigm is that it lacks empirical evidence.

2. Short run in this research refers to the time period where only operational performance is studied and technological change does not take place.

1. To empirically evaluate the relationships among prevention, appraisal, and failure quality costs, and how these costs impact quality and productivity performance.

The cost of poor quality, or quality costs, serve several purposes in a manufacturing system. First, they quantify quality-related problems in financial terms that will have an impact on upper management decision making. Second, they identify the segments of the cost control system that represent the most significant opportunities for total reductions in costs due to poor quality. Third, they provide opportunities to reduce customer dissatisfaction by addressing the after-the-sale costs due to poor quality that are often bore by the customer. Fourth, they expand cost control systems to address such costs as scrap, rework and warranty returns from an interdepartmental perspective. These costs, for departments outside of quality control, are often left uncaptured. Finally, if supplemented with a structured improvement program, publication of such cost data can stimulate responsible managers to initiate corrective actions [Juran (1988), p. 4.3].

There is limited research on how quality cost components can be effectively modelled. Currently, only general relationships among the cost categories have been well documented. More detailed case study analyses will contribute valuable insight into how the controllable cost

components (prevention and appraisal) can be managed to reduce internal and external failure costs and subsequently total quality costs in various technologies.

This research will also address whether these cost components can be related to quality measures. Many differing measures of quality have been defined and analyzed by researchers [Garvin(1988), Juran(1974,1988,1993), Lancaster(1979), Taguchi(1978)]; however, few have investigated the interrelationships among quality measures and quality cost components. This research attempts to model the association of quality cost components to specific dimensions of quality defined by Garvin(1988).

Another related objective of this research is to determine whether quality cost components can be related to productivity measures. Minimal research has addressed the relationship between quality cost management and its impact on productivity.

## **2. To study the relationship between quality and productivity performance in the short run.**

As Garvin comments, "The mechanisms connecting [quality and productivity] are only dimly understood" [Garvin(1988),p.89]. Therefore, another objective of this research is to provide insight into how the **quantity** of "good" output produced is related to the **quality** of output produced. Although many researchers advocate that quality

and productivity are positively correlated in the long run, few have considered the relationship in the short term. Unfortunately, organizational decision making is often based on short-run quality and productivity measurement and evaluation. Investigating this short-run relationship will aid organizations in understanding not only how variability in one of these performance measures impacts the other, but more importantly, how each can be simultaneously improved.

In this study, in order to understand the short run relationship between quality and productivity, production function specifications are augmented to include quality dimensions. The results of these augmented specifications incorporating the quality dimensions are evaluated in relation to the original production function specifications to provide insight into the impact of quality performance on productivity. The levels of input resources required to facilitate organizational efficiency with respect to output quantity will be compared to required levels of these same resources when the output measure is quality. This investigation will provide evidence as to whether quality and productivity are competing interests, or organizational objectives that can be met simultaneously in the short term, through appropriate allocations of input resources. A positive relationship between quality and productivity can be confirmed through an analysis of these resource

allocations because "a better understanding of the connection between quality and productivity requires an examination of their common sources of improvement" [Garvin (1988), p.84].

**3. To evaluate Data Envelopment Analysis as a method to support the modeling of the relationships among productivity, quality, and quality costs.**

This research uses Data Envelopment Analysis (DEA) as a tool for modeling the relationships among productivity, quality, and quality costs. "DEA involves an application of mathematical programming to observed data to locate frontiers which can then be used to evaluate the efficiency of each of the (processes) responsible for the observed output and input quantities" [Banker, et al.(1989),p.127].

The technique compares the efficiency of similar observations, called decision making units (DMUs), "by explicitly considering their use of multiple inputs (resources) and multiple outputs. It provides a measure of efficiency that is explicitly sensitive to the output mix" [Sherman(1984),p.12]. Implementation of this technique highlights the inefficient DMUs, from a relative standpoint, and identifies the amounts of inefficiency in each of the inputs and outputs [Banker, et al.(1989), p.127].

DEA has been an effective technique in productivity measurement. This technique allows the organization to

locate and subsequently reduce inefficiencies in the manufacturing process, either by increasing production throughput at constant levels of input resource usage (output increasing efficiency) or by decreasing input resource usage required to meet output requirements (input reducing efficiency) [Fare, Lovell (1978)].

There is limited research, however, applying DEA to models having quality and quality cost specifications. This thesis applies the technique to models constructed with quality-related input and output measures. The resulting efficiency performance measures not only provide an empirical investigation of the productivity-quality link, but also serve to evaluate the feasibility of DEA's use outside its traditional application of measuring and evaluating technical efficiency.

### **1.3. General Description of Methodology**

The first step of the methodology is to identify input/output specifications necessary to model the conceptual quality, cost, and productivity links discussed by researchers such as Juran and Garvin. Next, a specific technology is chosen as a case study for the evaluation of these relationships. Given the data available in the chosen case study, various production function specifications are defined. These specifications are empirically evaluated

using a computational approach called Data Envelopment Analysis. The organizational performance measures calculated by this approach are studied to determine if the conceptual associations are present in the specific application. Conclusions on the relationships among quality costs, quality, and productivity based on these model results are then presented. Finally, recommendations for future research with respect to modeling these performance measures are discussed.

#### **1.4. Assumptions**

This research is not intended to provide a specific quality and productivity improvement strategy; rather, it is a general investigation of the interrelationships among quality costs, quality, and productivity. An understanding of the fundamental relationships among these performance measures is necessary for the development of any effective improvement technique.

A case study approach is used in this research. That is, the production function specifications are applied to a specific technology to provide an empirical evaluation of the theoretical associations discussed in Chapter 2, which is the Literature Review. The results of this study may not be capable of extrapolation to other technologies. The methodology presented in this research, however, may be

applied to any technology to verify any reported relationships.

The case study identified for this research has been previously evaluated by Triantis (1984) using production function-based specifications. This research is concerned with augmenting the specifications developed during that study with quality-related inputs and outputs. The efficiency measures and relative ranks of observations derived during the initial study are assumed accurate. No additional verification of these results are included. Further, the initial evaluation of the data set by Seaver and Triantis (1989) determined that observation 20 was characterized by 90% idle time, and isolated it as an outlier, that is, "an observation (or a subset of observations) which appears to be inconsistent with the remainder of that set of data" [Barnett and Lewis(1984), p.4]. This observation has therefore been removed from the data set prior to this analysis<sup>(3)</sup>.

Data limitations in the selected case study dictate the development of static, short run models of quality,

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3. Observation 20 was characterized by extensive down time and limited production of specialized basis weight products. Although CCR and BCC formulations were attempted with the observation included, every model identified this month as the only efficient month, with all others having an efficiency value less than 0.10. Deleting the outlier from the study facilitated a more meaningful empirical evaluation of quality, productivity, and cost in this application. Additionally, Seaver and Triantis (1992,1994) have identified this observation as an influential data point.



productivity, and quality cost. This narrows the scope of this investigation to organizational performance modeling in the short run. Modeling of long run relationships, especially those involving quality cost expenditures, may not have the same results.

Quality cost components in any of the production function specifications are based on the definitions given by Juran and detailed in *The Quality Control Handbook* (1988). It is assumed that the data set generated from the case study contains sufficient information to provide accurate measurements of these cost components.

This research is confined to only two of the many dimensions of quality outlined by Garvin (1988). A product-based definition of quality is applied to the case study to investigate the performance dimension<sup>(4)</sup>, while a manufacturing-based definition is used to evaluate the conformance dimension<sup>(5)</sup>. These two dimensions lend themselves to empirical analysis; their measures focus on the production process and on the quantities of inherent product characteristics. Since many other dimensions are not included in this research, only a subset of all quality

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4. These measures will focus on quality defined as quantities of specified attributes that are considered primary operating characteristics of the product.

5. These measures will focus on quality defined as the degree to which products from the manufacturing process meet specifications of design.

measurements are evaluated. Conclusions regarding the relationships among quality, quality cost, and productivity may therefore be biased given these limitations. Although other dimensions of quality, such as durability, serviceability, and reliability can be applied using this same methodology, the use of these dimensions may result in different relationships among quality, cost, and productivity.

#### **1.5. Organization of the Thesis**

Chapter 1 discusses the need for identifying the relationships among quality costs and their impact on quality and productivity performance. It also states the objectives of this thesis; first, to examine these various relationships in the short run, and second, to introduce DEA as one possible tool to model these relationships. The specific assumptions and assertions of the research, and an overview of the methodology used to study these relationships are also presented. Chapter 2 discusses the relevant research in the measurement and modeling of quality, the quality-cost and the quality-productivity relationships, and previous applications of DEA. Chapter 3 presents a methodology for accomplishing each of the objectives defined in Chapter 1, and then applies the methodology to the specific case study of a linerboard

manufacturing facility. Chapter 4 summarizes and interprets the results of the analyses presented in Chapter 3. Chapter 5 discusses conclusions of the research. Chapter 6 provides recommendations for future research in the area of productivity, quality, and cost modeling.

## CHAPTER 2. LITERATURE REVIEW

### 2.1. Defining Quality

The most extensive discussion of the various views of quality is provided by Garvin in *Managing Quality* (1988). He explores five distinct, and often competing, viewpoints of quality: transcendent, user-based, value-based, manufacturing-based, and product-based. The ambiguity of the term "quality", and the difficulty of addressing its improvement is rooted in an understanding of these various definitions and how they are embraced by different groups within an organization.

The transcendent definition explores the most philosophical definition of quality. It emphasizes product or manufacturer reputation, and because of its subjectivity, has little quantitative merit. It is an elusive definition that provides organizations limited empirical means by which to measure and improve product quality.

Quality expressed by the user-based definition, often advocated by marketing personnel, is based on meeting consumer requirements. "User based definitions start from the premise that quality 'lies in the eyes of the beholder'" [Garvin(1988),p.43]. This approach emphasizes the ability for successful organizations to identify product attributes that are preferred among the majority of the users, and an

end product design that is receptive to those critical parameters. There are two problems with this approach,

the first is practical: how to aggregate widely varying individual preferences so that they lead to meaningful definitions of quality at the market level. The second is more fundamental: how to distinguish those product attributes that connote quality from those that simply maximize consumer satisfaction [Garvin(1988), p.43].

In the value based approach, quality is identified by the consumer as an acceptable balance between excellence and worth. Here, quality is subjectively identified by a product that "provides performance or conformance at an acceptable price or cost" [Garvin(1988),p.45]. Surveys have shown that consumers are not purchasing products on the basis of higher performance or lower cost alone, but rather the combination of the two. However, quantifying two concepts like excellence and worth can lead to difficulties in empirical evaluation of quality measures based on this definition.

Next, there is the manufacturing-based definition. Whereas the user based, value based, and transcendent definitions are oriented toward the consumer, this approach centers around engineering design and production considerations. Here, quality is conformance to the specifications of design; any variation in these specifications leads to economic penalties in the form of high defect and scrap rates. This is the most common

definition of quality utilized in the development of measures for the evaluation of industrial processes. Taguchi(1978) also stresses this approach in defining quality. He advocates the development of a "loss function" quantifying the loss that a product imparts on society from the time that it is produced [Garvin(1988), p.54]. A reliance on this definition of quality has weaknesses, as well; it often results in limiting the link between quality and product characteristics by focusing only on the internal measure of conformance [Garvin(1988),p.45].

Finally, as explained by Garvin, the product-based approach implies that "differences in quality reflect differences in the quantity of some ingredient or attribute possessed by a product" [Garvin(1988),p.42]. Because quality is linked to the quantity of an attribute, high quality using this definition can usually only be achieved at a higher cost. Further, assuming that all customers have similar preferences in product attributes, quality simply becomes a matter of maximizing the quantity of the critical attributes at a minimum cost. This approach is quite consistent with the definition of quality advocated by Lancaster(1979). He states that a product is merely a bundle of characteristics, and that level of "quality" is represented by the amount of these characteristics per unit of quantity. Consumers will perceive higher quality as one

that has more desirable characteristics per unit. The weakness in this approach is the assumption that all consumers will identify the same characteristics as desirable. The product-based definition "fails to accommodate differences in tastes" [Garvin(1988),p. 43].

Only after an organization has defined quality can it pursue an effective measurement and improvement program. Several researchers have studied how to best quantify product quality requirements. Garvin states that it is imperative to measure quality through variables that address various, often competing, components called "dimensions". Specifically, these dimensions include: performance (how well the primary operating characteristics of a product are executed); features (how many secondary characteristics supplement the product's basic functioning); reliability (the probability that the product will malfunction within a specified time period); conformance (the degree to which the product meets its specifications of design); durability (the amount of use one gets from the product before it breaks down and replacement is preferable to repair); serviceability (the ease of repair or replacement of a product or its components); aesthetics (how appealing the product looks, feels, sounds, tastes, or smells); and perceived quality (the reputation that the product possesses) [Garvin(1988), p.50].

The scope of the definition of quality used in this research is limited by the use of ex-post production and accounting statements in the given case study. Two of Garvin's eight dimensions of quality will be empirically evaluated. Measures derived from the product-based definition will be used to evaluate the performance dimension of quality while measures derived from the manufacturing-based definition will be used to evaluate the conformance dimension of quality.

## **2.2. The Relationships among Quality Costs and Between Quality Costs and Product Quality**

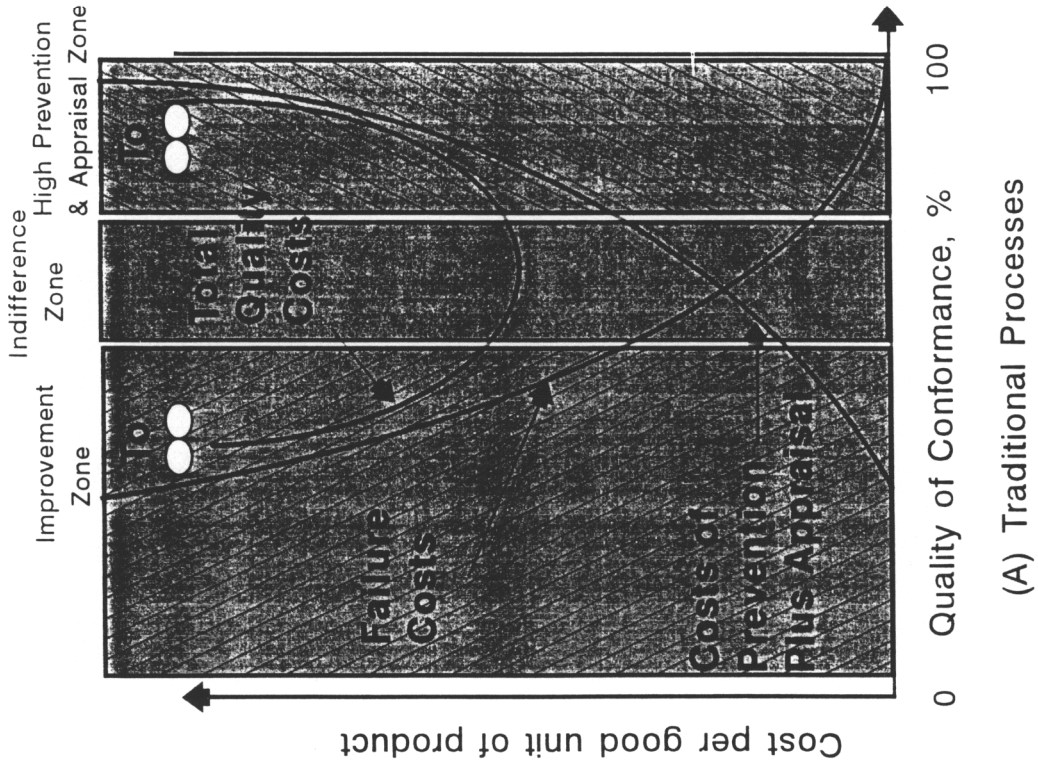
In *The Quality Control Handbook* (1988), Juran defines total quality cost as the cost of poor quality. Quality costs, he claims, provide a method of quality measurement for the production process by converting quality into economic measures. Any cost that is the result of the production of a defective product is a quality cost.

Quality costs described by Juran can be segregated into four categories. Internal Failure Costs are "costs associated with defects that are found prior to transfer of the product to the customer" [Juran(1988), p.4.5]. They include such costs as scrap, rework, sorting, re-inspection and re-testing. External Failure Costs are those "costs associated with defects that are found after product is

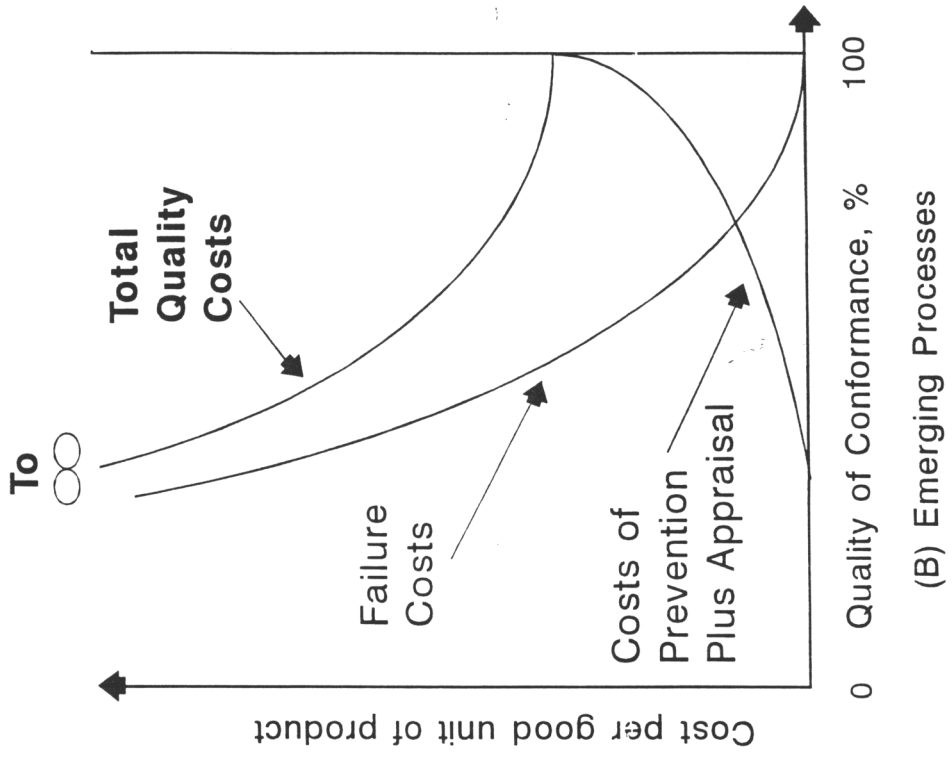


shipped to the customer" [Juran(1988), p.4.5]. Examples of these costs include warranty replacement, allowances, field service repairs, and the handling of customer complaints. These two categories represent the costs that would disappear in the event of a defect-free product. Appraisal Costs are "those costs incurred to determine the degree of conformance to quality requirements" [Juran(1988), p.4.5]. Examples of these costs are labor and material costs of inspections to incoming, in-process, and final product, test and measurement equipment calibration, and the evaluation of stock. Prevention costs are defined as "costs incurred to keep failure and appraisal costs to a minimum" [Juran(1988), p.4.4]. Quality planning, training, supplier certification, and new product reviews are examples of these types of costs.

The relationship among these four cost categories is illustrated in Figure 1 [Juran(1993), p.25]. The X-axis of each graph is quality, as measured by conformance to established specifications. The Y-axis is the cost of each good unit of output. Both models demonstrate that prevention and appraisal costs are zero at 0% conformance, but rise at different rates as perfection is approached. Model A in Figure 1 assumes that human inspection will never achieve perfection, no matter what level of prevention and appraisal investment; model B of Figure 1, however,



(A) Traditional Processes



(B) Emerging Processes

Figure 1. Interrelationships Among Quality Cost Components

represents late twentieth century conditions where "priorities on prevention became higher. New technology reduced the inherent failure rates of materials and products" [Juran(1988), p.4.19]. Further, the recent introduction of more automated processes has reduced human error during production and inspection. "Collectively, these developments have resulted in an ability to achieve perfection at finite costs" [Juran(1988), p.4.19].

The models also demonstrate that failure costs should move in an opposite direction to prevention and appraisal costs. This claim is rooted in the assumption that the most costly condition is when a customer finds a defect. Defects, and their resulting costs, can be reduced by early prevention and inspection prior to extensive value-adding activities. Therefore, as investments of prevention and appraisal expenditures are made, quality of conformance is increased, the possibility of early detection is increased, and the cost of each of those defects is lower.

The total quality cost curve in Model A of Figure 1 can be separated into three zones, the improvement zone, the indifference zone, and the high prevention and appraisal cost zone. Total quality costs are minimized at the center of the indifference zone. This is the point at which cost of improvement projects intended to decrease total quality costs actually become higher than the savings gained from

these projects. When these projects are undertaken, the organization shifts to the high appraisal zone. Here, auditing and other methods of reduced inspection should be considered to achieve an equivalent level of quality at a lower total cost. Finally, when prevention and appraisal costs are too low, the organization is in the quality improvement zone. Here, "the approach is to identify specific improvement projects and pursue them to improve the quality of conformance and thereby reduce the costs of poor quality" [Juran(1988), p.4.19].

Several researchers have further analyzed the interrelationships of quality costs. Campanella and Corcoran (1983) consider Model A depicted in Figure 1, but emphasize the distinct effects of prevention and appraisal. They assert that "an increase in the cost of prevention should result in a larger decrease in the cost of failure, thereby reducing total quality costs" [Campanella(1989), p.105]. Further, these prevention costs may also cause appraisal costs to decrease. Similarly, increases in appraisal costs reduce total failure costs because they help to identify more nonconforming products prior to distribution, thus decreasing external costs. Campanella and Corcoran state that since these relationships hold true only until the "point of saturation", when quality improvement investments become larger than their realized

savings, the identification of this optimum point should be part of the quality cost analysis. However, "it should be obvious that increases in expenditures for prevention and appraisal will not show immediate reductions in failure costs because of the time lag between cause and effect" [Campanella(1989), p.105]. The authors present a study where several measurement bases are specified, the ratio of total quality cost to each of these measurement bases is calculated, and these ratios are depicted in charts for trending purposes. These quality cost index charts were used to highlight the cause and effect lags for prevention and appraisal costs observed in the study.

Kume (1985) confirms the need for additional research in modeling quality costs in his discussion of model A in Figure 1. He claims that conceptually, the figure is correct, but "failure cost and prevention and appraisal cost should be considered separately. Failure costs represent waste; they are genuine losses, because they would not be expended if quality were perfect" [Kume(1985), p.18]. Prevention and appraisal costs, however, are spent to reduce failure, and while lower prevention and appraisal costs result in higher failure costs, higher expenditures do not necessarily result in decreased failure costs. The quality of the prevention and appraisal expenditures, and not the quantity, is important.

Many authors have advocated use of these total quality costs as an effective means of measuring and monitoring organizational quality. Sullivan (1983) proposes that the definition, measurement, and improvement of quality be accomplished entirely through quality costs. Quality of the process, he states, can be measured by lost revenue attributed to defects. He details an accounting system of quality costs that uses pareto analysis to highlight opportunities for process quality improvement.

Researchers have also linked quality costs to other measures of product quality. Most of the studies have asserted a negative relationship between the various quality dimensions and total quality costs. For example, many claim that poor conformance leads to excessive failure costs in the form of scrap, rework, field repairs, and warranty claims. Garvin (1988) completed a study of U.S. and Japanese manufacturers of air conditioners. The companies were ranked and grouped by defect and field failure performance. The results illustrated that "improved conformance and reliability were strongly associated with lower quality costs. As expected, warranty costs rose as quality declined--an increase in field failures meant an increase in the volume of repair. More significantly, when quality declined, total quality costs rose as well" [Garvin(1988), p.83].

In this research, we are primarily concerned with the relationship among the quality cost components and their effect on measures of quality in the short run. Inputs for each of the production models will be prevention and appraisal cost measures, while outputs will be failure cost, conformance, or performance measures. The effect of each of these components on total quality costs will be empirically evaluated. Juran's claims of a positive relationship between prevention and appraisal costs and improved conformance will also be investigated.

### **2.3. The Productivity-Quality Link**

Garvin (1988) discusses how productivity is affected by the quality of the input and outputs of a production process and notes that there is an important distinction between these performance measures in the short-run versus the long-run. In the short-run, when quality can be measured in terms of reliability or conformance and productivity in terms of a total productivity, these variables may move in opposite directions. It is inevitable that new corrective action, training, and other quality planning and improvement programs will initially slow down production. However, once the up-front investments of time and money have been realized and these programs have been adopted, the long-term relationship between the two measures is positive. This

positive correlation, Garvin (1988) asserts, is due to their common sources of improvement: efforts to simplify assembly reduce opportunities for human error and decrease labor costs for manufacturing and rework; capital expenditures for improved equipment combined with preventive maintenance reduce down time and delayed orders; and training increases efficiency and decreases defects due to human error [Garvin(1988), p.85].

Feigenbaum (1981) claims that the positive relationship between productivity and quality is clear when a more accurate definition of productivity is identified. "Junk output", those products which are defective and not sellable, should not be included in productive output rates, because they have no business value. Additionally, he indicates that many companies devote up to 40% of their resources to rework, re-test, and field service for their poor quality products. There is no better way to reduce total costs, and increase quality and true productivity, than to convert this "hidden" plant into productive use. Feigenbaum concludes that the only way to improve productivity is to use preventive measures to eliminate failure costs.

Scherkenbach (1992) extends this claim of a positive relationship between productivity and quality by emphasizing the long-term benefits:



Reduction of waste transfers man hours and machine hours from the manufacture of defectives into the manufacture of additional product. In effect, the capacity of a production line is increased. The benefits of better quality through improvement of the process are thus not just better quality, and the long-range improvement of market share that goes along with it, but greater productivity and much better profit as well [Scherkenbach(1992), p.19].

Several case studies supporting this contention have been documented. Williams (1984), describes the effects of improved preventive maintenance and employee training on the output of an injection molding process. In the study, productivity ratios are based on output quantity measures such as the number of units produced in each direct labor hour and the value of sales for each direct labor hour worked. Quality is defined as conformance to requirements and numerical measurements are developed to determine the cost of defects. Pareto analysis is then employed to identify key improvement areas. Day (1988) defines a loss function based on Taguchi concepts. He demonstrates that an increase in conformance causes a decreased scrap and rework rate, an increased rate of productivity, and a decreased loss function. Chandra and Ullman (1986) state that "there is a direct and immediate connection between quality and productivity in that the output measures should really be deflated by the proportion of product that does not work at all, and the labor and other inputs increased by any repairs required to make the product work" [Chandra and Ullman(1986), p.2]. They then propose that the quality-

productivity link be modeled by incorporating a quality measure into the traditional input-output specification for productivity. According to Chandra and Ullman, the output function **OUTPUT = F(LABOR, CAPITAL, MATERIAL, ENERGY, QUALITY COSTS)** should be investigated at all levels of the economy for this purpose.

These studies assert that productivity and quality, when defined properly, are positively correlated in the long term, but they differ in their conclusions of their short term relationship. This research will empirically evaluate the short term link between the performance and conformance dimensions of quality and productivity by comparing efficiency measures that are derived from input and output quantity measures with those efficiency measures that are derived from some combination of input/output quantity and quality measures.

#### **2.4. Measurement of Efficiency of Production**

A production technology which transforms  $n$  inputs represented by the  $n \times 1$  column vector  $X^i = (x_1^i, x_2^i, \dots, x_n^i)^T \in R_+^n$  into net output  $y^i \in R_+$  can be modeled by a production function  $f: R_+^n \rightarrow R_+$  or by an input correspondence  $L: R_+ \rightarrow L(y^i)$  subset of  $R_+^n$ . For any  $y^i \in R^+$ ,  $L(y_i)$  represents the subset of all vectors  $X^i \in R_+^n$  which produce at least output quantity  $y^i$ .

Similarly, the maximum output quantity obtainable from the input vector  $X^i$  is represented by  $f(X^i)$ . The inverse relationship between  $f$  and  $L$  is defined by Seaver and Triantis (1989):

$$L(y^i) = \{X^i : f(X^i) \geq y\}$$

$$f(X^i) = \max \{y^i : X^i \in L(y^i)\}, i=1..n \text{ observations}$$

The input correspondence  $L$  satisfies the following weak set of axioms, suggested by Shephard (1974), which are assumed valid for every production technology:

$$(1) 0 \in \text{of } L(y^i) \text{ for all } y^i \geq 0, L(0) = R_+^n.$$

This axiom implies that free production is not feasible; there cannot be positive output quantities without the consumption of positive input quantities.

$$(2) \text{ If } |y^i_1| \rightarrow +\infty \text{ as } l \rightarrow +\infty, \text{ then}$$

$$\bigcap_{l=1}^{\infty} L(y^i) = \emptyset.$$

This axiom states that infinite production is not feasible. Finite inputs cannot produce infinite outputs.

$$(3) \text{ If } X^i \in L(y^i), \tau X^i \in L(y^i) \text{ for}$$

$$\tau \geq 1.$$

This axiom is referred to as the "weak disposability of inputs" and states that proportional increases of inputs cannot decrease output.

$$(4) L(\theta y^i) \text{ subset of } L(y^i) \text{ for } \theta \geq 1$$

This axiom is the "weak disposability of outputs" and

states that proportional increases in output cannot be achieved if inputs are reduced, or, proportional decreases in outputs remains producible with no change in inputs.

(5)  $L$  is a closed correspondence.

The correspondence between inputs and outputs is closed. This fifth axiom allows for the existence of an efficient unit isoquant described in the final assumption.

(6) The efficient unit isoquant is never upward sloping and is always convex to the origin.

This assumption implies that, in a two dimensional space, if two input bundles can each produce one unit of output, then so can a weighted average of the two.

In Figure 2, a traditional production function is depicted where two inputs,  $X_1$  and  $X_2$ , are used to produce a unit output  $y_0$ . The isoquant,  $y_0$ , identifies all possible combinations of the two inputs that result in the same output level  $y_0$ . The negative slope of the isoquant indicates that an increase in  $X_1$  will result in increased output, unless  $X_2$  is reduced to compensate. The amount by which  $X_2$  must be reduced to compensate for a single unit of increase in  $X_1$  is called the marginal rate of technical substitution between  $X_1$  and  $X_2$ . It is graphically represented by the slope of the isoquant [Triantis (1994)].

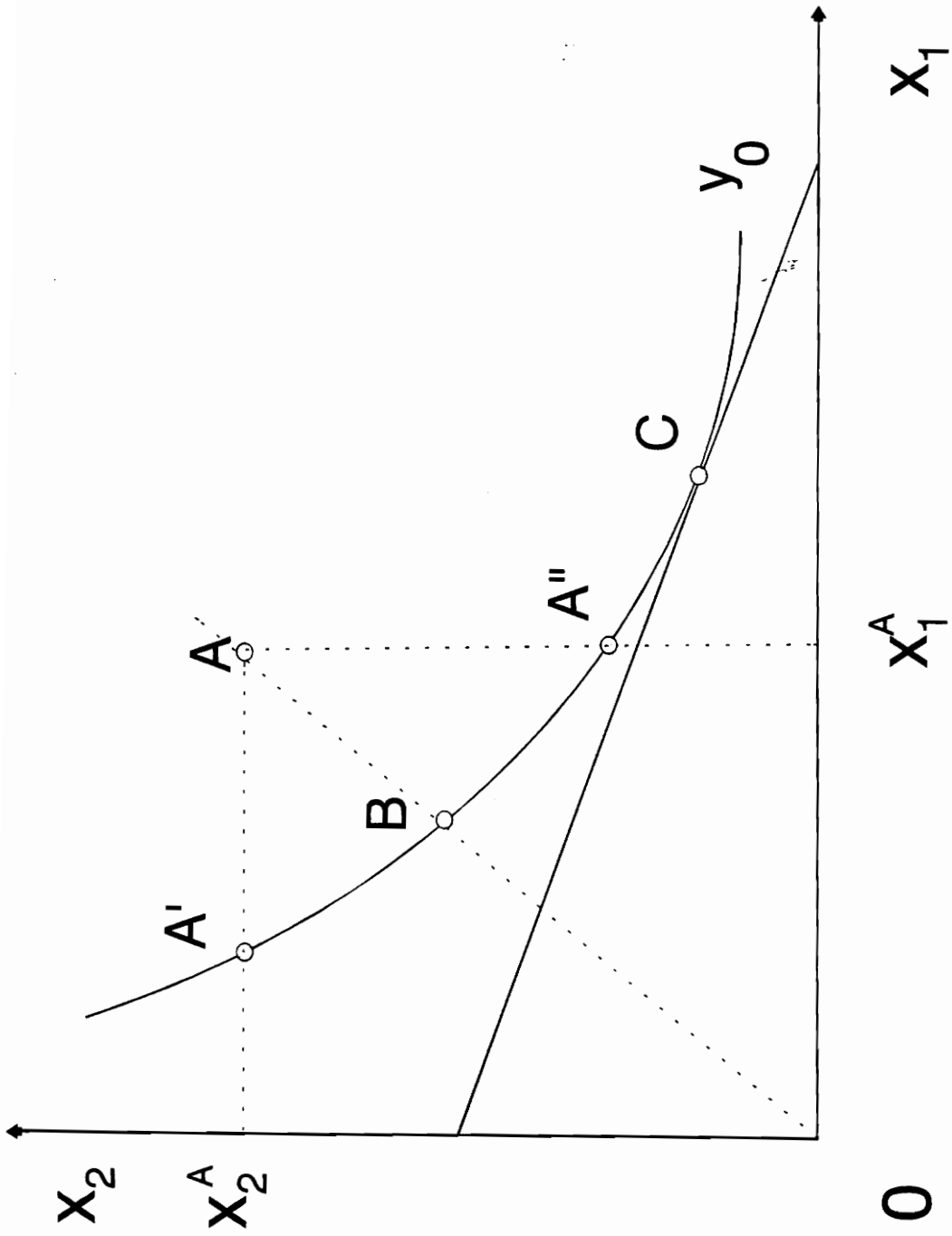


Figure 2. Input Reducing Technical Efficiency

Technical efficiency can also be represented in Figure 2. Assume two firms, A and B, are producing output at the same level  $Y_0$ . Firm A requires equiproportionally more of  $X_1$  and  $X_2$  to produce the same output and is therefore considered less efficient with respect to firm B. A measure of the technical efficiency that compares the input bundle consumed to what is required to produce a constant level is defined as  $\theta = OB/OA$ . An alternative measure,  $\theta' = 1 - (OB/OA)$ , can be interpreted as the proportion by which the level of inputs could be reduced while holding the level of output constant.

Whereas  $\theta$  and  $\theta'$  are considered radial efficiency measures, there are non-radial measures of technical efficiency as well. Non-radial technical efficiency of the inputs can be expressed as follows:

$$\theta_{X1} = (X_1^A A'') / (X_1^A A)$$

$$\theta_{X2} = (X_2^A A') / (X_2^A A)$$

Since firm A does not lie on the curve  $y_0$  in Figure 2, it has input technical efficiency values  $(\theta_{X1}, \theta_{X2})$  less than 1.00. To improve  $\theta_{X1}$ , firm A must reduce its level of input  $X_1$  per unit of output  $y_0$  to move closer to point A". When this occurs, the distance  $X_1^A A$ , the denominator in the efficiency ratio above, is reduced thus resulting in increased input technical efficiency with respect to  $X_1$ . If  $\theta_{X2}$  is improved in a similar manner,

point A moves along the diagonal depicted in Figure 2 towards point B. When the coordinates of point A and point B are the same, firm A lies on the isoquant and is considered efficient [Triantis(1994)].

The isoquant is therefore the standard, or "frontier", by which efficiency performance is calculated. It can be a continuous function, as shown in Figure 2, or a piecewise convex function connecting actual data observations. It can be generated as a theoretical, or absolute, frontier by considering technological/engineering information, or generated as a best-practice frontier from ex-post input and output data from decision making units in the sample. In either case its purpose is the same; it separates technically efficient input bundles from the inefficient input bundles. It "envelopes" inefficient bundles which lie to the northeast of the efficient isoquant, indicating that equiproportional decreases in the quantities of inputs, combined with maintaining constant output quantities, are required to make the unit technically efficient.

In Figure 2 the production technology is represented as an input correspondence. It can also be represented as an output correspondence as indicated by Figure 3. In this figure, four decision making units produce two outputs,  $y_1$  and  $y_2$ , with a single input  $X$ . This function may also be a continuous function or a piece-wise concave function.

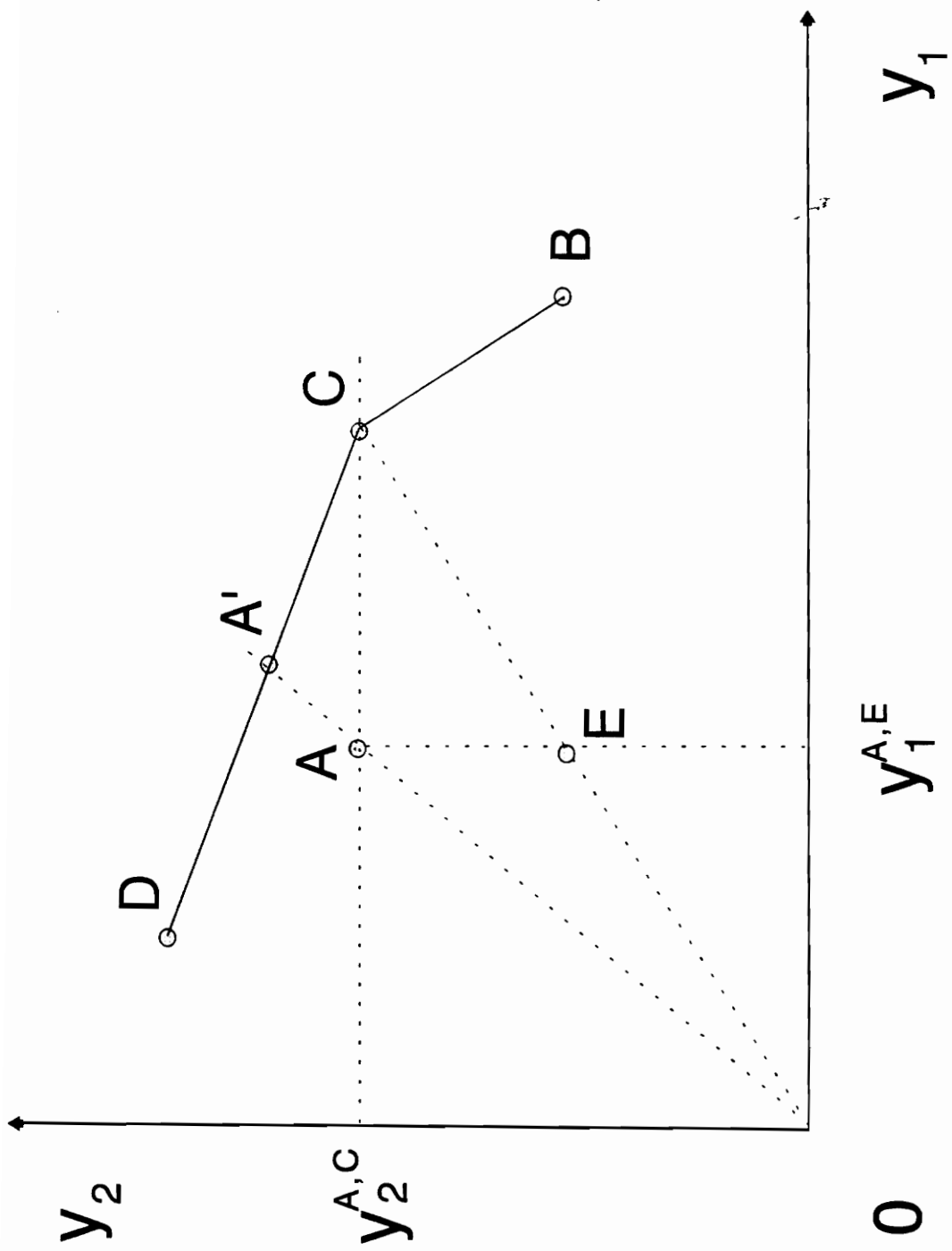


Figure 3. Output Increasing Technical Efficiency



Inefficient output bundles, such as DMUs A and E are "enveloped" by the function, indicating that increases in quantities of outputs  $y_1$  and  $y_2$  are possible given a constant level of input X. The technical efficiency of DMU A is  $OA'/OA$ .

Figures 2 and 3 illustrate that the concept of technical efficiency can be explained in the context of the input space (input reducing technical efficiency) or in the context of the output space (output increasing technical efficiency). Specifically, input reducing technical efficiency measures "denote the maximum amount by which the vector  $X^i$  of all production inputs for the  $i^{\text{th}}$  observation can be equiproportionately reduced and still produce an output no larger than  $y^i$ " [Triantis(1992), p.5]. Likewise, output increasing technical efficiency measures indicate the quantity by which output can be increased and still be producible by a constant vector of input quantities.

In general, these two measures of technical efficiency will not be identical for any production technology [Fare, Lovell(1978)] unless the organization is experiencing constant returns to scale. Constant returns to scale occurs when proportionately equal increases in all inputs lead to an equivalent increase in all outputs. When an organization does not experience constant returns to scale, it has scale inefficiencies, meaning proportional increases in all inputs

result in proportionally greater (or smaller) increases in all outputs.

## 2.5. Data Envelopment Analysis (DEA) Models

DEA is a linear programming technique that compares the relative efficiency of a unit's transformation of multiple inputs into outputs to other similar units called Decision Making Units (DMUs). It locates those DMUs with the best utilization of inputs and outputs, thus defining the envelopment surface. DEA compares all DMUs to this surface to "identify units that are relatively inefficient, the magnitude of the inefficiency, and the alternative paths to reduce the inefficiencies" [Sherman(1984), p.13].

The analysis begins by evaluating each DMU's transformation of inputs  $X_1, X_2, \dots, X_m$  into outputs  $Y_1, Y_2, \dots, Y_t$ . When considering the set of all  $n$  DMUs,  $X$  is an  $m \times n$  matrix of input measures such that  $X_{m, j_0}$  is defined as the  $m^{\text{th}}$  input for  $j_0^{\text{th}}$  DMU. Similarly,  $Y$  is an  $t \times n$  matrix of output measures such that  $Y_{t, j_0}$  is the  $t^{\text{th}}$  output for the  $j_0^{\text{th}}$  DMU.

DEA determines the unique set of coefficients,  $u_r$  and  $v_i$ , for each  $DMU_{j_0}$  that maximizes the efficiency ratio of its outputs to inputs. In linear programming terms, this ratio is a radial measure of the technical efficiency of

DMU<sub>j<sub>0</sub></sub> and can be obtained by solving the following constant returns to scale "CCR" model:

$$\text{Max } h_o = \frac{\sum_{r=1,t} u_r Y_{r,j_0}}{\sum_{i=1,m} v_i x_{i,j_0}} \quad (M1)$$

subject to

$$\frac{\sum_{r=1,t} u_r Y_{r,j}}{\sum_{i=1,m} v_i x_{i,j}} \leq 1, \quad j=1, \dots, n$$

$$u_r, v_i \geq \epsilon, \quad \text{for all } r \text{ and } i$$

where,

$Y_{r,j}$  is the amount of output  $r$  from unit  $j$

$x_{i,j}$  is the amount of input  $i$  from unit  $j$

$u_r$  is the weight given to output  $r$

$v_i$  is the weight given to input  $i$

$n$  is the number of units (DMUs)

$t$  is the number of outputs

$m$  is the number of inputs

$\epsilon$  is a small positive number

[Boussofiane, et al.(1991), p.1]

The  $u$  and  $v$  weights selected for DMU  $j_0$  maximize its efficiency ratio (objective function) subject to the constraint that when those same weights are applied individually to all other DMUs, none has an efficiency ratio

greater than 1. If this maximum efficiency ratio for  $j_0$  is equal to 1, then the unit  $j_0$  is considered efficient. If the maximum efficiency ratio is less than 1, then  $j_0$  is inefficient. Expressed differently, if  $j_0$  is inefficient, then there exists no set of weights  $u$  and  $v$  that can be chosen such that its efficiency ratio exceeds or equals that of every other DMU in the sample. Further, the  $u$  and  $v$  values calculated for  $j_0$  can be used to identify the path to relative efficiency for the DMU. From an input decreasing perspective, the  $v_1, \dots, v_m$  multipliers identify the increase in technical efficiency of  $j_0$  capable with a one unit decrease in the associated input, given unchanged output quantities. Similarly, from an output increasing view, the  $u_1, \dots, u_t$  multipliers identify the improvement resulting from a one unit increase in the associated output, given unchanged consumption of inputs. Finally, "for an inefficient unit (DMU) the solution identifies corresponding efficient units (i.e. efficient with the same weights) which are said to form a peer group for the inefficient unit" [Boussofiane, et al.(1991), p.2].

The DEA model (M1) is a fractional linear program that can be converted into a linear form to apply linear programming methods:

$$\text{Max } h_0 = \sum_{r=1,t} u_r Y_{r,j_0} \quad (\text{M2})$$

subject to

$$\sum_{i=1,m} v_i x_{i,j_0} = 100$$

$$\sum_{r=1,t} u_r Y_{r,j} - \sum_{i=1,m} v_i x_{i,j} \leq 0, \quad j=1, \dots, n$$

$$-u_r \leq -\epsilon, \quad r=1, \dots, t$$

$$-v_i \leq -\epsilon, \quad i=1, \dots, m$$

[Boussofiane, et al.(1991), p.2]

This primal model, however, presents computational problems because it has  $m + t$  variables ( $m$  total  $u$  weights and  $t$  total  $v$  weights) and  $1 + m + t + n$  constraints. Given that the number of DMUs ( $n$ ) is usually much larger than the number of variables ( $m + t$ ), solving the dual formulation of M2 is generally less time consuming [Boussofiane, et al. (1991)]. The dual can be written as follows:

$$\text{Min } 100Z_0 - \epsilon \sum_{r=1,t} S_r^+ - \epsilon \sum_{i=1,m} S_i^- \quad (\text{M3})$$

subject to

$$\sum_{j=1,n} \tau_j Y_{r,j} - S_r^+ = Y_{r,j_0} \quad r=1, \dots, t$$

$$Z_0 x_{i,j_0} - \sum_{j=1,n} \tau_j x_{i,j} - S_i^- = 0 \quad i=1, \dots, m$$

$Z_0$  unrestricted

$$\tau_j, S_r^+, S_i^- \geq 0 \text{ for all } j, r, \text{ and } i$$

[Boussofiane, et al.(1991), p.2]

The M3 model emphasizes relative efficiency issues with the selection of the  $\tau_j$ . These values are used to construct a more desirable composite unit with outputs  $\sum \tau_j Y_{r,j}$  for all  $r=1, \dots, t$  and inputs  $\sum \tau_j x_{i,j}$  for all  $i=1, \dots, m$  that can outperform the unit  $j_0$ . If  $j_0$  is inefficient, slacks will be  $> 0$  and  $Z_0$  will be smaller than 1.0. With this result, " $Z_0$  will represent the maximum proportion of its input levels unit  $j_0$  should be expending to secure at least its current output levels" [Boussofiene, et al.(1991)]. Similarly, when slacks=0 and  $Z_0=1$ ,  $j_0$  is considered efficient and it is concluded that no such composite unit exists that can outperform  $j_0$ .

For organizations experiencing non-constant returns to scale, a math programming formulation which takes into account scale inefficiencies must be used to compute radial technical efficiency measures. The "BCC" formulation was proposed by Banker, et al.(1989):

$$\begin{aligned} \text{Min } h^- &= (\sum_{i=1, m} S_i^+ + \sum_{r=1, t} S_r^-) && \text{(M4)} \\ &\text{subject to} \\ h x_{ij_0} - \sum_{j=1, n} x_{ij} \tau_j - S_i^- &= 0, \quad i=1, \dots, m \\ \sum_{j=1, n} Y_{rj} \tau_j - S_r^+ &= Y_{r_0}, \quad r=1, \dots, t \\ \sum_{j=1, n} \tau_j &= 1 \\ \tau_j, S_i^+, S_r^- &\geq 0 \end{aligned}$$

[Boussofiene, et al.(1991), p.12]

The only difference between this BCC model and the traditional CCR model is the addition of the convexity constraint requiring that multipliers  $\tau_j$  sum to 1. A model with this constraint eliminates scale inefficiency and yields a measure of the technical efficiency of  $j_0$ . It ensures that the composite unit be of similar scale size as the unit  $j_0$  and therefore not an extrapolation of another composite unit operating at a different scale size [Boussofiane, et al. (1991)].

For a given unit  $j_0$ , a comparison between the aggregate technical and scale efficiency identified using the CCR (M3) and the segregated technical efficiency using the BCC (M4) can be made. The resulting efficiency will always be lower using the BCC model due to the additional convexity constraint. Only when the composite unit identified in M4 is operating at the most productive scale size will these two models yield the same efficiency, in other words, "if there exists an optimal solution to M3 such that the sum of  $\tau_j^*$  is equal to 1.0" [Boussofiane, et al.(1991), p.12].

## **2.6. Applications of DEA**

Since the initial DEA study by Charnes, Cooper, and Rhodes (1978), the technique has been used extensively across various industries as a method of productivity measurement and improvement. Seiford (1990) has developed a

comprehensive bibliography of nearly 400 studies of DEA applications. The majority of the research has been focussed on service industries such as hospital and health care, banking, education, utilities, and transportation. For example, Sherman (1981) used DEA to determine a set of inefficient hospitals, and to identify the reduction of beds as a basis for improved productivity. In applying the technique he found that cost reductions could also be achieved by reducing personnel, without affecting output levels. Pina (1992) measured the productivity of various health centers being introduced by the Spanish Health Service. He found that the centers having a lower population level consumed an equivalent amount of resources, but were efficient primarily because they were more successful in capturing and maintaining the population as clients of the public health service. Pina (1992) concluded DEA in this application provide useful information for decisions that were made by the health centers in a decentralized manner.

The banking industry has been well represented in DEA applications. Sherman (1984) evaluated branches of a bank for relative efficiency using DEA. The branches identified as most efficient were studied for operating techniques that could be implemented in productivity improvement strategies at the inefficient branches. He determined that other



evaluation techniques, such as profitability measures and operating ratios, were unable to identify the inefficiencies highlighted by DEA. Oral (1992) studied 44 bank branches of a major commercial bank using DEA. He determined that the technique successfully isolated branches with inefficient resource utilization, and was complementary to financial ratios, the traditional method of productivity evaluation in the industry.

There are numerous case studies that compare DEA to other methods of productivity measurement. Thanassoulis (1993) compared DEA to regression analysis as a means of assessing comparative performance in a set of hypothetical hospitals. The estimates of relative efficiency, marginal input-output values, and target input-output levels using DEA were determined to be more accurate using DEA, but that regression analysis offered more stability of accuracy. The technique has also been compared to Cobb-Douglas results by Bjurek(1990). In this research, the productivity of 400 social insurance offices in Sweden were evaluated using each of the techniques, and a rank correlation was performed on the results. The correlations indicated that the rank differences in DEA and Cobb-Douglas were quite small. Finally, DEA results have been evaluated with productivity ratios. Miliotis (1992) compared DEA results to simple results from simple productivity indices tracked by the

Greek Public Power Corporation. Inefficiencies are traced to management control of inputs, the design of the supply system, and various environmental factors. He concludes that DEA results are more reliable than productivity indices and provide a better understanding of the resources that are related to operating efficiency and those that are related to the supply system.

Applications of DEA involving quality measurements or quality costs are limited. In one such example, Metzger(1993) evaluates the effect of prevention and appraisal costs on productivity. He asserts that money invested on quality must ultimately contribute to increased productivity within the organization. He attempts to quantify the benefits of quality costs and concludes that DEA can be used to determine strategies to help improve their efficiency. Barr (1994) develops failure-prediction models for banks using DEA. He claims that the models detect troubled banks up to two years prior to their insolvency. Since a bank's success is a function of "management quality", Barr includes a management quality measure in the production models. When this measure is removed, however, the model results are worse, as evidenced by a poor fit to the data and poor classification accuracy.

DEA in this study will be used to evaluate the efficiency of a linerboard production facility. The same

data set will be modelled from a productivity, quality, and quality cost perspective. A comparison of the resulting efficiency values for observations using each of these specifications will provide empirical analysis of the interrelations among these performance measures.

## CHAPTER 3. METHODOLOGY

### 3.1. Overview

The objectives of this research will be met by completing the methodology depicted in Figure 4. First, input/output production function specifications to model the quality, cost, and productivity links are identified. These specifications primarily address the conceptual relationships among quality cost components introduced by Juran(1988,1993) and the quality-productivity relationships discussed by Garvin(1988).

Second, a specific technology is selected for empirical evaluation of these specifications. A case study of a linerboard production facility conducted from 1980 through 1982 is presented for this evaluation. The facility converts various forms of wood into pulp, which is then refined, distributed to paper machines, and transformed into linerboard.

Production function specifications are then defined for this facility. Variables included in specific models are chosen from the data reported in the production and financial statements during the two year time period.

Next, a computational approach is determined. The selection of Data Envelopment analysis (DEA) and its advantages, given the various data limitations presented in

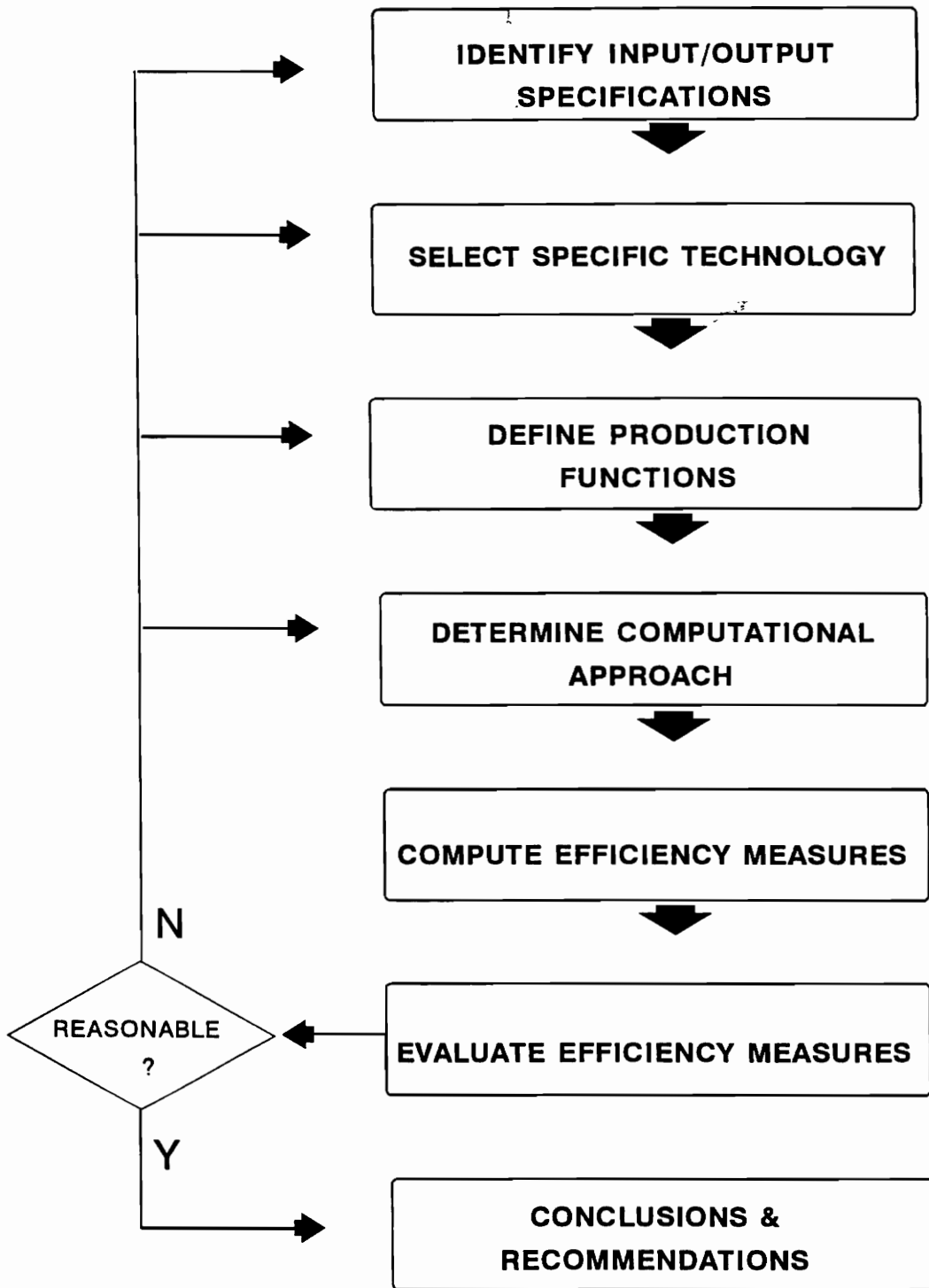


Figure 4. Methodology

the linerboard production case study, are discussed. Given the multiple inputs and outputs identified in each of the models, the technique computes monthly efficiency measures for the facility.

The calculated efficiency measures are then evaluated to address the two fundamental assertions of this thesis that 1) input/output production function analysis can be used to empirically evaluate the relationships between quality, productivity, and cost, and 2) the organizational performance measures calculated by Data Envelopment Analysis are meaningful and that the technique is appropriate for this evaluation.

The final step in the methodology is a discussion of the conclusions of this research and the recommendations for future research of the modelling of productivity, cost, and quality relationships.

### **3.2. Input/Output Specifications**

The following specification will be modeled to evaluate the relationships among the components of quality costs:

$$\text{TOTAL FAILURE COSTS} = F(\text{PREVENTION}, \text{APPRAISAL}) \quad (S1)$$

Failure costs are those costs that are incurred due to the production and distribution of defective material. They include internal failure costs and external failure costs.

The inputs in the cost function are the costs expended to prevent failures (prevention) and the costs expended in the evaluation of product quality and the detection and rectification of failures (appraisal).

The production function approach discussed in section 2.4, Measurement of Efficiency of Production, can be applied in the modeling of quality cost performance. Here,  $X^i$  is a  $2 \times 1$  column vector of the two inputs to this function, prevention and appraisal costs.  $L(y^i)$  represents the subset of all cost input vectors which can produce at least output quantity  $y^i$ , as defined by total failure costs. Efficiency values using this function identifies the organization's ability to transform controllable quality costs into failure costs.

In order to comply with Shephard's set of axioms assumed valid for this function, however, the output measure must be converted into a desirable output; in the case of this cost model it is the inverse of total failure costs. Using this modified function, all axioms hold. First, prevention and appraisal expenditures cannot produce non-positive failure costs (axiom 1). Next, finite levels of prevention and appraisal cannot eliminate all failure costs,

resulting in infinite output of the inverse of these costs (axiom 2). Third, the weak disposability of inputs and outputs hold for the modified function; increased investments of prevention and appraisal costs cannot result in higher failure costs (lower inverse of failure costs) and proportional increases (decreases of the inverse) in failure costs are possible, even without changes in the levels of prevention and appraisal expenditures (axioms 3 and 4). Axiom 5, which states that there exists an efficient allocation of controllable quality costs that minimize (maximize the inverse of) total failure costs holds true. Finally, if two different allocations of prevention and appraisal expenditures result in a single unit of failure costs, then a weighted average of these two expenditure levels will also result in a single unit of failure costs.

Figure 2 can be adapted to the quality cost function framework. In this case,  $x^1$  represents the level of prevention costs per unit of failure costs produced, while  $x^2$  represents appraisal expenditures per unit of failure costs produced. Observation B identifies a time period or organization that most efficiently allocates these input costs to reduce total failure costs and observation A identifies a time period or organization that requires higher levels of prevention and appraisal to maintain the



same level of failure cost output. The level of inefficiency in prevention ( $X^1$ ), for example, is defined as  $\theta_X^1 = (X^{1A} A'') / (X^{1A} A)$ . To improve  $\theta_X^1$ , the organization must move closer to  $A''$  by reducing the levels of prevention and appraisal expenditures necessary to achieve the same levels of failure costs. If the organization is operating at  $A''$ , B, or C, it is on the efficient frontier and therefore is efficiently allocating its controllable quality costs to increase the inverse of its total failure costs (and therefore decrease its total failure costs).

Models addressing this quality cost specification will empirically evaluate the interrelationships among these cost categories described by Juran in *The Quality Control Handbook* (1988). The following specifications will be used to model and evaluate productivity:

$$GOOD\ QUANTITY = F(PREVENTION, APPRAISAL) \quad (S2)$$

$$GOOD\ QUANTITY = F(LABOR, MATERIAL, ENERGY, CAPITAL)^{(6)} \quad (S3)$$

$$GOOD\ QUANTITY = F(LABOR, MATERIAL, ENERGY, CAPITAL, PREVENTION, APPRAISAL) \quad (S4)$$

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6. Good Quantity =  $F(\text{Labor}_{p,q}, \text{Material}_{p,q}, \text{Capital}_{p,q}, \text{Energy}_{p,q})$  is the preferred function for this model. For the quality function, resources allocated to address quality ( $\text{labor}_q$ ) should be segregated from those resources allocated for production ( $\text{labor}_p$ ). Limited data, however, supports only one estimate of these resource measures.

These specifications allow for three distinct approaches to productivity modeling. Specification S2 defines output as "Good" quantity and the inputs as prevention and appraisal costs. This specification assesses the organization's ability to properly allocate these controllable quality costs to maximize defect-free output quantity. Specification S3 does not account for quality considerations. It depicts the transformation of input resources (raw materials, energy, labor and capital investments) to output quantity. The final productivity specification (S4) combines these two by creating a specification that considers prevention and appraisal investments as additional resource inputs that can be controlled by organizations to maximize defect-free output production.

The production function approach discussed in section 2.4, Measurement of Efficiency of Production, can be applied in the modeling of productivity. Here,  $X^i$  is either a 2 x 1 column vector of the two cost inputs (S2), a 4 x 1 column vector of the four resource allocations, labor, material, energy, and capital (S3), or a 6 x 1 column vector formed by all six input variables (S6).  $L(y^i)$  in each of the three specifications represents the subset of all cost or resource input vectors which can produce at least output quantity  $y^i$ . Efficiency values using these specifications identify the

organization's ability to transform controllable quality costs and/or input resources into output quantity.

All of Shephard's axioms hold true for these specifications: prevention, appraisal, or resource expenditures cannot produce non-positive levels of output quantity; finite levels of these expenditures cannot result in the production of infinite levels of output quantity; increases in these allocations cannot result in lower quantities of production; proportional decreases in quantity of output produced are possible, even without changes in the levels of prevention, appraisal, or resource expenditures; there exists an efficient level of prevention and appraisal expenditures (S2), resource allocations (S3), or level of all six inputs (S4) that maximize the output quantity of the process.

Adapting Figure 2 to these productivity specifications, observation B identifies a time period or organization that efficiently allocates either controllable quality costs (S2), input resources (S3), or the combination of quality costs and resources (S4) to increase the quantity of output. Observation A identifies a time period or organization that requires higher levels of prevention and appraisal expenditures, or utilizes more resources in the production of an equivalent quantity of output. As the organization is able to move from point A to B, it maintains the same

quantity of output, but does so with fewer controllable quality costs or input resources. When the organization operates at point B, it is on the efficient frontier and is producing high quantities of output with the least possible amount of expenditures or resources.

Models of these productivity specifications will be compared to models of the following quality specifications to evaluate of the productivity-quality link discussed by Garvin in *Managing Quality*(1988).

$$\text{PRODUCT QUALITY} = F(\text{PREVENTION}, \text{APPRAISAL}) \quad (\text{S5})$$

$$\text{PRODUCT QUALITY} = F(\text{LABOR}, \text{MATERIAL}, \text{ENERGY}, \text{CAPITAL}) \quad (\text{6}, \text{7}) \quad (\text{S6})$$

As detailed in Chapter 2, "Product Quality" measures can be related to specific dimensions identified by Garvin. Each of these specifications will be empirically evaluated

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7. The model  $BW_1, BW_2, BW_3, BW_4, BW_5 = F(\text{LABOR}, \text{MATERIAL}, \text{ENERGY}, \text{CAPITAL})$  was also developed to investigate the relationship between productivity and quality. Here, the inputs were resources, but the five output types ( $BW_x$ ) were represented by the quantity of tons of liner produced at each of five distinct quality (basis weight) levels. The goal of this model was to determine if resource efficiency was more likely when output was at high quality levels. The results, however, identified two problems. First, when using a model with eight variables, and only 24 data points, the degrees of variation and their potential causes could not be established. Second, all observations using this model had efficiency values of 1.00, indicating collinearity among the output variables, and therefore failed to identify any distinction in resource efficiency for the various quality levels.

using measures addressing only the performance and conformance dimensions of quality. Therefore, results of the models developed from specification (S5) present empirical evaluations of the relationship between these specific dimensions of quality and quality costs.

The second quality specification (S6) is an extension of the traditional production specification described in (S3). Here, however, this model is concerned with the quality of the output rather than the quantity. By varying the output measure in these two specifications, direct comparisons can be made of the associated model results. These comparisons will provide insight into the relationship between product quality and productivity. Again, the performance and conformance dimensions of quality identify the parameters of the quality-productivity relationship investigated by these specifications.

The production function approach discussed in section 2.4, Measurement of Efficiency of Production, can be applied in the modeling of quality output performance. Here,  $x^i$  is either a 2 x 1 column vector of the two cost inputs (S5) or a 4 x 1 column vector of the four resource allocations, labor, material, energy, and capital (S6).  $L(y^i)$  in each specification represents the subset of all cost or resource input vectors which can produce at least output product quality  $y^i$ . Efficiency values using these specifications

identify the organization's ability to transform either controllable quality costs or input resources into quality output.

All of Shephard's axioms hold true for these specifications<sup>(8)</sup>: prevention, appraisal, or resource expenditures cannot produce non-positive levels of quality output; finite levels of these expenditures cannot result in the production of products having infinite levels of quality; increases in these expenditures cannot result in the production of lower quality output; proportional decreases in output quality are possible, even without changes in the levels of prevention, appraisal, or resource expenditures; there exists an efficient level of prevention and appraisal expenditures, or resource allocations that maximize the output quality of the process.

Adapting Figure 2 to these quality output specifications, observation B identifies a time period or organization that efficiently allocates either controllable quality costs (S5) or input resources (S6) to increase output quality. Observation A identifies a time period or

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8. Models using measures of quality that address the conformance dimension, such as scrap percentage or yield rate, require the output measure of the model to be the inverse of this measure so that Shephard's third axiom is not violated. The production function approach for this case can be applied in the same manner as the quality cost model.

organization that requires higher levels of prevention and appraisal expenditures, or utilizes more resources in the production of an equivalent level of output quality. As the organization is able to move from point A to B, it maintains the same quality of output, but does so with fewer controllable quality costs or input resources. When the organization operates at point B, it is on the efficient frontier and is maintaining a level of output quality with the least possible amount of expenditures or resources.

### **3.3. Linerboard Production Technology**

The theoretical cost, quality, and productivity specifications are evaluated using a series of specific models applied to a linerboard manufacturing facility case study. A description of the linerboard technology has been detailed by Triantis(1984,1989):

The fiber is primarily composed of wood that arrives at the mill in the form of sawdust, logs, and chips. The wood fiber is converted into chip form. The chips are then steam cooked within a chemical solution of caustic soda and sodium sulfide in a pressure vessel. The contents of the vessel, now called pulp, are discharged to the receiving tank. The pulp then moves to "refining"--defined as the mechanical action of beating the fiber. This beating increases the fiber flexibility and its internal bonding ability. Chemicals are added to the mixture to further alter its properties. The pulp is then distributed to the paper machine where it is transformed into various grades of linerboard [Triantis(1989), p.52].

An empirical analysis of the models using data collected from twenty-four consecutive monthly operating

statements published by a paper mill from December 1980 through November 1982. The operating statements detailed various production measures such as the type and quantity of each liner manufactured for the month and per operating hour, as well as the quantities of raw materials needed to produce the monthly output. The statements also detailed financial information such as the standard costs of inventories, the value of linerboard sold and shipped, and cost variances associated with the monthly production of linerboard.

In addition to the production and accounting data, the concepts of Garvin were applied to the operating statements and various conformance and performance quality measures were identified. Further, Juran's cost definitions were used to develop quality cost measures for the linerboard facility.

The data set was completed by including the labor, material, energy, and capital measurements defined by Triantis (1984) in earlier research of the same operating statements.

### **3.4. The Cost, Quality, and Productivity Models**

**3.4.1. Cost Models.** The cost specification identified earlier will be evaluated using the following cost function:



$$INV(INTERNAL\$+EXTERNAL\$) = F(PREVENTION\$+APPRAISAL\$) \quad (F1)$$

Where,

**PREVENTION\$** =Scheduled Down time\*Tons/hour\*Profit\$/ton.

**APPRAISAL\$** =Inspection Costs

**INTERNAL\$** (failure cost)=Unscheduled Down time\*Tons/hr

\*Profit\$/ton + Reject Tons\*Mfg Cost/ton produced

**EXTERNAL\$** (failure cost)=Returns/Discounts+Late Delivery

Monthly prevention costs for the facility are measured by the costs incurred due to routine, scheduled maintenance. This maintenance represents an investment of labor to improve quality and efficiency by reducing the likelihood of unscheduled machine down time and the production of nonconforming material. Multiplying lost production hours for this scheduled maintenance by the average hourly production rate identifies the prevention costs in lost tons of production. By multiplying this quantity by the average dollars in profit that the mill could have earned from each of these tons, this cost is converted to lost dollars. Appraisal costs are identified in the accounting statements as the "inspection costs" for the linerboard facility. The internal failure costs are a combination of two reported indicators, lost opportunity costs due to unscheduled maintenance and lost actual manufacturing costs due to rejected tons. When proper preventive maintenance is not

performed, the likelihood of unscheduled machine repairs and down time increases. The dollar cost of this down time is calculated using the same equation as in the prevention cost component. The average investment of materials and labor per ton of liner produced is reported as manufacturing\$/ton. Therefore, the second component of the internal failure cost equation is the total lost manufacturing costs for each of the tons rejected during inspection at the paper machine process. External failure costs are measured as the sum of the costs incurred due to: customer returns, the discounted sale of nonconforming linerboard, and deductions from total monthly sales due to late delivery of shipments.

The output of this model is the inverse of the sum of all internal and external failure costs. The inverse is specified in order to comply with the third axiom (section 2.4) of all valid production technologies. This axiom, the "weak disposability of inputs" states that increases in inputs cannot decrease output. Here, it is expected that investments of prevention and appraisal expenditures cannot result in an increase in internal and external failure costs, but rather can result in an increase in  $INV(INTERNAL\$+EXTERNAL\$)$ . Therefore model (S1) has been modified accordingly.

**3.4.2. Productivity Models.** Productivity of the linerboard facility is evaluated by the following models:

**TONS PRODUCED= F(LABOR, MATERIAL, ENERGY, CAPITAL) (F2)**

**TONS PRODUCED= F(LABOR, MATERIAL, ENERGY, CAPITAL,  
PREVENTION\$+APPRAISAL\$) (F3)**

The first model has been developed by Triantis(1984) and evaluated by Triantis and Seaver(1989, 1992, 1994) for the linerboard facility. The efficiency measures derived from model (F2) identify efficient levels of input resource utilization for linerboard production. The definitions of the various input and output resource measurements specified by Triantis (1984) are adopted in this research:

**TONS PRODUCED**- Actual physical output of all types of linerboard of the mill. It is measured in paper machine tons.

**LABOR**- Manufacturing labor, measured in thousands of current dollars, consumed in the monthly production period. It does not include the labor for clerical, supervisory, or engineering functions.

**MATERIAL**- Monthly net raw material consumption measured in thousands of current dollars. It primarily is the dollar value of the tons of wood fiber and chemicals purchased minus the value of the by-products and secondary products generated by the recovery processes.

**ENERGY**- The total energy consumption in billions of BTUs observed during each monthly period.

**CAPITAL**- Measured in thousands of current dollars, it is defined as the mill depreciation charged to the profit and loss statement in addition to any capital leases incurred during the month [Triantis(1984), p.84-86].

The second productivity model (F3) augments F2 by including the controllable quality cost investments, **PREVENTION\$+APPRAISAL\$**, to address the productivity-cost relationship. Further empirical evidence of this relationship will be provided by a comparison of models F1 and F2.

**3.4.3. Quality/Input Resource Models.** Quality is evaluated by the following four models. Models (F4) and (F5) evaluate the productivity-quality link by expanding a production-based specification to include quality output measures addressing Garvin's performance and conformance dimensions, respectively. Models (F6) and (F7) study the relationship between prevention and appraisal costs and these two dimensions of quality.

**BASIS WEIGHT= F (LABOR, MATERIAL, ENERGY, CAPITAL) (F4)**

**INV (SCRAP%) = F (LABOR, MATERIAL, ENERGY, CAPITAL) (F5)**

**BASIS WEIGHT= F (PREVENTION\$+APPRAISAL\$) (F6)**

**INV (SCRAP%) = F (PREVENTION\$+APPRAISAL\$) (F7)**

**BASIS WEIGHT** is a quality measure that addresses the performance dimension. The basis weight (BW) of the

linerboard is the pounds of fiber in 1000 square feet. The basis weight is controlled in the refining process and paper machine operations. It determines the strength of the paper by defining its tensile and burst strengths. Applying the product-based definition of quality, the higher the basis weight, the stronger the liner, and therefore higher the quality of paper. The monthly measures of basis weight are represented by an average outgoing liner basis weight, weighted by the percentage of tons produced of each type of liner.

It is assumed that all consumers consider basis weight as a desirable characteristic in linerboard and that there is a one-to-one correspondence between this product attribute and the performance dimension of quality. Higher basis weight, therefore identifies higher quality.

**SCRAP%** is derived from a manufacturing-based definition of quality and addresses the conformance dimension. It is calculated as the ratio of rejected tons to total tons produced for the month. It is assumed that equivalent inspection criteria are applied to all types of liner produced and that variations in quantities of rejected tons of linerboard are due strictly to process variations, and not due to selected types of liner produced during the month.

The inverse of  $scrap\%$  is used in the analysis in order to comply with the third axiom (section 2.4) of all valid production technologies. This axiom, the "weak disposability of inputs" states that increases in inputs cannot decrease output. Here, it is expected that investments of prevention and appraisal expenditures cannot result in an increase in  $SCRAP\%$ , but rather can result in an increase in  $INV(SCRAP\%)$ . Therefore, models (F5) and (F7) have been defined accordingly.

### **3.5. Data Envelopment Analysis (DEA) as the Modeling Tool**

This research evaluates an ex-post data set to identify and assimilate observations characterized by efficient performance using various production-based, quality-based, and cost-based models. Common characteristics of these observations having similar efficiency performance in each model are then identified. Finally, interrelationships among the three performance measures are investigated by comparing changes in relative efficiency of observations using each of these models.

Given this framework for quality, productivity, and cost evaluation, a linear programming approach such as data envelopment analysis has several advantages over statistical techniques, such as multiple least squares linear regression and ratio analysis. Since all of the models chosen for this

research have several inputs and a single output, using an input to output ratio approach creates several individual comparisons, one for each input. Obtaining an efficiency measure therefore requires a transformation of these comparisons, based on a specified weighting system, to a single index that assimilates all ratios. DEA, however, reduces the emphasis on pre-specified weights; it "does not require apriori weights to reflect the relative importance of components in order to obtain a suitable efficiency measure" [Banker, et al.(1989), p. 128]. The technique assigns unique weights to the modeling components as part of an optimal solution. If a unit is identified as inefficient with the most favorable set of weights, then DEA concludes it cannot be an efficient unit.

DEA also has advantages over regression analysis in this application. An essential step in the methodology undertaken in this study is the identification of observations with efficient performance and segregation of these observations from those with strongly inefficient performance in each of the alternative specifications. A resulting comparison of salient characteristics among the isolated observations in each classification in the various models can then provide empirical evidence of the interrelationships among quality, productivity, and cost. With regression, observations are not easily separated

between efficient and strongly inefficient relative performance. "The estimates are formed from observations which contain inefficient behavior in unknown proportions" [Banker, et al.(1989), p.129], and therefore define central tendencies, rather than extremes. Because frontier estimates are used to effect the efficiency evaluations in DEA, these extremes in efficiency performance are identified by the mathematical programming solutions.

Further, whereas linear regression uses an entire data set of n observations to optimize a single estimating function, DEA evaluates each observation individually by "using n optimizations for the same n observations in order to obtain efficiency evaluations for each DMU" [Banker, et al.(1989), p.129]. It therefore derives a distinct estimating function, and defines efficiency increasing opportunities, for each unit in the sample.

These efficiency increasing opportunities are highlighted by DEA when it identifies a "peer group" of units for each inefficient unit. For each unit assessed, DEA assigns to the unit unique input/output weights that show it in its most productive light [Boussofiane(1991), p. 4]. The peer group is the set of units that is efficient when using the inefficient unit's weights. This research relies on the advantage of DEA to isolate monthly observations for further evaluation. Specifically, it will



focus on whether there are consistencies among the resource allocation strategies or production performance of these efficient observations.

Finally, the technique offers flexibility in model formulation that is necessary in this particular application. First, it allows for the development of models with multiple inputs and outputs, assuming little collinearity, and second, it has the capability of evaluating both constant returns to scale (CCR) formulations and non-constant returns to scale (BCC) formulations<sup>(9)</sup>.

The Integrated Data Envelopment Analysis System (IDEAS) software program<sup>(10)</sup> is a FORTRAN code developed by Ali (1989) that solves DEA models. Among the model selections available in IDEAS is the M4 formulation (BCC) described in section 2.5. The software requires the designation and quantity of input resource variables, output measure variables, and observations be entered into the PARAM.DAT file. Similarly, the measurements of these variables for each observation must be entered into the MODEL.DAT file.

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9. The linerboard facility is exhibiting non-constant returns to scale throughout the two year period [Triantis (1984)]. All specifications in this study will be appropriately evaluated using the "BCC" (M4) formulation.

10. The version 1.0.1 of IDEAS, released in July, 1989 by Ali(1989) is used in this research.

IDEAS then solves the dual model of the M4 formulation<sup>(11)</sup> using the provided data, and generates an output report IDEAS.TAB (see appendix 1).

The IDEAS.TAB report includes several tables that display various efficiency data generated during the model solution. One table provided shows the values of  $\theta$ , the sum-of-the-slacks, and  $\iota$  for each DMU. A second table of slack values lists the values of the slacks associated with each output and input measure for each DMU. Finally, the range of the weights (multipliers) are provided for each DMU [Ali(1989), p.9].

The sum-of-the-slacks provides a measure of the discrepancy between the actual input values of the DMU and the projected values on the envelopment surface. This measure is always greater than, or equal to, zero. The only way this measure is equal to zero is when the actual and projected points are the same.

11. The dual of M4 that is calculated by IDEAS is:

$$\begin{aligned}
 & \text{Max } h_o = \sum_{r=1,t} u_r Y_{r,j_o} + w \\
 & \text{subject to} \\
 & \sum_{i=1,m} v_i x_{i,j_o} + w = 100 \\
 & \sum_{r=1,t} u_r Y_{r,j} - \sum_{i=1,m} v_i x_{i,j} \leq 0, \quad j=1,\dots,n \\
 & -u_r \leq -\epsilon, \quad r=1,\dots,t \\
 & -v_i \leq -\epsilon, \quad i=1,\dots,m
 \end{aligned}$$

Where  $w$  is dual variable corresponding to the convexity constraint.

When this occurs, the efficiency value  $\theta$  equals 1.000. As these slacks increase, DMUs move off of the envelopment surface and  $\theta$  decreases. According to Ali (1989),  $\theta$  is always equal to, or less than another measure of input efficiency reported in the IDEAS.TAB report,  $\theta$ . Whereas  $\theta$  measures only that portion of inefficiency realized when inputs are proportionately reduced,  $\theta$  measures total inefficiency. According to the research of Ali, when the impact of changes in the sum-of-slacks is desired,  $\theta$  provides a better gauge for management [Ali(1989), p.13]. Since each of the individual  $\theta$  values for a DMU measure its relative efficiency in transforming inputs to outputs for a given specification, changes in the  $\theta$  value for the same DMU due to changes in the input/output specification yield valuable information. By evaluating the specification's effect upon the  $\theta$  value for given DMUs using various quality-based, cost-based, and productivity-based specifications, empirical evidence of their interrelationships can be presented.

### **3.6. Evaluation of the DEA Results**

**3.6.1. Interpretation of the Quality Cost Model.** The relationships among the quality cost components will be empirically evaluated using model (F1). Since the inverse

of the total failure costs is the output measure in this model, a higher level of output is identified by lower failure costs. In this model efficiency can be increased through 1) reduced total failure costs (thus increasing the inverse) given constant levels of prevention and appraisal quality cost expenditures, or 2) reduced levels of prevention and appraisal costs while maintaining constant total failure costs. For example, assume Month A has \$10 in prevention and appraisal costs and \$100 in resulting failure costs, Month B also has \$10 in prevention and appraisal costs, but only \$20 in failure costs. The output measures for the two months are 0.01 (1/100) and 0.05 (1/20), respectively. Since the input costs for the months are the same and Month B has lower total failure costs, it is the more efficient month.

The highest efficiency values when DEA is performed using this cost model identify the months that most efficiently allocate controllable prevention and appraisal costs to reduce total resulting failure costs. Similarly, the lowest efficiency values identify those months that have inefficient allocations of these costs.

Once the efficiency values for each observation are determined, all observations are ranked by decreasing efficiency. Those observations with efficiency of 1.000 are identified as members of the efficient set while those

months with efficiency values less than 0.38<sup>(12)</sup> are identified as members of the inefficient set. The analysis then focuses on the identification of the quality cost characteristics of the months in each extreme set. Any characteristics that are related to the resulting efficiency of quality cost allocation will provide insight into the relationship among quality costs, and how these costs can be effectively controlled and allocated.

### **3.6.2. Interpretation of Productivity Model.**

Productivity of the linerboard facility is evaluated using model (F2). The labor, raw material, energy utilization, and capital expenditure measures defined by Triantis (1984) are the input resources and the output measure is the tons of liner produced. DEA results will indicate the facility's effectiveness in transforming these resources into manufactured tons of linerboard each month.

Efficiency values of 1.000 in this application identify the months during which the facility most efficiently allocates labor, raw materials, energy, and capital to maximize total tons of production; they are considered

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12. The efficiency value 0.38 is chosen as the cutoff point for extreme inefficiency in the analysis of all cost models. Selecting 0.38 creates a large gap in the efficiency data and therefore provides a means to adequately separate months with extreme behavior with respect to efficiency. Months exceeding this value of efficiency tend to be much closer to an efficiency value of 1.00 than 0.38.

components of the efficient set. Similarly, efficiency values less than 0.95<sup>(13)</sup> identify those months having ineffective allocations of these resources; they comprise the relatively inefficient set.

Operating characteristics that are common among months in the efficient set provide insight into the conditions that may be necessary to achieve efficiency of the input resources. Characteristics that are common among the most inefficient months suggest conditions that may be negatively related to efficiency using this model specification.

Once the conditions influencing the efficiency measure using this productivity model can be determined, then these measures can be further evaluated to provide insight into the relationship between productivity and quality cost performance. For each month in the efficient set using the production model (F2), its efficiency and relative rank will be evaluated in the quality cost model (F1). A positive relationship between productivity and cost can be illustrated by a similar performance of the months in each of the models. If at least 80% of the efficient months in

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13. An efficiency value of 0.95 is used as the cutoff point for which inefficiency is investigated in the productivity model. Only one observation in the data set is inefficient using the cutoff point of 0.92 established by Triantis and Seaver (1992) for this model. Selecting this higher efficiency cutoff creates two more populated and segregated groups from the data. This facilitates a more complete analysis, especially with respect to inefficiency, when the model is compared to quality and cost models in this study.

the productivity model are also efficient in the cost model, it can be concluded that there is a positive relationship between the measures. Similarly, if 80% of the months efficient in the productivity model are cost inefficient, a negative relationship can be concluded. If neither of these criteria apply, no conclusions regarding the relationship between productivity and quality costs can be made. Finally, if there is empirical evidence that the converse of this relationship holds true, then it can be concluded that organizations attempting to improve the effectiveness of their quality cost expenditures may also improve productivity in the process.

**3.6.3. Interpretation of the Quality Models.** DEA results of quality models (F4) and (F5) can be compared to the productivity model (F2) to address the productivity versus quality link. Since the inputs of the models in each case are raw materials, energy, labor, and capital, changes in the efficiency of the individual months can be attributed strictly to changes in the output measure from quantity (**TONS PRODUCED**) to performance and conformance dimensions of quality (**BASIS WEIGHT** and **INV(SCRAP%)**). For each of the efficient months using the productivity model, its relative efficiency using the two quality output models is evaluated. Efficient months using the quality output models have

efficiency values of 1.000, while those months with values less than 0.40 are identified as inefficient<sup>(14)</sup>.

A positive relationship between the relative efficiency value and ranks of the months using models (F2) and (F4) indicates a positive short term relationship between productivity and quality, when quality is defined by a measure that addresses the performance dimension. If at least 80% of the efficient months in the productivity model are also efficient in the performance model, it can be concluded that there is a positive relationship between the measures when quality is defined by the performance dimension. Similarly, if 80% of the months efficient in the productivity model are performance inefficient, a negative relationship can be concluded. If neither of these criteria apply, no conclusions regarding the relationship between productivity and the performance dimension of quality can be made. A positive result will support the assertion that there is not a "penalty" to produce higher quality output.

A positive relationship between the relative efficiency

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14. The efficiency value 0.40 is chosen as the cutoff point for extreme inefficiency in the analysis of all quality models. Selecting the value 0.40 creates a large gap in the efficiency data and therefore provides a means to adequately separate months with extreme behavior with respect to efficiency. Months exceeding this value of efficiency tend to be much closer to an efficiency value of 1.00 than 0.40.



and rank of months using models (F2) and (F5) will provide empirical evidence of a positive short term relationship between productivity and the conformance dimension of quality. If at least 80% of the efficient months in the productivity model are also efficient in the conformance model, it can be concluded that there is a positive relationship between the measures when quality is defined by the conformance dimension. Similarly, if 80% of the months efficient in the productivity model are inefficient in the conformance model, a negative relationship can be concluded. If neither of these criteria apply, no conclusions regarding the relationship between productivity and the conformance dimension of quality can be made. A positive result will indicate that input resources committed to a reduction of the "hidden plant" of nonconforming production will also result in increased productivity under those same levels of investments.

The quality versus cost relationship will be separated into two distinct comparisons: (1) the performance vs cost relationship, and (2) the conformance vs cost relationship. The performance-cost link will be evaluated through several specifications. First, the results of the model identifying effective allocation of resources with respect to performance output model (F4) will be compared to those of the quality cost model (F1). The members of the efficient

and strongly inefficient sets for each of these models will be identified. A positive short term relationship between quality and cost will be demonstrated if 80% of the months having performance dimension efficiency are also cost efficient. Similarly, if observations that have inefficient resource allocations with respect to performance tend to be cost efficient to the same degree, empirical evidence of a negative relationship between quality and cost will be established.

The quality versus cost relationship can be further evaluated by changing the output measure of the quality cost model to the performance dimensions of quality model (F6). The changes in efficiency values for each observation demonstrates the effectiveness of prevention and appraisal allocations when the output measure changes from failure costs to performance output. If members of the efficient set are consistent from one model to the other, there is evidence of a positive relationship between performance and quality costs. This result will provide empirical evidence for the assertion that effective allocations of costs not only provide financial benefits, but also may contribute to higher quality output with respect to performance.

The quality versus cost relationship is also investigated using the conformance dimension in a similar manner. For example, a positive relationship between the

efficiency with respect to the conformance dimension of quality (F7) and quality cost efficiency (F1) can be illustrated by 80% of the efficient members in one model also appearing as efficient members in the other model. A positive relationship among these results may provide empirical evidence to suggest that organizations attempting to increase conformance to quality specifications may also improve the effectiveness of their cost expenditures in the process.

### **3.7. Conclusions and Recommendations for Extensions of this Research**

Recommendations for extensions of research in this area will be based on conclusions formulated from the DEA results of the various cost, quality, and productivity models. Three issues will be addressed in the conclusion: first, whether is DEA an appropriate tool for modeling these relationships; second, whether the proper input/output relationships have be chosen; and third, whether these relationships can be applied to other processes.

There is limited research detailing the use of DEA in modeling performance measures in the manufacturing environment. The appropriateness of this technique for such applications will be based on the empirical evaluation of various quality, cost, and productivity models using the

linerboard manufacturing case study. The efficiency values and comparisons of the relative ranks of these values using the various models will indicate whether similar conclusions on the relationships between these measures can be made. Given that the empirical analysis has been completed on ex-post data, the adequacy of the tool in handling an incomplete data set can also be evaluated.

This research will also conclude whether the proper input/output relationships have been identified to address quality, cost, and productivity in the study. Further, the issue of whether there is adequate data reporting to support the analysis of these relationships will be addressed. Therefore, inconsistencies in the analysis may not be a function of the effectiveness of DEA, but rather a function of the models developed or the adequacy of the data collected in this study to accurately measure each of the inputs and outputs.

The final issue to be addressed in the conclusion is whether these input/output relationships can be applied beyond the single technology evaluated during this study. Here, there must be a determination of whether the relationships among quality, cost, and productivity identified in this study have been influenced by the technology or the conditions of the particular case study selected.

## CHAPTER 4. RESULTS

### 4.1. Evaluation of the Cost Model

The results of the quality cost model (F1) are summarized in Table 1 (detailed reports for cost models are illustrated in Appendix 1).

**Table 1. Quality Cost Efficiency Profile**

Rank	DMU	Input Reducing Technical Efficiency	Classification
1	16	1.000	Efficient
2	2	1.000	
3	19	1.000	
4	24	0.652	
5	22	0.583	
6	17	0.448	
7	10	0.379	
8	1	0.347	
9	6	0.282	
10	13	0.269	Inefficient
11	21	0.257	
12	3	0.252	
13	15	0.242	
14	23	0.240	
15	9	0.237	
16	1	0.232	
17	8	0.231	
18	7	0.229	
19	14	0.223	
20	5	0.206	
21	4	0.184	
22	12	0.154	
23	11	0.094	

The model confirms that total quality costs for the linerboard facility are lower when prevention and appraisal costs are allocated efficiently. The two months with the lowest total quality costs, months 16 and 19, both are efficient with respect to cost allocation. Month 2, the third member of the efficient set also has relatively low total quality costs of \$144,231. Likewise, the model also effectively identifies months with high total quality costs in the inefficient set. Of the nine most inefficient months (11,12,4,5,14,7,8,9,1), only month 7 did not have total quality costs exceeding \$200,000.

Although total quality costs are reduced when prevention and appraisal costs are efficiently allocated, this short term case study does not demonstrate that it is most frequently due to increased levels of prevention + appraisal expenditures, as claimed by Juran. In fact, the results indicate that the months with lower prevention and appraisal allocations are more likely to be cost efficient, not inefficient. The following example illustrates this point. Months with high prevention and appraisal expenditures, such as 13, 21, 22, and 23, do tend to have lower resulting internal and external costs (see Appendix 5), but these months do not appear in the efficient set. When the facility invests higher expenditures of prevention and appraisal costs, it fails to reduce failure costs and

total quality costs to a proportional amount allowing it to operate on the efficient frontier. For example, in month 22, increased prevention and appraisal costs of \$53,681 resulted in reduced internal and external failure costs of \$51,394. During this month, though successfully lowering failure costs through increased controllable costs, the facility was not determined to be as cost efficient as month 19, when it also limited failure costs (\$50,934), but was able to do so through much lower controllable cost expenditures (\$31,709).

The results indicate that the conceptual relationship between increased prevention and appraisal costs and reduced failure costs and total quality costs may have been disguised for two reasons. First, other process conditions, not reported in the accounting statements, may have impacted monthly failure cost totals. All months in the first year of the study (observations 1 through 12) are members of the inefficient set. In general, it appears that cost allocations became more effective at reducing total quality costs in the second year, particularly beyond month 16. Second, due to limited data addressing the controllable cost categories, approximations of these cost components may be inadequate. A more detailed cost reporting and accounting system for the facility may have identified more cost

expenditures or reductions that could be attributed to prevention and appraisal activities.

**4.2. Evaluation of the Productivity Model**

The results of the production-based model (F2) are summarized in Table 2 (detailed reports for production models are illustrated in Appendix 2).

**Table 2. Productivity Profile**

<b>Rank</b>	<b>DMU</b>	<b>Input Reducing Technical Efficiency</b>	<b>Classification</b>
1	6	1.000	<b>Efficient</b>
2	1	1.000	
3	24	1.000	
4	13	1.000	
5	9	1.000	
6	19	1.000	
7	22	1.000	
8	16	1.000	
9	21	1.000	
10	10	1.000	
11	11	0.997	
12	15	0.988	
13	23	0.986	
14	4	0.963	
15	5	0.956	
16	8	0.953	
17	17	0.947	<b>Inefficient</b>
18	7	0.942	
19	18	0.937	
20	3	0.933	
21	14	0.927	
22	12	0.926	
23	2	0.921	



The results highlight the effectiveness of the model in identifying and segregating periods of extreme performance with respect to productivity [Seaver and Triantis (1989,1992,1994)].

The most notable observation is that months that have efficient allocation of resources with respect to output quantity are not necessarily the months with the highest absolute production quantities. Further, months with inefficient allocation of resources are not always those with the lowest quantities of production. For example, an emphasis on absolute quantities would have failed to identify months 10,13,21,22 as efficient. The production during these months were all among the six lowest quantities. Furthermore, months that were identified and categorized as inefficient by DEA, such as 12 (23,253 tons), 7 (22,905 tons), and 18 (22,754 tons), would have been incorrectly determined to be above average production performance.

These results illustrate several dangers of pursuing the misguided, short-term, management objective of maximizing absolute quantities of production. First, management may incorrectly evaluate true productivity and have a false indication of its performance. Second, this inefficiency may be inadvertently perpetuated by continuing to endorse any practices or conditions that contributed to

the poor performance. Third, should resources be efficiently allocated when production quantities are low, management's perception of a poor performance will prevent them from recognizing and repeating effective practices and conditions.

Production problems in the linerboard facility are identified by the DEA results of this model. In general, months in the efficient set are characterized by high tons produced/operating hour. All five of the months with the highest tons/operating hour are in the efficient set. Only two production start-up months (10, 22) are efficient with respect to production but not characterized by high tons/operating hour. Similarly, five of the most inefficient members (2,3,12,14,18) all ranked within the lowest eight months with respect to tons/operating hour.

Efficient months are also characterized by low unscheduled down time. This statistic represents the effectiveness of the linerboard facility to produce without costly down time. All ten efficient months had minimal down time. In fact, none of the ten were ranked below the top thirteen with respect to this measure.

The results of this empirical analysis suggest that efficient usage of resource has little to do with absolute production in tons. Rather, effectiveness with respect to resource allocation is influenced by such factors as down

time and output per operating hour. Therefore, productivity performance measurement, and the associated decision-making processes effected by such data, are faulty if they rely solely on absolute production quantities. Efficiency measures using this model are not biased by such data and provide a clearer indication of facility productivity performance.

#### **4.3. Evaluation of the Productivity-Cost Link**

The productivity-cost link is most effectively evaluated by comparing the DEA results of the productivity model (F2) to those of the quality cost model (F1). The comparison, or efficiency profile, is shown on the top of Figure 5.

The profile illustrates four comparisons: the relationship between cost and productivity when the facility is allocating its resources efficiently (Row A in Figure 5) and inefficiently (Row B in Figure 5) with respect to productivity, as well as when the facility is efficiently (Column C in Figure 5) and inefficiently (Column D in Figure 5) allocating quality costs. Those observations that do not fall within the definitions of efficient or inefficient behavior for productivity(cost) are characterized as "observations with no apparent productivity (cost) classification" on the matrix.

		C	D	Observations With No Apparent Cost Classification	Apparent Relationship Between Cost and Productivity
		Cost Efficient Observations	Cost Inefficient Observations		
A	Production Efficient Observations	16, 19	1, 6, 9, 10, 13, 21	22, 24	NONE
B	Production Inefficient Observations	2	18, 3, 14, 12, 7	17	POSITIVE
Observations With No Apparent Productivity Classification		-	11, 4, 5, 8, 23, 15		
Apparent Relationship Between Cost and Productivity		NONE	NONE		

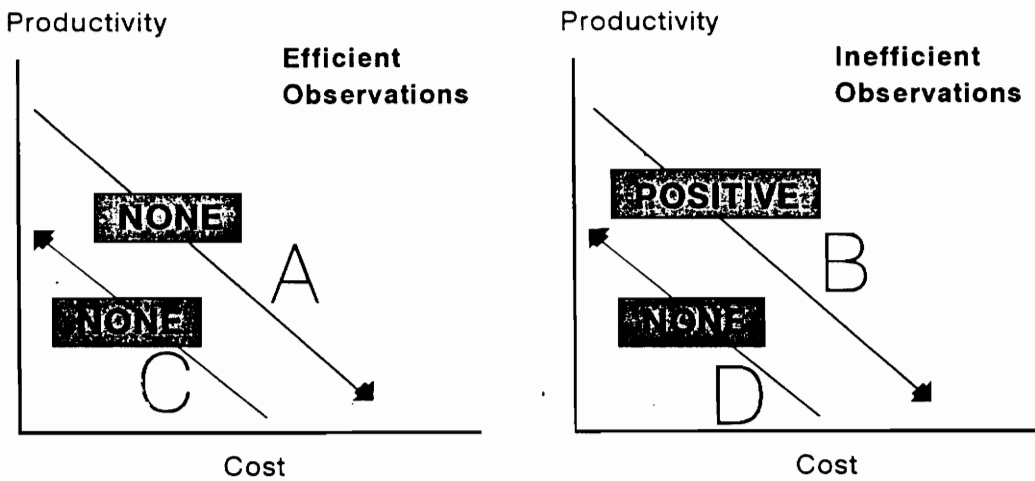


Figure 5. Productivity vs. Cost Profile

In general, the results suggest a positive relationship between cost efficiency and productivity. Of the seven months identified as having inefficient resource allocation with respect to productivity, only month 2, a start-up month with poor energy utilization and low production quantities, is efficient in the cost model (Row B in Figure 5). Inefficient months with respect to both cost and productivity (3, 7, 12, 14, 18) have several salient characteristics. First, they have high total quality costs. All five of these months are among the ten highest months with respect to total quality costs. Second, the high quality costs are primarily due to high internal and external failure costs during these periods.

This positive relationship between inefficient resource allocation with respect to productivity and cost inefficiency provides empirical evidence that these performance measures are not competing interests. Further, it suggests that poor resource allocation not only lowers output, but also contributes to higher failure costs and total quality costs, and quality cost inefficiencies.

The converse of this relationship, however, does not hold. When the facility ineffectively allocates its quality costs, a relationship to the efficiency using the productivity model (Column D in Figure 5) for those periods is not apparent. The set of months with inefficient cost

allocations was equally divided into months having efficient productivity performance (1,6,9,10,13,21) and inefficient productivity performance (3,7,12,14,18). Months in the first set, where inefficient cost allocations did not impact productivity, were characterized by high prevention and appraisal expenditures (see Appendix 5) that did not significantly reduce failure costs. Months in the second set, however, were cost inefficient primarily due to excessive internal and external failure costs (see Appendix 5). It is expected that higher rates of rejected linerboard and unscheduled down time affecting these failure costs would be more detrimental to productivity than excessive prevention and appraisal costs.

In addition to establishing a positive relationship between productivity and cost inefficiency, the comparison of these models also addresses the common misguided belief that increased prevention and appraisal spending adversely affects production. Consider the months with prevention and appraisal expenditures greater than \$50,000 (11,13,12,21,22). With the exception of 12, these months were also characterized by extremely low quantities of tons produced (see Appendix 5), and could have been improperly identified as providing evidence that increased prevention and appraisal costs negatively impacts production. However DEA results indicate that three of those months (13,21,22)

actually had efficiency values=1.000 in the productivity model. This result suggests that resource effectiveness is not necessarily directly related to absolute quantities of production or prevention and appraisal expenditures. Therefore, production reporting that relies on solely on these indicators, and does not consider resource efficiency, may lead to faulty decision making by management.

The evaluation of F3, **TONS= F(LABOR, MATERIAL, ENERGY, CAPITAL, PREVENTION\$+APPRAISAL\$)**, did not yield any further information with respect to the relationship between productivity and quality cost. The efficiency measures and relative ranks of the months using F3 remained nearly the same as those determined using F2. Only during the two months having the most extreme levels of prevention and appraisal allocation did this model provide unique results. The set of efficient months using each of these models was the same, with the exception of month 2, which had the lowest **PREVENTION\$+APPRAISAL\$** (\$11,228) and moves from inefficient in F2 to efficient in F3, where prevention and appraisal costs are included. Further, the most inefficient months remain the same in each of the models, with the exception of month 11, which had the highest **PREVENTION\$+APPRAISAL\$** (\$121,829) and moves from an observation not exhibiting extreme behavior in the F2 model to extremely inefficient in the F3 model.

#### 4.4. Evaluation of the Quality Input Resource Models

The result of the performance-based model (F3) is summarized in Table 3 (detailed reports for performance models are illustrated in Appendix 3).

**Table 3. Performance Efficiency Profile**

Rank	DMU	Input Reducing Technical Efficiency	Classification
1	22	1.000	Efficient
2	21	1.000	
3	14	1.000	
4	3	0.569	Inefficient
5	23	0.521	
6	10	0.489	
7	13	0.448	
8	11	0.432	
9	2	0.386	
10	4	0.380	
11	19	0.374	
12	24	0.364	
13	12	0.329	
14	16	0.329	
15	5	0.320	
16	8	0.317	
17	7	0.309	
18	15	0.305	
19	6	0.298	
20	17	0.295	
21	1	0.294	
22	18	0.293	
23	9	0.277	



When the effectiveness of resource allocation is evaluated with respect to basis weight, a measure of the performance dimension of quality, months 14, 21, and 22 are determined to be efficient. The average basis weight of liner produced was 59.7 during month 14 (the highest of all months in the study), 51.5 during month 21 (23rd highest), and 54.3 during month 22 (12th highest). These absolute basis weight measure ranks suggest that there is little relationship between levels of basis weight and potential efficient allocation of resources identified in this model.

An investigation into the characteristics that influence this result verifies that quality is not appropriately modelled in this specification and/or resources contributing to quality are not appropriately included. There is evidence that some other factor influencing the efficiency of the resources with respect to performance is not captured in the proposed model. The three efficient months are the months with the most scheduled idle time and are the three lowest production months as well. The resources required during these periods are also much lower. These reduced levels of resources, combined with even an average basis weight output measure, falsely highlight these months as the most efficient.

There is, however, useful information contained in an analysis of the months identified as having the lowest

inefficiency using this quality model. Of the eight most inefficient months using this model (1,6,7,8,9,15,17,18), all are characterized by low (less than 54.0) basis weight measurements. Month 9 had the highest basis weight output of any month in this set, yet it ranked only 15th in the two year study. This result suggests that operating at a lower basis weight tends to lead to inefficient resource allocation. There are a number of possible explanations for the inefficiency at these levels; for example, more frequent or longer machine setups, lower production run quantities that may not take advantage of economies of scale, the use of older machinery for these types of linerboard, or more expensive materials used in the processing of these lower basis weights. More specific data reporting by the facility is necessary to identify why distinctly higher resource allocations are required for lower-grade liner production.

Since the conformance specification includes a normalized output-related measure (**SCRAP%**), it is reasonable that this model (F5) can provide more valuable empirical analysis of the relationship between resource levels and quality output. The results in Table 4 (detailed reports for conformance models are shown in Appendix 4) illustrate that this model is more effective than the basis weight model in flagging poor quality performance.

**Table 4. Conformance Efficiency Profile**

<b>Rank</b>	<b>DMU</b>	<b>Input Reducing Technical Efficiency</b>	<b>Classification</b>	
1	19	1.000	<b>Efficient</b>	
2	21	1.000		
3	22	1.000		
4	8	0.745		
5	10	0.547		
6	6	0.537		
7	13	0.537		
8	11	0.473		
9	14	0.471		
10	16	0.372		<b>Inefficient</b>
11	7	0.361		
12	2	0.357		
13	3	0.352		
14	24	0.345		
15	5	0.340		
16	1	0.333		
17	15	0.329		
18	12	0.323		
19	17	0.319		
20	18	0.312		
21	23	0.310		
22	4	0.309		
23	9	0.304		

When the effectiveness of resource allocation is evaluated with respect to scrap percentage rate, a measure of the conformance dimension of quality, months 19, 21, and 22 are determined to be efficient. Months 21 and 22, the two months with the lowest production in the study, are also identified by the performance model as efficient. Month 19, on the other hand, is the fourth highest production month

(25,437 tons), and also has the lowest scrap percentage rate (.09%).

Differences in production quantities levels lead to an inconsistency between DEA results and relative ranking of the months with respect to absolute scrap rates. Resources are allocated efficiently in months 19, 21, and 22, despite the fact that in months 21 and 22, the scrap rates were the highest of any month in the study. Quantity of rejected tons, however, were low in each of the three months.

While the performance and conformance models tend to isolate similar months as being efficient, they formulate disparate inefficient sets. Only months 9, 17, and 18, which combine low basis weight production with high levels of rejected tons are identified as inefficient, independent of the quality dimension modeled. As expected, months with the highest quantities of rejected tons are more effectively isolated in the inefficient set of the conformance model rather than the performance model. For example, consider the six months with the highest quantities of rejected tons (4,9,17,18,23,24). These months represent the six most inefficient months using the conformance model, but in the performance model, only three of these months (9, 17, 18) have relatively low efficiencies. Further, two of the months identified as most inefficient in the performance model (6 and 8) actually were two of the lowest quantities

of rejected tons (69 tons and 34 tons respectively) of any month in the study. These were not identified as inefficient in the conformance model.

#### **4.5. Evaluation of the Quality-Cost Link**

The model results provide empirical support for Garvin's conceptual claims that the link between quality costs and quality is dependent on the dimension of quality modeled. Figure 6 illustrates the results of the performance (F4) vs quality cost (F1) efficiency profile.

When the performance dimension is specified using the basis weight measure, there is evidence of a negative relationship between quality and quality cost efficiency at the facility (Row A and Column C in Figure 6). This result agrees with Garvin's assertion that quality measures addressing a product-based definition generally can only be improved through increased cost. In this study, higher basis weight, a product-based quality measure, is identified by more pounds of fiber (and more material cost) per 1000 square feet of liner. It is not unexpected that when the facility most efficiently allocates its resources to increase this dimension of quality (Row A in Figure 6), the result is poor cost efficiency. There are no months that are efficient with respect to both performance and cost. Of the three months determined to be efficient with respect to

		C	D	Observations With No Apparent Cost Classification	Apparent Relationship Between Cost and Performance
		Cost Efficient Observations	Cost Inefficient Observations		
A	Performance Efficient Observations	-	14, 21	22	NEGATIVE
B	Performance Inefficient Observations	2, 16, 19	12, 4, 5, 7, 8, 1, 9, 15, 6, 18	24, 17	NONE
Observations With No Apparent Performance Classification		-	11, 23, 3, 13, 10		
Apparent Relationship Between Cost and Performance		NEGATIVE	POSITIVE		

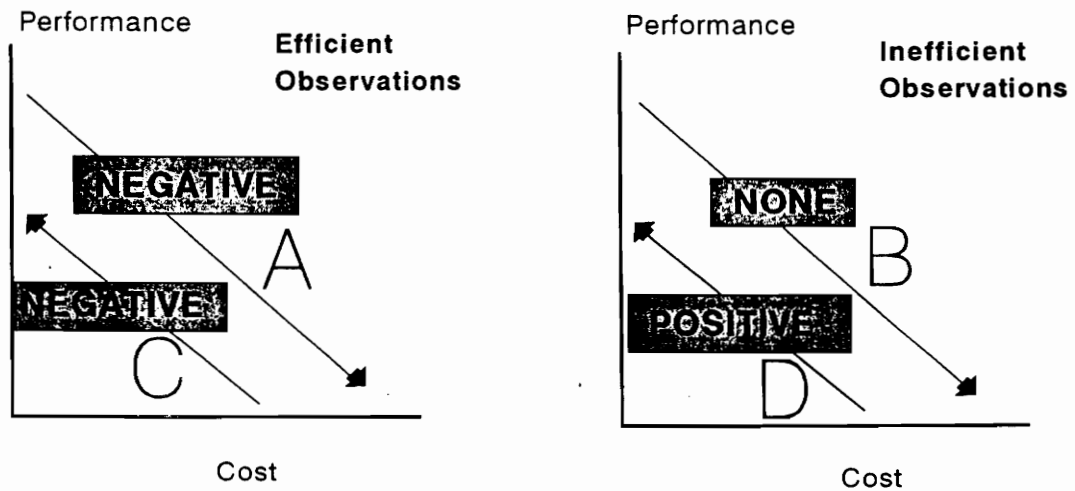


Figure 6. Performance vs. Cost Profile

basis weight (14, 21, 22), two have efficiency values less than 0.38 in the cost model (14, 21), while month 22 only achieved an efficiency of 0.58. This is due, in part, to the high failure costs/ton and total quality costs/ton characterized by efficient months using this model. In fact, months 14, 21, and 22 have the three highest total quality costs/ton of any months in the study.

There is empirical evidence to support the converse of this relationship as well. When the facility allocates costs efficiently (Column C in Figure 6), the result is ineffective resource allocation with respect to the performance dimension of quality. All cost effective months (2, 16, 19) have efficiency values less than 0.40 in the basis weight quality model. This result implies a trade-off in resource and quality cost allocations. The distinct negative relationship between efficient performance and quality cost behavior is not present when the facility operates inefficiently. For example, consider the fifteen months having inefficient resource allocation with respect to performance. As previously discussed, three of these months are cost efficient (2, 16, 19), but ten are determined to be cost inefficient (1,4,5,6,7,8,9,12,15,18). This suggests that when the facility is not effectively managing their resources to generate quality output, it may or may not affect its quality cost performance.

Given the specified rule that at least 80% of the inefficient observations with respect to one measure must be inefficient with respect to the other measure in order to assert a positive relationship, Column D of Figure 6 illustrates a conflicting conclusion. According to the figure, whether costs are inefficiently or efficiently allocated (Column C and D in Figure 6), the result is that the resource allocation with respect to performance is inefficient.

The relationship between quality and cost changes when the conformance dimension is defined in (F5). The DEA results, illustrated in Figure 7, provide empirical evidence to confirm Garvin's contention that poor conformance leads to higher quality costs. Consider row B in Figure 7. Of the fourteen months with efficiency less than 0.38 in the conformance model, ten of those months are also cost inefficient. As expected, the months that are inefficient with respect to both conformance and quality cost are characterized by high failure costs and high total quality costs (see Appendix 5). Of these months, 23 has the lowest amount of failure costs (\$118,971), which ranks as only the ninth lowest in the study. Further, the month in the inefficient set with the lowest total quality cost is 18 (\$160,652), which ranks only tenth among all months. The DEA results therefore illustrate that when the facility fails to



		C	D	Observations With No Apparent Cost Classification	Apparent Relationship Between Cost and Conformance
		Cost Efficient Observations	Cost Inefficient Observations		
A	Conformance Efficient Observations	19	21	22	NONE
B	Conformance Inefficient Observations	2, 16	12, 4, 5, 7, 1, 9, 23, 15, 3, 18	24, 17	POSITIVE
Observations With No Apparent Conformance Classification		-	11, 14, 8, 13, 6, 10		
Apparent Relationship Between Cost and Conformance		NONE	POSITIVE		

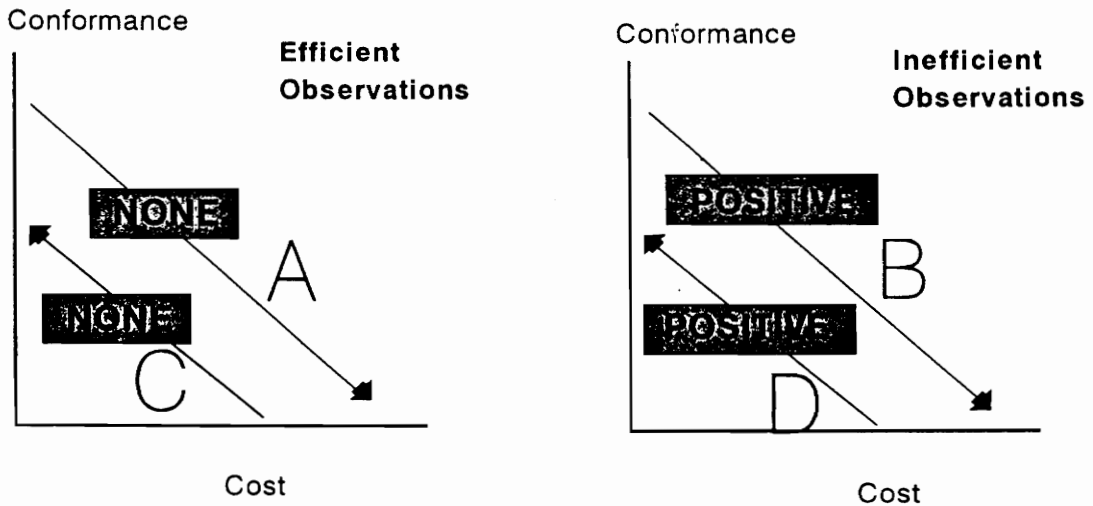


Figure 7. Conformance vs. Cost Profile

operate efficiently with respect to conformance, failure costs and total quality costs are increased, thus leading to ineffective cost allocations as well.

The conformance vs cost profile also suggests that when the facility is cost inefficient (Column D in Figure 7), it also leads to resource inefficiency with respect to conformance. Of the seventeen months identified in the study having inefficient allocations of quality costs, only one (month 21) was efficient with respect to conformance. This month had the highest scrap rate of all months, but effective utilization of resources allowed it to be identified as efficient.

The relationship between quality costs and quality is therefore affected by the quality dimension specified<sup>(15)</sup>. When the performance dimension is chosen, there is clearly a negative relationship between quality costs and quality; however, when the conformance dimension of quality is evaluated, there is a positive relationship between inefficient allocations of quality cost and quality with respect to conformance. These conflicting DEA model results emphasize the need for management to understand that there are differences among the performance and conformance

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15. Investigating this relationship by comparing the DEA results of F5 and F7 to cost model (F1), as described in section 3.6.3, did not contribute further evidence to support or contradict the relationships already identified.

dimensions of quality and that effectively allocating resources to achieve efficient behavior may have divergent effects on quality costs.

#### **4.6. Evaluation of the Quality-Productivity Link**

The short term relationship between quality and productivity can be evaluated by comparing the resource allocation efficiency in models having three different output measures. The productivity model (F2) defines the output measure as **TONS PRODUCED**. Its efficient allocations can be compared to those identified by the performance model (F3), which changes the output measure to average **BASIS WEIGHT**, and the conformance model (F5), which uses **INV(SCRAP%)** as its measure of output.

The DEA results define the conformance vs productivity profile in Figure 8. When the conformance dimension is specified there is empirical evidence in this study to suggest a positive relationship between productivity and quality. The results indicated by row A in Figure 8 suggest that all three months that are efficient with respect to conformance (19, 21, 22) are also efficient with respect to productivity. This can be accomplished, according to Feigenbaum(1981), by addressing the common sources of improvement between the two measures. In the linerboard facility, one common source of improvement for quality and

		C	D	Observations With No Apparent Productivity Classification	Apparent Relationship Between Conformance and Productivity
		Production Efficient Observations	Production Inefficient Observations		
A	Conformance Efficient Observations	19, 21, 22	-	-	POSITIVE
B	Conformance Inefficient Observations	1, 24, 16, 9	12, 3, 2, 7, 18, 17	15, 5, 4, 23	NONE
Observations With No Apparent Conformance Classification		6, 10, 13	14		
Apparent Relationship Between Conformance and Productivity		NONE	POSITIVE		

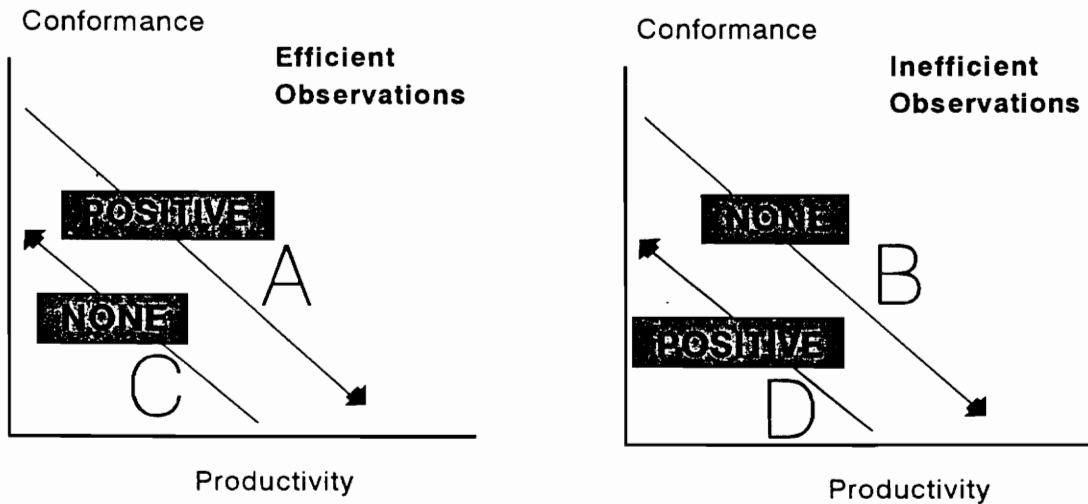


Figure 8. Conformance vs. Productivity Profile

productivity is the quantity of rejected tons. Months 19, 21, and 22 have low rejected tons. In fact, only month 21, the 15th lowest month, has more than 150 rejected tons. Similarly, the results indicated by column D in Figure 8 provide additional support for this observation. Six months are identified as inefficient with respect to both productivity and conformance (18,3,12,2,17,7). Only one of these, month 7, had less than 200 rejected tons. The remaining months were all among the bottom half of all months ranked with respect to this characteristic. The study therefore confirms that when the linerboard produces within specification and thus operates with lower rejected tons, resources are then allocated efficiently with respect to "good" production.

Because the models measure two different outputs, "good" output (**TONS PRODUCED**) and "bad" output (**SCRAP%**), the converse of their relationship does not hold true. The result indicated in column C in Figure 8 illustrates that when the facility is efficient with respect to quantity of tons produced, it does not necessary operate efficiently with respect to conformance. Of the ten efficient months in the productivity model, only three months (19, 21, 22) also have resource allocations that are efficient with respect to

conformance, while four others (1,9,16,24), are inefficient with respect to this dimension of quality. This conclusion may be due to the fact that the conformance measurement in this study was obtained from the paper machine process. Had sufficient data been available, conformance measures should have been evaluated at all phases of the production process, thus presenting a more complete evaluation of the conformance versus productivity relationship.

Nonetheless, an investigation into why the months are segregated into two distinct groups of conformance efficiency provides empirical evidence of the quality vs productivity relationship. Months that are also conformance inefficient are characterized by high production quantities and high production per operating hour (see Appendix 5), but also high rejected tons. In fact, only month 16 has less than 200 rejected tons. Another distinction between the groups is their level of prevention and appraisal expenditures. Those months that allocate resources to be efficient with respect to both quality and productivity have relatively high controllable quality cost expenditures (ranks of 4th, 5th, and 19th highest, respectively), while those that are inefficient with respect to conformance have low prevention and appraisal allocations (13th, 22nd, 23rd, and 15th, respectively). This result indicates that the facility is more likely to operate efficiently with respect

to both conformance and productivity by increasing its controllable quality costs to help prevent the production of rejected tons.

Figure 9 illustrates the comparison between quality and productivity when the performance dimension is specified. The quality-productivity link using this dimension is not clear in the linerboard study. There is no empirical evidence to suggest that the resource allocation efficiency changes in a particular direction when the monthly output measure is changed from quality to productivity (see row A of Figure 9). Of the three months identified by DEA as having efficient resource allocation with respect to performance, two are efficient with respect to productivity (21, 22), while one is inefficient with respect to productivity (14). The two efficient months had relatively low basis weight averages of 51.53 and 54.34 respectively, but were identified as efficient with respect to productivity due to effective allocation of limited input resources during those low output months. Month 14, on the other hand, was efficient with respect to performance because output liner had the highest average basis weight (59.7) of any month in the study, but was resource inefficient with respect to quantity of tons produced due to extensive down time for unscheduled maintenance.

The results of row B in Figure 9 illustrate that

		C	D	Observations With No Apparent Productivity Classification	Apparent Relationship Between Performance and Productivity
		Production Efficient Observations	Production Inefficient Observations		
A	Performance Efficient Observations	21, 22	14	-	NONE
B	Performance Inefficient Observations	16, 24, 19, 9, 1, 6	12, 2, 17, 7, 18	5, 4, 15, 8	NONE
Observations With No Apparent Performance Classification		10, 13	3		
Apparent Relationship Between Performance and Productivity		NONE	POSITIVE		

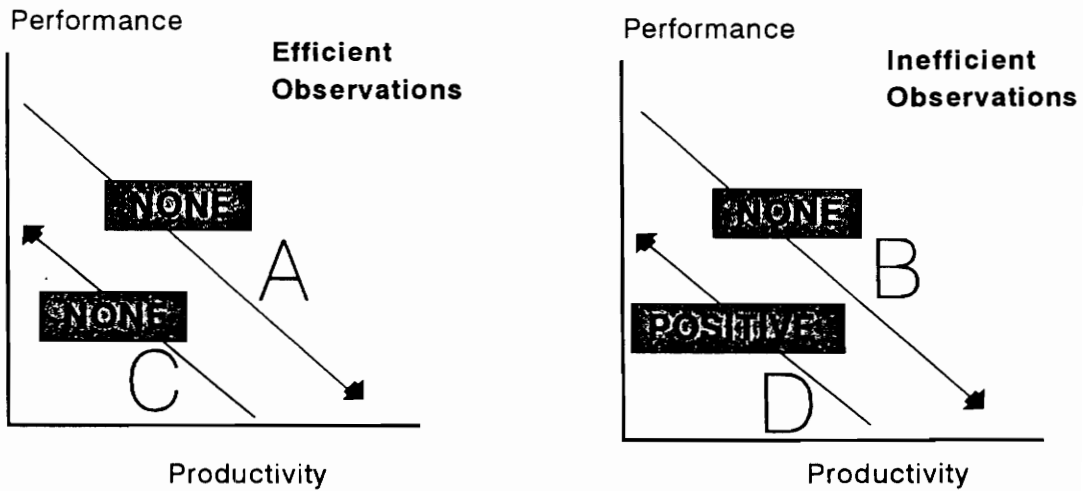


Figure 9. Performance vs. Productivity Profile



performance inefficiency also has no relationship to productivity. Of the sixteen months identified as poorly allocating resources with respect to basis weight, six months were characterized by the high quantity of output and high tons per operating hour (see Appendix 5) and were therefore production efficient (16,24,19,9,1,6), but five had relatively low quantities of output and low tons per operating hour and were production inefficient (12,2,17,7,18).

These DEA results highlight the effect of evaluating quality measures that address various dimensions of quality. Management, at least in this case study, may only identify a strong positive relationship between quality and productivity when the conformance dimension of quality is specified. It is important to note, however, that there was no empirical analysis to suggest that either of the dimensions had a negative relationship with productivity.

## CHAPTER 5. CONCLUSIONS

This research demonstrates that input-output analysis can be applied to investigate the various performance measures of quality, productivity, and cost. Further, Data Envelopment Analysis can be used to support the modeling of the specifications developed during this research to address interrelationships among these measures. The model results provide empirical evidence for several of Garvin's conceptual claims concerning quality, productivity, and cost.

The short-term, snapshot evaluation characterized by the DEA approach, however, failed to provide conclusive evidence for Juran's contention that total quality costs can be decreased through increased prevention and appraisal expenditures. The analysis also did not illustrate a second conceptual relationship that increased prevention and appraisal quality costs result in increased quality output. In fact, increased total quality costs and reduced quality output efficiency were realized at higher expenditures of controllable quality costs. Two data issues contributed to this inconsistency. First, the monthly operating statements for the linerboard mill did not specifically identify and report quality costs. For example, many of the costs typically allocated to the prevention category, such as

quality training, development and implementation of inspection procedures, vendor certifications, and capability studies, were not reported in the statements. This resulted in approximations of the cost components that may not have been sufficiently defined. Second, the two year time period covered by this study may not have been long enough to realize the benefits of increased prevention and appraisal expenditures. In this respect, data envelopment analysis may not have been the most appropriate tool for the evaluation of this specification. A multivariate regression analysis, using lagged data, may have provided more meaningful results for the quality cost relationships.

The productivity model  **$TONS\ PRODUCED = F(LABOR, MATERIAL, ENERGY, CAPITAL)$**  provided meaningful results. This model identified months as efficient that were characterized by low down time, low quantities of rejected material, and high tons produced per operating hour. This result verifies that the model can be evaluated on a monthly basis to provide the organization with productivity measurement through more appropriate efficiency values, rather than misleading measures of absolute quantities produced.

A comparison of the productivity and quality cost models also has valuable conclusions. The DEA results effectively illustrate that when an organization is resource inefficient with respect to productivity, it is also more

likely to allocate its quality costs inefficiently. Thus, at least in this short term study, a positive relationship between the efficiency of quality costs and productivity is empirically verified. Resource inefficiency, therefore, has several disadvantages for the organization; it decreases productivity, and contributes to high total quality costs and cost inefficiency as well.

The research effectively illustrates that dimensions of quality have different relationships with quality costs. The DEA results verify Garvin's assertions that when the conformance dimension is specified, there is a positive relationship between cost efficiency and quality output efficiency. However, when the performance dimension is considered, a negative relationship is present. This conclusion emphasizes the necessity of organizations to define and understand their quality measurement and reporting systems, and how changes in these measures can affect cost allocations.

The success in evaluating the short term quality-productivity link was also dependent on the quality dimension specified. There was no clear relationship between performance and productivity when the basis weight measure was used in the DEA models. However, using the scrap % measure in the models provided empirical evidence of a positive relationship between conformance and

productivity. This relationship therefore demonstrates that allocating resources efficiently to address the conformance dimension of quality not only results in increased resource efficiency with respect to output quantity, but also decreases total quality costs through increased cost efficiency as well.

## CHAPTER 6. RECOMMENDATIONS FOR FUTURE RESEARCH

The relationships among quality costs, quality, and productivity were empirically evaluated on a limited scope in this research. Additional research is needed to confirm the associations identified in this case study. Empirical evidence of the quality vs cost and quality vs productivity relationships needs to be presented that considers all eight of Garvin's quality dimensions, rather than only conformance and performance. The associations must be evaluated across several technologies beyond the single linerboard facility studied in this research.

To continue to explore these relationships, extensive, properly constructed, case studies are necessary. Each of these studies must begin by establishing sufficient data gathering and reporting systems within the production environment. These systems must support evaluation of additional dimensions of quality and provide adequate definition of the four quality cost components. They must also contain sufficient data to provide meaningful estimates of resource allocations and production quantities for the processes addressed by the specific quality and cost measurements. Further, these resource measures should be segregated into quality-related allocations and productivity-related allocations. Finally, the data set

evaluated in the research should also provide a description of the management decisions taken in response to the performance reports. The effects of management decision making on resulting performance efficiency measures should be studied to better address the short-term relationships between quality, cost, and productivity.

Once studies establish complete data sets, additional evaluation of quality, cost, and productivity relationships using DEA is required. Given decision making information, the strengths of DEA in providing efficiency information for individual DMUs needs to be exploited. The tool's effectiveness may have been demonstrated in the linerboard case study if sufficient information was available for verification of the model results. Finally, further evaluation of the effectiveness of the tool can be provided by studies of several different technologies, as well as studies that contrast DEA model results to results obtained through statistical techniques such as multiple regression and/or correlation analysis for the same data sets.

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**APPENDIX 1.**  
**Quality Cost BCC Model Results**

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: DATA ENVELOPMENT ANALYSIS --- MODEL: P-BCC

DMU	NAME	THETA	SUM OF SLACKS	IOTA	ALPHA
1	M1280	.25483	12720.00	.23249	-569149.49552
2	M0181	1.00000	.00	1.00000	-145038.82287
3	M0281	.31924	30450.00	.25222	-454324.94114
4	M0381	.24404	35660.00	.18404	-594312.98206
5	M0481	.25795	29120.00	.20616	-562277.33184
6	M0581	.28150	.00	.28150	-635925.90527
7	M0681	.23728	5080.00	.22897	-611260.87444
8	M0781	.26317	17460.00	.23149	-551116.52466
9	M0881	.26072	13150.00	.23708	-556309.40022
10	M0981	.37859	.00	.37859	-202384.71500
11	M1081	.09430	.00	.09430	-1573738.39966
12	M1181	.16106	6260.00	.15410	-900550.54652
13	M1281	.26920	.00	.26920	-401751.80937
14	M0182	.24378	12450.00	.22286	-594945.94451
15	M0282	.24363	1010.00	.24193	-595333.47253
16	M0382	1.00000	.00	1.00000	-191128.82287
17	M0482	.45780	2970.00	.44843	-316817.07960
18	M0582	.34698	.00	.34698	-427197.97926
19	M0682	1.00000	.00	1.00000	-140709.87465
20	M0882	.25708	.00	.25708	-286292.31906

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: DATA ENVELOPMENT ANALYSIS --- MODEL: P-BCC

DMU	NAME	THETA	SUM OF SLACKS	IOTA	ALPHA
21	M0982	.58328	.00	.58328	-238223.39759
22	M1082	.23956	.00	.23956	-642418.12780
23	M1182	.65224	.00	.65224	-240461.14070

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: SLACK VALUES

	inv-I+E	PREV+APP
M1280	12720.0	.0
M0181	.0	.0
M0281	30450.0	.0
M0381	35660.0	.0
M0481	29120.0	.0
M0581	.0	.0
M0681	5680.0	.0
M0781	17460.0	.0
M0881	13150.0	.0
M0981	.0	.0
M1081	.0	.0
M1181	5260.0	.0
M1281	.0	.0
M0182	12450.0	.0
M0282	1010.0	.0
M0382	.0	.0
M0482	2970.0	.0
M0582	.0	.0
M0682	.0	.0
M0882	.0	.0

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: SLACK VALUES

	inv-I+E	PREV+APP
M0982	.0	.0
M1082	.0	.0
M1182	.0	.0

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: RANGE OF WEIGHTS

inv-I+E	.000000635	.000007107
PREV+APP	.000008208	.000089063

TABLE: OCCURRENCE OF DMUS IN FACETS

UNIT	NAME	NUMBER OF FACETS
16	M0382	23
2	M0181	18
19	M0682	5

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: DATA ENVELOPMENT ANALYSIS --- MODEL: P-BCC

DMU	NAME	THETA	SUM OF SLACKS	IOTA	ALPHA
1	M1280	.47339	281706.72	.13917	-842877.70000
2	M0181	.45860	212244.24	.17422	-746324.10000
3	M0281	.47074	267576.16	.12767	-779940.50000
4	M0381	.40857	261809.93	.10824	-871753.40000
5	M0481	.41111	244682.51	.12003	-840609.50000
6	M0581	.38302	164570.80	.18612	-835778.50000
7	M0681	.42103	214446.15	.15500	-806031.30000
8	M0781	.38462	184481.91	.14575	-772312.60000
9	M0881	.39768	240378.25	.13010	-898338.30000
10	M0981	.49371	62868.89	.36953	-506247.40000
11	M1081	.43290	116548.69	.23103	-577367.00000
12	M1181	.41667	242341.56	.14085	-878647.10000
13	M1281	.62164	126981.09	.39322	-555920.80000
14	M0182	.51704	172078.13	.36087	-1101925.59116
15	M0282	.43943	227672.99	.15894	-811698.00000
16	M0382	.37586	164507.80	.19433	-906231.20000
17	M0482	.38050	191199.59	.15190	-836398.00000
18	M0582	.36332	175616.71	.15671	-850028.50000
19	M0682	1.00000	.00	1.00000	-847969.80000
20	M0882	1.00000	.00	1.00000	-464135.97736

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: DATA ENVELOPMENT ANALYSIS --- MODEL: P-BCC

DMU	NAME	THETA	SUM OF SLACKS	IOTA	ALPHA
21	M0982	1.00000	.00	1.00000	-249401.40000
22	M1082	.37389	183918.14	.16086	-863357.90000
23	M1182	.40333	197709.86	.27463	-1536256.24257

TABLE: SLACK VALUES

	INV(I+E)	cap	matls	energy	labor
M1280	132100.0	53.0	938.2	148615.6	.0
M0181	119380.0	31.4	587.2	92245.7	.0
M0281	149830.0	54.8	837.6	116853.8	.0
M0381	155040.0	60.5	968.2	105741.2	.0
M0481	148500.0	51.4	723.8	95407.4	.0
M0581	93850.0	61.1	872.2	69787.5	.0
M0681	124460.0	55.2	796.9	89134.1	.0
M0781	136840.0	18.8	713.0	46910.1	.0
M0881	132530.0	71.5	945.9	106831.0	.0
M0981	62330.0	15.2	517.9	.0	5.7
M1081	116010.0	19.6	515.3	.0	3.8
M1181	125640.0	75.8	740.0	115885.8	.0
M1281	30800.0	34.1	748.0	95398.9	.0
M0182	126925.1	14.4	.0	45138.6	.0
M0282	120390.0	60.9	220.7	107001.4	.0
M0382	73290.0	66.7	202.5	90948.6	.0
M0482	122350.0	40.1	88.8	68720.6	.0
M0582	116190.0	36.3	56.5	59333.9	.0
M0682	.0	.0	.0	.0	.0
M0882	.0	.0	.0	.0	.0

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: SLACK VALUES

	INV(I+E)	cap	matls	energy	labor
M0982	.0	.0	.0	.0	.0
M1082	110520.0	46.6	52.2	73299.3	.0
M1182	92533.7	58.1	.0	105118.1	.0

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: RANGE OF WEIGHTS

INV(I+E)	.000000651	.000401071
cap	.000000651	.000004010
matls	.000001103	.000989965
energy	.000000651	.000004010
labor	.000000651	.000004010

TABLE: OCCURRENCE OF DMUS IN FACETS

UNIT	NAME	NUMBER OF FACETS
21	M0982	23
20	M0882	3
19	M0682	1

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI



TABLE: DATA ENVELOPMENT ANALYSIS --- MODEL: P-BCC

DMU	NAME	THETA	SUM OF SLACKS	IOTA	ALPHA
1	M1280	.74687	210624.23	.60479	-1482494.62566
2	M0181	1.00000	.00	1.00000	-1047342.47480
3	M0281	.80351	158072.27	.68102	-1290516.23519
4	M0381	.66885	156134.94	.56744	-1539649.34906
5	M0481	.68429	127421.18	.59776	-1472503.40695
6	M0581	.63669	30836.63	.61636	-1516725.18933
7	M0681	.67536	104102.08	.60564	-1493033.49070
8	M0781	.69073	69400.64	.64086	-1391663.86002
9	M0881	.67151	126898.37	.58822	-1523525.37491
10	M0981	.84459	20369.57	.82715	-1168307.53417
11	M1081	.43841	115787.69	.38905	-2345952.80200
12	M1181	.57455	183247.90	.47763	-1890696.44118
13	M1281	.62164	129577.38	.42120	-646452.80000
14	M0182	.87351	120932.63	.81818	-2185498.55800
15	M0282	.73372	133042.66	.68321	-2633993.07767
16	M0382	1.00000	.00	1.00000	-1993816.51069
17	M0482	.89414	28326.89	.88027	-2042124.37512
18	M0582	.80196	35547.86	.78646	-2293518.25007
19	M0682	1.00000	.00	1.00000	-879677.80000
20	M0882	1.00000	.00	1.00000	-548270.20377

TABLE: DATA ENVELOPMENT ANALYSIS --- MODEL: P-BCC

DMU	NAME	THETA	SUM OF SLACKS	IOTA	ALPHA
21	M0982	1.00000	.00	1.00000	-1028700.44229
22	M1082	.67795	57345.99	.65713	-2753558.25463
23	M1182	1.00000	.00	1.00000	-1979772.82524

TABLE: SLACK VALUES

	INV(I+E)	P+A	cap	matls	energy	labor
M1280	73680.8	.0	50.1	853.6	136039.7	.0
M0181	.0	.0	.0	.0	.0	.0
M0281	78344.4	.0	52.6	663.0	79012.3	.0
M0381	90618.8	.0	62.1	894.1	64559.9	.0
M0481	81304.4	.0	47.0	484.1	45585.8	.0
M0581	26877.9	.0	63.3	731.5	3164.0	.0
M0681	63373.2	.0	53.5	623.1	40052.3	.0
M0781	68754.0	.0	10.1	625.1	.0	11.3
M0881	62898.0	.0	80.7	850.4	63069.2	.0
M0981	19690.0	.0	37.7	605.3	.0	36.6
M1081	115246.5	.0	20.0	516.8	.0	4.3
M1181	87321.3	.0	82.6	609.4	95234.6	.0
M1281	30800.0	2596.3	34.1	748.0	95398.9	.0
M0182	91537.2	.0	.0	.0	29379.8	15.6
M0282	62891.5	.0	54.5	.0	70096.7	.0
M0382	.0	.0	.0	.0	.0	.0
M0482	28300.7	.0	14.7	.0	.0	11.6
M0582	35520.0	.0	14.6	.0	.0	13.3
M0682	.0	.0	.0	.0	.0	.0
M0882	.0	.0	.0	.0	.0	.0

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: SLACK VALUES

	INV(I+E)	P+A	cap	matls	energy	labor
M0982	.0	.0	.0	.0	.0	.0
M1082	50782.8	.0	19.1	.0	6544.1	.0
M1182	.0	.0	.0	.0	.0	.0

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: RANGE OF WEIGHTS

INV(I+E)	.000000363	.000372421
P+A	.000001137	.000025598
cap	.000000363	.000001824
matls	.000000426	.000928970
energy	.000000363	.000001824
labor	.000000363	.000988711

TABLE: OCCURRENCE OF DWUS IN FACETS

UNIT	NAME	NUMBER OF FACETS
21	M0982	23
2	M0181	20
23	M1182	6
19	M0682	3
16	M0382	2
20	M0882	1

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

**APPENDIX 2.**  
**Productivity BCC Model Results**

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: DATA ENVELOPMENT ANALYSIS --- MODEL: P-BCC

DMU	NAME	THETA	SUM OF SLACKS	IOTA	ALPHA
1	M1280	.29543	.00	.29543	-102469.13677
2	M0181	1.00000	.00	1.00000	-26112.65247
3	M0281	.34249	.00	.34249	-81796.23262
4	M0381	.30424	.00	.30424	-106999.54709
5	M0481	.30717	.00	.30717	-101231.87832
6	M0581	.70020	.00	.70020	-46307.00000
7	M0681	.27671	.00	.27671	-110050.82960
8	M0781	.28715	.00	.28715	-99222.49776
9	M0881	1.00000	.00	1.00000	-43066.00000
10	M0931	.24620	2949.00	.21839	-106064.62663
11	M1081	.09216	517.00	.09034	-283334.37276
12	M1181	.18996	.00	.18996	-162134.26850
13	M1281	.12402	3389.00	.10793	-210547.79596
14	M0182	.24378	4665.00	.20023	-107113.50504
15	M0282	.27590	.00	.27590	-107183.27522
16	M0382	1.00000	.00	1.00000	-34410.65247
17	M0482	.52784	.00	.52784	-57039.44731
18	M0582	.39395	.00	.39395	-76912.32007
19	M0682	.44730	.00	.44730	-73742.42825
20	M0882	.17404	11142.00	.09978	-150038.44507

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: DATA ENVELOPMENT ANALYSIS --- MODEL: P-BCC

DMU	NAME	THETA	SUM OF SLACKS	IOTA	ALPHA
21	M0982	.20916	12107.00	.11218	-124846.75837
22	M1082	.27742	.00	.27742	-115660.35202
23	M1182	.75837	.00	.75837	-43292.39630

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: SLACK VALUES

	TONS	P+A
M1280	.0	.0
M0181	.0	.0
M0281	.0	.0
M0381	.0	.0
M0481	.0	.0
M0581	.0	.0
M0681	.0	.0
M0781	.0	.0
M0881	.0	.0
M0981	2949.0	.0
M1081	517.0	.0
M1181	.0	.0
M1281	3389.0	.0
M0182	4665.0	.0
M0282	.0	.0
M0382	.0	.0
M0482	.0	.0
M0582	.0	.0
M0682	.0	.0
M0882	11142.0	.0

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: SLACK VALUES

	TONS	P+A
M0982	12107.0	.0
M1082	.0	.0
M1182	.0	.0

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: RANGE OF WEIGHTS

TONS	.000003529	.001356269
P+A	.000008208	.000089063

TABLE: OCCURRENCE OF DMUS IN FACETS

UNIT	NAME	NUMBER OF FACETS
16	M0382	23
2	M0181	21
9	M0881	2

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: DATA ENVELOPMENT ANALYSIS --- MODEL: P-BCC

DMU	NAME	THETA	SUM OF SLACKS	IOTA	ALPHA
1	M1280	1.00000	.00	1.00000	-3037703.54234
2	M0181	.92550	10692.54	.92126	-2522176.47000
3	M0281	.93336	3.76	.93336	-3572612.78323
4	M0381	.96280	140.08	.96275	-2976214.71809
5	M0481	.95551	3.75	.95551	-3071392.36228
6	M0581	1.00000	.00	1.00000	-3568772.69348
7	M0681	.94176	.00	.94176	-3248269.99215
8	M0781	.95314	314.44	.95301	-2448146.66560
9	M0881	1.00000	.00	1.00000	-2217303.95936
10	M0981	1.00000	.00	1.00000	-1407596.08480
11	M1081	.99743	24.94	.99739	-604092.35512
12	M1181	.92568	35.74	.92568	-5200320.86200
13	M1281	1.00000	.00	1.00000	-2070587.56548
14	M0182	.93919	31762.28	.92689	-2583264.49690
15	M0282	.98879	6287.12	.98848	-20769811.92230
16	M0382	1.00000	.00	1.00000	-3531871.32904
17	M0482	.94731	13.61	.94731	-2534250.67614
18	M0582	.93685	19.82	.93685	-2583624.42324
19	M0682	1.00000	.00	1.00000	-963212.88723
20	M0882	1.00000	.00	1.00000	-493440.66935

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: DATA ENVELOPMENT ANALYSIS --- MODEL: P-BCC

DMU	NAME	THETA	SUM OF SLACKS	IOTA	ALPHA
21	M0982	1.00000	.00	1.00000	-1095067.63463
22	M1082	.98563	9.44	.98562	-1204007.77137
23	M1182	1.00000	.00	1.00000	-1342775.39972

TABLE: SLACK VALUES

	tons	cap	natls	energy	labor
N1280	.0	.0	.0	.0	.0
N0181	.0	.0	.0	10679.1	13.4
N0281	.0	2.0	1.9	.0	.0
N0381	.0	.0	140.1	.0	.0
N0481	.0	.0	.0	.0	3.7
N0581	.0	.0	.0	.0	.0
N0681	.0	.0	.0	.0	.0
N0781	.0	.0	273.8	.0	40.7
N0981	.0	.0	.0	.0	.0
N0981	.0	.0	.0	.0	.0
N1081	.0	6.6	.0	.0	18.4
N1181	.0	35.7	.0	.0	.0
N1281	.0	.0	.0	.0	.0
N0182	.0	.0	.0	31747.3	15.0
N0282	.0	24.3	.0	6262.8	.0
N0382	.0	.0	.0	.0	.0
N0482	.0	.0	.0	.0	13.6
N0582	.0	.0	.0	.0	19.8
N0682	.0	.0	.0	.0	.0
N0882	.0	.0	.0	.0	.0

TABLE: SLACK VALUES

	tons	cap	natls	energy	labor
N0982	.0	.0	.0	.0	.0
N1082	.0	.0	.0	.0	9.4
N1182	.0	.0	.0	.0	.0

TABLE: RANGE OF WEIGHTS

tons	.000031163	.000111612
cap	.000000048	.002608623
natls	.000000280	.000129662
energy	.000000048	.000002027
labor	.000000326	.005498144

TABLE: OCCURRENCE OF DMS IN FACETS

UNIT	NAME	NUMBER OF FACETS
6	N0581	18
21	N0982	17
23	N1182	15
1	N1280	13
16	N0382	11
13	N1281	9
20	N0882	5
9	N0881	4
10	N0981	2
19	N0682	1

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: DATA ENVELOPMENT ANALYSIS --- MODEL: P-BCC

DMU	NAME	THETA	SUM OF SLACKS	IOTA	ALPHA
1	M1280	1.00000	.00	1.00000	-2912646.65370
2	M0181	1.00000	.00	1.00000	-2126792.69889
3	M0281	.97392	36375.10	.96356	-3509629.99373
4	M0381	.96423	191.22	.96416	-2797209.53093
5	M0481	.95783	.00	.95783	-2623260.35735
6	M0581	1.00000	.00	1.00000	-3416261.21351
7	M0681	.94364	23.88	.94363	-2561833.83722
8	M0781	.96508	337.50	.96494	-2403172.33656
9	M0881	1.00000	.00	1.00000	-1281969.95360
10	M0981	1.00000	.00	1.00000	-1709846.06539
11	M1081	.99743	75111.42	.90826	-842330.41985
12	M1181	.92568	25187.60	.92072	-5077671.83994
13	M1281	1.00000	.00	1.00000	-5064574.81658
14	M0182	.93972	30720.18	.93829	-21579771.14781
15	M0282	.98879	20764.74	.98791	-23614233.25190
16	M0382	1.00000	.00	1.00000	-3381267.53122
17	M0482	.95722	4.05	.95722	-2432612.83649
18	M0582	.93715	20.04	.93715	-7942347.89559
19	M0682	1.00000	.00	1.00000	-91728640.21162
20	M0882	1.00000	.00	1.00000	-29029652.25269

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: DATA ENVELOPMENT ANALYSIS --- MODEL: P-BCC

DMU	NAME	THETA	SUM OF SLACKS	IOTA	ALPHA
21	M0982	1.00000	.00	1.00000	-977097.42018
22	M1082	.98563	23510.34	.97526	-2266304.62809
23	M1182	1.00000	.00	1.00000	-3202448.68221

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI



TABLE: SLACK VALUES

	TONS	P+A	cap	matls	energy	labor
M1280	.0	.0	.0	.0	.0	.0
M0181	.0	.0	.0	.0	.0	.0
M0281	.0	.0	1.4	837.3	35536.5	.0
M0381	.0	.0	.0	191.2	.0	.0
M0481	.0	.0	.0	.0	.0	.0
M0581	.0	.0	.0	.0	.0	.0
M0681	.0	.0	.0	23.9	.0	.0
M0781	.0	.0	.0	307.6	.0	23.9
M0881	.0	.0	.0	.0	.0	.0
M0981	.0	.0	.0	.0	.0	.0
M1081	.0	75086.5	6.6	.0	.0	18.4
M1181	.0	25151.9	35.7	.0	.0	.0
M1281	.0	.0	.0	.0	.0	.0
M0182	.0	.0	.0	.0	30699.9	20.3
M0282	.0	14477.6	24.3	.0	6262.8	.0
M0382	.0	.0	.0	.0	.0	.0
M0482	.0	.0	.0	.0	.0	4.0
M0582	.0	.0	.0	.0	.0	20.0
M0682	.0	.0	.0	.0	.0	.0
M0882	.0	.0	.0	.0	.0	.0

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: SLACK VALUES

	TONS	P+A	cap	matls	energy	labor
M0982	.0	.0	.0	.0	.0	.0
M1082	.0	23500.9	.0	.0	.0	9.4
M1182	.0	.0	.0	.0	.0	.0

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: RANGE OF WEIGHTS

TONS	.000030510	.000278233
P+A	.000000011	.000004302
cap	.000000011	.00309542
matls	.000000235	.000166511
energy	.000000042	.000003362
labor	.000000011	.004096530

TABLE: OCCURRENCE OF DMUS IN FACETS

UNIT	NAME	NUMBER OF FACETS
6	M0581	19
16	M0382	18
1	M1280	16
21	M0982	16
22	M1182	14
10	M0981	7
2	M0181	5
9	M0881	4
20	M0882	4
19	M0682	2
13	M1281	2

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

**APPENDIX 3.**  
**Performance Dimension BCC Model Results**

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: DATA ENVELOPMENT ANALYSIS --- MODEL: P-BCC

DMU	NAME	THETA	SUM OF SLACKS	IOTA	ALPHA
1	M1280	.25483	2180.00	.20536	-44060.00000
2	M0181	1.00000	.00	1.00000	-11228.00000
3	M0281	.85825	.00	.85825	-35171.00000
4	M0381	.35744	.00	.35744	-46008.00000
5	M0481	.25795	310.00	.25083	-43528.00000
6	M0581	.23937	1230.00	.21315	-46907.00000
7	M0681	.23728	1310.00	.20959	-47320.00000
8	M0781	.26317	5240.00	.14035	-42664.00000
9	M0881	.26072	1160.00	.23378	-43066.00000
10	M0981	.24620	2230.00	.19730	-45606.00000
11	M1081	.09216	640.00	.08691	-121829.00000
12	M1181	.16211	.00	.16211	-69715.00000
13	M1281	.12402	820.00	.11496	-90532.00000
14	M0182	1.00000	.00	1.00000	-46057.00000
15	M0282	.24363	2320.00	.19329	-46087.00000
16	M0382	.84328	.00	.84328	-14796.00000
17	M0482	.45780	3120.00	.33059	-24526.00000
18	M0582	.33951	1190.00	.30353	-33071.00000
19	M0682	.46534	.00	.46534	-31708.00000
20	M0882	.17404	3450.00	.12056	-64514.00000

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: DATA ENVELOPMENT ANALYSIS --- MODEL: P-BCC

DMU	NAME	THETA	SUM OF SLACKS	IOTA	ALPHA
21	M0982	.20916	640.00	.19724	-53682.00000
22	M1082	.62026	.00	.62026	-49732.00000
23	M1182	.85974	.00	.85974	-18615.00000

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: SLACK VALUES

	BW	P+A
M1280	2180.0	.0
M0181	.0	.0
M0281	.0	.0
M0381	.0	.0
M0481	310.0	.0
M0581	1230.0	.0
M0681	1310.0	.0
M0781	5240.0	.0
M0881	1160.0	.0
M0981	2230.0	.0
M1081	640.0	.0
M1181	.0	.0
M1281	820.0	.0
M0182	.0	.0
M0282	2320.0	.0
M0382	.0	.0
M0482	3120.0	.0
M0582	1190.0	.0
M0682	.0	.0
M0882	3450.0	.0

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: SLACK VALUES

	BW	P+A
M0982	640.0	.0
M1082	.0	.0
M1182	.0	.0

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: RANGE OF WEIGHTS

BW	.000008208	.000654426
P+A	.000008208	.000089063

TABLE: OCCURRENCE OF DNUS IN FACETS

UNIT	NAME	NUMBER OF FACETS
2	M0181	23
14	M0182	9

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: DATA ENVELOPMENT ANALYSIS --- MODEL: P-BCC

DMU	NAME	THETA	SUM OF SLACKS	IOTA	ALPHA
1	M1280	.47339	151146.72	.29407	-842877.70000
2	M0181	.51151	93653.10	.38602	-746324.10000
3	M0281	.74395	136156.49	.56938	-779940.50000
4	M0381	.50799	111817.66	.37972	-871753.40000
5	M0481	.43556	96786.64	.32043	-840609.50000
6	M0581	.38302	71310.80	.29770	-835778.50000
7	M0681	.42103	90656.15	.30856	-806091.30000
8	M0781	.38462	52241.91	.31697	-772312.60000
9	M0881	.39768	108368.35	.27705	-898338.30000
10	M0981	.49371	2128.89	.48951	-506247.40000
11	M1081	.43290	538.69	.43196	-577367.00000
12	M1181	.46548	120295.54	.32857	-878647.10000
13	M1281	.62164	96361.09	.44830	-555920.80000
14	M0182	1.00000	.00	1.00000	-574675.20000
15	M0282	.43943	108962.99	.30519	-811698.00000
16	M0382	.43074	91975.83	.32925	-906231.20000
17	M0482	.38050	71329.59	.29522	-836398.00000
18	M0582	.36332	59976.71	.29276	-850028.50000
19	M0682	.44363	59068.21	.37397	-847969.80000
20	M0882	1.00000	.00	1.00000	-350855.97736

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: DATA ENVELOPMENT ANALYSIS --- MODEL: P-BCC

DMU	NAME	THETA	SUM OF SLACKS	IOTA	ALPHA
21	M0982	1.00000	.00	1.00000	-353665.97736
22	M1082	.59696	65864.20	.52067	-863357.90000
23	M1182	.53226	150947.26	.36430	-898695.90000

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: SLACK VALUES

	BW	cap	matls	energy	labor
M1280	1540.0	53.0	938.2	148615.6	.0
M0181	.0	31.8	661.2	92960.1	.0
M0281	.0	70.6	1355.6	134730.3	.0
M0381	.0	68.5	1217.2	110532.0	.0
M0481	.0	52.8	770.1	95963.8	.0
M0581	590.0	61.1	872.2	69787.5	.0
M0681	670.0	55.2	796.9	89134.1	.0
M0781	4600.0	18.8	713.0	46910.1	.0
M0881	520.0	71.5	945.9	106831.0	.0
M0981	1590.0	15.2	517.9	.0	5.7
M1081	.0	19.6	515.3	.0	3.8
M1181	.0	81.5	833.1	119380.9	.0
M1281	180.0	34.1	748.0	95398.9	.0
M0182	.0	.0	.0	.0	.0
M0282	1680.0	60.9	220.7	107001.4	.0
M0382	.0	72.4	240.1	91663.3	.0
M0482	2480.0	40.1	88.8	68720.6	.0
M0582	550.0	36.3	56.5	59333.9	.0
M0682	.0	59.4	295.5	58713.3	.0
M0882	.0	.0	.0	.0	.0

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: SLACK VALUES

	BW	cap	matls	energy	labor
M0982	.0	.0	.0	.0	.0
M1082	.0	57.9	116.1	65690.1	.0
M1182	.0	88.1	.0	150844.2	15.0

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: RANGE OF WEIGHTS

BW	.000001113	.000105207
cap	.000001103	.000002850
matls	.000001103	.000489300
energy	.000001103	.000002850
labor	.000001103	.000002850

TABLE: OCCURRENCE OF DMUS IN FACETS

UNIT	NAME	NUMBER OF FACETS
21	M0382	23
14	M0182	11
20	M0882	2

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: DATA ENVELOPMENT ANALYSIS --- MODEL: P-BCC

DMU	NAME	THETA	SUM OF SLACKS	IOTA	ALPHA
1	M1280	.74687	138796.65	.64465	-1357934.36750
2	M0181	1.00000	.00	1.00000	-870159.67210
3	M0281	.93842	110113.89	.84413	-1167847.59889
4	M0381	.70871	75454.58	.65400	-1379183.66374
5	M0481	.68429	46147.05	.65009	-1349447.14464
6	M0581	.63659	4907.81	.63315	-1384116.29170
7	M0681	.67538	41726.37	.64467	-1359257.01734
8	M0781	.69073	5611.63	.68631	-1271050.17744
9	M0881	.67151	64893.64	.62522	-1401775.21426
10	M0981	.84459	2498.15	.84219	-1039376.64144
11	M1081	.43841	545.30	.43813	-2001534.92430
12	M1181	.58983	101170.07	.52843	-1647546.06533
13	M1281	.62164	98957.38	.46856	-646452.80000
14	M0182	1.00000	.00	1.00000	-620732.20000
15	M0282	.73372	72269.25	.70432	-2458404.60949
16	M0382	.96924	67926.30	.93270	-1859114.06892
17	M0482	.89414	3389.01	.89239	-1939413.79920
18	M0582	.80196	1351.82	.80134	-2162183.67865
19	M0682	.78238	69.88	.78235	-2056723.42986
20	M0882	1.00000	.00	1.00000	-434990.20377

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: DATA ENVELOPMENT ANALYSIS --- MODEL: P-BCC

DMU	NAME	THETA	SUM OF SLACKS	IOTA	ALPHA
21	M0982	1.00000	.00	1.00000	-437800.20377
22	M1082	.74752	27348.53	.73585	-2343218.65668
23	M1182	1.00000	.00	1.00000	-1618010.68868

TABLE: SLACK VALUES

	BW	P+A	cap	matls	energy	labor
M1280	1853.2	.0	50.1	853.6	136039.7	.0
M0181	.0	.0	.0	.0	.0	.0
M0281	.0	.0	68.0	1202.6	108843.4	.0
M0381	.0	.0	68.1	1099.4	74287.0	.0
M0481	30.2	.0	47.0	484.1	45585.8	.0
M0581	949.0	.0	63.3	731.5	3164.0	.0
M0681	997.5	.0	53.5	623.1	40052.3	.0
M0781	4965.0	.0	10.1	625.1	.0	11.3
M0881	893.3	.0	80.7	850.4	63069.2	.0
M0981	1818.6	.0	37.7	605.3	.0	36.6
M1081	4.1	.0	20.0	516.8	.0	4.3
M1181	.0	.0	85.8	693.5	100390.8	.0
M1281	180.0	2596.3	34.1	748.0	95398.9	.0
M0182	.0	.0	.0	.0	.0	.0
M0282	2118.1	.0	54.5	.0	70096.7	.0
M0382	103.9	.0	100.2	.0	67702.5	19.7
M0482	3362.8	.0	14.7	.0	.0	11.6
M0582	1324.0	.0	14.6	.0	.0	13.3
M0682	.0	.0	60.6	.0	.0	9.2
M0882	.0	.0	.0	.0	.0	.0

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: SLACK VALUES

	BW	P+A	cap	matls	energy	labor
M0982	.0	.0	.0	.0	.0	.0
M1082	.0	.0	43.1	.0	27305.5	.0
M1182	.0	.0	.0	.0	.0	.0

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: RANGE OF WEIGHTS

BW	.000000407	.000095118
P+A	.000001547	.000013375
cap	.000000407	.000002299
matls	.000000500	.000509257
energy	.000000407	.000002299
labor	.000000407	.000002299

TABLE: OCCURRENCE OF DMUS IN FACETS

UNIT	NAME	NUMBER OF FACETS
21	M0982	23
2	M0181	19
14	M0182	9
23	M1182	7
20	M0882	2

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI



**APPENDIX 4.**  
**Conformance Dimension BCC Model Results**

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: DATA ENVELOPMENT ANALYSIS --- MODEL: P-BCC

DMU	NAME	THETA	SUM OF SLACKS	IOTA	ALPHA
1	M1280	.51556	153954.40	.33291	-842877.70000
2	M0181	.48079	92480.01	.35688	-746324.10000
3	M0281	.50460	118964.99	.35207	-779940.50000
4	M0381	.43148	107104.47	.30862	-871753.40000
5	M0481	.45426	95697.41	.34041	-840609.50000
6	M0581	.60126	53579.69	.53715	-835778.50000
7	M0681	.47135	88693.00	.36133	-806091.30000
8	M0781	.85814	87556.28	.74477	-772312.60000
9	M0881	.42482	108329.14	.30423	-898338.30000
10	M0981	.54823	588.46	.54707	-506247.40000
11	M1081	.47359	580.87	.47259	-577367.00000
12	M1181	.45806	118280.80	.32344	-878647.10000
13	M1281	.70850	95535.08	.53665	-555920.80000
14	M0182	.52576	44925.94	.47142	-826664.87919
15	M0282	.46154	107608.93	.32897	-811698.00000
16	M0382	.46957	88827.63	.37155	-906231.20000
17	M0482	.39965	67241.86	.31925	-836398.00000
18	M0582	.37967	57563.68	.31195	-850028.50000
19	M0682	1.00000	.00	1.00000	-847969.80000
20	M0882	1.00000	.00	1.00000	-369925.00672

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: DATA ENVELOPMENT ANALYSIS --- MODEL: P-BCC

DMU	NAME	THETA	SUM OF SLACKS	IOTA	ALPHA
21	M0982	1.00000	.00	1.00000	-249401.40000
22	M1082	.39372	71944.60	.31039	-863357.90000
23	M1182	.43584	108930.17	.34532	-1203406.20250

TABLE: SLACK VALUES

	%INV*10K	cap	matls	energy	labor
M1280	.0	50.1	988.3	152916.0	.0
M0181	.0	28.8	597.4	91853.8	.0
M0281	.0	52.6	870.8	118041.6	.0
M0381	.0	59.1	1001.5	106043.9	.0
M0481	.0	47.9	760.4	94889.3	.0
M0581	.0	47.2	1155.4	52377.1	.0
M0681	.0	51.6	847.3	87794.2	.0
M0781	.0	.0	1425.6	86102.8	27.8
M0881	.0	70.5	984.9	107273.8	.0
M0981	.0	14.1	565.0	.0	9.3
M1081	.0	19.1	555.1	.0	6.7
M1181	.0	74.9	776.2	117429.7	.0
M1281	.0	26.9	800.1	94708.0	.0
M0182	.0	13.6	.0	44912.3	.0
M0282	.0	59.6	213.0	107336.3	.0
M0382	.0	62.0	159.5	88606.2	.0
M0482	.0	37.8	74.4	67129.6	.0
M0582	.0	34.1	42.1	57487.5	.0
M0682	.0	.0	.0	.0	.0
M0882	.0	.0	.0	.0	.0

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: SLACK VALUES

	%INV*10K	cap	matls	energy	labor
M0982	.0	.0	.0	.0	.0
M1082	.0	44.5	35.1	71865.0	.0
M1182	.0	57.7	.0	108872.4	.0

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: RANGE OF WEIGHTS

%INV*10K	.000006192	.000024527
cap	.000000831	.000004010
matls	.000001103	.000595043
energy	.000000831	.000004010
labor	.000000831	.000004010

TABLE: OCCURRENCE OF DNUS IN FACETS

UNIT	NAME	NUMBER OF FACETS
19	M0682	23
21	M0982	23
20	M0882	3

VERSION 1.0.0 . . . . . IDEAS . . . . . AGHA IQBAL ALI

TABLE: DATA ENVELOPMENT ANALYSIS --- MODEL: P-BCC

DMU	NAME	THETA	SUM OF SLACKS	IOTA	ALPHA
1	M1280	1.00000	.00	1.00000	-14847.75246
2	M0181	.36160	2540.00	.29974	-41081.71542
3	M0281	.11544	1070.00	.10712	-128623.22703
4	M0381	.08825	2060.00	.07600	-168255.02344
5	M0481	.09949	.00	.09949	-159135.46036
6	M0581	.26144	.00	.26144	-171542.74005
7	M0681	.09678	.00	.09678	-173053.11487
8	M0781	.43165	.00	.43165	-156025.74161
9	M0881	.09427	1300.00	.08602	-157495.88853
10	M0931	.08902	700.00	.08483	-166784.87652
11	M1081	.03333	1380.00	.03023	-445538.62916
12	M1181	.06075	.00	.06075	-254953.46372
13	M1281	.05439	.00	.05439	-331082.93736
14	M0182	.08815	4850.00	.05936	-168434.22045
15	M0282	.08809	2420.00	.07374	-168543.93291
16	M0382	.45921	.00	.45921	-54110.18359
17	M0482	.16554	2420.00	.13856	-89393.59035
18	M0582	.12277	2750.00	.10003	-120943.35507
19	M0682	1.00000	.00	1.00000	-115358.75246
20	M0882	.06293	7030.00	.03314	-235932.98083

TABLE: DATA ENVELOPMENT ANALYSIS --- MODEL: P-BCC

DMU	NAME	THETA	SUM OF SLACKS	IOTA	ALPHA
21	M0982	.07563	5560.00	.04731	-196319.46984
22	M1082	.08164	2250.00	.06927	-181873.99638
23	M1182	.21810	2000.00	.18873	-68076.57932

TABLE: SLACK VALUES

	%INV*10K	P+A
M1280	.0	.0
M0181	2540.0	.0
M0281	1070.0	.0
M0381	2060.0	.0
M0481	.0	.0
M0581	.0	.0
M0681	.0	.0
M0781	.0	.0
M0881	1300.0	.0
M0981	700.0	.0
M1081	1380.0	.0
M1181	.0	.0
M1281	.0	.0
M0182	4850.0	.0
M0282	2420.0	.0
M0382	.0	.0
M0482	2420.0	.0
M0582	2750.0	.0
M0682	.0	.0
M0882	7030.0	.0

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TABLE: SLACK VALUES

	%INV*10K	P+A
M0982	5560.0	.0
M1082	2250.0	.0
M1182	2000.0	.0

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TABLE: RANGE OF WEIGHTS

%INV*10K	.000002244	.000067350
P+A	.000008208	.000246305

TABLE: OCCURRENCE OF DMUS IN FACETS

UNIT	NAME	NUMBER OF FACETS
1	M1280	23
19	M0682	23

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TABLE: DATA ENVELOPMENT ANALYSIS --- MODEL: P-BCC

DMU	NAME	THETA	SUM OF SLACKS	IOTA	ALPHA
1	M1280	1.00000	.00	1.00000	-936112.43961
2	M0181	1.00000	.00	1.00000	-927306.09819
3	M0281	.76240	19126.95	.74708	-1248065.64115
4	M0381	.63592	10391.04	.62889	-1477163.91486
5	M0481	.66376	236.99	.66360	-1415837.97186
6	M0581	.71532	987.54	.71465	-1455441.61755
7	M0681	.66148	421.57	.66118	-1425780.51423
8	M0781	.90047	81918.66	.85562	-1826678.65986
9	M0881	.63760	5492.79	.63386	-1469728.07544
10	M0981	.85670	706.58	.85602	-1029527.76155
11	M1081	.47359	5457.46	.46579	-699196.00000
12	M1181	.56968	69165.28	.53057	-1768340.38130
13	M1281	.70850	107790.91	.54175	-646452.80000
14	M0182	.87351	29935.55	.85865	-2014545.72909
15	M0282	.73511	47284.72	.73084	-11074909.65192
16	M0382	1.00000	.00	1.00000	-31927080.07448
17	M0482	.89494	25.99	.89493	-1915944.47037
18	M0582	.80281	27.56	.80280	-2133818.57964
19	M0682	1.00000	.00	1.00000	-879677.80000
20	M0882	1.00000	.00	1.00000	-455793.60837

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TABLE: DATA ENVELOPMENT ANALYSIS --- MODEL: P-BCC

DMU	NAME	THETA	SUM OF SLACKS	IOTA	ALPHA
21	M0982	1.00000	.00	1.00000	-303083.40000
22	M1082	.68047	14.37	.68047	-11900911.22326
23	M1182	1.00000	.00	1.00000	-28811375.13645

TABLE: SLACK VALUES

	XINV*10K	P+A	cap	matls	energy	labor
M1280	.0	.0	.0	.0	.0	.0
M0181	.0	.0	.0	.0	.0	.0
M0281	.0	.0	26.8	286.8	18813.3	.0
M0381	.0	.0	38.3	533.3	9819.4	.0
M0481	.0	.0	25.0	212.0	.0	.0
M0581	.0	.0	40.7	946.8	.0	.0
M0681	.0	.0	32.8	388.7	.0	.0
M0781	.0	.0	.0	1395.9	80491.2	31.6
M0881	.0	.0	54.2	472.2	4966.4	.0
M0981	.0	.0	34.8	635.1	.0	36.7
M1081	.0	4876.6	19.1	555.1	.0	6.7
M1181	.0	.0	67.9	464.4	68633.0	.0
M1281	.0	12255.8	26.9	800.1	94708.0	.0
M0182	540.1	.0	.0	.0	29379.8	15.6
M0282	.0	.0	40.5	.0	47244.2	.0
M0382	.0	.0	.0	.0	.0	.0
M0482	.0	.0	14.5	.0	.0	11.5
M0582	.0	.0	14.3	.0	.0	13.3
M0682	.0	.0	.0	.0	.0	.0
M0882	.0	.0	.0	.0	.0	.0

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TABLE: SLACK VALUES

	XINV*10K	P+A	cap	matls	energy	labor
M0982	.0	.0	.0	.0	.0	.0
M1082	.0	.0	14.4	.0	.0	.0
M1182	.0	.0	.0	.0	.0	.0

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TABLE: RANGE OF WEIGHTS

XINV*10K	.000000496	.000021335
P+A	.000001137	.000032614
cap	.000000032	.000530119
matls	.000000547	.000601972
energy	.000000032	.000003299
labor	.000000032	.001313018

TABLE: OCCURRENCE OF DMUS IN FACETS

UNIT	NAME	NUMBER OF FACETS
19	M0682	22
21	M0982	21
2	M0181	16
1	M1280	14
23	M1182	7
16	M0382	2
20	M0982	1

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**APPENDIX 5.**  
**Monthly Input/Output Data by Relative Ranks**



QUALITY COST  
RELATIVE RANKS

RELATIVE RANK	DMU/ MONTH	BY TOTAL P+A\$	DMU/ MONTH	BY P+A\$ /TON	DMU/ MONTH	BY % TOTL COSTS	DMU/ MONTH	BY TOTAL I+E\$
1	11	121,829	20	14.62	13	59.7	19	50,934
2	13	90,531	21	8.69	22	51.1	22	51,394
3	12	69,716	22	8.31	11	48.9	13	61,041
4	21	64,513	11	6.75	21	45.5	10	75,622
5	22	53,681	13	5.97	19	38.4	21	77,389
6	23	49,732	14	3.31	10	37.6	16	82,457
7	7	47,320	12	3.00	12	32.5	6	99,285
8	6	46,907	10	2.92	6	32.1	20	114,898
9	15	46,087	15	2.09	23	29.5	24	114,945
10	14	46,056	7	2.07	15	25.5	23	118,971
11	4	46,009	8	2.04	7	24.9	11	127,293
12	10	45,606	23	2.03	14	22.4	18	127,580
13	1	44,060	1	1.94	1	21.6	2	133,003
14	5	43,528	5	1.85	9	21.1	15	134,807
15	9	43,066	4	1.84	18	20.6	17	138,469
16	8	42,664	6	1.73	8	19.8	7	142,637
17	3	35,170	3	1.72	5	16.7	12	145,078
18	18	33,072	9	1.57	4	15.4	14	159,382
19	19	31,709	18	1.45	16	15.2	1	160,080
20	17	24,526	19	1.25	17	15.0	9	161,192
21	20	19,526	17	1.09	20	14.5	8	173,206
22	24	18,614	24	0.74	24	13.9	5	217,058
23	16	14,795	2	0.60	3	13.6	3	223,586
24	2	11,228	16	0.55	2	7.8	4	252,947

QUALITY COST  
RELATIVE RANKS-Continued

RELATIVE RANK	DMU/ MONTH	BY I+E\$ /TON	DMU/ MONTH	BY TOTAL QCOSTS	DMU/ MONTH	BY QCOSTS /TON
1	19	2.00	19	82,643	19	3.25
2	16	3.07	16	97,252	16	3.62
3	6	3.65	22	105,076	24	5.28
4	13	4.02	10	121,227	6	5.38
5	24	4.55	24	133,560	23	6.87
6	10	4.84	20	134,423	18	7.06
7	23	4.85	21	141,902	17	7.22
8	18	5.61	2	144,231	9	7.47
9	9	5.89	6	146,192	10	7.76
10	15	6.12	13	151,572	2	7.77
11	17	6.14	18	160,652	15	8.21
12	7	6.23	17	162,995	7	8.29
13	12	6.24	23	168,703	1	8.98
14	1	7.04	15	180,894	12	9.24
15	11	7.05	7	189,957	13	9.99
16	2	7.16	1	204,140	8	10.31
17	22	7.96	9	204,258	5	11.07
18	8	8.27	14	205,438	4	11.96
19	5	9.22	12	214,793	3	12.64
20	4	10.12	8	215,870	11	13.80
21	21	10.42	11	249,122	14	14.78
22	3	10.92	3	258,756	22	16.27
23	14	11.47	5	260,586	21	19.11
24	20	86.01	4	298,956	20	100.63

PRODUCTIVITY MEASUREMENT DATA

RELATIVE RANK	DMU/ MONTH	TONS PROD MONTH	TNS/HR
1	9	27,348.4	9 39.13
2	6	27,173.0	24 37.45
3	16	26,864.0	16 37.40
4	19	25,437.8	19 36.75
5	24	25,285.0	6 36.52
6	4	25,006.6	4 36.35
7	23	24,540.3	23 36.27
8	5	23,549.4	15 36.20
9	12	23,252.7	17 36.04
10	7	22,905.0	7 35.91
11	18	22,753.3	20 35.75
12	1	22,726.0	21 35.62
13	17	22,561.1	1 35.57
14	15	22,024.9	13 35.49
15	8	20,945.0	5 35.44
16	3	20,467.6	18 35.30
17	2	18,565.5	3 34.77
18	11	18,049.0	12 34.73
19	10	15,616.5	22 33.29
20	13	15,176.8	14 33.15
21	14	13,901.1	2 32.87
22	21	7,423.7	8 31.40
23	22	6,459.1	10 27.50
24	20	1,335.9	11 26.04

QUALITY MEASURE  
RELATIVE RANKS

RELATIVE RANK	DMU/ MONTH	BY BASIS WEIGHT	DMU/ MONTH	BY SCRAP %	DMU/ MONTH	BY REJECT TONS
1	20	85.50	19	0.09	19	22.50
2	14	59.72	8	0.16	20	25.00
3	23	57.65	6	0.25	8	34.00
4	3	57.56	16	0.50	6	69.00
5	4	55.69	13	0.76	13	115.10
6	24	55.63	7	0.84	16	135.00
7	19	55.46	5	0.91	22	145.40
8	16	55.15	12	0.94	10	167.50
9	12	54.99	1	1.00	7	193.50
10	2	54.98	10	1.07	11	208.60
11	5	54.67	3	1.12	5	215.20
12	22	54.34	9	1.15	12	217.50
13	11	54.34	11	1.16	1	225.00
14	13	54.16	24	1.25	3	230.00
15	9	53.82	4	1.26	2	249.00
16	18	53.79	23	1.29	21	250.30
17	6	53.75	17	1.32	14	270.00
18	7	53.67	15	1.32	15	290.00
19	1	52.80	2	1.34	17	297.00
20	10	52.75	18	1.38	18	314.00
21	15	52.66	20	1.87	4	314.50
22	17	51.86	14	1.94	9	315.50
23	21	51.53	22	2.25	23	315.70
24	8	49.74	21	3.37	24	316.30

**APPENDIX 6.**  
**Summary Performance Information by Month**

MONTH/ DMU	EFFICIENT IN BCC MODELS	INEFFICIENT IN BCC MODELS	OPERATIONAL SUMMARY
1	INV(SCR%) = F(P+A) TONS = F(L, M, E, C)	BW = F(L, M, E, C)	Shut down month. Produced primarily low basis weight linerboard. High unscheduled maintenance resulting in high I+E costs. High material usage, but average tons produced.
2	INV(I+E) = F(P+A) BW = F(P+A) TONS = F(P+A) INV(%) = F(P+A)	TONS = F(L, M, E, C)	Start up month. High scrap rate due to wrinkles in paper during start up. Low total tons and tons/hr produced. Poor energy and labor efficiencies.
3	BW = F(P+A) BW = F(L, M, E, C)	TONS = F(L, M, E, C)	Produced primarily high basis weight linerboard. No preventive maintenance, but high downtime for unscheduled repairs resulting in high I+E and total quality costs. New machine setup caused rejects.
4	NONE	INV(I+E) = F(P+A) INV(%) = F(L, M, E, C)	Highest I+E and total quality costs. Low appraisal costs contributing to low P+A/I+E ratio. High quantity of rejected tons due to problems with bearing boxes and spreader bar. High basis weight linerboard produced.
5	NONE	INV(I+E) = F(P+A)	High returns resulting in high external costs. 3rd highest I+E\$ and 2nd highest total quality costs.
6	TONS = F(P+A) TONS = F(L, M, E, C)	BW = F(L, M, E, C)	High tons and tons/hr produced. Low appraisal contributing to low P+A/I+E ratio. Low scrap % rate during the month.
7	NONE	NONE	Several shutdowns and start ups caused rejects and high downtime. High preventive maintenance, but low appraisal costs.

MONTH/ DMU	EFFICIENT IN BCC MODELS	INEFFICIENT IN BCC MODELS	OPERATIONAL SUMMARY
8	INV(SCR%) = F(P+A) INV(%) = F(L, M, E, C)	BW = F(P+A)	Low tons/hr produced. Although low scrap rate, high I+E costs resulted in high total quality costs. Production of primarily low basis weight linerboard.
9	TONS = F(P+A) TONS = F(L, M, E, C)	BW = F(L, M, E, C) INV(%) = F(L, M, E, C)	Highest tons produced. Low preventive maintenance resulting in low P+A/I+E ratio. High scrap% due to grade many grade changes.
10	INV(%) = F(L, M, E, C) TONS = F(L, M, E, C)	NONE	Low quantity of tons produced, primarily low basis weight linerboard. Higher than standard prevention due to maintenance work during Labor Day shutdown.
11	NONE	INV(I+E) = F(P+A) TONS = F(P+A) INV(%) = F(P+A) BW = F(P+A)	High prevention and appraisal spending. Average quality output (scrap % & basis weight). Low tons produced.
12	NONE	INV(I+E) = F(P+A) BW = F(P+A) TONS = F(P+A) TONS = F(L, M, E, C)	High prevention but no reduction in I+E costs. High rejects due to draw problems and poor washed stock.
13	TONS = F(L, M, E, C)	INV(I+E) = F(P+A) BW = F(P+A) TONS = F(P+A)	High prevention due to end of the year maintenance. Low failure costs resulting in highest P+A/I+E ratio. Low scrap %. Christmas shutdown caused lower production.
14	BW = F(L, M, E, C) BW = F(P+A)	INV(I+E) = F(P+A) TONS = F(L, M, E, C)	High scrap % resulting in high internal and total quality costs. Low tons produced, but primarily high basis weight linerboard.

MONTH/ DMU	EFFICIENT IN BCC MODELS	INEFFICIENT IN BCC MODELS	OPERATIONAL SUMMARY
15	NONE	NONE	High scrap %. Primarily lower basis weight linerboard produced.
16	INV(I+E) = F(P+A) BW&TONS = F(P+A) INV(%) = F(P+A) TONS = F(L,M,E,C)	NONE	High tons produced. Low prevention and appraisal resulting in low P+A/I+E ratio. Primarily lower basis weight linerboard produced, with few rejected tons.
17	NONE	INV(%) = F(L,M,E,C) BW = F(L,M,E,C)	Average tons produced. Low prevention and appraisal resulting in low P+A/I+E ratio. Primarily lower basis weight linerboard produced, with few rejected tons.
18	NONE	BW = F(L,M,E,C) TONS = F(L,M,E,C) INV(%) = F(L,M,E,C)	High scrap rate with average tons produced.
19	INV(I+E) = F(P+A) INV(%) = F(P+A) TONS = F(L,M,E,C) INV(%) = F(L,M,E,C)	NONE	Lowest I+E and total quality costs. High basis weight linerboard produced with lowest scrap rate of any month. Relatively high production quantities.
20	N/A REMOVED FROM DATA SET	N/A REMOVED FROM DATA SET	Lowest tons produced in study. Although low rejected tons, quantities cause scrap rate to be highest. Low basis weight linerboard produced. Low prevention, but highest appraisal spending.
21	BW = F(L,M,E,C) TONS = F(L,M,E,C) INV(%) = F(L,M,E,C)	INV(%) = F(P+A) BW = F(P+A) TONS = F(P+A)	Low tons produced. Average quantities of rejected tons, but scrap rate high. Low basis weight linerboard produced. High prevention and appraisal resulting in low internal failure cost.



MONTH/ DMU	EFFICIENT IN BCC MODELS	INEFFICIENT IN BCC MODELS	OPERATIONAL SUMMARY
22	$INV(I+E) = F(P+A)$ $INV(\%) = F(L, M, E, C)$ TONS = F(L, M, E, C) BW = F(L, M, E, C)	$INV(\%) = F(P+A)$ TONS = F(P+A)	High prevention and appraisal spending resulting in low I+E and total quality costs. Although low quantities of rejected tons, low production cause scrap rate to be high.
23	$BW = F(L, M, E, C)$	$INV(\%) = F(L, M, E, C)$	High prevention and appraisal spending. High basis weight linerboard produced.
24	$INV(I+E) = F(P+A)$ $BW = F(P+A)$ TONS = F(P+A) TONS = F(L, M, E, C)	NONE	High tons produced. Low prevention and appraisal resulting in low I+E and total quality costs. High rejected quantity, but average scrap rate. High basis weight linerboard produced.

**APPENDIX 7.**  
**Detailed Raw Data Report--All Variables**

		QUALITY COST DATA								
		PREVENT	APPRAISAL			INTERNAL		EXTERNAL		
DMU	MONTH	SCHED MAINT -\$- LOST	INSPECT COSTS	TOTAL PREV+ APPR COSTS	(P+A) % OF TOTAL QUAL COSTS	TOTAL INT FAILURE COSTS	(INT) % OF TOTAL QUAL COSTS	TOTAL EXT FAILURE COSTS	(EXT) % OF TOTAL QUAL COSTS	
1	12/80	27,518	16,542	44,060	21.6	117,768	57.7	42,312	20.7	
2	1/81	4,305	6,923	11,228	7.8	98,603	68.4	34,400	23.9	
3	2/81	0	35,170	35,170	13.6	193,651	74.8	29,935	11.6	
4	3/81	27,042	18,966	46,009	15.4	214,609	71.8	38,338	12.8	
5	4/81	30,721	12,807	43,528	16.7	140,050	53.7	77,008	29.6	
6	5/81	39,528	7,379	46,907	32.1	53,275	36.4	46,010	31.5	
7	6/81	39,485	7,835	47,320	24.9	94,913	50.0	47,724	25.1	
8	7/81	25,917	16,747	42,664	19.8	137,198	63.6	38,008	17.6	
9	8/81	7,844	35,222	43,066	21.1	153,131	75.0	8,061	3.9	
10	9/81	24,885	20,721	45,606	37.6	57,108	47.1	18,513	15.3	
11	10/81	43,128	78,701	121,829	48.9	103,903	41.7	23,390	9.4	
12	11/81	37,350	32,365	69,716	32.5	124,079	57.8	20,998	9.8	
13	12/81	50,429	40,103	90,531	59.7	48,619	32.1	12,422	8.2	
14	1/82	0	46,056	46,056	22.4	143,117	69.7	16,266	7.9	
15	2/82	5,862	40,225	46,087	25.5	111,303	61.5	23,504	13.0	
16	3/82	0	14,795	14,795	15.2	46,362	47.7	36,094	37.1	
17	4/82	12,385	12,141	24,526	15.0	112,021	68.7	26,448	16.2	
18	5/82	13,110	19,961	33,072	20.6	101,082	62.9	26,498	16.5	
19	6/82	4,139	27,569	31,709	38.4	7,161	8.7	43,773	53.0	
20	7/82	0	19,526	19,526	14.5	5,716	4.3	109,458	81.4	
21	8/82	0	64,513	64,513	45.5	70,115	49.4	7,275	5.1	
22	9/82	0	53,681	53,681	51.1	46,045	43.8	5,349	5.1	
23	10/82	10,341	39,391	49,732	29.5	104,353	61.9	14,618	8.7	
24	11/82	0	18,614	18,614	13.9	90,200	67.5	24,745	18.5	

QUALITY COST DATA-continued  
COSTSPER TONPRODUCED

DMU	MONTH	TOT NON- CONFORM COSTS (I+E)	TOTAL QUALITY COSTS	QCOSTS \$/TON	PREV /ton	APPR\$ /ton	INT\$ /ton	Ext\$ /ton	P+A\$ /TON	I+E\$ /TON
1	12/80	160,080	204,140	8.98	1.21	0.73	5.18	1.86	1.94	7.04
2	1/81	133,003	144,231	7.77	0.23	0.37	5.31	1.85	0.60	7.16
3	2/81	223,586	258,756	12.64	0.00	1.72	9.46	1.46	1.72	10.92
4	3/81	252,947	298,956	11.96	1.08	0.76	8.58	1.53	1.84	10.12
5	4/81	217,058	260,586	11.07	1.30	0.54	5.95	3.27	1.85	9.22
6	5/81	99,285	146,192	5.38	1.45	0.27	1.96	1.69	1.73	3.65
7	6/81	142,637	189,957	8.29	1.72	0.34	4.14	2.08	2.07	6.23
8	7/81	173,206	215,870	10.31	1.24	0.80	6.55	1.81	2.04	8.27
9	8/81	161,192	204,258	7.47	0.29	1.29	5.60	0.29	1.57	5.89
10	9/81	75,622	121,227	7.76	1.59	1.33	3.66	1.19	2.92	4.84
11	10/81	127,293	249,122	13.80	2.39	4.36	5.76	1.30	6.75	7.05
12	11/81	145,078	214,793	9.24	1.61	1.39	5.34	0.90	3.00	6.24
13	12/81	61,041	151,572	9.99	3.32	2.64	3.20	0.82	5.97	4.02
14	1/82	159,382	205,438	14.78	0.00	3.31	10.30	1.17	3.31	11.47
15	2/82	134,807	180,894	8.21	0.27	1.83	5.05	1.07	2.09	6.12
16	3/82	82,457	97,252	3.62	0.00	0.55	1.73	1.34	0.55	3.07
17	4/82	138,469	162,995	7.22	0.55	0.54	4.97	1.17	1.09	6.14
18	5/82	127,580	160,652	7.06	0.58	0.88	4.44	1.16	1.45	5.61
19	6/82	50,934	82,643	3.25	0.16	1.08	0.28	1.72	1.25	2.00
20	7/82	114,898	134,423	100.63	0.00	14.62	4.28	81.94	14.62	86.01
21	8/82	77,389	141,902	19.11	0.00	8.69	9.44	0.98	8.69	10.42
22	9/82	51,394	105,076	16.27	0.00	8.31	7.13	0.83	8.31	7.96
23	10/82	118,971	168,703	6.87	0.42	1.61	4.25	0.60	2.03	4.85
24	11/82	114,945	133,560	5.28	0.00	0.74	3.57	0.98	0.74	4.55

PRODUCTIVITY DATA

DMU	MONTH	TONS PROD	CAPITAL MEASURE	MATLS MEASURE	ENERGY MEASURE	LABOR MEAS	TON /HR	PROFIT \$/TON	SALES \$/TON
1	12/80	22,726.0	376.0	3272.3	839034	195.4	35.6	79.7	227.3
2	1/81	18,565.5	341.0	2612.4	743169	201.7	32.9	65.5	298.4
3	2/81	20,467.6	382.0	3077.0	776285	196.5	34.8	69.9	304.4
4	3/81	25,006.6	454.0	3865.0	867208	226.4	36.3	71.7	305.8
5	4/81	23,549.4	429.0	3246.5	836709	225.0	35.4	74.9	308.5
6	5/81	27,173.0	486.0	3872.0	831179	241.5	36.5	76.9	307.7
7	6/81	22,905.0	428.0	3342.6	802100	219.7	35.9	74.2	306.8
8	7/81	20,945.0	374.0	3442.1	768256	240.5	31.4	72.8	304.2
9	8/81	27,348.4	494.0	3914.7	893697	232.6	39.1	72.6	306.0
10	9/81	15,616.5	284.0	2286.4	503478	199.0	27.5	71.1	304.4
11	10/81	18,049.0	334.0	2601.5	574209	222.5	26.0	72.1	305.9
12	11/81	23,252.7	482.0	3242.1	874701	222.0	34.7	73.4	307.3
13	12/81	15,176.8	256.0	2186.0	553330	148.8	35.5	71.5	304.9
14	1/82	13,901.1	273.0	1150.0	573070	182.2	33.1	27.4	304.9
15	2/82	22,024.9	423.0	1892.5	809172	210.5	36.2	22.8	296.9
16	3/82	26,864.0	510.0	2164.1	903311	246.1	37.4	22.5	296.3
17	4/82	22,561.1	434.0	1838.9	833882	243.1	36.0	28.6	302.7
18	5/82	22,753.3	444.0	1836.9	847493	254.6	35.3	12.6	287.6
19	6/82	25,437.8	485.0	2296.2	844938	250.6	36.8	12.6	288.0
20	7/82	1,335.9	56.0	24.4	48059	32.0	35.7	-55.2	228.7
21	8/82	7,423.7	148.0	393.6	283022	115.2	35.6	-1.7	280.1
22	9/82	6,459.1	125.0	610.9	248573	92.5	33.3	9.8	286.6
23	10/82	24,540.3	459.0	1773.5	860878	247.4	36.3	12.6	287.0
24	11/82	25,285.0	467.0	1390.6	896596	242.3	37.5	4.0	277.4

QUALITY MEASUREMENT DATA

DMU MONTH	BASIS WT WEIGHT BY % TONS	BW BY % MFG\$	SCRAP %	INV(%) *10000	REJECT TONS
1 12/80	52.80	53.71	1.00	10000	225.00
2 1/81	54.98	55.04	1.34	7460	249.00
3 2/81	57.56	57.93	1.12	8930	230.00
4 3/81	55.69	56.32	1.26	7940	314.50
5 4/81	54.67	55.16	0.91	10990	215.20
6 5/81	53.75	54.09	0.25	40000	69.00
7 6/81	53.67	53.04	0.84	11900	193.50
8 7/81	49.74	50.46	0.16	62500	34.00
9 8/81	53.82	54.06	1.15	8700	315.50
10 9/81	52.75	51.89	1.07	9350	167.50
11 10/81	54.34	54.99	1.16	8620	208.60
12 11/81	54.99	55.43	0.94	10640	217.50
13 12/81	54.16	54.27	0.76	13160	115.10
14 1/82	59.72	60.20	1.94	5150	270.00
15 2/82	52.66	52.93	1.32	7580	290.00
16 3/82	55.15	55.09	0.50	20000	135.00
17 4/82	51.86	56.02	1.32	7580	297.00
18 5/82	53.79	54.30	1.38	7250	314.00
19 6/82	55.46	55.32	0.09	111111	22.50
20 7/82	85.50	82.38	1.87	5350	25.00
21 8/82	51.53	67.53	3.37	2970	250.30
22 9/82	54.34	53.11	2.25	4440	145.40
23 10/82	57.65	57.55	1.29	7750	315.70
24 11/82	55.63	55.64	1.25	8000	316.30

## ABOUT THE AUTHOR

Robert McNelis is the Quality Assurance Manager for Siemens-Pelton & Crane in Charlotte, North Carolina. In this position, he is responsible for ensuring compliance to regulatory agency requirements and implementing the ISO-9001 Quality Management Standard. His department also conducts pre-production quality assurance activities such as hazard analyses, reliability testing, and performance validation testing for a wide range of medical devices.

Prior to joining Siemens-Pelton & Crane, Mr. McNelis was the Quality Engineer at Performance Friction Corporation in Clover, South Carolina. Among his duties were initiating productivity and product quality improvement programs, developing a quality cost reporting system, and conducting quality circles meetings and training seminars. He also gained experience applying logistics and human factors engineering to military weapons systems development as an Associate Staff Member with the BDM Corporation in McLean, Virginia.

Mr. McNelis holds a B.S. degree in Statistics from Virginia Polytechnic Institute and State University.