MEASURING THE ACADEMIC EFFICIENCY OF THE FOUR CAMPUSES OF THE UNIVERSITY FOR DEVELOPMENT STUDIES USING DATA ENVELOPMENT ANALYSIS

By

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DECLARATION

I hereby declare that this submission is my own work towards the MSc degree and that, to the best of my knowledge, it contains no material previously published by another person nor material which has been accepted for the award of any other degree of the University, except where due acknowledgement has been made in the text.

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DEDICATION

To my dearly loved wife, Mrs Comfort Korkor Sam

ABSTRACT

The purpose of this paper is to utilize data envelopment analysis (DEA) to measure academic efficiency of the four campuses of University for Development Studies. DEA has been recognized as a robust tool that is used for evaluating the performance of profit and non-profit institutions. The proposed approach is deployed based on empirical data collected from the four campuses. On an efficiency scale of 0–1.0, DEA analysis assesses the relative efficiency of every campus relative to the rest of the campuses in terms of academic performance. For inefficient campuses, DEA analysis provides quantitative guidance on how to make them efficient.

The 2010/11 academic year data from the four campuses of University for Development Studies were used. Four input variables and five output variables were identified. The input variables were lecture to student ratio, cost per student, library facilities and academic staff to non-academic staff ratio. Output variables were estimated as: classes obtained (that is first class, second class upper, second class lower, third class and pass). Three campuses (Tamale, Nyankpala and Wa) formed the efficiency frontier and the fourth campus (Navrongo) was found inefficient for the academic year.

There was an indication that reduction in academic staff to non-academic staff ratio as input has a larger effect on efficiency of Navrongo campus than does in input cost per student ratio. For Navrongo campus to be on the efficiency frontier , it is better for cost per student ratio as input to be reduced more than the library facilities.

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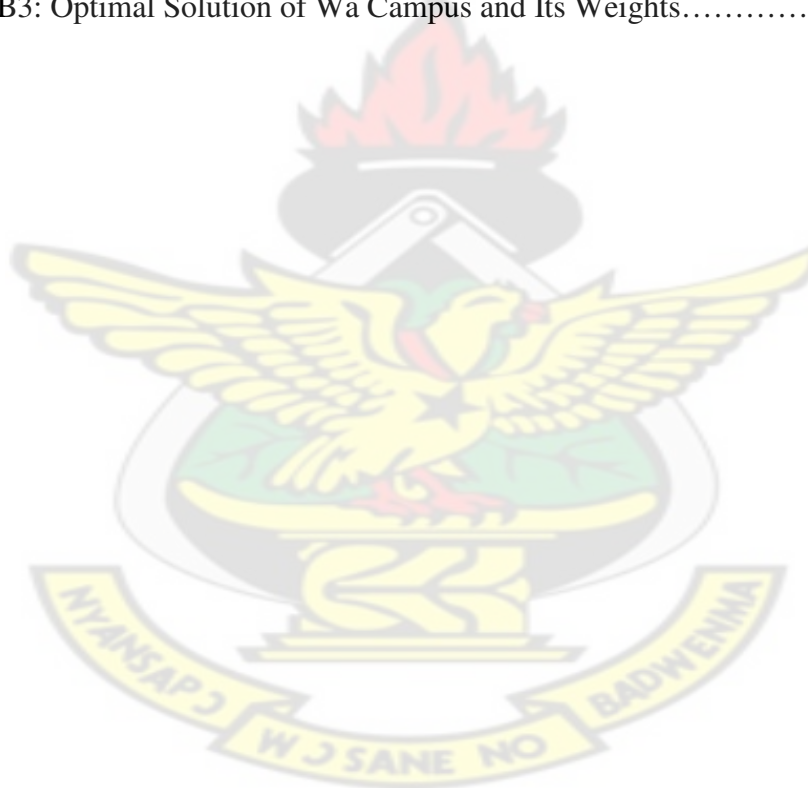
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LIST OF ABBREVIATIONS

Notation	Meaning
DEA	Data Envelopment Analysis
UDS	University for Development Studies
DMU	Decision Making Unit
PNDC	Provisional National Defense Council
CHE	Centre for Higher Education
USNWR	US News and World Report
CCR	Charnes, Cooper and Rhodes
DCCR	Dual Charnes, Cooper and Rhodes
GLM	General Linear Model
GPA	Grade Point Average
LSAT	Law School Admission Test
SFA	Stochastic Frontier Analysis
NSW	New South Wales
ECU	European Currency Unit
OLS	Ordinary Least Squares
FTE	Full Time Equivalent

IPA   Independence Practice Associations

HMO   Health Maintenance Organisation

MTF   Military Treatment Facility

DoD   Department of Defense

TL   Tamale

NK   Nyankpala

NV   Navrong
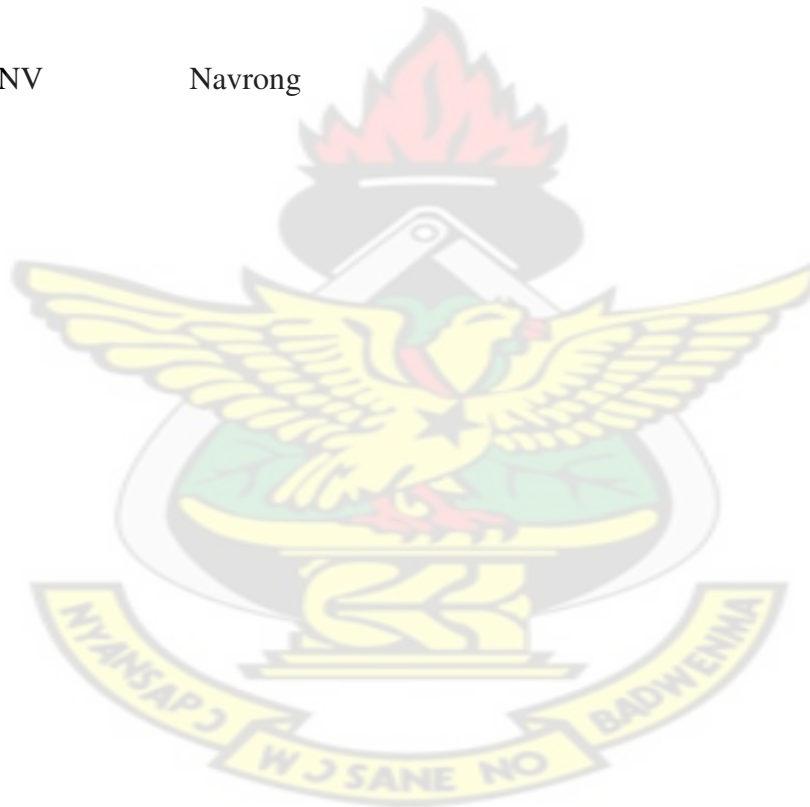
CHAPTER 1

INTRODUCTION

The scrutiny upon Governments has demanded public organizations to increase the efficiency in using the resources they manage. Moreover, there has also been a greater autonomy for the governmental units resulted from the decentralization processes that recently took place in a number of countries. These changes call for the use of new management techniques able to value the performance of these units and to provide tools that can contribute to the improvement of decision-making processes in the public sector.

However, to evaluate activities framed inside the non-lucrative public sector, the usefulness of certain representative indicators of the effectiveness and efficiency of an organization becomes rather limited. This is indeed the case of fundamental concepts such as profitability, commonly applied in the case of lucrative organizations, which cannot readily be applied to analyzing public issues.

As Boussofiane and Dyson (1991) indicated profitability should not be the only performance measure even for profit making organizations. They argue that environment factors outside the company control can affect performance. Thus, when the unit of analysis in an organization (public or private) without lucrative aims, subject to multiple objectives and whose outputs cannot always be expressed in quantitative terms; the assessment of its activity needs a combination of performance indicators.

In situations in which each input and output cannot be added in a significant index of productive efficiency, it is useful that the application of the Data Envelopment Analysis

model (DEA) be used as a tool to measure the relative efficiency of a group of homogeneous Decision Making Units (DMU).

This thesis describes the use of DEA methodology to assess academic efficiency of the four campuses within the University for Development Studies (UDS) according to data of the year 2010/2011.

1.1 HISTORY OF UDS

UDS was established in May 1992 by the PNDC Law 279. It began academic work in September 1993 with the admission of thirty-nine (39) students into the Faculty of Agriculture (FOA) at the Nyankpala campus.

The Faculty of Integrated Development Studies (FIDS), Faculty of Planning and Land Management (FPLM) and Faculty of Education, Law and Business Studies(FELBS), Wa. School of Medicine and Health Sciences (SMHS), Tamale, Faculty of Renewable Natural Resources (FRNR), Nyankpala, Faculty of Applied Science (FAS) and Faculty of Mathematical Science (FMS), Navrongo and the Graduate School now in Tamale were phased in from 1994 to date. The University can now boast of four (4) campuses namely: Nyankpala, Navrongo, Wa and Tamale.

The mission of the University is to run programmes that will effectively and efficiently combine academic work with community-participation and extension.

The University's principal objective is to address and find solutions to the environmental problems and socio-economic deprivations that have characterized northern Ghana in particular and are also found in some rural areas throughout the rest of the country.

Accordingly, UDS consciously and systematically run programmes that are targeted to prepare individuals to establish their own careers in specialized areas. Further, it equips these practitioners with requisite knowledge to enable them to live and function in any deprived community in the country.

Currently the University runs seven faculties, one school and two centres of excellence. Furthermore, there are postgraduate programmes in the Social Sciences, Agriculture and Sciences leading to the award of masters, MPhil and doctorate degrees.

UDS also runs a community-technical interface programme. This is a combination of the academic and community-based field practical work known as the Third Trimester Field Practical Programme (TTFPP). It covers a trimester in each academic year and cuts across all faculties in an integrated approach, and ensures that students live and work closely in communities to formulate specific interventions to address specific challenges.

The Centre for Continuing Education and Inter-disciplinary Research (CCEIR) at Tamale campus ensures coordination of all research activities of the University. The Gender Programme Unit also leads in the process of gender mainstreaming in the policies and programmes. Navrongo and Wa campuses are hosting the two French Language Centres of the University,

(University for Development Studies' 10th Congregational Report, 2009)

1.2 DATA ENVELOPMENT ANALYSIS

DEA was developed by Charnes *et al*. (1978) and Banker *et al*. (1989).DEA is a method used for the measurement of efficiency in cases where multiple input and output factors are observed and when it is not possible to turn these factors into one aggregate input or

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output factor. This is a linear programming based technique which is applied to assess the efficiency of organizations.

DEA provides a comparative efficiency indicator of the units to evaluate. The units analyzed are called decision-making units (DMUs). In DEA, the relative efficiency of DMU is defined as the ratio of the total weighted output to the total weighted input. If the homogeneity is maintained, the outputs and inputs indicators can be expressed in any unit of measurement.

DEA can be applied in many fields such as: health care (hospitals, doctors) ,education (schools, universities) ,banks, manufacturing, management evaluation, fast food restaurants, retail stores, police stations, tax offices, prisons, defense bases (army, navy, air force) and production plants.

A few of the characteristics that make DEA powerful are: DEA can handle multiple input and multiple output models, It does not require an assumption of a functional form relating inputs to outputs, DMUs are directly compared against a peer or combination of peers, inputs and outputs can have very different units and it can be applied to non-profit making organizations.

1.3 VARIABLES

The results of DEA model are sensitive to the inputs and outputs factors. Indeed, an accurate selection of the input and output indicators, which are best adapted to the objective of the analysis, is critical to the success of the study. Next; the variables that would be considered to be included in the analysis would be discussed.

1.3.1 Input variables

The inputs variables are units of measurement, which represent the factors used to carry out the delivery of services. The identification and measurement of these factors is crucial in a fair evaluation of the economy and efficiency in the programs and services management. Previous studies on other performance models (Johnes, 1996) have shown that inputs of Universities can be categorized in various ways. In our case, we classify the inputs used by a campus in four ways. The input variables used in the study are as follows:

1. Lecture to Student Ratio

2. Cost per Student Ratio

3. Academic to Non-Academic Staff

4. Library Facilities

1.3.2 Output variables

Output variables measure the yield or the level of activity of programmes and services. A broad range of outputs of Universities can be found in Segers (1990). The output indicator used in the study is the classes obtained (i.e. first, second upper, second lower, third and pass).

1.4 PROBLEM STATEMENT

In general, Universities with satellite campuses spend heavy amounts and resources to ensure sustainability, coordination and the efficiency of the campuses. However, not much work has been done to assess the performance of the satellite campuses.Therefore,

this study sought to measure the academic efficiency of the four campuses of the UDS using DEA.

1.5 OBJECTIVES OF STUDY

a. To assess the academic efficiency of students performance on the four campuses using DEA.

b. To provide results to University planners to improve efficiency of the four campuses.

1.6 JUSTIFICATION

The result of this study may inform University management in making plans to improve the efficiency on the various campuses through its inputs and outputs indicators. Campuses which are less efficient will evaluate and measure their activities to match up with the most efficient one. The most efficient campus becomes the target for the other campuses.

1.7 SCOPE AND LIMITATIONS

The study considered only inputs and outputs elements that are paramount to the efficiency of the Universities' campuses. The study was restricted to the four campuses of UDS. The analysis was based on data obtained from the Planning Unit, Finance Office, Academic Affairs Unit and Work and Physical Development of UDS.

1.8 METHODOLOGY

1.8.1 Data Collection

Secondary data on staff, students, library facilities and expenditure were collected from the four campuses of the university.The data was on 2010/2011 academic year. The data

comprised of number of lecturers, students, non-academic staff, expenditure and classes
of students obtained.

1.8.2 Data Analysis

DEA was performed on the data obtained. Software used in analyzing and drawing
conclusions about the data obtained included Solver (Linear Programming-simplex
method), and other relevant mathematical formula.

1.9 ORGANIZATION

The thesis is divided into five (5) main chapters.

a. Chapter 1, Overview of the thesis topic under consideration.

b. Chapter 2, Review literature relating to the scope of study.

c. In Chapter 3, An in depth analysis of some of the underlying principles of DEA
used in the study.

d. Chapter 4, Describes the results and analysis of the data collected using the
necessary tools.

e. Chapter 5, Conclusions and recommendations.

CHAPTER 2

LITERATURE REVIEW

This chapter deals with general literature on DEA, applied to a wide field of diversity in the assessment of efficiency.

Barros, (2007), analyzed the efficiency of the Lisbon Police Force precincts witha two-stage DEA. In the first stage, the study estimated the DEA efficiency scores and compares the precincts with each other. The aim of this procedure is to seek out those best practices that will lead to improve performance of all of the precincts. The author ranks the precincts according to their efficiency for the period 2000-2002. In the second stage, he estimated a Tobit model in which the efficiency scores are regressed on socio-economic issues, identifying social causes which vary across the city and affect deterrence policy. The study considers economic implications of the work.

Usher and Savino (2006) compared nineteen (19) ranking systems from Australia, Canada, China, USA, Hong-Kong, Italy, Poland, Germany, Spain and the United Kingdom. They pointed out the fact that the difference in the content of the systems can be ascribed to the geographical location and culture, and refer to the standardization issue of results. However, there is agreement on the best institutions and category based rankings. International ranking systems can be complemented with indicators that would allow inter-institutional performance comparison.

Garcia-Sanchez (2006), established a procedure for evaluating the efficiency of providing the water supply. This procedure has allowed the author realized that the proposed indicators have a discriminating capability in the analysis of the service, and to reject criticisms traditionally assigned to the sensitivity of the DEA technique in relation

to degrees of freedom. The article studies efficiency and also illustrate of the use of the technique of DEA.

According to Bretschneider and his associates (2005), the purpose of their article is two-fold. First, it critically examines the underlying assumptions associated with "best practices research" in Public Administration in order to distill an appropriate set of rules to frame research designs for best practice studies. Second, it reviews several statistical approaches that provide a rigorous empirical basis for identification of "best practices" in public organizations - methods for modeling extreme behavior (i.e., iteratively weighted least squares and quartile regression) and measuring relative technical efficiency.

Ouellette, and Vierstraete (2005), studied the efficiency of Quebec's school boards during a period of severe cutbacks in their finance is examined using DEA. The average efficiency is found to be relatively high. In spite of this, potential savings could be achieved if school boards were fully efficient. Results depended heavily on school boards' socio-economic conditions. They were subjected to Tobit analysis and the boards' corrected efficiencies recalculated. The inefficiencies cost $800 million ofwhich $200 million came from unfavorable socio-economic conditions.

Moore *et al.*, (2005), applied DEA as a response to their view that the literature describing the performance of municipal services often uses imperfect or partial measures of efficiency. DEA has emerged as an effective tool for measuring the relative efficiency of public service provision. This article uses DEA to measure the relative efficiency of 11 municipal services in 46 of the largest cities in the United States over a period of 6 years. In addition, this information is used to explore efficiency differences between cities and services and provide input into astatistical analysis to explore factors

that may explain differences inefficiency between cities. Finally, the authors discuss municipal governments' use of performance measures and problems with collecting municipal data for benchmarking.

Van Dyke (2005) does a detailed presentation and comparison of ranking systems (Asiaweek, The Center, CHE, Good Guides, The Guardian, Macleans, Melbourne Institute, Perspektywy, The times and USNWR) regarding indicators and attributes the difference in the systems to the variety of objectives, systems, culture and availability of data.

Casu *et al*., (2004), for the period 1994-2000, in an efficiency analysis of the European banking institutions found that Italian banks had an 8.9% productivity increase, Spanish banks had a 9.5% increase, while German, French and English banks had 1.8%, 0.6% and 0.1% productivity increase, respectively. The main reason for such improvement in efficiency for the Italian and Spanish banks was the cost reduction that these institutions managed to achieve.

Dill and Soo (2004), criticized rankings systems regarding statistical validity, the selection of indicators that reflected quality and the negative impact on university performance. They concentrated on USNWR, Australian Good University Guide, Macleans, Times Good University Guide and Guardian University Guide. They examine validity, comprehensiveness, comprehensibility and functionality of the systems and reach the conclusion that the system can be supplemented with other indicators and reflect the quality of an institution in a better way.

Schure *et al*., (2004), estimated the productivity of the European banking sector for the period 1993-1997. They found that larger commercial banks were more productive on

the average than smaller banks. However, the Italian and the Spanish banks were found to be the least efficient.

Brockett *et al*., (2003), in a study on Health Maintenance Organizations (HMO), which employ Independent Practice Associations (IPA) versus those that employ group/staff arrangements in a 'game-theoretic' DEA model was evaluated. In this model, the authors combine the two-person zero sum game approach with DEA, evaluating the results from both society's and the consumers' perspectives. Individual DMUs from one group are compared to the collective second group (or the efficient frontier from the second group). This technique is relevant when there are components of a system that may be in competition with each other. Specifically, the civilian network component of the military health care system versus the MTF components might be evaluated using this unique DEA approach.

Similarly, Brockett and his associates (2003), employed the same combined DEA and Ordinary Least Squares (OLS) methodology in evaluating advertising programs for military recruitment. The authors evaluated a "service specific" program for advertising in comparison with a "joint program." Using data from a previously conducted "designed experiment" advertising study, the authors showed that joint recruitment efforts are less efficient then service specific recruiting.

Casu and Molyneux (2003), employed DEA to investigate whether the productivity efficiency of European banking systems had improved and converged towards a common European frontier between 1993 and 1997. The geographical coverage of the study was France, Germany, Italy, Spain and the United Kingdom. All the data generated were reported in ECU as the reference currency. Their results indicated relatively low average efficiency levels. Nevertheless, it was possible to detect a slight

improvement in the average efficiency scores over the period of analysis for almost all banking systems in the sample, with the exception of Italy.

Woodbury *et al*., (2003), reviews municipal efficiency measurement in Australia to advance the argument that the present reliance on partial measures of performance is inadequate and should be heavily augmented by DEA. The authors summarize progress made in efficiency measurement on a state-by-state basis and then examine performance measurement in water and waste water as a more detailed case study. On the basis of this evidence, the authors argue that DEA provides the best means of providing public policy makers with the necessary information on municipal performance.

Drake and Simper (2002), this study uses both parametric and nonparametric techniques to analyze scale economies and relative efficiency levels in policing in England and Wales. Both techniques suggest the presence of significant scale effects in policing and considerable divergence in relative efficiency levels across police forces.

Fernandez *et al*., (2002), studied the economic efficiency of 142 financial intermediaries from eighteen countries over the period 1989-1998 and the relationship between efficiency, productivity change and shareholders' wealth maximization. The authors applied DEA to estimate the relative efficiency of commercial banks of different geographical areas (North America, Japan and Europe). The European banks were from Austria, Belgium, Denmark, Finland, Germany, Ireland, Italy, Luxemburg, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom. The three preferred outputs were total investments, total loans, and non-interest income plus other operating income. In parallel, the four input variables were property, salaries, other operating expenses and total deposits. All these values were expressed in billions of US dollars.

Their results showed that commercial bank productivity across the world had grown significantly (19.6%) from 1989 to 1998.

This effect had been principally due to relative efficiency improvement, with technological progress having a very moderate effect.

Maudos *et al*. (2002), analyzed the cost and profit efficiency of European banks in ten countries, including Italy, for the period 1993-1996. They used multiple regression analysis along with DEA and they split their sample in large, medium and small banks. Their results indicated that only medium sized banks were profit efficient.

Lozano-Vivas *et al*., (2002), examined banking efficiency in ten European countries among which was Italy, for 1993. The authors adopted the value added approach and analyzed also the macroeconomic environment where the banks operated. Their results showed that banking efficiency was low in Europe during that time period. Furthermore, the banks in Italy and Netherlands were the only ones which were not able to operate in a unified European banking system compared to the most efficient banks of the other sample countries.

Worthington and Dollery (2002), used the planning and regulatory function of 173 New South Wales (NSW) local governments, several approaches for incorporating contextual or nondiscretionary inputs in DEA are compared. Non-discretionary inputs (or factors beyond managerial control) in this context include the population growth rate and distribution, the level of development and non-residential building activity, and the proportion of the population from a non-English speaking background. The approaches selected to incorporate these variables include discretionary inputs only, non-discretionary and discretionary inputs treated alike and differently, categorical inputs, 'adjusted' DEA, and 'endogenous' DEA. The results indicate that the efficiency scores of

the five approaches that incorporated non-discretionary factors were significantly positively correlated. However, it was also established that the distributions of the efficiency scores and the number of councils assessed as perfectly technically efficient in the six approaches also varied significantly across the sample.

Sun (2002), employed DEA to measure the relative efficiency of the 14 police precincts in Taipei city, Taiwan. The results indicate how DEA may be used to evaluate these police precincts from commonly available police statistical data for the years 1994–1996. To sharpen the efficiency estimates, the study uses window analysis, slack variable analysis, and output-oriented DEA models with both constant and variable returns to scale. The problem of the presence of nondiscretionary input variables is explicitly treated in the models used. Potential improvements in technical efficiency of police precincts are examined by readjusting the particular output/input indicators. The analysis indicates that differences in operating environments, such as resident population and location factors, do not have a significant influence upon the efficiency of police precincts.

Mante and O'Brien (2002), this paper provides a review and an illustration of the DEA methodology for measuring the relative efficiency of public sector organizations performing similar tasks. The study focuses on measuring the relative technical efficiency of State secondary schools in a geographical region in the Australian State of Victoria. It recognizes that state secondary schools, like other non-profit making organizations, produce multiple outcomes by combining alternative discretionary and non-discretionary inputs.

Bikker (2001), examined the banking productivity of a sample of European banks in various countries, along with was Italy also, for the period 1989-1997. His results

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indicated that the most inefficient banks were first the Spanish ones, followed by the French and the Italian banks. The most productive banks were the one in Luxemburg, in Belgium and in Switzerland.

Hasan *et al*.,(2000), analyzed the banking industries of Belgium, Denmark, France, Germany, Italy, Luxemburg, Netherlands, Portugal, Spain and the United Kingdom. First, the authors attempted to evaluate the efficiency scores of banking industries operating in their own respective countries. Later, they used a common frontier to control the environmental conditions of each country. The results based on cross-country efficiency scores suggested that the banks in Denmark, Spain and Portugal were relatively the most technically efficient and successful. Especially, when the banks of these countries tried to enter into any other European country of the sample were most efficient. On the other hand, the banks in France and Italy were found to be the least efficient institutions among the ones.

Drake and Simper (2000), utilized DEA to estimate the productivity of the English and Welsh police forces and to determine whether there are categorical scale effects in policing using multiple discriminant analysis (MDA). The article demonstrated that by using DEA efficiency results, it is possible to make inferences about the optimal size and structure of the English and Welsh police forces.

Worthington (1999), sampled one hundred and sixty-eight New South Wales local government libraries to analyze the efficiency measures derived from the non-parametric technique of data envelopment analysis. Depending upon the assumptions employed, 9.5 percent of local governments were judged to be overall technically efficient in the provision of library services, 47.6 percent as pure technically efficient, and 10.1 percent as scale efficient. The study also analyses the posited linkages between comparative

performance indicators, productive performance and non-discretionary environmental factors under these different model formulations.

Pastor *et al*., (1997), analyzed the productivity, efficiency and differences in technology in the banking systems of United States, Spain, Germany, Italy, Austria, United Kingdom, France and Belgium for the year 1992. Using the non-parametric approach DEA together with the Malmquist index, they compared the efficiency and differences in technology of several banking systems. Their study used the value added approach. Deposits, productivity assets and loans nominal values were selected as measurements of banking output, under the assumption that these are proportional to the number of transactions and the flow of services to customers on both sides of the balance sheet. Similarly, personnel expenses, no-interest expenses, other than personnel expenses were employed as a measurement of banking input. According to the results France had the banking system with the highest efficiency level followed by Spain, while UK presented the lowest level of efficiency.

Allen and Rai (1996), estimated a global cost function using an international database of financial institutions for fifteen countries. Their sample was divided into two groups according to the country's regulatory environment. Universal banking countries (Australia, Austria, Canada, Switzerland, Germany, Denmark, Spain, Finland, France, Italy, United Kingdom and Sweden) permitted the functional integration of commercial and investment banking, while separated banking countries (Belgium, Japan and US) did not. Large banks in separated banking countries exhibited the largest measure of input inefficiency and had anti-economies of scale. All other banks had significantly lower inefficiency measures. Moreover, small banks in all countries showed significant levels

of economies of scale. Italian banks, along with French, UK and US ones were found less efficient from Japanese, Austrian, German, Danish, Swedish and Canadians ones.

Arnold *et al*., (1996), illustrated how DEA may be coupled with traditional Ordinary Least Squares analysis of loglinear models to produce satisfactory efficiency estimations. In this study, the authors show that the OLS regression and Stochastic Frontier Analysis (SFA) do not provide results consistent with economic theory or expectations, because they deal with "central tendency" estimates without allowing for differences in efficient and inefficient performers. DEA is then employed to determine efficient public secondary schools in Texas. Subsequently, a dummy variable reflecting efficient versus inefficient schools is incorporated into OLS regression models. The results illustrate that the combined methodology approach produces results consistent with economic theory and successfully combines estimation for efficient and inefficient behavior as identifiable components in one model.

Altunbas and Molyneux (1996), examined the banking systems of France, Germany, Italy and Spain for economies of scale and scope. They found differences among the four markets regarding economies of scale. However, the latter were significant only for the Italian banks, which gained as they succeeded in lowering costs.

Pedraja-Chaparro and Salinas-Jiminez (1996), the objective of the article is to provide a measure of technical efficiency of the Administrative Litigation Division of the Spanish High Courts. The concept of efficiency to be measured and the most adequate technique for carrying out the efficiency analysis are selected by considering the specific characteristics of public production. The analysis is undertaken by using (DEA) and various homogeneity tests (returns to scale and restrictions on weights) are applied in order to ensure a correct comparison between Courts.

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In 1995, John W. Young contributed a report to the "Educational and Psychological Measurement" bimonthly journal entitled, "A Comparison of Two Adjustment Methods for Improving the Prediction of Law School Grades." Young (1995), wrote, "Criticisms about the effectiveness of preadmission measures generally focus only on limitations of the predictors". As the title suggests, Young (1995), sought to detect any changes in the predictive validity of the law school admissions test (LSAT) on law school performance when the criterion was changed from first-year grade point average (GPA) to the cumulative GPA (1995). He suggested that many predictive validity studies were inherently limited due their reliance on first year GPA as the criterion. Institutional studies favoured first year GPAs because they are easy to obtain and are a well-defined criterion (1995). Further, cumulative GPAs contain "noise" generated by unique grade distributions of the varying combinations of courses taken by students (1995).

Young (1995), viewed the first-year GPA criterion as "neither a sufficient nor an adequate measure of a student's overall achievement" and suggested that a cumulative GPA would offer more advantage. Thus, he proposed using a previously validated grade adjustment method to correct for the interruptive nature of the cumulative GPA.Young (1995), was the first to use his method in a study on post-graduate performance.

Young (1995), obtained data from four accredited U.S. law schools, choosing one school from the West (School A), one from the South (School B), and two from the Northeast (C and D, respectively). Three of the schools were public and one private. Using item response theory (IRT) and the (statistical) general linear model (GLM), Young (1995), generated figures that equated grades from different course (using a rating scale) and displayed optimizing characteristics of the least squares approach.

The results of Young's grade adjustment methods were minor, indicating that the correlation of predictive validity of the law school admissions test (LSAT) was only slightly improved (1995).Young (1995), attributed the low improvement to the similarity of the law courses taken by the students. In other words, previous efforts using the same adjustment methods yielded greater results because of the greater variation in chosen courses among undergraduate students. In law school, everyone essentially takes the same courses. Thus, correlation improvements based on course differences "would likely have little impact in changing the relative rankings of students" (Young, 1995). School D (from the Northeast) displayed an 83 percent greater correlation between LSAT and future performance than the other three schools. Young (1995), explained this disparity emphasizing that School D had a significantly higher variation of LSAT scores than the other three schools.

Favero and Papi (1995), used the non-parametric Data Envelopment Analysis on a cross sectionof 174 Italian banks in 1991 to measure the technical and the scale efficiencies of the Italian banking industry. In implementing both the intermediation and the asset approach the traditional specification of inputs was modified to allow for an explicit role of financial capital. In addition, regression analysis was used on a bank specific measure of inefficiency to investigate determinants of banks' efficiency. According to the empirical results, efficiency was best explained by productivity specialization by bank size and to a lesser extent by location (north-Italian banks were more efficient than south-Italian banks).

Ozcan and Bannick (1994), used DEA to study trends in Department of Defense hospital efficiency from 1998-1999 using 124 military hospitals and data from the American Hospital Association Annual Survey. In a 1995 study, these authors also compared DoD

hospital efficiency with that of Veteran's Administration hospital efficiency (n=284)

using 1989 data. These studies were conducted at the strategic level under a different

operational paradigm, prior to the large-scale adoption of managed care.

Berg *et al*., (1992), introduced the Malmquist index as a measurement of the

productivity change in the banking industry. They focused on the Norwegian banking

system during the deregulation period 1980-1989. Their results indicated that

deregulation lead into a more competitive environment. The increase of productivity was

faster for larger banks, due to the increased antagonism they faced.

Mihara (1990). Mihara's efficiency analysis of the utilization of personnel at Navy

Medical Treatment Facilities using 1987-1988 data provided implications for resource

allocation. In this study, Mihara initially employed DEA to provide efficiency scores

pertaining to the utilization of personnel at individual U.S. Navy hospitals. Efficient

facilities were then further analyzed using least squares methods to baseline physician

requirements (which were deemed workload and beneficiary dependent) and

professional staff requirements (which were deemed physician dependent). "In other

words, the optimal composition of personnel in terms of output can be determined from

the structural equations of hospitals that are efficient." This study reveals that DEA

methodologies might be used in conjunction with other tools to provide implications for

resource allocation. Mihara's work, while relevant, was primarily driven by raw

workload statistics. While workload is an important aspect for resource allocation, it is

not the only input or output to be considered. Readiness, prevention, training, and

prevention measures are important as well.

Charnes *et al*., (1985), conducted arguably the first Data Envelopment Analysis in a

military health care facility. These authors evaluated the efficiency of 24 Army military

hospitals using criteria that are still relevant for inclusion in this analysis. The authors

selected traditional workload criteria for analysis of outputs including personnel trained,

relative work product, and clinic visits. These outputs are considered traditional

elements of production in health care and are relevant for inclusion along with other less

traditional factors. For inputs, the study evaluated Full Time Equivalent (FTE)

employees by specific category, inpatient expenditures, outpatient expenditures,

weighted procedures, occupied bed days, and operating room hours(2). Despite the fact

that the research was conducted 20 years previously, most of the variables included

retain relevance for measuring the traditional workload functions, although the paradigm

in military health care has shifted towards prevention and health promotion instead of

treatment. Most impressively, a training output is specifically included in this study,

although prevention, readiness, and other aspects are absent, as they were less relevant

measures in the 1980s.
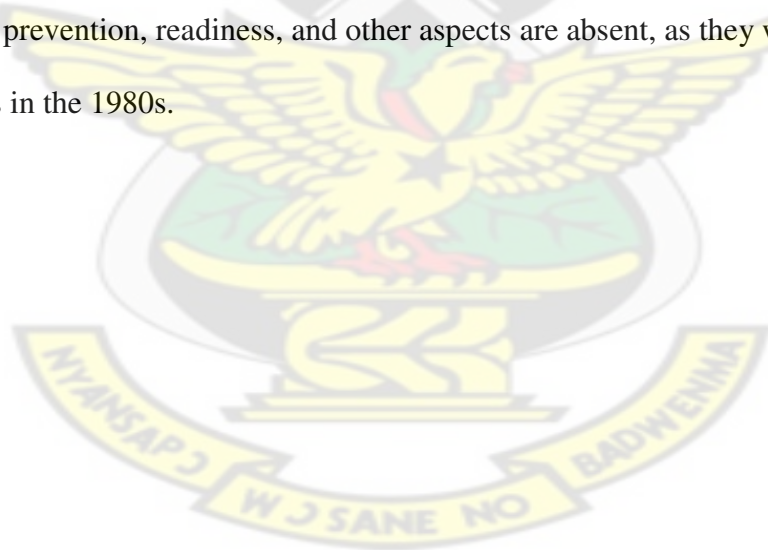
CHAPTER 3

METHODOLOGY

3.1 INTRODUCTION

This chapter deals with one of the fundamental DEA models, the CCR model which was initially proposed by Charnes and his associates in 1978.

DEA is a flexible, mathematical programming approach for the assessment of efficiency, where efficiency is (in general) defined as a linear combination of the weighted outputs divided by a linear combination of the weighted inputs.

In DEA modeling (CCR model), we assume that there are number (n)DMU_s, each of which has 'm' inputs and 'r' outputs of common types. All inputs and outputs are assumed to be nonnegative, but at least one input and one output are positive. The following notations were used throughout this study.

Indices:

i=1, 2…, n,

j=1, 2…, m,

k=1, 2…, r,

Notation:

DMU_i is the ith DMU,

DMU_o is the target DMU,

x_{ji} is the amount of input j consumed by DMU_i ,

$x_i = (x_{ji})_{mx1}$ is the column vector of inputs consumed by DMU_i ,

$x_o = (x_{jo})_{mx1}$ is the column vector of inputs consumed by the target DMU ,

$X = (x_{ji})_{mxn}$ is the matrix of inputs ,

y_{ki} is the amount of output k produced by DMU_i ,

$y_i = (y_{ki})_{rx1}$ is the column vector of outputs produced by DMU_i ,

$y_o = (x_{ko})_{rx1}$ is the column vector of outputs produced by the target DMU ,

$Y = (y_{ki})_{rxn}$ is the matrix of outputs ,

u_j is the weight of input j,

$U = (u_j)_{mx1}$ is the column vector of input weights,

v_k is the weight of output k,

$V = (v_k)_{rx1}$ is the column vector of output weights,

$\lambda = (\lambda_i)_{nx1}$ is the matrix of outputs , $\lambda \in R^n$ is the column vector of a linear combination of n DMU_s,

θ is the objective value (efficiency) of the Charnes-Cooper-Rhodes (CCR) model.

3.1.1 Input-Oriented CCR model

In the CCR model, the multiple-inputs and multiple-outputs of each DMU are aggregated into a single virtual input and a single virtual output, respectively. The input-oriented CCR model for target DMU_o can be expressed by the following fractional programming model:

$$\text{Max } \theta = \frac{v_1 y_{1o} + v_2 y_{2o} + \cdots + v_r y_{ro}}{u_1 x_{1o} + u_2 x_{2o} + \cdots + u_m x_{mo}}$$

$$\text{s.t } \frac{v_1 y_{1i} + v_2 y_{2i} + \cdots + v_r y_{ri}}{u_1 x_{1i} + u_2 x_{2i} + \cdots + u_m x_{mi}} \leq 1, \ i = 1, \dots, n \qquad (3.1)$$

$$u_1, u_2, \dots, u_m \geq 0$$

$$v_1, v_2, \dots, u_r \geq 0.$$

Let $\theta^*, u^* \text{ and } v^*$ be the optimal objective value (efficiency value), the optimal input weights and the optimal output weights, respectively.

The objective of this model is to determine the input weights and output weights that maximizes the ratio of a virtual output to a virtual input for DMU_o. The constraints restrict the ratio of the virtual outputs to the virtual inputs for every DMU to be less than or equal to one (1). This implies that the maximal efficiency, θ^*, is at most one (1). In the input-oriented CCR model, a DMU is inefficient if it is possible to reduce any input without increasing any other inputs and achieve the same level of output.

Under the assumption that all outputs and inputs have non-zero worth, DMU_o in the above model will be efficient if θ^* is equal to 1. If $\theta^* < 1$, it is possible to produce the given output $(y_{1o}, y_{2o}, \dots, y_{ro})$ using a smaller vector of inputs which may be obtained

as a linear combination of the input vectors of other DMU_s. The efficiencies of all DMU_s are obtained by solving model (3.1) n times, once for each DMU as the target DMU:

Charnes and Cooper developed a transformation from a linear fractional programming problem to an equivalent linear programming problem. By using His transformation; the fractional CCR model (3.1) can be transformed into the following linear programming model:

$$\text{Max } \theta = v_1 y_{1o} + v_2 y_{2o} + \cdots + v_r y_{ro}$$

$$\text{s.t.} u_1 x_{1o} + u_2 x_{2o} + \cdots + u_m x_{mo} = 1$$

$$v_1 y_{1i} + v_2 y_{2i} + \cdots + v_r y_{ri} \leq u_1 x_{1i} + u_2 x_{2i} + \cdots + u_m x_{mi} , i = 1, \dots, n$$

$$u_1, u_2, \dots, u_m \geq 0$$

$$v_1, v_2, \dots, u_r \geq 0. \tag{3.2}$$

The above linear CCR model and its dual can be written in the following vector-matrix form:

(CCR)   max $v^T y_o$

s.t. $u^T x_o = 1$

$$-u^T X + v^T Y \leq 0 \tag{3.3}$$

$$u \geq 0$$

$$v \geq 0$$

(DCCR)   min θ

s.t. $\theta x_o - X\lambda \geq 0$ (3.4)

   $Y\lambda \geq y_o$

   $\lambda \geq 0.$

Note that the Dual Charnes, Cooper and Rhodes (DCCR) model has a feasible solution,

$for\ \theta = 1, \lambda_i = 0$ for i$\neq$0, and $\lambda_o = 1.$

Therefore, the optimal value θ^* of the DCCR model is not greater than the constraint

$Y\lambda \geq y_o$ forces λ to be a nonzero vector. This along with $\theta x_o - X\lambda \geq 0$ implies that

$\theta^* > 0.$ Therefore, $0 < \theta^* \leq 1$. Thus, the DCCR model has an optimal solution.

From the strong duality theorem of linear programming, the CCR model also has an

optimal solution and the optimal objective values of the CCR and DCCR models are

equal.

3.1.2 Interpretation of the CCR model:

The target DMU (DMU$_o$) is being compared with a linear combination of other DMU$_s$.

The objective of the CCR model is to find a vector of weights such that the efficiency of

DMU, relative to other DMU$_s$ is maximized, provided that no other DMU$_s$ or linear

combination of other DMUs could achieve the same output levels with smaller amount

of any input.

3.1.3 Interpretation of the DCCR model:

DMU_o is efficient if no linear combination of other DMU_s can produce the same or higher output levels using less of all inputs. θ Indicates a possible proportional reduction in inputs (x_o). Reduction in inputs x_o can be viewed as a radial movement from (x_o, y_o) toward the production frontier.

$\theta^* = 1$ implies that no linear combination of other DMUs has $X\lambda < x_o$ and $Y\lambda \geq y_o$. Otherwise, we can further reduce θ^* while $X\lambda \leq \theta^* x_o$ still holds. Thus, θ^* is not an optimal solution because we can find $\theta < \theta^*$ that satisfies all the constraints.

On the other hand, $\theta^* < 1$ indicates that the resulting linear combination of DMU_s acts as a benchmark for DMU_o. θ^* can also be interpreted as the largest ratio of x_o to $X\lambda$ which outputs are at least equalized, i.e, $Y\lambda \geq y_o$.

3.1.4 Determination of Efficiency

To determine which DMU_s are efficient, we introduce the definition of Pareto-Koopmans efficiency as follows:

Definition of Pareto-Koopmans Efficiency: A DMU is fully efficient if and only if it is impossible to improve any input or output without worsening some other inputs or outputs.

From the above definition, the DMU_o with $\theta^* = 1$ may not be Pareto-Koopmans Efficient if it is possible to make additional improvement (lower input or higher output) without worsening any other input or output. Therefore, we introduce a vector of input excesses (s^-) and output shortfalls (s^+) as follows:

$s^- = \theta x_o - X \lambda$, and $s^+ = Y \lambda - y_o$

Where $s^- \geq 0$, $s^+ \geq 0$ are defined as slack vectors for any feasible solution (θ, λ) of the DCCR model (3.4).

Based on the slack vectors, a DMU is Pareto-Koopmans efficient if it satisfies the following two conditions:

    (1) $\theta^* = 1$

    (2) $s^- = 0$ and $s^+ = 0$

The first condition is referred to as a weak efficiency, technical efficiency of "Farrell efficiency" after M.J. Farrell (1957).

For the CCR model, the Pareto-Koopmans efficiency is called the CCR efficiency.

We summarize the CCR-efficiency conditions for a DMU as follows.

1. If $\theta^* < 1$, then the DMU is CCR-efficiency.

2. If $\theta^* = 1$, and there is nonzero slacks, i.e., $s^{-*} \neq 0$, or $s^{+*} \neq 0$, then the DMU is CCR-inefficient. From the complementary slackness conditions of linear programming, the elements of the vectors u^* and v^* corresponding to the positive slacks must be zero. Thus, the DMU with $\theta^* = 1$ is CCR-inefficient if there is not at least one optimal u^* and v^* such that $u^* > 0$ and $v^* > 0$.

3   If $\theta^* = 1$ with zero slack, then the DMU is CCR-efficient. From the

strong theorem of complementarity, there exist optimal u^* *and* v^* such

that $u^* > 0$ *and* $v^* > 0$.

The inefficiency that occurs from the slack variables is called the "mix inefficiency". To

determine the efficiency of a DMU, we have to solve the following two-phase linear

programming problem:

Phase 1: Solve the DCCR model (3.4). θ^* is equal to the optimal objective value $(u^{*T} y_o)$

of the CCR model (3.3).

Phase 2: Use θ^* from phase 1 to solve the following LP with (λ, s^-, s^+) as variables.

$$\max e^T s^- + e^T s^+$$

s.t. $s^- = \theta^* x_o - X \lambda$

$s^+ = Y \lambda - y_o$ (3.5)

$\lambda \geq 0$

$s^- \geq 0 , s^+ \geq 0$

Where $= (1, \dots, 1)^T$, $e^T s^- = \sum_{j=1}^m s_j^-$ and $e^T s^+ = \sum_{k=1}^r s_k^-$, s_j^- is the input excess of

the jth input, and s_k^- is the output shortfall of the kth output.

An optimal solution $(\lambda^*, s^{-*}, s^{+*})$ of phase 2 is called the max-slack solution. If the

max-slack solution satisfies $s^{-*} = 0$ and $s^{+*} = 0$, then it is called zero slack.

Phase 2 finds an optimal solution that maximizes the sum of input excesses and output shortfalls obtainable with θ^* from phase 1. If a DMU has $\theta^* = 1$, $s^{-*} = 0$ and $s^{+*} = 0$, it is CCR-efficient.

For an efficient DMU_0, a "reference set", Eo, is defined based on the max-slack solution as follows:

$\text{Eo} = \{i| \lambda_i^* > 0, i = 1, \dots, n\}$.

The linear combination of the reference set is the projected point on the efficient frontier of the inefficient DMU_0. The relationship between the optimal solution of DMU_0 and its reference set can be given as:

$$\theta^* x_o = \sum_{i \in Eo} x_i \lambda_i^* + s^{-*}$$

$$y_o = \sum_{i \in Eo} y_i \lambda_i^* - s^{+*}$$

From this relationship, the efficiency of the DMU_0 with (x_o, y_o) can be improved by reducing the input values x_o radially by the ratio θ^* and then reducing the remaining input excesses by s^{-*}. From the output viewpoint, the efficiency can be improved by increasing the outputs y_o by the output shortfalls, s^{+*}.

The CCR model (3.3) is developed on the assumption of "constant return to scale" of DMU_s. For the long-run analysis, the scale of firm's operations should be considered. The amount of increased outputs associated with increased inputs is fundamental to the long-run nature of the firm's production process. From the economic theory, there are three types of "return to scale":

1. Constant returns to scale (CRS), an increase in the amount of inputs consumed leads to a proportional increase in the amount of outputs produced.

2. Increasing return to scale (IRS), an increase in the amount of inputs consumed leads to a larger than proportional increase in the amount of outputs produced.

3. Decreasing returns to scale (DRS), an increase in the amount of inputs consumed leads to a smaller than proportional increase in the amount of outputs produced.
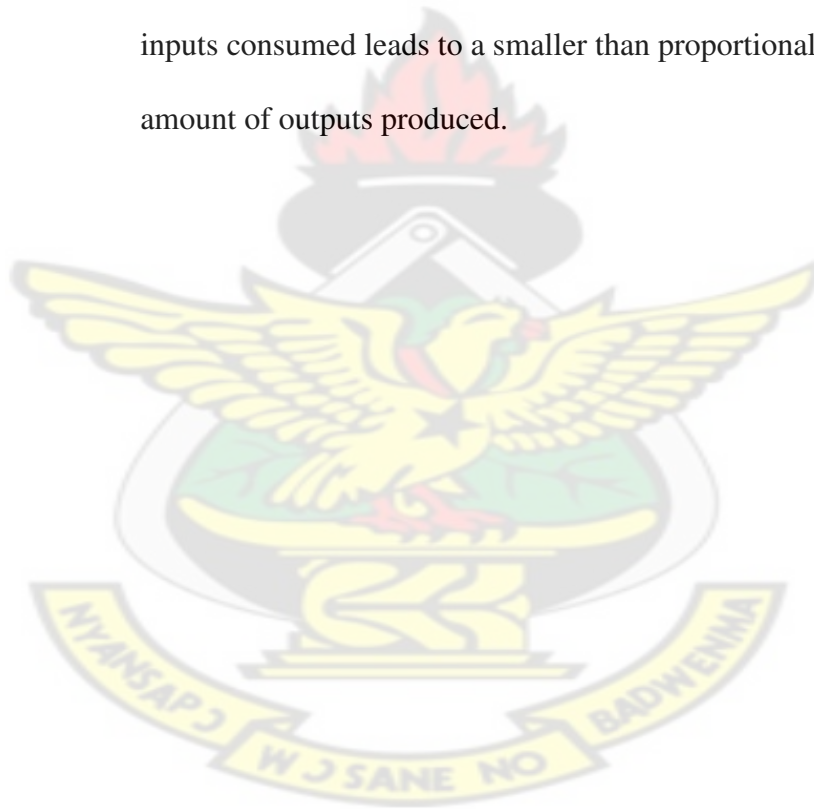
CHAPTER 4

RESULTS AND ANALYSIS OF DATA

4.1 INTRODUCTION

This chapter describes the results and the analysis of the factors which may be associated with the efficiency score. It also looks at the linear programming problems formulated out of the data.

4.2 EFFICIENCY MODELING

With the inputs and outputs identified in the previous sections, the basic DEA model for a given campus system can be formulated as follows:

$$\text{Target DMU } (\text{Max } \theta) = v_1 y_{1o} + v_2 y_{2o} + \cdots + v_r y_{ro}$$

$$\text{s.t. } u_1 x_{1o} + u_2 x_{2o} + \cdots + u_m x_{mo} = 1$$

$$v_1 y_{1i} + v_2 y_{2i} + \cdots + v_r y_{ri} \leq u_1 x_{1i} + u_2 x_{2i} + \cdots + u_m x_{mi}, \qquad i = 1, \dots, n$$

$$u_1, u_2, \dots, u_m \geq 0$$

$$v_1, v_2, \dots, u_r \geq 0.$$

y_r = amount of output r

v_r = weight assigned to output r

x_i = amount of input i

u_i = weight assigned to input i

The linear programming formulated out of the data (refer to APPENDIX A for the data)

Max: Tamale $= 6v_1 + 114v_2 + 59v_3 + 10v_4$;

Subject to: $0.0390u_1 + 57u_2 + u_3 + u_4 = 1$;

$6v_1 + 114v_2 + 59v_3 + 10v_4 - (0.0390u_1 + 57u_2 + u_3 + u_4) \leq 0$;

$v_1 + 181v_2 + 227v_3 + 10v_4 - (0.0310u_1 + 121u_2 + u_3 + 0.5255474u_4) \leq 0$

$v_1 + 185v_2 + 307v_3 + 21v_4 + 4v_5 - (0.0205u_1 + 130u_2 + u_3 + 1.1076923u_4) \leq 0$;

$145v_2 + 668v_3 + 21v_4 + 181v_5 - (0.0077u_1 + 77u_2 + 2u_3 + 1.2533333u_4) \leq 0$;

$$v_1, v_2, v_3, v_4, v_5, u_1, u_2, u_3, u_4 \geq 0$$

Max: Nyankpala $= v_1 + 181v_2 + 227v_3 + 10v_4$;

Subject to: $0.0310u_1 + 121u_2 + u_3 + 0.5255474u_4 = 1$;

$6v_1 + 114v_2 + 59v_3 + 10v_4 - (0.0390u_1 + 57u_2 + u_3 + u_4) \leq 0$;

$v_1 + 181v_2 + 227v_3 + 10v_4 - (0.0310u_1 + 121u_2 + u_3 + 0.5255474u_4) \leq 0$;

$v_1 + 185v_2 + 307v_3 + 21v_4 + 4v_5 - (0.0205u_1 + 130u_2 + u_3 + 1.1076923u_4) \leq 0$;

$145v_2 + 668v_3 + 21v_4 + 181v_5 - (0.0077u_1 + 77u_2 + 2u_3 + 1.2533333u_4) \leq 0$;

$$v_1, v_2, v_3, v_4, v_5, u_1, u_2, u_3, u_4 \geq 0$$

Max: Navrongo $= v_1 + 185v_2 + 307v_3 + 21v_4 + 4v_5;$

Subject to: $0.0205u_1 + 130u_2 + u_3 + 1.1076923u_4 = 1;$

$$6v_1 + 114v_2 + 59v_3 + 10v_4 - (0.0390u_1 + 57u_2 + u_3 + u_4) \leq 0;$$

$$v_1 + 181v_2 + 227v_3 + 10v_4 - (0.0310u_1 + 121u_2 + u_3 + 0.5255474u_4) \leq 0;$$

$$v_1 + 185v_2 + 307v_3 + 21v_4 + 4v_5 - (0.0205u_1 + 130u_2 + u_3 + 1.1076923u_4) \leq 0;$$

$$145v_2 + 668v_3 + 21v_4 + 181v_5 - (0.0077u_1 + 77u_2 + 2u_3 + 1.2533333u_4) \leq 0;$$

$$v_1, v_2, v_3, v_4, v_5, u_1, u_2, u_3, u_4 \geq 0$$

Max: Wa $= 145v_2 + 668v_3 + 21v_4 + 181v_5;$

Subject to: $0.0077u_1 + 77u_2 + 2u_3 + 1.2533333u_4 = 1;$

$$6v_1 + 114v_2 + 59v_3 + 10v_4 - (0.0390u_1 + 57u_2 + u_3 + u_4) \leq 0;$$

$$v_1 + 181v_2 + 227v_3 + 10v_4 - (0.0310u_1 + 121u_2 + u_3 + 0.5255474u_4) \leq 0;$$

$$v_1 + 185v_2 + 307v_3 + 21v_4 + 4v_5 - (0.0205u_1 + 130u_2 + u_3 + 1.1076923u_4) \leq 0;$$

$$145v_2 + 668v_3 + 21v_4 + 181v_5 - (0.0077u_1 + 77u_2 + 2u_3 + 1.2533333u_4) \leq 0;$$

$$v_1, v_2, v_3, v_4, v_5, u_1, u_2, u_3, u_4 \geq 0$$

Table 4.1: Descriptive statistics for DEA results.

Items	Scores
Total number of DMUs	4.00
Number of efficient DMUs	3.00
Number of inefficient DMUs	1.00
Maximum efficiency	1.00
Minimum efficiency	0.86
Average efficiency	0.97

Source: Author's construct, April 2012

Excel solver software is used to run the CCR model. Table 4.1 summarizes the

descriptive statistics of the results. The maximum efficiency score is 1.00, while the

minimum efficiency score is 0.86.The efficiency score average is 0.97.This means that

the input for an average unit could be reduced by 3%.

Table4.2:Efficiency scores of the campuses

Campuses	Efficiency
Tamale	1.00
Nyankpala	1.00
Navrongo	0.86
Wa	1.00

Source: Author's construct, April 2012

Table 4.2 shows the scores of the four campuses obtained from DEA using CCR model. These efficiency scores were under the following conditions:

1. All data and all weights are positive

2. Efficiency scores must lie between zero and unity

3. The same weights for the target campus are applied to all campuses

The following three (3) campuses (Tamale, Nyankpala and Wa) are efficient and are considered to have better academic performances. These efficient campuses have an efficiency score equal to one (1.00). They are on the efficient frontier. The three campuses are more efficient in converting the inputs into better academic performance of students as compared to Navrongo campus (0.86) which is inefficient.
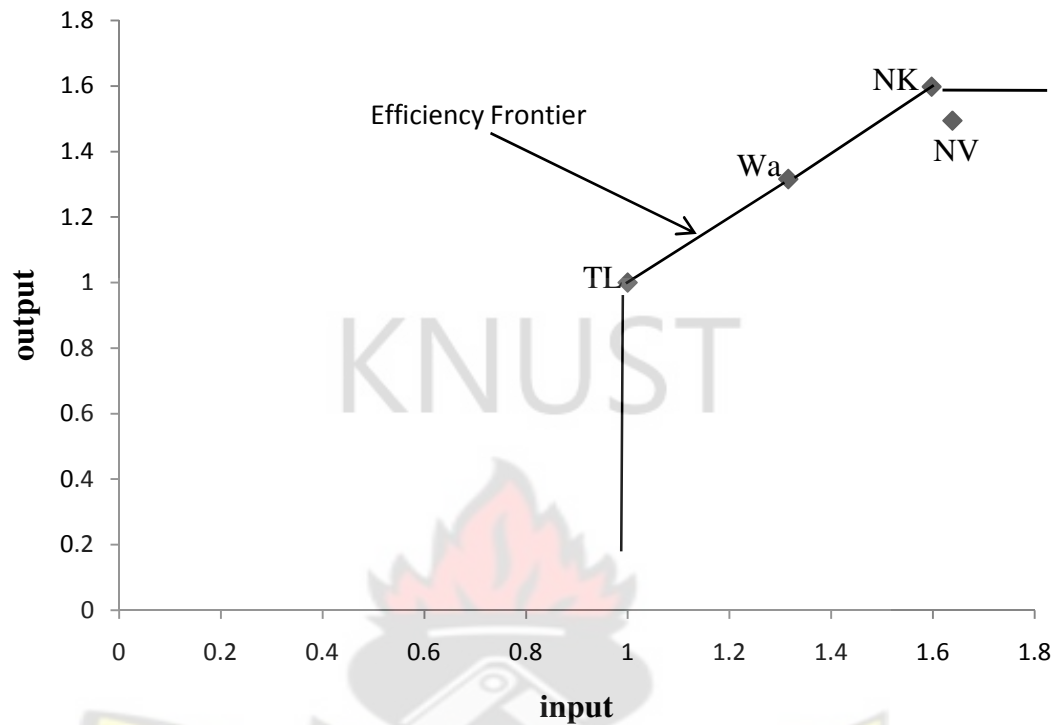
Figure 4.1: Efficiency Frontier for the Campuses

Source: Author's construct, April 2012

Figure 4.1 shows that Tamale, Nyankpala and Wa campuses are efficient since they lie on the efficiency frontier. Since Navrongo campus lies below the efficiency frontier, it is inefficient. Its efficiency can be determined by comparing it to any of the efficient campuses.

4.3 ANSWER REPORT ON TAMALE AS THE TARGET DMU

Table 4.3:Target Cell (Max)

Cell	Name	Original Value	Final Value
K2	Tamale weighted output	189	1

Source: Author's construct, April 2012

Table 4.4: Adjustable Cells

Cell	Name	Original Value	Final Value
B7	weight (V_1)1st Class	1.0000	0.0000
C7	weight (V_2) 2nd Class Upper	1.0000	0.0087
$D7	weight (V_3) 2nd Class Lower	1.0000	0.0001
E7	weight (V_4) 3rd Class	1.0000	0.0000
F7	weight (V_5) Pass	1.0000	0.0000
$G7	weight(U_1) Lecture to Student Ratio	1.0000	0.0000
$H7	weight (U_2) Cost per Student Ratio	1.0000	0.0118
I7	weight (U_3) Library Facilities	1.0000	0.0000
J7	weight (U_4) Academic to Non-Academic Staff Ratio	1.0000	0.3281

Source: Author's construct, April 2012

From Tables 4.3 and 4.4, we can see that the optimal solution to linear programming

(LP) has the value one (1) and the best input and output weights are $U_1 = 0, U_2 =$

$0.0118, U_3 = 0, U_4 = 0.3281,$

$V_1 = 0, V_2 = 0.0087, V_3 = 0.0001, V_4 = 0$ and $V_5 = 0.$

Let now observe the difference between the optimal weights $U_2 = 0.0118$ and $U_4 =$

0.3281. The ratio $\frac{U_4}{U_2} = 28$ suggests that it is advantageous for Navrongo campus to

weight input (Academic to Non academic staff ratio) 28 times more than input weight

(Cost per Student ratio) in order to maximize the efficiency. It shows that a reduction in

input U_4 has a bigger effect on efficiency than does a reduction in input U_2.

Table 4.5:Constraints of the Model

Cell	Name	Cell Value	Formula	Status	Slack
L2	Tamale weighted input	1.0000	L2=1	Not Binding	0.0000
N2	Tamale working	0.0000	N2<=0	Binding	0.0000
N3	Nyankpala working	0.0000	N3<=0	Binding	0.0000
N4	Navrongo working	-0.2557	N4<=0	Not Binding	0.2557
N5	Wa working	0.0000	N5<=0	Binding	0.0000

Source: Author's construct, April 2012

Table 4.5, also indicates that the three working constraints (Tamale, Nyankpala and Wa)

with a slack value of zero are said to be binding because they are satisfied with equality

at the LP optimal.

4.4 SENSITIVITY REPORT

Table 4.6: Adjustable cells

Cell	Name	Final Value	Reduced Cost	Objective Coefficient	Allowable Increase	Allowable Decrease
B7	weight (V_1)1st Class	0.0000	0.0000	6	0	1E+30
C7	weight (V_2) 2nd Class Upper	0.0087	0.0000	114	0	0
D7	weight (V_3) 2nd Class Lower	0.0001	0.0000	59	0	0
E7	weight (V_4) 3rd Class	0.0000	0.0000	10	0	1E+30
F7	weight (V_5) Pass	0.0000	0.0000	0	0	1E+30
G7	Weight(U_1) Lecture to Student Ratio	0.0000	0.0000	0	0	1E+30
H7	weight (U_2) Cost Per Student Ratio	0.0118	0.0000	0	0	0
I7	weight (U_3) Library Facilities	0.0000	0.0000	0	0	1E+30
J7	weight (U_4) Academic to non-Academic Staff Ratio	0.3281	0.0000	0	0	0

Source: Author's construct, April 2012

From Table 4.6, having, $U_1 = 0, U_2 = 0.0118, U_3 = 0, U_4 = 0.3281, V_1 = 0, V_2 =$

$0.0087, V_3 = 0.0001, V_4 = 0$ and $V_5 = 0$. Suppose we vary the coefficient of V_2 in the

objective function. The solution value for V_2 is 0.0087 and the objective function

coefficient for V_2 is 114. The allowable increase or decrease tells us that, provided the coefficient for V_2 in the objective function lies between $114 + 0 = 114$ and $114 - 0 = 114$, the values of the variables in the optimal LP solution will remain unchanged.

Again, the solution value for V_3 is 0.0001 and the objective function coefficient for V_3 is 59. The allowable increase or decrease tells us that, provided the coefficient for V_3 in the objective function lies between $59 \pm 0 = 59$, the values of the variables in the optimal LP solution will remain unchanged. Similar conclusions can be drawn about $U_1, U_2, U_3, U_4, V_1, V_4$, and V_5.

Table 4.7: Constraints of the Model

Cell	Name	Final Value	Shadow Price	Constraint R.H. Side	Allowable Increase	Allowable Decrease
L2	Tamale weighted input	1.0000	1.0000	1	1E+30	0.999999999
N2	Tamale working	0.0000	1.0000	0	0.036725235	0.812757636
N3	Nyankpala working	0.0000	0.0000	0	0.354022117	0.516530473
N4	Navrongo working	-0.2557	0.0000	0	1E+30	0.255716675
N5	Wa working	0.0000	0.0000	0	1.319066139	0.043313299

Source: Author's construct, April 2012

From Table 4.7, we can study the effect of changing the right-hand side of Wa constraint. If the right-hand side of Wa constraint lies between 0+1.319066=1.319066 and 0- 0.043313= -0.043313, the objective function change will be exactly zero (0).

Again, if the right-hand side of Tamale constraint lies between 0+0.0367252=0.0367252 and 0-0.8127576 = -0.8127576, the objective function change will be exactly one (1).

4.5 ANSWER REPORT ON WA AS THE TARGET DMU

Table 4.8: Target Cell (Max)

Cell	Name	Original Value	Final Value
K5	Wa weighted output	1015	1

Source: Author's construct, April 2012

Table 4.9: Adjustable Cells

Cell	Name	Original Value	Final Value
B7	weight (V_1)1st Class	1.0000	0.0000
C7	weight (V_2) 2nd Class Upper	1.0000	0.0066
$D7	weight (V_3) 2nd Class Lower	1.0000	0.0001
E7	weight (V_4) 3rd Class	1.0000	0.0000
F7	weight (V_5) Pass	1.0000	0.0000
$G7	weight(U_1) Lecture to Student Ratio	1.0000	0.0000
$H7	weight (U_2) Cost per Student Ratio	1.0000	0.0090
I7	weight (U_3) Library Facilities	1.0000	0.0000
J7	weight (U_4) Academic to Non-Academic Staff Ratio	1.0000	0.2493

Source: Author's construct, April 2012

From Tables 4.8 and 4.9, we can see that the optimal solution to linear programming (LP) has the value one (1) and the best input and output weights are $U_1 = 0, U_2 = 0.0090, U_3 = 0, U_4 = 0.2493, V_1 = 0, V_2 = 0.0066, V_3 = 0.0001, V_4 = 0$ and $V_5 = 0$.

Let now observe the difference between the optimal weights $U_2 = 0.0090$ and $U_4 = 0.2493$. The ratio $\frac{U_4}{U_2} = 28$ suggests that it is advantageous for Navrongo campus to weight input (Academic to Non academic staff ratio) 28 times more than input weight (Cost per Student ratio) in order to maximize the efficiency. It shows that a reduction in input U_4 has a bigger effect on efficiency than does a reduction in input U_2.

Table 4.10 : Constraints of the Model

Cell	Name	Cell Value	Formula	Status	Slack
N2	Tamale working	0.0000	N2<=0	Binding	0.0000
N3	Nyankpala working	0.0000	N3<=0	Binding	0.0000
N4	Navrongo working	-0.1943	N4<=0	Not Binding	0.1943
N5	Wa working	0.0000	N5<=0	Binding	0.0000
L5	Wa weighted input	1.0000	L5=1	Not Binding	0.0000

Source: Author's construct, April 2012

Table 4.10, also indicates that the three working constraints (Tamale, Nyankpala and Wa) with a slack value of zero are said to be binding because they are satisfied with equality at the LP optimal.

4.6 SENSITIVITY REPORT

Table 4.11: Adjustable cells

Cell	Name	Final Value	Reduced Cost	Objective Coefficient	Allowable Increase	Allowable Decrease
B7	weight (V_1)1stClass	0.0000	0.0000	0	0	1E+30
C7	weight (V_2) 2nd Class Upper	0.0066	0.0000	145	0	0
D7	weight (V_3) 2nd Class Lower	0.0001	0.0000	668	0	0
E7	weight (V_4) 3rd Class	0.0000	0.0000	21	0	1E+30
F7	weight (V_5) Pass	0.0000	0.0000	181	0	1E+30
G7	weight(U_1) Lecture to Student Ratio	0.0000	0.0000	0	0	1E+30
H7	weight (U_2) Cost per Student Ratio	0.0090	0.0000	0	0	0
I7	weight (U_3) Library Facilities	0.0000	0.0000	0	0	1E+30
J7	weight (U_4) Academic to Non-Academic Staff Ratio	0.2493	0.0000	0	0	0

Source: Author's construct, April 2012

From Table 4.11, having, $U_1 = 0, U_2 = 0.0090, U_3 = 0, U_4 = 0.2493, V_1 = 0, V_2 = 0.0066, V_3 = 0.0001, V_4 = 0$ and $V_5 = 0$. Suppose we vary the coefficient of V_2 in the objective function. The solution value for V_2 is 0.0066 and the objective function coefficient for V_2 is 145.The allowable increase or decrease tells us that, provided the

coefficient for V_2 in the objective function lies between 145 + 0=145 and 145-0 = 145, the values of the variables in the optimal LP solution will remain unchanged.

Again, the solution value for V_3 is 0.0001 and the objective function coefficient for V_3 is 668. The allowable increase or decrease tells us that provided the coefficient for V_3 in the objective function lies between 668±0 =668, the values of the variables in the optimal LP solution will remain unchanged. Similar conclusions can be drawn about $U_1, U_2, U_3, U_4, V_1, V_4$, and V_5.

Table 4.12: Constraints of the Model

Cell	Name	Final Value	Shadow Price	Constraint R.H. Side	Allowable Increase	Allowable Decrease
N2	Tamale working	0.0000	0.0000	0	0.027850805	0.648476839
N3	Nyankpala working	0.0000	0.0000	0	0.273395209	0.383659681
N4	Navrongo working	-0.1943	0.0000	0	1E+30	0.194340416
N5	Wa working	0.0000	1.0000	0	0.989298497	0.032931782
L5	Wa weighted input	1.0000	1.0000	1	1E+30	0.999999999

Source: Author's construct, April 2012

From Table 4.12, we can study the effect of changing the right-hand side of Wa constraint. If the right-hand side of Wa constraint lies between 0+0.9893=0.9893 and 0-

45

0.03293= -0.03293, the objective function change will be exactly one (1). Again, if the right-hand side of Tamale constraint lies between 0+0.02785=0.02785 and 0-0.6485 = -0.6485, the objective function change will be exactly zero (0).

4.7 ANSWER REPORT ON NYANKPALA AS THE TARGET DMU

Table 4.13: Target Cell (Max)

Cell	Name	Original Value	Final Value
K3	Nyankpala weighted output	419	1

Source: Author's construct, April 2012

Table 4.14: Adjustable Cells

Cell	Name	Original Value	Final Value
B7	weight (V_1) 1st Class	1.0000	0.0000
C7	weight (V_2) 2nd Class Upper	1.0000	0.0051
$D7	weight (V_3) 2nd Class Lower	1.0000	0.0003
E7	weight (V_4) 3rd Class	1.0000	0.0000
F7	weight (V_5) Pass	1.0000	0.0000
$G7	weight(U_1) Lecture to Student Ratio	1.0000	0.0000
$H7	weight (U_2) Cost per Student Ratio	1.0000	0.0063
I7	weight (U_3) Library Facilities	1.0000	0.2448
J7	weight (U_4) Academic to non-Academic Staff Ratio	1.0000	0.0000

Source: Author's construct, April 2012

From Tables 4.13 and 4.14, we can see that the optimal solution to linear programming (LP) has the value one (1) and the best input and output weights are $U_1 = 0, U_2 = 0.0063, U_3 = 0.2448, U_4 = 0, V_1 = 0, V_2 = 0.0051, V_3 = 0.0003, V_4 = 0$ and $V_5 = 0$.

Let now observe the difference between the optimal weights $U_2 = 0.0063$ and $U_3 = 0.2448$. The ratio $\frac{U_3}{U_2} = 39$ suggests that it is advantageous for Navrongo campus to weight input (Library facilities) 39 times more than input weight (Cost per Student ratio) in order to maximize the efficiency. It shows that a reduction in input U_3 has a bigger effect on efficiency than does a reduction in input U_2.

Table 4.15: Constraints of the Model

Cell	Name	Cell Value	Formula	Status	Slack
N2	Tamale working	0.0000	N2<=0	Binding	0.0000
N3	Nyankpala working	0.0000	N3<=0	Binding	0.0000
N4	Navrongo working	-0.0080	N4<=0	Not Binding	0.0080
N5	Wa working	0.0000	N5<=0	Binding	0.0000
L3	Nyankpala weighted input	1.0000	L3=1	Not Binding	0.0000

Source: Author's construct, April 2012

Table 4.15, also indicates that the three working constraints (Tamale, Nyankpala and Wa) with a slack value of zero are said to be binding because they are satisfied with equality at the LP optimal.

4.8 SENSITIVITY REPORT

Table 4.16: Adjustable cells

Cell	Name	Final Value	Reduced Cost	Objective Coefficient	Allowable Increase	Allowable Decrease
B7	weight (V_1)1st Class	0.0000	0.0000	1	0	1E+30
C7	weight (V_2)2nd Class Upper	0.0051	0.0000	181	0	0
D7	weight (V_3)2nd Class Lower	0.0003	0.0000	227	0	0
E7	weight (V_4)3rd Class	0.0000	0.0000	10	0	1E+30
F7	weight (V_5) Pass	0.0000	0.0000	0	0	1E+30
G7	weight(U_1) Lecture to Student Ratio	0.0000	0.0000	0	0	1E+30
H7	weight (U_2) Cost per Student Ratio	0.0063	0.0000	0	0	0
I7	Weight (U_3) Library Facilities	0.2448	0.0000	0	0	0
J7	weight (U_4) Academic to Non-Academic Staff Ratio	0.0000	0.0000	0	0	1E+30

Source: Author's construct, April 2012

From Table 4.16, having,$U_1 = 0, U_2 = 0.0063, U_3 = 0.2448, U_4 = 0, V_1 = 0, V_2 =$
0.0051, $V_3 = 0.0003, V_4 = 0$ and $V_5 = 0$. Suppose we vary the coefficient of V_2 in the
objective function. The solution value for V_2 is 0.0051 and the objective function
coefficient for V_2 is 181. The allowable increase or decrease tells us that, provided the
coefficient for V_2 in the objective function lies between 181 + 0=181 and 181-0 = 181,
the values of the variables in the optimal LP solution will remain unchanged.

Again, the solution value for V_3 is 0.0003 and the objective function coefficient for V_3 is 227. The allowable increase or decrease tells us that provided the coefficient for V_3 in the objective function lies between $227 \pm 0 = 227$, the values of the variables in the optimal LP solution will remain unchanged. Similar conclusions can be drawn about $U_1, U_2, U_3, U_4, V_1, V_4$, and V_5.

Table 4.17: Constraints of the Model

Cell	Name	Final Value	Shadow Price	Constraint R.H. Side	Allowable Increase	Allowable Decrease
N2	Tamale working	0.0000	0.0000	0	0.093959195	0.021407078
N3	Nyankpala working	0.0000	1.0000	0	0.006730093	0.243534189
N4	Navrongo working	-0.0080	0.0000	0	1E+30	0.007972781
N5	Wa working	0.0000	0.0000	0	0.088676431	0.242708808
L3	Nyankpala weighted input	1.0000	1.0000	1	1E+30	0.999999997

Source: Author's construct, April 2012

From Table 4.17, we can study the effect of changing the right-hand side of Wa constraint. If the right-hand side of Wa constraint lies between 0+0.0887=0.0887 and 0-0.2427= -0.2427, the objective function change will be exactly zero (0).

Again, if the right-hand side of Nyankpala constraint lies between 0+0.0067= 0.0067

and 0-0.2435 = -0.2435, the objective function change will be exactly one (1).

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CHAPTER 5

CONCLUSION AND RECOMMENDATION

This chapter summarizes the major findings and conclusions. It also provides recommendations for University Management and students.

5.1 CONCLUSION

When considering this analysis as a whole, one must also give consideration to the variables selected as outputs and inputs. When classes obtained were selected as outputs and lecture to student ratio, cost per student ratio, library facilities and academic to non-academic staff ratio were selected as inputs, they were selected in an attempt to show the most important attributes pertinent to the problem at hand.

This paper contributes a DEA approach for academic performance of students. A point of departure for the DEA approach compared to existing methods is the input–output framework. Compared to each other, DEA measures the efficiency of academic performance of students in utilizing their expenses on students, lecture to student ratio and staff to maximize the classes obtained by students. Therefore, the DEA approach relates resources expended on students to academic performance.

The analysis identifies Tamale, Nyankpala and Wa campuses as efficient. They serve as the ''benchmark'' for the campuses and can be utilized as role models to which inefficient campus (Navrongo) may adjust its resources in order to become efficient. There was an indication that when Tamale was set as target DMU for Navrongo campus, the reduction in input that is academic to non-academic staff ratio has a larger effect on efficiency of Navrongo campus than does in input cost per student ratio. In otherwords, the cost per student ratio for Navrongo campus should be reduced by management.

There was also indication that Navrongo constraint was not binding because it was not satisfied with equality at the LP optimal. Similar conclusions were drawn when Wa was set as target DMU for Navrongo campus.

Again, when Nyankpala campus was set as a target DMU for Navrongo campus, it indicated that in order to achieve Navrongo campus as efficient, it is better to reduce cost per student more than the library facilities. In other words, management may reduce the expenditure on students in order to be at the frontier.

5.2 RECOMMENDATION

1. University Management should be able to reduce the expenditure on students at Navrongo campus. This challenge may be tackled by addressing wastage of chemicals and reagents on the part of students in the laboratories. This will reduce the frequent repetition of students' laboratory procedures which add to cost. The campus inherited old structures for its inception. The cost of repairs and replacement add to the bill incurred at the campus.

2. We recommend the findings of this thesis to the University Management and students who conduct diverse studies on the efficiency of academic performance to use DEA-CCR model to measure.

3. Further studies should involve comparative analysis of models for additional academic years.

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