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Measuring the Efficiency of Technical Education in UNRWA:

Gaza Training Center (GTC) - Case Study

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Abstract

Data envelopment analysis (DEA) model is a linear programming based technique for measuring the relative performance of organizational units. A common measure for relative efficiency is weighted sum of outputs divided by weighted sum of inputs.

In this research, we present the mathematical background and characteristics of DEA model, and give a short case study on UNRWA-Gaza Training Center where we apply the DEA model to evaluate the relative efficiency of 8 technical diploma programs.

The technical efficiency and scale efficiency are also investigated. Major Courses Hours per week, students per one instructor, allocated budget including consumable supply, minor and major equipment, software and other needed components and number of enrolled students are used for input data. The number of graduates who work in related fields is used as output data. These inputs and outputs are determined through a questionnaire survey for the total population of 8 technical diploma staff members.

The results show that the technical diploma programs with 100% aggregate efficiency is only one which is Business and Office Practice diploma program "BOP". Four technical diploma programs, architecture engineering, banking, business and office practice and communication are technically efficient. The aggregate inefficiency of banking, architecture engineering and communication is caused by scale efficiency. The efficiency analysis not only provides an efficiency score for each technical diploma program but also how much and in what areas an inefficient unit needs to be improved in order to be efficient. The results suggest that 4 technical diploma programs (Civil Engineering, Industrial Electronics, Graphic Design, and Programming & Database) need structural reform to improve their technical efficiency.

Acknowledgement

I would like to thank my supervisor at Islamic University, **Prof. Yousif Ashour** who has provided insight and has had a significant input to my thesis.

I must thank my wife for putting up with my late hours, my spoiled weekends, my bad temper, but above all for putting up with me and surviving the ordeal.

Dedication:

I dedicate this work to the memory of my mother, who sacrificed every thing in her life for me and my brothers so that we can have better future. I also thank her for pushing me to success.

Abbreviations:

Abbreviation	Description
AE	: Architecture Engineering diploma program
BCC	: Banker, Charnes and Copper model
BK	: Banking diploma program
BOP	: Business and Office Practice diploma program
CCR	: Charnes, Copper and Rhodes Model
CE	: Civil Engineering diploma program
COLS	: Corrected Ordinary Least Squares
COMM	: Communication diploma program
DEA	: Data Envelopment Analysis
DMU	: Decision Making Unit
ELECT	: Industrial Electronics diploma program
GD	: Graphic Design diploma program
GTC	: Gaza Training Center
OLS	: Ordinary Least Squares
PDB	: Programming and Database diploma program
SFA	: Stochastic Frontier Analysis
TES	: Technical Education System
TFP	: Total Factor Productivity
UNRWA	: United Nations for Relief and Works Agency

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Chapter 1 General Introduction

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This chapter introduces the problems to be addressed, the research objectives and the research hypothesis in this thesis. This chapter also includes general information of research methodology and the structure of the thesis.

1-1 Background

The special attention, that both governmental authorities and non- profit and international organizations have always paid to the technical education system (TES) Saxena, Wedhwa and Kummar and (2005).

Technical Education System is the key source of knowledge generation for any country. It is an important facilitator of economic development that grows at a much faster rate, create a lot of opportunities but at the same time requires sufficient control over the technical colleges or centers to follow the quality standards of education (Liberatore and Nydick, 1999). TES is facing huge challenges because of constraints in resources such as finance, trained teachers, infrastructure, placement, research development, and costly technologies (Bodin and Gass, 2003).

In addition to these mentioned challenges, the Palestinian people suffer from the Israeli occupation as a main obstacle that faces any development in the field of technical education.

As Israeli occupation already found, UNRWA has delivered its services to Palestinian people. Today, UNRWA is the main provider of basic services- especially in Technical Education sector for the Palestinian refugees in Palestine. Accordingly UNRWA is in need to monitor and evaluate the performance of TES in order to improve the quality of technical education. In practice, UNRWA did not conduct an efficiency study for its educational and training centers.

Different techniques have been applied to study the efficiency of a group of organizations or operating units. The common feature of these techniques is that they all involve setting targets for cost reduction that are independent of the actual cost reduction achieved by the company over the regulatory review period. The methodologies differ in the mathematical techniques, and consequently in their data requirements. The methodologies for efficiency definition are classified into three categories, partial methods, total methods and reference methods. Where total methods are classified into two categories which are frontier analysis and index methods. The frontier analysis methods include parametric and non-parametric techniques where each method has advantages and disadvantages.

Data Envelopment Analysis (DEA) is one of the most widely used approaches because of its sound mathematical basis and non-parametric nature. Under this methodology, the frontier is made up of linear combinations of the best-performing decision making units (DMUs) in the sample.

With respect to the technique used to measure the relative efficiency of educational center, most of studies choose non-parametric approximations and, specifically, DEA (Bates, 1997 or Chakraborty et. al, 2001). The DEA is an effective approach in dealing with this kind of decision problems because of its dependency on the relative ratio of system inputs and outputs. It is capable to determine the best performing programs in the sample.

Therefore, DEA will be greatly suitable to conduct this study in order to find out the efficiency scores of technical diploma programs and to identify the best performers.

1-2 Data Envelopment Analysis (DEA):

The study uses DEA approach to analyze data. In light of the point made in the introduction for this research, it was essential to use a methodology that could asses and compare efficiency among eight technical diploma programs.

The other reasons for use of DEA as an analysis tools are what it has the flexibility in handling multiple input and output measures, which are essential in this study.

The basic requirement for using DEA is identifying inputs and outputs variables in order to measure the relative efficiency, where it is difficult to identify these inputs and outputs (Worthington 2001).

This research attempts to systematically measure the efficiency and draw recommendations for developing and improving the TES at UNRWA through the Gaza Training Center (GTC) Technical Diploma Programs as a case study. This research will measure the efficiency of GTC Technical Diploma Programs based on DEA as a measurement technique.

1-3 Objectives:

This research primarily focuses on application of DEA technique for evaluating the efficiency of eight technical diploma programs. The research has the following objectives:

- To determine the quantitative input and output variables of TES at UNRWA-GTC.
- To apply the DEA models in order to find the efficiency scores of TES at UNRWA-GTC.
- To identify the best performers of UNRWA-GTC technical diploma programs.
- To identify the inefficient diploma programs in order to specify the potential improvements that can be applied on the inefficient technical programs' inputs and outputs.

1-4 Research Methodology:

The study of technical education efficiency comprised of several stages in which a step-by–step move towards data collection and data analysis took place. The various stages or steps involved in conducting this research are outlined in Figure 1.1:

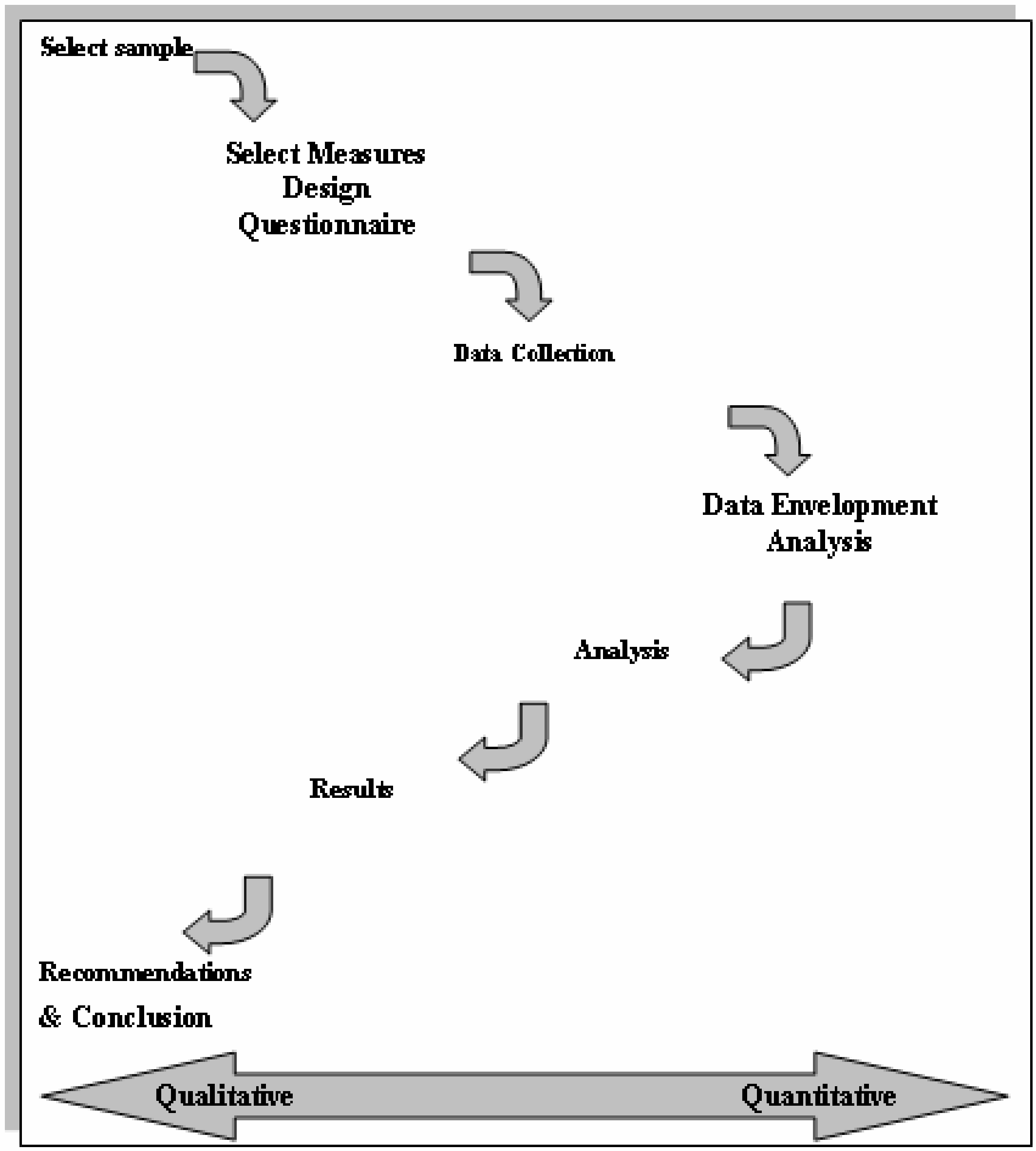

Figure 1.1: Steps involved in study of UNRWA Technical Education

The investigation involves the following steps:

First, technical diploma programs were identified which would form the sample for this study. The sample for this study consists of eight Technical diploma programs which have at least two groups of graduates.

Second, conducting interviews with senior instructors and managers to identify parameters (inputs and outputs) to be measured.

Third, a detailed questionnaire was prepared using the input of measures from the interview with seniors. Seniors suggested major courses' hours per week, allocated budget, number of students per instructor, number of enrolled students, student grades, student's attendance record and instructor's salary as input variables. They suggested number of graduates, number of graduates work in related fields and worked graduate's salary as output variables. The questionnaire is filled by managers, senior instructors and instructors as well. The different sections of questionnaire are explained in Appendix A.

Fourth, setting the inputs and outputs variables according to questionnaire analysis (See Appendix B and Appendix C).

Fifth, collecting input and output data through conducting an interview with senior instructors and head of alumni department.

Sixth, applying DEA method to calculate the efficiency score, Frontier analyst software is used as the mathematical programming and optimization tool.

Seventh, discussing the efficiency analysis results

Lastly, drawing recommendations and conclusion.

Research Sample:

The sample consists of eight Technical diploma programs with at least two groups of graduates (see Table1.1).

Table 1.1: Technical diploma programs of two groups of graduates

No	Diploma program	Type Of Study
1.	Programming & database	Technical
2.	Business and office practice	Technical
3.	Banking	Technical
4.	Industrial Electronics	Technical
5.	Communication	Technical
6.	Graphic Design	Technical
7.	Civil Engineering	Technical
8.	Arch. Engineering	Technical

1-5 Organization of the thesis

This thesis is organized into five chapters:

Chapter one introduces the problems to be addressed and the research objectives in this thesis. This chapter also includes general information of research methodology and the structure of the thesis.

Chapter two provides background introduction of UNRWA-GTC technical and vocational education system , and an overview of the current issues related to efficiency studying in general and specially DEA as a tool for efficiency measurement.

Chapter three describes how to apply DEA to calculate the efficiency score of GTC technical education system, and the analysis of the factors which may be associated with the efficiency score.

Chapter four explains how DEA calculates the relative efficiency using CCR and BCC model, and explains the aspects of frontier analysis software.

Chapter five summarizes and discusses the results of this study.

1-6 Frontier Analyst Software:

The study uses the software package called *frontier analyst* as an efficiency analysis tools. *Frontier analyst* is a windows based efficiency analysis tool, which uses a technique called DEA to examine the relative performance of organizational units, which carry out similar functions. It is, therefore suited for use in organizations which operate through a system of outlets (such as retail outlets, banks, and so on) and for use with public sector or "not for profit" organizations, such as hospitals, schools, and other "unit based" public sector organizations.

As part of the analysis, the inputs (resources) and outputs (products) associated with business process are identified. These variables are classified as controlled and uncontrolled variables. A ratio of output over input is calculated across all of the variables, which results in an efficiency score for each of the units being analyzed. The comparison is peer based and so the potential improvements identified for inefficient units should be realistic and achievable.

Regarding our research, we will use the frontier analyst software to find out the efficiency scores of the eight technical diploma programs, and to obtain the target changes in inputs and outputs in order to make the inefficient DMU be efficient.

Chapter 2 Literature Review

Chapter 2 Literature Review

This chapter provides a detailed literature review on two topics related to the subject of current research. The first section provides a background description of UNRWA GTC vocational and technical diploma programs.

The second section provides an overview of the current issues related to efficiency studying in general and specially DEA as a tool for efficiency measurement.

2-1 Gaza Training Center's technical education system:

Gaza Training Center (GTC) is the second largest of UNRWA's eight Technical and Vocational Training Centers, and the largest one in Gaza Strip. It was inaugurated in 1953 in order to provide Technical and vocational diploma programs in several field of education.

GTC began its first journey in 1953 with one trade course (Auto Mechanic) and then new courses were added bringing the number to 14 trade courses and 17 technical courses. These courses were designed to meet the impending demand of the Arab market for skilled manpower. The trade and semi-professional courses offered at GTC are of two years' duration, and classified as follows:

a. Vocational Training Courses (Trade courses):-

1. Diesel and Con. Equip. Mech.
2. Auto Mechanics.
3. Auto Body Repair.
4. Refrigeration and Air Conditioning.
5. Plumber and Central Heating.
6. Auto Electrical Systems.
7. Smithery & Welding.
8. Machining/ Welding and Aluminum Fabrication.
9. General Electrical installations.
10. Radio/TV Maintenance.
11. Office Equipment and Computer Maintenance.
12. Building Finishing Decoration.
13. Building Const. Craftsmanship.
14. Carpenter & Furniture Making.

The academic requirements for the 14 trade courses are the successful completion of the third prep. class i.e., (9 years of schooling) and first secondary class (10 years of schooling).

b. Semi-Professional Courses (Technical Courses):

1. Business and Office Practice.
2. Banking and Financial Management.
3. Commerce & Trade.
4. Executive Secretary.
5. Programming and Data Base.
6. Computer Technology.
7. Industrial Electronics & Computer Technology.
8. Telecommunication.
9. Electro Mechanic Engineering.
10. Marine Engineering.
11. Civil Engineering.
12. Architecture Engineering.
13. Dress Making.
14. Graphic Design.
15. Food Processing Technology.
16. Safety & Hygiene.
17. Physiotherapy.

The statistics of technical diploma's graduates at GTC including our study sample since 1991 are provided in Appendix D.

As UNRWA-GTC seeks to provide distinguished technical and vocational education and training that would prepare qualified graduates to have job opportunities available in the labor market and would help achieve decent living for the Palestine refugee society. It provides a free of charge education and delivery.

GTC aims to improve and optimize vocational and technical education for young Palestine refugees to increase their employability and access to the labor market.

Our study will discuss the technical efficiency of the technical diploma programs at UNRWA- GTC.

In order to explore the level of input resource utilization to produce the needed output.

Accordingly, our study identifies the needed inputs and outputs that can be used in the education or the training process.

2-3 Efficiency

A wide range of efficiency measurement methodologies is available. The common feature of these techniques is that they all involve setting targets for cost reduction that are independent of the actual cost reduction achieved by the company over the regulatory review period. The methodologies differ in the mathematical techniques, and consequently in their data requirements. In Coelli (2004) regarding the techniques that are used in measuring the efficiency, we briefly describe different techniques that can be used in efficiency analysis:

a. Partial methods :

Partial (uni-dimensional) measures of performance (performance indicators), such as minutes lost per customer, is the simplest way to perform comparisons between different companies. The main drawback of uni-dimensional measures is that they fail to account for the relationships between different input and output factors.

b. Index methods

Index Methods use index-based techniques to aggregate input and output variables of the company. Total Factor Productivity (TFP) is an index of the ratio of all output quantities (weighted by revenue shares) and all input quantities (weighted by cost shares). Index number theory is used to overcome the different nature of variables

c. Non-Parametric Frontier methods

Frontier methods are based on the concept that, given a certain sample, all companies should be able to operate at an optimal efficiency level that is determined by other efficient companies in the same sample. These efficient companies are usually referred to as the “peer firms” and determine the “efficiency frontier”. The “efficiency frontier” is formed from the observed performance of the companies in the analyzed sample, as determined by the relationships between the inputs and outputs of the sampled units. The companies that form the efficiency frontier use the minimum quantity of inputs to produce the same quantity of outputs. The "efficiency frontier" is used as a yardstick against which the comparative performance of all other companies (that do not lie on the frontier) is measured. The distance to the efficiency frontier provides a measure for the (in) efficiency. Frontier methods can be divided into non-parametric and parametric methods. Non-parametric methods do not impose any functional form on the relationship between inputs and outputs. The most used non-parametric approach is Data Envelopment Analysis(DEA). Under this methodology, the frontier is made up of linear combinations of the best-performing companies in the sample

d. **Parametric Frontier methods**

Parametric methods impose a functional form on the frontier using estimation for production or cost functions. They require more knowledge about the production or cost functions and also about the distribution of errors. However, to test for the validity of the assumptions and to fine-tune the weight assigned to each variable, a large number of networks are required. Parametric frontiers could be estimated by some variant of Ordinary Least Squares (OLS) or by Corrected Ordinary Least Squares (COLS). Under OLS, the frontier is based on the average cost function while COLS tightens the criterion and shifts the frontier towards the best performing company. Stochastic Frontier Analysis (SFA) attempts to estimate an efficient cost frontier that does incorporate the possibility of measurement error or chance factors in the estimation of the efficient frontier. This method first allows for the adjustment of individual costs for stochastic factors and then calculates efficiency scores in a way similar to COLS. The efficiency scores are usually higher than under the COLS method precisely because the most efficient company under COLS will be assumed to be subject to some negative stochastic factor affecting its actual costs. While this method incorporates stochastic factors, it still requires the specification of a functional form for the efficient frontier. It further requires the specification of a probability function according to which stochastic errors are distributed.

Efficiency is one of the most popular topic when studying TES Wedhwa, Kummar and Saxena(2005). By simple definition, efficiency is the measure of how much output generated compared to the input.

Efficiency= weight of outputs/weight of inputs

Generally, efficiency can be categorized into two groups:

1 Technical Efficiency: Technical efficiency means producing maximum output with given inputs; or equivalently, using minimum inputs to produce a given output.

2 Economic Efficiency: Economic efficiency measures producing maximum value of output with given value of inputs; or equivalently, using minimum value of inputs to produce a given value of output.

Technical efficiency is measured by the relationship between the physical quantities of output, and economic efficiency is measured by the relationship between the value of the output and the value of the input. Using technical efficiency, there is always relative efficiency score. When the system is called inefficient, there is claiming that the desired output could be achieved with less input, or that the input employed could produce more of the output desired. When examining the economic efficiency, the value of output over the value of input can get an absolute efficiency score. Economic efficiency can help to examine profitability for an investment better than technical efficiency.

Since the purpose of this study is to improve the productivity of technical education diploma programs at UNRWA-GTC, the research focuses on the technical efficiency and economic efficiency will not be discussed. The following section provides a detailed introduction on technical efficiency.

2-2-1 Technical Efficiency Measurements:

There are two main approaches used to measure technical efficiency, parametric and non-parametric frontier approaches. The parametric/ econometric frontier approach (Aigner and Chu, 1968; Aigner et al., 1977; Meeusen and van den Broeck, 1977) specifies a functional form for the cost, profit, or production relationship among inputs, outputs, and environmental factors, and allows for random error. Both the inefficiencies and the random errors are assumed to be orthogonal to the input, output, or environmental variables specified in the estimating equation. The sensitivity of efficiency estimates to misspecification has been demonstrated using Monte Carlo simulations, where both the true functional form of the technology and the distribution of efficiency across observations are known (Gong and Sickles 1992; Banker, Gadh, and Gorr 1993). From these studies, researchers found out that parametric approaches are best applied to industries with well-defined technologies to minimize the risk of misspecification. For industries with imprecise technologies, such as the service sector, non-parametric approaches are more flexible and could be more desirable to use (Charnes, Cooper, Rhodes 1978).

DEA is a non-parametric frontier approach, which begins with Farrell (1957) who drew upon the work of Debreu (1951) and Koopmans (1951) to define a simple measurement of efficiency that could account for multiple inputs. The DEA frontier is formed as the piecewise linear combinations that connect the set of best practice observations, yielding a production possibilities set. DEA does not require the explicit specification of the form of the underlying production relationship. As a non-parametric approach, however, DEA does not allow for random error. If random error exists, measured efficiency may be confounded with these random deviations from the true efficiency frontier.

As well, statistical inference and hypothesis tests cannot be conducted for the estimated efficiency scores.

Bootstrap methods may be used to resolve some of these problems. A detailed discussion on DEA is provided in the following section.

2-2-2 DEA Method

DEA is commonly used to evaluate the efficiency of a group of producers (also called decision making units or DMUs) such organizations, firms, departments or operating units. A typical statistical approach evaluates producers relative to an average producer. In contrast, DEA is an extreme point method which compares each producer with only the "best" producers. A fundamental assumption behind an extreme point method is that if a given producer, A, is capable of producing Y(A) units of output with X(A) inputs, then other producers should also be able to do the same if they were to operate efficiently. Similarly, if producer B is capable of producing Y(B) units of output with X(B) inputs, then other producers should also be capable of the same production schedule. Producers A, B, and others can then be combined to form a composite producer with composite inputs and composite outputs. Since this composite producer does not necessarily exist, it is sometimes called a virtual producer.

The heart of the DEA technique lies in finding the "best" virtual producer for each real producer. If the virtual producer is better than the original producer by either making more output with the same input or making the same output with less input then the original producer is *inefficient*. Some of the subtleties of DEA are introduced in the various ways that producers A and B can be scaled up or down and combined.

The procedure of finding the best virtual producer can be formulated as a linear program.

Assume there are data on k inputs (denoted by the vector x_i) and m outputs (denoted by the vector y_i) on each of N firms DMUs. The k*n input matrix, X, and the m*n output matrix, Y, represent the data of all N DMUs. The purpose of DEA is to construct a non-parametric envelopment frontier over the data points such that all observed points lie on or below the production frontier. For the simple example of an industry where one output is produced using two inputs, it can be visualized as a number of intersecting planes forming a tight cover over a scatter of points in two-dimensional space. To measure technical efficiency, one has to solve the following linear programming problem for each DMU_j, j = 1; . . . ;N (Charnes et al., 1978; Fare et al., 1985):

$$Max\,\theta = \frac{\sum_{r=1}^{m} u_r y_{r0}}{\sum_{i=1}^{k} v_i x_{i0}} \tag{2-1}$$

$$\text{Subject to } \frac{\sum_{r=1}^{m} u_r y_{rj}}{\sum_{i=1}^{k} v_i x_{ij}} \leq 1 \quad \text{for each DMU in the Sample,}$$

$$j = 1, \ldots, N \quad u_r > 0, v_i > 0$$

where m is the number of outputs; u_r is the weight of output r; y_{r0} is the amount of output r produced by the DMU evaluated; k is the number of inputs; v_i is the weight of input i; and x_{i0} is the amount of input i used by the DMU. The value of θ obtained will be the efficiency score for the ith DMU. It will satisfy$\theta \leq 1$, with a value of 1 indicating a point on the frontier and hence a technically efficient DMU, according to the Farrell (1957). Note that the linear programming problem must be solved N times, once for each DMU in the sample. A value of θ is then obtained for each DMU.

2-2-3 Organizational efficiency and DEA

The focus of efficiency analysis is as an organizational locus of production, often referred to as a decision-making unit (DMU). In this study, the DMU is assumed usually to be the school, although there may be circumstances when the Local Authority (LA) is the organization under scrutiny. The DMUs consume various costly inputs (labor, capital, etc.) and produce valued outputs. Efficiency analysis is centrally concerned with measuring the competence with which inputs are converted into valued outputs. In general, it treats the organization as a black box, and does not seek to explain *why* it exhibits a particular level of efficiency (Fried et al., 1993).

The terms ”productivity‘ and ”efficiency‘ are often used interchangeably, which is unfortunate since they are not precisely the same thing. Productivity is the ratio of some (or all) valued outputs that an organization produces to some (or all) inputs used in the production process. Efficiency incorporates the concept of the production possibility frontier, which indicates feasible output levels given the scale of operation. Thus the concept of productivity may embrace but is not confined to the notion of efficiency.

A starting point for examining the basic notion of efficiency is shown in Figure 2.1, which illustrates the case of just one input and one output. The line OC indicates the simplest of all technologies: no fixed costs and constant returns to scale. A technically efficient organization would then produce somewhere on this line, which can be thought of as the production possibility frontier. Any element of inefficiency would result in an observation lying strictly below the line OC. For an inefficient organization located at P0, the ratio X_0P_0/ X_0P_0* offers an indication of how far short of the production frontier it is falling, and therefore a measure of its efficiency level.

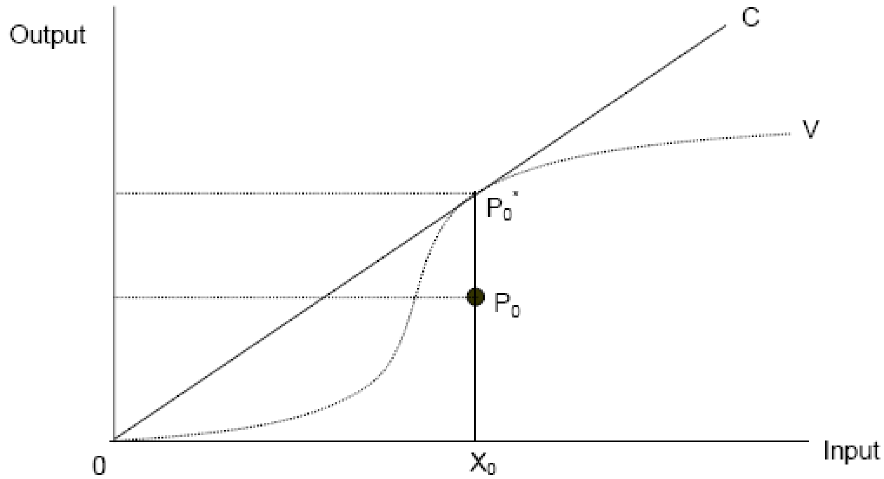

Figure 2.1:Efficiency measurement under constant returns to scale

Many other technologies are possible. For example, the curve OV indicates a frontier with variable returns to scale. Up to the point P_0^*, the ratio of output to input decreases (increasing returns to scale), thereafter it increases (decreasing returns to scale).

The notion of a production frontier can be extended to multiple outputs and a single input (say, costs). Figure 2.2 illustrates the case with two outputs. For the given technology, the isocost curve CC gives the feasible combination of outputs that can be secured for a given input. At a higher level of costs the isocost curve moves out to C'C'. These curves indicate the shape of the production possibility frontiers at given levels of input. An inefficient DMU lies inside this frontier. We define the marginal rate of transformation to be the sacrifice of output 2 required to produce a unit of output 1, indicated at any particular point on CC by the slope of the curve −

(P_2/P_1). It is usually assumed that - as in Figure2.2 - for a given level of input the slope becomes steeper as the volume of output 1 produced increases.

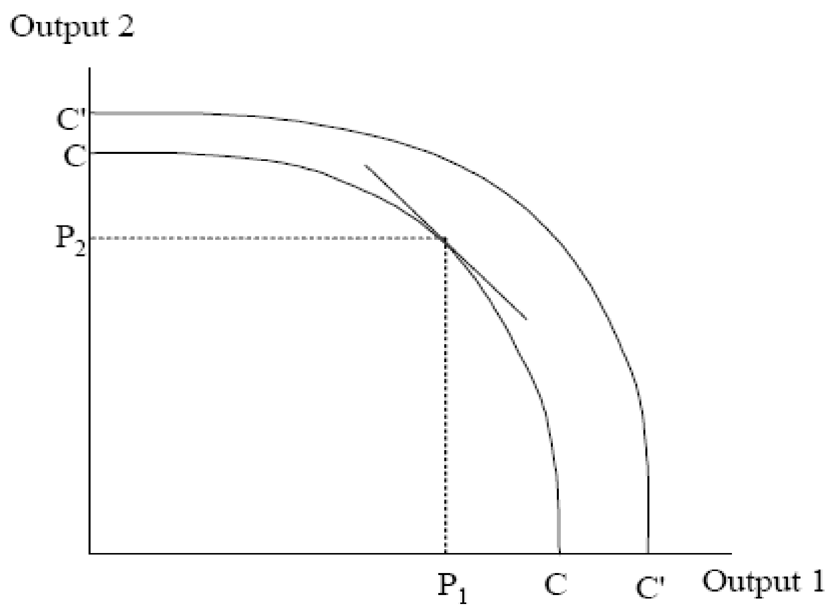

Figure 2.2: The case of two outputs

Likewise in input space we examine the case of two inputs and one output, as in Figure 2.3. The isoquant QQ indicates the feasible mix of inputs that can secure a given level of output, with inefficient DMUs lying beyond this curve.

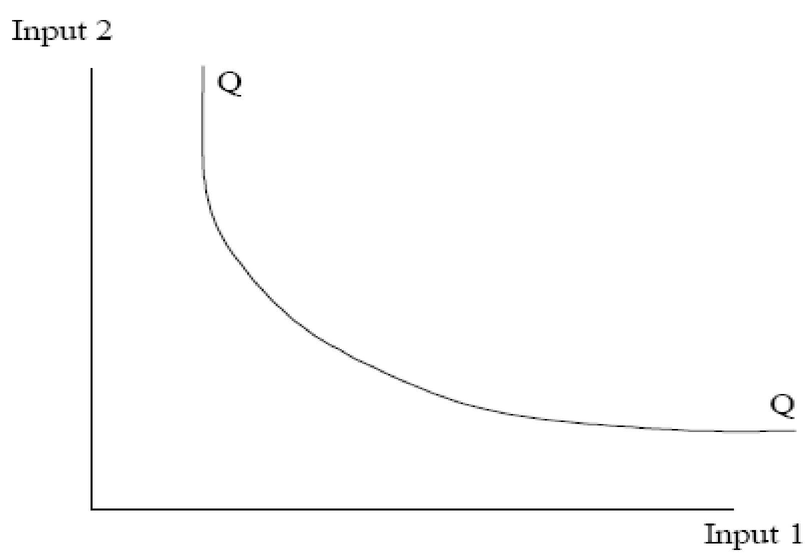

Figure 2.3: The case of two inputs

Extending the analysis to the general case of multiple inputs and multiple outputs, we define the overall efficiency *eff0* of organization zero to be the ratio of a weighted sum of outputs to a weighted sum of inputs. Mathematically, if organisation 0 consumes a vector of *m* inputs $\mathbf{X_0}$ and produces a vector of *s* outputs $\mathbf{Y_0}$, its overall efficiency is measured by applying weight vectors **U** and **V** to yield:

$$eff_0 = \frac{\sum_{s=1}^{S} U_s Y_{s0}}{\sum_{m=1}^{M} V_m X_{m0}} \qquad \textbf{(2.1)}$$

where:

$Ys0$ is the amount of the s^{th} output produced by organization 0;

Us is the weight given to s^{th} output;

$Xm0$ is the amount of the m^{th} input consumed by organization 0;

Vm is the weight given to the m^{th} input.

The weights U and V indicate the relative importance of an additional unit of output or input. On the input side, the weights V might reflect the relative market prices of different inputs. It is often the case that - with the notable exception of capital inputs - these can be measured with some accuracy. Then, if the actual input costs incurred by organization 0 are C_0, the ratio:

$$Ceff_0 = \frac{\sum_{m=1}^{M} V_m X_{mi0}}{C_0} \qquad \textbf{(2.2)}$$

indicates the extent to which the organization is purchasing its chosen mix of inputs efficiently (that is, the extent to which it is purchasing its chosen inputs at lowest possible prices).

However, the organization may not be using the correct mix of inputs. This can be illustrated using a simple two input model. For some known production process, the isoquant QQ in Figure 2.4 shows the use of minimum inputs required to produce a unit of a single output. The points P_1 and P_2 lie on the isoquant and therefore - given the chosen mix of inputs - cannot produce more outputs.

When the unit costs of inputs are known, it is possible to examine the input price (or allocative) efficiency of the two units. Suppose the market prices are V_1^* and V_2^*. Then the cost minimizing point on the isoquant occurs where the slope is $-V_1^*/V_2^*$ (shown by the straight line BB). In Figure 2.4 this is the point P_1, which is input price efficient. However, although technically efficient, the point P_2 is not efficient with respect to prices, as a reduction in costs of $P_2P_2^*$ is possible. The price efficiency of P_2 is therefore given by the ratio OP_2^*/OP_2.

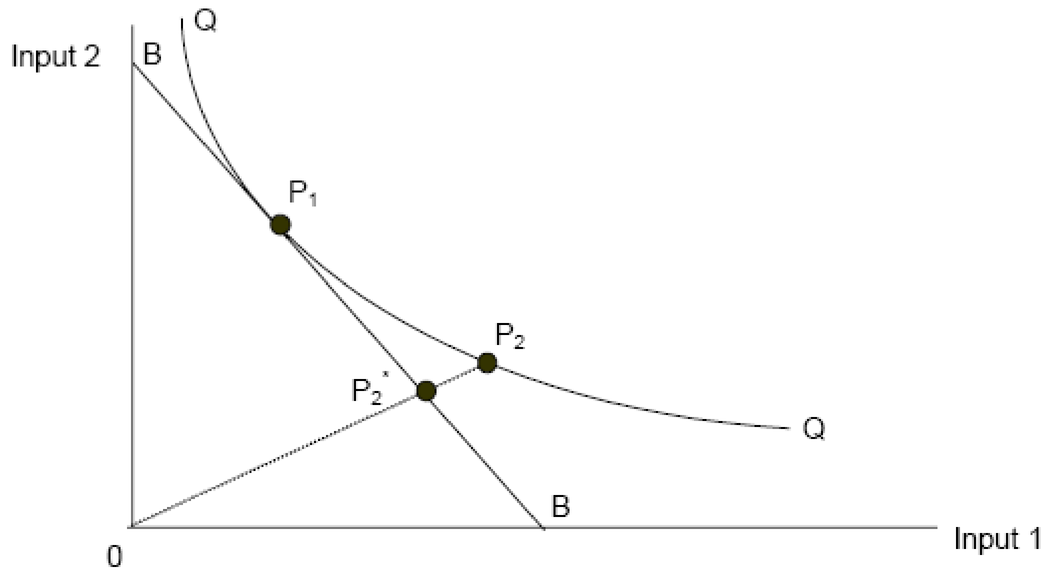

Figure 2.4: Allocative efficiency with two inputs

Analogous arguments can be deployed to examine the allocative efficiency of organizations in output space. Figure 2.5 illustrates the case where a single input is used to produce two outputs. If the relative values U_1 and U_2 of the outputs are known, and the production possibilities are given by the curve CC, then organization P_1 is producing at its allocatively efficient point while organization P_2 exhibits some allocative inefficiency.

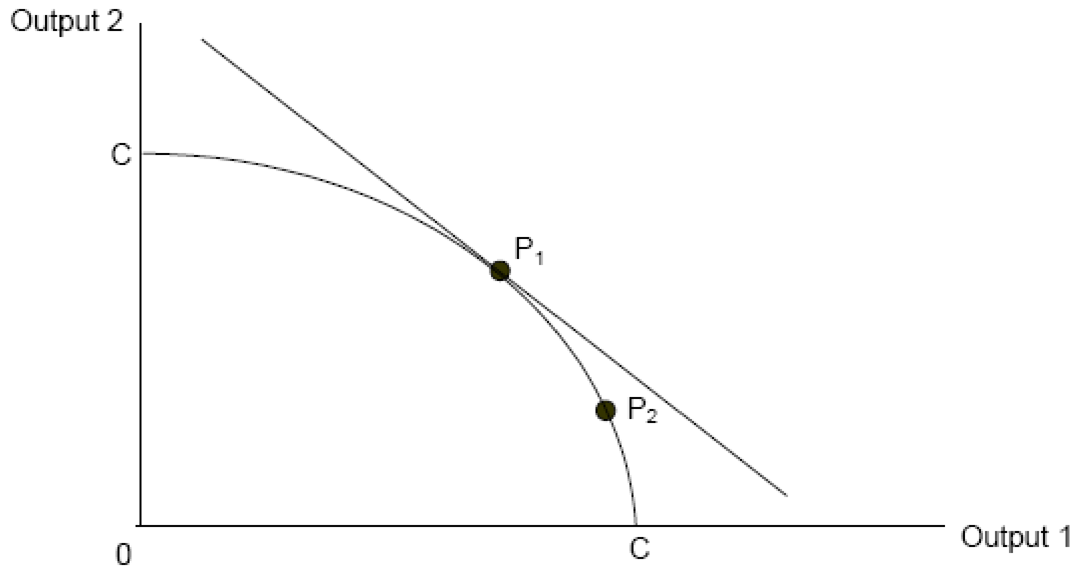

Figure 2.5: Allocative efficiency with two outputs

Although organizations may exhibit allocative inefficiency in purchasing the wrong mix of inputs or producing the wrong mix of outputs, we have so far explored only those organizations that lie on the frontier of technical production possibilities. However, it is likely that, particularly in a non-market environment, many organizations are not operating on the frontier. That is, they also exhibit an element of technical inefficiency (also referred to as managerial inefficiency or X-inefficiency).

This is illustrated in Figure 2.6 by the points P_3 and P_4. Organization P_3 purchases the correct mix of inputs, but lies inside the isoquant QQ. It therefore exhibits a degree of technical inefficiency, as indicated by the ratio OP_1/OP_3. Organization P_4 both purchases an incorrect mix of inputs and lies inside the isoquant QQ. Its technical inefficiency is indicated by the ratio OP_2/OP_4. Thus its overall level of inefficiency OP_2^*/OP_4 can be thought of as the product of two components: technical inefficiency OP_2/OP_4 and allocative inefficiency OP_2^*/OP_2.

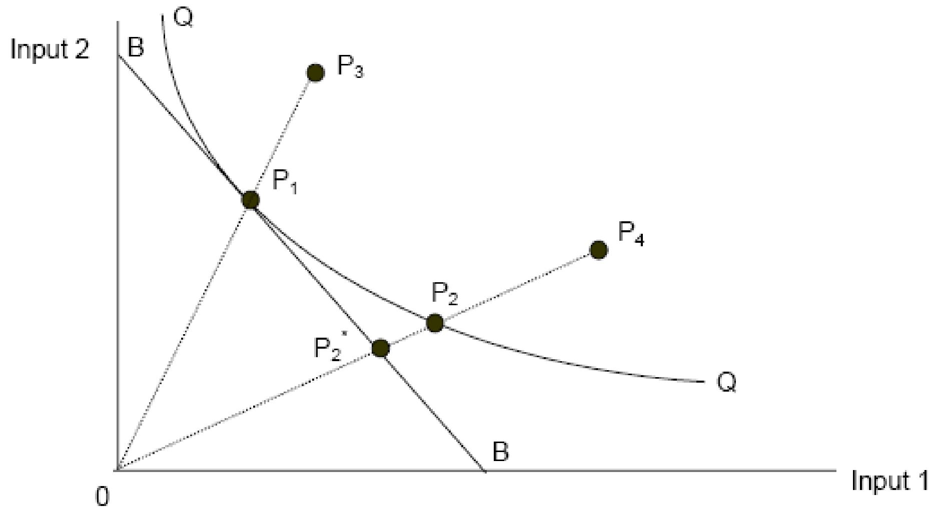

Figure 2.6: Technical and Allocative inefficiency

Weight restrictions and cross-efficiency models

There are important questions relating to the objectives encompassed by any index of efficiency. Is it legitimate for the central policy maker to attach a uniform set of objectives to all organizations? If so, is it further legitimate to apply a uniform set of weights to these objectives? If so, how should they be chosen? If not, what is the extent of legitimate variation, and who should choose? These are fundamental issues, the answers to which determine whether or not creating a single measure of organizational performance is warranted. In our view, organizations can be ranked in this way only if the policy maker may legitimately (a) set objectives and (b) attach weights to those objectives.

When considering organizations working in the public sector, the set of output weights ought to reflect societal values. However it is not a simple matter to derive such weights, particularly when organizations face multiple objectives and there is disagreement as to organizational priorities. Ultimately the selection of objectives in the public services is a job for the politicians charged with reconciling conflicting claims on public resources. The main role for analysts is to clarify the choices required of policy makers, to provide evidence on popular preferences, and to develop measurement instruments that most faithfully reflect the chosen objectives. Note that policy makers are effectively attaching a zero weight to any output that is excluded from the efficiency index.

In principle, the set of weights to be used in an efficiency index could be derived from a range of sources, such as economic studies of willingness to pay or conjoint analysis. However, rather than being externally agreed upon, in most efficiency analysis studies the weights are generated as a by-product of the statistical estimation process. Indeed, some see this as an attractive feature of the methods (Cooper et al., 2000).

When undertaking econometric analysis, it is not a trivial matter to take account of multiple outputs. Approaches include the creation of a single index of outputs, estimation of a cost rather than production function, or the use of distance functions (Coelli and Perelman, 2000, Lothgren, 2000, Shephard, 1970). Irrespective of the approach, the estimated magnitude of the weight for each output usually corresponds to the value implicit in the sample mean cost of producing an additional unit of output. Using a linear model, the weight attached to an output indicates the value of an additional unit of that output, which remains constant for all levels of attainment of the output. If a logarithmic model is used, the weight indicates the percentage increase in attainment implied by a one percent increase in the output. Hence the econometric approach is conservative in the sense that it implies that the existing output choices of organizations (on average) reflect the values placed by society on the outputs. If this is not true, the estimated weights will not be appropriate.

In conventional DEA both input and output weights are allowed to vary freely, so that each organization is evaluated in the best possible light. Indeed one quite frequently finds in unconstrained DEA that the highest efficiency score for an organization can be secured simply by assigning a zero weight to one or more outputs on which it performs poorly. In order to understand the role played by weights in DEA it is useful to examine the simple two input model (Figure 2.7). For some known production process, the isoquant QQ shows the use of minimum inputs required to produce a unit of output, assuming constant returns to scale. The points P^* and PT lie on the isoquant and are therefore efficient in Farrell's technical sense.

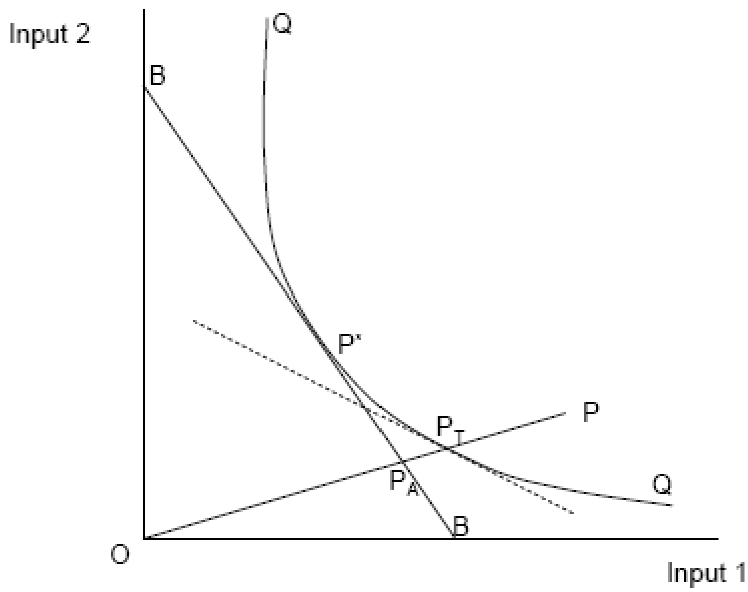

Figure 2.7: Fixed and variable weights

However, when the unit costs of inputs are known, it is possible in addition to examine the input price (or allocative) efficiency of the two units. Suppose the costs are C_1^* and C_2^*. Then the cost minimizing point on the isoquant occurs where the slope is $-C_1^*/C_2^*$ (shown by the straight line BB). In Figure 2.7 this is the point P^*, so that point is also allocatively efficient. However, the point P_T is not efficient with respect to prices, as a reduction in costs is feasible. The price efficiency of P_T is therefore given by the ratio OP_A/OP_T. The DMU represented by point P also exhibits technical efficiency, indicated by the ratio OP_T/OP.

The classical application of DEA places no constraints (other than positivity) on weights, and so allows a DMU's efficiency to be assessed using the weights most favourable to its own circumstances. It therefore yields a measure of technical efficiency. In this example, therefore, DMU P will be evaluated using weights that place the allocatively efficient point of the frontier at P_T rather than P_A. These optimal weights C_1^P and C_2^P for DMU P are represented by the slope of the tangent at the point P_T, indicated by the dotted line with slope $-C_1^P/C_2^P$ in the diagram. Clearly very ”extreme‘ DMUs would favour extreme weights, attaching a zero weight to one or other of the inputs. (Note that the weights can be multiplied by an arbitrary scalar, so it is only the *ratio* of the weights the slope of the dotted line in which we are interested.)

This ”weight flexibility‘ gives rise to a conundrum. If the inputs or outputs given zero weight in the analysis for a particular DMU are important, then the measure of efficiency must surely be deficient in placing no consequence on them. If on the other hand they are not important, then why were they included in the analysis in the first place? It is concerns of this sort that have led to the development of various schemes for placing limits on variations in weights.

By placing constraints on weights, the region of search for those weights is reduced, and so a DMU's efficiency assessment cannot increase, and may decrease. At the extreme, if no flexibility in weights is allowed, DEA becomes classical ratio analysis, in which a unit's efficiency is measured as its ratio of weighted outputs to weighted inputs, with weights equivalent to the known input and output prices. In Figure 2.7, this measure is equivalent to ”overall‘ efficiency, measured relative to other DMUs. Thus, as increasingly severe constraints are placed on weights, so the measure of efficiency derived moves from one of relative *technical* efficiency to one of relative *overall* efficiency.

An intermediate approach to imposing weight restrictions is illustrated in Figure 2.8. Here the dotted lines represent the maximum and minimum ratio of weights the analysts feels are acceptable. For DMUs with optimal weights between these two limits, there is no change to the DEA assessment the units continue to be assessed with respect to the isoquant QQ between points M_1 and M_2. However, for DMUs with optimal weights outside this range, efficiency is assessed with respect to the dotted tangent lines representing the weight limits. For example, the efficiency of point R is assessed relative to point R_R on the tangent rather than point RQ on the frontier. Imposing weight restrictions has the effect of limiting the ability of DMUs to ”choose‘ extreme weights, and therefore reduces the assessed efficiency of DMUs with extreme optimal weights, whilst leaving unchanged the efficiency of DMUs with less extreme choices.

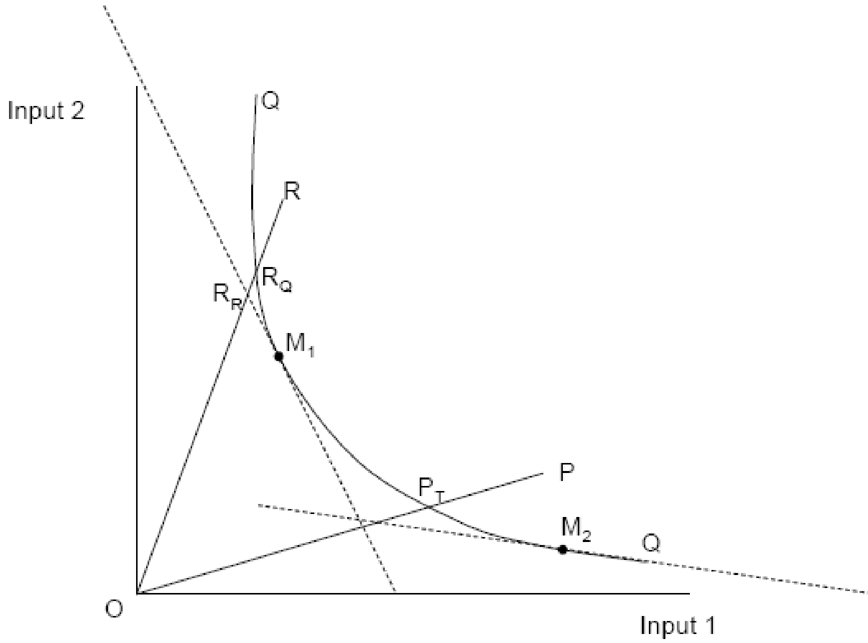

Figure 2.8: Weight restrictions

There has been some attention to rules for restricting the flexibility of weight variations (Allen et al., 1997), but the efforts to date have been poorly informed by economic theory, and mainly confined to technical considerations (Pedraja-Chaparro et al., 1999). The lack of a single set of weights implies that it is never appropriate to rank DEA efficiency scores in a conventional format. The fundamental difficulty with applying weight restrictions is the same as encountered whenever seeking to choose any set of weights who should choose the restrictions, and how should they choose?

A number of approaches have been suggested as mechanisms for addressing the lack of knowledge about the magnitude of weights, and the arbitrary efficiency scores that DEA can yield for ”extreme‘ DMUs. Amongst the most informative is the calculation of ”cross-efficiencies‘ (Doyle and Green, 1994). For each DMU 0 a set of efficiencies $\{e_{0j}\}$ is calculated, where j ranges from 1 to N, the number of DMUs in the sample. Efficiency e_{0j} indicates the efficiency score for DMU 0 if the optimal weights selected by DMU j are applied. Thus, e_{00} is the conventional DEA score for DMU 0, and because this seeks to cast DMU 0 in the best possible light, none of the remaining e_{0j}

scores can be higher than e_{00}. Cross-efficiencies offer valuable insights into the ”robustness‘ of a DMUs unconstrained efficiency score.

However, it is worth noting that once DEA moves beyond simple models with just a handful of inputs and outputs there are often multiple solutions for optimal weights that offer identical efficiency measures. That is, there is often not a unique set of weights that yields the DMU‘s maximum efficiency level. This offers challenges for the systematic application of the cross-efficiency principle.

Decomposing efficiency

Figure 2.9 illustrates the various notions of efficiency that can be examined in the case of just two inputs and a single output, with constant returns to scale. Figure shows the inputs required to produce a given level of output. The isoquant QQ shows the production frontier, in the sense that for any level of input 1, it shows the minimum level of input 2 required to produce the output. All DMUs must therefore lie on or to the north east of the isoquant.

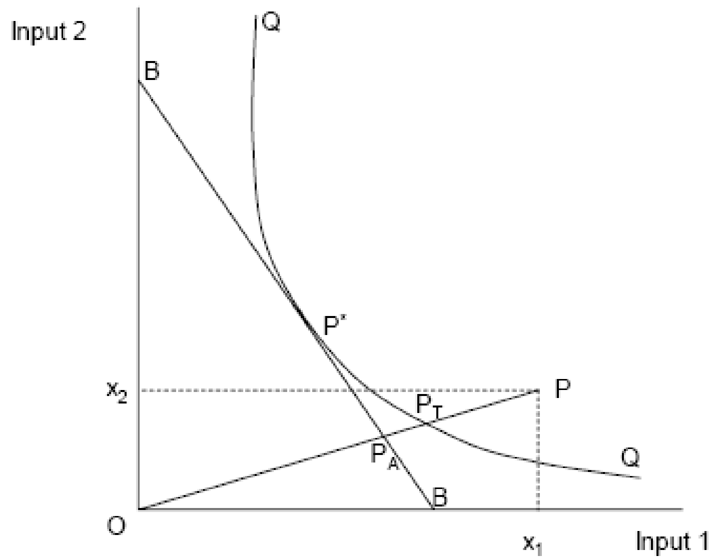

Figure 2.9: Production possibilities with two inputs, one output

Consider a DMU P that consumes physical inputs x_1 and x_2 to produce the output. It is technically inefficient because it does not lie on the isoquant. The traditional radial measure of inefficiency is OP_T/OP, the proportion by which it is feasible to reduce all inputs and still produce the required output.

A technically efficient production choice such as P_T may not be allocatively efficient because- given the relative prices of the two inputs w_1 and w_2 - the output can be produced at lower total cost. The line BB has slope $-w_1/w_2$ and passes through the allocatively efficient point P^*. It indicates the minimum cost point of production.

The overall inefficiency of DMU P is therefore indicated by the ratio OP_A/OP which can be written as the product of OP_T/OP and OP_A/OP_T. The first ratio is the technical inefficiency, the second is allocative inefficiency.

This analysis assumes that, although the DMU makes an incorrect choice of inputs, and uses them inefficiently, it nevertheless purchases them at the correct market prices w_1 and w_2, with total cost $W^* = x_1w_1 + x_2w_2$. It is however possible that it purchases inefficiently, at a higher total cost

$W_P<W^*$. This suggests a third component of inefficiency, indicated by the ratio W^*/W_P. Total inefficiency can now be decomposed into:

a. Technical inefficiency OP_T/OP;

b. Allocative inefficiency OP_A/OP_T;

c. Cost inefficiency W^*/W_P;

This analysis suggests a need to calculate inefficiency using three different types of input measure:

a. Disaggregated physical inputs

b. Physical inputs aggregated at market prices

c. Actual costs.

If DEA is used, this implies a need to run the model first with disaggregated physical inputs and then with the inputs aggregated at market prices in order to estimate the ratios OP_T/OP and OP_A/OP. The cost inefficiency can be calculated trivially as the ratio W^*/W_P without resort to DEA.

2-2-4 DEA and Frontier Analysis:

DEA proceeds by constructing a frontier (a benchmark) composed of best practice performers and then measures efficiency relative to that frontier. Thus the best practice performers are the benchmark on which the performance of others is to be evaluated. To demonstrate the working of DEA, consider a production process in which statistical data is available in the form of one input and one output. Figure 2.10 illustrates such a production process where many producers are included i.e. as points in the figure. DEA proceeds by constructing a best practice frontier as shown in the figure. A producer situated along this frontier produces greatest output using given input and uses least input given the output that it produces.

Those producers lying below this frontier are inefficient; they could have managed their production using less input and could have produced more output using the same amount of inputs. The efficiency of the best practice producers will be equal to 1(100%) while those inefficient will be less than 1. Figure 2.11 gives a numerical example of how the improvement potential for a producer such as J may be calculated. The benchmark producer, that J should be compared to, uses 2 units of input to produce same amount of output as J. However, J uses more input (5 units) to produce the same amount. Thus J efficiency is measured by the distance LK/JK =2/5= 0.4 implying that it could have produced what it produces today by using only 40% of its input i.e. it has a saving potential of 60%. Note that J can alternatively improve its efficiency by using less input, producing more output or a combination of both.

Now a natural question to ask is how producer J can improve its performance in practice. There is a natural answer to this question. Obviously it should use less input to produce its current output, produce more output using the current level of input or simply a combination of both. But the most appealing answer is that producer can in fact learn from the best practice frontier situated along the line segment L to M. The learning can take place simply by contacting those producers or the analyzer can initiate seminars where the best practice producers explain the way they do their things.

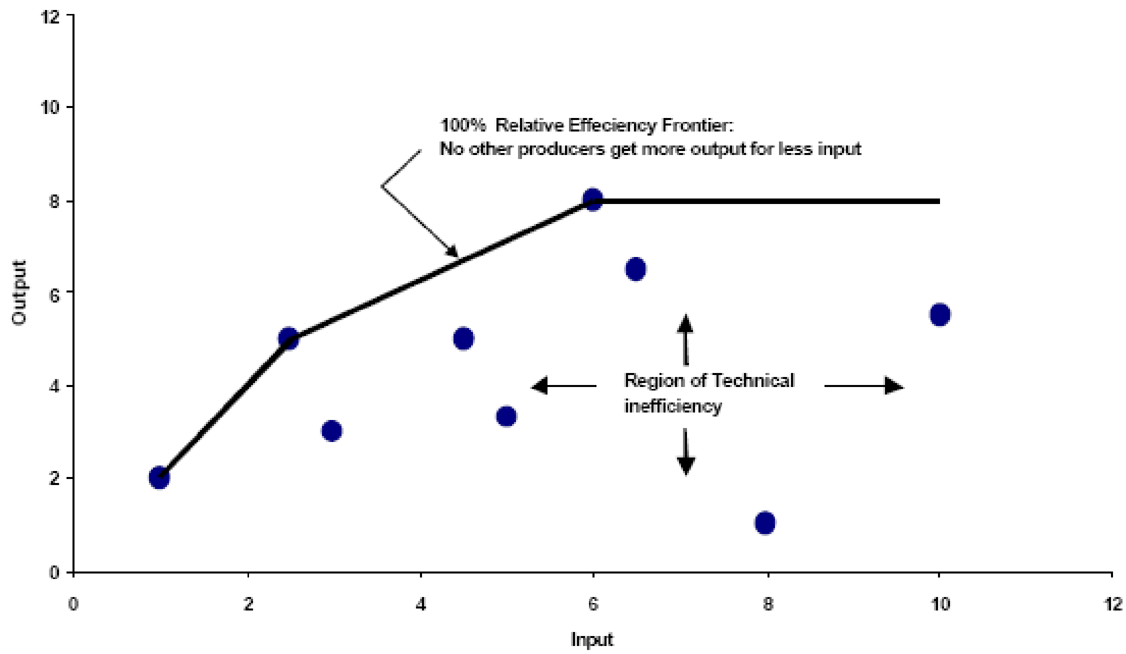

Figure 2.10: Input-output production space

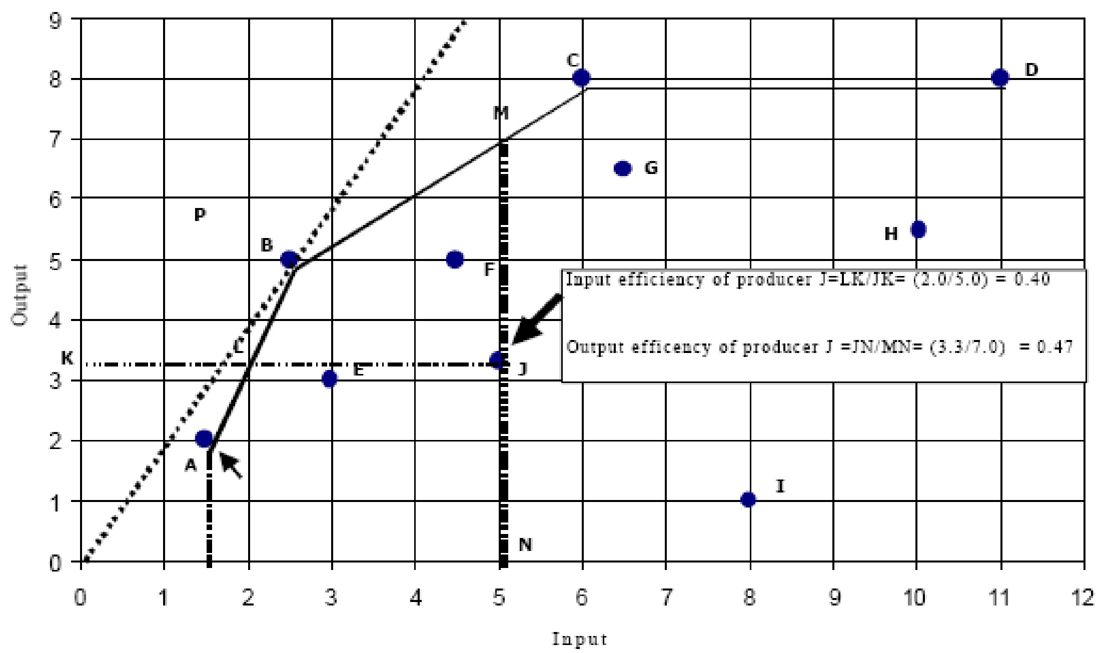

Figure 2.11: Calculating performance measure in DEA

There are other methodological considerations in DEA that should be considered when developing comparative performance assessment of producers. The first one concerns the "returns to scale" to consider; constant, economies of scale or diseconomies of scale. Constant return to scale implies that one unit of input results into one unit of output, economies of scale imply that one unit of input results in more than one unit of output and diseconomies of scale imply that one unit of input results into less than one unit of output. In Figure 2.11, it can easily be seen that the frontier line A –B allows for both economies and diseconomies of scale. If constant return to scale were assumed then the frontier would have been the stippled line from the origin; in which the most efficient producer would have been B only. Thus DEA readily allows for the consideration of the scale of operation.

A second methodological consideration is the prevalent claims that comparative performance assessments are infeasible because factors beyond the control of producers or service providers can, and often affect relative performance. Such factors are often termed "uncontrollable " variables. In transit services an example of uncontrollable variable could be the characteristics of the area of operation such as topography. DEA readily allows for the inclusion of such variables so that the final results are adjusted for the impact of such variables.

In relation to the example above, it should be noted that DEA can easily tackle production processes with many inputs and many outputs. In such a case a linear programming problems is solved using computer software.

This study will use the frontier analysis for analyzing a multiple of inputs and one output included with in the UNRWA-GTC technical education system in order to determine the relative efficiency and allocate resources more efficiently.

Due to its non-parametric feature and its ability to combine multiple inputs and outputs, DEA has been found to be a powerful tool when used appropriately. A few of the *characteristics that make it powerful are* (Bhat, Verma and Reuben 2001) :

a. DEA can handle multiple input and multiple output models.

b. It doesn't require an assumption of a functional form relating inputs to outputs.

c. DMUs are directly compared against a peer or combination of peers.

d. Inputs and outputs can have very different units. For example, X1 could be in units of trips taken and X2 could be bus fare of monthly pass.

The same features that make DEA a powerful tool can also create problems.

The following limitations must be considered when choosing whether or not to use DEA.

Since DEA is an extreme point technique, noise (even symmetrical noise with zero mean) such as measurement error can cause *significant problems* (Bhat, Verma and Reuben 2001):

a. DEA is good at estimating "relative" efficiency of a DMU but it converges very slowly to "absolute" efficiency. In other words, it can tell you how well you are doing compared to your peers but not compared to a "theoretical maximum."

b. Since DEA is a nonparametric technique, statistical hypothesis tests are difficult and are the focus of ongoing research.

c. Since a standard formulation of DEA creates a separate linear program for each DMU, large problems can be computationally intensive.

d. The standard DEA approach has the disadvantage that it cannot distinguish between changes in relative efficiency brought about by movements towards or away from the efficiency frontier in a given year and shifts in this frontier over time.

e. The DEA method assigns mathematically optimal weights to all inputs and outputs being considered. It empirically derives the weights so the maximum weight is placed on those favorable variables and the minimum weight is placed on the unfavorable variables. The underlying assumption of this method is that it is equally acceptable to specialize in producing any output or consuming any input. In many cases this kind of free specialization without weight restrictions is not acceptable or desirable and may lead to highly unreliable conclusions.

f. Double of outputs plus inputs should be less than or equal sample size.

In the next chapter, we will provide full details about the nature of inputs, outputs, and how to model and analyze them.

Chapter 3 Data Collection and Modeling

Chapter 3 Data Collection and Modeling

This chapter describes how to apply DEA to calculate the efficiency score of GTC technical education system, and the analysis of the factors which may be associated with the efficiency score.

The process starts from understanding and analyzing data. After defining the inputs and outputs from the source data, a frontier analyst software is developed to help calculate the efficiency of technical diploma programs at UNRWA-GTC.

3-1 Description of Data:

The data used in this research is provided by both alumni department at GTC and seniors of the technical departments.

The sample for this study consists of eight Technical diploma programs of at least two groups of graduates and this sample data are used in the analysis phase, the technical diploma programs which are included in our study are:

a. Programming & Database
b. Business and Office Practice
c. Banking
d. Industrial Electronics
e. Communication
f. Graphic Design
g. Civil Engineering
h. Arch. Engineering

3-2 Description of Inputs and Outputs:

The first step in a DEA is to identify the inputs and outputs that can be potentially used to define the efficiency of technical education system.

Inputs

The resources or inputs are units of measurement which represent the factors used to conduct the technical education services.

Previous studies on other performance models (Johns 1996, Emilio 2003) have shown that the inputs of universities can be categorized in various ways, where human resources, financial resources and material resources could be considered as inputs.

In addition, the study of Emilio (2003) mentioned that the registered student and number of teaching hours are input indicators for the teaching process.

With respect to inputs variables, the questionnaire was used to select the research's measures (inputs and outputs). The questionnaire was distributed to all academic and administrative staff who work in the eight technical diploma programs in order to cover the total population with 100%. The total population was 29 staff members who work in the eight technical diploma programs. The staff members who filled the questionnaire were classified as follows:

a. 25 Technical instructors work in the eight diploma programs.
b. Two Seniors instructors for the eight diploma programs.
c. Two Managers

To analyze the data collected though the questionnaire (shown in Appendix A), the factor analysis approach which is provided by SPSS statistical software was used to perform the analysis.

The factor analysis was conducted for both input and output variables. Where the analysis of suggested inputs produce three inputs (see Appendix B discussion), WSTH, I/S, AB. However another input (ES) is added according to the seniors' recommendations. So we will consider **WSTH, I/S, AB, ES** as inputs where:

a. **WSTH** : Number Of major courses hours per week

b. **I/S** : Number Of students per instructor.

c. **AB** : Amount of allocated budget per year

d. **ES** : Number of enrolled students per year

Outputs

Outputs indicators measure the yield or the level of activity of programs and services.

Abroad range of outputs of universities can be found in segers (1990).

Furthermore, it is always useful to disclose indicators that provide information about quantity and quality of the activity (Pina& Torres 1995).

The study of Wadhwa, Kumar and Saxena (2005) has shown that participation in the labor market is one of the best output indicators in measuring the efficiency of technical education system. In addition we can consider that number of graduates as one of output indicators that can be used to measure the teaching efficiency Emilio (2003).

In our case, factor analysis is conducted for suggested outputs. The analysis of the suggested outputs produced one output only (GSF) (see Appendix C discussion).

So **GSF** will be considered as an output indicator where:

GSF : Number of graduates working in their Field.

Table 3.1 shows the analysis sheet of four inputs and one output we have used in our research. Table 3.1 shows that the collected sample include the latest two groups of graduates for each specialization.

Table 3- 1: The inputs and outputs of technical diploma program -GTC

No	Diploma program	Input							Output
		WSTH				I/S	AB	ES	GSF
		S1	S2	S3	S4				
1.	Programming & database								
2.	Business and office practice								
3.	Banking								
4.	Industrial Electronics								
5.	Communication								
6.	Graphic Design								
7.	Civil Engineering								
8.	Arch. Engineering								

Group1-Graduates

Group2-Graduates

The second step in a DEA is to find and collect the input and output data that will be used to define the efficiency of technical education system. Table 3.2 shows the input and output data of eight technical diploma programs at GTC:

Table 3.2 The Input/output collected for the last two groups of graduates at GTC:

No	Diploma program	Input							Output
		WSTH				I/S	AB	ES	GSF
		S1	S2	S3	S4				
1.	Programming & database	16	27	32	33	3/25	5200	25	12
						2/25	4000	25	10
2.	Business and office practice	7	19	21	35	4/24	3700	24	20
						4/23	3000	23	17
3.	Banking	10	12	27	32	3/25	4200	25	10
						3/26	3100	26	14
4.	Industrial Electronics	13	14	35	29	4/23	5100	23	10
						4/25	3000	25	9
5.	Communication	30	31	32	36	3/18	8500	18	3
						4/25	5000	25	6
6.	Graphic Design	12	30	29	26	4/24	6300	24	7
						4/27	3500	27	3
7.	Civil Engineering	24	27	16	22	2/25	8300	25	4
						2/26	5000	26	13
8.	Arch. Engineering	20	18	26	25	2/22	7900	22	8
						2/23	5000	23	7

In order to calculate the efficiency scores of the eight technical diploma programs we calculate the average values of input and output variables which are listed in table 3.2. Table 3.3 shows the average values of input and output variables of eight technical diploma programs at GTC:

Table 3.3 The average of input and output variables for the last two groups of graduates:

No	Diploma program	Input				Output
		WSTH	I/S	AB	ES	GSF
1.	Programming & database	27	10	4600	25	11
2.	Business and office practice	20.5	5.88	3350	23.5	18.5
3.	Banking	20.25	8.50	3650	25.5	12
4.	Industrial Electronics	22.75	6	4050	24	9.5
5.	Communication	32.25	6.14	6750	21.5	4.5
6.	Graphic Design	24.25	6.38	4900	25.5	5
7.	Civil Engineering	22.25	12.75	6650	25.5	8.5
8.	Arch. Engineering	22.25	11.25	6450	22.5	7.5

3-3 Efficiency modeling

The Third step in a DEA is to model the inputs and outputs as a linear programming method**.**

Since our study aims to measure the technical efficiency, and the technical efficiency reflects the maximal outputs from a given set of inputs therefore the research problem is a maximization problem.

Hence, with the inputs and outputs identified in the previous sections, the basic DEA model for a given technical education system can be formulated as follows:

$$\textbf{Max} \quad \theta = \frac{U_1(GSF)}{V_1(WSTH) + V_2(IS) + V_3(AB) + V_4(ES)}$$

$$\textbf{S.t.} \quad \frac{U_1(GSF)_j}{V_1(WSTH)_j + V_2(IS)_j + V_3(AB)_j + V_4(ES)_j} <= 1 \textit{ for all diploma program}$$

$$U_1>0; \; V_1,\ldots,V_4>0; \; j=1,2,\ldots 8$$

Where :

GSF_j: is the total number of graduates who work in specialization j.

$WSTH_j$: is the total number of major courses hours in specialization j per week.

IS_j: is the number of students per instructor in specialization j.

AB_j: is the a mount of allocated budget assigned to specialization j.

ES_j: is total number of enrolled students in specialization j.

U_j : weight given to output j.

v_j : weight given to input j.

3-4 CCR and BCC Efficiency models

After modeling the research problem as a maximization problem we have to specify the efficiency model whether Charnes, Copper and Rhodes(1978)(CCR) model or Banker, Charnes, Copper(1984) (BCC) efficiency model in order to find the efficiency scores and analyzing the efficiency of DMUs. The following two points express the need of using CCR and BCC models in evaluating the efficiency:

1. **CCR Model**:

   CCR gives a measure of overall efficiency of each DMU, such that technical efficiency and scale efficiency are aggregated into one value. This model assumes that there are constant returns to scale (i.e. an increase in inputs results in a proportionate increase in outputs). It assumes that all DMUs work at optimal scale.

2. **BCC Model**:

   BCC model is pure technical efficiency, and assumes that there are variable returns to scale or increasing and decreasing returns to scale.

In this research using CCR and BCC are very important in order to ensure whether all DMUs work at optimal scale or not. If the DMUs work at optimal scale then CCR model must be used otherwise BBC must be used.

In chapter five the efficiency using the two models CCR and BCC will be calculated and evaluated in order to give a high flexibility and several opinions for decision makers.

Chapter 4 Analysis

Chapter4 Analysis

In the analysis phase, the CCR and BCC models are applied in order to give flexibility and different opinions about efficiency scores from one side and potential improvement from the other side. The analysis process is divided into two parts, in the first part the problem was analyzed as a maximization problem using CCR model, and in the second part the problem was analyzed as a maximization problem using BCC model.

The following two issues are very important to be considered in the efficiency analysis phase:

4-1 Input/output architecture of TES:

The inputs and outputs that are associated with the business process being analyzed also have to be classified as either controllable or non controllable variables. Controllable variables are those over which the management of the organization has control and can be allowed to vary. Outputs are controllable, while inputs may be either controllable or uncontrollable. Uncontrollable variables are those whose characteristic of use are outside the control of the management of the organization. A fresh vision of efficiency evaluation may be developed in this regard.

Figure 4.1 gives the detailed information about the emphasis that the analysis uses for each input/output variable. Table 4.1 shows the input and output architecture of TES whether it is controllable or uncontrollable.

Unit Name	Active	WSTH	I/S	AB	ES	GSF
PDB	☑	27.00	10.00	4,600.00	25.00	11.00
BOP	☑	20.50	5.88	3,350.00	23.50	18.50
BK	☑	20.25	8.50	3,650.00	25.50	12.00
ELECT	☑	22.75	6.00	4,050.00	24.00	9.50
COMM	☑	32.25	6.14	6,750.00	21.50	4.50
GD	☑	24.25	6.38	4,900.00	25.50	5.00
CE	☑	22.25	12.75	6,650.00	25.50	8.50
AE	☑	22.25	11.25	6,450.00	22.50	7.50

Figure 4.1: DEA based formulation of Input-Outputs variables and DMU

Figure 4.1 shows the frontier analyst interface for inputs and outputs values which are extracted from Table 3.3.

Table 4.1: Input/Output Architecture:

Controlled Input	Uncontrolled Input	Output
AB	**WSTH**	**(GFS)**
ES	IS	

4-2 DEA based orientation for TES:

There are many different ways to view an education system and each view gives a different perspective of the attributes which define "good" performance. Ideally a performance measurement system should give an accurate assessment of how well an organization is performing (based on chosen parameters), along with providing information on how operations can be improved. Information such as how the inputs (resources) are linked to the resultant outputs (product or services), is useful in order to identify what 'drives" result. A DEA data set is simply a group of units (DMUs) and the values of their inputs and outputs, to be included in the analysis. DEA requires a data set of homogeneous units. Homogeneity refers to the degree of similarity between units. The operational goals of the units should be similar, as should their operational characteristics. A certain amount of pre-processing may be required to identify "outliers" in the data. Outliers are units that exhibit markedly different inputs/ outputs values from the rest of the data. Therefore, their operating characteristics may vary in some way. Some of the key features of DEA based analysis is elaborated and justified accordingly.

Peer group (Reference Set): One of the benefits of using DEA is that it identifies peers for inefficient units. A peer is a unit which is found to be efficient, with similar combination of weights as that of an inefficient unit. Where two or more of these efficient units act as peers for an efficient unit, they provide a peer group for the inefficient unit. The peer group is also known as the reference set of an inefficient unit. The characteristics of the units in the reference set provide the targets for the inefficient units to work towards.

Return to scale: The choice of which model to be used for the analysis of the data set depends on the character of the data and the process which is being analyzed. The analysis of returns to scale is the identification of increasing and decreasing returns to scale. The values which result from the solution of the DEA algorithm can be used as part of a further calculation to indicate the state in which a unit is operating – constant, increasing or decreasing returns to scale. If a unit is operating with increasing returns to scale, an increase in the input results in a more than proportionate increase in the output. If a unit is operating at decreasing returns to scale, then an increase in inputs results in less than proportionate increase in outputs. At constant returns to scale an increase in inputs results in a proportionate increase in outputs.

Identifying efficient operating practices: An important feature of DEA is the ability to identify efficient units, the reference set, which can be examined in order to identify appropriate targets for inefficient units to work towards. In the case study, we have identified the most efficient and inefficient institutes. In our view DEA also enlightened the view of performance improvement and bottleneck remedies.

Distribution of virtual inputs and virtual outputs: The product of the inputs and the optimal weights for those inputs determines the values of the virtual inputs for a unit. Similarly, the product of outputs and the optimal weights for those outputs determines the values of the virtual outputs. Computing these virtual input and output values allows the analyst to determine which inputs or outputs ate the driving factors of a unit maximum efficiency score.

Weight Restriction: Weight restriction should be used with care. The optimization performed in DEA is unbiased and the analysis will try to show each unit in the best possible light, regardless of whether or not this means that one or more inputs or outputs are effectively ignored.

Setting improvement targets: It is possible to set targets for the inefficient units to achieve desired outputs. A combination of input/output levels can be identified, based on the performance of peers, which act as a benchmark for the inefficient units to work towards. This information shows the input/output changes that must be made for the inefficient units to become efficient.

Resource allocation: DEA identifies inefficient units and provides information about how resources can be more efficiently assigned to give maximum efficiency. However, common sense and the practicalities of the physical world dictate that other factors be considered before the re-allocation of resources is actually carried out. It may not be physically possible to transfer resources from one area to another. Alternatively, if resources are redirected from unit A to unit B because of inefficiency of the former – this might result in an increased inefficiency if the target unit then is not able to fully utilize its other resources. Another consideration is that DEA is a method based on observed best practices. Any change made to the input/output profile of one unit will , to some extent, affect the efficiency score of numerous other units, since DEA efficiency is derived relative to other units in the data set and is not based on some definition of an ideal production frontier. Any suggested modifications in the input/output level require that the DEA assessment be repeated to ensure that this change will not have a detrimental effect on the efficiency of the unit being analyzed and that of its peers.

Frontier analyst software v3.2.2 is used as an efficiency analysis tool in order to find the efficiency scores and potential improvement for the inefficient DMUs in case of applying both CCR and BCC models. The result of frontier analysis using CCR and BCC models will be mentioned and discussed in the next chapter.

Chapter 5 Results and Discussion

Chapter5 Results and Discussion

This chapter outlines the principle results which show the maximization of each DMU on both a constant scale model (CCR) and a variable scale model (BCC).

CCR model assume that there is a constant return to scale which means that it is only appropriate when all DMUs or firms are operating at an optimal scale Charnes et al.(1978), where CCR model is the aggregate measure of technical and scale efficiency.

Nevertheless, as firms may not be operating at optimal scale due to imperfect competition or constraints, Baker et al.(1984) suggested the use of variable returns to scale (BCC) that allows the calculation of technical efficiency.

Actually two models are used in the analysis , CCR and BCC and the results show some variations in efficiency scores between CCR and BCC, and the obtained results show that there is a variation between technical efficiency computed by BCC and the aggregate efficiency computed by CCR, where at optimal scale(scale efficiency =100%) the technical efficiency and aggregate efficiency should be equal, Fatios (2006). Therefore this variation is basically caused by the scale efficiency which means that the DMUs are not operating on the optimal scale and increasing in input does not yield the same increase in output.

Accordingly, a variable return to scale (BCC) is preferred in measuring and analyzing the efficiency of technical diploma programs (DMUs).

In the following two sections, we will explain and discuss the results of DEA analysis of the two models and show the reason of selecting and adopting BCC in measuring the efficiency of technical diploma programs .

5-1 Using CCR Model:

The relative efficiencies of eight technical diploma programs (DMUs) are evaluated by CCR model (Table5.1). In the CCR model, the result shows the efficiency scores of DMUs, and in our case study out of eight technical diploma programs there is one technical diploma program with 100% efficiency which is BOP.

Table 5.1: CCR Efficiency scores of DMUs

DMU	AE	BK	*BOP*	CE	COMM	ELECT	GD	PDB
Score	42.34	65.67	*100.00*	42.34	26.59	50.32	24.91	55.89

Potential improvement: The potential improvement required in various DMUs is shown in Figures 5.1, 5.2, 5.3, 5.4, 5.5, 5.6 and 5.7 (e.g. non efficient units). The percentage change in each input and output that the unit would have to make in order to become efficient is shown in these graphs. Input/output variables are along the Y axis, and the potential percentage improvement along the X axis. The percentage difference between these values is displayed in the potential improvement column.

The actual column indicates the values of the inputs used and the values of outputs actually produced by DMU.

The target column shows the amount of inputs and outputs that the DMU should be using or producing in order to be efficient.

In our case, we select the units, PDB, BK, ELECT, COMM, GD, CE, and AE, which are less efficient.

Tables 5.2, 5.3, 5.4, 5.5, 5.6, 5.7 and 5.8 show what percentage the technical diploma programs (PDB, BK, ELECT, COMM, GD, CE, and AE) need to either increase its outputs or decrease its inputs in order to be 100% aggregate efficient.

a. PDB Potential Improvement:

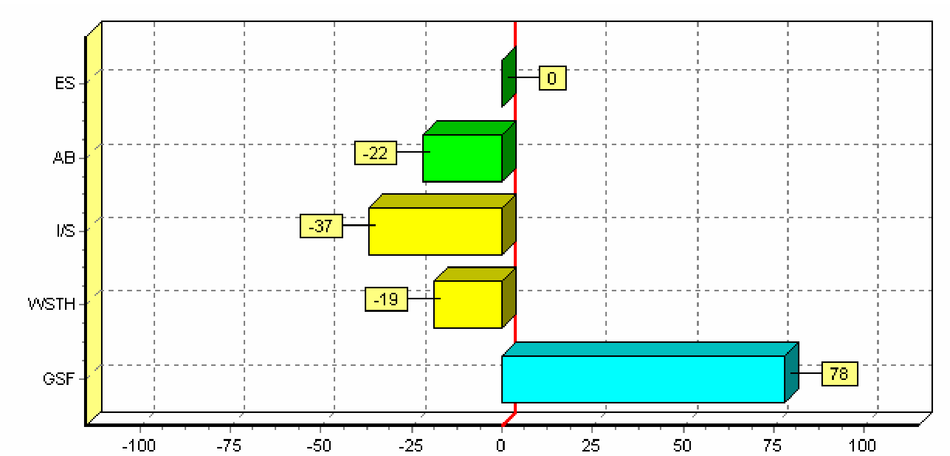

Figure 5.1: CCR Potential Improvement Summary of DMU (PDB)

Figure 5.1 shows that there is room for improvement in output variable(GSF) by 78%. We can notice that the reductions can be made in three input variables as follows: reducing AB by 22%, reducing I/S by 37% and reducing WSTH by 19%.

Table 5.2 shows the numerical values of potential improvement of inefficient decision unit PDB :

Table 5.2: CCR Potential Improvement Summary of Inefficient DMU (PDB)

Input/Output	Actual	Target	Potential improvement
ES	25	25	0
AB	4600	3563.83	-22.53
I/S	10	6.26	-37.45
WSTH	27	21.81	-19.23
GSF	11	19.68	78.92

Note that the potential improvement graph and percentage are generated by the frontier analyst software which is discussed in the analysis chapter.

b. BK Potential Improvement:

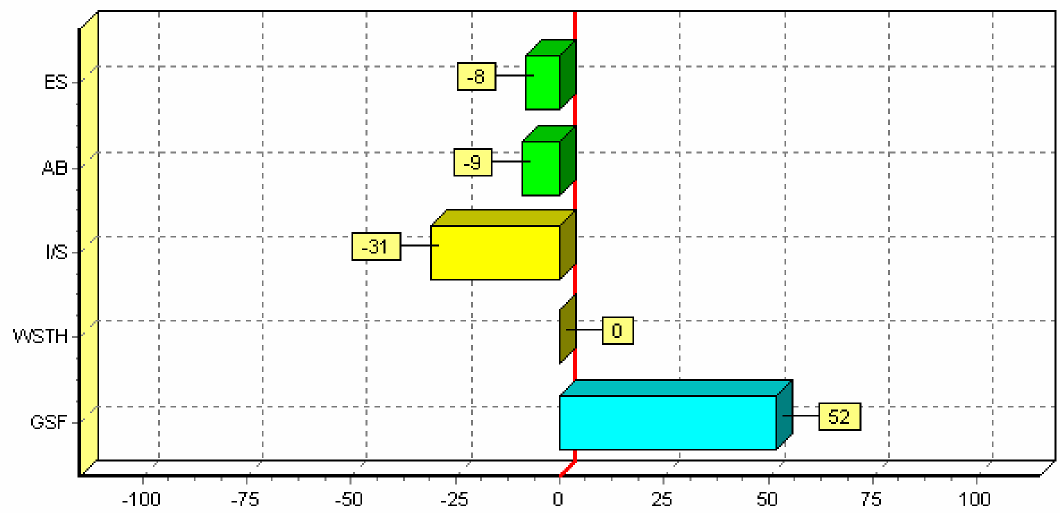

Figure 5.2: CCR Potential Improvement Summary of DMU (BK)

The above figure 5.2 shows that there is room for improvement in output variable(GSF) by 52%. We can notice that the reductions can be made in three input variables as follows: reducing ES by 8%, reducing AB by 9% and reducing I/S by 31%.

Table 5.3 shows the numerical values of potential improvement of inefficient decision unit BK:

Table 5.3: CCR Potential Improvement Summary of Inefficient DMU (BK)

Input/Output	Actual	Target	Potential improvement
ES	25.5	23.21	-8.97
AB	3650	3309.15	-9.34
I/S	8.5	5.81	-31.67
WSTH	20.25	20.25	0
GSF	12	18.27	52.29

c. ELECT Potential Improvement:

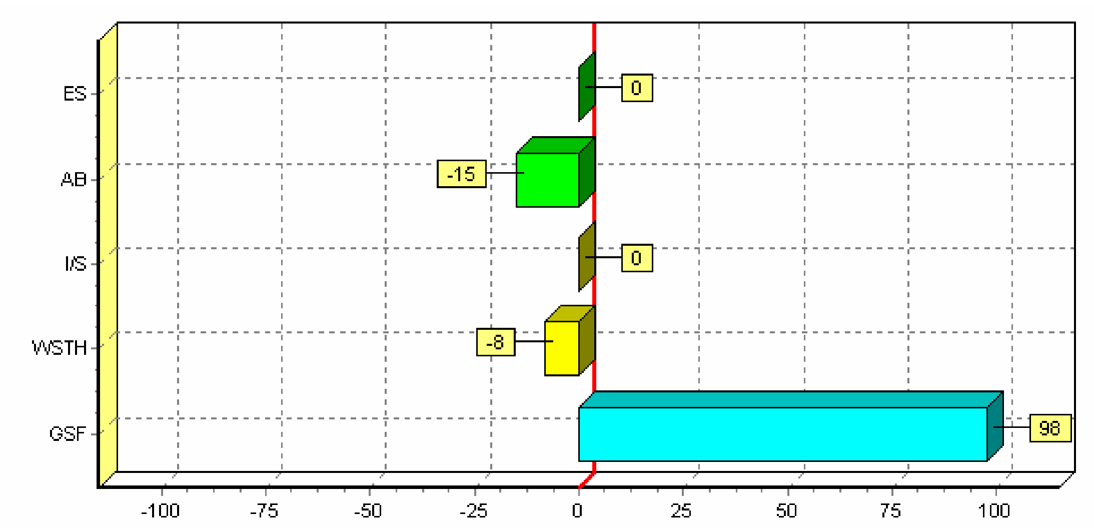

Figure 5.3: CCR Potential Improvement Summary of Inefficient DMU (ELECT)

Figure 5.3 shows that there is room for improvement in output variable(GSF) by 98%. And we can notice that the reductions can be made in two input variables as follows: reducing AB by 15%, and reducing WSTH by 8% .

Table 5.4 shows the numerical values of potential improvement of inefficient decision unit ELECT :

Table 5.4: CCR Potential Improvement Summary of Inefficient DMU (ELECT)

Input/Output	Actual	Target	Potential improvement
ES	24	23.98	-0.09
AB	4050	3418.37	-15.6
I/S	6	6	0
WSTH	22.75	20.92	-8.05
GSF	9.5	18.88	98.71

d. COMM Potential Improvement:

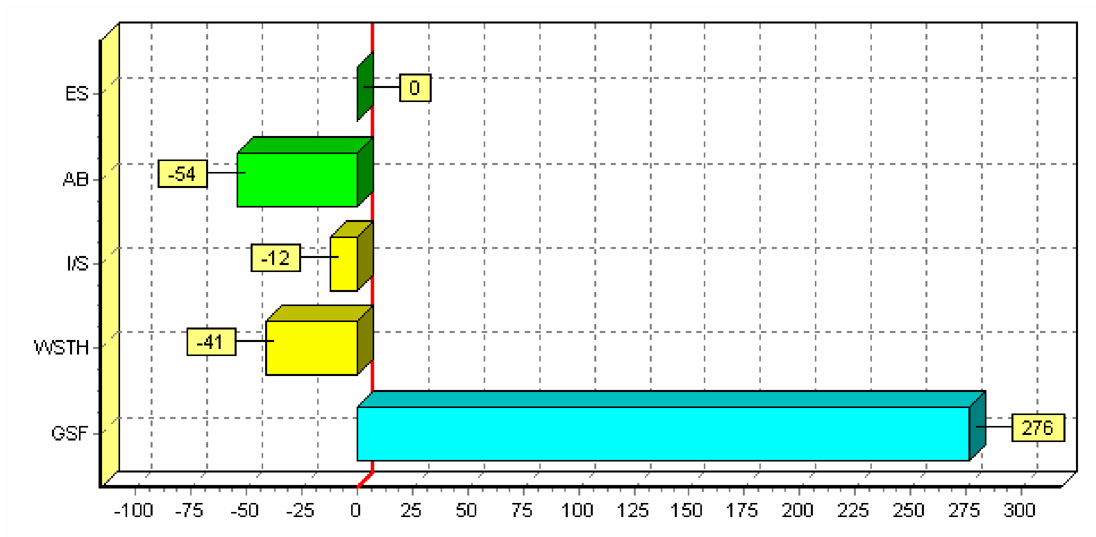

Figure 5.4: CCR Potential Improvement Summary of Inefficient DMU (COMM)

Figure 5.4 shows that there is room for improvement in output variable(GSF) by 276%. And we can notice that the reductions can be made in three input variables as follows: reducing AB by 54%, reducing I/S by 12% and reducing WSTH by 41%.

Table 5.5 shows the numerical values of potential improvement of inefficient decision unit COMM :

Table 5.5: CCR Potential Improvement Summary of Inefficient DMU (COMM)

Input/Output	Actual	Target	Potential improvement
ES	21.5	21.5	0
AB	6750	3064.89	-54.59
I/S	6.14	5.38	-12.38
WSTH	32.25	18.76	-41.84
GSF	4.5	16.93	276.12

e. GD Potential Improvement:

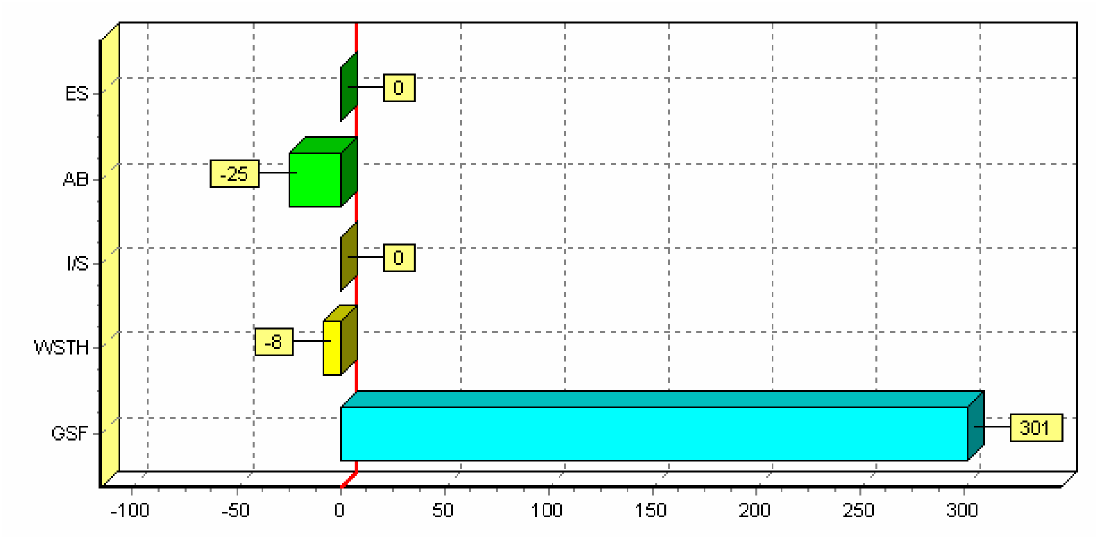

Figure 5.5: CCR Potential Improvement Summary of Inefficient DMU (GD)

The above figure 5.5 shows that there is room for improvement in output variable(GSF) by 301%. We can notice that the reductions can be made in two input variables as follows: reducing AB by 25%, and reducing WSTH by 8%.

Table 5.6 shows the numerical values of potential improvement of inefficient decision unit GD:

Table 5.6: CCR Potential Improvement Summary of Inefficient DMU (GD)

Input/Output	Actual	Target	Potential improvement
ES	25.5	25.5	-0.01
AB	4900	3634.86	-25.82
I/S	6.38	6.38	0
WSTH	24.25	22.24	-8.28
GSF	5	20.07	301.46

f. CE Potential Improvement:

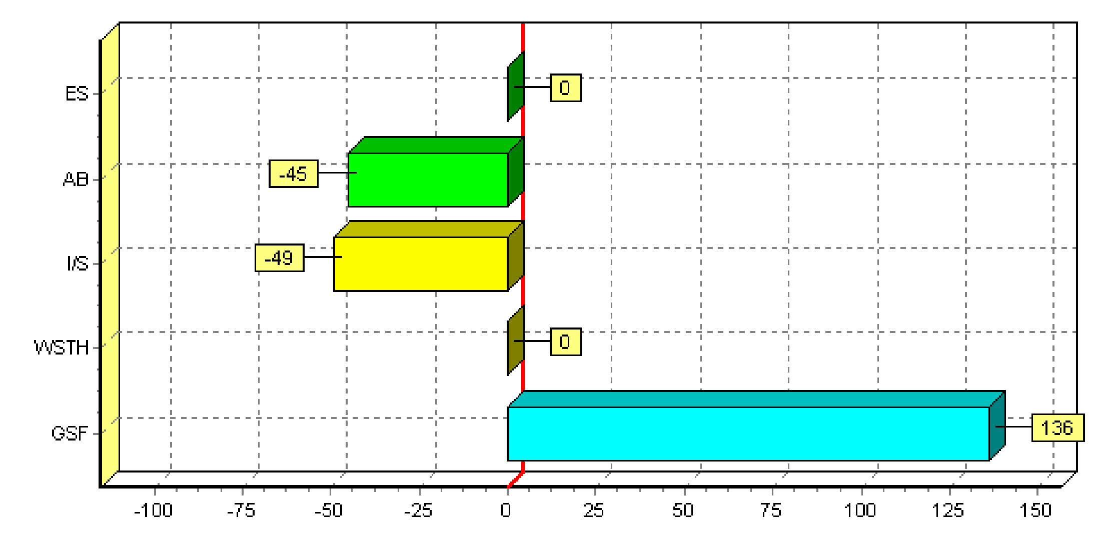

Figure 5.6: CCR Potential Improvement Summary of Inefficient DMU (CE)

The above figure 5.6 shows that there is room for improvement in output variable (GSF) by 136%. we can notice that the reductions can be made in two input variables as follows: reducing AB by 45%, and reducing I/S by 49%.

Table 5.7 shows the numerical values of potential improvement of inefficient decision unit CE :

Table 5.7: CCR Potential Improvement Summary of Inefficient DMU (CE)

Input/Output	Actual	Target	Potential improvement
ES	25.5	25.5	0
AB	6650	3635.11	-45.34
I/S	12.75	6.38	-49.96
WSTH	22.25	22.24	-0.02
GSF	8.5	20.07	136.17

g. AE Potential Improvement:

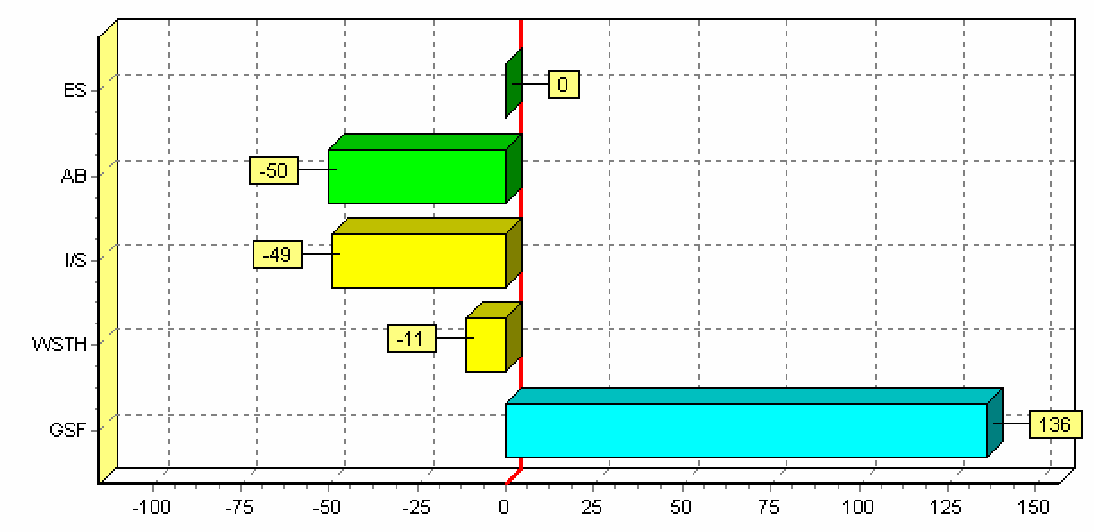

Figure 5.7: CCR Potential Improvement Summary of Inefficient DMU (AE)

The above figure 5.7 shows that there is room for improvement in output variable(GSF) by 136%. We can notice that the reductions can be made in three input variables as follows: reducing AB by 50%, reducing I/S by 49% and reducing WSTH by 11%.

Table 5.8 shows the numerical values of potential improvement of inefficient decision unit AE :

Table 5.8: CCR Potential Improvement Summary of Inefficient DMU (AE)

Input/Output	Actual	Target	Potential improvement
ES	22.5	22.5	0
AB	6450	3207.45	-50.27
I/S	11.25	5.63	-49.96
WSTH	22.25	19.63	-11.79
GSF	7.5	17.71	136.17

Improvement Summary: The possible improvements are identified by the analysis. The potential improvement is calculated by the DEA analysis for each variable and by the unit count. The pie chart 5.8 shows the relative percentage of potential improvement for each input/output. This is achieved by adding up the potential improvements for each unit.

The result shows that the largest potential improvement is possible for GSF(i.e.68.21%) and then followed by AB, I/S, WSTH and ES(figure 5.8).

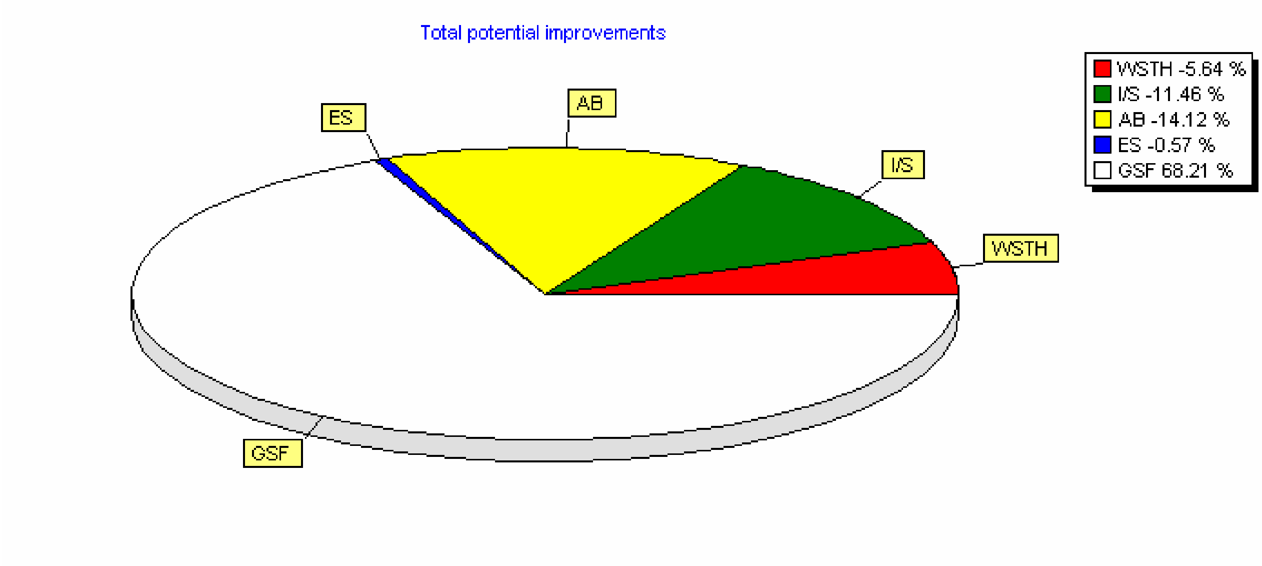

Figure 5.8: CCR Improvement summary of all input-output variables

5-2 Using BCC Model:

We evaluate the relative efficiencies of eight technical diploma programs (DMUs) with BCC model (Table5.9). In the BCC model, the results show the efficiency scores of DMUs, and in our case study out of 8 technical diploma programs there are four technical diploma program with 100% efficiency which are BOP, Bk, AE, COMM.

Table 5.9: BCC Efficiency scores of DMUs

DMU	*AE*	*BK*	*BOP*	CE	*COMM*	ELECT	GD	PDB
Score	100.00	100.00	100.00	45.95	100.00	51.35	27.03	59.46
Scale	constant	constant	constant	increasing	constant	increasing	increasing	increasing

Potential improvement: The potential improvement required in various DMU's is shown in Figures 5.9, 5.10, 5.11, 5.12 (e.g. nonefficient units). The percentage change in each input or output that the unit would have to make in order to become efficient is shown in these graphs. Input/output variables are along the Y axis, and the potential percentage improvement along the X axis. The percentage difference between these values is displayed in the potential improvement column.

In the study, the units, CE, ELECT,GD, and PDB, which are less efficient are selected. Tables 5.10, 5.11, 5.12 and 5.13 show what percentage the technical diploma programs(CE, ELECT,GD, and PDB) need to either increase its outputs or decrease its inputs in order to be 100% technically efficient.

a. PDB Potential Improvement:

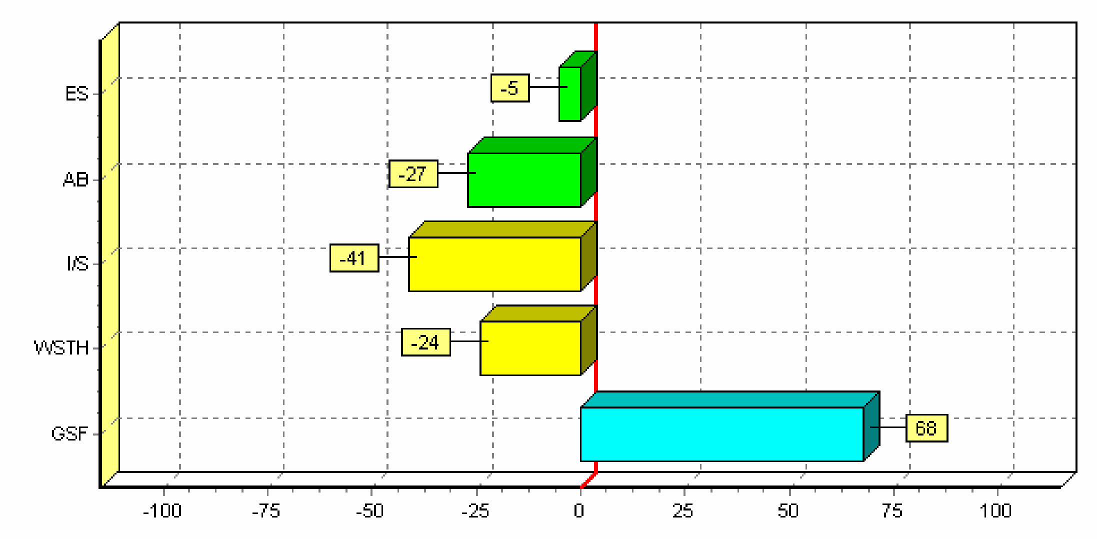

Figure 5.9: BCC Potential Improvement Summary of Inefficient DMU (PDB)

Figure 5.9 shows that there is room for improvement in output variable(GSF) by 68%. We can notice that the reductions can be made in four input variables as follows: reducing ES by 5%, reducing AB by 27%, reducing I/S by 41% and reducing WSTH by 24%.

Table 5.10 shows the numerical values of potential improvement of inefficient decision unit PDB :

Table 5.10: BCC Potential Improvement Summary of Inefficient DMU (PDB)

Input/Output	Actual	Target	Potential improvement
ES	25	23.5	-5.22
AB	4600	3350	-27.17
I/S	10	5.88	-41.2
WSTH	27	20.5	-24.07
GSF	11	18.5	68.18

b. ELECT Potential Improvement:

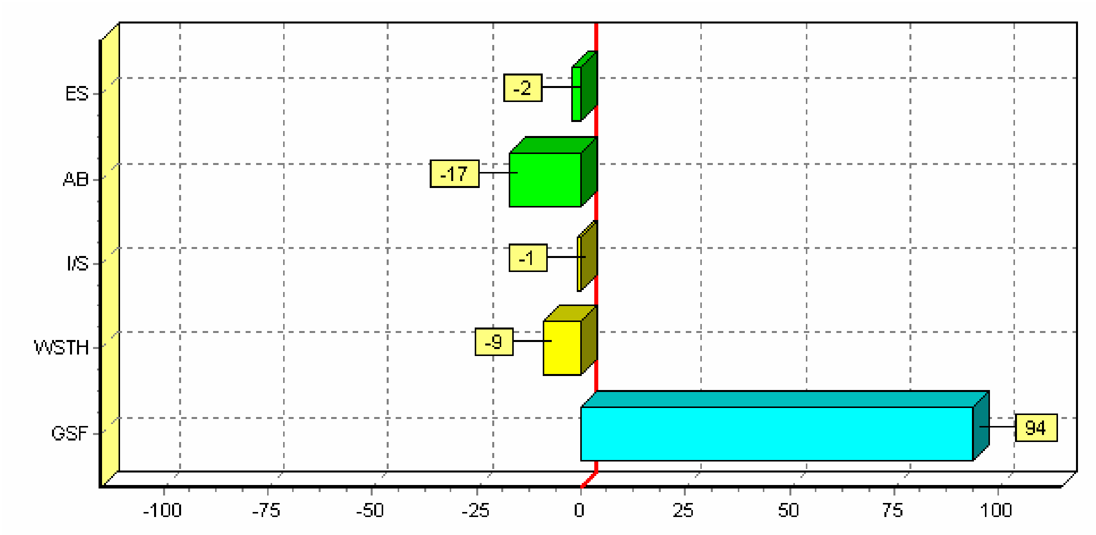

Figure 5.10: BCC Potential Improvement Summary of Inefficient DMU (ELECT)

Figure 5.10 shows that there is room for improvement in output variable(GSF) by 94%. We can notice that the reductions can be made in 4 input variables as follows: reducing ES by 2%, reducing AB by 17%, reducing I/S by 1% and reducing WSTH by 9%.

Table 5.11 shows the numerical values of potential improvement of inefficient decision unit ELECT.

Table 5.11: BCC Potential Improvement Summary of Inefficient DMU (ELECT)

Input/Output	Actual	Target	Potential improvement
ES	24	23.5	**-2.08**
AB	**4050**	**3350**	-17.28
I/S	**6**	**5.88**	-1.75
WSTH	22.75	20.5	-9.89
GSF	9.5	18.5	94.74

c. GD Potential Improvement:

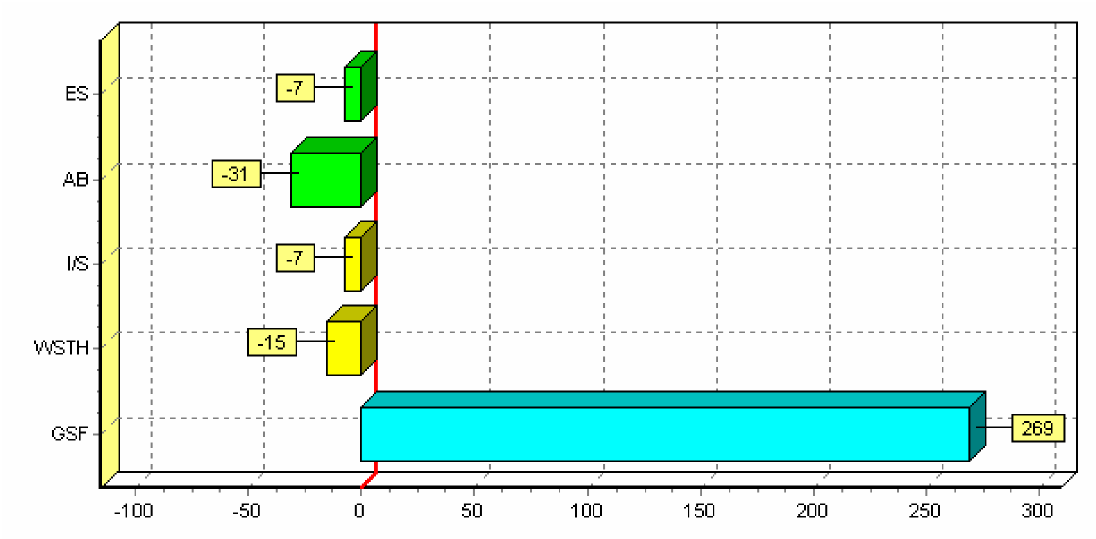

Figure 5.11: BCC Potential Improvement Summary of Inefficient DMU (GD)

Figure 5.11 shows that there is room for improvement in output variable(GSF) by 269%. We can notice that the reductions can be made in 3 input variables as follows: reducing ES by 7%, reducing AB by 31%, reducing I/S by 7% and reducing WSTH by 15%.

Table 5.12 shows the numerical values of potential improvement of inefficient decision unit GD :

Table 5.12: BCC Potential Improvement Summary of Inefficient DMU (GD)

Input/Output	Actual	Target	Potential improvement
ES	25	25	-7.41
AB	4600	3563.83	-31.53
I/S	10	6.26	-7.45
WSTH	27	21.81	-15.23
GSF	11	19.68	269.92

d. CE Potential Improvement:

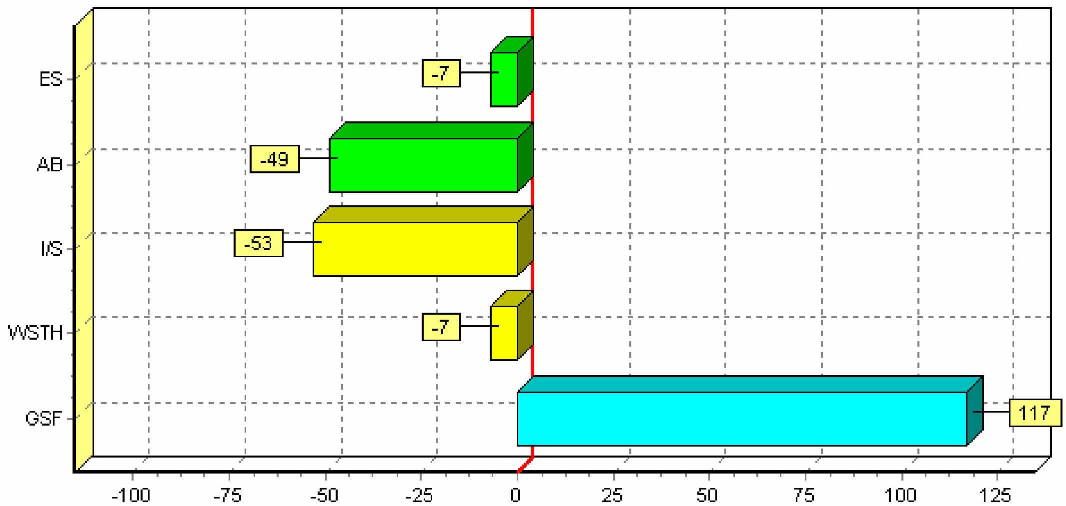

Figure 5.12: BCC Potential Improvement Summary of Inefficient DMU (CE)

Figure 5.12 shows that there is room for improvement in output variable(GSF) by 117%. We can notice that the reductions can be made in 4 input variables as follows: reducing ES by 7%, reducing AB by 49%, reducing I/S by 53% and reducing WSTH by 7%.

Table 5.13 shows the numerical values of potential improvement of inefficient decision unit CE:

Table 5.13: BCC Potential Improvement Summary of Inefficient DMU (CE)

Input/Output	Actual	Target	Potential improvement
ES	25.5	23.5	-7.84
AB	6650	3350	-49.62
I/S	12.75	5.88	-53.88
WSTH	22.25	20.5	-7.87
GSF	8.5	18.5	117.65

Improvement Summary:

The result shows that the largest potential improvement is possible for GSF(i.e.63.85%) and then followed by AB, I/S, WSTH and ES(figure 5.13) because if the slice is largest then greatest efficiency gains can be made at this slice.

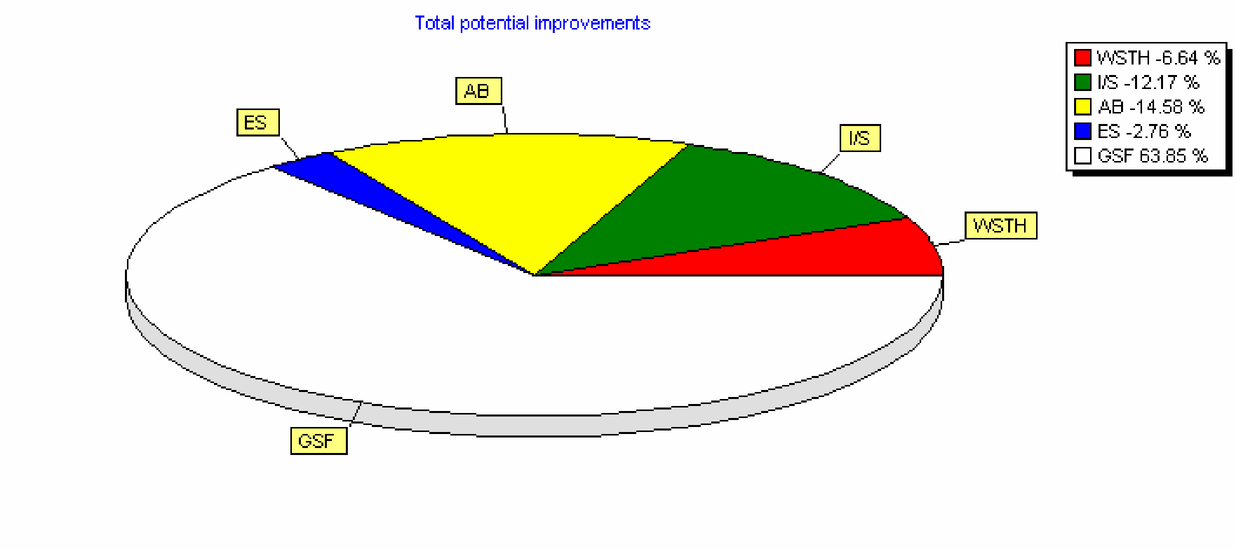

Figure 5.13: Improvement summary of all input-output variables

5-3 Potential improvement using CCR:

This section explains the potential improvement on CCR and BCC models. The following is the summary of potential improvements on these two models.

5-3-1 Summary of potential improvement using CCR Model:

Table 5.14: Efficiency score, actual and target improvement on CCR

Unit name	Score	RTS	Actual WSTH	Actual I/S	Actual AB	Actual ES	Actual GSF	Target WSTH	Target I/S	Target AB	Target ES	Target GSF
AE	42.34	0	22.25	11.25	6450.00	22.50	7.50	19.63	5.63	3207.45	22.50	17.71
BK	65.67	0	20.25	8.50	3650.00	25.50	12.00	20.25	5.81	3309.15	23.21	18.27
BOP	100.00	0	20.50	5.88	3350.00	23.50	18.50	20.50	5.88	3350.00	23.50	18.50
CE	42.34	0	22.25	12.75	6650.00	25.50	8.5	22.24	6.38	3635.11	25.50	20.07
COMM	26.59	0	32.25	6.14	6750.00	21.50	4.50	18.76	5.38	3064.89	21.50	16.93
ELECT	50.32	0	22.75	6.00	4050.00	24.00	9.50	20.92	6.00	3418.37	23.98	18.88
GD	24.91	0	24.25	6.38	4900.00	25.50	5.00	22.24	6.38	3634.86	25.50	20.07
PDB	55.89	0	27.00	10.00	4600.00	25.00	11.00	21.81	6.26	3563.83	25.00	19.68

Table 5.15: The percentage of potential improvement on CCR

Unit name	Percent WSTH	Percent I/S	Percent AB	Percent ES	Percent GSF
AE	-11.8	-50.0	-50.3	0.0	136.2
BK	0.0	-31.7	-9.3	-9.0	52.3
BOP	0.0	0.0	0.0	0.0	0.0
CE	0.0	-50.0	-45.3	0.0	136.2
COMM	-41.8	-12.4	-54.6	0.0	276.1
ELECT	-8.1	0.0	-15.6	-0.1	98.7
GD	-8.3	0.0	-25.8	0.0	301.5
PDB	-19.2	-37.4	-22.5	0.0	78.9

RTS is the return to scale column which explains whether we have increasing, decreasing or constant return to scale where:

Zero: means that there is a constant return to scale.

1 : means an increase in inputs results in a more than proportionate increase in outputs(increasing return to scale)

-1 : means an increase in inputs results in less than proportionate increase in outputs(decreasing return to scale)

5-3-2 Summary of potential improvement using BCC Model:

Table 5.16: Efficiency score, actual and target improvement on BCC

Unit name	Score	RTS	Actual WSTH	Actual I/S	Actual AB	Actual ES	Actual GSF	Target WSTH	Target I/S	Target AB	Target ES	Target GSF
AE	100.00	0	22.25	11.25	6450.00	22.50	7.50	22.25	11.25	6450.00	22.50	7.50
BK	100.00	0	20.25	8.50	3650.00	25.50	12.00	20.25	8.50	3650.00	25.50	12.00
BOP	100.00	0	20.50	5.88	3350.00	23.50	18.50	20.50	5.88	3350.00	23.50	18.50
CE	45.95	1	22.25	12.75	6650.00	25.50	8.50	20.50	5.88	3350.00	23.50	18.50
COMM	100.00	0	32.25	6.14	6750.00	21.50	4.50	32.25	6.14	6750.00	21.50	4.50
ELECT	51.35	1	22.75	6.00	4050.00	24.00	9.50	20.50	5.88	3350.00	23.50	18.50
GD	27.03	1	24.25	6.38	4900.00	25.50	5.00	20.50	5.88	3350.00	23.50	18.50
PDB	59.46	1	27.00	10.00	4600.00	25.00	11.00	20.50	5.88	3350.00	23.50	18.50

Table 5.17: The percentage of potential improvement on BCC

Unit name	Percent WSTH	Percent I/S	Percent AB	Percent ES	Percent GSF
AE	0.0	0.0	0.0	0.0	0.0
BK	0.0	0.0	0.0	0.0	0.0
BOP	0.0	0.0	0.0	0.0	0.0
CE	-7.9	-53.9	-49.6	-7.8	117.6
COMM	0.0	0.0	0.0	0.0	0.0
ELECT	-9.9	-2.0	-17.3	-2.1	94.7
GD	-15.5	-7.8	-31.6	-7.8	269.1
PDB	-24.1	-41.2	-27.2	-6.0	68.2

5-4 Summary of diploma programs' efficiency and the potential improvements:

Table 5.18 shows the aggregate efficiency, technical efficiency and scale efficiency depending on table 5.1 and table 5.9 in order to explain the inefficiency of some DMUs where scale efficiency can be defined to be CCR aggregate efficiency over BCC technical efficiency (Banker, Charnes, Cooper(1984)). :

Table 5.18: The Efficiency of Technical Diploma programs

DMU	Aggregate Efficiency (CCR Model)	Technical Efficiency (BCC Model)	Scale Efficiency (CCR/BCC)
AE	42.34	100.00	42.34
BK	65.67	100.00	65.67
BOP	*100.00*	100.00	100.00
CE	42.34	45.95	92.14
COMM	26.59	100.00	26.59
ELECT	50.32	51.35	97.99
GD	24.91	27.03	92.16
PDB	55.89	59.46	94.00

Table 5.18 shows that there is a variation between the technical efficiency calculated by BCC and the aggregate efficiency calculated by CCR which means that the DMUs do not work at optimal scale, where the constant efficiency model (CCR) is used in case of all DMUs work at optimal scale. Therefore using and adopting the BCC model in the analysis of technical diploma program is preferred.

5-5 Influence of output maximization on technical efficiency:

In the previous summary (tables 5.15 and table 5.17), it was mentioned that the percentage of improvements that can be applied in order to make the inefficient technical programs become technically efficient. Tables 5.19 and 5.20 show the influence of output maximization on the inefficient programs.

Table 5.19: The inputs/outputs after applying the potential improvement on output.

Unit Name	Active	WSTH	I/S	AB	ES	GSF
PDB	☑	27.00	10.00	4,600.00	25.00	18.50
BOP	☑	20.50	5.88	3,350.00	23.50	18.50
BK	☑	20.25	8.50	3,650.00	25.50	12.00
ELECT	☑	22.75	6.00	4,050.00	24.00	18.50
COMM	☑	32.25	6.14	6,750.00	21.50	4.50
GD	☑	24.25	6.38	4,900.00	25.50	18.50
CE	☑	22.25	12.75	6,650.00	25.50	18.50
AE	☑	22.25	11.25	6,450.00	22.50	7.50

Table 5.19 shows the input and output values after finding the potential improvements.

Table 5.20: The technical efficiency after applying the potential improvement on outputs.

Unit name	Score	Actual WSTH	Actual I/S	Actual AB	Actual ES	Actual GSF	Target WSTH	Target I/S	Target AB	Target ES	Target GSF
AE	100.00	22.25	11.25	6450.00	22.50	7.50	22.25	11.25	6450.00	22.50	7.50
BK	100.00	20.25	8.50	3650.00	25.50	12.00	20.25	8.50	3650.00	25.50	12.00
BOP	100.00	20.50	5.88	3350.00	23.50	18.50	20.50	5.88	3350.00	23.50	18.50
CE	100.00	22.25	12.75	6650.00	25.50	18.50	20.50	5.88	3350.00	23.50	18.50
COMM	100.00	32.25	6.14	6750.00	21.50	4.50	32.25	6.14	6750.00	21.50	4.50
ELECT	100.00	22.75	6.00	4050.00	24.00	18.50	20.50	5.88	3350.00	23.50	18.50
GD	100.00	24.25	6.38	4900.00	25.50	18.50	20.50	5.88	3350.00	23.50	18.50
PDB	100.00	27.00	10.00	4600.00	25.00	18.50	20.50	5.88	3350.00	23.50	18.50

Table 5.20 shows that after applying the potential improvement on output the inefficient programs become 100% technically efficient. So management should take this target improvement in consideration in order to raise the technical efficiency of inefficient DMUS.

5-6 Influence of inputs reduction on technical efficiency:

In the previous summary (tables 5.15 and table 5.17) we mention the percentage of improvements that can be obtained in order to make the inefficient technical programs become technically efficient. The below tables 5.21 and 5.22 show the influence of input minimization on the inefficient programs.

Table 5.21: The inputs/outputs after applying the potential improvement on inputs.

Unit Name	Active	WSTH	I/S	AB	ES	GSF
PDB	☑	20.47	5.88	3,351.60	23.51	11.00
BOP	☑	20.50	5.88	3,350.00	23.50	18.50
BK	☑	20.25	8.50	3,650.00	25.50	12.00
ELECT	☑	20.47	5.88	3,351.60	23.51	9.50
COMM	☑	32.25	6.14	6,750.00	21.50	4.50
GD	☑	20.47	5.88	3,351.60	23.51	5.00
CE	☑	20.47	5.88	3,351.60	23.51	8.50
AE	☑	22.25	11.25	6,450.00	22.50	7.50

Table 5.22: The technical efficiency after applying the potential improvement on inputs.

Unit name	Score	Actual WSTH	Actual I/S	Actual AB	Actual ES	Actual GSF	Target WSTH	Target I/S	Target AB	Target ES	Target GSF
AE	100.00	22.25	11.25	6450.00	22.50	7.50	22.25	11.25	6450.00	22.50	7.50
BK	100.00	20.25	8.50	3650.00	25.50	12.00	20.25	8.50	3650.00	25.50	12.00
BOP	100.00	20.50	5.88	3350.00	23.50	18.50	20.50	5.88	3350.00	23.50	18.50
CE	100.00	20.47	5.88	3351.60	23.51	8.50	20.47	5.88	3351.60	23.51	11.00
COMM	100.00	32.25	6.14	6750.00	21.50	4.50	32.25	6.14	6750.00	21.50	4.50
ELECT	100.00	20.47	5.88	3351.60	23.51	9.50	20.47	5.88	3351.60	23.51	11.00
GD	100.00	20.47	5.88	3351.60	23.51	5.00	20.47	5.88	3351.60	23.51	11.00
PDB	100.00	20.47	5.88	3351.60	23.51	11.00	20.47	5.88	3351.60	23.51	11.00

Table 5.22 shows that after applying the potential improvement on inputs the inefficient programs become 100% technically efficient. Where the potential improvement on inputs is mentioned in table 5.16.

Conclusion and Recommendations

- **Conclusion:**

In this research, a detailed questionnaire was prepared using the input of measures from the preliminary interviews with seniors for determining the GTC-TES inputs and outputs.

The factor analysis of this questionnaire gives the significant input and output variables that already used to measure the relative efficiency of GTC technical diploma programs; accordingly the first objective is satisfied.

To achieve the second objective, the relative efficiency scores of eight technical diploma programs are measured at UNRWA-GTC with inputs and outputs data for the latest two groups of graduates using two Data Envelopment Analysis models, CCR model and BCC model. DEA is a linear programming based technique for measuring the relative efficiency of organizational units.

The ability of DEA to identify the inefficient units is one of the main benefits of using this technique. Because the performance assessment is relative, the benchmarks and targets for improvement should be realistic and achievable.

Through the analysis of DEA results, the relative efficiencies of 8 technical diploma programs are evaluated in order to identify the efficient and inefficient programs. We find that only one program with 100% aggregate efficiency which is business and office practice program, and there are four programs with 100% technical efficiency which are architecture engineering, banking, businesses and office practice and communication.

According to BCC model the 4 technical diploma programs (Civil Engineering, Industrial Electronics, Graphic Design, and Programming & Database) are technically inefficient.

And the potential improvement needed for these inefficient diploma programs to become technically efficient is as follows:

a. **Civil engineering(CE):**

   Civil engineering diploma program needs either increase its actual output (GSF) by 117% or decrease its inputs ES, AB, I/S and WSTH by 7%, 49%, 53% and 7% respectively in order to be technically efficient.

b. **Graphic Design(GD):**

   Graphic design diploma program needs either increase its actual output (GSF) by 269% or decrease its inputs ES, AB, I/S and WSTH by 7%, 31%, 7% and 15% respectively in order to be technically efficient.

c. **Industrial Electronics(ELECT):**

   Industrial Electronics diploma program needs either increase its actual output (GSF) by 94% or decrease its inputs ES, AB, I/S and WSTH by 2%, 17%, 1% and 9% respectively in order to be technically efficient.

d. **Programming and Database(PDB):**

   Programming and database diploma program needs either increase its actual output (GSF) by 68% or decrease its inputs ES, AB, I/S and WSTH by 5%, 27%, 41% and 24% respectively in order to be technically efficient.

Accordingly the third and fourth objectives are satisfied.

It is important to envision new TES architectures using DEA evolution in order to make them more efficient, utilizing the use of inputs and maximizing the outputs.

- **Recommendations:**

1. It is recommended to use DEA as an efficiency analysis tool. It is more sophisticated than primitive tools because the DEA models can help managers to identify the inefficient operations and take the right remedial actions for continuous improvement. In addition DEA is quantitative method therefore it is faster and more accurate in collecting and analyzing data.
2. It is important to benefit from the efficiency scores and potential improvement of the inefficient technical diploma program which are obtained by the two models, CCR and BCC in order to derive more meaningful business insights for managers in making resources planning decisions.
3. Management should take the efficiency scores and the potential improvements that were obtained from the analysis results of this research in order to improve the performance of the inefficient technical diploma programs(Civil Engineering, Industrial Electronics, Graphic Design, and Programming & Database) to become 100% technically efficient.
4. There should be a unified database system at every technical diploma program, because, in fact, the main problem facing those who try to apply models analysis is the availability of data.
5. It is very essential to conduct more studies using Data Envelopment Analysis approach to involve all GTC technical diploma programs.
6. It is suggested to promote greater focus on TES-DEA based integration to explore many new opportunities.

7. It is recommended to seek for other inputs and outputs that may affect the efficiency of technical education system at UNRWA-GTC such as student grades and graduate's salary.
8. It is strongly recommended to study the efficiency variations in Palestine middle colleges in order to evaluate the performance of our technical colleges with respect to outsiders.

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Appendix A: Questionnaire:

Dear Managers, Seniors and Instructors ,

Kindly note that the relative efficiency is measured through finding the ratio of outputs' weight to inputs' weight. And our research aims to measure the relative efficiency of 8 technical diploma programs at UNRWA-GTC as a basic requirement to accomplish the master degree in business administration. Senior instructors suggest several inputs and outputs.

In this questionnaire, it will be highly appreciated if you rate the importance of the suggested inputs and outputs in order to accredit and use them in our research.

Note that the importance ratings range from 5 (very important) to 1 (not important).

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Master of Business Administration.

Please, Fill in the space your personal information and put (✓) in the space that corresponds to your opinion:

First Section: Personal information:	
1.	**The department you have worked in (dept):**
2.	**Position (Manger/Senior/ Instructor) :**

Second Section: Input Variables:

	Variable	**Very Important (5)**	**Important (4)**	**Average Important (3)**	**Some what Important (2)**	**Not Important (1)**
1.	Number of major courses hours per week (WSTH)					
2.	Allocated budget (AB)					
3.	Number of students per instructor (IS)					
4.	Number of enrolled students (ES)					
5.	Student grades (Sgrade)					
6.	Students' Attendance record (Satt)					
7.	Instructor salary (ISalary)					

Third Section: Output Variables:

	Variable	**Very Important (5)**	**Important (4)**	**Average Important (3)**	**Some what Important (2)**	**Not Important (1)**
1.	Number of graduates (GS)					
2.	Number of graduates work in related fields (GSF)					
3.	Graduate's salary (GSSalary)					

Appendix B: Questionnaire inputs' Analysis:

To analyze the questionnaire inputs shown in Appendix A, we used the factor analysis approach which is provided by SPSS statistical software.

There are three stages in factor analysis:

1. First, a correlation matrix is generated for all the variables. A correlation matrix is a rectangular array of the correlation coefficients of the variables with each other.
2. Second, factors are extracted from the correlation matrix based on the correlation coefficients of the variables.
3. Third, the factors are rotated in order to maximize the relationship between the variables and some of the factors.

Several inputs and outputs variables were identified which influence the efficiency of technical education at UNRWA-GTC. Where the questionnaire variables are defined as follows:

Dept: Department

Measurement Level: Ordinal

Value Labels:

1.00	Bop : Business and office Practice
2.00	Bk: Banking
3.00	PDB: Programming and Database
4.00	ELECT: Industrial Electronics
5.00	AE: Architecture Engineering
6.00	CE: Civil Engineering
7.00	GD: Graphic Design
8.00	COMM: Communication

- **Post: Position**

  Measurement Level: Ordinal

  Value Labels:

1.00	Instructor
2.00	Senior
3.00	Manager

- **WSTH, AB, IS, ES, Sgrade, Satt, ISalary, GSF, GS, GSSalary:**

  Measurement Level: Ordinal

  Value Labels:

1.00	Not Important
2.00	Some What Important
3.00	Average Important
4.00	Important
5.00	Very Important

Input Dataset:

DEPT	POST	WSTH	AB	IS	ES	SGRADE	SATT	ISALARY
	3	5	4	4	4	4	4	4
	3	5	5	4	4	2	2	1
1	1	5	5	5	4	1	1	1
1	1	5	4	5	5	2	1	1
1	1	5	4	4	5	2	2	2
1	1	4	4	4	4	1	1	2
2	1	5	5	5	4	3	1	1
2	1	5	5	5	5	1	1	1
2	1	4	4	4	3	3	2	2
3	1	5	5	5	5	3	2	1
3	1	5	5	5	4	2	1	2
3	1	5	5	5	5	1	1	2
4	1	4	4	5	5	2	1	1
4	1	4	4	4	4	1	1	1
4	1	5	5	5	4	2	1	1
4	1	5	5	5	5	2	1	1
5	1	4	5	5	4	3	1	1
5	1	5	5	5	4	2	1	1
6	1	5	5	5	5	2	1	2
6	1	4	5	5	4	1	1	2
7	1	5	5	5	4	2	1	1
7	1	4	5	5	5	1	1	1
7	1	5	5	5	3	3	2	1
7	1	4	5	5	4	2	1	1
8	1	5	5	5	5	3	1	1
8	1	4	5	5	4	1	1	1
8	1	4	4	5	4	2	1	1
1	2	5	5	5	5	1	1	1
4	2	5	5	5	4	2	1	1

Interpretation of input analysis results:

- **Descriptive Statistics**

The first output from the analysis is a table of descriptive statistics for all the variables under investigation. Typically, the *mean*, *standard deviation* and *number of respondents* (N) who participated in the survey are given. Looking at the *mean*, one can conclude that *number of students per instructor* is the most important variable because it has the highest *mean* of 4.79.

Factor Analysis

Descriptive Statistics

	Mean	Std. Deviation	Analysis N
WSTH	4.66	.484	29
AB	4.72	.455	29
IS	4.79	.412	29
ES	4.31	.604	29
SGRADE	1.97	.823	29
SATT	1.28	.649	29
ISALARY	1.34	.670	29

- **The Correlation matrix**

The next output from the analysis is the correlation coefficient. A correlation matrix is simply a rectangular array of numbers which gives the correlation coefficients between a single variable and every other variable in the investigation. The correlation coefficient between a variable and itself is always 1, hence the principal diagonal of the correlation matrix contains 1s. The correlation coefficients above and below the principal diagonal are the same. The determinant of the correlation matrix is shown at the foot of the table below.

Correlation Matrix[a]

		WSTH	AB	IS	ES	SGRADE	SATT	ISALARY
Correlation	WSTH	1.000	.364	.167	.257	.238	.200	.049
	AB	.364	1.000	.637	.063	-.122	-.338	-.380
	IS	.167	.637	1.000	.267	-.127	-.580	-.509
	ES	.257	.063	.267	1.000	-.265	-.226	-.097
	SGRADE	.238	-.122	-.127	-.265	1.000	.620	.282
	SATT	.200	-.338	-.580	-.226	.620	1.000	.677
	ISALARY	.049	-.380	-.509	-.097	.282	.677	1.000

a. Determinant = 5.320E-02

- **Kaiser-Meyer-Olkin (KMO) and Bartlett's Test**

The next item from the output is the Kaiser-Meyer-Olkin (KMO) and Bartlett's test. The KMO measures the sampling adequacy which should be greater than 0.5 for a satisfactory factor analysis to proceed. Looking at the table below, the KMO measure is 0.564. From the same table, we can see that the Bartlett's test of sphericity is significant. That is, its associated probability is less than 0.05. In fact, it is actually 0.000. This means that the correlation matrix is not an identity matrix.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.564
Bartlett's Test of Sphericity	Approx. Chi-Square	72.854
	df	21
	Sig.	.000

- **Communalities**

The next item from the output is a table of communalities which shows how much of the variance in the variables has been accounted for by the extracted factors. For instance over 88% of the variance in *ES* is accounted for while 68.1% of the variance in *ISALARY* is accounted for.

Communalities

	Initial	Extraction
WSTH	1.000	.802
AB	1.000	.763
IS	1.000	.764
ES	1.000	.884
SGRADE	1.000	.732
SATT	1.000	.883
ISALARY	1.000	.681

Extraction Method: Principal Component Analysis.

- **Total Variance Explained**

The next item shows all the factors extractable from the analysis along with their ***Eigen values***, the percent of variance attributable to each factor, and the cumulative variance of the factor and the previous factors. Notice that the first factor accounts for 40.853% of the variance, the second 22.411% and the third 15.445%. All the remaining factors are not significant.

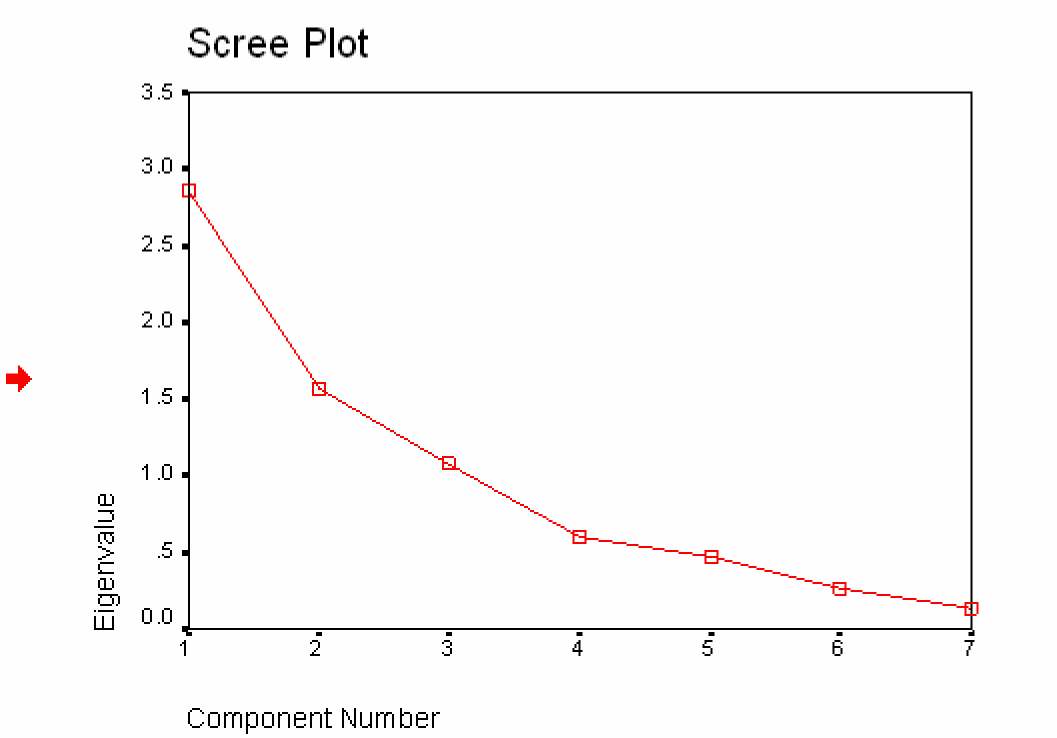
Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.860	40.853	40.853	2.860	40.853	40.853	2.344	33.487	33.487
2	1.569	22.411	63.264	1.569	22.411	63.264	1.914	27.342	60.829
3	1.081	15.445	78.708	1.081	15.445	78.708	1.252	17.879	78.708
4	.600	8.570	87.279						
5	.481	6.874	94.152						
6	.267	3.815	97.967						
7	.142	2.033	100.000						

Extraction Method: Principal Component Analysis.

Scree Plot

The scree plot is a graph of the Eigen values against all the factors. The graph is useful for determining how many factors to retain. The point of interest is where the curve starts to flatten. It can be seen that the curve begins to flatten between factors 3 and 4. Note also that factor 4 has an Eigen value of less than 1, so only three factors have been retained (WSTH, IS, AB).



- **Component (Factor) Matrix**

The table below shows the loadings of the seven variables on the three factors extracted. The higher the absolute value of the loading, the more the factor contributes to the variable. The gap on the table represent loadings that are less than 0.5, this makes reading the table easier. We suppressed all loadings less than 0.5.

Component Matrix[a]

	Component		
	1	2	3
WSTH		.861	
AB	-.652	.509	
IS	-.802		
ES			.846
SGRADE	.549	.548	
SATT	.870		
ISALARY	.770		

Extraction Method: Principal Component Analysis.

a. 3 components extracted.

- **Rotated Component (Factor) Matrix**

The idea of rotation is to reduce the number factors on which the variables under investigation have high loadings. Rotation does not actually change anything but makes the interpretation of the analysis easier. Looking at the table below, we can see that WSTH and ES are substantially loaded on Factor (Component) 3 while SGRADE , WSTH and SATT are substantially loaded on Factor 2 . All remaining variables are substantially loaded on Factor1. These factors can be used as variables for further analysis.

Rotated Component Matrix[a]

	Component		
	1	2	3
WSTH		.644	.524
AB	.860		
IS	.847		
ES			.920
SGRADE		.806	
SATT	-.556	.753	
ISALARY	-.678		

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 7 iterations.

Comment:

According to the factor analysis, there are three significant inputs which are number of major courses hours per week (WSTH), number of students per instructor (I/S) and allocated budget (AB).

Appendix C: Questionnaire Outputs' Analysis:

To analyze the questionnaire outputs shown in Appendix A, we used the factor analysis approach which is provided by SPSS statistical software.

Output Dataset

Dept	POST	GSF	GS	GSSALARY
	3	4	4	3
	3	5	2	2
1	1	5	2	2
1	1	5	2	2
1	1	5	1	2
1	1	5	1	1
2	1	5	1	1
2	1	5	2	3
2	1	5	2	3
3	1	5	2	1
3	1	4	1	2
3	1	5	2	2
4	1	4	2	1
4	1	5	2	2
4	1	5	1	2
4	1	5	1	2
5	1	4	1	3
5	1	5	1	2
6	1	4	2	3
6	1	5	3	2
7	1	5	2	2
7	1	5	1	2
7	1	5	2	2
7	1	5	1	2
8	1	5	1	1
8	1	3	1	4
8	1	5	1	1
1	2	5	1	1
4	2	5	1	1

Interpretation of Output analysis results:

- **Descriptive Statistics**

The first output from the analysis is a table of descriptive statistics for all the variables under investigation. Typically, the *mean*, *standard deviation* and *number of respondents* (N) who participated in the survey are given. Looking at the *mean*, one can conclude that *number of students work in related fields* is the most important variable because it has the highest *mean* of 4.76.

Output Factor Analysis

Descriptive Statistics

	Mean	Std. Deviation	Analysis N
GSF	4.76	.511	29
GS	1.59	.733	29
GSSALARY	1.97	.778	29

- **The Correlation matrix**

The next output from the analysis is the correlation coefficient. A correlation matrix is simply a rectangular array of numbers which gives the correlation coefficients between a single variable and every other variable in the investigation. The correlation coefficient between a variable and itself is always 1, hence the principal diagonal of the correlation matrix contains 1s. The correlation coefficients above and below the principal diagonal are the same. The determinant of the correlation matrix is shown at the foot of the table below.

Correlation Matrix[a]

		GSF	GS	GSSALARY
Correlation	GSF	1.000	-.086	-.560
	GS	-.086	1.000	.287
	GSSALARY	-.560	.287	1.000

a. Determinant = .624

- **Kaiser-Meyer-Olkin (KMO) and Bartlett's Test**

The next item from the output is the Kaiser-Meyer-Olkin (KMO) and Bartlett's test. The KMO measures the sampling adequacy which should be greater than 0.5 for a satisfactory factor analysis to proceed. Looking at the table below, the KMO measure is 0.497. From the same table, we can see that the Bartlett's test of sphericity is significant. That is, its associated probability is less than 0.05. In fact, it is actually 0.006. This means that the correlation matrix is not an identity matrix.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.497
Bartlett's Test of Sphericity	Approx. Chi-Square	12.355
	df	3
	Sig.	.006

- **Communalities**

The next item from the output is a table of communalities which shows how much of the variance in the variables has been accounted for by the extracted factors. For instance over 78% of the variance in *GSSALARY* is accounted for while 23.5% of the variance in *GS* is accounted for.

Communalities

	Initial	Extraction
GSF	1.000	.649
GS	1.000	.235
GSSALARY	1.000	.784

Extraction Method: Principal Component Analysis.

- **Total Variance Explained**

The next item shows all the factors extractable from the analysis along with their ***Eigen values***, the percent of variance attributable to each factor, and the cumulative variance of the factor and the previous factors. Notice that the one factor accounts for 55.573% of the variance. All the remaining factors are not significant.

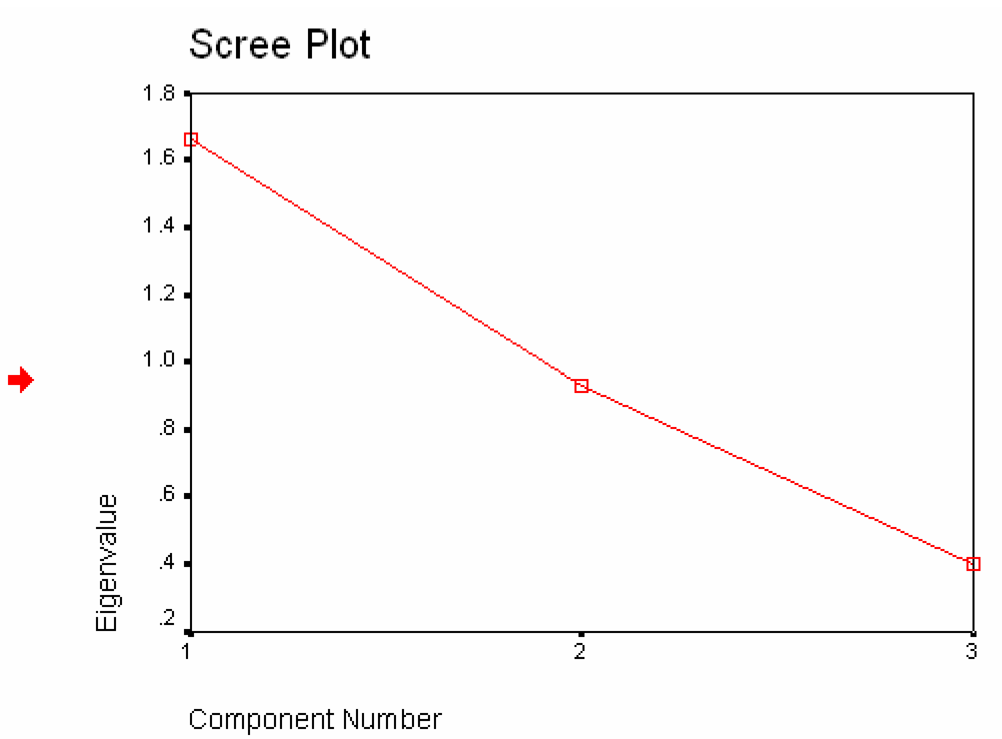
Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.667	55.573	55.573	1.667	55.573	55.573
2	.931	31.034	86.607			
3	.402	13.393	100.000			

Extraction Method: Principal Component Analysis.

- **Scree Plot**

The scree plot is a graph of the Eigen values against all the factors. The graph is useful for determining how many factors to retain. The point of interest is where the curve starts to flatten. Note that factor 1 has an Eigen value of greater than 1, so only one factor has been retained (GSF).



- **Rotated Component (Factor) Matrix**

The idea of rotation is to reduce the number factors on which the variables under investigation have high loadings. Rotation does not actually change anything but makes the interpretation of the analysis easier. Looking at the table below, we can see that there is only one significant component which is GSF.

Rotated Component Matrix[a]

a. Only one component was extracted. The solution cannot be rotated.

Comment:

According to the factor analysis, there is one significant output which is number of graduates who work in their field (GSF).

Appendix D: The statistics of UNRWA –GTC diploma graduates since 1991

Year	B.O.P	Ind. Electronics	Asst. Architectur	Bank.&Fan. Management	Asst. Const.	Graphic Design	Computer Information	Telecom-munication
1991	23							
1992	21							
1993	21	15						
1994	24	11						
1995	18	11						
1996	20	15						
1997	27		23					
1998	24	14	22					
1999	21	20	23	25				
2000	26	20			22		23	
2001	26	11	21	23	2	30		
2002	24	13			20		28	
2003	24	18	15	24		26		
2004	25	20			22		25	25
2005	21	22	17	21	0	19	0	0
2006	24	20	0	0	17	0	23	15
Total	**369**	**210**	**121**	**93**	**83**	**75**	**99**	**40**