EVALUATION OF PRODUCTIVITY AND QUALITY PERFORMANCE IN A NEWSPAPER PREPRINT INSERTION PROCESS

by

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(ABSTRACT)

Productivity and quality of a manufacturing process are seen as important factors for short and long term success of a company. Measuring productivity and quality provides the means to assess performance trends of the process, providing a powerful management tool for decision making. Data Envelopment Analysis is a tool that can be used to measure productivity and quality performance.

Productivity and quality performance were measured using Data Envelopment Analysis for a newspaper preprint insertion process. Hybrid performance models combining productivity and quality performance were also evaluated using Data Envelopment Analysis. Finally, the possible underlying relationship between productivity and quality was investigated.

The major findings of this research are:

- Productivity and quality performance trends obtained from the study provide a realistic assessment of performance of the newspaper preprint insertion process.
- The trends of the hybrid performance models were not able to accurately assess the performance of the newspaper preprint insertion process.
- There does not seem to be a link between productivity and quality in the newspaper preprint insertion process for the time period studied.

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TABLE OF CONTENTS

Chapter 4 THE NEWSPAPER PREPRINT INSERTION PROCESS

Chapter 5 MATHEMATICA DEA APPLICATION

Chapter 6 RESULTS

LIST OF FIGURES

LIST OF TABLES

Chapter 1. INTRODUCTION

1.1 Background

Ever since the invention of the modern printing press by Johannes Gutenberg in the 1450s, printed paper has become an instrument for fueling human progress. Dissemination of information has allowed the exchange of ideas across the world. One of the greatest impacts of printing in modern life is the newspaper. Newspapers provide almost instant dissemination of up to date information on current events.

This power of dissemination has made the newspaper an excellent medium for reaching the public. It is for this reason primarily that newspapers are an ideal platform for advertisement. Advantages of newspaper advertisement are that it can be used to target specific areas, and can be delivered in a quick, timely manner to reach a large percentage of the population. A modern form of advertising in newspapers is the inclusion of preprints in the fold of the paper. These preprints are inserted in the newspaper and delivered with it.

Today's newspaper reader expects prompt delivery of the daily paper as well as good "quality" when that paper arrives at his doorstep or is picked up at a newsstand. "Quality" is referred in terms of content of information (relevant, up to date) as well as to the physical condition in which the newspaper is delivered.

This requirement for "quality" means that newspaper production is severely time constrained. Large volumes of newspapers must be printed in a very short time period. This sets high strains in the newspaper production process. On the other hand, not only must the production of the newspaper be delayed the maximum allowable time (to include the most current information), but large quantities must be produced and delivered to the distribution centers in a timely manner. There is no excuse for the late delivery of newspapers. Because of this constraint, the emphasis in production has been placed on meeting production deadlines, and productivity and quality performance of the process have been placed in a secondary place.

The advent of other advertisement mediums such as direct mailing and electronic information transfer are creating new competition for the newspaper production process. Not only must large number of newspapers be produced in a timely manner, additionally, the cost of production and quality of the product must be optimized to maintain a profit margin and solid advertisement customer base.

Another constraining element of the newspaper industry is the increasing need to provide greater advertising flexibility. Advertisers want to be able to reduce the size of the distribution areas to better target their market. At the same time, they are demanding more flexibility in the type of advertisement they can place in the newspaper.

This growing competition in addition to the new advertisement demands are placing greater emphasis on productivity and quality of the newspaper production process and the quality of the product. Speed of production is no longer the only prevailing concern.

These new emerging demands on the newspaper industry are specially being felt in the insertion process of the preprint into the fold of the newspaper. Not only is the inserting process experiencing an increase in the variety of preprint configurations to insert, but also the complexity of the preprints themselves is increasing.

Traditionally in the short-run, productivity and quality have been viewed as opposing interests in production processes. The increase of one is often viewed as having a negative impact on the other and vice versa. It is commonly thought that productivity increases cannot be achieved without a negative impact on the quality of the product produced; the more you want to produce with less resources, the lower the quality of the product produced. At the same time quality improvements are seen as disruptive to production causing productivity declines; the better quality of product you want to make the more resources one needs to invest.

These views of the short-term relationship between productivity and quality undermine the positive long term effects that quality improvement efforts have on productivity. Among other positive effects, quality improvements will make the process more clear and help eliminate redundancies in the process. Even more, it can be argued that a long term quality improvement strategy is essential for long term productivity gains.

1.2 Research Objectives

The main goal of the research is to investigate this underlying short-term relationship between productivity and quality by measuring their performance in a specific newspaper preprint insertion process. Productivity and quality performance will be measured using Data Envelopment Analysis (Boussofaine[2, p. 1]). It is anticipated that one of the outcomes of this research will be a better understanding of the definition of productivity and quality performance for the specific newspaper inserting production process.

A Data Envelopment Analysis software application will also be developed using Mathematica 2.2.2 to compute the performance of the process through time. This software application is capable of analyzing data sets of variable formats.

1.3 Productivity Performance

In an increasingly competitive environment, productivity growth is often seen as one of the most important survival strategies for any organization. As stated earlier, productivity growth is becoming an important concern in the newspaper preprint insertion process.

Productivity of a process can be defined as the relationship between the outputs generated and the variable inputs provided to produce these outputs. Variable inputs are resources that the process consumes to produce outputs (goods and services).

Productivity growth can be obtained by achieving a reduction of input resources while maintaining the production of output constant. At the same time, productivity growth can also be obtained by increasing the production of output while maintaining a constant level of input resources. The increase in productivity performance usually leads to increased profits and/or reduction in operating costs.

This decrease in resource consumption and/or increase in output production can be achieved through productivity improvement initiatives. Before any improvement initiatives can be implemented, there must be clear knowledge of the factors impacting productivity and their relative importance. Once the influential factors of productivity are understood, improvement initiatives can focus on addressing the effects of those factors.

Also, a productivity measurement system is essential to evaluate the actual effect of improvement initiatives on productivity performance. To carry out productivity measurement of a process, data for the relevant input/output variables must be collected and a framework for productivity measurement needs to be applied.

1.4 Quality Performance

Due to increasing pressures, quality is fast becoming a factor of great strategic importance in today's manufacturing environment (Garvin[8, p. xi]). Because of reasons stated earlier, the newspaper preprint insertion process is not isolated from these external pressures. Similarly as with productivity, an increase in quality performance can be achieved through quality improvement initiatives.

Although considered an important factor in an organization's success, quality remains one of the most misunderstood concepts within the organizational environment, leading to contradictory interpretations within the same organization. Rarely do people agree on the exact definition of quality of a product or a process. It is this perception of quality that has erroneously categorized quality as one of those intangible entities that cannot be directly dealt with.

The following example illustrates this misconception. The marketing department of the organization might view that offering an additional product attribute will have a positive impact on quality as perceived by the customer. At the same time, the manufacturing department might view adding the same attribute as creating an excessive deviation from original product tolerance specifications; possibly producing a greater percentage of defective products (nonconformances). Both these departments of the organization have a legitimate argument for considering that the addition of the attribute will have a positive or negative impact on quality.

These contradictory perspectives as to what quality is have their root causes in the multiple definitions and dimensions inherent to the term quality. From the previous explanation, while the marketing department of an organization defines quality from a user-based perspective (the specific attributes found in the product that are considered fit for use for the consumer), the manufacturing department is defining that same term quality from a manufacturing-based perspective (the percentage of non-conforming output products manufactured). As just illustrated, the term quality can have multiple interpretations for the different individuals and departments in an organization.

Garvin[9, p. 40] describes five different approaches to defining quality. They include the transcendent, product-based, user-based, manufacturing-based and value-based approach. Garvin[8, p. 49] goes on to identify eight dimensional characteristics of quality of a product. They include performance, features, reliability, conformance, durability, serviceability, aesthetics and perceived quality. These eight dimensional characteristics of quality comprise the different perspectives people take on quality.

The manufacturing-based definition of quality states that "quality [means] conformance to requirements" (Garvin[9, p. 41]). It is this dimension of product conformance to specifications by which manufacturing processes can effectively define quality performance. The conformance dimension of quality is defined as "the degree to which a product's design and operating characteristics meet pre-established standards" (Garvin[9, p. 52]). This dimension is a good measure of quality in the mass production manufacturing environment, where the main concern with quality issues is the conformance of product attributes to specifications.

1.4.1 Costs of Nonconformance

Nonconformance costs are those costs incurred due to lack of product conformance to specifications. These costs have a far more reaching effect than simply the monetary value of the scrapped nonconforming product. Factors in the cost of nonconformance include among others the production time loss due to nonconforming product runs, overproduction to cover for nonconforming production, preventive actions to assure product conformance, and control costs to assure products are produced according to specifications.

All these factors can account for a significant percentage of production costs. Costs related to rework due to this lack of quality are considered to account for 15-40% of the production costs (Garvin[9, p. 84]). When all these factors of the cost of nonconformance are evaluated, the importance of quality in the process becomes apparent.

1.5 The Productivity and Quality Link

There is a positive link between productivity and quality in manufacturing processes. The simplest correlation can be stated as follows: "less rework means more time devoted to manufacturing acceptable products and less scrap means fewer wasted materials" (Garvin[9, p. 84]). Further, poor quality can be blamed for the "hidden plant" which utilizes 15 to 40% of the facility's resources for rework of defective products (Garvin[9, p. 84]). The general understanding is that making things right the first time around will render a process more productive; i.e. fewer resources producing the same output.

The long term effects of quality improvement will have a positive effect on productivity. Also, the interrelationship between quality and productivity provides common sources for improvement. Among others, they include standardization of processes and components, equipment improvements, and maintenance improvements. These changes in the long run should have a positive effect on both quality and productivity.

Why is it then that quality improvement is often seen as adversely affecting productivity in manufacturing processes? The main reason is that quality improvement initiatives can disrupt production in the short-term. Quality improvement initiatives many times trigger fundamental changes in the process that require time and effort to accommodate. Because of this, quality improvement has been reluctantly received by manufacturing departments. But, the negative effects of quality improvement on production are thus short lived and long-term implications of quality should tend to provide an increase in productivity.

Another major reason for the negative assessment of quality improvement on productivity comes from the methods used to evaluate productivity. For accounting purposes, productivity of a system is often measured as the total output over inputs, without excluding unacceptable output from "good" output. By using this measurement method for productivity, it is evident that any quality improvement would generally not translate to an increase in the organization's productivity measure, although an increase in "actual" productivity of "good" products would occur.

1.6 Using DEA to Measure Productivity and Quality Performance

It has been stated that to carry out productivity and quality improvement initiatives, it is essential to determine both quality and productivity performance of the process. Without any feedback on the performance level of the process, improvement actions cannot concentrate in solving the most critical productivity and quality problems. Thus, it becomes necessary to create a measurement system that quantifies quality and productivity performance levels and identifies areas for possible improvement.

Data Envelopment Analysis (DEA) is a measurement tool that both quantifies efficiency performance levels of process observations and provides insight into the reasons for such performance levels. DEA was first proposed by Charnes et al. in 1978 (Boussofiane[2, p. 1]). It uses a linear programming approach to optimize a productivity ratio by assigning weights to different input/output variables (Boussofiane[2, p. 2]). There is further explanation of DEA in section 3.3.

DEA is a good tool for evaluating process performance. The main reasons for the selection of DEA as the measurement tool are stated as follows:

- DEA can be used to model processes with multiple input/output variables.
- DEA provides a single quantity value for efficiency performance. This single value clearly quantifies the efficiency performance level of specific observations.
- Actual observations that are determined to perform efficiently are used by DEA to construct the standard[1]. Observations are compared to actual observations rather than to unrealistic ideal standards.
- DEA provides bench-marking for inefficient observations. DEA identifies the efficient observations to which an inefficient observation should be compared.

[1] Each observation is compared to a convex combination of actual observations.

- DEA can assess the contribution of individual variable factors of production on the efficiency performance of a specific observation. DEA can pinpoint the resource that is having the greatest impact on performance.
- DEA provides great flexibility in the selection of process variables. DEA accepts variables that are measured in terms of volume, cost, hours, etc. Variations of DEA models even allow for the inclusion of categorical data.
- Different variations of DEA allow for flexibility in the modeling of the process. DEA models allow for the evaluation of efficiency of the process either from an "output increasing" or an "input reducing" perspective.

1.7 Newspaper Preprint Insertion Process

The Newspaper Preprint Insertion Process (NPIP) consists of three basic steps. First, the newspaper section is received from the printing presses and its fold opened. Second, specific machines then proceed to insert preprints in the newspaper sections. Third, these packets consisting of sections and preprints are then stacked in bundles and packaged for delivery to newspaper distributors. The NPIP is becoming increasingly complex.

Since newspapers began inserting preprints in the late 1960s (Harris[10, p. ii]), there has been a continuous growth in the demand for inserting preprints in newspapers. Traditionally, newspaper plants were designed to house mostly printing presses and supporting equipment (Harris[10, p. 1]). With the demand of preprints, newspaper plants had to incorporate the NPIP in existing facilities. It is for this reason that many NPIPs had to be placed in areas of the plant that had not been specifically designed for the NPIP and did not provide the best conditions for this process.

The importance of the NPIP within the newspaper industry is continuously increasing. The percentage of total newspaper revenues obtained from preprint process revenues has experienced a steady growth in the past 25 years. This growing contribution of preprint revenue in the newspaper industry puts an even greater emphasis on the need for evaluation of quality and productivity performance.

1.8 Overview of the Methodology

As stated earlier, the main objective of this research is to evaluate the short-term productivity and quality link of the newspaper preprint insertion process. A software application is also required to be able to quantify quality and productivity performance. The methodology used in this research is illustrated in figure 1.1.

The first step of the research is to obtain a clear definition of the NPIP and its boundaries. An appropriate study period and evaluation intervals[2] must then be selected for the process. The next step consists of the definition of the relevant process input/output variables that represent both productivity and quality. Data for input/output variables will then be collected for the selected study period. Productivity and quality relationships (functions) will be then specified. Data Envelopment Analysis (Boussefaine[2, p. 1]) will be applied for each production relationship (model) and the resulting efficiency performance measures computed and recorded. The performance measures will then be evaluated for each of the production relationships (models). The underlying relationship between productivity and quality performance will then be assessed. Finally, insight into possible production process improvements that would lead to performance improvements both in productivity and quality will be considered.

[2] The evaluation interval refers to the time intervals in which the collected data is grouped (months, weeks, days, etc.).

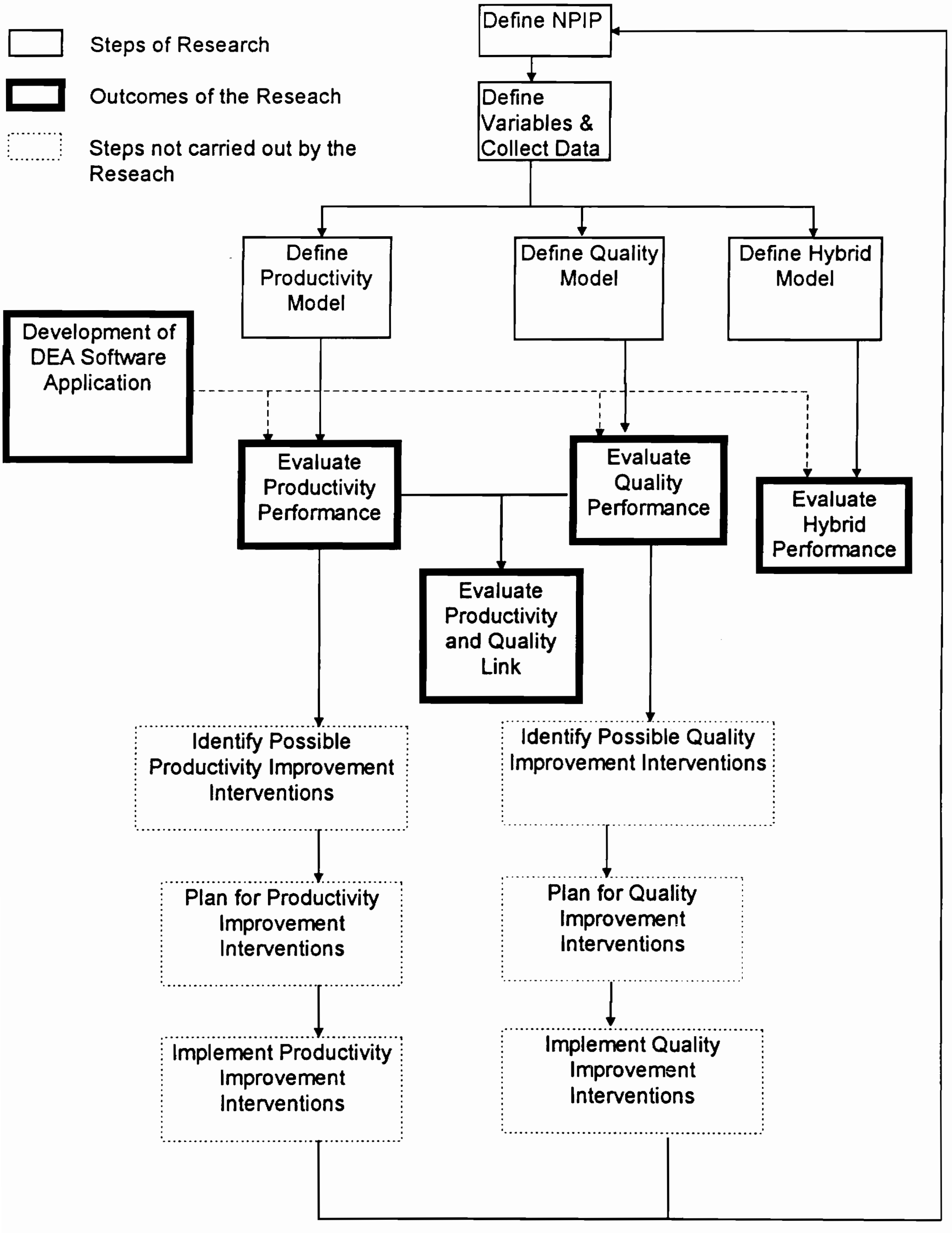

Figure 1.1 Research Methodology

1.9 Document Organization

Chapter 1 provides an introduction and overview of the research goals. Chapter 2 explains productivity and quality management of the NPIP. Chapter 3 provides an understanding of production theory and DEA. Chapter 4 describes the NPIP, its variables and the different productivity and quality models. Chapter 5 explains the software application developed for this research and ways it can be enhanced. The results of this research are included in Chapter 6. Conclusions from the results are included in Chapter 7. Appendices referenced in this research document are included after Chapter 7.

Chapter 2. A PRODUCTIVITY AND QUALITY MANAGEMENT PERSPECTIVE FOR THE NPIP

2.1 NPIP Productivity Management

Although traditionally organizational management has practiced the management of productivity, it has been mainly done in an informal fashion (Sumanth[14, p. 51]). This has led to productivity being ill defined and subjectively measured.

The productivity management process can be defined as a process that entails strategic and action planning and a critical focus on ongoing and effective implementation of productivity improvement (Bell-Burnham[3, p. 26]). This requires a structured approach to productivity management. The following section presents the key elements of productivity improvement.

2.1.1 Key Elements of Productivity Improvement

Four key elements of productivity management are presented by Bell-Burnham[3, p. 13]. Technology, involvement, innovation and managerial direction are the elements that drive productivity improvement. Any productivity improvement initiative should center around these four elements.

Technology

Technology is defined as an "applied science or scientific method for achieving a practical purpose; the totality of the means employed to provide objects necessary for human subsistence and comfort" (Bell-Burnham[3, p. 13]). Technology changes can have a tremendous impact on productivity gains if correctly implemented, but technology by itself does not assure productivity gains.

Many times, new technological equipment or processes are viewed as the key to productivity improvement. Often though, these new capital intensive technological changes actually result on decreased productivity performance. Increased consumption of input resources occurs with no evident gains in output production. This negative effect on productivity has its roots in a lack of understanding of the manufacturing process.

Technological change, although a potentially useful element of productivity improvement, must be coherent with overall productivity improvement strategy. Other elements of productivity management such as learning must complement technological changes to provide continuous productivity improvement.

Involvement

Involvement is another key element of productivity improvement. Involvement means commitment to the company's goals and objectives. Companies need to involve their workforce in the productivity improvement process, making them part of the solution, not the problem (Bell-Burnham[3, p. 13]). To increase involvement in productivity improvement, company employees need to be motivated to achieving the corporate goals and objectives.

To increase motivation people need to be clear on their roles in the company and have positive feedback on their efforts. Employees need to know what the factors affecting productivity are, so they can improve those factors. Managers must also make clear the distinction between a team effort in productivity improvement and individual efforts. This will allow for a reward system that everyone can agree with. The organization's and supervisors' leadership roles also have an important impact on workforce motivation. Many policies and procedures often stand in the way of motivation (Bell-Burnham[3, p. 221-223]).

Innovation

Innovation can be defined as "the introduction of something new; a new idea, method, or device" (Bell-Burnham[3, p. 14]). Innovation can bring improvement to the productivity of a process. New ingenious ways of doing things may, among others, simplify the process, reduce input resources and/or increase output production, and make the process more clear. Innovation can be anything from a rearrangement of production operations to a complete redefinition of the process.

Managerial Direction

Managerial direction is a key element of productivity management. Managers must set a clear, long-term direction for productivity improvement. They must allocate the appropriate resources and be the driving force for productivity improvement. Productivity improvement initiatives will not succeed without a strong and determined management (Bell-Burnham[3, p. 15]).

2.1.2 Steps to NPIP Productivity Management

Successful productivity improvement requires a well planned strategy to apply the key elements of productivity management. This strategy consists of a series of well coordinated productivity management steps. These productivity management steps consist of first properly defining the NPIP. Secondly, the productivity of the NPIP needs to be properly defined and modeled.

The main output of the NPIP are packets containing the newspaper section with preprints inserted in them. A series of machine operations insert the preprints in the fold of the newspaper section and they are subsequently stacked into bundles. The machines are loaded by operators that also supervise the operation of the machines. The productivity of the NPIP is determined by the production of packets as a function of resource utilization.

After defining and modeling productivity, a measurement system for the NPIP needs to be developed. The next step consists of the evaluation of the productivity results. From the evaluation of results, productivity improvement initiatives can be subsequently planned and implemented. Productivity performance can thereafter be measured to evaluate the effect of productivity improvement implementations. Figure 2.1 provides a flow diagram of the productivity management steps.

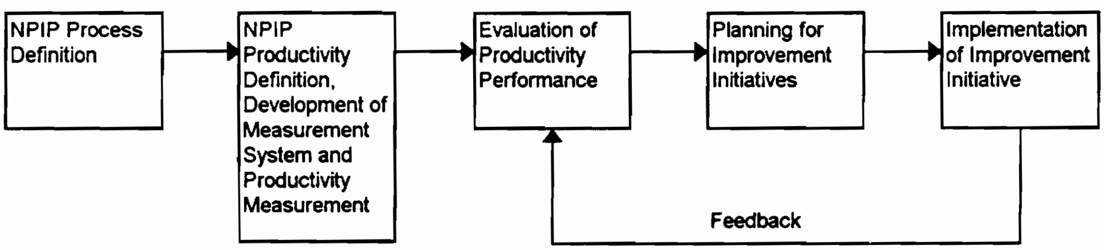

Figure 2.1 NPIP Productivity Management Steps

Feedback of productivity performance improvements is also critical for effective productivity management. Feedback is needed to provide encouragement for further productivity management initiatives. The following sections describe the productivity management steps in more detail.

2.1.3 NPIP Productivity Definition, Modeling & Measurement

To be able to obtain productivity performance results, productivity of the NPIP must first be properly defined. This means the relevant productivity input/output variables need to be identified and defined. The proper definition of input/output variables is essential because large amounts of resources can be invested in a comprehensive productivity management implementation, but little will result unless productivity of the process has been properly defined and modeled.

Traditionally, productivity inputs have been defined on the basis of direct labor resource utilization as it affects the production of output (Bell-Burnham[3, p.34]). In today's increasingly capital intensive processes, labor has become one more production resource which in many cases is not the resource with the greatest impact on productivity (Chew[4, p. 3]). Other resources, such as raw materials, capital and overhead costs play a mayor role in productivity performance (Chew[4, p. 4]).
Defining these inputs/outputs of the process may not be a simple task. The process usually produces multiple products and/or services. In addition, the organization experiences continuous price and cost change of its inputs and outputs, as well as engineering redesign of its products, services and/or process to meet multiple customer requirements (Sink[13, p. 31]).

This complexity in defining input/output variables requires the selection of a flexible computational approach to model NPIP productivity. Also, the computational approach should provide productivity measurement results that are clear and simple to interpret. The Data Envelopment Analysis (DEA) computational approach not only allows for flexibility in the definition of input/output variables, it also provides results that are easy to understand and interpret.

The costs associated with obtaining accurate productivity measurement data should be weighed against the potential benefits that this enhanced accuracy provides. Many times, a less accurate data collection system will prove as valuable as one of greater accuracy whose costs are exceedingly high. Implementation and maintenance of productivity measurement system must in no way exceed the potential productivity gains that can be obtained from its implementation. The degree of accuracy of the productivity measurement system should rely on the existing data and only on limited additional data collection.

2.1.4 Productivity Evaluation and Improvement Strategy

After the productivity measurement system is in place, productivity performance of the NPIP can be measured. The results will indicate productivity trends of the process. Conclusions can then be drawn from the results and improvement initiatives can be triggered. These areas for improvement should focus on clear identifiable areas where productivity will be positively affected. Also, standards can be constructed from the collected results for future evaluation of performance. It should be noted that the productivity improvement initiatives should be carried out in accordance with the overall strategic company management plan.

2.2 NPIP Quality Management

Quality management has evolved from rudimentary inspection of manufactured products to a much broader strategic corporate goal (Garvin[9, p. 21]). Four distinct periods for quality management were identified by Garvin. Quality management originally emphasized uniformity of production through inspection. Later this century, it evolved to encompass quality control of the process using statistical tools and techniques. A new perspective on quality management was introduced by Armand Feigenbaum during the

1950s (Garvin[9, p. 13]). This perspective of "total quality control" was mainly focused on quality assurance in all stages of production, from design to the market, and became the new driver in quality management. The latest trend in quality management is its evolution to becoming a strategic corporate function (Garvin[9, pp. 3-20]).

The aspect of quality management most important in manufacturing processes is the products' conformance to specifications. This narrower view of quality allows for a clear definition and quantification of quality in manufacturing. Quality performance levels for the process can thus be set, and quality improvement initiatives can be planned and implemented. This is the perspective of quality management that the NPIP focuses on.

There are two complementary perspectives of quality management in manufacturing. The traditional perspective states that some level of defects (nonconforming products) is acceptable, as long as it is within acceptable limits. Another perspective on quality management is that the only acceptable standard of quality is zero defects (Garvin[9, p. 18]). These two perspectives of quality management are discussed in the following section of quality costs.

2.2.1 Costs of Quality of Conformance

Costs directly associated with quality of conformance can be categorized as *internal failure costs*, *external failure costs*, *appraisal costs* and *prevention costs* (Juran-Gryna[12, p. 24]). The first two cost categories are costs related to quality cost of nonconformance. The second two categories are costs associated with the implementation of a quality management system designed to reduce the first two cost categories. The following is an explanation of these four costs.

Internal failure costs are those costs incurred before the product is shipped out to the customer. These include scrap, rework, failure analysis, scrap and rework suppliers, one hundred percent sorting inspection, reinspection and retesting, avoidable process losses and downgrading of product price due to nonconformance (Juran-Gryna[12, pp. 16-17]). *External failure costs* are those costs incurred after the product is shipped out to the customer. These include warranty charges, complaint adjustment, returned material, and allowances made to customers for failing to meet specifications (Juan-Gryna[12, p. 17]). *Appraisal costs* are those incurred to determine the degree of adherence of the product to specifications. These include incoming material inspection, in-process and final inspection and testing, maintaining accuracy of test equipment, inspection and testing of materials and services, evaluation of stock of products and product testing for degradation (Juran-Gryna[12, p. 17]).
Prevention costs are those costs incurred to maintain *failure* and *appraisal costs* at the lowest level possible. They include quality planning, new-products review, process control, quality audits, supplier quality evaluation, and training (Juran-Gryna[12, p. 18]).

In addition to these four assignable costs of quality, *hidden costs* due to poor quality also play a mayor role. *Hidden costs* from poor quality include loss of potential sales, redesign of products, changing of manufacturing processes, software changes, lowering of standards to allow poor quality, extra manufacturing, scrap not reported, necessity of extra capacity, and creation of process excesses (Juran-Gryna[12, pp. 22-23]). Although these *hidden costs* may not be readily measurable it is important to be aware of their potential impact on production.

Juran and Gryna propose two economic models of quality of conformance. The first model is constructed for conditions which prevailed during much of the twentieth century (Juran-Gryna[12, p. 24]). In this model, most of the quality management expenditures are focused on *appraisal*, with little investment on *prevention*. The model assumes that an increase in *appraisal* and *prevention* will reduce the costs associated with *internal* and *external failures*. Figure 2.2 illustrates this first economic model of quality of conformance.

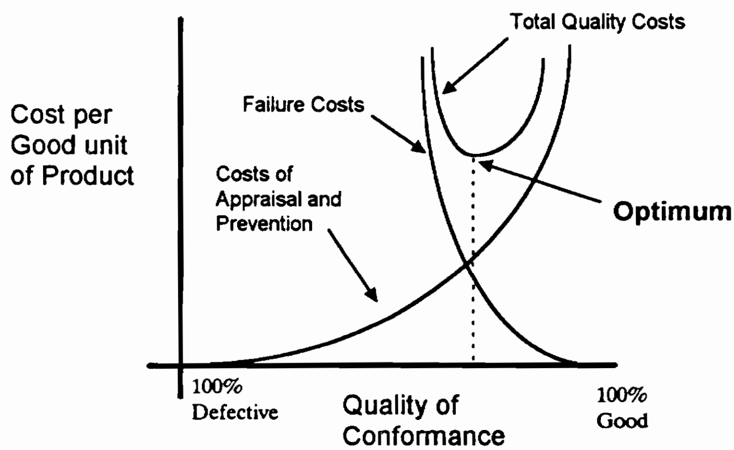

Figure 2.2 Traditional Model for Optimum Quality Costs (Juran-Gryna[12, p. 25])

Note that to achieve zero defects (100% good) the expenditures in *appraisal* and *prevention* would reach infinity. In this model thus, zero defects are impossible. The optimum operating point is where the cost of *internal* and *external failures* combined with *appraisal* and *prevention costs* (total quality costs) are minimized. Operating practices lying to the left of the optimum operating point can be optimized through improvement initiatives. Operating practices lying to the right of the optimum mean that *appraisal costs* are excessive for the cost of nonconformance reductions obtained. Under these operational conditions it is advisable to study the costs per defect, verify existing standards, and reduce inspections to lower overall *appraisal costs* (Juran-Gryna[12, p. 26]).

The second economic model of quality of conformance proposed by Juran-Gryna represents conditions of late twentieth century manufacturing (Juran-Gryna[12, p. 25]). *Prevention* in this model takes a priority role over *appraisal*. This model is based in the fact that new technology such as robotics and automation reduces the sources of human error both in production and *appraisal* tasks (Juran-Gryna[12, p. 25]). Figure 2.3 illustrates this second model in more detail.

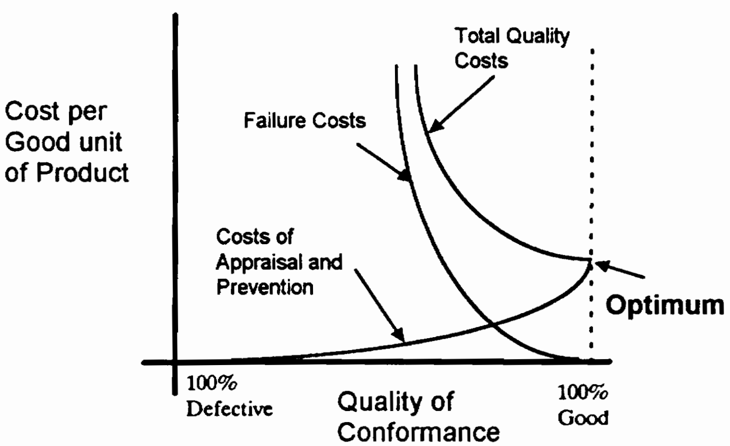

Figure 2.3 Emerging Model for Optimum Quality Costs (Juran-Gryna[12, p. 25])

Note that zero defects (100% good) is the operating optimum of this model. This model assumes that a finite expenditure on *appraisal* and *prevention* can effectively get rid of the problems of nonconformances in production. This model places a strong emphasis on technology's capability of eliminating human input in the process that could lead to error. Zero defects is obtained when an optimum level of expenditures on *prevention* and *appraisal* is reached. Thus, quality management should focus on improvement efforts to reach zero defect levels (Juran-Gryna[12, p. 25]).

The high volume production of one million newspapers per production day of the NPIP, along with the constrained production time available for its production make it infeasible to target a zero defect level. Thus, quality management in the NPIP should focus on the first perspective of accepting some non-zero level of defects. This does not mean that zero defects could not be the ultimate goal of NPIP quality management. With the introduction of automation and robotics into the NPIP, a level of zero defects could be achieved. But at this time, with the current level of technology, acceptable limits of nonconformance should be realistically set.

The NPIP does not presently have resources specifically dedicated to *appraisal* and *prevention* of nonconformance. Because of this, it can be considered that the NPIP lies to the left of total quality cost curve of both the traditional and the emerging economic model of the quality of conformance (Juran-Gryna[12, p. 25]). That means there is much room for improvement at the NPIP before an optimum quality operating point is reached. The following are the basic steps to an effective quality management strategy similar to those of productivity management.

2.2.2 Steps to NPIP Quality Management

Similar to productivity management, quality management should be driven by continuous improvement. A systematic approach to quality management is necessary for long-term benefits of quality improvement. Quality management steps consist of first defining the NPIP and then modeling the appropriate input/output variables that represent quality of conformance of the process. Third, a quality measuring system should be implemented. Fourth, quality performance is then measured and the results evaluated. From the evaluation of results, quality improvement initiatives can be subsequently planned and implemented. Quality performance can thereafter be measured to evaluate the effect of quality improvement implementations. Figure 2.4 provides a flow diagram of the quality management steps.

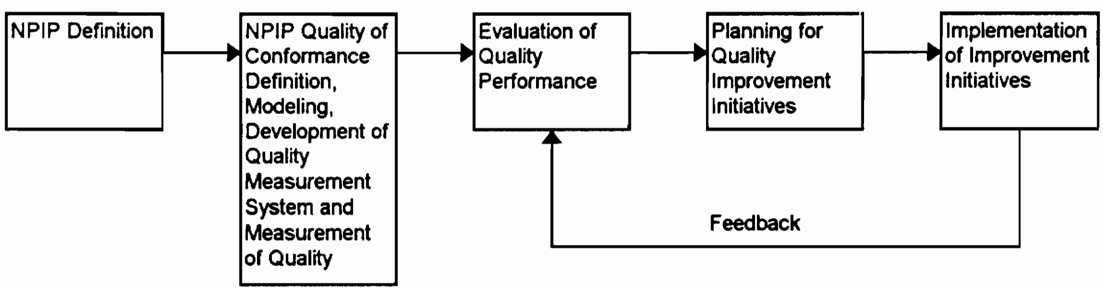

Figure 2.4 NPIP Quality Management Steps

Quality is often viewed as something that cannot be measured, thus feedback is essential to provide encouragement for further quality management initiatives. The following sections describe the NPIP quality management steps in more detail.

2.2.3 Defining, Modeling and Measuring Quality of Conformance

Properly defining the input/output variables of quality performance is essential to the success of a quality management initiative. Because of the multiple definitions and dimensions inherent to the term quality, a consistent way of defining quality must be identified. There should be no confusion as to the definition of the term quality to all those involved in the NPIP.

Quality output variables should assess the quality of conformance of the process. Possible outputs of the quality models include measures of nonconformance. Input variables of quality are all those resources that affect the nonconformance of the NPIP. As with the productivity measurement system, a flexible computational approach should be used to assess quality performance, both to allow for flexibility in the definition of input/output variables and to provide results that are easy to understand and interpret.

Also, the costs associated with obtaining additional accuracy in quality performance measurement should be contrasted with the benefits that this additional accuracy will provide. There is usually little data available to accurately measure quality. Usually, added data collection is necessary to obtain accurate quality measurements. The added accuracy of additional data collection should justify the increased costs associated with the quality measurement system.

2.2.4 Quality of Conformance Evaluation and Improvement Strategy

After obtaining quality performance results with the quality measurement system, evaluation of these results should be carried out. This evaluation will assess quality trends of the NPIP process. Factors that cause these trends can then be identified by assigning known causes to the trends. An improvement strategy can then focus in eliminating those factors.

It should be noted that an effective quality improvement strategy requires involvement of both workforce and management. Quality improvement initiatives many times seem contradictory to production goals such as productivity and profitability unless they are well understood by everyone in the production process. It is for this reason that everyone should understand the implications of quality improvement strategies.

Chapter 3. CONCEPTS

3.1 Production Function

A production function is an abstract representation of the relationship between outputs and inputs of a production technology. When a production function is defined, technical efficiency is presupposed meaning that we are obtaining the maximum amount of output from every different combination of inputs. The following is a representation of a production function of a specific technology with a single output and two inputs.

$$q = f(x_1, x_2) \tag{3.1}$$

where x_1 and x_2 are the variable inputs and q is the output quantity. This function fully describes the interrelationship between outputs and inputs of a system. For example, for a given level of inputs such as x_1^0 , x_2^0 we obtain an output level q^0 .

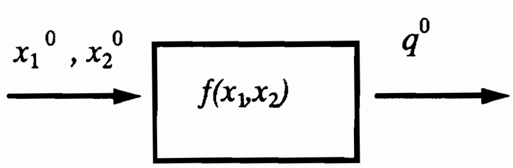

Figure 3.1 Production Process

This production function is subject to a series of assumptions. They are stated as follows:

- The production function assumes that all the fixed inputs required in production are accounted for. Fixed inputs are a concern of long-term organizational planning and are not modeled by the production function. This first assumption indicates that the production function only models variable inputs, since fixed inputs have no effect on the level of output produced.

- The production function of equation (3.1) is a single valued function with continuous first and second order derivatives. However, one can also have some non-continuous representations of the production function.

- The production function is only defined by non-negative values of input and output levels. This means that there cannot be negative inputs or outputs for the production function.

- The production function presupposes technical efficiency in the process, i.e. assumes that the maximum output is obtained from every possible input combination.

The period of time for which the production function is modeled is an important consideration when evaluating a production function. A short-run production function is subject to the following restrictions:

1) It must be sufficiently short so that fixed inputs remain unchanged for the period of time for which the production function is effective.
2) It must also be sufficiently short so it is not altered by a change in the technology.
3) It must be long enough to allow for the completion of the technical processes.

The long-run production function can be obtained by relaxing the first condition, providing a period of time long enough to allow variation of the fixed inputs. The main difference between the short-run and the long-run production function is that the long-run production function contains more variable inputs. The following example illustrates the difference between the short-run and long-run production function.

Let us assume that the capital input resources of a manufacturing process are the machinery utilized and the building used. The plant changes machinery every five years and relocates to a new building every ten years, incurring a cost every time this occurs. When the production function is modeled for a one year time span (short-run), capital can be excluded as an input variable since it can be considered a fixed input; no change in capital expenditures occurs. On the other hand, when the production function is modeled for a twenty year time span (long-run), capital must be included as an input variable since it has a direct impact on the output production of the process.

3.2 Isoquant

The concept of the isoquant can be derived from the production function. An isoquant is the locus of all combinations of inputs that will yield a constant level of output. Using the same production function as section 3.1, if the output level q of the production function is held constant, one can plot all the possible combinations of input resources x_1 and x_2 that will yield that constant level of output. Since the representation of the production function of equation (3.1) is continuous, the isoquant represents an infinite amount of input combinations. An isoquant with output level specified at q^0 is represented as follows:

$$q^0 = f(x_1, x_2) \qquad (3.2)$$

Note that x_1 and x_2 are the only variables of equation (3.2). This function represents all the possible combinations of x_1 and x_2 that will yield an output level of q^0. Figure 3.2 illustrates various isoquants, each representing a different output level.

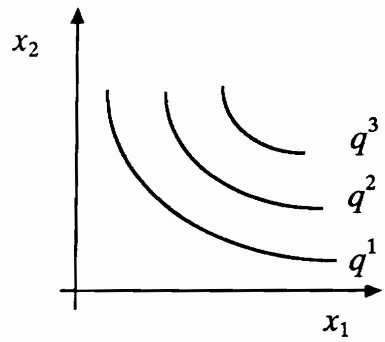

Figure 3.2 Isoquants

Note that the isoquants from Figure 3.2 have an increasing value as they get further away from the origin, meaning that $q^3 > q^2 > q^1$.

3.3 Data Envelopment Analysis (DEA)

Data Envelopment Analysis (DEA) is a mathematical programming approach that evaluates the efficiency of discrete observations or decision making units (DMUs) with multiple input-multiple output variables. DEA defines efficiency performance as the weighted sum of outputs over the weighted sum of inputs.

$$Efficiency = \frac{weighted\ sum\ of\ outputs}{weighted\ sum\ of\ inputs} \tag{3.3}$$

There are six basic assumptions of production theory that must hold when using DEA. They are stated as follows:

1) There cannot be output unless there is some level of input usage. This assumption assures that there cannot be any free output unless some resources are invested.
2) There cannot be infinite production with finite input usage. This assumption assures that the production of output is bounded by the level of input resources invested.
3) Any proportional increase in input usage does not decrease outputs (strong disposability of inputs). This assumption assures that increasing input resources will never have a detrimental impact on the production of output.
4) There is the possibility of decreasing outputs with no change in input usage (strong disposability of outputs). This assumption assures that the same consumption of resources can produce different levels of output.
5) There is a closed correspondence between inputs and outputs.
6) The isoquant must be convex to the origin.

The DEA assumptions are realistic for most manufacturing processes. The only assumption that could be challenged for the process evaluated in this research is the strong disposability of inputs. Under certain operating conditions, an increase in input resource consumption could actually lead to a decrease in output production.

DEA creates an envelopment surface referred to as the *empirical production function* or the *efficient frontier.* This *efficient frontier* is created from actual observations. A characteristic of this frontier is that all observations (DMUs) are either on or enveloped by this *efficient frontier.* The efficiency of a particular DMU is obtained by comparing the performance of that DMU to the *efficient frontier.*

Figure 3.3 illustrates an isoquant formed by a set of seven different observations (DMU_A, DMU_B, DMU_C, DMU_D, DMU_E, DMU_F, DMU_G) with the constructed *efficient frontier.* Note that since we are evaluating an isoquant, all observations have the same output level (refer to section 3.2). As in the previous section, this example considers a system with two inputs (x_1 and x_2) and a single output q.

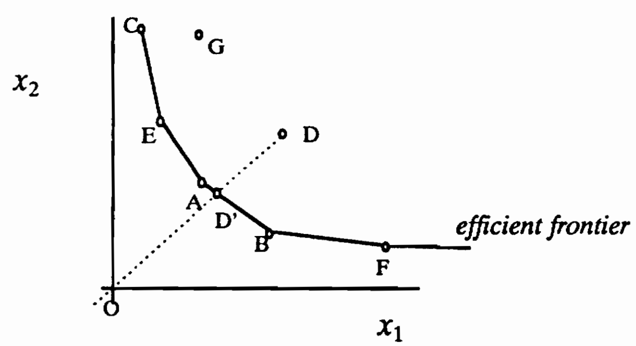

Figure 3.3 Input Frontier

Note that points C, E, A, B and F form the *efficient frontier*, where G and D are enveloped by this *efficient frontier.* When evaluating the efficiency of the observation, DEA will render C, E, A, B and F fully efficient while rendering G and D as inefficient.

The downward sloping and convexity to the origin for the isoquant is a restriction of production function theory that must hold for DEA. This restriction allows for the assumption that all the observations residing between the line segment of two efficient observations can also be considered efficient. For example note that any point laying in the line segment AB (for example D') can be considered a possible operating point. For the line segment AB to form part of the *efficient frontier*, there cannot be any points lying in the area formed by points A, B, O.

The radial efficient reference point for point D is point D'. Point D' can be considered the radial efficient reference point of D because point D' has been reached by proportionally decreasing all input variables (x_1 and x_2). This means that for observation D to become efficient, a proportional decrease of inputs x_1 and x_2 must occur until point D' is reached. The efficiency performance of observation D will be the ratio between the distances of line segment OD' and OD defined as

$$efficiency(DMU_D) = \frac{OD'}{OD}$$

This efficiency performance can be viewed as the comparison of performance of an actual DMU_D to a hypothetical (efficient) $DMU_{D'}$, that is the weighted average of DMU_A and DMU_B.

Note that the efficiency measure that is obtained using DEA is a *relative efficiency* or *best practice efficiency* measure since we are constructing the frontier from actual data points instead of using a blueprint engineering standard. The efficiency performance of each DMU will be in comparison to a weighted average of actual operating DMUs. Further, DEA will tell what combination of efficient DMUs will render an inefficient DMU efficient.

DEA can be used to compute the relative efficiency of multiple systems with the same production technology (cross-section of observations) or simply compare the relative efficiency of one system through time (time series) or both (panel data). Different DEA models exist that evaluate the efficiency performance of DMUs. All these models are derived from the original CCR model proposed in by Charnes, Cooper, and Rhodes in 1978. The following section describes this original DEA model in detail.

3.3.1 The CCR Model

Charnes, Cooper, Rhodes (1978) proposed a linear programming model to compute the efficiency performance of DMU_{j0}. The formulation of that model is as follows:

$$
\begin{aligned}
&Max\ \ h_0 = \frac{\sum_{r=1}^{s} u_r y_{rjo}}{\sum_{i=1}^{m} v_i x_{ijo}} \\
&Subject\ to \qquad\qquad\qquad\qquad\qquad\qquad (3.4) \\
&\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1, \qquad\qquad j = 1, \ldots, n, \\
&u_r, v_i \ge \varepsilon, \quad \forall\ r \ and\ i
\end{aligned}
$$

where the known parameters are:[1]

n is the total number of DMUs in the data set,

s is the number of output variables,

m is the number of input variables,

y_{rj} is the amount of output r produced by DMU_j,

x_{ij} is the amount of input resource i used by DMU_j,

[1] This same formulation is used in the output increasing and input reducing models described in Appendix A.

ε is a small positive number,

and the variables are:

u_r is the weight given to output r,

v_i is the weight given to input i.

Note that μ_r, and v_i, are the unknown parameters that need to be calculated. Also note that the objective function h_0 is actually the weighted sum of outputs over the weighted sum of inputs (refer to equation (3.3)).

The model calculates the weight values of u_r and v_i that maximize the objective function h_0 subject to the restrictions of equation (3.4). The advantage of this approach is that if DEA renders a DMU inefficient, it is a clear statement that it is inefficient because not even the most favorable combination of weights could render it efficient. At the same time, this becomes a disadvantage when considering efficient DMUs. One cannot be completely certain if these efficient DMUs are rendered efficient because of good overall performance or because the chosen weights helped to render that particular DMU efficient.

3.3.2 DEA Models

The formulation of the CCR model is a starting point for many other DEA models that can be used to analyze the efficiency of a system or process. All these models are derived from the general formulation just described (CCR). The basic difference between models are two:(a) the orientation of the model;(b) the restrictions associated with the model.

3.3.2.1 DEA Orientations

There are two basic orientations that can be used to evaluate the efficiency performance of observations. To solve the programming function of equation (3.4) as a linear program one can either maximize the numerator keeping the denominator constant, or decrease the denominator while keeping the numerator constant. The first approach is referred to as output increasing model (OIM) and the second approach is referred to as the input reducing model (IRM).

The output increasing model[2] will find the output weights that maximize the numerator of the maximization function of equation (3.4). The efficiency performance obtained from this model will indicate how efficient the DMU is in maximizing output for a given level of input usage. This orientation is commonly used to model systems where the main objective is to increase the production of output.

Similarly, the input decreasing model[3] will determine the input weights that minimize the denominator of the maximization function of equation (3.4). Its efficiency performance will reflect how efficient the observation is in minimizing its inputs to obtain that fixed level of output. This orientation is commonly used to model systems whose main goal is to reduce the consumption of input resources to obtain a fixed amount of output.

3.3.2.2 Model Restrictions

The main restriction that can be relaxed when formulating a DEA model is the type of envelopment surface that is used by the model. Depending on the envelopment surface,

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[2] Appendix A includes the formulation of the Output Increasing Model.
[3] Appendix A includes the formulation of the Input Reducing Model.

the efficiency standing of DMUs may differ. The two basic types of surfaces are constant returns-to-scale (CRS) and variable returns-to-scale (VRS).

Variable returns-to-scale (VRS) envelopment surface restriction is used to model systems where a proportionally equal increase/decrease in inputs lead to non-proportional increase/decrease in output. Figure 3.4 illustrates the characteristics of the VRS restriction.

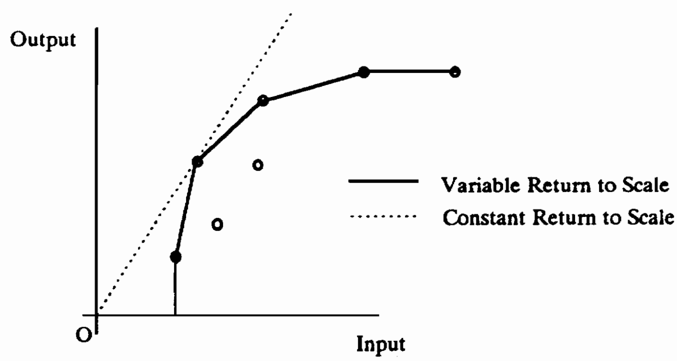

Figure 3.4 Return to Scale Restriction

Note that the envelopment surface of the VRS is constructed by the weighted combination of actual observations. All the efficient operating points lie in the line segments connecting efficient observations. Initially, an increase in input resource consumption does not provide any increase in production. This is the case where there is a strong disposability of inputs, meaning that there can be no added production of output even if the input levels are increased. Similarly, there is a possibility that maintaining the same level of in input may reduce the production of output. This is the case where there is a strong disposability of outputs.

Constant returns-to-scale (CRS) envelopment surface restriction is used to model systems where an increase/decrease in input leads to a proportional increase/decrease in output. From Figure 3.4 it can be noted that the envelopment surface of the CRS restriction has a constant slope. Only one observation is lying on the *efficient frontier*. All the rest of the observations will be rendered inefficient.

The difference between variable and constant returns to scale can be best explained with an example. Consider a company specialized in creating fashion designs. The company hires designers to create these designs. Currently, for the company to be efficient, a designer must make three designs per month. If the performance of the company can be modeled using CRS, it means that any additional fashion designer that is hired will need to increase total output by three designs for the company to perform efficiently.

On the other hand, if the company performance is modeled with VRS, the hiring of an additional designer does not mean that a proportional output increase of three designs will maintain the company's same efficiency performance. If the output is increased by three designs, the efficiency may actually drop. The more designers in the company, the faster the ideas for new designs will be discussed, resulting in an increase in the creation of designs. Thus a company that is only able to maintain a proportional increase when a new designer is hired, may perform less efficiently in comparison to other companies with the equivalent number of designers.

Chapter 4. THE NEWSPAPER PREPRINT INSERTION PROCESS

4.1 Overview of the Production Process

The newspaper preprint insertion process (NPIP) comprises all the steps involved in the transformation of incoming preprints and newspaper sections into bundles ready for delivery to the newspaper distributors. Three major sequential operations are performed in this process. They are as follows:

1) The *opening* of the fold of the newspaper section and the *insertion* of preprints in the fold, producing an intermediate product called a packet;
2) The *stacking* of packets to form bundles;
3) The *wrapping* and *palletizing* of bundles.

Of these three operations, the first operation has the greatest impact on the performance of the process, both from a productivity and a quality perspective. Not only is productivity mainly dependent on the performance of this operation, but most quality problems can also be traced back to causes originating during this first phase of the process. It is for this reason that performance variables of this phase of the process are in this research used to represent some of the variables that reflect the overall process performance.

The NPIP occurs two days a week, 52 weeks/year. Each of these two production days produces distinctly different products. Thus, weekly production is divided into *day one* and *day two* products. Production time for each one of these days ranges from about 6 to 8 hours and the process produces more than one million packets each production day. The following sections describe the NPIP in more detail.

4.2 NPIP Interactions

The NPIP forms part of the greater newspaper production process. Being physically located inside the newspaper production facility, NPIP interacts with other processes within the facility and its performance is dependent on the performance of those other processes. The two main departments that interact with the NPIP are the *Press Room* and the *Warehouse*. The *Press Room* is responsible for the printing of the newspaper section where the preprints are to be inserted. The *Warehouse* is the section where preprints necessary for the insertion into the newspaper are stored. The following figure illustrates the interactions between the systems.

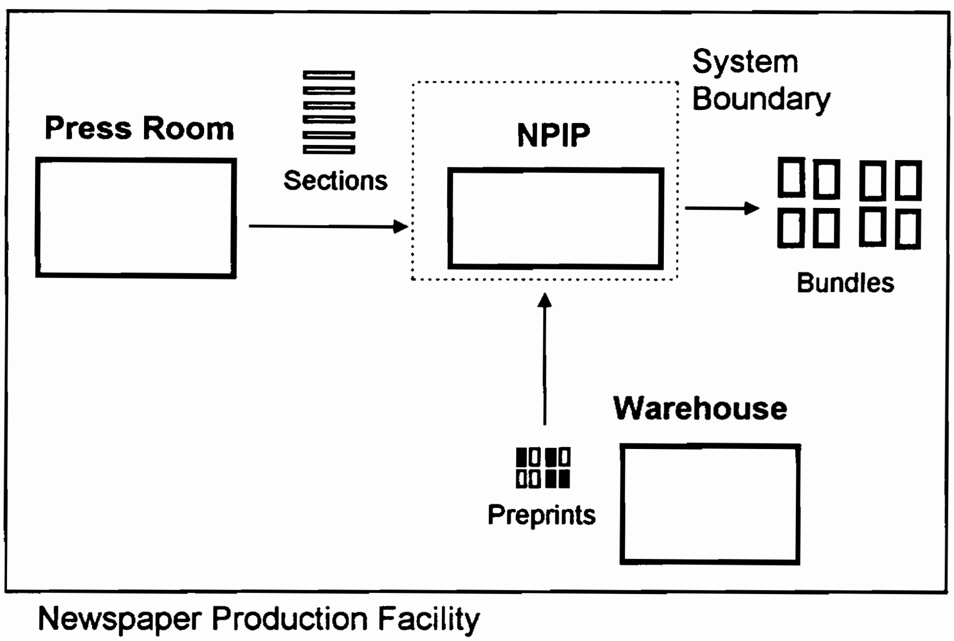

Figure 4.1 NPIP Interactions with the Press Room and the Warehouse

The performance of these three processes are interrelated, but an evaluation of these interdependencies goes beyond the purpose of this study. For the evaluation of the performance of the NPIP, it will be assumed that the performance of the *Press Room* and

Warehouse departments remains uniform throughout the study period. Thus, performance of the NPIP will be considered independent of the performance of both the *Press Room* and the *Warehouse*.

4.3 Product Definitions and Characteristics

The output product of the NPIP are *bundles* of *packets* that are delivered to the distributors. During the different phases of the process, there are a set of incoming and intermediate products. They can be categorized as follows:

(a) *Preprints*: Incoming product that is inserted into the fold of the newspaper section. They vary in size, shape and texture; (b) *Newspaper Sections*: Incoming product where preprints are inserted; (c) *Packets*: Intermediate product that is the result of the insertion process phase; (d) *Bundles*: The output product that is a wrapped stack of *packets*. This is the output product that is delivered to the distributors. Figure 4.2 provides a visual representation of the NPIP products.

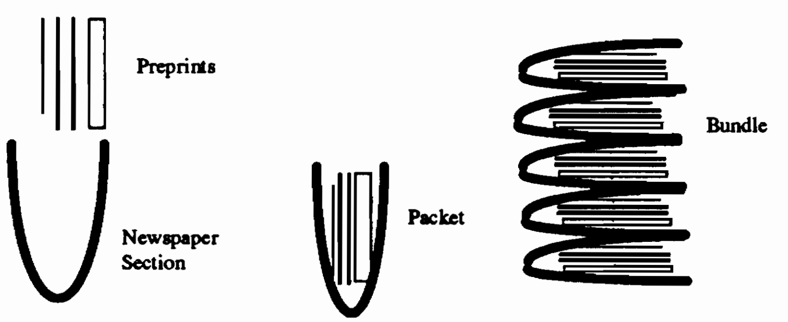

Figure 4.2 Visual Representation of Products of the Process

Each one of the NPIP products has different characteristics and attributes. Table 4.1 provides further understanding of all these products and their characteristics.

Table 4.1 NPIP Product Characteristics

Product	*Input/Output Description*	*Daily Types*	*Daily Quantity*	*Effects on the Quantity of Daily Production*
Preprints (INCOMING)	Outputs of the Warehouse and inputs for the NPIP	The amount of advertisers	As many as were sold by the Sales Department	Affects the complexity of production, the production rate, and the number of conforming output products
Sections (INCOMING)	Outputs of the Press Room and inputs for the NPIP	Downtown Uptown Suburb	As many as were ordered by management plus some slack	Affects the scrap and slack in production, and the liability for not meeting quota
Packets (INTERMEDIATE)	Outputs of the NPIP	The amount of production zones	As many as were ordered by management	Affects the liability for not meeting quota
Bundles (OUTPUT)	Outputs of the NPIP	The amount of distribution zones	As many as were ordered by management	Affects the liability for not meeting quota

4.4 NPIP Production Organization

There are six identical parallel *production lines* in the process. Each one of these *production lines* has a *crew* assigned to it which is responsible for the completion of an individual *production quota*. The following figure illustrates the production process layout.

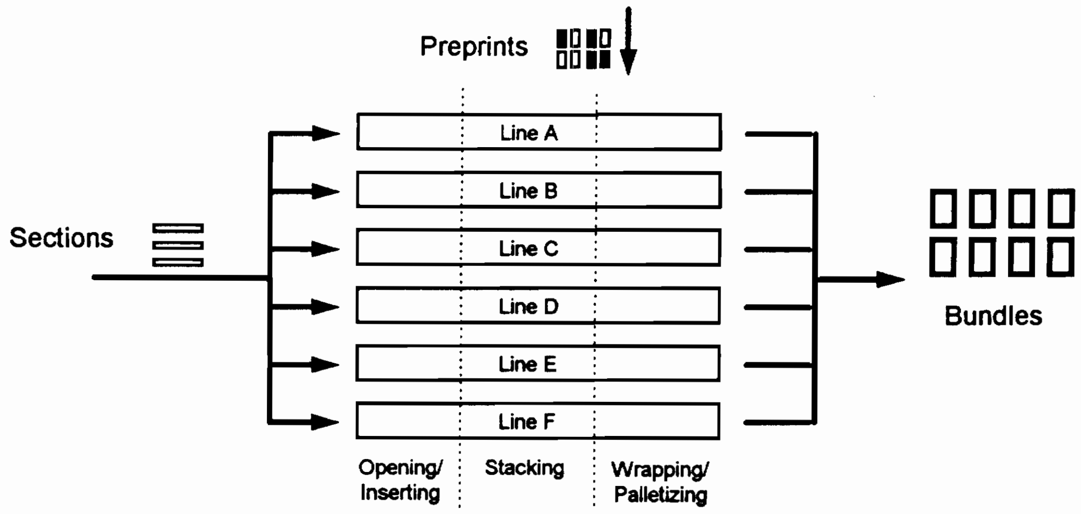

Figure 4.3 Six Parallel Production Lines

Production is divided into different *production zones*, each zone having a unique preprint mix. The *production zones* provide coverage for three distinct *areas*: Downtown, Uptown and Suburb. Each one of these *areas* requires a unique newspaper section type.

At the beginning of each shift, each *production line* is assigned a specific *production quota*. Each *production quota* is composed of specific *production zones*, along with the batch size for each one of these *production zones*. Change over set-up time is required to change from one *production zone* to another. Work is distributed as equally as possible among the different *production lines*, taking into account the number of *production zones*, the amount of preprints included per *production zone* and the amount of packets to be produced by each *production line*. Production is run until the daily demand of packets is satisfied. A main characteristic of this process is that production output is constrained by the daily demand for products. Table 4.2 illustrates the different terms relevant to the production process.

Table 4.2 NPIP Production Organization Terms

Term	*Description*	*Types*	*Variations*	*Quantity*
Production zone	A production zone constitutes a specific packet production batch. The zone has a unique batch size and preprint mix.	Infinite variation	Preprint type Production batch size Newspaper section type	Depends on the daily production requirements
Area	The area where the paper is going to be delivered	Downtown Uptown Suburb	Newspaper section type	Three
Production Line	Physical entity where the transformation of inputs into outputs occurs	Six identical parallel lines	Can either be active or passive	Six, not all of them always active
Crew	Group of workers assigned to work on a specific shift and on a specific production line	One type only	All are considered the same	One per production shift per active production line
Production Quota	The zone batches each production line crew is required to complete per production period	Infinite variation	The number and requirements of each zone	One per production shift per active production line

The following is an example of the a possible production schedule for a *day one* shift. On this particular production day, only lines A, B, C and F are active. A total of 425,000 packets need to be produced for 9 different production zones. Each production zone has a different requirement of the types of preprints it needs to insert. The following table summarizes the production quota requirement for each production line.

Table 4.3 Example of a *Day one* Production Schedule

Production Distribution	Production Zone Number	Preprints to be Inserted	Area of Distribution	Batch Size
Crew of Line A Production Quota	15	LawLow SuperMarket Nailit Home Improvement	Downtown	15,000
	23	UFO Electronics	Suburb	25,000
	29	Nailit Home Improvement	Uptown	35,000
Crew of Line B Production Quota	13	LawLow SuperMarket	Uptown	25,000
	56	UFO Electronics	Downtown	70,000
Crew of Line C Production Quota	37	Nailit Home Improvement UFO Electronics Suits r Us	Suburb	80,000
	47	LawLow SuperMarket Wow Clothestore	Uptown	35,000
Crew of Line F Production Quota	63	UFO Electronics	Suburb	115,000
	25	Suits r Us UFO Electronics	Downtown	25,000

Note that the combination of preprints to be inserted and type of Newspaper Section is different in each production zone. In this example, there are six different types of preprints that must be inserted into the fold of three distinct types of newspaper sections. At the same time, each production zone produces a different batch size for each unique output product. This constant change of preprint mix, newspaper section and batch size creates an almost infinite amount of output products that can be produced. This makes it hard to establish a standard of quality and productivity performance for the NPIP. A *complexity* *factor* was formulated to quantify both the complexity of production and product produced. Details on the formulation of the *complexity factor* are included in Appendix D.

4.5 Description of Input/Output Variables

The variables chosen both for the productivity and quality model provide a comprehensive representation of both productivity and quality performance of the NPIP. Although ideally one would prefer a process with clearly identifiable independent variables, the NPIP has variables that are difficult to define and quantify. Although all the models assume all variables to be independent from one another, there are undoubtedly interdependencies between the variables of the models. An attempt was made to check the correlation of the input/output variables[1]. Variables found to be interdependent were excluded from the analysis. Variables that were found to remain constant throughout the study period were also excluded from the analysis.

The data available only allowed partial or indirect measurement of some of the variables of the models. That data were still used to partially measure some variables of the models. The following sections describe the productivity and quality variables in further detail.

4.5.1 Input/Output Variables Used for Productivity Assessment

The same input variables were used for both productivity models P1 and P2 (refer to sections 4.3.1 & 4.3.2). An extensive evaluation of the possible productivity input and output variables was carried out. The following is a description of all the input variables considered for the models.

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[1] Bivariate regression analysis was used; refer to Appendix C.

Input Variables Included in the Productivity Models

a) Actual *machine hours* employed during a production period is a representation of the capital usage during production. It also serves as a surrogate variable representing energy usage in production. This variable was measured by summing the total hours of production of all the active production lines during the production period (one day).

b) *Labor* utilized during each production period was also considered an important productivity input variable. This variable was measured by summing the amount of hours employed by the two distinct types of line workers, the crewmen and the assistants.

c) The *maintenance & setup*[2] variable provides an indication of the amount of preventive maintenance carried out before each production period. This variable was measured by the amount of labor hours dedicated to *maintenance & setup* for each production period.

Input Variables Not Included in the Productivity Models

d) *Raw materials* was considered an important productivity input variable. Raw materials could be considered as any consumable input in the process which is used to produce output. This variable was not included in the analysis because no measure for this variable was found.

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[2] This variable was found to have no impact on the quality and productivity models. It is believed this is because of the inclusion of setup into the variable.

e) No measures were found for the allocation of *miscellaneous* and *overhead* costs. These variables were considered of small impact in the productivity performance of the process.

Output Variables of the Productivity Models

Even though the complexity of output varied within the same production period, two distinct productivity output variables were identified. A production period contained two production days, each having a distinct output. Thus, the productivity output variables were chosen to be the following:

a) An output variable of the productivity model is the amount of products produced during production *day one*. The parameter used to measure this variable is the quantity of packets produced on *day one.*

b) The second output variable of the productivity model is the amount of products produced during production *day two*. The parameter used to measure this variable is the quantity of packets produced on *day two*.

These output variables were used differently for the productivity models P1 and P2 (refer to section 4.3.1 & 4.3.2). Model P1 used these variables as output variables. Model P2 used these same output variables multiplied by a *complexity factor*[3]. Table 4.4 contains a summary description of the input/output variables incorporated into the productivity models.

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[3] Refer to Appendix D for details in the formulation of the *complexity factor*.

Table 4.4 NPIP Variable description of Productivity Models

Variables of the Productivity Models (P1 & P2)	*Type of Variable*	*Description of Variables*	*Variable Measurement*
Products of *day one*	OUTPUT	The amount of *day one* packet production per production period	Number of *day one* papers produced multiplied by a *complexity factor*[4]
Products of *day two*	OUTPUT	The amount of *day two* packet production per production period	Number of *day two* papers produced multiplied by a *complexity factor*[5]
Labor	INPUT	The total amount of Labor hours (Crewman + Assistant) employed per production period.	Number of total crewman and assistant hours per production period
Machine hours	INPUT	Total machine hours accumulated by all active production lines during a production period	Summation of machine hours of all active production lines
Maintenance & setup	INPUT	Total amount of resources employed to maintain and set-up the system per production period	Number of set-up and maintenance hours used per production period

[4] This measure corresponds only to the P2 model; the P1 model does not incorporate the *complexity factor* in the *day one* packet variable
[5] This measure corresponds only to the P2 model; the P1 model does not incorporate the *complexity factor* in the *day two* packet variable

4.5.2 Input/Output Variables Used for Quality Assessment

Quality of the process can be defined as the conformance of the output product to specifications. More specifically, quality of the process can be quantified as the conformance of packets produced. An exhaustive evaluation to obtain quality variables was performed. All the identified quality input variables are described subsequently.

Input Variables Included in the Quality Models

a) The same *complexity factor*[6] as the one used for model P2 was used as an input variable for some of the quality models. This variable provides an indication of the complexity of the production process and the product produced during each production period. This variable was also factored into the output variables in one of the quality models (Q3). It is considered that by factoring the *complexity factor* into the output provides an indication of levels of nonconformance considering the effects of the complexity of the production process and product produced.

b) Similarly as in the productivity model, the *maintenance & setup* variable provides an indication of the amount of preventive maintenance carried out before each production period. The importance of preventive maintenance in quality is discussed in section 2.2.1. This variable was measured by the amount of labor hours dedicated to *maintenance & setup* for each production period.

c) The inverse of *machine hours* [7]was also used as an input variable in some of the quality models. This variable provides an indication of the utilization of the machines. It is considered that the longer the machines are used, the total amount of nonconformances will increase.

[6] Details in the formulation of the *complexity factor* are included in Appendix D.

[7] The inverse of machine hours is used to assure that the strong disposability of inputs and outputs assumptions (refer to section 3.3) holds.

Input Variables Not Included in the Quality Model

d) *Appraisal* was also considered an important quality input variable. This variable quantifies the amount of resources allocated for controlling the process to ensure that products conform to specifications (section 2.2.1 describes the importance of this variable in the quality model). This important input quality variable was not included in the model since no direct measure for this variable could be readily obtained.

Output Variables of the Quality Model

Quality of the process is considered the degree to which products conform to specifications. Three types of nonconformance were identified during the first operation of the process, the opening of the newspaper fold and the insertion of preprints. As stated earlier, the insertion phase is the prime contributor to the quality performance of the process. Thus, nonconformance variables of the quality model can be obtained by measuring non-conformance parameters of the insertion phase of the NPIP.

a) The first type of non-conformance during the insertion phase is the production of products which include excessive preprints. The parameter used to measure this variable was the amount of packets produced with more preprints than desired. This parameter is also referred to as the amount of *doubles* produced.

b) The second type of nonconformance during the insertion process is production loss due to the inability of inserting preprints. This would cause the shipping of incomplete and/or unsatisfactory products. The parameter used to measure this variable was the amount of *misses* produced.

c) The third type of nonconformance output variable was the amount of products that the process failed to produce. The parameter used to measure this variable was the amount of newspaper sections that failed to open during insertion. This variable is also referred to as the amount of *unopened jackets* produced.

The inverse of these three types of nonconformances are used in the quality models to measure the conformance levels of the process. The models are formulated in that way to assure that the strong disposability of inputs and outputs assumptions hold (refer to section 3.3).

As with productivity, the *complexity factor*[8] was incorporated into the output variables in one of the quality models. Table 4.5 describes the different input/output variables used in the quality models.

[8] The formulation of the *complexity factor* is included in Appendix D.

Table 4.5 Quality Model Table

Variables of the Quality Model (Q1, Q2 & Q3)	*Type of Variable*	*Description of Variable*	*Measurement Used for Variable*
Inverse of Misses	OUTPUT	The inverse of the output lost to repeated machine misses when hoppers fail to seize inserts.	The inverse of the amount of repeated machine misses per production period.
Inverse of Doubles	OUTPUT	The inverse of the output lost due to doubles created when the hoppers seize more than one insert for insertion.	The inverse of the amount of doubles occurring during the production period
Inverse of Unopened Jackets	OUTPUT	The inverse of the output lost due to unopened jackets created when the paper fails to fully open when the insertion process occurs.	The inverse of the amount of unopened jackets occurring during the production period
Complexity Factor[9]	INPUT	This variable assesses both the complexity of production and the complexity of the product produced.	The formulation used to measure this variable is described in Appendix D.
Preventive Maintenance	INPUT	Total amount of resources employed to maintain and set-up the system per production period.	Count of set-up and maintenance hours consumed per production period.
Change Overs	INPUT	The inverse of the number of zones production was divided into at the production period. To reflect the changeovers experimented (Garvin[9, p. 155]). Many change overs cause more defects.	Inverse of the production zone count per production period.

[9] The *complexity factor* was factored into the output for quality model Q3.

4.6 Specification of the Productivity Models

Two main productivity models were evaluated in this research. The reason for the development of two different productivity models was the difficulty inherent in defining the productivity output variables of the process. The NPIP produces various types of outputs, which are hard to categorize and quantify. Both the production amount as well as the product produced vary widely from one production period to another. During the same production period, there are many different production zones. Also, the product produced varies with the amount and types of preprints inserted in the newspaper section. Thus the measurement of production output becomes a complex task.

The first productivity model P1 evaluates productivity assuming that all the outputs produced in the process are uniform. The output variables for this model are simply the total amount of packets produced during the two days of a production period.

The second productivity model P2 evaluates productivity by including a *complexity factor* into the calculation of output production. This is done by multiplying the *complexity factor* by each type of output variable.

Table 4.6 at the end of this chapter contains a summary table of the productivity models. A comparison between results of models P1 & P2 is included in section 6.3. The following sections describe these models in detail.

4.6.1 The P1 Productivity Models

The P1 productivity models attempt to model the output of the process in the simplest manner possible, by simply quantifying the amount of packets produced on each production period. Although these models make the computation of productivity simple, the models ignore the fact that the complexity of production differs from one production period to another.

The important P1 productivity input variables include *machine hours*, *maintenance & setup* and *labor*. The output variables of the process are simply the amount of products produced each day of production. These output variables are the total packet production of *day one* and *day two*, respectively. The rationale behind this model is that *machine hours*, *labor* and *maintenance & setup* represent the production resources. As they increase, so will the production of output. Equation (P1) represents the P1 productivity performance of the NPIP.

$$\textit{(day one, day two)} = g_{P1}(\textit{machine hours, maintenance \& setup, labor}) \qquad \text{(P1)}$$

The correlation analysis of the input variables indicated that the variable *maintenance & setup* did not have any correlation to P1 output variables[10]. A modified productivity model P1b is proposed which does not include this last variable. Equation (P1b) represents the P1b productivity performance of the NPIP.

$$\textit{(day one, day two)} = g_{P1b}(\textit{machine hours, labor}) \qquad \text{(P1b)}$$

The results from the DEA evaluation of model P1 are included along with model P1b in section 6.1. A comparison between P1 and modified P1b is also carried out in that section.

[10] Refer to the correlation analysis in Appendix C.

4.6.2 The P2 Productivity Models

The only distinction of the P2 productivity models in relation to P1 is that the productivity output variables were multiplied by a *complexity factor*[11]. This *complexity factor* quantifies the complexity of the production process and the complexity of the product produced.

The input variables of the P2 productivity model include *machine hours, maintenance & setup* and *labor.* The output variables of the productivity model are the same as the P1 models, but each output parameter is multiplied by the *complexity factor* (*CF*). P2 productivity performance is defined in equation (P2).

$$(CF \times day\ one,\ CF \times day\ two) = g_{P2}(machine\ hours,\ maintenance\ \&\ setup,\ labor) \qquad \text{(P2)}$$

Similarly as with model P1, correlation analysis of input variables indicated that the variable *maintenance & setup* did not have any correlation to the output variables of model P2[12]. A modified productivity model P2b was developed which did not include *maintenance & setup*. Equation (P2b) represents the P2b productivity performance of the NPIP.

$$(CF \times day\ one,\ CF \times day\ two) = g_{P2b}(machine\ hours,\ labor) \qquad \text{(P2b)}$$

The results from the DEA evaluation of model P2 and P2b are included in section 6.2. Section 6.3 also compares the results of models P1 and P2.

---

[11] The *complexity factor* is formulated in Appendix D.
[12] Refer to correlation analysis in Appendix C.

4.7 Specification of the Quality Models

Three different quality models were constructed to evaluate the quality performance of the NPIP. Quality is modeled as the conformance to specifications. The main purpose of the three models is to evaluate different possible combination of variables that have an impact on quality of the process.

Table 4.6 at the end of this chapter includes a summary table of the quality models. A comparison of the three quality models is carried out in section 6.7. The following sections describe the quality models in detail.

4.7.1 The Quality Models

The first model of quality Q1 considers the complexity of production and product produced as the main variable affecting the quality of conformance. The input variables of the quality model Q1 are the *simplicity* of production (inverse of the *complexity factor*) and the *maintenance & setup* allocated to preventive maintenance. Quality output of the NPIP is considered the level of conformance counted as the inverse of *doubles, misses* and *unopened jackets*. The rational behind this model is that as the *simplicity* of production and *maintenance & setup* increase, the levels of conformance will also increase. Equation (Q1) represents the Q1 quality model of the NPIP.

$$\left(\frac{1}{doubles}, \frac{1}{misses}, \frac{1}{un.\,jackets}\right) = g_{Q1}\left(\frac{1}{complexity\ factor}, maintenance\ \&\ setup\right) \qquad \text{(Q1)}$$

As with the productivity models, the correlation analysis of input and output variables of the quality model indicated that the variable *maintenance & setup* did not have any correlation to the output variables of model Q1[13]. A modified quality model Q1b which

[13] Refer to correlation analysis in Appendix C.

excluded *maintenance & setup* was formulated. Equation (Q1b) represents model Q1b quality performance of the NPIP.

$$\left(\frac{1}{doubles}, \frac{1}{misses}, \frac{1}{un.\,jackets}\right) = g_{Q1b}\left(\frac{1}{complexity\ factor}\right) \qquad \text{(Q1b)}$$

The results from the evaluation of models Q1 and Q1b using the DEA Application are included in section 6.4.

4.7.2 The Q2 Quality Models

The second quality model incorporates the inverse of *machine hours* as an input variable to the original Q1 model. This variable is included to represent the time dedicated to production. It is considered that an increase in the duration of production will cause an increase in the total amount of nonconformance experienced by the process.

The input variables of the quality model Q2 are the *simplicity* of production (inverse of the *complexity factor*), the *maintenance & setup*, and the inverse of *machine hours*. Model Q2 output variables of the NPIP are identical to those of quality model Q1 (inverse of *doubles*, *misses* and *unopened jackets*). Equation (Q2) represents the Q2 quality model of the NPIP.

$$\left(\frac{1}{doubles}, \frac{1}{misses}, \frac{1}{un.\,jackets}\right) = g_{Q2}\left(\frac{1}{complexity\ factor}, maint.\ \&\ setup, \frac{1}{machine\ hours}\right) \qquad \text{(Q2)}$$

The maintenance & setup variable was also found to have no correlation to the output variables of model Q2[14]. A modified quality model Q2b excluding *maintenance & setup* was formulated. Equation (Q2b) represents model Q2b quality performance of the NPIP.

---

[14] Refer to correlation analysis in Appendix C.

$$\left(\frac{1}{doubles}, \frac{1}{misses}, \frac{1}{un.\,jackets}\right) = g_{Q2b}\left(\frac{1}{complexity\ factor}, \frac{1}{machine\ hours}\right) \qquad \text{(Q2b)}$$

Results from the evaluation of models Q2 and Q2b using the DEA Application are included in section 6.5.

4.7.3 Quality Model Q3

A third quality model Q3 was formulated to include the *complexity factor* in the output variables of the quality model. The *complexity factor* factors in the complexity of production and product produced into the level of conformance of the production output.

This inclusion as an output was selected because the *complexity factor* is not necessarily an input resource and it may not be appropriate to treat it as such, as in the Q1 and Q2 models. As the *complexity factor* increases, the levels of conformance should be increased to reflect this increase in complexity of production and product produced.

The input variables of the quality model Q3 are the *maintenance & setup*, and the inverse of *machine hours*. Model Q3 output variables are the *complexity factor* multiplied by the inverse of *doubles*, *misses* and *unopened jackets*. Equation (Q3) represents the Q3 quality model of the NPIP.

$$\left(CF \times \frac{1}{doubles}, CF \times \frac{1}{misses}, CF \times \frac{1}{un.\,jackets}\right) = g_{Q3}\left(maint.\ \&\ setup, \frac{1}{machine\ hours}\right) \qquad \text{(Q3)}$$

As in all other models, the *maintenance & setup* variable was found to have no correlation to the output variables of model Q3[15]. A modified quality model Q3b excluding *maintenance & setup* was formulated. Equation (Q3b) represents model Q3b quality performance of the NPIP.

$$(CF \times \frac{1}{doubles}, CF \times \frac{1}{misses}, CF \times \frac{1}{un.jackets}) = g_{Q3b}(\frac{1}{machine\ hours}) \qquad \text{(Q3b)}$$

Results from the evaluation of models Q3 and Q3b using the DEA Application are included in section 6.6.

4.8 Multivariate Regression Analysis for the Productivity and Quality Models

Multivariate regression analysis was used to statistically confirm the statistical significance of the input variables for the productivity and quality formulations. It was found that *machine hours*, and in most cases *labor* were significant for the productivity formulations and that *machine hours* was significant for the quality formulations in which was included. These results were obtained by using the correlation analysis tool of SAS for Windows software. The results of these analyses are included in Appendix C.

4.9 Specification of the Hybrid Models

Two hybrid models were developed which combined both quality and productivity performance of the process. These models are presented as an alternative to the separate

[15] Refer to correlation analysis in Appendix C.

quality and productivity performance evaluations of the process. The hybrid models combine the variables of both quality and productivity described in sections 4.2.1 and 4.2.2.

Table 4.6 at the end of this chapter contains a summary table of the hybrid models. A comparison of both hybrid models is carried out in section 6.10. The following sections describe the hybrid models in more detail.

4.9.1 H1 Hybrid Model

The first hybrid model incorporates the *complexity factor* as an input variable. The input variables of the hybrid model H1 are the *complexity factor*, *labor*, and *machine hours*. The output variables are *day one*, *day two* and *doubles*, *misses*, and *unopened jackets*. The rationale behind this model is that an increase in the complexity of production, *labor* and *machine hours* resources will produce an increase in the amount of output production as well as nonconformance levels. Model H1 is formulated in equation (H1).

$$(\textit{Doubles, Misses, Un. Jackets, day one, day two}) = g_{H1}(\textit{complexity factor, labor, machine hours}) \quad \text{(H1)}$$

Results from the evaluation of model H1 using DEA Application are included in section 6.8. Models H1 and H2 are compared in section 6.10.

4.9.2 The H2 Hybrid Model

The second hybrid model incorporates the *complexity factor* in the output side. The input variables of the hybrid model H2 are *labor* and *machine hours*. The output variables are *day one*, *day two*, *doubles*, *misses*, and *unopened jackets* multiplied by the *complexity factor*. The rationale of this model is that an increase in *labor* and *machine hours* resources will produce an increase in the levels of nonconformance and output production with the *complexity factor* incorporated in the output. Equation (H2) illustrates model H2.

$$(CF \times Doubles, CF \times Misses, CF \times Un.Jackets,\ CF \times day\ one,\ CF \times\ day\ two) = g_{H2}(\ labor,\ machine\ hours) \qquad \text{(H2)}$$

Results from the evaluation of model H2 using DEA Application are included in section 6.9. Model H2 is compared to model H1 in section 6.10.

Table 4.6 Summary of Model Variables†

Model	Doubles	Misses	Un. Jackets	Day one	Day two	CF	Labor	Maint. & Setup	Machine hours
P1				Reg	Reg		Reg	Reg	Reg
P1b				Reg	Reg		Reg		Reg
P2				(CF) Reg	(CF) Reg		Reg	Reg	Reg
P2b				(CF) Reg	(CF) Reg		Reg		Reg
Q1	Inv	Inv	Inv			Reg		Reg	
Q1b	Inv	Inv	Inv			Reg			
Q2	Inv	Inv	Inv			Reg		Reg	Inv
Q2b	Inv	Inv	Inv			Reg			Inv
Q3	(CF) Inv	(CF) Inv	(CF) Inv					Reg	Inv
Q3b	(CF) Inv	(CF) Inv	(CF) Inv						Inv
H1	Reg	Reg	Reg	Reg	Reg	Reg	Reg		Reg
H2	(CF) Reg	(CF) Reg	(CF) Reg	(CF) Reg	(CF) Reg		Reg		Reg

† Reg means the use of that variable; Inv means the use of the inverse of that variable; the inclusion of (CF) means that variable is multiplied by the complexity factor.

Chapter 5. MATHEMATICA DEA APPLICATION

5.1 Motivation for Development of the DEA Software Application.

Some existing software programs used for Data Envelopment Analysis (DEA) are constrained by the limited data size (number of observations (DMUs) and input and output variables) they allow. The data sets contained in this research exceed the limitations imposed by these programs. In addition, new DEA models are constantly emerging that require an application that can be easily modified to incorporate these new models. It is for these reasons that a DEA Software Application was developed. The following requirements were considered when developing the DEA Application.

Comprehensives- The application must contain multiple DEA models to be useful for testing different sets of constraints. It must be easy to modify to use different DEA models.

Flexibility- The application must be able to accept different data structures without requiring any changes of the internal coding. This means that any data set, if correctly formatted, can be read by the application.

Ease of Use- The application must have an interface that is easy to use and understand. Any user must be able to use the application without any prior knowledge of using the application.

Modularity- The application developed must be easy to modify, allowing for future inclusion of additional DEA models and/or modifications. This means that the application must be transparent and adding models straight forward (section 5.5 illustrates how to add models to the existing application).

The application developed in Mathematica meets all the requirements just indicated. Mathematica 2.2.2 was chosen as the development tool primarily because of its availability and apparent capability for development of such an application. The following section explains the requirements necessary to use the DEA Application.

5.2 Requirements to Use the DEA Application

Before running the DEA Application it is necessary to have a basic knowledge of operating Mathematica 2.2.2. Refer to the Introduction in the "Mathematica User's Guide" for further details on working in the Mathematica environment (Wolfram[16, p. 44]).

The requirements necessary to run the DEA Application are as follows:

- Mathematica 2.2.2 or compatible version needs to be installed on your computer.
- DEA Application needs to be loaded in your computer.
- An *ASCII* (*Text Only*) format input data file containing the data set has to be created (refer to section 5.3 for details on creating the input data file).
- Knowledge of the number of input variables, output variables, and observations (DMUs), and the appropriate DEA model to be applied.

Once all these requirements are met, the DEA Application can be run (refer to section 5.4). The following section illustrates how the input data file must be formatted.

5.3 Format of Input Data File

This DEA Application requires the user to have available a file containing the data set of input and output variables of the system/process to be evaluated. The input data file must have a specific format to be correctly read by the DEA Application. The following criteria must be met to create an input data file that is compatible with the DEA Application.

- The data set must be in tabular form, each column of the input data file should correspond to an output/input variable. Only numerical values must be included in the table (no table headings should be included).
- All output columns must precede the input columns. There is no requirement for prioritization among the outputs or among the inputs.
- Each row of the input data file must correspond to an observation (DMU).
- The input data file must contain the complete data set, with values for every single entry.
- The input data file must be saved as *ASCII* (*Text Only*) format.

The following example illustrates the format required for the input data file.

<u>Example of the Input Data File Format</u>

A company with four similar steel beam manufacturing plants wants to compare their annual performance using DEA. The collected data for the four plants is as follows:

Table 5.1 Steel Beam Plant Data

Steel Beam Plant Evaluated	Beams Produced (OUTPUT)	Workers Employed (INPUT)	Tons of Steel Consumed (INPUT)
Plant A	1,300	75	41.5
Plant B	2,400	170	65.7
Plant C	1,550	65	35.3
Plant D	3,000	210	110.2

The format for the corresponding input data file would be as follows:

```
1300    75     41.5
2400    170    65.7
1550    65     35.3
3000    210    110.2
```

Note that the output column precedes the input columns. Also note that only the actual data values are included in the input data file. This input data file table must be saved in *ASCII* or *Text Only* format.

5.4 Running the DEA Application

To run the DEA Application first start Mathematica 2.2.2 or compatible version. Once inside Mathematica, activate the DEA Application by opening the file dea.ma. The title of this Mathematica Notebook should be *Mathematica DEA Application 1.0*[1]. This DEA Application is divided in to three main modules. The subsequent sections describe each one of these modules in detail.

[1] The code of the *Mathematica DEA Application* 1.0 is included in Appendix E.

5.4.1 DEA Application Module 1

The first module provides a short explanation of the application and the requirements to run the application. It also provides instructions of how to format the input data file required to run the application. Although reading this module will provide a better understanding of the DEA Application, this module is for informative purposes and is not necessary for running the application.

5.4.2 DEA Application Module 2

The second module is responsible for reading the input data file into the application. This module must be run before using any of the DEA models. To run this module of the application, highlight the module (Specification and Reading of Input Data File) and press the Mathematica Execution button (or SHIFT-ENTER). You will be prompted to enter the following:

How many outputs: Enter the *number* of output columns of the input data file.
How many inputs: Enter the *number* of input columns of the input data file.
How many observations: Enter the *number* of observations (rows) of the input data file.
Name of input data file: Enter the *file name* of the input data file, including the directory path.
Value for Sigma: Enter a small *numerical value*, for example 0.001. This variable has no effect on the DEA models of the present *Mathematica DEA Application 1.0.* It has been included for future DEA models that may require such variable.

Once this module of the application has been run, different DEA models in module 3 can be run for this input data file without having to execute this module of the application again. To evaluate a different input data file, run modules of the application again entering the appropriate information for the new input data file.

This DEA Application also allows for the evaluation of only part of the observations of an input data file. When prompted for "How many observations" there is the option of entering a *number* that is less than the total amount of rows of the input data file. The application will then only read as many rows as the *number* entered for that entry.

5.4.3 DEA Application Module 3

This module of the DEA Application contains actual DEA models which can be run. Module 2 must be correctly executed before this module can be run. The module presently contains two DEA models, but more models can be easily added (Refer to section 5.5 for details in adding additional DEA models).

The two models included in this module 3 are the input reducing model (IRM) and the output increasing model (OIM). To run the IRM or OIM for the currently read data set (input data file) simply highlight either the IRM or OIM submodule and press the Mathematica Execution button (or SHIFT-ENTER). The application will then automatically run the DEA model and output the results. The following section explains how the obtained results are interpreted.

5.4.4 Interpreting IRM/OIM Results After Running the DEA Application

After successfully running one of the DEA models of module 3, Mathematica will print the output of the evaluation. This output will be located at the end of the submodule containing the DEA model that has been evaluated. The first number of this output will be the observation (DMU) number followed by the efficiency performance of that particular observation. Also included in the output are the values of all the variables in the DEA model. The following example illustrates the format of the output.

Example of Output Format

The example of section 5.2.1 was evaluated using the DEA Application. The IRM was the DEA model evaluated in module 3. The following results were printed at the end of the IRM submodule after running the IRM model.

```
1
{0.866667, {theta -> 0.866667, z[1] -> 0, z[2] -> 0, z[3] -> 1., z[4] -> 0}}
2
{1., {theta -> 1., z[1] -> 0, z[2] -> 1., z[3] -> 0, z[4] -> 0}}
3
{1., {theta -> 1., z[1] -> 0, z[2] -> 0, z[3] -> 1., z[4] -> 0}}
4
{1., {theta -> 1., z[1] -> 0, z[2] -> 0, z[3] -> 0, z[4] -> 1.}}
```

The tabulated results are as follows:

Table 5.2 Example Efficiency Performances

Steel Beam Plant	Efficiency performance
Plant A	86.7%
Plant B	100%
Plant C	100%
Plant D	100%

The results indicate that all plants are producing efficiently except Plant A. This plant is only using its resources 86.7% efficiently.

5.5 Adding DEA Models to the Mathematica DEA Application 1.0

Additional DEA models can be attached to this DEA Application. Although, different ways of constructing DEA models may be possible in Mathematica, it is recommended that the following procedure be followed because of its simplicity and its consistency with the already existing DEA Application coding.

The additional model should be incorporated at the end of module 3, following the models already in existence. The model constructed should have these three main sections, the *array of constraints*, the *array of variables* and the *efficiency calculations* sections. Before describing how to construct these sections in more detail it is necessary to explain all the *internal variables* of the application that will be needed when creating these sections.

5.5.1 Internal Variables of the DEA Application

There are some *internal variables* that this application utilizes that will be required for the creation of an additional model. The following illustrates these *internal variables* and their significance.

- `obs`: This *internal variable* has the value of the total amount of observations (rows) of the input data file to be evaluated by the model.
- `in`: This *internal variable* has the value of the number of inputs (input columns) of the input data file.
- `out`: This *internal variable* has the value of the number of outputs (output columns) of the input data file.
- `x[i,j]`: This array of *internal variables* contains the values of inputs for all the observations. The `i` corresponds to the input variable and `j` to the observation (DMU) that input belongs to.

- y[i,j]: This array of *internal variables* contains the values of outputs of all the observations. The i corresponds to the output variable and j to the observation (DMU) that output belongs to.

The following example explains the *internal variables* definitions.

Example of Mathematica DEA Application Internal Variables

The example in section 5.2.1 is used to illustrate *internal variable* values. The data set in the input data file for that example is tabulated as follows :

1300	75	41.5
2400	170	65.7
1550	65	35.3
3000	210	110.2

After running module 2 properly for this example (refer to section 5.4.2), the following *internal variables* would be automatically defined.

out = 1

in = 2

obs = 4

x[1,1] = 75; x[2,1] = 41.5; x[1,2] = 170; x[2,2] = 65.7; x[1,3] = 65; x[2,3] = 35.3; x[1,4] = 210; x[2,4] = 110.2

y[1,1] = 1300; y[1,2] = 2400; y[1,3] = 1550; y[1,4] = 3000

These variables and their values will be used to compute the evaluation of the DEA models.

5.5.2 Creating the Array of Variables

The first step to constructing an additional DEA model is specifying the variables of the model. This can be done by creating an *array of variables* for which each array entry is a variable name. The structure of this *array of variables* is further explained using the IRM as an example. The coding for the *array of variables* for the IRM is as follows:

□ Array of Variables

```
allIRM[1] = theta
Do[allIRM[1+i] = z[i], {i,obs}]
```

In this example, the *array of variables* is called allIRM and it has a size of obs+1. The values of the array would be allIRM[1] = theta, allIRM[2] = z[1], allIRM[3] = z[2],..... allIRM[obs+1] = z[obs]. This array includes all the variables used in the IRM model. After the *array of variables* is complete, the *array of constraints* can then be created.

5.5.3 Creating the Array of Constraints

The second step to constructing an additional DEA model is stating the set of constraints of the maximization/minimization function. This can be done by creating an *array of constraints* in which each array entry is a constraint of the DEA model. The structure of this *array of constraints*is further explained using the IRM as an example. The coding for the *array of constraints* for the IRM is formulated as follows:

□ Array of Constraints

```
Do[ineqIRM[i] = Sum[ z[j] x[i,j],{j,obs}] <= theta x[i,l] ,{i,in}]
Do[ineqIRM[i+in] = Sum[ z[j] y[i,j],{j,obs}] >= y[i,l] ,{i,out}]
```

[2] Note that l corresponds to the number of the current observation being evaluated (DMU_l).

```
ineqIRM[in+out+1] = Sum[ z[j],{j,obs}] == 1
Do[ineqIRM[in+out+1+i] = z[i]>=0,{i,obs}]
ineqIRM[in+out+1+obs+1] = theta >= 0
```

In this example, the *array of constraints* is called `ineqIRM` and it has a size of `in+out+1+obs+1`. The values of the array correspond to the following set of constraints of the IRM model[3]:

The first set of constraints corresponds to $\sum_{j=1}^{n} z_j x_{ij} \le \Theta x_i^0$, $i = 1, 2, \ldots, m$

The second set of constraints corresponds to $\sum_{j=1}^{n} z_j y_{rj} \le y_r^0$, $r = 1, 2, \ldots, s$

The third set of constraints corresponds to $\sum_{j=1}^{n} z_j = 1$

The fourth set of constraints corresponds to $z_i \ge 0$, $i = 1, 2, \ldots, obs$

The last constraint corresponds to $\Theta \ge 0$

After this second step in the construction of the DEA model is complete, the last step necessary to create the DEA model is the actual efficiency calculation formulation.

[3] Refer to Appendix A for information on the IRM formulation.

5.5.4 Efficiency Calculations

Once both the *array of variables* and the *array of constraints* have been defined, the actual efficiency calculations can be carried out. This is performed by calling upon the Mathematica function *ConstrainedMin* (for a minimization problem) or *ConstrainedMax* (for a maximization problem). The inputs that this function requires are the actual minimization or maximization function, *the array of constraints,* and *the array of variables.* The linear programming function for both minimization and maximization would have the following characteristics:

ConstrainedMin[*minimization function, array of constraints, array of variables*]

ConstrainedMax[*maximization function, array of constraints, array of variables*]

The following example illustrates the formulation of efficiency calculation used for the IRM model.

□ Efficiency Calculations

```
Do[effIRM[l] = ConstrainedMin[ theta, Array[ineqIRM,in+out+1+obs+1],
                              Array[allIRM,1+obs]]; Print[l];
                              Print[effIRM[l]], {l,obs}]
```

The efficiency performances are recorded in the array effIRM. The minimization function is Θ, the constraints are in the *array of constraints* ineqIRM and the variables are defined in the *array of variables* allIRM.

After the step of creating the *Efficiency Calculations* is completed, the DEA model is ready to be included into module 3 of the *Mathematica DEA Application 1.0.*

Chapter 6. RESULTS

All the models were evaluated using the DEA Application developed for this research (referenced in Chapter 5). All of the 41[1] observations evaluated were ordered sequentially, corresponding to consecutive production periods. Each production period consists of two eight hour shifts. All productivity, quality and hybrid models were evaluated using the input reducing formulation[2]. The following sections evaluate the results of these models in detail.

[1] Data for 52 weeks (observations) was collected, but only 41 weeks were used in the analysis because of 11 weeks with incomplete data.
[2] The output production of the NPIP is fixed for every production period.

6.1 Efficiency results of productivity Model P1

All 41 observations for the productivity model P1 were evaluated using the Mathematica DEA Application. Table B.1 in Appendix B contains the data set used to run this model on the DEA Application. The efficiency results of the productivity model P1 are tabulated in table 6.1.

Table 6.1 Efficiency Performance of Productivity Model P1

Observation	Model P1 Efficiency Performance	Observation	Model P1 Efficiency Performance
1	100.0%	21	91.7%
2	94.3%	22	100.0%
3	100.0%	23	100.0%
4	92.0%	24	100.0%
5	100.0%	25	100.0%
6	100.0%	26	100.0%
7	98.7%	27	84.5%
8	99.4%	28	96.5%
9	90.6%	29	97.0%
10	98.4%	30	90.9%
11	86.3%	31	100.0%
12	75.7%	32	94.9%
13	84.7%	33	100.0%
14	84.6%	34	100.0%
15	81.4%	35	100.0%
16	88.8%	36	100.0%
17	100.0%	37	100.0%
18	82.1%	38	96.0%
19	100.0%	39	84.3%
20	100.0%	40	82.5%
		41	83.4%

Approximately half of all observations were found to be to 100% efficient for the P1 model. Observation 12 had the lowest efficiency performance with 75.7% efficiency. This observation had the combination of high *machine hours*, *labor*, and *maintenance & setup* without an equivalent high amount of output. Similarly, observation 15 had the second lowest efficiency performance with 81.4% efficiency. The main factor that contributed to this low performance was the high *labor* consumption without a proportional increase in output production.

6.1.1 Grouping of Efficiency Performance Results of Model P1

For further evaluation of the results, observations were grouped in three basic categories. The categories were *efficient*, *partially efficient*, and *inefficient* observations. Observations with efficiency Performances of 100% were grouped as *efficient*. Observations with efficiency performances between 90% and 99% were considered *partially efficient*. Finally, observations with efficiency performances 89% or lower were considered *inefficient*.[3] Table 6.2 illustrates the grouping of observations.

Table 6.2 Grouping of P1 Efficiency Performance

Efficient Observation Number	Partially Efficient Observation Number	Inefficient Observation Number
1	2	11
3	4	12
5	7	13
6	8	14
17	9	15
19	10	16
20	21	18
22	28	27
23	29	39
24	30	40
25	32	41
26	38	
31		
33		
34		
35		
36		
37		

Note that most of the observations are either *efficient* or *partially efficient*. Only approximately one fourth of the observations were found to be *inefficient*. Since the observations were ordered in the data set to correspond to consecutive production periods,

[3] The cutoff points of 100% and 90% were arbitrarily set to provide means for evaluating the efficiency results.

it can be observed that productivity trends occurred during the study period. Figure 6.1 illustrates model P1 productivity trends of the NPIP.

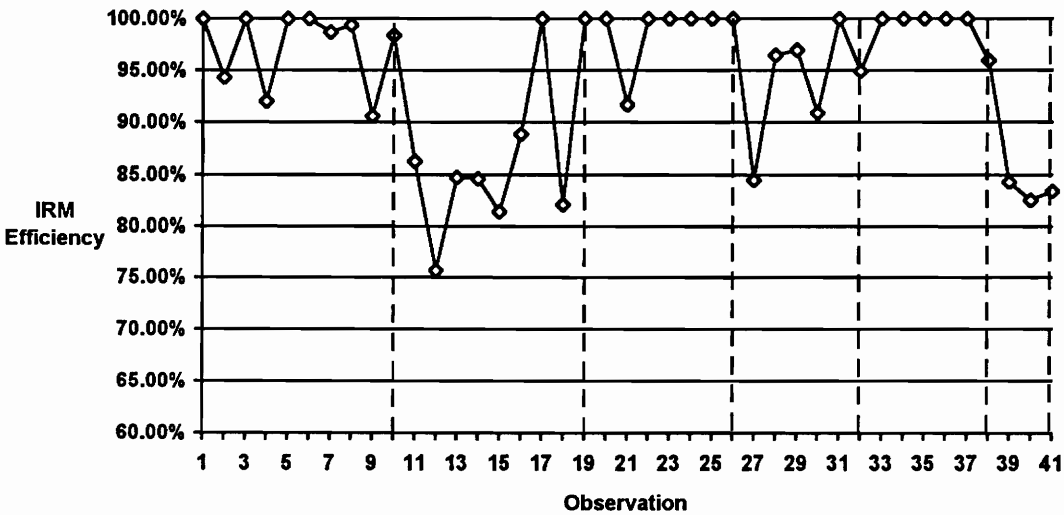

Figure 6.1 Efficiency Performance of Model P1

The graph of figure 6.1 can be divided into six distinct intervals. The first interval expands from observation 1 to observation 10. This first interval is categorized by *efficient* and *partially efficient* performance. In the second interval, from observation 11 to observation 18, there is a sharp drop in performance. Most observations are *inefficient* during this interval. On the third interval, expanding from observation 19 to 26, performance remains *efficient* for the most part. In the fourth period, starting at observation 27, another drop in performance occurs. Most observations during this interval are *partially efficient* or *inefficient*. The fifth interval expands from observation 33 to observation 37. This interval is categorized by *efficient* performance. The sixth interval expanding from observation 38 to 41 is characterized by a sharp decline in productivity. Most observations during this interval are *inefficient*.

The sharp drop in performance during the second interval is explained by the fact that a change in management occurred during the beginning of that interval. This drop in efficiency performance is expected to occur until the new management became experienced with the NPIP process. The other two intervals where there is a drop in efficiency are explained by the fact that during those intervals there was an actual increase in demand for preprints in the NPIP. Since model P1 does not include any *complexity factor* into the model, these increases in the volume of preprints to be inserted is reflected in the drop in productivity performance.

6.1.2 Efficiency results of productivity Model P1b

A modified version of model P1 was also evaluated using the DEA Application. This modified P1b model differs from P1 in that the input variable *maintenance & setup* was eliminated in model P1b. This variable was found to have no relationship with either inputs or outputs of model P1[4]. Table B.1 in Appendix B contains the data set used to run this model. The results of model P1b are illustrated in table 6.3.

[4] Refer to correlation analysis in Appendix C.

Table 6.3 Efficiency Performance of Productivity Model P1b

Observation	Model P1b Efficiency Performance	Observation	Model P1b Efficiency Performance
1	100.0%	21	91.7%
2	94.3%	22	100.0%
3	100.0%	23	100.0%
4	92.0%	24	100.0%
5	100.0%	25	100.0%
6	100.0%	26	98.4%
7	98.7%	27	82.0%
8	99.4%	28	96.2%
9	90.6%	29	94.6%
10	98.4%	30	90.9%
11	86.3%	31	93.6%
12	75.7%	32	94.9%
13	84.7%	33	100.0%
14	84.6%	34	100.0%
15	81.4%	35	100.0%
16	88.8%	36	100.0%
17	100.0%	37	100.0%
18	80.9%	38	94.7%
19	95.6%	39	82.2%
20	93.9%	40	82.5%
		41	82.9%

The efficiency performance results of both model P1 and P1b are very similar. This indicates that the impact on productivity performance of the input variable *maintenance & setup* can be considered negligible. Figure 6.2 compares the results of the two models.

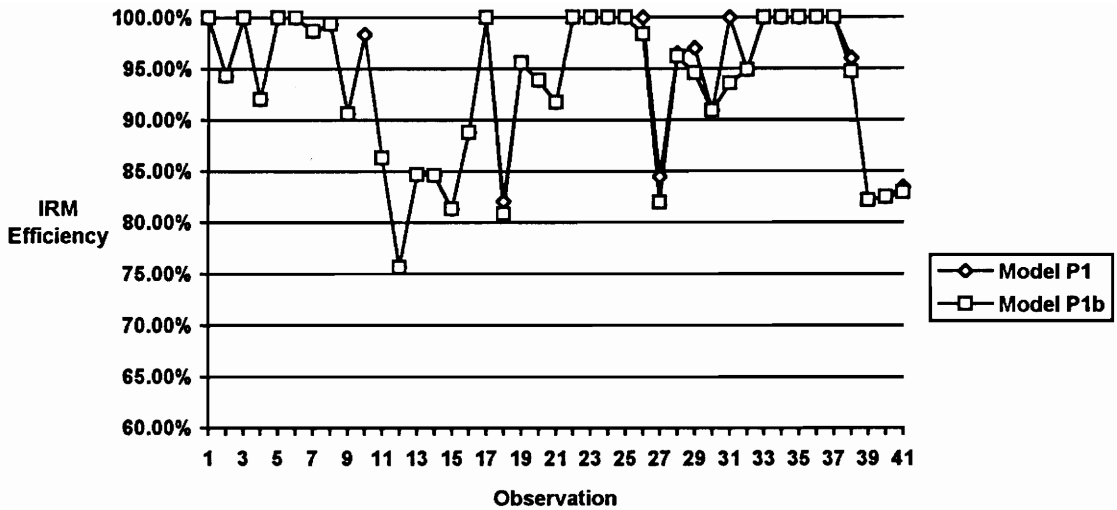

Figure 6.2 Comparison of the Efficiency Performance of Model P1 & P1b

Note that the results of these two models are almost identical. An evaluation using linear regression found a correlation coefficient between the results of P1 and P1b to be $R^2 = 0.951$. Since the results of both model P1 and modified P1b are almost identical, model P1b is used for comparison with model P2.

6.2 Efficiency Results of Productivity Model P2

Similar to productivity model P1, all 41 observations for the productivity model P2 were evaluated using the Mathematica DEA Application. The data set used for this evaluation is included in Table B.2 in Appendix B. The efficiency results of the productivity model P2 are tabulated in table 6.4.

Table 6.4 Efficiency Performance of Productivity Model P2

Observation	Model P2 Efficiency Performance	Observation	Model P2 Efficiency Performance
1	100.0%	21	90.7%
2	86.6%	22	97.6%
3	100.0%	23	100.0%
4	92.9%	24	100.0%
5	99.9%	25	100.0%
6	100.0%	26	100.0%
7	89.9%	27	85.5%
8	91.8%	28	100.0%
9	90.1%	29	95.4%
10	92.4%	30	90.4%
11	87.0%	31	100.0%
12	78.3%	32	96.7%
13	90.2%	33	98.4%
14	88.0%	34	100.0%
15	83.5%	35	100.0%
16	88.1%	36	100.0%
17	100.0%	37	100.0%
18	89.0%	38	90.9%
19	100.0%	39	91.3%
20	100.0%	40	92.0%
		41	100.0%

As with model P1, approximately half of all observations were found to be 100% efficient for model P2. The same as with model P1, observations 12 and 15 were found to be the ones with the lowest performance with 78.3% and 83.5% efficiency respectively.

6.2.1 Grouping of Efficiency Performance Results of Model P2

Observations were grouped in the same three categories as in the productivity model P1. The are *efficient* (observations with 100% efficiency), *partially efficient* (observations with 90-99% efficiency), and *inefficient* (observations with 89% or lower efficiency)[5]. The grouping results are summarized in table 6.5.

Table 6.5 Grouping of P2 Efficiency Performance

Efficient Observation Number	Partially Efficient Observation Number	Inefficient Observation Number
1	4	2
3	5	7
6	8	11
17	9	12
19	10	14
20	13	15
23	21	16
24	22	18
25	29	27
26	30	
28	32	
31	33	
34	38	
35	39	
36	40	
37		
41		

The grouping results of the are very similar to those of the P1 model. The productivity intervals for model P2 are illustrated in figure 6.3.

[5]The cutoff points of 100% and 90% were arbitrarily set to provide means for evaluating the efficiency results.

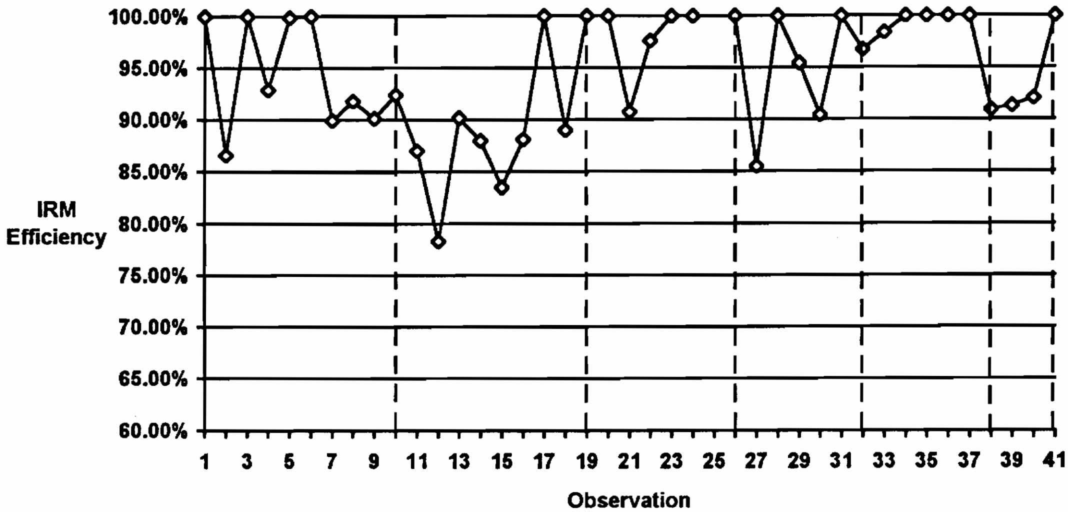

Figure 6.3 Efficiency Performance of Model P2

Model P2 also had the same intervals of productivity trends as model P1 (refer to section 6.1.1). There are two main differences between model P1 and P2 results. Model P2 is more *partially efficient* and *inefficient* during the first interval in comparison to the *efficient* trend of model P1 results during that same period. Also, in the sixth interval, *inefficient* performance in model P1 is reduced to *partially efficient* and *efficient* performance in the P2 model.

The main reason for these differences in the first and sixth interval is due to the fact that model P2 incorporates a *complexity factor* into the output variable. During the early observations, *the complexity factor* is low. This translates to a lower output quantity during observations in the first interval. Similarly, the sixth interval is characterized by a high *complexity factor*. This creates a higher output quantity, thus increasing productivity performance in comparison to productivity model P1.

6.2.2 Efficiency Results of Productivity Model P2b

As in model P1, a modified version of model P2 was evaluated using the DEA Application. This modified P2b model differs from P2 in that it does not include *maintenance & setup* as an input variable. This variable was found to have no relationship with either inputs or outputs of the model P2[6]. Model P2b was evaluated using the Mathematica DEA Application. Table B.2 in Appendix B contains the data set used to run this model. The results of model P2b are illustrated in table 6.6.

Table 6.6 Efficiency Performance of Productivity Model P2b

Observation	Model P2b Efficiency Performance	Observation	Model P2b Efficiency Performance
1	100.0%	21	90.7%
2	86.6%	22	97.6%
3	100.0%	23	100.0%
4	92.9%	24	100.0%
5	99.8%	25	100.0%
6	100.0%	26	96.7%
7	89.9%	27	83.4%
8	91.8%	28	99.6%
9	90.1%	29	92.4%
10	92.4%	30	90.4%
11	87.0%	31	91.8%
12	78.3%	32	96.6%
13	90.2%	33	98.4%
14	88.0%	34	100.0%
15	83.5%	35	100.0%
16	88.1%	36	100.0%
17	100.0%	37	100.0%
18	85.3%	38	90.7%
19	96.1%	39	88.9%
20	91.6%	40	92.0%
		41	100.0%

[6] Refer to correlation analysis in Appendix C.

The efficiency performance of the productivity model P2 & P2b are very similar. Since similar results were obtained with the productivity model P1 & P1b, the *maintenance & setup* variable does not seem to have much impact on the productivity performance of the NPIP. Figure 6.4 illustrates the results from model P2 and P2b.

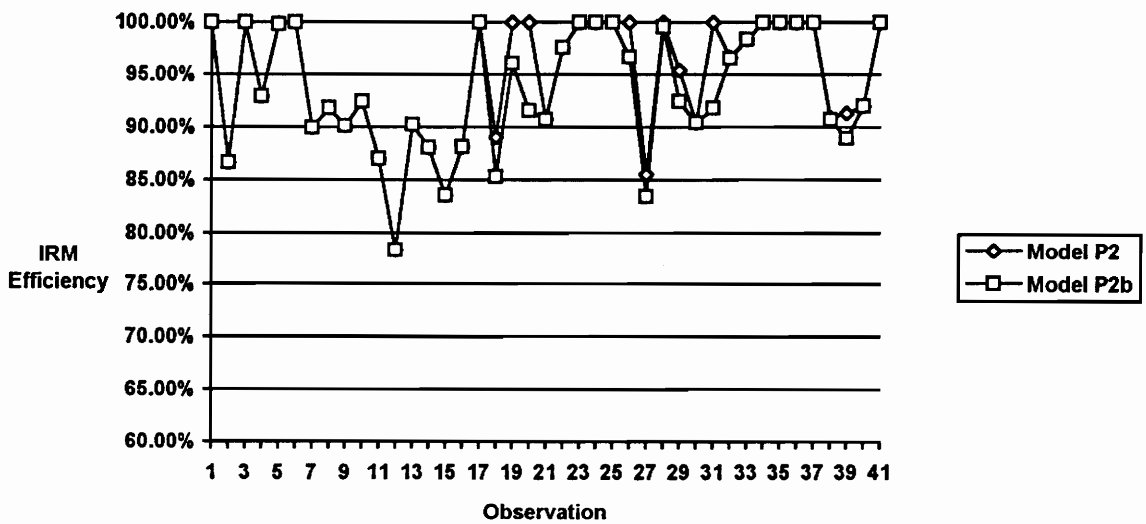

Figure 6.4 Comparison Efficiency Performance of Models P2 & P2b

The efficiency performance of both model P2 & P2b are very similar. An evaluation using bivariate linear regression found a correlation coefficient between the efficiency results of P2 and P2b to be $R^2 = 0.8828$. Since the results of both model P2 and modified P2b are almost identical, and the *maintenance & setup* variable seems to be irrelevant to productivity performance, model P2b is used for comparison with model P1.

6.3 Comparison of Productivity Models P1 and P2

A comparison of results for productivity models P1 and P2 was carried out. The modified versions P1b and P2b were used to evaluate both models. The results of model P1b and P2b are illustrated in figure 6.5.

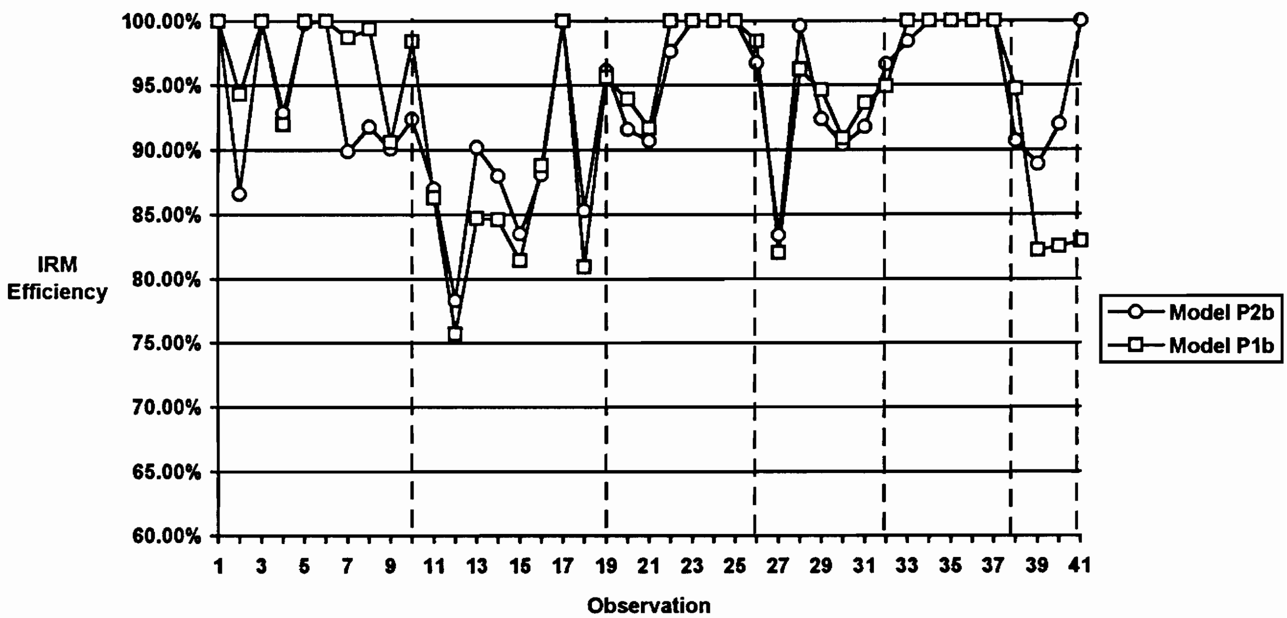

Figure 6.5 Comparison of Efficiency Performance of Models P1b & P2b

One main difference between the results of models P1 and P2 is that model P1 renders the first interval *efficient* for the most part, while model P2 renders this interval *partially efficient* or *inefficient* for the most part. The other main difference between the models is the efficiency trend of the sixth interval. Model P1 renders this interval mostly *inefficient*, while model P2 renders this interval only *partially efficient* or *efficient*.

The reason for these discrepancies between the models P1 and P2 is the inclusion of the *complexity factor* in the output variables of model P2. The results from both models substantiate the effects that the inclusion of the *complexity factor* has on the productivity performance of the NPIP. The first interval of observations is characterized by a lower complexity of production and output product. This is reflected by a lower productivity performance for model P2 in comparison to model P1. On the other hand, the sixth interval is characterized by high complexity in production and product produced. This translates into a higher productivity performance for the productivity model P2 during this interval in comparison to model P1.

The results of models P1 and P2 were compared using a bivariate regression analysis. The correlation coefficient was found to be $R^2 = 0.6374$. Although the correlation analysis does not indicate a strong similarity between P1 and P2, both models follow the basically the same trend as illustrated in figure 6.5.

A comparison of the collinearity between output variables (with and without *complexity factor*) and input variables was carried out[7]. The results of this correlation analysis indicate that the inclusion of the *complexity factor* strengthens the correlation between inputs and outputs. Thus, correlation analysis indicates that model P2 provides a better representation of productivity performance compared to P1. This model is likely to provide more representative results.

[7] Refer to correlation coefficients in Appendix C

6.4 Efficiency results of quality Model Q1

All 41 observations for the quality model Q1 were evaluated using the Mathematica DEA Application. Table B.3 in Appendix B contains the data set used to run this model on the DEA Application. The efficiency results of the quality model Q1 are tabulated in table 6.7.

Table 6.7 Efficiency Performance of Quality Model Q1

Observation	Model Q1 Efficiency Performance	Observation	Model Q1 Efficiency Performance
1	100.0%	21	91.8%
2	85.0%	22	92.5%
3	89.0%	23	99.4%
4	90.9%	24	99.3%
5	87.5%	25	100.0%
6	93.8%	26	96.9%
7	91.5%	27	93.6%
8	90.5%	28	100.0%
9	92.3%	29	100.0%
10	89.1%	30	99.3%
11	95.0%	31	100.0%
12	99.4%	32	96.4%
13	98.3%	33	98.4%
14	93.6%	34	93.9%
15	97.5%	35	95.4%
16	92.1%	36	95.8%
17	97.5%	37	93.6%
18	99.1%	38	95.7%
19	100.0%	39	94.7%
20	100.0%	40	94.9%
		41	100.0%

Only about one third of the observations were found to be 100% efficient for the Q1 model. The observation with the lowest efficiency performance was observation 2 with only an 85.0% efficiency. The main cause for this poor performance is the low conformance levels incurred during that period, while the input levels had not significantly decreased. Observation 5 had the second lowest efficiency performance with an 87.5% efficiency. Similarly as in observation 2, the low performance was mainly due to the low conformance levels without significant reduction of inputs.

6.4.1 Grouping of Efficiency Performance Results of Model Q1

Grouping was also performed for the quality model Q1 results. Performance results were grouped in three categories; *efficient*, *partially efficient*, and *inefficient* observations. Observations with 100% efficiency were grouped as *efficient*. Observations with efficiency performance between 95% and 99% were considered *partially efficient*. Finally, observations with efficiency performance 95% or lower were considered *inefficient*[8]. Table 6.8 illustrates the grouping of observations.

Table 6.8 Grouping of Q1 Efficiency Performance

Efficient Observation Number	Partially Efficient Observation Number	Inefficient Observation Number
1	11	2
19	12	3
20	13	4
25	15	5
28	17	6
29	18	7
31	23	8
41	24	9
	26	10
	30	14
	32	16
	33	21
	35	22
	36	27
	38	34
		37
		39
		40

Note that from the categories defined most of the observations are either *partially efficient* or *inefficient*. The grouping of observations also indicates there were trends of quality performance in the NPIP. These trends can be separated into different performance intervals. Figure 6.6 illustrates the trends and intervals of quality performance for model Q1.

[8] The cutoff points of 100% and 95% were selected arbitrarily to group efficiency results.

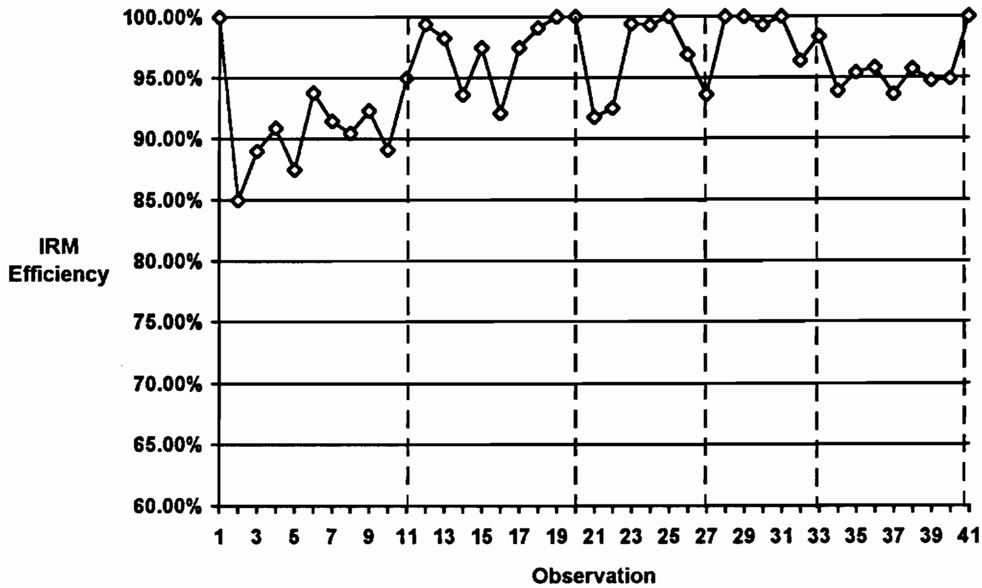

Figure 6.6 Efficiency Performance of Model Q1

The first interval of model Q1 trend is characterized by *inefficient* quality performance. This first interval expands from observation 1 to observation 11. The second interval is characterized by constant fluctuation of quality performance. This second interval covers observation 12 to observation 20. The third interval (from observation 21 to observation 27) is characterized by mostly *inefficient* and *partially efficient* observations. The fourth interval is characterized by mostly *efficient* and *partially efficient* observations. This interval expands from observation 28 to observation 33. Finally, the fifth interval is characterized by mostly *partially efficient* observations.

6.4.2 Efficiency results of quality Model Q1b

As with the productivity models, a modified version of model Q1 was also evaluated using the DEA Application. The modified Q1b model does not include the variable *maintenance & setup* as an input variable in the model. The variable was found to have no positive relationship with the outputs of model Q1[9]. Table B.3 in Appendix B contains the data set used to run this model. The results of model Q1b are illustrated in table 6.9.

Table 6.9 Efficiency Performance of Quality Model Q1b

Observation	Model Q1b Efficiency Performance	Observation	Model Q1b Efficiency Performance
1	100.0%	21	91.8%
2	85.2%	22	91.7%
3	88.9%	23	97.3%
4	90.9%	24	98.4%
5	87.5%	25	100.0%
6	93.8%	26	93.7%
7	91.5%	27	91.8%
8	90.5%	28	98.3%
9	92.3%	29	100.0%
10	89.1%	30	99.3%
11	95.0%	31	88.8%
12	99.4%	32	96.4%
13	98.3%	33	98.4%
14	93.6%	34	93.9%
15	97.5%	35	95.4%
16	92.0%	36	95.8%
17	96.1%	37	93.6%
18	93.7%	38	95.7%
19	98.0%	39	92.2%
20	93.4%	40	94.9%
		41	100.0%

The efficiency performance results of both model Q1 and Q1b are very similar. The same observations as in model Q1 were found to be the most *inefficient* in model Q1b (observations 2 and 5). The main discrepancy between Q1 and Q1b is the efficiency performance for observation 31. Efficiency performance for this observation in the Q1 model was found to be 100% while model Q1b rendered it with an efficiency score of 88.3%. This discrepancy is due to the fact that the value for the *maintenance & setup* was zero during that production period. Except for observation 31, the impact of *maintenance*

[9] Refer to correlation analysis in Appendix C for the correlation coefficients.

& setup on quality was considered negligible. Figure 6.7 illustrates the comparison of results from models Q1 and Q1b.

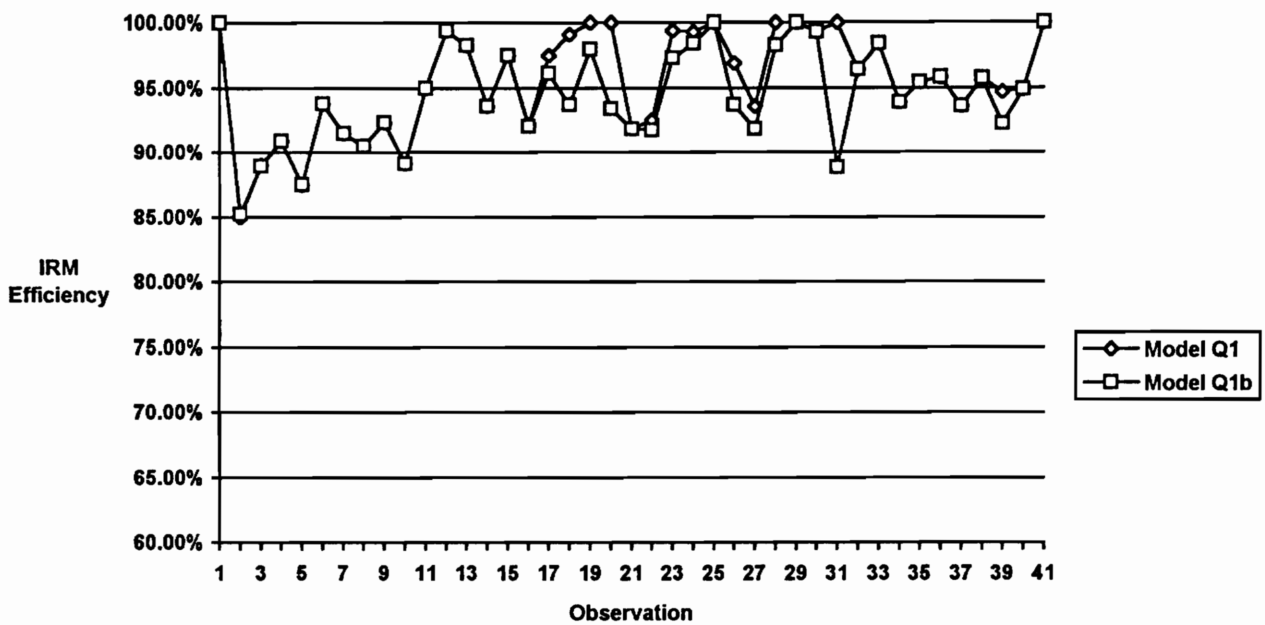

Figure 6.7 Comparison of Efficiency Performance of Models Q1 Q1b

The results of both these models are almost identical. An evaluation using bivariate linear regression found a correlation coefficient between the results of Q1 and Q1b to be $R^2 = 0.7088$. Note that although the correlation coefficient is not very large, the scatter plot shows that the models provide identical results except for some outlying observations (namely observation 31). Model Q1b is used for comparison with quality models Q2 and Q3.

6.5 Efficiency Results of the Q2 Quality Model

All 41 observations for the quality model Q2 were evaluated using the Mathematica DEA Application. This model incorporates the inverse of *machine hours* as an input variable to the quality model. The data set used to evaluate this model is included in Appendix B (table B.3). The efficiency results of the quality model Q2 are tabulated in table 6.10.

Table 6.10 Efficiency Performance of Quality Model Q2

Observation	Model Q2 Efficiency Performance	Observation	Model Q2 Efficiency Performance
1	100.0%	21	93.4%
2	89.5%	22	92.5%
3	89.0%	23	99.4%
4	91.9%	24	99.3%
5	88.1%	25	100.0%
6	93.8%	26	97.2%
7	96.6%	27	100.0%
8	94.9%	28	100.0%
9	93.7%	29	100.0%
10	93.1%	30	100.0%
11	96.0%	31	100.0%
12	100.0%	32	100.0%
13	99.2%	33	100.0%
14	94.2%	34	94.9%
15	99.0%	35	100.0%
16	97.1%	36	95.8%
17	97.5%	37	99.9%
18	100.0%	38	99.6%
19	100.0%	39	100.0%
20	100.0%	40	99.8%
		41	100.0%

Model Q2 results in greater efficiency performance than quality model Q1. About two fifths of the observations were rendered with 100% efficiency in model Q2. The observation with the lowest efficiency performance was observation 5 with an 88.1% efficiency. The main cause for the poor performance observation is the low conformance levels incurred during that period, while the input levels had not significantly decreased. Observation 3 had the second lowest performance level with a 89.0% efficiency. The low performance was also due to the low conformance levels incurred while the input levels had not been significantly reduced.

6.5.1 Grouping of Efficiency Performance Results of Model Q2

For consistency purposes, the performance results were grouped in the same three categories as model Q1; *efficient*, *partially efficient*, and *inefficient* observations. Again, observations with 100% efficiency were grouped as *efficient*; between 95% and 99% were considered *partially efficient*; and efficiency performance 95% or lower were considered *inefficient*.[10] Table 6.11 illustrates the grouping of observations.

Table 6.11 Grouping of Q2 Efficiency Performance

Efficient Observation Number	Partially Efficient Observation Number	Inefficient Observation Number
1	7	2
12	11	3
18	13	4
19	15	5
20	16	6
25	17	8
27	23	9
28	24	10
29	26	14
30	34	21
31	36	22
32	37	34
33	38	
35	40	
39		
41		

Note that the predominant categories of the model Q2 results are *efficient* and *partially efficient* observations. Figure 6.8 illustrates the trends and intervals of quality performance for model Q2.

[10] The cutoff points of 100% and 95% were arbitrarily set to provide means for evaluating the efficiency results.

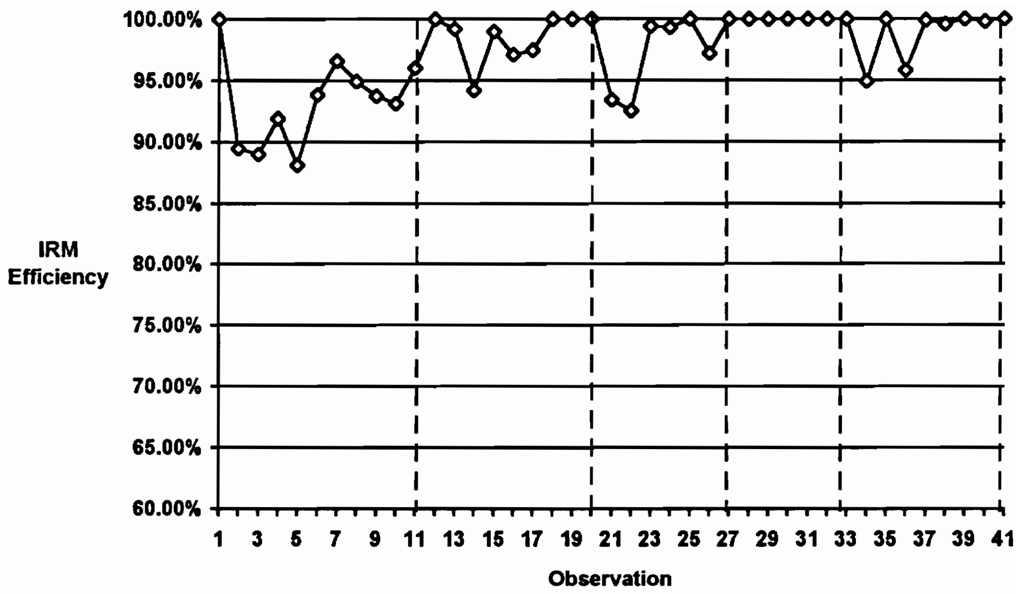

Figure 6.8 Efficiency Performance of Quality Model Q2

The trends of model Q2 are very similar to those of model Q1. Model Q2 has the same interval trends but smoothed out in comparison with model Q1. The first interval is characterized by *inefficient* quality performance. The second interval is fluctuates but is mostly *partially efficient*. The third interval is characterized by mostly *inefficient* and *partially efficient* observations. The fourth interval is characterized by having all observations *efficient*. Finally, the fifth interval is characterized by mostly *partially efficient* observations.

6.5.2 Efficiency results of quality Model Q2b

A modified version of model Q2 was also evaluated using the DEA Application. The modified Q2b model does not include the variable *maintenance & setup* as an input variable in the model. The variable was found to have no positive relationship with the outputs of model Q2[11]. Table B.3 in Appendix B contains the data set used to run this model. The efficiency results of model Q2b are illustrated in table 6.12.

Table 6.12 Efficiency Performance of Quality Model Q2b

Observation	Model Q2b Efficiency Performance	Observation	Model Q2b Efficiency Performance
1	100.0%	21	93.4%
2	89.5%	22	91.7%
3	89.0%	23	97.3%
4	90.9%	24	98.4%
5	88.1%	25	100.0%
6	93.8%	26	94.5%
7	96.6%	27	99.6%
8	94.9%	28	98.3%
9	93.7%	29	100.0%
10	93.1%	30	100.0%
11	96.0%	31	97.1%
12	100.0%	32	99.3%
13	99.2%	33	99.7%
14	94.2%	34	94.9%
15	99.0%	35	100.0%
16	96.7%	36	95.8%
17	96.1%	37	99.9%
18	99.2%	38	97.8%
19	100.0%	39	100.0%
20	94.4%	40	99.8%
		41	100.0%

As in the case between Q1 and Q1b, results of models Q2 and Q2b were practically identical. The same observations 5 and 3 were found to be the most *inefficient* in model

[11] Refer to correlation analysis in Appendix C for the correlation coefficient.

Q2b. *Maintenance & setup* do not seem to have any impact on the quality performance of model Q2. Figure 6.9 illustrates the comparison of efficiency results of models Q2 and Q2b.

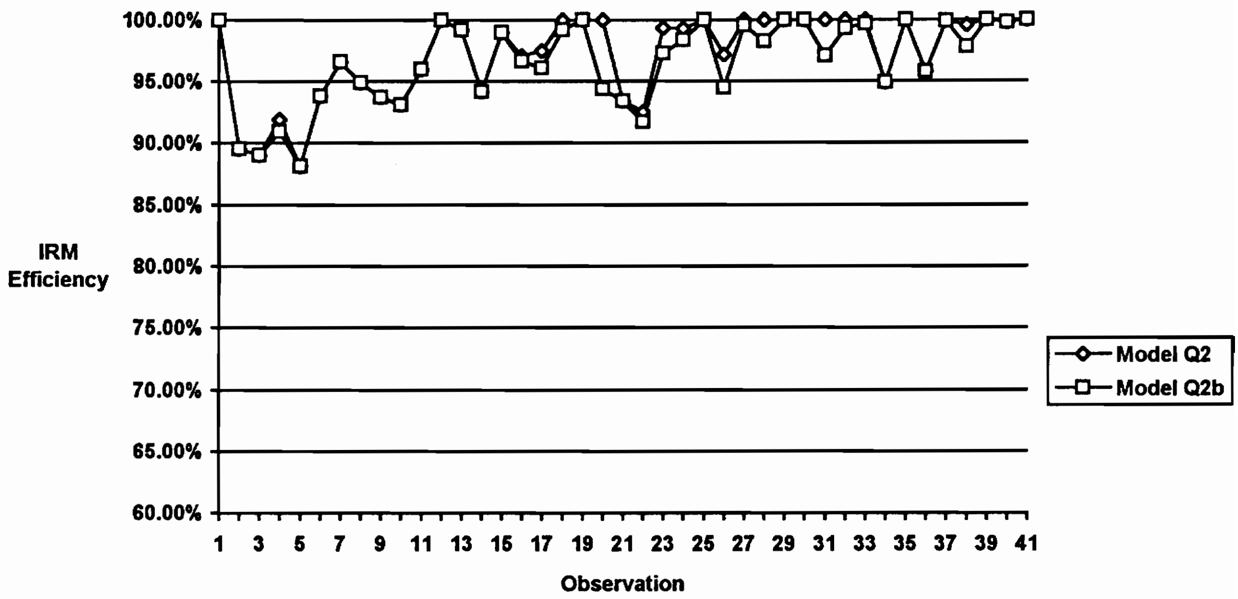

Figure 6.9 Comparison of Efficiency Performance of Models Q2 & Q2b

The results of these two models are practically the same. An evaluation using bivariate linear regression found the correlation coefficient R^2 to be 0.9033 between the results of Q2 and Q2b. Modified model Q2b is used for comparison with quality models Q1 and Q3.

6.6 Efficiency results of quality Model Q3

Model Q3 was the last quality model to be evaluated using the Mathematica DEA Application. The main difference between this model and the other quality models is that this model incorporates the *complexity factor* into the output variables instead of including it as an input variable[12]. The data set used to evaluate this model is included in Appendix B (table B.4). Quality performance efficiency results of the quality model Q3 are included in table 6.13.

Table 6.13 Efficiency Performance of Quality Model Q3

Observation	Model Q3 Efficiency Performance	Observation	Model Q3 Efficiency Performance
1	100.0%	21	91.6%
2	83.4%	22	88.9%
3	73.0%	23	84.1%
4	73.7%	24	93.1%
5	83.3%	25	100.0%
6	80.1%	26	95.4%
7	93.7%	27	100.0%
8	91.4%	28	91.1%
9	90.8%	29	100.0%
10	90.4%	30	100.0%
11	92.9%	31	100.0%
12	100.0%	32	100.0%
13	96.2%	33	100.0%
14	88.7%	34	93.9%
15	96.0%	35	100.0%
16	97.2%	36	91.3%
17	86.9%	37	99.2%
18	100.0%	38	99.3%
19	100.0%	39	100.0%
20	100.0%	40	97.9%
		41	100.0%

Model Q3 efficiency performance results are similar to both models Q1 and Q2. All models follow the same quality performance trends. The main difference of the results of model Q3 is that fluctuations of quality performance are more accentuated than in the

[12] Refer to The Q3 Quality Model in section 4.7.3 for the details of the inclusion of this *complexity factor* into the output variables.

other quality models. For example, the observation with the lowest quality performance for model Q3 was observation 3 with a 73.0% efficiency. This is the same result as model Q2, but the quality performance is 15% lower. The lowest quality performance observation of model Q1 is also 12% higher than model Q3.

The observation with the second lowest efficiency performance was observation 4 with a 73.7% efficiency. Like all other low performance of other observations, these observations had low conformance levels while the input levels had not been significantly reduced.

6.6.1 Grouping of Efficiency Performance Results of Model Q3

Model Q3 performance results were grouped in same three categories as model Q1 and Q2; *efficient*, *partially efficient*, and *inefficient* observations. Observations with 100% efficiency were grouped as *efficient*; between 95% and 99% were considered *partially efficient*; efficiency performance 95% or lower were considered *inefficient*. Table 6.14 illustrates the grouping of observations.

Table 6.14 Grouping of Q3 Efficiency Performance

Efficient Observation Number	Partially Efficient Observation Number	Inefficient Observation Number
1	13	2
12	15	3
18	16	4
19	26	5
20	37	6
25	38	7
27	40	8
29		9
30		10
31		11
32		14
33		17
35		21
39		22
40		23
		24
		28
		34
		36

Note that observations are polarized to either the efficient or inefficient categories. This feature distinctly distinguishes this model from models Q1 and Q2. Figure 6.10 illustrates the trends and intervals of quality performance for model Q3.

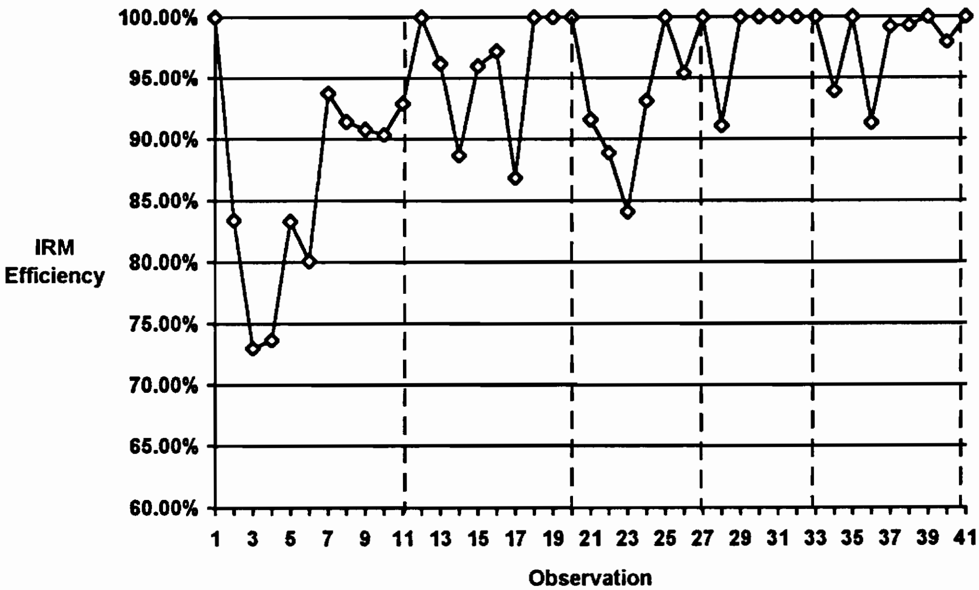

Figure 6.10 Efficiency Performance of Model Q3

Model Q3 results had the same interval trends as models Q1 and Q2. Note though that inefficiency is much more accentuated in model Q3. The first interval of model 3 is characterized by *inefficient* quality performance. The second interval is mostly *partially efficient* and *inefficient*. The third interval is characterized by mostly *inefficient* and *partially efficient* observations. The fourth interval follows an *efficient*. trend. Finally, the fifth interval is characterized by fluctuations in the quality performance of observations.

6.6.2 Efficiency Results of Quality Model Q3b

A modified version of model Q3 was also evaluated using the DEA Application. The modified Q3b model does not include the variable *maintenance & setup* as an input variable in the model. The variable was found to have no positive relationship with the output variables of model Q3. Table B.4 in Appendix B contains the data set used to run this model. The results of model Q3b are illustrated in table 6.15.

Table 6.15 Efficiency Performance of Quality Model Q3b

Observation	Model Q3b Efficiency Performance	Observation	Model Q3b Efficiency Performance
1	100.0%	21	91.4%
2	83.4%	22	88.3%
3	73.0%	23	81.3%
4	73.7%	24	87.4%
5	83.3%	25	100.0%
6	80.1%	26	93.2%
7	93.7%	27	98.2%
8	91.4%	28	85.5%
9	90.8%	29	100.0%
10	90.4%	30	100.0%
11	92.3%	31	95.5%
12	100.0%	32	99.7%
13	96.2%	33	97.0%
14	88.7%	34	93.8%
15	96.0%	35	100.0%
16	97.1%	36	84.3%
17	86.3%	37	99.2%
18	99.9%	38	94.5%
19	99.1%	39	100.0%
20	92.2%	40	97.9%
		41	96.9%

The results of both model Q3 and Q3b were practically identical. The same observations 3 and 4 were found to be the most *inefficient* in model Q3b. The *maintenance & setup* variable seems to have practically no impact on the quality performance of model Q3. Figure 6.11 illustrates the comparison of results from models Q3 and Q3b.

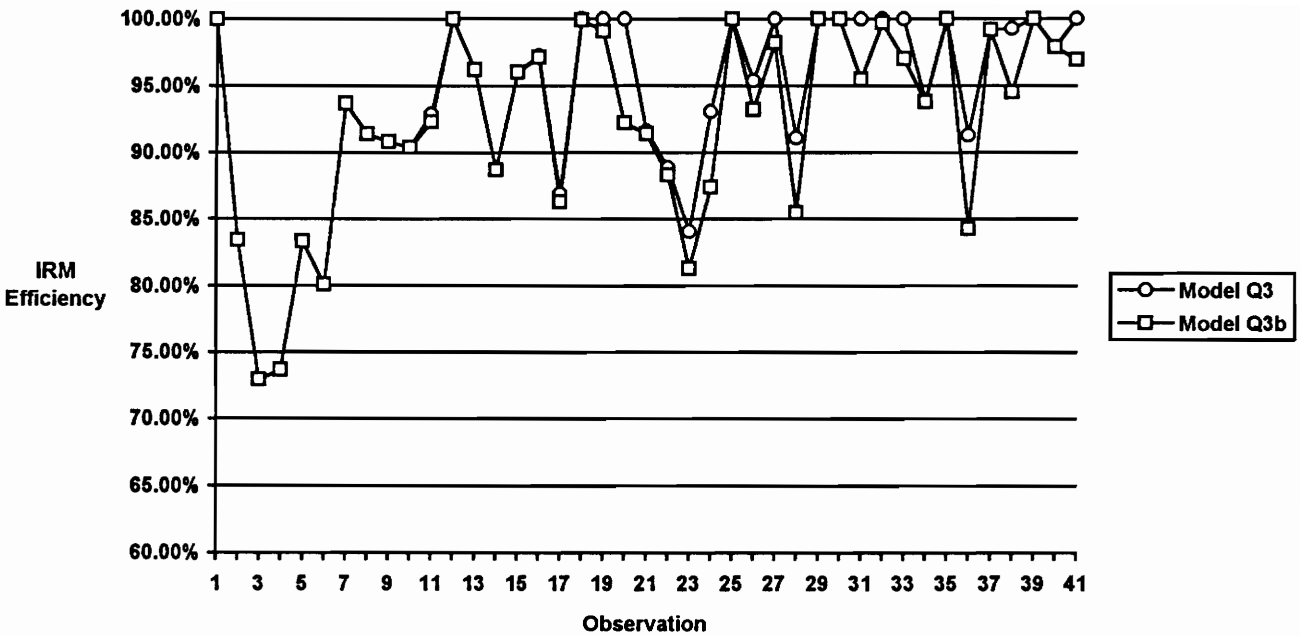

Figure 6.11 Comparison of Efficiency Performance of Models Q3 & Q3b

Results of models Q3 and modified Q3b are almost identical. The main discrepancy between models Q3 and Q3b is observation 20 where quality performance drops from 100.0% efficient for Q3 and to 92.2% efficiency for modified Q3b due to the low *maintenance & setup* of observation 20. An evaluation using bivariate linear regression found a correlation coefficient between the results of Q3 and Q3b to have an $R^2 = 0.9147$. This high correlation coefficient substantiates the claim that *maintenance & setup* has little impact on the quality performance of model Q3. Thus, modified model Q3b will be used for comparison with quality models Q1 and Q2.

6.7 Comparison of Quality Models Q1, Q2, & Q3

The quality performance results of the three quality models were compared. Modified Q1b Q2b and Q3b were the models used for this comparison . The quality performance results of models Q1b, Q2b, and Q3b are illustrated in figure 6.12.

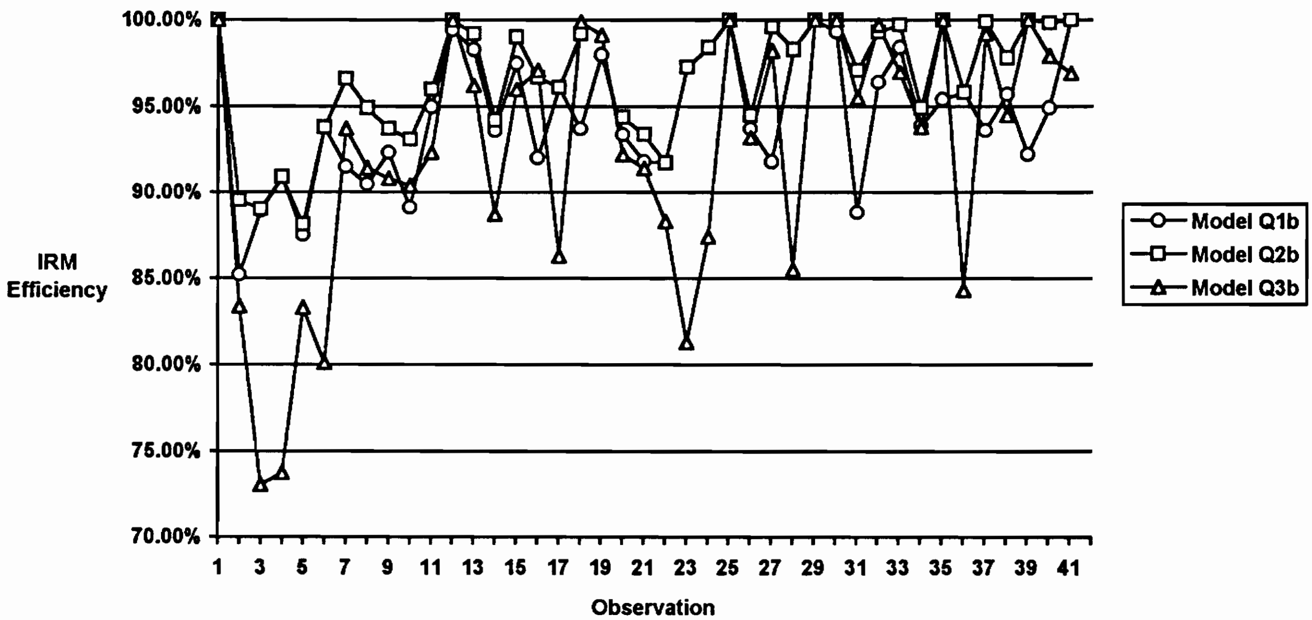

Figure 6.12 Comparison of Efficiency Performance of Models Q1b, Q2b & Q3b

The main difference between the results of the quality models is that while the efficiency performance of Q1 and Q2 remains mostly between 90 and 100% efficiency, the performance of Q3 fluctuates in a much greater range.

The reason for these discrepancies between the models Q1 and Q2, and model Q3 is the inclusion of the *complexity factor* in the output variables of model Q3. The first interval of observations is characterized by a lower complexity of production and output product produced. This causes the output variables of model Q3 to be lower than in models Q1 and Q2. That is manifested by the sharper drop in quality performance of model Q3 during the first interval in comparison to Q1 and Q2.

6.8 Efficiency results of hybrid Model H1

Model H1 was the first hybrid model to be evaluated using the Mathematica DEA Application. The main difference between this model and hybrid model H2 is that this model incorporates the *complexity factor* as an input variable[13]. The data set used to evaluate this model is included in tables B.1 and B.3 of Appendix B. Quality performance efficiency results of the quality model H1 are illustrated in table 6.16.

Table 6.16 Efficiency Performance of Hybrid Model H1

Observation	Model H1 Efficiency Performance	Observation	Model H1 Efficiency Performance
1	100.0%	21	96.2%
2	100.0%	22	100.0%
3	100.0%	23	100.0%
4	99.5%	24	100.0%
5	100.0%	25	100.0%
6	100.0%	26	100.0%
7	100.0%	27	97.2%
8	100.0%	28	98.8%
9	100.0%	29	98.8%
10	100.0%	30	98.1%
11	97.9%	31	100.0%
12	98.0%	32	98.3%
13	91.7%	33	100.0%
14	93.1%	34	100.0%
15	94.7%	35	97.8%
16	97.4%	36	100.0%
17	100.0%	37	100.0%
18	97.2%	38	100.0%
19	97.3%	39	100.0%
20	97.2%	40	98.5%
		41	99.3%

The observation with the lowest performance for model H1 was observation 13 with a 91.7% efficiency. The observation with the second lowest performance was observation 9 with a 93.1% efficiency. The hybrid performance results of model H1 are illustrated in figure 6.13.

[13] Refer to Appendix D for the formulation of the *complexity factor*.

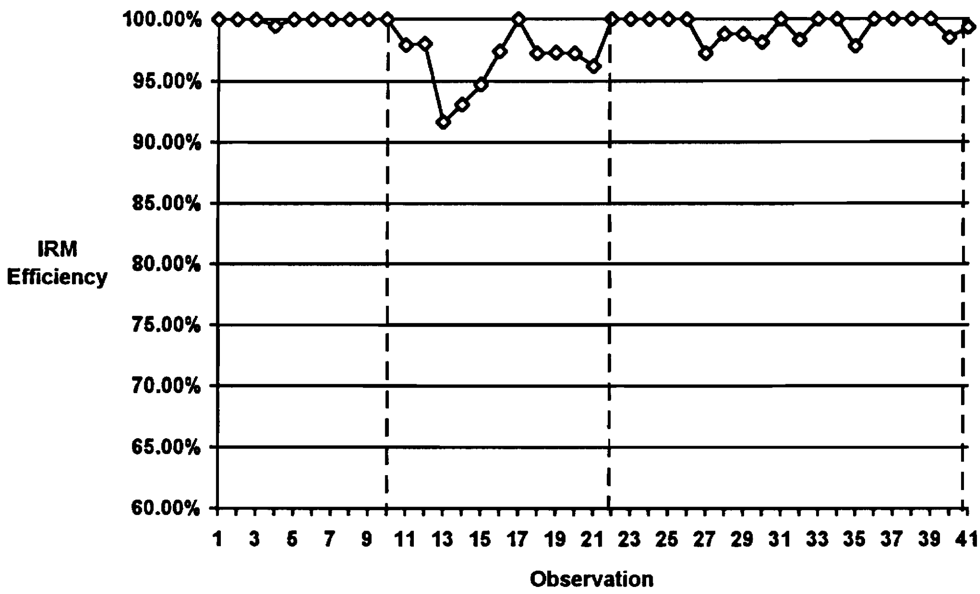

Figure 6.13 Efficiency Performance Model H1

Three different trends were identified from the H1 results. The first trend lasting until observation 10 is characterized by mostly efficient performance. The second trend from observation 11 to 22 is characterized by a drop in efficiency performance. The third trend, starting in observation 23 is characterized by mostly efficient performance.

6.9 Efficiency Results of Hybrid Model H2

Model H2 was evaluated using the Mathematica DEA Application. The difference between H1 and H2 is that H2 incorporates the *complexity factor* into the hybrid output variables instead of including it as an input variable[14]. The data set used to evaluate this model are included in tables B.2 and B.3 of Appendix B. Hybrid performance efficiency results of the hybrid model H2 are included in table 6.17.

Table 6.17 Efficiency Performance of Hybrid Model H2

Observation	Model H2 Efficiency Performance	Observation	Model H2 Efficiency Performance
1	100.0%	21	92.4%
2	100.0%	22	100.0%
3	100.0%	23	100.0%
4	100.0%	24	100.0%
5	99.8%	25	100.0%
6	100.0%	26	100.0%
7	94.8%	27	89.3%
8	92.3%	28	100.0%
9	100.0%	29	94.6%
10	94.7%	30	91.0%
11	97.6%	31	99.5%
12	89.5%	32	98.1%
13	92.2%	33	98.7%
14	91.8%	34	100.0%
15	90.6%	35	100.0%
16	89.1%	36	100.0%
17	100.0%	37	100.0%
18	90.2%	38	90.8%
19	96.6%	39	100.0%
20	92.6%	40	100.0%
		41	100.0%

The results of H2 provided much more inefficient performance than model H1. The observation with the lowest performance for model H2 was observation 16 with an 89.1%

[14] Refer to "Hybrid Model H2" in section 4.9.2 for details in the inclusion of this *complexity factor* into the output variables.

efficiency. The second lowest performer was observation 27 with an 89.3% efficiency. Figure 6.14 illustrates the results of model H2.

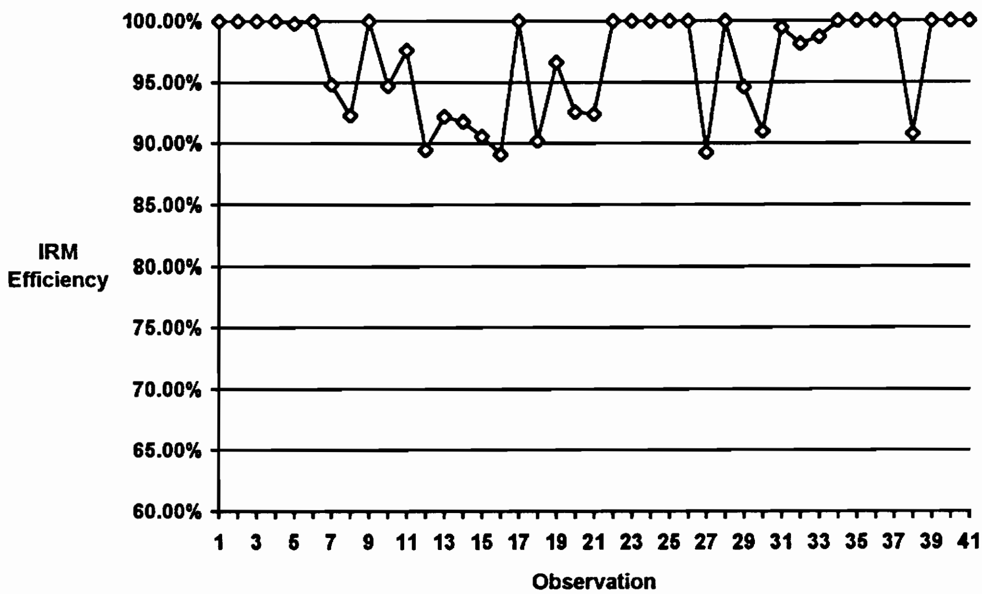

Figure 6.14 Efficiency Performance of Model H2

No clear trends were distinguished for the efficiency results of model H2.

6.10 Comparison of Hybrid Models H1 and H2

The efficiency performance results of models H1 and H2 were compared. The main difference between H1 and H2 is that H1 incorporates the *complexity factor* as an input variable, while the H2 model incorporates the *complexity factor* into the output variables. Figure 6.15 contains the trends of hybrid models H1 and H2.

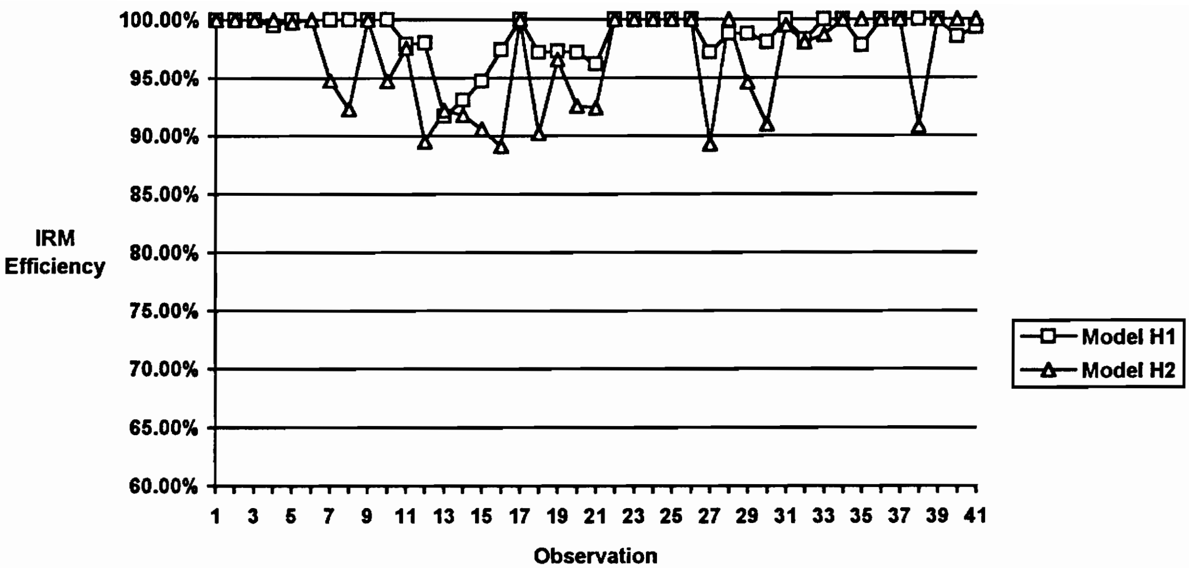

Figure 6.15 Comparison of Efficiency Performance of Models H1 & H2

There does not seem to be any correspondence between both models. The correlation coefficient between H1 and H2 was found to be $R^2 = 0.1274$. This coefficient indicates that there is no real correlation between results of model H1 and H2.

6.11 Additional Results from Correlation Analysis

Some important results were obtained from correlation analysis among input/output variables of both quality and productivity models. The following sections describe the most relevant results of the correlation analysis.

6.11.1 Lack of Relationship of Unopened Jackets to Input/Output Variables

The *unopened jackets* nonconformance output variable was found to have no correlation with the input variables of the quality models. On the other hand, the other two types of nonconformance (*doubles* and *misses*) were found to have a strong correlation with the input variables of the quality models[15]. This indicates that *unopened jackets* was affected by other factors as opposed to the factors affecting doubles and misses. This result may point to interacting processes such as the *Printing Press* as the root cause of *unopened jacket* nonconformance.

6.11.2 Strong Relationship between Doubles and Misses

Correlation analysis also indicated that there was a strong relationship in the quality model between *doubles* and *misses* nonconformance variables[16]. When one of these types of nonconformances is high, usually the other will also be high. This indicates that there very well may be common sources that cause these nonconformances. Further research needs to be carried out to investigate the interrelationship between these two types of nonconformances.

6.11.3 Relevance of the Complexity Factor

Correlation analysis helped to assess the relevance of the inclusion of the *complexity factor* in both the quality and productivity models. The results indicate that when the *complexity factor* was factored into the output variables, the relationship between inputs and outputs was strengthened for both the quality and productivity models. Similarly, when the *complexity factor* was used as an input variable in the quality models, a strong relationship was found between this variable and the output variables of the model. These results

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[15] Refer to tables C.3 and C.4 in Appendix C.
[16] Refer to table C.3 in Appendix C.

indicate that *the complexity factor* enhances the validity of the productivity and quality models it was used in.

6.12 Comparisons of the Productivity and Quality Performance

Two comparisons were made between the results of the productivity and quality models. The first comparison was between productivity model P1b and quality model Q2b. These models did not incorporate the *complexity factor* into the output variables. Figure 6.16 illustrates the results of models P1b and Q2b.

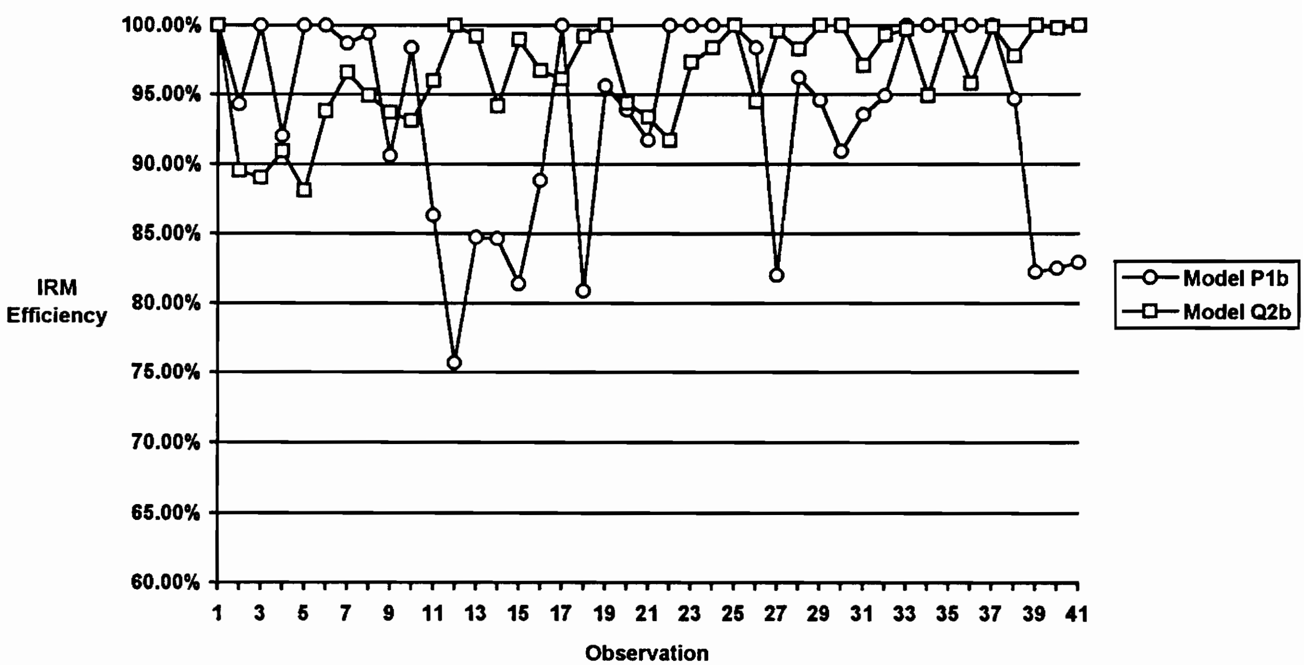

Figure 6.16 Comparison of Efficiency Performance of Models P1b & Q2b

There does not seem to be any relationship between quality and productivity performance when models P1b and Q2b are evaluated.

Models P2b and Q3b were used for the second comparison between productivity and quality. These models incorporated the *complexity factor* into the output variables. Figure 6.17 illustrates the efficiency results of both models P2b and Q3b.

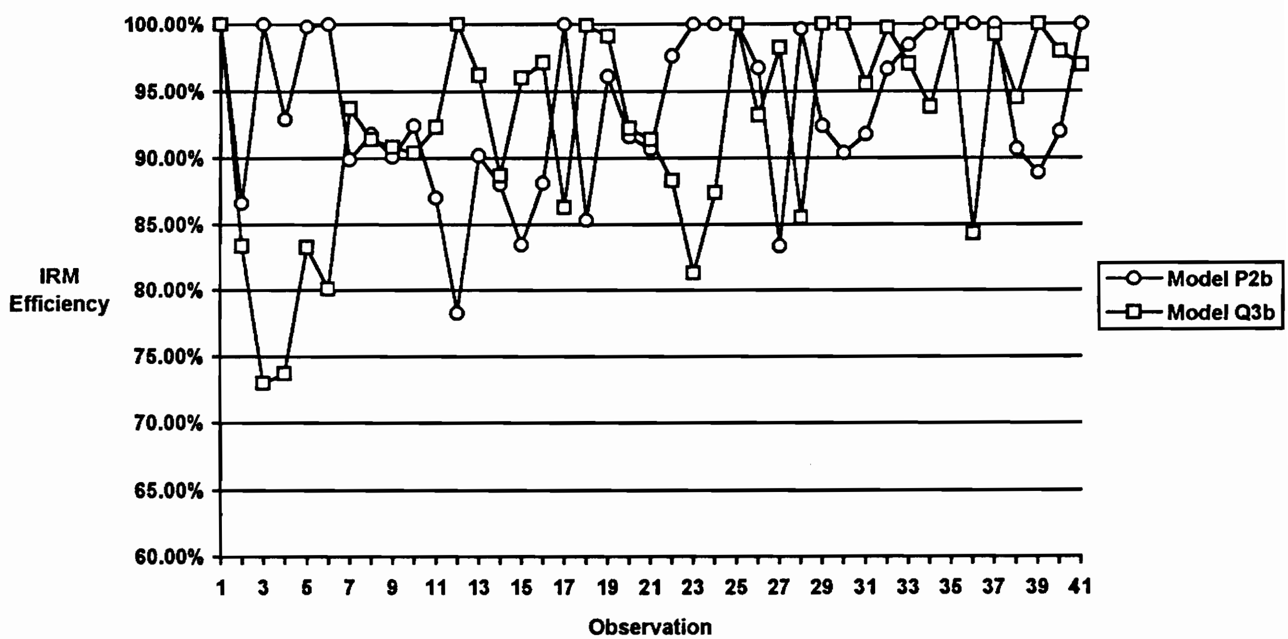

Figure 6.17 Comparison of Efficiency Performance of Models P2b & Q3b

Similarly as with the first comparison, no relationship between quality and productivity performance was found for this second comparison. This indicates that for the study period selected there seems to be no correlation between quality and productivity in the NPIP.

Chapter 7. CONCLUSIONS & RECOMMENDATIONS

7.1 Productivity Conclusions

The productivity results indicate that the productivity models P1 and P2 realistically portray the productivity performance of the NPIP. From the results of sections 6.1 and 6.2, it can be noted that the P1 and P2 specifications modeled productivity accurately, reflecting productivity performance trends that could be traced back to events that occurred in the NPIP. Periods where productivity had been affected by external parameters were found to have low efficiency performance with the models.

7.2 Quality Conclusions

The quality results also confirmed the validity of the quality models. Although some trends could not be explained by conclusive external factors, most periods of expected low quality performance were correctly identified by the quality models Q1, Q2 and Q3. The inclusion of multiple quality models allowed for the evaluation of different quality inputs. Despite their differences, all three models were consistent in assessing the quality trends of the NPIP. It can be argued that quality model Q3 provided a better representation of quality performance than Q1 and Q2 because it had more variability.

7.3 Productivity & Quality Link

One of the main goals of the research was to address the underlying productivity and quality link in the NPIP. The results of the research do not indicate that a relationship between quality and productivity exists in the NPIP for the study period evaluated. This does not mean that there is not a long-term dependency between quality and productivity. Simply, there does not seem to be any a correlation for the study period selected.

7.4 Usefulness of the Complexity Factor

One of the most important outcomes of this research is the definition of the *complexity factor*[1]. The inclusion of the complexity factor enhanced both productivity and quality models by strengthening the relationship between inputs and outputs. Also, when used as an input variable, the *complexity factor* showed a strong correlation with the outputs of the quality models.

7.5 Inconclusive Hybrid Models

Hybrid models were formulated to combine productivity and quality into one performance measure. The hybrid models H1 and H2 did not provide any conclusive evidence of effectively modeling the combination of productivity and quality performance. No marked trends of hybrid performance could be interpreted from the results obtained. Further, the results of both H1 and H2 could not be coherently related. These inconclusive results only indicate that further research into modeling hybrid models needs to be carried out.

[1] Refer to Appendix D for the definition of the *complexity factor*.

7.6 Recommendations for Future Research

The outcome of this research provide a suggestion for future research. Recommendations for further research can be summarized into three things:

One of the needs for further research would be obtaining more complete representation of inputs and outputs for the models. Although, the results of the models provide a realistic assessment of quality and productivity performance, more variables for which data could not be collected such as energy consumption and appraisal and prevention costs are needed for more comprehensive productivity and quality models. This would enhance the results as well as provide further insight into productivity and quality performance.

The research found no positive or negative underlying relationship between productivity and quality performance in the NPIP. Evaluating a longer study period may show that there is an underlying relationship between productivity and quality.

The study of the hybrid model should also be expanded in future research. Although the results of the hybrid models H1 and H2 were inconclusive, further research in the possible combination of quality and productivity performance into a single performance measure needs to be considered. Obtaining a single model that tracks the combination of productivity and quality performance could prove to be extremely advantageous as a management tool.

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Appendix A Output Increasing and Input Reducing Formulations

Output Increasing Model (OIM) Formulation

The formulation for the output increasing model (OIM) can be stated as follows:[1]

Objective Function

$$\max_{z} \Theta$$

Subject to:

$$\sum_{j=1}^{n} z_j x_{ij} \le x_{ij_0}, \qquad i = 1,2,\ldots\ldots, m \qquad \text{(A.1)}$$

$$\sum_{j=1}^{n} z_j y_{rj} \le \Theta y_{rj_0}, \qquad r = 1,2\ldots\ldots, s \qquad \text{(A.2)}$$

$$\sum_{j=1}^{n} z_j = 1 \qquad \text{(A.3)}$$

$$\Theta \ge 0, \quad z_j \ge 0, \quad j = 1,2,\ldots\ldots,n$$

The variable Θ is the radial output increasing technical efficiency for the particular DMU_{j0}. Θ provides a value for the potential increase in production for a particular DMU_{j0}. This potential increase in production will be one if the DMU_{j0} is efficient and greater than one for inefficient DMUs.

For example, if the efficiency performance of a particular DMU_{j0} is 1.2, this means that an additional 20% increase in output production maintaining the same fixed input would be necessary before that particular DMU_{j0} would be rendered efficient.

[1] The notation for the variables is the same as section 3.3.1.

The first set of constraint equations[2] (A.1) specifies that the hypothetical DMU cannot use more input resources than the amount that actual DMU_{j0} uses. This hypothetical DMU is constructed by taking the weights of actual DMUs for each input (each constraint equation represents one input variable). The second set of constraint equations (A.2) states that the hypothetical DMU constructed as the weighted average of the actual DMUs has outputs greater or equal to the actual DMU_{j0}. The third constraint (A.3) is included so that the variable returns to scale holds[3].

Input Reducing Model (IRM) Formulation

The formulation for the input reducing model (IRM) can be stated as follows:

Objective Function

$$\min_{z} \Theta$$

Subject to:

$$\sum_{j=1}^{n} z_j x_{ij} \leq \Theta x_{ij_o}, \qquad i = 1, 2, \ldots, m \qquad (A.4)$$

$$\sum_{j=1}^{n} z_j y_{rj} \leq y_{rj_o}, \qquad r = 1, 2, \ldots, s \qquad (A.5)$$

$$\sum_{j=1}^{n} z_j = 1 \qquad (A.6)$$

$$\Theta \geq 0, \quad z_j \geq 0, \quad j = 1, 2, \ldots, n$$

The variable Θ is the input technical efficiency measure for the particular DMU_{j0}. Θ provides a measure for the radial input efficiency measure of a particular DMU_{j0} in the production of a

[2] Inequalities of the first and second set of constraints are applied to allow that DMUs chosen as efficient can lie on the flat segment of the *efficient frontier*.

[3] Variable returns to scale are discussed in section 3.3.2.2.

fixed output level. This efficiency measure will be one if DMU_{j0} is efficient and lower than one for an inefficient DMU.

For example, let us assume that the input efficiency performance of a particular DMU_{j0} is 0.95. This means that an additional 5% proportional decrease in all inputs would be necessary before that particular DMU_{j0} could be rendered efficient.

The first set of constraint equations[4] (A.4) specifies that the hypothetical DMU (left hand side of the equation) will have inputs that are proportional to the inputs that the actual DMU_{j0} utilizes. This hypothetical DMU is constructed by taking the weights of actual DMUs for each input (each constraint equation represents one input variable). Also, these constraints indicate that the hypothetical DMU uses less than or equal inputs to the DMU_{j0} that is being evaluated. The second constraint (A.5) specifies that the hypothetical DMU (left hand side of the equation) should have weights that will assure that it produces at least the same level of output that the actual DMU_{j0} produces. This hypothetical DMU is constructed by taking the weights of actual DMUs for each output. Note that each constraint equation represents an output variable. The third constraint (A.3) is included so that the variable returns to scale holds[5].

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[4] Inequalities of the first and second set of constraints are applied to allow that DMUs chosen as efficient can lie on the flat segment of the *efficient frontier*.

[5] Variable returns to scale are discussed in section 3.3.2.2.

Appendix B DATA SUMMARY

Table B.1 Data of Models P1 & P1b

Production Period	*Day one* Output/1000	*Day two* Output/1000	Maintenance & Setup hours	Machine hours	Labor hours
1	585	633	175	78.03	1640
2	690	818	154	114.93	1829
3	719	619	175	88.81	1455
4	750	689	189	105.48	1876
5	834	604	175	96.89	1832
6	777	708	189	99.80	2098
7	691	901	204	124.10	2210
8	841	895	189	128.52	2112
9	833	890	210	139.26	2373
10	860	899	205	132.61	2045
11	733	913	217	145.76	2411
12	855	909	168	173.00	3009
13	830	920	200	153.16	2555
14	802	848	217	139.25	2334
15	752	898	196	150.57	2436
16	800	890	84	146.36	1771
17	725	893	49	120.47	2217
18	819	894	35	154.61	2240
19	822	895	14	131.18	2194
20	784	890	14	129.75	2035
21	811	886	112	134.24	2004
22	787	856	42	121.62	1464
23	626	806	28	107.68	1425
24	709	795	42	116.00	1211
25	775	866	28	116.45	1492
26	699	870	21	128.31	1514
27	862	868	49	157.81	2056
28	747	876	35	122.83	1767
29	729	885	28	127.34	1745
30	689	916	84	140.75	1847
31	942	958	0	156.99	2053
32	954	963	91	157.08	2002
33	875	970	91	151.51	1867
34	885	978	91	143.52	1937
35	978	978	91	153.58	1928
36	814	978	84	142.34	1890
37	997	958	91	169.34	2281
38	788	971	77	148.41	2078
39	952	953	70	179.59	2843
40	904	948	119	171.53	3103
41	903	926	78	167.42	3152

Table B.2 Data of Models P2 & P2b

Production Period	C.FxDay *one* Output/1000	C.FxDay *two* Output/1000	Maintenance & Setup hours	Machine hours	Labor hours
1	448	485	175	78.03	1640
2	594	704	154	114.93	1829
3	598	514	175	88.81	1455
4	678	623	189	105.48	1876
5	681	494	175	96.89	1832
6	726	662	189	99.80	2098
7	638	833	204	124.10	2210
8	784	834	189	128.52	2112
9	833	890	210	139.26	2373
10	819	857	205	132.61	2045
11	758	944	217	145.76	2411
12	896	952	168	173.00	3009
13	896	993	200	153.16	2555
14	819	866	217	139.25	2334
15	782	934	196	150.57	2436
16	803	894	84	146.36	1771
17	744	916	49	120.47	2217
18	861	940	35	154.61	2240
19	829	903	14	131.18	2194
20	760	862	14	129.75	2035
21	794	867	112	134.24	2004
22	742	807	42	121.62	1464
23	619	797	28	107.68	1425
24	688	771	42	116.00	1211
25	742	829	28	116.45	1492
26	688	857	21	128.31	1514
27	862	868	49	157.81	2056
28	762	894	35	122.83	1767
29	711	863	28	127.34	1745
30	689	916	84	140.75	1847
31	950	966	0	156.99	2053
32	1000	1009	91	157.08	2002
33	895	993	91	151.51	1867
34	931	1028	91	143.52	1937
35	1013	1013	91	153.58	1928
36	845	1016	84	142.34	1890
37	1091	1048	91	169.34	2281
38	791	975	77	148.41	2078
39	1040	1041	70	179.59	2843
40	1015	1065	119	171.53	3103
41	1069	1096	78	167.42	3152

Table B.3 Data of Model Q1, Q1b, Q2 & Q2b

Observation	Inverse of Doubles/1000	Inverse of Misses/1000	Inverse of Un. Jackets/1000	Maintenance & Setup hours	Inverse of Complexity Factor	Inverse of Machine hours
1	0.096	0.056	0.032	175	1.306	1.282
2	0.024	0.026	0.016	154	1.162	0.87
3	0.037	0.034	0.022	175	1.203	1.126
4	0.022	0.022	0.026	189	1.106	0.948
5	0.043	0.033	0.024	175	1.224	1.032
6	0.032	0.027	0.02	189	1.070	1.002
7	0.02	0.026	0.019	204	1.082	0.806
8	0.02	0.023	0.021	189	1.073	0.778
9	0.01	0.017	0.021	210	1.000	0.718
10	0.018	0.02	0.018	205	1.050	0.754
11	0.01	0.015	0.022	217	0.967	0.686
12	0.009	0.011	0.026	168	0.954	0.578
13	0.013	0.014	0.022	200	0.927	0.653
14	0.014	0.016	0.021	217	0.979	0.718
15	0.011	0.015	0.024	196	0.961	0.664
16	0.018	0.016	0.021	84	0.996	0.683
17	0.021	0.02	0.019	49	0.975	0.83
18	0.015	0.015	0.012	35	0.951	0.647
19	0.019	0.024	0.017	14	0.991	0.762
20	0.023	0.02	0.023	14	1.032	0.771
21	0.018	0.019	0.021	112	1.021	0.745
22	0.02	0.023	0.019	42	1.050	0.822
23	0.022	0.024	0.021	28	1.007	0.929
24	0.025	0.02	0.028	42	1.027	0.862
25	0.035	0.032	0.02	28	1.044	0.859
26	0.017	0.022	0.02	21	1.022	0.779
27	0.013	0.015	0.022	49	1.000	0.634
28	0.018	0.02	0.023	35	0.980	0.814
29	0.02	0.017	0.032	28	1.026	0.785
30	0.019	0.015	0.029	84	1.000	0.71
31	0.012	0.014	0.018	0	0.992	0.637
32	0.015	0.013	0.023	91	0.954	0.637
33	0.014	0.014	0.027	91	0.977	0.66
34	0.016	0.015	0.011	91	0.951	0.697
35	0.018	0.013	0.022	91	0.965	0.651
36	0.011	0.012	0.024	84	0.963	0.703
37	0.01	0.01	0.018	91	0.914	0.591
38	0.014	0.016	0.025	77	0.996	0.674
39	0.007	0.009	0.015	70	0.916	0.557
40	0.008	0.01	0.015	119	0.890	0.583
41	0.008	0.01	0.018	78	0.845	0.597

Table B.4 Data of Model Q3 & Q3b

Observation	CFx Inverse of Doubles/1000	CFx Inverse of Misses/1000	CFx Inverse of Un. Jackets/1000	Maintenance & Setup hours	Inverse of Machine hours
1	0.07351	0.043	0.0245	175	1.282
2	0.02065	0.022	0.01377	154	0.87
3	0.03076	0.028	0.01829	175	1.126
4	0.01989	0.02	0.02351	189	0.948
5	0.03513	0.027	0.01961	175	1.032
6	0.02991	0.025	0.01869	189	1.002
7	0.01848	0.024	0.01756	204	0.806
8	0.01864	0.021	0.01957	189	0.778
9	0.01	0.017	0.021	210	0.718
10	0.01714	0.019	0.01714	205	0.754
11	0.01034	0.016	0.02275	217	0.686
12	0.00943	0.012	0.02725	168	0.578
13	0.01402	0.015	0.02373	200	0.653
14	0.0143	0.016	0.02145	217	0.718
15	0.01145	0.016	0.02497	196	0.664
16	0.01807	0.016	0.02108	84	0.683
17	0.02154	0.021	0.01949	49	0.83
18	0.01577	0.016	0.01262	35	0.647
19	0.01917	0.024	0.01715	14	0.762
20	0.02229	0.019	0.02229	14	0.771
21	0.01763	0.019	0.02057	112	0.745
22	0.01905	0.022	0.0181	42	0.822
23	0.02185	0.024	0.02085	28	0.929
24	0.02434	0.019	0.02726	42	0.862
25	0.03352	0.031	0.01916	28	0.859
26	0.01663	0.022	0.01957	21	0.779
27	0.013	0.015	0.022	49	0.634
28	0.01837	0.02	0.02347	35	0.814
29	0.01949	0.017	0.03119	28	0.785
30	0.019	0.015	0.029	84	0.71
31	0.0121	0.014	0.01815	0	0.637
32	0.01572	0.014	0.02411	91	0.637
33	0.01433	0.014	0.02764	91	0.66
34	0.01682	0.016	0.01157	91	0.697
35	0.01865	0.013	0.0228	91	0.651
36	0.01142	0.012	0.02492	84	0.703
37	0.01094	0.011	0.01969	91	0.591
38	0.01406	0.016	0.0251	77	0.674
39	0.00764	0.01	0.01638	70	0.557
40	0.00899	0.011	0.01685	119	0.583
41	0.00947	0.012	0.0213	78	0.597

Appendix C CORRELATION ANALYSIS OF INPUT/OUTPUT VARIABLES

Correlation analysis between variables was performed for three different purposes:

- To assure that input variables are independent from one another.
- To assure that output variables are independent from one another.
- To assure that there is some dependence between inputs and outputs.

All these three requirements are necessary for running DEA. Correlation analysis for all the models was performed using bivariate linear regression analysis. The correlation coefficient (R) was computed to measure the strength of the relationship between variables (Lyman Ott[13, p. 461]). R^2 represents that proportion of the total variability of the dependent variable that is accounted for by the independent variable (Lyman Ott[13, p. 464]). Values of R^2 approaching one suggest a strong correlation between the variables evaluated (Lyman Ott[13, p. 461]).

The following tables provide a summary of the correlation coefficient results. The shaded entries indicate that the relationship between those variables is not the desired one.

Table C.1 Summary of Results of R^2 of Variables of Models P1 & P1b

	Maint. & Setup	Machine Hours	Labor	Day one	Day two
Maint. & Setup	---------	0.0254	0.0885	0.0082	0.1006
Machine Hours	0.0254	---------	0.4798	0.5378	0.6902
Labor	0.0885	0.4798	---------	0.2513	0.1709
Day one	0.0082	0.5378	0.2513	---------	0.2993
Day two	0.1006	0.6902	0.1709	0.2993	---------

Table C.2 Summary of Results of R^2 of Variables of Models P2 & P2b

	Maint. & Setup	Machine Hours	Labor	CFxDay one	CFxDay two
Maint. & Setup	---------	0.0254	0.0885	0.032	0.0944
Machine Hours	0.0254	---------	0.4798	0.773	0.8126
Labor	0.0885	0.4798	---------	0.3986	0.306
CFxDay one	0.032	0.773	0.3986	---------	0.682
CFxDay two	0.0944	0.8126	0.306	0.682	---------

Table C.3 Summary of Results R^2 of Variables of Models Q1, Q1b, Q2 & Q2b

	Machine Hours	Maint. & Setup	Complexity Factor (CF)	Inverse of Doubles	Inverse of Misses	Inverse of Un. Jackets
Machine Hours	---------	0.0254	0.7969	0.7436	0.8658	0.1166
Maint. & Setup	0.0254	---------	0.0904	0.0202	0.0343	0.0112
Complexity Factor	0.7969	0.0904	---------	0.6844	0.809	0.1263
Inverse of Doubles	0.7436	0.0202	0.6844	---------	0.8675	0.1525
Inverse of Misses	0.8658	0.0343	0.809	0.8675	---------	0.0808
Inverse of Un. Jackets	0.1166	0.0112	0.1263	0.1525	0.0808	---------

Table C.4 Summary of Results of R^2 of Variables of Models Q3 & Q3b

	Machine Hours	Maint. & Setup	CFx Inverse of Doubles	CFx Inverse of Misses	CFx Inverse of Un. Jack.
Machine Hours	---------	0.0254	0.7522	0.8301	0.0006
Maint. & Setup	0.0254	---------	0.0086	0.0155	1E-06
CFx Inverse of Doubles	0.7522	0.0086	---------	0.8069	0.0017
CFx Inverse of Misses	0.8301	0.0155	0.8069	---------	0.0162
CFx Inverse of Un. Jack.	0.0006	1E-06	0.0017	0.0162	---------

Table C.5 Summary of Results of R^2 of Variables of Model H1

	Machine Hours	Labor	Complexity Factor (CF)	Inverse of Doubles	Inverse of Misses	Inverse of Un Jackets	Day one	Day two
Machine Hours	———	0.4798	0.7969	0.7436	0.8658	0.1166	0.5378	0.6902
Labor	0.4798	———	0.3984	0.2182	0.286	0.1076	0.2513	0.1709
Complexity Factor (CF)	0.7969	0.3984	———	0.6844	0.809	0.1263	0.3482	0.6344
Inverse of Doubles	0.7436	0.2182	0.6844	———	0.8675	0.1525	0.2811	0.531
Inverse of Misses	0.8658	0.286	0.809	0.8675	———	0.0808	0.4113	0.6221
Inverse of Un. Jackets	0.1166	0.1076	0.1263	0.1525	0.0808	———	0.1695	0.0922
Day one	0.5378	0.2513	0.3482	0.2811	0.4113	0.1695	———	0.2993
Day two	0.6902	0.1709	0.6344	0.531	0.6221	0.0922	0.2993	———

Table C.6 Summary of Results of R^2 of Variables of Model H2

	Machine Hours	Labor	Inverse of Doubles	Inverse of Misses	Inverse of Un Jackets	CFxDay one	CFxDay two
Machine Hours	———	0.4798	0.7436	0.865	0.1166	0.773	0.8126
Labor	0.4798	———	0.2182	0.286	0.1076	0.3986	0.306
Inverse of Doubles	0.7436	0.2182	———	0.8675	0.1525	0.4498	0.5946
Inverse of Misses	0.8658	0.286	0.8675	———	0.0808	0.6393	0.7448
Inverse of Un. Jackets	0.1166	0.1076	0.1525	0.0808	———	0.1872	0.1179
CFxDay one	0.773	0.3986	0.4498	0.6393	0.1872	———	0.682
CFxDay two	0.8126	0.306	0.5946	0.7448	0.1179	0.682	———

Appendix D COMPLEXITY FACTOR

A *complexity factor* (CF) was developed to account for both the complexity of the production process and the complexity of the product produced during different production periods. The parameter used to measure the complexity of the production process was the number of production zones serviced per production period[6]. This parameter provided an indication of the number of change overs that were incurred during a given production period.

Similarly, the parameter used to measure the complexity of the product produced was the average number of preprints included per packet. This parameter provided an indication of the complexity of the output product produced. Table D.1 contains the values of both *number of production zones* and *average number of preprints per packet* for all of the observations of the data set.

Table D.1 Data Used to Compute the *Complexity Factor*

Observation	Average # of Preprints/Packet	# of Production Zones	Observation	Average # of Preprints/Packet	# of Production Zones
1	2.19	66	21	4.72	123
2	2.86	94	22	3.58	128
3	2.49	89	23	4.67	133
4	3.47	103	24	4.12	133
5	2.36	86	25	3.76	134
6	3.34	130	26	4.42	136
7	3.50	116	27	4.45	150
8	3.45	124	28	4.61	165
9	4.26	156	29	3.69	153
10	3.88	126	30	4.57	145
11	5.28	157	31	4.39	160
12	5.34	170	32	5.08	179
13	5.79	192	33	4.52	171
14	4.87	157	34	5.34	174
15	5.18	167	35	4.81	175
16	4.41	155	36	5.40	158
17	5.43	145	37	5.86	209
18	5.72	163	38	4.31	159
19	5.21	135	39	6.51	186
20	4.28	127	40	8.06	184
			41	10.29	213

[6] The average batch size of each production zone was also considered to affect the complexity of production. This variable was not included in the calculation of the *complexity factor* because no measure was found for it.

The first step in computing the complexity factor consists in multiplying the average number of preprints per packet by the number of production zones for each observation. This value is then divided by the base value of both the average number of preprints per packet and the number of production zones. The following equation illustrates this first step to creating the *initial complexity factor.*

$$Initial\ CF = \frac{average\ \#\ of\ preprints\ /\ packet}{Base\ average\ \#\ of\ preprints\ /\ packet} \times \frac{\#\ of\ production\ zones}{Base\ \#\ of\ production\ zones} \qquad \text{(D.1)}$$

The base value for the *average number of preprints per packet* was calculated by taking the average of the *average number of preprints per packet* for all the observations. This base *average number of preprints per packet* was found to be 4.65. The base value for the *number of production zones* was calculated by taking the average of the *number of production zones* for all the observations. This base *number of production zones* was found to be 147.

This *initial complexity factor* was found to have a large deviation from its mean. A frequency diagram for this *initial complexity factor* is shown in figure D.1.

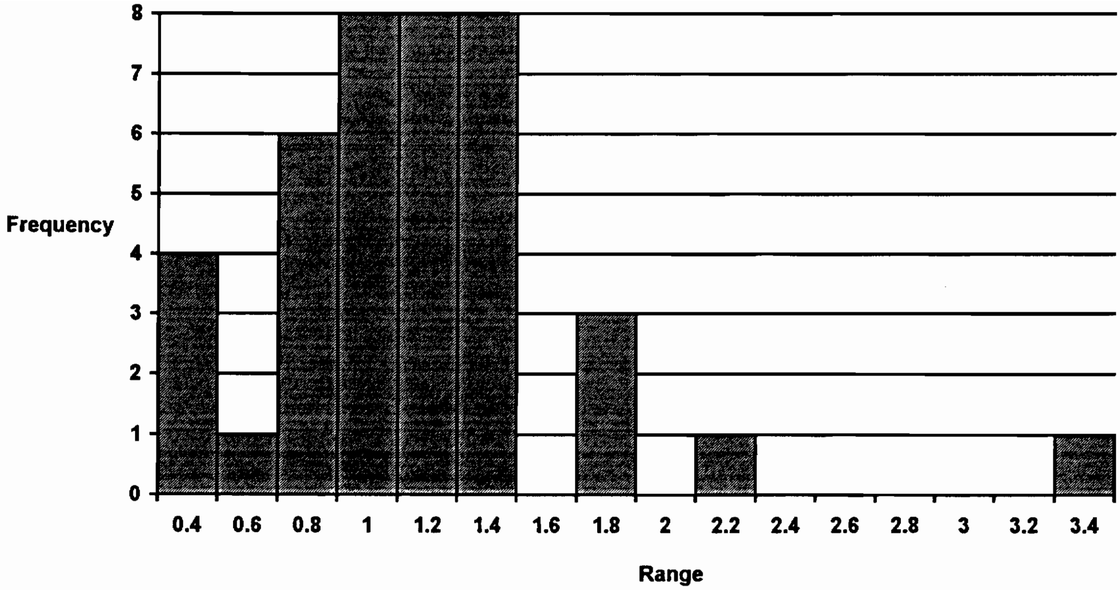

Figure D.1 Frequency Diagram of Initial Complexity Factor

This large deviation does not provide an accurate interpretation of the actual complexity of production. Evaluation of the NPIP indicates that the complexity of production does not fluctuate so widely between 0.4 and 3.4. For this reason, the natural logarithm function was applied to this *initial complexity factor* to reduce the deviation of the *complexity factor*. The equation used to compute the final *complexity factor* is formulated as follows:

$$CF = \frac{Ln\left(\dfrac{average\ \#\ of preprints\,/\,packet}{Base\ average\ \#\ of preprints\,/\,packet} \times \dfrac{\#\ of production\ zones}{Base\ \#\ of production\ zones}\right)}{Average\ numerator\ value} \qquad \text{(D.2)}$$

The *average numerator value* was included in the equation to obtain a *complexity factor* that deviates around the mean of one. Table D.2 contains all the values of the *complexity factor*.

Table D.2 Complexity Factor Values

Observation	Initial CF†	Natural Log CF	Final CF*
1	0.212	4.975	0.765
2	0.393	5.593	0.861
3	0.324	5.402	0.831
4	0.523	5.880	0.905
5	0.296	5.311	0.817
6	0.636	6.075	0.935
7	0.594	6.006	0.924
8	0.625	6.058	0.932
9	0.972	6.500	1.000
10	0.716	6.193	0.953
11	1.212	6.720	1.034
12	1.327	6.810	1.048
13	1.625	7.013	1.079
14	1.118	6.639	1.021
15	1.265	6.763	1.040
16	1.000	6.528	1.004
17	1.151	6.669	1.026
18	1.362	6.837	1.052
19	1.029	6.556	1.009
20	0.795	6.299	0.969
21	0.849	6.363	0.979
22	0.712	6.128	0.943
23	0.929	6.431	0.989
24	0.819	6.305	0.970
25	0.738	6.223	0.957
26	0.847	6.399	0.984
27	0.976	6.503	1.000
28	1.112	6.633	1.021
29	0.826	6.336	0.975
30	0.970	6.497	1.000
31	1.027	6.554	1.008
32	1.331	6.814	1.048
33	1.131	6.651	1.023
34	1.359	6.834	1.051
35	1.230	6.735	1.036
36	1.249	6.750	1.038
37	1.791	7.111	1.094
38	1.001	6.529	1.004
39	1.770	7.099	1.092
40	2.168	7.301	1.123
41	3.204	7.692	1.183

*Note that the average numerator value was found to be 6.5.

† A frequency diagram of the initial complexity factor is included in figure D.1.

Mathematica DEA Application 1.0

■ MODULE 1 Introduction and Requirements

This Mathematica Notebook has been developed to analyze data using the Data Envelopment Analysis Model. This Notebook requires the user to have available a file containing the data set of input and output parameters of the system. The data must saved in ASCII format and contain the complete data set for the observations (Decision Making Units) to be modelled. The file must have the following characteristics:
Columns- outputs and inputs, all output columns preceeding input columns;i.e. y1 then y2 then x1 x2 x3 columns and so forth.
Rows- Observations(DMUs).
It requires to have these characteristics:

1	4	6
2	5	7
2	4	7

In the following section you will be asked to enter the appropiate information necessary to run the model. You must make sure that the parameters you enter are correct, because the model will give wrong results if the parameters are not entered correctly.

MODULE 2 Specification and Reading of Input Data File

Specifying Input Parameters

```
$PrePrint = Short[#,2]& ;
Input["How many outputs?"];
out = %
Input["How many inputs?"];
in = %
Input["How many observations?"];
obs = %
Input["Input a value for Sigma?"];
sig = %
```

Reading the Data File

```
InputString["Please type in the complete
file name along with the directory where
the file is located.  i.e.  c:\data\datafile.dat"];
filename = %
OpenRead[filename]
```

Creating Variables and giving them test values

```
datamatrix =Do[
        Do[ (y[i,k] = Read[filename,Number]),{i,out}];
        Do[ (x[j,k] = Read[filename,Number]),{j,in}]
        ,{k,obs}]
```

MODULE 3 DEA Models

■ Input Reducing Model (IRM)

□ Array of Constraints

```
Do[ ineqIRM[i] = Sum[ z[j] x[i,j],{j,obs}] <= theta x[i,l]
                ,{i,in}]
Do[ ineqIRM[i+in] = Sum[ z[j] y[i,j],{j,obs}] >= y[i,l]
                    ,{i,out}]
ineqIRM[in+out+1] = Sum[ z[j],{j,obs}] == 1
Do[ ineqIRM[in+out+1+i] = z[i]>=0,{i,obs}]
ineqIRM[in+out+1+obs+1] = theta >= 0;
            Print[ineqIRM[in+out+1+obs+1]]
```

□ Array of Variables

```
allIRM[1]= theta
Do[allIRM[1+i]= z[i],{i,obs}]
```

□ Efficiency Calculations

```
Do[effIRM[l]=
ConstrainedMin[ theta,
            Array[ineqIRM,in+out+1+obs],
            Array[allIRM,1+obs]];
            Print[l];Print[effIRM[l]],{l,obs}]
```

■ Output Increasing Model (OIM)

□ Array of Constraints

```
hello =Do[ ineqOIM[i] = Sum[ z[j] x[i,j],{j,obs}] <= x[i,1];
                    Print[ineqOIM[i]],{i,in}]

Write[the_outfile,hello];Close[the_outfile]
Do[ ineqOIM[i+in] = Sum[ z[j] y[i,j],{j,obs}] >=
                                      thetaOIM y[i,1];
                    Print[ineqOIM[i+in]],{i,out}]
ineqOIM[in+out+1] = Sum[ z[j],{j,obs}] == 1;
                       Print[ineqOIM[in+out+1]]
Do[ ineqOIM[in+out+1+i] = z[i]>=0;
                 Print[ineqOIM[in+out+1+i]],{i,obs}]
Array[ineqOIM,in+out+1+obs]
```

□ Array of Variables

```
allOIM[1]= thetaOIM
Do[allOIM[1+i]= z[i];Print[allOIM[1+i]],{i,obs}]
Array[allOIM,1+obs]
```

□ Efficiency Calculations

```
Do[effOIM[l]=
ConstrainedMax[ thetaOIM,
            Array[ineqOIM,in+out+1+obs],
            Array[allOIM,1+obs]];
            Print[effOIM[l]],{l,obs}]
```