إقرار

أنا الموقع أدناه مقدم الرسالة التي تحمل العنوان:

Evaluation of Academic Departments Efficiency Using Data Envelopment Analysis (DEA) and Shannon's Entropy Approaches.

أقر بأن ما اشتملت عليه هذه الرسالة إنما هي نتاج جهدي الخاص، باستثناء ما تمت الإشارة إليه حيثما ورد، وإن هذه الرسالة ككل، أو أي جزء منها لم يقدم من قبل لنيل درجة أو لقب علمي أو بحثي لدى أية مؤسسة تعليمية أو بحثية أخرى.

DECLARATION

The work provided in this thesis, unless otherwise referenced, is the researcher's own work, and has not been submitted elsewhere for any other degree or qualification

Student's name: Ibrahim H. Kuhail | اسم الطالب: إبراهيم حامد عبد كحيل

Signature: | التوقيع:

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Islamic University of Gaza

Faculty of Higher Education

School of Business Administration

Evaluation of Academic Departments Efficiency Using Data Envelopment Analysis (DEA) and Shannon's Entropy Approaches

Prepared by

Ibrahim H. Kuhail

Submitted to:

Prof. Yousif H. Ashour

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نتيجة الحكم على أطروحة ماجستير

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Evaluation of Academic Departments Efficiency Using Data Envelopment Analysis (DEA) and Shannon's Entropy Approaches

وبعد المناقشة التي تمت اليوم الأحد 21 شـــعبان 1434 هـــ، الموافــق 2013/06/30م الســـاعة الحادية عشرة صباحاً، اجتمعت لجنة الحكم على الأطروحة والمكونة من:

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وبعد المداولة أوصت اللجنة بمنح الباحث درجة الماجستير في **كلية *التجارة*/ قسم إدارة الأعمال**.

واللجنة إذ تمنحه هذه الدرجة فإنها توصيه بتقوى الله ولزوم طاعته وأن يسخر علمه في خدمة دينه ووطنه.

والله ولي التوفيق ،،،

عميــد الدراسات العليا

أ.د. فــؤاد علي العاجز

ABSTRACT

This thesis applies Data Envelopment Analysis (DEA) and Shannon's Entropy to assess the relative technical efficiencies of the academic departments at Islamic University of Gaza (IUG). The outputs considered are Graduates (GR), Promotions (PROM) and Public Service Activities (PSA); while the inputs utilized by the departments are Full-Time Academic Staff (FAS), Part-Time Academic Staff (PAS), Academic Staff Salaries (ASS) and Training Resources (TR). The aggregate efficiency indicates whether the resources have been utilized efficiently by a department and the efficiency score helps identify the weak areas where more effort should be devoted to increase efficiency. Without assigning weights for research variables, the CCR results show that the average of aggregate efficiency scores is 76% and 12 departments out of 33 are efficient, while the BCC results show that the average of aggregate efficiency is 84.6% and 18 DMUs are considered efficient. In general, IUG departments have good efficiency scores. Potential improvements are then evaluated for each inefficient DMU by both minimizing inputs and maximizing outputs. Super efficiency is evaluated to rank the rest of the efficient departments. Further, multiple-regression model is built to relate the super-efficiency score with research variables. Promotion has the highest coefficient among all variables. Weights of variables were obtained using Shannon's entropy. Accordingly the aggregate CCR efficiency became 87% which indicates that assigning weights to variables results in better overall efficiency. Finally, recommendations for future work suggest focusing on promotion output variable that requires academic staff to increase their research works in publications and papers. In addition, inefficient departments are recommended to focus more on their weak variables and learn from their benchmarks.

ملخص تنفيذي

تهدف الدراسة إلى تقييم الكفاءة الفنية النسبية للأقسام الأكاديمية لبرامج البكالوريس في الجامعة الإسلامية في الفترة ما بين 2008 و 2010م . بالأضافة إلى تحديد مدخلات و مخرجات (متغيرات الدراسة) و تحديد الأقسام ذات الكفاءة الكاملة و الأقسام ذات الكفاءة التي تقل عن 100%، وقياس التحسينات اللازمة للأقسام التي تقل كفاءتها عن 100%. بالإضافة إلى دراسة أثر تحديد أوزان المتغيرات المحددة بطريقة شانون على كفاءة الأقسام.

اعتمدت الدراسة نموذج التحليل المغلف (DEA) لقياس الكفاءة النسبية للأقسام الأكاديمية لبرامج البكالوريس في الجامعة الإسلامية وتم تطبيق الدراسة على 33 قسم. كما تم استخدام طريقة شانون لتحديد الأوزان النسبية لمدخلات ومخرجات الدراسة. تم تطبيق نموذج التحليل المغلف (DEA) لقياس الكفاءة النسبية للأقسام الأكاديمية لبرامج البكالوريس في الجامعة الإسلامية. وتم تحديد المدخلات و المخرجات اللازمة لنموذج الكفاءة. وقد شملت المخرجات: أعداد الخريجين، ترقيات الهيئة الأكاديمية، الأنشطة اللامنهجية للاقسام. في حين شملت المدخلات: أعداد الهيئة الأكاديمية – دوام كلي ، أعداد الهيئة الأكاديمية – دوام جزئي، رواتب الهيئة الأكاديمية، و الموارد التدريبية. بعدها، تم قياس الكفاءة الفنية النسبية للأقسام الأكاديمية باستخدام برنامج قياس الكفاءة (EMS) و برنامج MaxDEA والتحسينات الازمة للاقسام التي تقل كفاءتها عن 100%. ثم، تم تحديد الأوزان باستخدام طريقة شانون ثم قياس الكفاءة مرة أخرى و دراسة الفرق بين النتائج. و كما وتم حساب الكفاءة العظمى (super- efficiency) للأقسام الكفئة. كما و تم استخدام نموذج الانحداء المتعدد (multiple-regression) لايجاد علاقة بين المتغيرات و كفاءة الاقسام. بينت نتائج الدراسة أن متوسط كفاءة الأقسام يساوي 76% ، و أن 12 قسم حصلوا على كفاءة 100% عند استخدام نموذج CCR. و عند استخدام نموذج BBC كان متوسط الكفاءة يساوي 84.6% و قد حصل 18 قسم على كفاءة 100%. بعد ذلك، تم حساب التحسينات اللازمة للأقسام التي تقل كفاءتها عن 100%. ثم، تم حساب الكفاءة العظمى للأقسام الحاصلة على كفاءة 100% و قد كان قسم العلوم المالية والمصرفية أعلاها كفاءة. بعد ذلك، تم تحديد الأوزان النسبية لمتغيرات الدراسة باستخدام طريقة شانون ، ومن ثم تم حساب الكفاءة مرة أخرى. وعليه، أصبح متوسط الكفاءة 87% مما يبين أن تحديد أوزان المتغيرات يؤثر على نتيجة الكفاءة. خلصت الدراسة بتوصيات عديدة منها: التركيز على متغير الترقيات الذي يلزم الطاقم الأكاديمي بزيادة الأبحاث و الأوراق العلمية المنشورة محلياً وعالمياً. كما أوصت الدراسة بضرورة التركيز نقاط الضعف للأقسام التي حصلت كفاءة أقل من 100% والاستفادة من القسم المعيار لهم. كما وأوصت بضرورة استخدام نموذج DEA في قياس كفاءة دوائر و أقسام أخرى في الجامعة، جامعات أخرى، و قطاعات أخرى كالصحة و البنوك.

DEDICATION

To My Parents…..

To My Wife ….

To My Daughter….

To My Brothers and Sister…….

To My Friends …..

ACKNOWLEDGMENT

Though only my name appears on the cover of this research, many people have contributed to make it possible. I owe my gratitude to all of them.

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GLOSSARY

Allocative Efficiency: This efficiency deals with the minimizing of cost of production with proper combination of inputs to a given level of outputs and a set of input costs. Allocative efficiency measures the DMU ability to minimize cost due to the proper combination of inputs.

BCC Model: It is another DEA model put by Banker, Charnes and Cooper in 1984 to measure the relative efficiencies of *DMU's*, and it assumes variable returns to scale

CCR Model: It is the first Data Envelopment Analysis (DEA) model put forward by Charnes, Cooper and Rhodes in 1978 to measure the relative efficiencies of *decision-making units* (*DMU's)* and it assumes constant returns to scale.

Constant Returns to Scale (CRS): It means that, if inputs are increased or decreased, outputs will be increased and decreased by the same proportions (if inputs are doubled, output will also be doubled).

Cost Efficiency (CE): An entity will be cost efficient only if, it is both technically and allocatively efficient.

Data Envelopment Analysis (DEA): is a relatively new data-oriented approach for evaluating the performance of a set of peer entities called Decision Making Units (DMUs) which convert multiple inputs into multiple outputs.

Decision Making Units (DMUs): They are the economic entities or units whose efficiencies will be measured by the model; those units should be homogeneous, work in the same field and have the same inputs and outputs variables.

Economic Efficiency: It means, producing the maximum value of output with a given value of inputs; or equivalently, using minimum value of inputs to produce a given value of output.

Efficiency: The DMU ability to produce the maximum amount of output with a given amount of inputs; or, using minimum amount of inputs to produce a given amount of output.

Modified Data Envelopment Analysis (MDEA): It is a DEA model that permits and allow ranking of the efficient units themselves (not only ranking the inefficient DMUs).

Pareto Efficiency: A central concept in economics is Pareto efficiency. A situation is said to be Pareto efficient if there is no way to rearrange things to make at least one person better off without making anyone worse off.

Pure Technical Efficiency: refers to the firm's ability to avoid waste by producing as much output as input usage allows.

Relative Efficiency(RE): A firm is to be rated as fully (100%) efficient on the basis of available evidence if and only if the performances of other peers do not show that some of its inputs or outputs can be improved without worsening some of its other inputs or outputs.

Scale Efficiency (SE): It measures the DMU's ability to work at its optimal level of operation. This efficiency affects and contributes to the DMU aggregate technical efficiency.

Shannon's Entropy: The concept of Shannon's entropy is the central role of information theory sometimes referred as measure of uncertainty. The entropy of a random variable is defined in terms of its probability distribution and can be shown to be a good measure of randomness or uncertainty.

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

Variable Returns to Scale (VRS): It means that, if inputs are increased or decreased, outputs will not be increased or decreased by the same proportions.

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LIST OF ABBREVIATIONS

AE	Allocative Efficiency.
ASS	Academic Staff Salaries
BCC	Banker, Charnes & Cooper.
CCR	Charnes, Cooper & Rhodes.
CRS	Constant Return to Scale.
CE	Cost Efficiency.
DEA	Data Envelopment Analysis.
DMU	Decision Making Unit.
DRS	Decreasing Return to Scale.
EE	Economic Efficiency.
EMS	Efficiency Measuring System.
FAS	Full-Time Academic Staff
GR	Graduates.
IRS	Increasing Return to Scale.
IUG	Islamic University of Gaza
MDEA	Modified Data Envelopment Analysis.
OE	Operating Expenses.
PAS	Part-Time Academic Staff
PSA	Public Service Activities.
PTE	Pure Technical Efficiency.
PROM	Promotions.
RE	Relative Efficiency.
SE	Scale Efficiency.
TE	Technical Efficiency.
TR	Training Resources.
VRS	Variable Return to Scale.

Chapter 1: INTRODUCTION

1.1 Background

1.2 Research Problem

1.3 Research Objectives

1.4 Research Importance

1.5 Research Methodology

1.6 Research Organization

This chapter shows a general background about the research. It is divided into six sections; the first section provides a background about higher education, while the second section discusses the research problem, the third section states the objectives of the research, the importance behind conducting this research is discussed in the fourth section, while the fifth section provides a brief overview of the methodology and finally, the sixth section describes the organization of the research

1.1 Background

Human resources are the main asset of the Palestinian people: since natural resources are scarce, their main chance for sustainable development lies in the ability to develop a knowledge-intensive economy, to acquire, master, and apply the knowledge and skills required by rapidly changing technologies, and to cater for a broad spectrum of products and services. Consequently, a high-quality system of tertiary education, tuned to the realities and needs of the Palestinian people and competitive on a regional and international scale is a recognized priority for national development[1].

Higher education is the backbone of development and economic growth in any country. Given that the academic institutions build the capacity required for a country's approved long-term plans, the education system, in particular, is one of the main factors a country relies on to increase its productivity in the long term and thus efficiently implement its strategic plans.

Still the need for more studies that concern with the efficiency and productivity of educational systems, considering the fact that the more employment of economic resources needed for increasing educational services, the more evaluation needed for these services. In addition, it is necessary to have standards to follow, by which all educational institutions could be questioned through the evaluation of efficiency of using resources (Inputs) achieving the aimed goals (Outputs) for which these resources were spent.

Yet the increase in studies of this type can also be attributed to the development of parametric and nonparametric techniques for estimating efficiency that has only recently moved beyond theoretical construction and gained popularity in more applied settings. These increasingly sophisticated

[1] Peace programme website : www.peace-programme.org (December 2012)

approaches have finally provided researchers both the ability and flexibility necessary for modeling the complex production processes and cost structures within higher education institutions. As a result, one can look across education systems in several countries and find a growing repository of empirical studies that shed new light on the understanding of higher education efficiency (Salerno, 2003).

Data Envelopment Analysis (DEA)

DEA is a nonparametric method in operations research and economics for the estimation of production frontiers. It is used to empirically measure productive efficiency of decision making units (or DMUs).

Charnes, Cooper, and Rhodes (1978) described DEA as a mathematical programming model applied to observational data that provides a new way of obtaining empirical estimates of relations, such as the production functions and/or efficient production possibility surfaces that are cornerstones of modern economics.

Shannon's Entropy

Shannon entropy is the average unpredictability in a random variable, which is equivalent to its information content. The entropy of a random variable is defined in terms of its probability distribution and can be shown to be a good measure of randomness or uncertainty.

1.2 Research Problem

The research problem came from the great importance of higher education sector in Palestine as it is crucial to providing the necessary manpower of main professions in the community. In addition to large number of higher education institutions are existed in Palestine as there are 49 higher educational institutions where about 214 thousands of students are enrolled and about 30,000 graduated yearly.[2] Further, it is necessary to have standards by which all educational institutions could be questioned through the evaluation of efficiency of using resources (Inputs) and achieving the goals (Outputs) for which these resources were spent. Moreover, few studies have studied the efficiency of academic institutions at Palestine; one of these studies is (Al Hindway, 2007) which aimed at measuring the technical efficiency of UNRWA technical education

[2] Palestinian Central Bureau of Statistics, http://www.pcbs.gov.ps (Jan 2013)

programs. Also, this study aims at measuring the efficiency of one of the biggest universities in Palestine and its efficiency is of great importance and interest to higher education stakeholders. Therefore, there is a need to assess the efficiency of the educational institutions.

1.3 Research Objectives

The primary objective of this research is to evaluate and measure the efficiency of the IUG departments using the input oriented DEA model and assigning weights to variables using Shannon's entropy. In addition to other objectives:

- Determine the efficiency variables in term of inputs and outputs.
- Determine the efficient and inefficient departments using DEA CCR and BCC input-oriented models.
- Determine the proper improvements needed for each inefficient department to reach the 100% efficiency.
- Determine the effects of assigning weights for each of research variable using Shannon's entropy approach on efficiency scores.

1.4 Research Importance

The importance of this research comes from the importance of higher education sector in Palestine as it is a crucial factor in country development and economic growth where the number of higher education institutions is 49 institutions where about 214 thousands of students are enrolled, while 14600 employees were employed[3]. This research is important because of the present tight economic conditions as well as the increasing demand on higher education dictate the need to use our scarce resources with maximum efficiency in order to achieve maximum output. Further, this study is of unique studies that aim at measuring the efficiency of university departments in Gaza strip and finally, it is believed that the results and recommendations have substantial implications which are very useful for managing educational departments and for decision makers in higher education sector.

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[3] Database of Higher Education : www.mohe.pna.ps (Jan 2013)

1.5 Research Methodology

The research will apply DEA model to measure the efficiency of IUG departments and Shannon's entropy to measure the efficiency results of deferent models.

Firstly, the Decision Making Units (DMUs) of the research will be identified. Secondly, the variables of the research in terms of inputs and outputs will be determined which adequately represent the DMU. These variables will be collected for each DMU over three-year study period that will be determined later. The next step is to measure the technical efficiency and pure technical efficiency of each DMU. Then, potential improvements of both inputs and outputs needed for each inefficient DMU to be 100% efficient will be calculated. Further, super-efficiency will be measured to rank the efficient department. Then, a multiple-regression model will be built to identify the relation between supper-efficiency score and research variables. After that, Shannon's entropy will be used to assign weights for variables. The effect of assigning weights on efficiency score will be measured. Finally, conclusion and recommendations will be drawn from the results achieved.

1.6 Research Organization

The research is organized into five chapters. The first chapter provides an introduction and an overview of the research. It discusses the education history in Gaza, objectives of the research, motivation of the research as well as methodology of the research. Chapter Two gives an overview of higher education in Palestine, efficiency, DEA and Shannon's Entropy. Moreover, it reviews literature related to performance evaluation and efficiency with emphasis on educational sector. Since Data Envelopment Analysis is the most widely-used method for measuring universities efficiency, its concept is briefly explained in this chapter to provide basic understanding of model development and its weaknesses.

The research methodology is discussed in Chapter 3. It explains in details the proposed research methodology for assessing efficiency of IUG departments. This chapter starts with determining DMUs, and then it gives an illustration of how the variables are selected and collected and finally introduces the used model and software. Chapter 4 presents the results obtained in this research and analysis of the results. It shows the results of each model used in the research including Shannon's entropy and compares results of each model, and then the proper improvements needed for inefficient DMUs in order to reach 100% efficiency will be calculated. Finally, chapter 5 concludes the research with suggestions for future research.

Chapter 2: LITERATURE REVIEW

This chapter shows an overview of higher education sector in Palestine, efficiency, DEA and Shannon' Entropy. First section gives an overview of higher education sector in Palestine while the second section provides a brief overview about efficiency, types of efficiency and approaches used to measure efficiency. The third section shows a background about DEA, its models, return to scale, orientation and model derivation strengths and weaknesses of DEA and Modified Data Envelopment Analysis. The fourth section provides a brief overview about Shannon's Entropy and finally the fifth section presents previous studies about using DEA in educational sector.

2.1 Higher Education in Palestine

Higher Education in Palestine is provided by 49 educational initiations distributed as follows:

Seven universities are located in the West Bank: Al Najah National University, Nablus and the American University of Jennin in the north, Birzeit University in the centre, three universities south of Jerusalem - Bethlehem University, Hebron University and the Hebron Polytechnic- and one in Jerusalem - Al Quds University. Also located in Jerusalem is Al Quds Open University. In addition, ten university colleges and fifteen community colleges are located in west bank. Whereas in Gaza, five universities are located in Gaza: Al Azhar, Islamic University of Gaza, Al- Aqsa, Palestine, Gaza, and Al Oma. In addition to 5 university colleges and 4 community colleges are located in Gaza Strip[4].

The Palestinian universities were established under very hard conditions and they continued to face serious difficulties caused by occupation, especially through repeated closures and the difficulties for staff and students to move freely and have access to classes. These difficulties explain their rather large number and their broad geographical dispersion.

There are 247 programs and specializations offered by the institutions of higher education in arts, sciences, commerce, economics, engineering, agriculture, law, pharmacy, medical professions, nursing, education, tourism and hotel management, etc.).

[4] Database of Higher Education : www.mohe.pna.ps (Jan 2013)

In Palestine, 201,389 students were enrolled in higher Education Institutions including universities, open universities and university colleges during the 2010/2011 academic year, in addition to 12,584 students were enrolled in community colleges during the same academic. This represents approximately 5% of Palestinian residents. On the other hand, number of graduates from Palestinian universities and colleges reached 28,753 and 2949 graduated from community colleges during 2009/2010 academic year.

With regard to employees, number of employees reached 14667 employees in 2010/2011 academic year distributed as: 6901 academic employees, 549 academic admin staff, 26 research staff, 2034 administrative staff, 984 teaching and research assistants, 1669 labors, 668 technicians, and 564 vocational staff[5].

Islamic University of Gaza

IUG is an independent academic institution located in Gaza. IUG is a home to the well-planned programs, a way to the different community levels and a place for researchers and good teachers. IUG is a member of four associations: International Association of Universities, Community of Mediterranean Universities, Association of Arab Universities and Association of Islamic Universities.

The university, according to its website, has 10 faculties capable of awarding B.A., B.Sc., M.A., M.Sc., Diploma and higher diploma in their respective disciplines. About 20396 students were enrolled in the academic year 2008-2009 while number of graduates in the same academic year was 3917 graduates[6].

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[5] Database of Higher Education : www.mohe.pna.ps (Jan 2013)
[6] Islamic University of Gaza website: www.iugaza.edu.ps (Jan 2013)

2.2 Efficiency

A firm's efficiency or productivity is the ratio of outputs to inputs and it depends on production, process technology, and differences in environments in which production occurs, among other variables while the firm's efficiency is a comparison between observed and optimal values of outputs and inputs.

The set of the optimal outputs, given the inputs (or the optimal inputs, given the outputs) is the efficient frontier (Wagner 2006). Fundamentally, efficiency can be defined as the ratio of outputs to inputs. For many production scenarios, it is imperative to consider multiple inputs and multiple outputs. Moreover, the computation of efficiency for the more realistic scenario of multiple inputs and outputs is difficult.

The terms productivity and efficiency are often used interchangeably. Productivity is the ratio of some (or all) valued outputs that an organization produces to some (or all) inputs used in the production process**.** On the other hand, efficiency is a relative concept and can only be calculated with respect to a reference point. Efficiency can incorporate 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.

2.2.1 Efficiency Categorization

Efficiency has many types, each of them has its own perspective about inputs and outputs as follows:

A. Relative Efficiency(RE):

A firm is to be rated as efficient on the basis of available evidence if and only if the performances of other peers do not show that some of its inputs or outputs can be improved without worsening some of its other inputs or outputs. (James, 2000)

B. Technical Efficiency (TE):

Technical efficiency means producing maximum output with given inputs; or equivalently, using minimum inputs to produce a given output. Technical efficiency is measured by the relationship between the physical quantities of output.

It deals with employing labor, capital and machinery as inputs to produce outputs based on the best practice in a given sample of decision making units, which means, given the same technology and the same external environment no waste of input resources is considered in producing the targeted outputs (Mette et al, 2007).

Technical Efficiency (TE) can be decomposed to product of Pure Technical Efficiency (PTE) and Scale Efficiency (SE). Pure Technical Efficiency refers to the firm's ability to avoid waste by producing as much output as input usage allows. In other words, it shows whether the DMU could reach the maximum production under certain restrictions. Scale efficiency refers to the firm's ability to work at its optimal scale. Consequently, the scale can also affect the efficiency of a DMU. According to the above discussion, the technical efficiency can therefore be regarded as the measurement that inputs are transformed into outputs, or just the output/input ratio (Shou & Bingzheng , 2006)

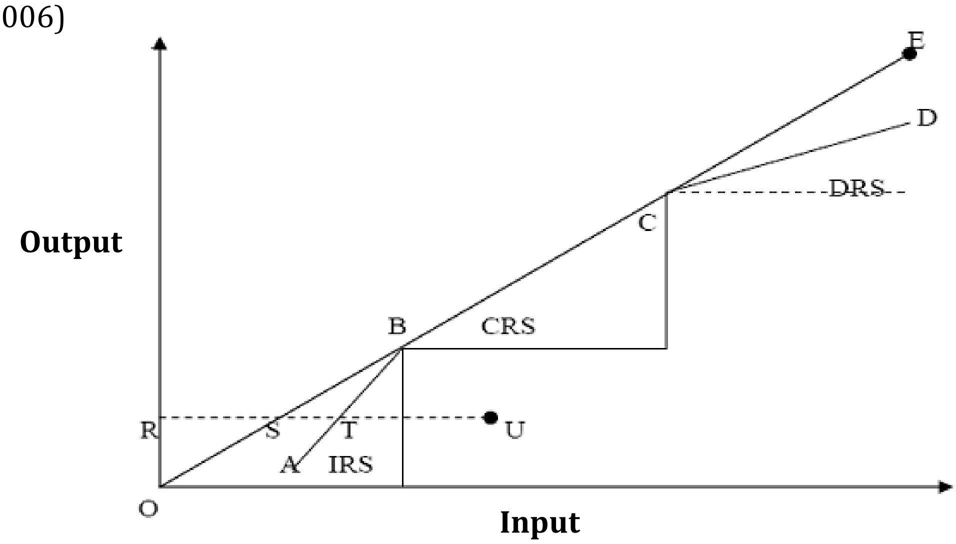

Fig. 2.1: Decomposition of Technical Efficiency

For convenience, only consider the case of one input (**x**) and one output (**y**). In Fig. 2.1, line **OE** denotes the production frontier with constant return to scale. Lines **AB** and **CD** are both production frontiers with variable return to scale. **ABCD** depicts how the production moves from increasing return to scale to constant return to scale, and to decreasing return to scale. Assume that **U** is the actual production point of a DMU. Then the following formula can be achieved:

Technical Efficiency = RS/RU

The definition of technical efficiency in this circumstance requires a certain output; the input at the frontier with Constant Return to Scale (CRS) is divided by the actual input. This definition is based on input. With the similar thinking, also the definition can be achieved based on output. Here, the frontier with constant return to scale denotes the efficient production. Any point on this frontier is technical efficient.

Pure Technical Efficiency = RT/RU

The definition of pure technical efficiency requires the same level of output; the input at the production line with Variable Return to Scale (VRS) is divided by the actual input. Note that in pure technical efficiency, production line with variable return to scale is used. From the perspective of economics, this will release the restrictions of scale. Therefore, the inefficiency only lies in the factors such as productivity, resource allocation and management.

Scale Efficiency = RS/RT

The definition of scale efficiency requires the same level of output, the input at the production frontier with constant return to scale is divided by the input at the production line with variable return to scale. In contrary to the case of pure technical efficiency, only the factor of scale is effective here, while the factors of productivity, resource allocation and management are excluded.

C. Allocative Efficiency (AE):

It deals with the minimizing of cost of production with proper combination of inputs to a given level of outputs and a set of input costs assuming that the entity examined is working with the full technical efficiency, allocative efficiency is expressed as percentage score of 100 for the entity using its inputs in proportion that minimizes the cost. In other words, an entity may be 100% technically efficient in using the best practice, but not fully efficient in regards to allocative efficiency which means best combination of inputs.

D. Cost Efficiency (CE):

It can be decomposed into technical efficiency and allocative efficiency; an entity will be cost efficient only if, it is both technically and allocatively efficient (Shou & Bingzheng, 2006).

E. Economic Efficiency (EE):

It is a combination of technical efficiency and allocative efficiency. It 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 and it is measured by the relationship between the value of the output and the value of the input (Bhat et al, 2001).

F. Pareto Efficiency

A central concept in economics is Pareto efficiency. A situation is said to be Pareto efficient if there is no way to rearrange things to make at least one person better off without making anyone worse off. Pareto efficiency is important because it provides a weak but widely accepted standard for comparing economic outcomes. It is a weak standard because there may be many efficient situations and the Pareto test doesn't tell us how to choose between them (Shou & Bingzheng 2006).

In this research, the relative technical efficiency concept is adopted because firstly, the efficiency is a relative term. Efficiency is never absolute; it is always relative to some criteria, this can be seen when one asks if farms are more efficient in the United States or China. The farming techniques in China are more efficient than those in the United States when measured in terms of output per unit of land, output per unit of fossil fuel, or output per unit of machinery. The farms in the United States are far more efficient in terms of output per man-hour. The statement that farms in one country is more efficient than farms in another makes no sense unless the criterion on which efficiency is measured is given. Secondly, the criterion for economic efficiency is value. A change that increases value is an efficient change and any change that decreases value is an inefficient change. Thirdly, to be on the production-possibilities frontier, all resources must be used. Unemployed resources indicate that more goods and services could be produced, which means that the entity was not on the frontier initially.

In addition, resources must be used properly. If society randomly assigns people to jobs or if it assigns jobs on nonprofessional basis, it will not produce as much as it could. It will require some people with little intellectual ability to perform jobs that require great intellectual ability, and it will require some people with little strength and endurance to perform jobs that demand much strength and endurance. If switching people among jobs can increase output, the original situation was not on the production-possibilities frontier and thus not economically efficient. So, the concept of efficiency is not absolute; it is relative. It cannot be said that DMU_X is absolutely efficient. A firm's efficiency level is dictated by price, cost and product complexity, while efficiency has increased the demand for and implementation of newer technologies, easier connectivity and more robust standards will continue to push industry efficiency even further.

2.3 Data Envelopment Analysis (DEA)

DEA began with Edwardo Rhodes's Ph.D. dissertation research at Carnegie Mellon University. This work by Charnes, Cooper and Rhodes originated in the early 1970s in response to the thesis efforts of Edwardo Rhodes at Carnegie Mellon University's School of Urban & Public Affairs, now the H.J. Heinz III School of Public Policy and Management in Pittsburgh, Pennsylvania, United States. Under the supervision of Cooper, this thesis was to be directed to evaluating educational programs for disadvantaged students (mainly black or Hispanic) in a series of large scale studies undertaken in U.S public schools with support from the Federal government. Attention was finally centered on Program follow through a huge attempt by the U.S. It was the challenge of estimating relative technical efficiency of the schools involving multiple outputs and inputs, without using the information on prices that resulted in the formulation of the CCR (Charnes, Cooper and Rhodes) ratio form of DEA and the first publication (James 2000). The initial DEA model, as originally presented in Charnes, Cooper, and Rhodes (CCR) (1978), was built on the earlier work of Farrell (1957). Since the DEA technique was first developed, it has been widely applied to industries as diverse as health care, finance, education and transportation and many other industries and organizations.

According to Tavares (2002), the DEA database has registered 3,203 DEA references, 2,152 authors and 1,242 keywords. The DEA references are distributed as seven publication types: event paper, journal paper, dissertation, book chapter, research paper, book and special journal editions related to DEA. DEA has been applied to several benchmarking studies and to the performance analysis of public institutions, such as schools, hospitals, but also of private ones, such as banks.

2.3.1 DEA Definition

Charnes, Cooper, and Rhodes (1978) described DEA as a mathematical programming model applied to observational data that provides a new way of obtaining empirical estimates of relations, such as the production functions and/or efficient production possibility surfaces that are cornerstones of modern economics.

DEA is a relatively new data-oriented approach for evaluating the performance of a set of peer entities called Decision Making Units (DMUs) which convert multiple inputs into multiple outputs (Olivier et al 2005).

The definition of a DMU is generic, flexible and will be explained later in this chapter. DEA is a method used for the measurement of efficiency in cases where multiple input and multiple output factors are observed and when it is not possible to turn these into one aggregate input or output factor. DEA, about which thousands of articles have been published, has been used in various fields.

2.3.2 DEA Graphical Illustration

The single input two-output or two-input one-output problems are easy to analyze graphically. To illustrate how DEA works graphically, lets take an example of three banks. Each bank has exactly 10 tellers (the only input), and it measures bank based on two outputs: checks cashed and loan applications. The data for these three banks are shown in Table2.1.

Table 2.1: Data for Three Banks Graphical Example

Bank	Tellers	Checks	Loan applications
A	10	1000	20
B	10	400	50
C	10	200	150

This numerical example is now solved graphically as shown in Fig. 2.2. (An assumption of constant returns to scale is made.)

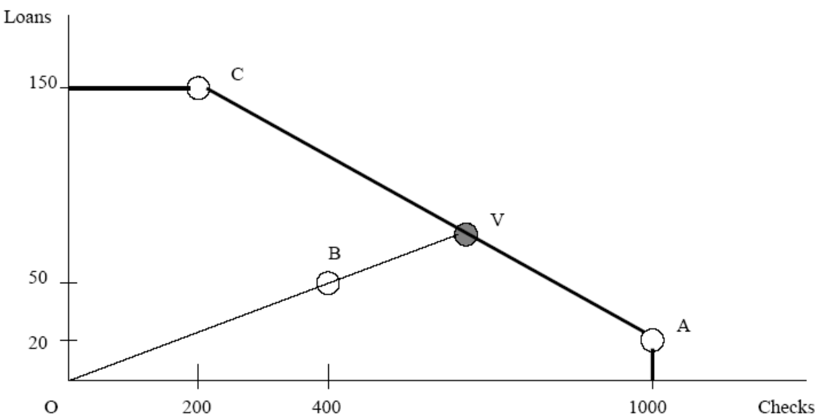

Fig. 2.2: Graphical Representation for The Three Banks Example.

The analysis of the efficiency for bank B looks like the following: If it is assumed that convex combinations of banks are allowed, then the line segment connecting banks A and C shows the possibilities of virtual outputs that can be formed from these two banks.

Similar segments can be drawn between A and B along with B and C. Since the segment AC lays beyond the segments AB and BC, this means that a convex combination of A and C will create the most outputs for a given set of inputs.

This line is called the efficiency frontier. The efficiency frontier defines the maximum combinations of outputs that can be produced for a given set of inputs. Since bank B lies below the efficiency frontier, it is inefficient. Its efficiency can be determined by comparing it to a virtual bank formed from bank A and bank C. The virtual player, called V, is approximately 54% of bank A and 46% of bank C. (This can be determined by an application of the lever law. Pull out a ruler and measure the lengths of AV, CV, and AC. The percentage of bank C is then AV/AC and the percentage of bank A is CV/AC).

The efficiency of bank B is then calculated by finding the fraction of inputs that bank V would need to produce as many outputs as bank B. This is easily calculated by looking at the line from the origin, O, to V. The efficiency of player B is OB/OV which is approximately 63%. Fig. 2.4 also shows that banks A and C are efficient since they lie on the efficiency frontier. In other words, any virtual bank formed from analyzing banks A and C will lie on banks A and C respectively.

Therefore since the efficiency is calculated as the ratio of OA/OV, banks A and C will have efficiency scores equal to 1.0. The graphical method is useful in these simple two dimensional examples but gets much harder in higher dimensions. The normal method of evaluating the efficiency of bank B is by using a linear programming formulation of DEA. Since this problem uses a constant input value of 10 for all of the banks, it avoids the complications caused by allowing different returns to scale.

2.3.3 DEA and Regression Analysis

There are two main approaches used to measure technical efficiency: parametric and nonparametric frontier approaches.

Researchers find 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 et al, 1978).

Both the parametric and the non-parametric (mathematical programming) approaches use all the information contained in the data. In the parametric approach, the single optimized regression equation is assumed to apply to all Decision Making Units (DMUs). DMUs are the economic entities or units whose efficiencies will be measured by the model; those units should be homogeneous, work in the same field and have the same inputs and outputs variables.

The nature of the DMUs is diverse. DEA has been used to study the efficiency of banks, hospitals, warehouses, public programs, development of software projects, academic departments at a foreign university, educational program proposals, retail institutions, market efficiency and welfare loss, insurance companies and salespeople (Coelli et al, 2005)

Data Envelopment Analysis (DEA) is a non-parametric approach, optimizes the performance measure of each DMU. This results in a revealed understanding about each DMU instead of the depiction of an "average" DMU. In other words, the focus of DEA is on the individual observations as represented by the *n* optimizations (one for each DMU) required in DEA analysis.

In contrast, regression analysis focuses on finding a plane that passes through an average for all inputs and outputs as shown in Fig. 2.3. Therefore, the parametric approach requires the imposition of a specific functional form (e.g., linear, quadratic etc.) when relating the independent variables to the dependent variable(s). The parametric approach also requires specific assumptions about the distributions of error terms (e.g., independently and identically normally distributed). In contrast, 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.

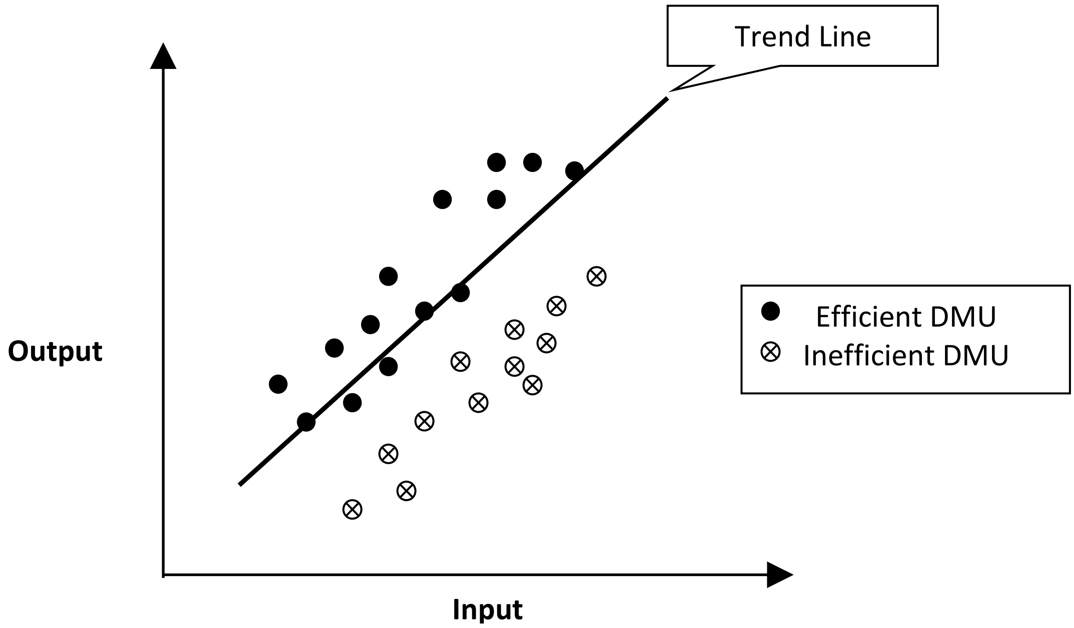

Fig. 2.3: Regression Analysis Approach

DEA calculates a maximal performance measure for each DMU relative to all other DMUs in the observed population. Each DMU not on the frontier is compared against a convex combination which is a linear combination of vectors in which the sum of the coefficients is one of the DMUs on the frontier facet closest to it.

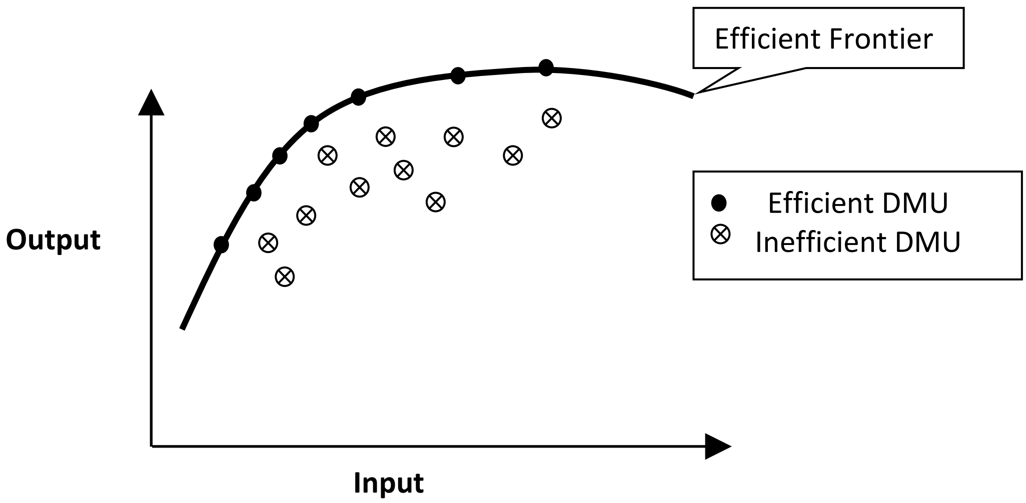

Fig. 2.4: Data Envelopment Analysis Approach

The solid line in Fig. 2.4 represents a frontier derived by DEA from data on a population of DMUs each utilizing different amounts of a single input to produce various amounts of a single output. It is important to note that DEA calculations, because they are generated from actual observed data for each DMU, produce only relative efficiency measures. The relative efficiency of each DMU is calculated in relation to all the other DMUs, using the actual observed values for the outputs and inputs of each DMU. The DEA calculations are designed to maximize the relative efficiency score of each DMU, subject to the condition that the set of weights obtained in this manner for each DMU must also be feasible for the other DMUs included in the calculation.

2.3.4 DEA Models

Data Envelopment Analysis (DEA) is a body of concepts and methodologies that have been in a collection of models with accompanying interpretive possibilities.

While each of these models addresses managerial and economic issues and provide useful results, their orientations are different. Thus models may focus on increasing, decreasing, or constant returns to scale as follow:

A. The CCR Model (**C**harnes, **C**ooper, and **R**hodes 1978)

- It yields an objective evaluation of all over efficiency.
- Identifies the sources and estimates the amount of thus-identified inefficiencies.
- Assumes Constant Return to Scale (CRS).

B. The BCC Model (**B**anker, **C**harnes &**C**ooper 1984)

- Distinguish between scale and technical inefficiencies.
- Estimate pure technical efficiency at a given scale of operation.
- Assume Variable Return to Scale (VRS) and identifying whether Increasing Returns to Scale (IRS), Decreasing Returns to Scale (DRS) or Constant Returns to Scale (CRS) possibilities are percent for further exploitation.

The difference between CRS and VRS will be explained in the next section.

C. The Multiplicative Models (Charnes et al., 1982,1983)

- It is a log-linear envelopment.
- A piecewise Cobb-Douglas interpretation of the production process (by reduction to the antecedent 1981 additive model of Charnes, Cooper, and Sieford).

D. The Additive Model (Charnes et al., 1985) and the extended additive model (Charnes et al., 1987)

- Relate DEA to earlier Charnes-Cooper (1959) inefficiency analysis and in the process.
- Relate the efficiency results to economic concept of Pareto optimality.

The models may determine an efficient frontier that may be piecewise linear, piecewise log-linear, or piecewise Cobb-Douglas (Charnes, 1994).

2.3.5 DEA and Return to Scale

There are two types of Return to Scale. Fixed or Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS). In CRS the outputs and inputs have linear relationship where they do not have in VRS. The relationship in VRS may be Increasing Return to Scale (IRS) or Decreasing Return to Scale (DRS) as shown in Fig. 2.5.

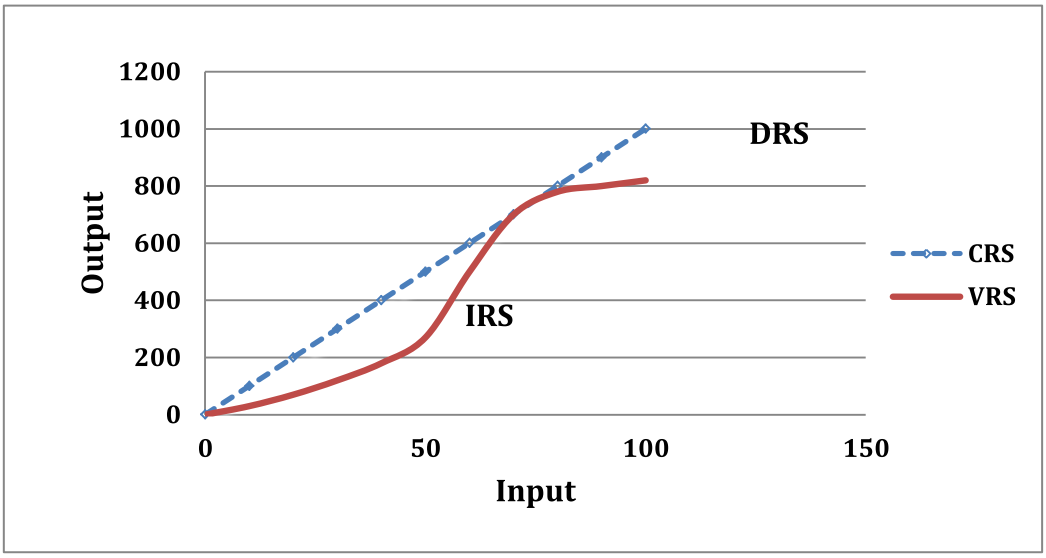

Fig. 2.5: Constant Return to Scale versus Variable Return to Scale

So, CRS means that, if inputs are increased or decreased, outputs will be increased and decreased by the same proportions (if inputs are doubled, output will also be doubled) and VRS means that, if inputs are increased or decreased, outputs will not be increased or decreased by the same proportions (Banker et al 2004).

2.3.6 Model Orientation

There are three types of model orientation. The first is input oriented measure that quantifies the input reduction which is necessary to become efficient holding the outputs constant. Second, the output oriented measure which quantifies the necessary output expansion holding the inputs constant while the non-oriented measure quantifies necessary improvements when both inputs and outputs can be improved simultaneously as shown in Fig. 2.6.

It seems that in applications, the choice of a certain measure mostly depends on three criteria:

- The "primal" interpretation, i. e. the meaning of the efficiency score with respect to input and output quantities,
- The "dual" interpretation, i. e. the meaning of the efficiency score with respect to input and output prices,
- The axiomatic properties of the efficiency measure (e. g. monotonicity, unit's invariance, indication of efficiency, continuity)(Cooper et al ,2004)

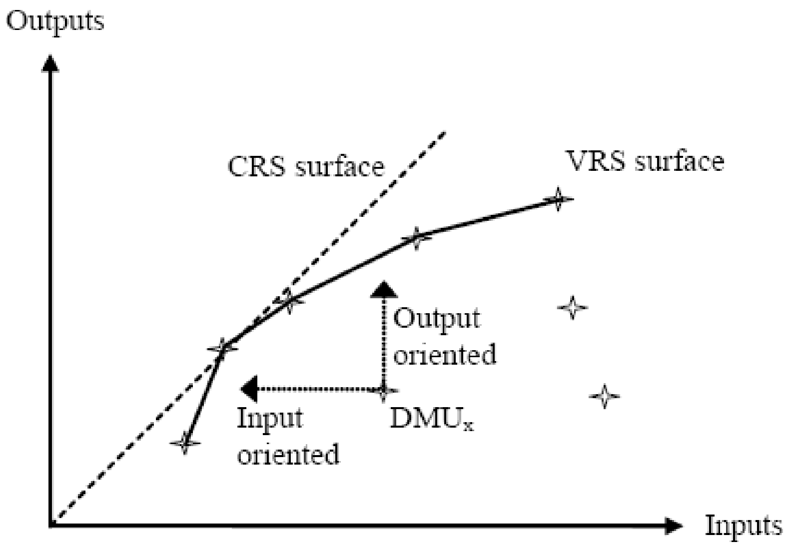

Fig. 2.6: Input-Oriented Versus Output-Oriented

2.3.7 Models Derivation

It is assumed that there are n DMUs to be evaluated. Each DMU consumes varying amounts of m different inputs to produce s different outputs. Specifically, $\boldsymbol{DMU_j}$ consumes amount x_{ij} of input i and produces amount y_{rj} of output r. We assume that $x_{ij} \geq 0$ and $y_{rj} \geq 0$ and further assume that each DMU has at least one positive input and one positive output value.

Now turn to the "ratio-form" of DEA. In this form, as introduced by Charnes, Cooper, and Rhodes, the ratio of outputs to inputs is used to measure the relative efficiency of the $j = 0$ to be evaluated relative to the ratios of all of the $j = 1, 2 \ldots n$. We can interpret the CCR construction as the reduction of the multiple-output /multiple-input situation (for each DMU) to that of a single 'virtual' output and 'virtual' input. For a particular DMU the ratio of this single virtual output to single virtual input provides a measure of efficiency that is a function of the multipliers. In mathematical programming parlance, this ratio, which is to be maximized, forms the objective function for the particular DMU being evaluated, so that symbolically

$$\max h_o(u,v) = \sum_r u_r y_{ro} / \sum_i v_i x_{io} \qquad \textbf{2.1}$$

where it should be noted that the variables are the u_r's , the v_i's , the y_{ro}'s and x_{io}'s are the weights of outputs, weights of inputs, observed output and input values, respectively, of DMUo , the DMU to be evaluated. Of course, without further additional constraints (developed below) equation 2.1 is unbounded.

A set of normalizing constraints (one for each DMU) reflects the condition that the virtual output to virtual input ratio of every DMU, including j=o, must be less than or equal to unity. The mathematical programming problem may thus be stated as:

$$\begin{aligned} &\max h_o(u,v) = \sum_r u_r y_{ro} / \sum_i v_i x_{io} \\ &\textit{subject to}: \\ &\sum_r u_r y_{rj} / \sum_i v_i x_{ij} \leq 1 \textit{ for } j = 1, \ldots\ldots, n, \\ &u_r \ , \ v_i \ \geq \ 0 \textit{ for all } i \textit{ and } r. \end{aligned} \qquad \textbf{2.2}$$

Note that a fully rigorous development would replace with u_r , v_i ≥ 0 with $u_r / \sum_{i=1}^{m} v_i x_{io}, u_r / \sum_{i=1}^{m} v_i x_{io} \geq \varepsilon > 0$, where ε is a Archimedean element smaller than any positive real number. This condition guarantees that solutions will be positive in these variables. It also leads to the ε>0 in (2.6) which, in turn, leads to the second stage optimization of the slacks as in (2.10).

The above ratio form yields an infinite number of solutions; if (u*, v*) is optimal, then (α_u*, α_v*) is also optimal for α > 0. However, the transformation developed by Charnes and Cooper (1962) for linear fractional programming selects a representative solution [i.e., the solution (u, v) for which $\sum_{i=1}^{m} v_i x_{io}$ = 1 and yields the equivalent linear programming problem in which the change of variables from (u, v) to (μ, v) is a result of the Charnes-Cooper transformation,

$$\begin{aligned}
&\max Z = \sum_{r=1}^{s} \mu_r y_{ro} \\
&\textit{Subject to}: \\
&\sum_{r=1}^{s} \mu_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0 \\
&\sum_{i=1}^{m} v_i x_{io} = 1 \\
&\mu_r, v_i \geq \varepsilon > 0
\end{aligned} \qquad \mathbf{2.3}$$

For which the LP dual problem is

$$\begin{aligned}
&\theta^* = \min \theta \\
&\textit{Subject to}: \\
&\sum_{j=1}^{n} x_{ij} \lambda_j = \theta x_{io} \quad , i = 1,2,......., m; \\
&\sum_{j=1}^{n} y_{rj} \lambda_j = y_{ro} \quad , r = 1,2,........, s; \\
&\lambda_j \geq 0 \qquad\qquad , j = 1,2,........., n.
\end{aligned} \qquad \mathbf{2.4}$$

Model, (2.4), is sometimes referred to as the "Farrell model" because it is the one used in Farrell (1957). In the economics portion of the DEA literature it is said to conform to the assumption of "strong disposal" because it ignores the presence of non-zero slacks. In the operations research portion of the DEA literature this is referred to as “weak efficiency”.

Farrell also failed to exploit the very powerful dual theorem of linear programming which we have used to relate the preceding problems to each other. This also caused computational difficulties for Farrell because he did not take advantage of the fact that activity analysis models can be converted to linear programming equivalent that provide immediate access to the simplex and other methods for efficiently solving such problems. Therefore, it now begins to bring these features of linear programming into play (Charnes,1994).

By virtue of the dual theorem of linear programming we have z* = θ*. Hence either problem may be used. One can solve say (2.4), to obtain an efficiency score. Because we can set θ = 1 and λ_{k}^{*} = 1 with $\lambda_{k}^{*} = \lambda_{o}^{*}$ and all other λ_{j}^{*} = 0, a solution of (2.4) always exists. Moreover this solution implies θ*≤ 1. The optimal solution, θ*, yields an efficiency score for a particular DMU. The process is repeated for each j i.e., solve (2.4), with (X_o, Y_o) = (X_k, Y_k), where X_k, Y_k represent vectors with components, X_{ik}, Y_{rk} and, similarly (X_o, Y_o) has components X_{ok}, X_{ok}. DMUs for which θ* < 1 are inefficient, while DMUs for which θ* = 1 are boundary points.

Some boundary points may be “weakly efficient” because we have non-zero slacks. This may appear to be worrisome because alternate optima may have non-zero slacks in some solutions, but not in others. However, we can avoid being worried even in such cases by invoking the following linear program in which the slacks are taken to their maximal values.

$$\begin{aligned}
&\max \sum_{i=1}^{m} s_i^{-} + \sum_{r=1}^{s} s_r^{+} \\
&\textit{Subject to}: \\
&\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^{-} = \theta^{*} x_{io} \quad , i = 1,2,\ldots\ldots, m; \\
&\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^{+} = y_{ro} \quad , r = 1,2,\ldots\ldots\ldots, s; \\
&\lambda_j , s_i^{-}, s_r^{+} \geq 0 \,\forall\, i,\ j,\ r.
\end{aligned} \qquad \textbf{2.5}$$

Where it notes the choices of s_i^- and s_r^+ do not affect the optimal θ* which is determined from model (2.4).

These developments now lead to the following definition based upon the "relative efficiency" definition which was given in section 2.2.1.

DEA Efficiency: The performance of DMU$_o$ is fully (100%) efficient if and only if both θ* = 1 and all slacks =0.

Weakly DEA Efficient: The performance of DMU$_o$ is weakly efficient if and only if both θ* = 1 and $s_i^{-*} \neq 0$ and/or $s_r^{+*} \neq 0$ for some *i* and *r* in some alternate optima.

It is to be noted that the preceding development amounts to solving the following problem in two steps:

$$\begin{aligned}
&\min \theta - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right) \\
&Subject\ to: \\
&\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta x_{io} \quad, i = 1,2,\ldots\ldots,m; \\
&\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = y_{ro} \quad, r = 1,2,\ldots\ldots,s; \\
&\lambda_j, s_i^-, s_r^+ \geq 0 \ \forall\, i,\, j,\, r.
\end{aligned} \qquad \mathbf{2.6}$$

Where the s_i^- and s_r^+ are slack variables used to convert the inequalities in (2.4) to equivalent equations. Here ε > 0 is an Archimedean element defined to be smaller than any positive real number. This is equivalent to solving (2.4) in two stages by first minimizing θ, then fixing θ = θ* as in (2.2), where the slacks are to be maximized without altering the previously determined value of θ = θ*.

Formally, this is equivalent to granting "preemptive priority" to the determination of θ* in (2.3). In this manner, the fact that the non-Archimedean element *ε* is defined to be smaller than any positive real number is accommodated without having to specify the value of *ε*.

Alternately, one could have started with the output side and considered instead the ratio of virtual input to output. This would reorient the objective from max to min, as in (2.2), to obtain:

$$\begin{aligned}
&\min = \sum\nolimits_i v_i x_{io} / \sum\nolimits_r u_r y_{ro} \\
&\textit{subject to} : \\
&\sum\nolimits_i v_i x_{io} / \sum\nolimits_r u_r y_{ro} \geq 1 \ \textit{for}\ j = 1, \ldots\ldots, n, \\
&u_r \ , v_i \ \geq \varepsilon > 0 \ \ \forall\ i\ , r.
\end{aligned} \qquad \mathbf{2.7}$$

Again, the Charnes-Cooper (1962) transformation for linear fractional programming yields model (2.8) (multiplier model) below, with associated dual problem, (2.9) (envelopment model), as in the following pair:

$$\begin{aligned}
&\min q = \sum_{i=1}^{m} v_i x_{ij} \\
&\textit{Subject to} : \\
&\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} \mu_r y_{rj} \geq 0 \\
&\sum_{r=1}^{s} \mu_r y_{ro} = 1 \\
&\mu_r , v_i \geq \varepsilon > 0 \quad \forall\ r , i
\end{aligned} \qquad \mathbf{2.8}$$

$$\begin{aligned}
&\max \Phi + \varepsilon(\sum_{i=1}^{m} s_i^{-} + \sum_{r=1}^{s} s_r^{+}) \\
&\textit{Subject to} : \\
&\sum_{j=1}^{n} x_{ij} \lambda_j + s_i^{-} = x_{io} \qquad , i = 1, 2, \ldots\ldots., m; \\
&\sum_{j=1}^{n} y_{rj} \lambda_j - s_r^{+} = \Phi y_{ro} \qquad , r = 1, 2, \ldots\ldots.., s; \\
&\lambda_j \geq 0 \qquad\qquad\qquad , j = 1, 2, \ldots\ldots..., n.
\end{aligned} \qquad \mathbf{2.9}$$

Here a model with an output oriented objective is used as contrasted with the input orientation in (2.6). However, as before, model (2.9) is calculated in a two-stage process. First, we calculate Φ* by ignoring the slacks. Then the slacks are optimized by fixing Φ* in the following linear programming problem,

$$\max \sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+$$

Subject to :

$$\begin{aligned}
&\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = x_{io} && , i = 1, 2, \ldots\ldots, m; \\
&\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = \Phi y_{ro} && , r = 1, 2, \ldots\ldots\ldots, s; \qquad \textbf{2.10} \\
&\lambda_j \geq 0 && , j = 1, 2, \ldots\ldots\ldots, n.
\end{aligned}$$

Then, the previous input-oriented definition of DEA efficiency to the following output-oriented version is modified.

- DMU$_o$ is **efficient** if and only if $\Phi^* = 1$ and $s_i^- = s_r^+ = 0$ for all *i* and r.
- DMU$_o$ is **weakly efficient** if $\Phi^* = 1$ and $s_i^- \neq 0$ and (or) $s_r^+ \neq 0$ for some i and r in some alternate optima.

Table (2.2) in the next page summarizes DEA Models and their types.

Table 2.2: DEA Models

Frontier Type	Envelopment / Primal Model	
	Input-oriented	**Output-oriented**
CRS	$\min \theta - \varepsilon(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+)$ *Subject to* : $\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta x_{io} \quad ,i = 1,2,.......,m;$ $\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = y_{ro} \quad ,r = 1,2,........,s;$ $\lambda_j \geq 0 \quad , j = 1,2,.........,n.$	$\max \Phi + \varepsilon(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+)$ *Subject to* : $\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = x_{io} \quad ,i = 1,2,.......,m;$ $\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = \Phi y_{ro} \quad ,r = 1,2,........,s;$ $\lambda_j \geq 0 \quad , j = 1,2,.........,n.$
VRS	**Add** $\sum_{i=1}^{n} \lambda_i = 1$	
DRS	**Add** $\sum_{i=1}^{n} \lambda_i \leq 1$	
IRS	**Add** $\sum_{i=1}^{n} \lambda_i \geq 1$	

Frontier Type	Multiplier/Dual Model	
	Input-Oriented	**Output-Oriented**
CRS	$\max Z = \sum_{r=1}^{s} \mu_r y_{ro}$ *Subject to* : $\sum_{r=1}^{s} \mu_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0$ $\sum_{i=1}^{m} v_i x_{io} = 1$ $\mu_r, v_i \geq \varepsilon > 0$	$\min q = \sum_{i=1}^{m} v_i x_{ij}$ *Subject to* : $\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} \mu_r y_{rj} \geq 0$ $\sum_{r=1}^{s} \mu_r y_{ro} = 1$ $\mu_r, v_i \geq \varepsilon > 0$

2.3.8 Strengths and Weaknesses of DEA

The major advantage of DEA over other methods that determine efficiency, such as cost–benefit analysis or regression, is that the relative weights of the variables do not need to be known, a priori. Multiple variations of this technique exist, differing in how the efficient frontier is determined and in how the distance to the frontier for inefficient DMUs is measured.

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:

- DEA can handle multiple input and multiple output models.
- It does not require an assumption of a functional form relating inputs to outputs because it is a non-parametric approach.
- DMUs are directly compared against a peer or a combination of peers.
- Inputs and outputs can have very different units. For example, X_1 could be in units of trips taken and X_2 could be bus fare of monthly pass.
- As pointed out in Cooper, Seiford and Tone (2000), DEA has also been used to supply new insights into activities (and entities) that have previously been evaluated by other methods
- Proven to be useful in uncovering relationships that remain hidden for other methodologies.
- The sources of inefficiency can be analyzed and quantified for every evaluated unit.

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.
- 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 with your peers but not compared to a theoretical maximum.

- Since a standard formulation of DEA creates a separate linear program for each DMU, large problems can be computationally intensive.
- 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 (Charnes,1994).

2.3.9 Modified Data Envelopment Analysis (MDEA)

Basic DEA models evaluate the relative efficiency of DMUs but do not allow ranking of the efficient units themselves. This fact represents a key weakness of basic DEA models. One way to rank efficient DMUs is to modify basic DEA models. One of them has been formulated by Andersen and Petersen (1989, 1993) but it can be unstable when one of the DMUs has a relatively small value for some of its inputs. Others (Najizadeh and Aryanezhad 2004) suggested proposes a new ranking algorithm that can be used for ranking efficient DMUs by DEA method and removes the foregoing difficulty**.** Charnes et al (1978) first introduced DEA as a new methodology for measuring relative efficiency. Not only has the theoretical development of DEA been quite remarkable, its use in practice has been expanded to address many public and private sector issues. While basic DEA models have many desirable features that have contributed to their rapid adoption by practitioners, there remain some weaknesses with the original models. For example, all efficient Decision Making Units (DMUs) have the same efficiency scores equal to one in both the CCR model developed by Charnes et al (1978) and in the BCC model developed by Banker et al (1984). Therefore, it is impossible to rank or differentiate the efficient DMUs with the CCR and BCC models.

However, the ability to rank or differentiate the efficient DMUs is of both theoretical and practical importance. Theoretically, the inability to differentiate the efficient units creates a spiked distribution at efficiency scores of one. This poses analytic difficulties to any post-DEA statistical inference analysis. In practice, further differentiation among efficient DMUs is also desirable and even necessary in many cases.

It is important to provide a full ranking of the whole set because of the following reasons. First, since DEA efficiency scores are basically a measurement for relative efficiency, one of the desirable results is essentially the position of each DMU compared to its peers. To provide a full ranking of the whole set is the only way to fulfill such a need.

Second, with the full ranking of the whole set, further statistical inferences of the ranks are made possible, which will provide insights into the question that ultimately interested in: what are those factors that significantly influence a DMU's efficiency?

To overcome this weakness, Andersen and Petersen (1993) presented the Modified DEA (MDEA) method. The core idea of MDEA is to exclude the DMU under evaluation from the reference set and therefore, the efficient DMUs will, in general, have different efficiency scores. The infeasibility problem with MDEA model was first noticed in Thrall (1996).

To overcome the problem encountered with Andersen and Petersen's model, a new ranking algorithm Najizadeh and Aryanezhad (2004) is proposed that can be used for ranking efficient DMUs. This algorithm removes the foregoing difficulty related to Andersen-Petersen's model.

Based on the (Najizadeh and Aryanezhad (2004) proposed model, in order to rank efficient DMUs in the CCR input oriented model by new algorithm the following steps should be done:

- Determining the efficiency scores of DMUs by using DEA method.
- Identifying the efficient DMUs (DMUs with efficiency scores equal to one)
- Determining virtual optimum DMU.
- Solving a linear program model for efficient DMUs and virtual optimum DMU.

In this case, the virtual optimum DMU will be the only Pareto Efficient DMU that will have the efficiency score equal to one and its slacks equal to zero. Therefore, the other DMUs, that were determined as efficient DMUs in stage B of this algorithm, will be ranked relative to this DMU (Cooper, et al 2004).

2.4 Shannon's Entropy

2.4.1 Definition

A statistical concept of entropy was introduced by Shannon in the theory of communication and transmission of information (Shannon 1948). It is formally similar to Boltzmann entropy associated with the statistical description of the microscopic conjurations of many-body systems and how it accounts for their macroscopic behavior (Castiglione et al. 2008). Establishing the relationships between statistical entropy, statistical mechanics and thermodynamic entropy was initiated by Jaynes (Jaynes 1982b).

In an initially totally different perspective, a notion of entropy rate was developed in dynamical systems theory and symbolic sequence analysis (Lesne et al. 2009). The issue of compression is sometimes rooted in information theory and Shannon entropy, while in other instances it is rooted in algorithmic complexity (Cover and Thomas 2006). As a consequence of this diversity of uses and concepts I may ask whether the use of the term entropy has any meaning.

Shannon initially developed information theory for quantifying the information loss in transmitting a given message in a communication channel (Shannon 1948). A noticeable aspect of Shannon approach is to ignore semantics and focus on the physical and statistical constraints limiting the transmission of a message, notwithstanding its meaning.

2.4.2 Theory

The source generating the inputs $x \epsilon X$ is characterized by the probability distribution $p(x)$. Shannon introduced the quantity $Ip(x) = -\, log_2\, p(x)$ as a measure of the information brought by the observation of x knowing the probability distribution p. In plain language, one could correctly say (Balian 2004) that $I_p(x)$ is the surprise in observing x, given prior knowledge on the source summarized in p. Shannon entropy $S(p)$ thus appears as the average missing information, that is, the average information required to specify the outcome x when the receiver knows the distribution p. It equivalently measures the amount of uncertainty represented by a probability distribution

The concept of Shannon's entropy is the central role of information theory sometimes referred as measure of uncertainty. The entropy of a random variable is defined in terms of its probability distribution and can be shown to be a good measure of randomness or uncertainty. This chapter mainly deals with its characterizations and properties. Properties for discrete finite random variable are studied. The study is extended to random vectors with finite and infinite values. The idea of entropy series is explained. Finally, the continuous case generally referred as differential entropy with different probability distributions and power inequality are studied.

Shannon's theorem also implies that no lossless compression scheme can compress all messages. If some messages come out smaller, at least one must come out larger. In practical use, this is not a problem, because we are generally only interested in compressing certain types of messages, for example English documents as opposed to gibberish text, or digital photographs rather than noise, and it is unimportant if our compression algorithm makes certain kinds of random sequences larger.

2.4.3 Shannon's Entropy Model

For a random variable X with values in a finite set X, *Shannon entropy* is defined as (Shannon 1948):

$$H(X) = -\sum_{x \in X} p(x) log_2 p(x) \geq 0$$

It quantifies the unevenness of the probability distribution p. In particular, the minimum $H(x) = 0$ is reached for a constant random variable, i.e. a variable with a determined outcome, which reacts in a fully localized probability distribution $p(x_0) = 1 \; and \; p(x) = 0 \; for \; x \neq x_0$. At the opposite, $H(x)$ is maximal, equal to $log_2(|X|)$, for a uniform distribution. $H(x)$ is also denoted:

$$S(p) = -\sum_{i=1}^{|X|} p(x_i) log_2 p(x_i)$$

Which underlines the fact that entropy is a feature of the probability distribution p. Entropy does not depend on the graph $x \rightarrow p(x)$, i.e., it is not a feature of the random variable itself but only of the set of its probability values. This property reflects in a permutation invariance of $H(X)$: let the variable $\sigma.X$ obtained by a permutation of the states, namely $Prob\big(\sigma.X = x_{\sigma(i)}\big) = p(x_i)$, then $H(X) = H(\sigma.X)$. Entropy trivially increases with the number of possible states: for an unbiased coin, $H = log_2 2 = 1$ while for an unbiased dice, $H = log_2 6 > 1$.

2.5 Previous Studies

In recent years, several studies have analyzed performance and efficiency in educational institutions using DEA approach. Each study differs in its scope, DMUs, and variables. An overview of the related literature is given in the sections below.

2.5.1 Global Studies

The study of McMillan M L. and Datta D., (1998) titled" **The Relative Efficiencies of Canadian Universities: A DEA Perspective"**

This study applied DEA to assess the relative efficiency of 45 Canadian universities using DEA in 1992 -1993. Outcomes are obtained from nine different specifications of inputs and outputs. The universities are categorized in to three categories: Comprehensive with medical school, Comprehensive without medical school, and primarily undergraduate. The result was most of the universities were relatively efficient. The relative efficiencies are quite consistent across the alternative specifications. A subset of universities including universities from each of three categories (comprehensive with medical school, comprehensive without medical school, and primarily undergraduate) are regularly found efficient and a subset quite inefficient but, overall and for most universities, the efficiency scores are relatively high. Regression analysis is used in an effort to identify further determinants of efficiency.

The study of Malcolm A. and Chris D., (1999) titled **"Technical and Scale Efficiency of Vocational Education and Training Institutions: The Case of the New Zealand Polytechnics"**

This study applied DEA to estimate the technical and scale efficiency of vocational education and training in 25 New Zealand polytechnics serving a total of 94,201 students. The average level of technical efficiency was high in 1995 and rose slightly. In terms of scale efficiency, only 4 polytechnics operated with constant returns to scale in 1995, 9 were producing too much output relative to the optimal scale, and 10 were producing too little output. In 1996, 6 of the polytechnics operated with constant returns to scale, 14 were producing too little output, and 1 was producing too much output.

The study of Lia L., Lee C., and Tzeg G. (2000) titled **"DEA Approach for the Current and the Cross Period Efficiency for Evaluating the Vocational Education"**

DEA was used to examine the relative managerial efficiency for evaluating current-period and cross-period efficiency of 38 technological institutes upgraded from junior colleges in Taiwan by 1998. The used inputs were Building Area, Faculty Number, Annual Expenditure, Library Collection, and Periodical Categories whereas the outputs were Number of Graduates, Research Expenditures and school-industry-collaboration and continuation education Income. The managerial efficiency variations of each individual institute in between 1995 and 1998 were also determined. The study results show that private schools perform significantly better than public schools in terms of managerial efficiency.

The study of Lopes A. M., and Lanzer E. A. (2002) titled **"Data envelopment analysis – DEA and fuzzy sets to assess the performance of academic departments: a case study at Federal University of Santa Catarina – UFSC"**

DEA and Fuzzy were used to assess the performance of Academic Departments at Federal University of Santa Catarina in Brazil. The model applied to a set of fifty-eight departments showed fifteen with low performance. A DEA model was used to simulate a process of cross-evaluation between departments. The results of DEA in the dimensions of teaching, research, service and quality were modeled as fuzzy numbers and then aggregated through a weighted ordered aggregator. A single index of performance for each department was generated. The proposal is to identify departments with low performance in one or more dimensions that should receive additional evaluation from an external auditing committee. Finally, model extensions can also be devised in the sense of making predictions of performance impacts from resource allocation alternatives along the general lines.

The study of Moreno A., and Tadepalli R. (2002) **titled "DEA analysis of the efficiency of Victorian technical and further education institutes'**

This study assessed academic department efficiency a public university. Data envelopment analysis (DEA) is proposed for evaluating the efficiency of 42 academic departments at a public university. The inputs are faculty salaries, staff salaries, operational budget, equipment budget, and building space allocated to each academic unit while the outputs are number of graduate majors, number of undergraduate majors, full time equivalents produced, student credit hours generated, and amount of grants awarded. DEA provides a single measure of efficiency for each academic unit. It also identifies the causes behind the inefficiencies exhibited by poor performing units, as well as the changes that these units need to make in order to improve their efficiencies. The study results show 22 of departments were relatively efficient.

The study of Saowanee L. et al (2003)**, Fuzzy data envelopment analysis (DEA): a possibility approach**

This paper developed DEA models using imprecise data represented by fuzzy. It was shown that fuzzy DEA models took the form of fuzzy linear programming which typically solved with the aid of some methods to rank fuzzy sets. As an alternative, a possibility approach was introduced in which constraints were treated as fuzzy events. The approach transformed fuzzy DEA models into possibility DEA models by using possibility measures of fuzzy events (fuzzy constraints). A numerical experiment was used to illustrate the approach and compare the results with those obtained with alternative approaches. The study suggested the solution of possibility DEA models with general membership functions for future works.

The study of Abbott M., and Doucouliagos C.,(2003) titled **"The efficiency of Australian universities: a data envelopment analysis'**

DEA is applied to analyze the performance of the Victorian TAFE institutes with respect to technical, allocative, scale and overall cost efficiency, undertaken through Data Envelopment Analysis (DEA). The inputs used were the total number of academic staff (full-time equivalent). The second input is the number of non-academic staff (fulltime equivalent). The third input is expenditure on all other inputs other than labor inputs. The fourth input is the value of non-current assets. Whereas the outputs are the number of equivalent full-time students (EFTS), the number of post-graduate and under-graduate degrees enrolled, as well as the number of post-graduate degrees conferred and the number of under-graduate degrees conferred. The study applied on 36 public Australian universities in 1995 founded that most of the universities were relatively efficient.

The study of Emilino Martin(2003), titled**: "An application of the data envelopment analysis methodology in the performance assessment of the Zaragoza University Departments"**

DEA models were used to measure the performance of the Zaragoza University Departments in Spain. The inputs and outputs measures concerned both teaching and research activities of the departments. The results reveal those departments that more efficiently carry out these activities. The results of model 1 showed 36 departments were efficient out of 52 departments. The study recommended taking more and different factors when obtaining the efficiency.

The study of Feny Y. J., La H., and Bi K. (2004), titled**: "An AHP/DEA method for measurement of the efficiency of R&D management activities in universities"**

This study used combination of analysis hierarchical process (AHP) and data envelopment analysis (DEA) for the assessment of the efficiency of R&D management activities in 29 universities in China. The measure consisted of the measurement of a university's previous and present R&D strength by AHP and the assessment of the relative efficiency of its growth in R&D strength against those of other universities by DEA, in which the management basis of the measured universities is taken into consideration. The application of the measured to assess the R&D management efficiency of 29 universities in China indicated the universities which have improved their management work achieved a high efficiency value regardless of whether their original R&D strengths were strong or weak. Such a measure is proved to be helpful for motivating the universities to keep on improving their R&D management. The measure is proved to be reasonable and practical for the assessment of management work and it can also provide insight into the evolution of the R&D management work in universities when it is used for a long period of time.

The study of Toylor B., and Harris G. (2004), titled**: "Relative Efficiency among South African Universities: A Data Envelopment Analysis"**

This study examined the relative efficiency of South African universities between 1994 and 1997 using Data Envelopment Analysis. After outlining the nature and limitations of the technique, a series of seven models were tested. Each used a consolidation of the annual output of graduates and research as the output variable and tested this against various input variables. A high degree of consistency and stability was found. Differences in efficiency during the four year period were studied and the article concludes with a discussion of four factors which appear central in explaining differences in efficiency between universities.

The study of Chiang Kao,and Hsi-Tai Hung (2008), titled**: "Efficiency analysis of university departments: An empirical study"**

This study used data envelopment analysis (DEA) to assess the relative efficiency of the academic departments at National Cheng Kung University in Taiwan. The outputs considered are total credit-hours, publications, and external grants; and the inputs utilized by the departments are personnel, operating expenses, and floor space. An assurance region is constructed by the top administrators of the university to confine the flexibility in selecting the virtual multipliers in DEA. Four groups of departments of similar characteristics are categorized via efficiency decomposition and cluster analysis. The aggregate efficiency indicates whether the resources have been utilized efficiently by a department and the efficiency decomposition helps identify the weak areas where more effort should be devoted so that the efficiency of the department can be improved.

The study of Soleimani-damaneh (2009), titled**: " Shannon's Entropy for combining the efficiency results of different DEA models: Method and application"**

This study applied DEA and Shannon's entropy on Iranian university to provide a methodology, based upon Shannon's entropy formula, for combining the efficiency results of different DEA models (viewpoints) for ranking DMUs. The study concluded that combining the efficiency results of different DEA models provides more realistic ranking results for managers of the university compared with using each of the DEA models individually. In addition, using a combination of DEA models compensate the pitfalls of each model.

2.5.2 Local Studies

The study of Al Hindawy Kamal (2007), titled: **"Measuring the Efficiency of Technical Education in UNRWA: Gaza Training Center (GTC) - Case Study"**

This study applied DEA model to evaluate the relative efficiency of 8 technical diploma programs. The used inputs were 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. While the used outputs were number of graduates who work in related fields is used as output data. The results showed 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 results suggested that 4 technical diploma programs (Civil Engineering, Industrial Electronics, Graphic Design, and Programming & Database) need structural reform to improve their technical efficiency.

The study of Hammad Ehab (2007), titled: **"Measuring the Efficiency of the banking sector in Palestine using Data Envelopment Analysis Approach"**

This study applied DEA model to measure and break down the technical efficiency of the banks working in Palestine through the period from 2002 to 2005. The inputs used were Labor, Fixed Assets and Total Deposits while the outputs used were Direct Credit Facilitation and Earning Assets. Two basic models of the DEA were used under the assumptions of constant returns to scale and the variable returns to scale; the study found that, there were differences among banks in relation to their technical efficiency scores, and the average pure technical efficiency score was 96.3%. The study compared the efficiency scores between local and foreign banks and found that local banks had a higher averaged score of technical efficiency than foreign banks, but the difference was statistically insignificant.

Comments on the previous studies:

It is noticed that large number of studies that applied DEA to assess or measure the efficiency of different DMUs in different applications such health, education, and banking sector. This proved the effectiveness of using DEA in measuring the efficiency of academic departments in IUG. In addition, different inputs and outputs were used in measuring the efficiency of different models. On educational level, table 2.3 summarized the inputs and outputs measures that used in different educational applications. Further, it is noticed that the majority of DEA studies didn't assign weights for the variable used. This gives a motivation for this study to assign weights for variables and investigate its effects of efficiency scores. The assignment of weights is drawn from the study that used Shannon's entropy to combine the results of different DEA models. The DEA local studies are limited. Two studies were discussed; one of them is related to this study but different in scope as it was applied on diploma programs. This also represents a motivation for this thesis as the scarcity of applying DEA in Gaza strip given its effectiveness in evaluating the technical efficiency.

Table (2.3): Summary of variables on Educational Studies Using DEA

Author (s)	Inputs	Outputs
Johnes, Jill (1996)	**1.** Raw material **2.** Labor service **3.** Human capital service **4.** Physical capital service **5.** Consumables **6.** Environmental factors **7.** Institutional characteristics.	**1.** Teaching activity **2.** Research activity **3.** Consultancy **4.** Cultural and social outputs
Spronk, (1999).	**1.** The amount of general expenditure. **2.** The amount of equipment expenditure.	**1.** The amount of research income. **2.** The number of undergraduate students. **3.** The number of post-graduate students on taught courses. **4.** The number of post-graduate students doing research **5.** University Grant Committee research rating
M. Abbott and C. Doucouliagos (2001)	**1.** The total number of academic staff (full-time equivalent). **2.** The number of non-academic staff (full-time equivalent). **3.** Expenditure on all other inputs other than labor inputs. **4.** The value of non-current assets	**1. Teaching output :** **a.** The Number of equivalent full time student. **b.** The number of post-graduate degrees enrolled. **c.** The number of under-graduate degrees enrolled. **d.** The number of post-graduate degrees conferred. **e.** The number of under-graduate degrees conferred. **2. Research output :** **a.** Quantity of research output. **b.** Quality of the work. Using the weighted indexes of research publication.
Morenoa and RaghuTadepalli (2002)	**1.** Faculty salaries **2.** Staff salaries **3.** Operational budget **4.** Equipment budget. **5.** Space allocated in square feet.	**1.** Number of graduate majors. **2.** Number of undergraduate majors. **3.** Full time equivalents produced. **4.** Student credit hours generated. **5.** Amount of grants awarded.

Author (s)	Inputs	Outputs
Karl-Heinz Leitner et al (2002)	**1.** Staff **2.** Room space **3.** Financial funds provided by third parties	**1.** Finished (ordered) projects and personal. **2.** Finished (ordered) projects of the department **3.** Publications: monographs **4.** Original papers **5.** Project reports **6.** Patents **7.** Presentations **8.** Other publications **9.** Number of examinations **10.** Number of finished supervised diploma theses. **11.** Number of finished supervised PhD-theses
Emilino Martin (2003)	**1.** Human resources **2.** Financial resources **3.** Material resources	**1.** Teaching Indicators **a.** Credits registered **b.** PhD Credits offered. **2.** Research Indicators **a.** PhD theses read during the last year. **b.** Researching annual incomes. **c.** Department research activity
Chiang Kaoa and Hsi-Tai Hung (2008)	**1.** Personnel **2.** Operating expenses **3.** Floor space.	**1.** Credit-hours **2.** Publications **3.** External grants

Chapter 3: RESEARCH METHODOLOGY

3.1 Decision Making Units "DMUs"

3.2 Variable Selection

3.3 Data Collection

3.4 Research Model

3.5 Research Software

This chapter describes the methodology of the research, it begins with illustrating the Decision Making Units of the research, and then explains how the variables of the research are selected and collected. Next, it describes the DEA and Shannon's models used to treat the data and finally, it gives a brief overview about the employed software.

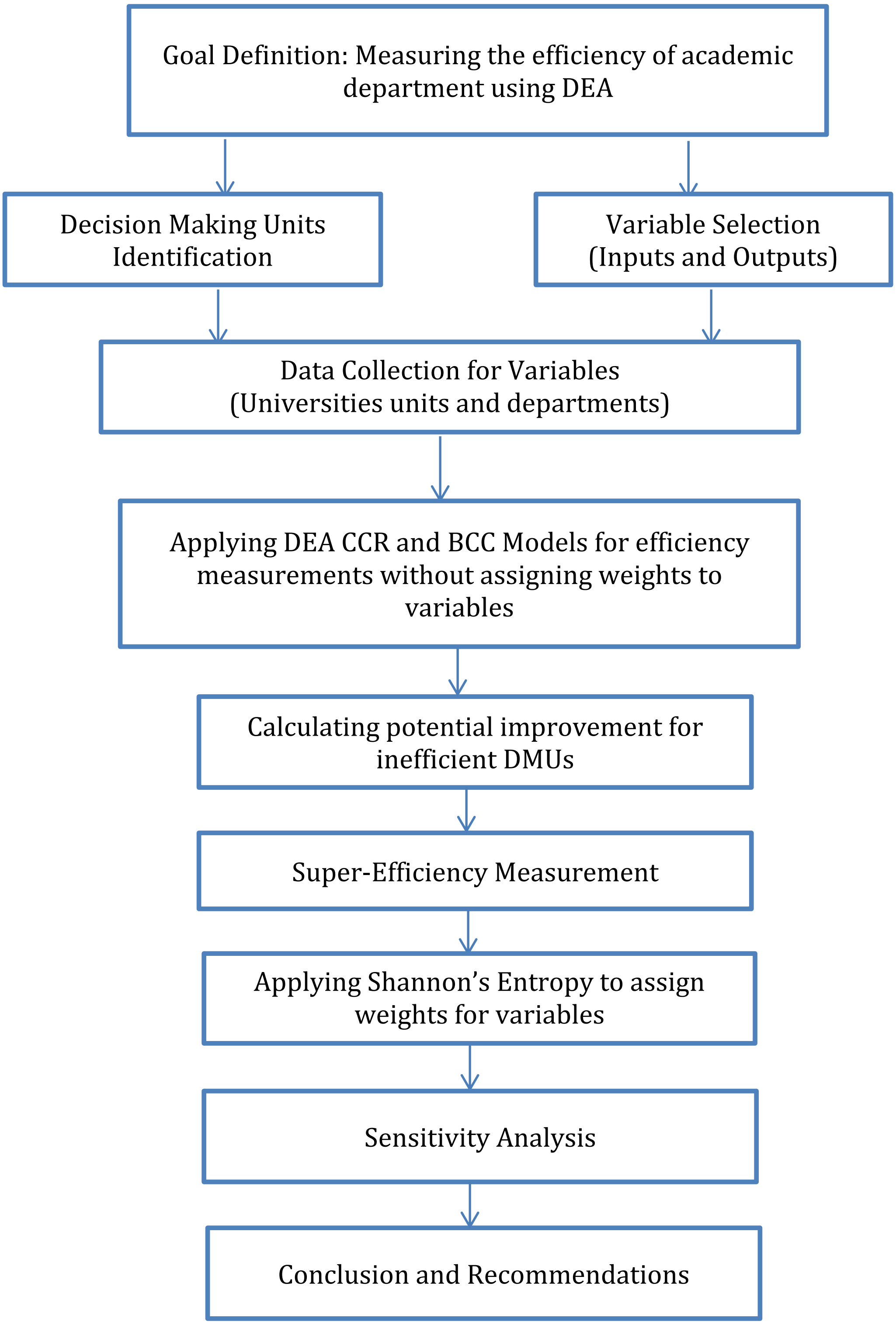

Fig.3.1: Research Methodology

3.1 Decision Making Units

The research is implemented on Islamic University of Gaza (IUG). IUG currently has ten faculties awarding BA., B.Sc., MA, M.Sc., MBBS, diploma, and higher diploma in a variety of disciplines and recently IUG has stated a PhD program for Ussoul El Deen.

The IUG awards the bachelor degree in 57 disciplines and the master degree in 20 disciplines, in addition to higher diploma in 2 educational disciplines and professional diploma in 9 disciplines. Table 3.1 shows the IUG facilities and bachelor departments.

The target of the research study is the bachelor programs, in other words, master degree and the high diploma are ignored to achieve the homogeneity between the DMUs, and if considered, the number of DMUs will significantly decrease.

The study period includes 2008-2009, 2009-2010 and 2010-2011 academic years and any department that has no graduates over the study period is excluded such as Medicine, Environmental and Mechanical engineering departments.

Education faculty is considered one DMU because of the huge overlap among its departments especially in the required courses and professors. So, to avoid this overlap all educational departments are considered one big DMU. For the same reason, the Economics and Journalism departments are merged with Economics and Political Sciences Journalism and Information departments respectively.

Eventually, considering all above, the research sample includes 33 DMUs spanning nine of the IUG faculties as shown in Table 3.2.

Table 3.1: IUG Faculties and Departments

Faculty	Department
Ussoul Eldeen	**1.** General Ussoul Eldeen
Shariah and law	**2.** Islamic Shariah **3.** Shariah and law
Arts	**4.** Arabic **5.** English **6.** Geography **7.** Geographical Information Systems **8.** Journalism & Media **9.** Social Work **10.** History And Archaeology **11.** Arabic &Journalism
Education	**12.** Arabic **13.** English **14.** Mathematics **15.** Science **16.** Primary Education **17.** Islamic Studies **18.** Social Studies **19.** Chemistry **20.** Physics **21.** Biology **22.** Psyco- Counseling **23.** Computer Education
Commerce	**24.** Business Administration **25.** Economics and Political Sciences **26.** Accounting **27.** Banking And Finance **28.** General (In English) **29.** Business Administration (In English) **30.** Accounting (In English) **31.** Economics & Political Sciences(In English) **32.** Economics & Applied Statistics
Science	**33.** Chemistry **34.** Mathematics **35.** Physics **36.** Biology **37.** Medical Technology **38.** Environment and Earth Science **39.** Mathematics-Computer **40.** Mathematics-Statistics **41.** Chemistry-Biochemistry **42.** Biotechnology **43.** Optometry

Table 3.1: IUG Faculties and Departments (Continued)

Faculty	Department
Nursing	**44.** General Nursing **45.** Midwifery
Information Technology "IT"	**46.** Computer Science **47.** Information Technology System. **48.** Software Development **49.** Multimedia and web development.
Engineering	**50.** Civil Engineering **51.** Architecture **52.** Electrical Engineering **53.** Computer Engineering **54.** Industrial Engineering **55.** Environmental Engineering **56.** Mechanical Engineering
Medicine	**57.** Medicine and surgery

Table 3.2: Decision Making Units

Faculty	DMU
Ussoul Eldeen	**1.** General Ussoul Eldeen
Shariah and law	**2.** Islamic Shariah **3.** Shariah and Law
Arts	**4.** Arabic **5.** English **6.** Geography **7.** Journalism & Information **8.** Social Work **9.** History And Archaeology
Education	**10.** Education
Commerce	**11.** Accounting **12.** Business Administration **13.** Economics and Political Sciences **14.** Banking And Finance **15.** Economics And Applied Statistics **16.** Accounting English **17.** Business Administration English
Science	**18.** Chemistry **19.** Mathematics **20.** Physics **21.** Biology **22.** Medical Technology **23.** Environment and Earth Science **24.** Optometry
Nursing	**25.** General Nursing
Information Technology "IT"	**26.** Computer Science **27.** Information Technology System. **28.** Software Development
Engineering	**29.** Civil Engineering **30.** Architecture **31.** Electrical Engineering **32.** Computer Engineering **33.** Industrial Engineering

3.2 Variable Selection

Variable selection is a most critical part of DEA. Because interest is in efficiency and management performance, the analysis concentrates on variables under the control of the DMU. Unlike other models, DEA has no formal tests to assess the merits of including or excluding variables (or DEA model choice). Instead, one must rely upon the sensitivity of the results to inclusion or exclusion of variables and judgment. The concern for variable selection is compounded by the fact that as the number of variables increases, the number of DMUs deemed efficient and the efficiency scores of the inefficient units will typically increase. Hence, it is particularly important at the variables included should reflect valuable component of input or output. In addition, it is advisable to keep the number of variables to less than one-third of the number of observations (McMillan, 1998).

Evaluation based on the efficiency score is directly affected by the input and output variables. That is, the inputs and outputs should be selected appropriately so as to express the performance of DMUs. For instance, the selection may be established on a particular theory, e.g. production versus intermediation approaches to bank behavior. Alternatively, expert knowledge or accepted practices can be useful in determining the variables (Morita et al, 2009). An accurate selection of the variables, which are best adapted to the objective of the analysis, is critical to the success of the study. This process is a strong controversial issue. On one hand, it is not easy to define the variables that more properly represent the outputs produced by educational units or the inputs that should be considered. On other hand, this kind of studies has to face the inaccuracy of information concerning the results of the higher education activity.

Although teaching and research have been considered by most researchers as the two major tasks of the university, they are difficult to measure (Martin 2003, and Abbott et al 2003). The research needs some indicators which are capable of representing the achievement of these two tasks. It also needs measures of the resources that the department has consumed in performing those two tasks. The selection of input and output factors for evaluating the performance of university departments using DEA has been discussed in several studies. There are at least two difficulties in deciding on the indicators. One is the availability of data. For example, some scholars suggest using the salary of the first job after graduation as a measure of the achievement of teaching. Unfortunately, these data are very difficult to acquire.

Besides, different professions have different salary standards. It would be unfair to compare the salary of an elementary school teacher with that of a medical doctor. The other difficulty is the measurement of quality, there lacks a common base for comparing the quality of different research work and subjectivity is usually involved (Kao & Hung, 2008). Furthermore, in some cases, the performance measure is not always clearly defined. For example, in evaluating baseball players, there are many variables which can be used to capture a player's performance. Thus, it is necessary to select a parsimonious set of inputs and outputs so as to capture the performance of a DMU's key activities. (Morita et al, 2009). In addition, some of the used variables are either cannot be measured or difficult to be applied on this study such as environmental factors, space allocated in square feet, quantity of research output, amount of grants awarded, cultural and social outputs, room space, patents, and researching annual income as shown in Table 2.3.

However, there were some common variables used in educational applications such as expenditure, students, academic staff, assets, salaries, training materials, and material for inputs and graduates, research, grants, publications, number of programs, and credit hours generated. Further, any higher educational institutions have three main objectives which are teaching, research and community service activities. Each of these three objectives can be represented by either input variables or output variables. For example, number of staff and number of students can represent the teaching objective in terms of inputs while number of graduates can represent it in terms of outputs. The research objective can be represented by number of publications as a measure of output.

3.2.1 Inputs

Although inputs in higher education tend to be easier to define and measure compared to outputs, the studies have given careful consideration to the specification of costs and/or inputs. As Martin (2003) pointed out the accuracy in identifying the inputs can help in achieving the accuracy in the efficiency measurement of the unit under study. With regard to type of input, Martin (2003) took a broad approach that helpfully sorts out the types and measures of inputs to be used in a DEA study.

While human resources usually comprise faculty and staff time and effort, financial and material inputs commonly consist of buildings, land, and equipment. In each of the three categories, alternate measures and alternative specifications are possible. For example, human resource inputs have also been measured as salaries and benefits, with the expenditure measure presumed to capture imperfectly quality as well as quantity of the time and effort (McMillan & Datta, 1998). Vink (1997) observed that institutions may differ in the use of certain types of input (e.g. capital or material input). Representative of a number of the studies using DEA methodology, Maripani (2007) used as input measures the number of non-academic staff, the number of full-time equivalent academic staff, non-labor expenditures, and average faculty and staff salaries. The most frequent input measures in the DEA models include operating expenditures, number of academic staff, number of other staff, number of non-academic staff, and Training Recourses. Thus, the research inputs include two inputs related to number of academic staff, one input related to academic staff salaries and the fourth one is related to fixed cost of training resources. At earlier stage in the research, number of academic staff was only one input without dividing it into two inputs (full and part time). However, correlation coefficient between the salaries of this input with salaries of academic staff was too high (0.96). Accordingly, it was divided into two inputs; one related to full time academic staff and the other related to part time academic staff.

- ***Number of Full time Academic Staff (FAC)***

  Number of full-time academic staff represents number of full-time academic staff who was employed under each DMU over the study period. This input represents the full-time academic staff of each department (DMU) according to the data collected from research and development department and personnel department.

- ***Number of Part time Academic Staff (PAC)***

  Number of part-time academic staff represents number of part-time academic staff who was employed under each DMU over the study period. This input represents the part-time academic staff of each department (DMU) according to the data collected from research and development department and personnel department.

- ***Salaries of Academic Staff (ASS)***

  Salaries of academic staff represent salaries of full-time and part-time academic staff who was employed under each DMU over the study period according to the data collected from finance unit.

- ***Training Recourses (TR)***

  Training Resources represent the fixed cost of laboratories, facilities, and special assistance units that utilized by DMU graduates over the three-year study period.

3.2.2 Outputs

The inputs and outputs of universities are generally recognized but, outputs especially, are not easily measured. Universities provide teaching, research, and service. Though various measures of these activities are commonly taken as measures of university output, they are often measures of an intermediate product. In the case of teaching or example, one would prefer measures of the learning that results from teaching but, instead, measures such as credit hours, student enrolments, and graduates proxy the teaching delivered under the assumption that there is a close relationship between them and learning. Research output is more difficult to measure. Ideally, one would like an index that reflected the quality and impact of the activities undertaken and their products, but no such index exists. Even relatively simple potential components like publication counts are difficult to obtain and are typically incomplete. Service is the most difficult output to measure. Given the diversity and sometimes even amorphous nature of contributions in this area, there is no composite and reliable index (McMillan, 1998).

In the studies reviewed, Martin (2003) used a scientific publication index and research activity income as research outputs. In addition, research income, number of graduates, undergraduates, post-graduates, and credit hours generated, number of PhD theses read, and external grants were the most common used outputs variables used as explained in Table 2.3. Considering all above and what mentioned in Literature Review chapter, the outputs of this research are as follows:

- ***Graduates (GR)***

  Graduates output represents number of students who graduate over the three-year study period of each DMU.

- ***Promotions (PROM)***

  Promotions output represents number of promotions of each DMU academic staff over the study period.

- ***Public Service Activities (PSA)***

  Public Service Activities represent number of workshops, conferences, and other extracurricular activities of each DMU over the study period.

The research variables (inputs and outputs) are summarized in Table 3.3.

Table 3.3: Research variables

Inputs	Outputs
Number of Full-time Academic Staff (FAS): Number of Full-time Academic Staff of each DMU over study period	**Graduates (GR):** number of students who graduate over the three-year study period.
Number of Part-time Academic Staff (PAS): Number of part-time Academic Staff of each DMU over study period	**Promotions (PROM):** Number of promotions of each DMU over the study period.
Academic Staff Salary(ASS): Annual Salary of academic Staff of each DMU over study period	**Public Service Activities (PSA):** number of meetings, workshops, conferences, and other extracurricular activities.
Training Resources (TR): Fixed cost of laboratories, facilities, ceremonies and special assistance units.	

The relationship between the number of departments and the number of performance measures is important. The number of departments relative to the number of input and output performance measures must be large enough to ensure that meaningful efficiency values are obtained. A rule of thumb is given by Banker et al. (1984) as [$\mathbf{s} + \mathbf{m} \leq \mathbf{n}/3$], where **s** is the number of outputs, **m** the number of inputs, and **n** the number of DMUs. In this research, the number of input and output performance measures is seven, which is less than one-third of the number of DMUs (eleven). Moreover, this rule of thumb is not universally accepted. Our sample size would be large enough if another popular rule: 2*s*m=24 were to be considered (33 vs. 24). The agreement attained on the number of inputs and outputs to include in the study, led us to abandon the idea of reducing this agreed upon number. So it is a strong evidence to support the number of DMUs which affects the accuracy of the results (Moreno & Tadepalli, 2002).

3.3 Data Collection

The data were collected over the three academic years of the study which are 2008-2009, 2009-2010, and 2010-2011. This means that each variable is considered along the three year. After that, the average of the three years is taken to minimize the expected error in the collected data and to get more accurate results. However, since the Training Resources (TR) represented by a fixed cost, it has been singled out from the pool of variables and treated differently. This variable was only considered once keeping in mind that the selection criterion is whether or not it has been utilized by graduates over the three-year study period.

The values of research variables were obtained directly from research and development unit, financial unit, public relations unit, registration and admission unit, research deanship, personnel department quality unit, and faculties' deans. Table 3.4 summarizes the method of collecting each variable.

Table 3.4: Data Collection Summary

Variable	Collection Method
1. Academic Staff Salary (ASS)	Financial unit
2. Number of Full-time Academic Staff (FAS)	Research and development unit
3. Number of Part-time Academic Staff (PAS)	Research and development unit
4. Training Resources (TR)	Resources development unit
5. Graduates (GR)	Research and development unit
6. Promotions (PROM)	Personnel department and Research deanship
7. Public Service Activities (PSA)	Public Relations unit and Research deanship

The salary of academic staff was obtained from financial unit through having the salaries of all faculties, then dividing the total faculty salary over the number of departments taking into consideration number of academic staff in each department. For example, the total salary of engineering faculty was 1494120 JOD in 2009 and there are five engineering departments with different number of academic staff. The total faculty salary is dividing into the five departments taking into account number of academic staff of each department. This was obtained over the study period years.

Number of Full-time and Part-time academic staff of each department was obtained from Research and development unit for the three years of study period.

Number of academic staff includes all positions of academic staff: teaching assistant, instructor, assistant professor, associate professor and professors.

Fixed cost of Training Resources was obtained from resources development unit. The cost of training resources includes the cost of laboratories, computers labs, and other assistant units that were utilized by graduates over the study period.

Number of graduates of each department was obtained from personnel department and research deanship for the three years of study period. It represents number of graduates who were graduated in the years of the study period.

Number of Promotions of each department was obtained from personnel department and research deanship for the three years of study period. It represents number of promotions of academic staff of each DMU in each year of the study period.

Number of public service activities of each department was obtained from public relations unit and Research deanship for the three years of study period. It represents number of meetings, workshops, conferences, and other extracurricular activities conducted by each DMU over the study period.

Table 3.5 shows the collected variables over 2008-2009, Table 3.6 shows the collected variables over 2009-2010 and Table 3.7 shows the collected variables over 2010-2011.

Table 3.5: Collected Variables over 2008-2009

DMU	FAS	PAS	ASS	TR	GR	Prom	PSA
1. General Ussoul Eldeen	37	21	966914	65000	225	4	5
2. Islamic Shariah	28	6	478093	0	311	1	4
3. Shariah and Law	2	6	112493	0	54	0	4
4. Arabic	23	1	387139	0	25	1	3
5. English	13	13	419400	0	45	1	7
6. Geography	8	6	225831	0	23	2	6
7. Journalism & Information	7	4	177439	0	32	2	9
8. Social Work	4	3	112915	0	66	0	1
9. History And Archaeology	9	5	225831	0	29	0	2
10. Education	33	39	974583	110000	1469	3	18
11. Accounting	12	5	257912	33200	160	1	4
12. Business Administration	13	6	288255	15700	59	1	6
13. Economics and Political Sciences	16	4	303426	15700	14	0	7
14. Banking And Finance	0	0	0	17500	46	0	3
15. Economics And Applied Statistics	0	0	0	15700	19	0	0
16. Accounting English	0	0	0	15700	57	0	0
17. Business Administration English	1	1	30343	15700	54	0	0
18. Chemistry	17	1	314431	350000	13	2	15
19. Mathematics	17	4	366836	45000	15	2	6
20. Physics	24	3	471647	650000	19	0	7
21. Biology	14	3	296963	600000	19	0	14
22. Medical Technology	7	2	157216	600000	7	0	9
23. Environment and Earth Science	7	4	192152	140000	2	0	4
24. Optometry	8	2	174684	250000	34	0	0
25. General Nursing	6	7	197104	98000	84	1	6
26. Computer Science	7	1	122552	79000	23	0	6
27. Information Technology System.	7	1	122552	79000	70	1	4
28. Software Development	2	0	30638	79000	17	0	0
29. Civil Engineering	20	18	545928	235000	213	0	9
30. Architecture	15	8	330430	60000	75	1	4
31. Electrical Engineering	12	6	258598	270000	81	2	5
32. Computer Engineering	11	8	272964	270000	87	1	3
33. Industrial Engineering	6	0	86199	246000	34	0	7

Table 3.6: Collected Variables over 2009-2010

DMU	FAS	PAS	ASS	TR	GR	Prom	PSA
1. General Ussoul Eldeen	38	9	1049843	65000	208	4	6
2. Islamic Shariah	28	7	536167	0	341	1	5
3. Shariah and Law	2	6	122552	0	65	0	5
4. Arabic	22	6	529056	0	58	1	4
5. English	13	8	396792	0	34	2	6
6. Geography	8	7	283423	0	34	1	13
7. Journalism & Information	8	4	226738	0	41	1	14
8. Social Work	4	4	151159	0	65	1	4
9. History And Archaeology	11	1	226738	0	34	1	4
10. Education	32	37	1038264	110000	1403	5	20
11. Accounting	11	7	313220	33200	113	1	9
12. Business Administration	13	7	348022	15700	60	0	15
13. Economics and Political Sciences	17	4	365423	15700	13	2	14
14. Banking And Finance	0	0	0	17500	60	0	7
15. Economics And Applied Statistics	0	0	0	15700	13	0	0
16. Accounting English	0	0	0	15700	83	0	0
17. Business Administration English	0	0	0	15700	58	0	0
18. Chemistry	16	3	418446	350000	14	0	14
19. Mathematics	16	3	418446	45000	5	1	4
20. Physics	22	0	484517	650000	11	0	5
21. Biology	13	4	374399	600000	10	1	9
22. Medical Technology	7	3	220235	600000	43	1	6
23. Environment and Earth Science	7	3	220235	140000	6	0	5
24. Optometry	4	2	132141	250000	16	0	2
25. General Nursing	9	3	324617	98000	86	1	6
26. Computer Science	6	1	106426	79000	9	0	2
27. Information Technology System.	7	3	152037	79000	38	1	4
28. Software Development	3	2	76018	79000	29	0	1
29. Civil Engineering	16	21	577139	235000	183	2	5
30. Architecture	14	11	389959	60000	58	2	15
31. Electrical Engineering	13	4	265172	270000	91	0	12
32. Computer Engineering	10	7	265172	270000	53	0	6
33. Industrial Engineering	4	0	62393	246000	34	0	10

Table 3.7: Collected Variables over 2010-2011

DMU	FAS	PAS	ASS	TR	GR	Prom	PSA
1. General Ussoul Eldeen	38	14	1065139	65000	174	4	4
2. Islamic Shariah	27	10	563146	0	358	1	8
3. Shariah and Law	1	8	136981	0	77	0	8
4. Arabic	23	8	621832	0	45	3	6
5. English	17	6	461360	0	39	3	7
6. Geography	7	2	180532	0	38	0	13
7. Journalism & Information	7	4	220650	0	41	0	16
8. Social Work	2	0	40118	0	69	1	5
9. History And Archaeology	10	4	280828	0	32	2	4
10. Education	31	32	1053270	110000	1573	4	12
11. Accounting	11	5	283750	33200	133	1	6
12. Business Administration	14	5	336953	15700	101	1	14
13. Economics and Political Sciences	17	3	354688	15700	14	0	17
14. Banking And Finance	0	0	0	17500	70	0	5
15. Economics And Applied Statistics	0	0	0	15700	13	0	0
16. Accounting English	0	0	0	15700	83	0	0
17. Business Administration English	0	2	35469	15700	56	0	0
18. Chemistry	17	1	445391	350000	22	2	10
19. Mathematics	19	0	470135	45000	13	3	3
20. Physics	21	0	519623	650000	21	2	3
21. Biology	13	2	371159	600000	9	0	7
22. Medical Technology	6	4	247440	600000	53	1	6
23. Environment and Earth Science	6	0	148464	140000	4	0	6
24. Optometry	5	2	173208	250000	33	0	3
25. General Nursing	9	2	338116	98000	100	2	7
26. Computer Science	5	1	100770	79000	18	0	3
27. Information Technology System.	6	0	100770	79000	41	1	3
28. Software Development	3	1	67180	79000	29	0	1
29. Civil Engineering	19	16	732463	235000	195	4	7
30. Architecture	12	1	272058	60000	71	2	17
31. Electrical Engineering	12	3	313913	270000	83	0	13
32. Computer Engineering	10	1	230203	270000	81	3	10
33. Industrial Engineering	6	0	125565	246000	36	1	8

The average of collected variables over the three-year study period is summarized in Table 3.8.

Table 3.8: Average of Collected Variables

DMU	FAS	PAS	ASS	TR	GR	Prom	PSA
1. General Ussoul Eldeen	37.7	14.7	1027299	65000	202	4.0	5.1
2. Islamic Shariah	27.7	7.7	525802	0	337	1.0	5.7
3. Shariah and Law	1.7	6.7	124009	0	65	0.0	5.7
4. Arabic	22.7	5.0	512676	0	43	1.7	4.1
5. English	14.3	9.0	425851	0	39	2.0	6.5
6. Geography	7.7	5.0	229929	0	32	1.0	10.7
7. Journalism & Information	7.3	4.0	208276	0	38	1.0	13.1
8. Social Work	3.3	2.3	101398	0	67	0.7	3.3
9. History And Archaeology	10.0	3.3	244466	0	32	1.0	3.2
10. Education	32.0	36.0	1022039	110000	1482	4.0	16.6
11. Accounting	11.3	5.7	284961	33200	135	1.0	6.1
12. Business Administration	13.3	6.0	324410	15700	73	0.7	11.5
13. Economics and Political Sciences	16.7	3.7	341179	15700	14	0.7	12.7
14. Banking And Finance	0.0	0.0	0	17500	59	0.0	5.0
15. Economics And Applied Statistics	0.0	0.0	0	15700	15	0.0	0.0
16. Accounting English	0.0	0.0	0	15700	74	0.0	0.0
17. Business Administration English	0.3	1.0	21937	15700	56	0.0	0.0
18. Chemistry	16.7	1.7	392756	350000	16	1.3	12.9
19. Mathematics	17.3	2.3	418473	45000	11	2.0	4.4
20. Physics	22.3	1.0	491929	650000	17	0.7	5.1
21. Biology	13.3	3.0	347507	600000	13	0.3	9.5
22. Medical Technology	6.7	3.0	208297	600000	34	0.7	6.7
23. Environment and Earth Science	6.7	2.3	186950	140000	4	0.0	5.1
24. Optometry	5.7	2.0	160011	250000	28	0.0	1.7
25. General Nursing	8.0	4.0	286612	98000	90	1.3	6.3
26. Computer Science	6.0	1.0	109916	79000	17	0.0	3.3
27. Information Technology System.	6.7	1.3	125119	79000	50	1.0	3.6
28. Software Development	2.7	1.0	57945	79000	25	0.0	0.7
29. Civil Engineering	18.3	18.3	618510	235000	197	2.0	7.0
30. Architecture	13.7	6.7	330816	60000	68	1.7	11.7
31. Electrical Engineering	12.3	4.3	279227	270000	85	0.7	9.9
32. Computer Engineering	10.3	5.3	256113	270000	74	1.3	6.3
33. Industrial Engineering	5.3	0.0	91386	246000	35	0.3	8.5
Average	**11.5**	**5.1**	**295630.2**	**131975.8**	**106.8**	**1.0**	**6.4**

From table 3.8, it is noticed that some DMUs have some variables with zero value. On the input level, Banking and Finance, Economics and Applied Statistics and Accounting English have zero values of number of academic staff and salary of academic staff as their entire academic are considered for other departments (accounting, business administration and economic and political sciences). In addition, some departments as Islamic Shariah has zero value for training resources as there is there was no training resources for this DMU over the study period. This could help those departments to get higher efficiency scores than others as low inputs with relatively high outputs give higher efficiency score.

On the output level, some departments as Optometry and others have zero values for promotion as there was no promotion for its academic staff over the study period. Also, some departments have zero values for public service activities as they didn't have any activity over the study period. This may affect the efficiency score of those departments negatively as low outputs with relatively high inputs give lower efficiency score.

3.4 Research Model

3.4.1 DEA Model

In this research, both CCR and BCC input oriented models are used to select the model that fairly represents the behavior of the system in this study

Due to the fact that in a university environment, it is easier to control the inputs rather than the outputs, the DEA input oriented model is used.

Efficiency can be defined as weighted sum of outputs over weighted sum of inputs as shown in equation

$$\mathrm{h_o}(u, v) = \sum_{\mathrm{r}} \mathrm{u_r y_{ro}} / \sum_{\mathrm{r}} \mathrm{v_i x_{io}} \tag{1}$$

Using the inputs and outputs of this research, the equation will be as follows:

$$\mathrm{h_o}(u, v) = \frac{\mathrm{u_1(GR)+u_2(PROM)+u_3(PSA)}}{\mathrm{v_1(FSN)+v_2(PAS)+v_3(ASS)+v_4(TR)}} \tag{2}$$

Where:

h_0: Relative efficiency of the department

GR: Average number of graduates.

PROM: Average number of promotions.

PSA: Average number of public service activities.

FAS: Average number of full-time academic staff.

PAS: Average number of full-time academic staff.

ASS: Average salaries of academic staff.

TR: Fixed cost of training resources.

u_r: Weight given to output, $r = 1, 2, 3$

v_i: Weight given to input, $i = 1, 2, 3,4$

$$\min \Theta - \varepsilon \left(\sum_{i=1}^{4} s_i^- + \sum_{r=1}^{3} s_r^+ \right)$$

Subject to:

$$\sum_{j=1}^{33} x_{ij}\,\lambda_j + s_i^- = \Theta x_{io}, i = 1,2,3,4;$$
$$\sum_{j=1}^{33} y_{rj}\,\lambda_j - s_r^+ = y_{ro}, r = 1,2,3; \tag{3}$$
$$\lambda_j \geq 0, \quad j = 1,2,\dots,33$$

For BCC model, the constraint $\sum_{i=1}^{33} \lambda_i = 1$ is added.

Where:

s_i^- and s_r^+: are slack variables used to convert the inequalities to equivalent equations and ε > 0 is an Archimedean element defined to be smaller than any positive real number.

***λ j* :** is the vector of intensity factors that defines the hypothetical DMU to which DMUjo is compared.

***θ*:** is the radial (input reducing) measure of technical efficiency.

The DMU will assign a weight of zero to unfavorable factors in order to obtain the highest efficiency score. This implies that the associated factors are eliminated from evaluation. Charnes et al. have noticed this problem; hence they require all weights to be greater than a small Archimedean number ε in calculating the efficiency. Theoretically, this lower bound ε solves the problem of ignoring certain factors. In practice, however, it is only able to distinguish an inefficient DMU from the efficient ones. Moreover, the selected weights may not really reflect the relative importance of the associated factors (Chiang & Hung, 2006).

In this research, the weights will be assigned in two ways. The first, it will be freely assigned by the software and calculate the efficiency. However, this will have pros and cons; the decision makers tend to highlight their strong areas and hide their weak areas which lead to bias the results. On other hand, important weights may be ignored and unimportant weights may be assigned to large weight.

The second way, the weights will be assigned using Shannon's Entropy method which will be discussed in next section.

3.4.2 Shannon Entropy Method

It is assumed that there are a set of DMUs consisting of $DMU_j;\ j = 1, \dots, n$ with input-output vectors$(x_j, y_j);\ j = 1, \dots, n$, in which $x_j = (x_{1j}, \dots x_{mj})$ and $y_j = (y_{1j}, \dots, y_{sj})$. Also, assume that these units have been evaluated by a set of different DEA models, $M = \{ M_1, M_2 \dots., M_k\}$ =
$\{ CCR, BCC\ (input\ oriented), BCC\ (output\ oriented), CCR(pessimistic\ view)\ , \dots.\}$
And the obtained efficiency results are listed in the following matrix E_{nxk}. Each row of E corresponded to a DMU and each of its columns corresponds to a model considered in M. Thus, E_{jl} exhibits the efficiency score of DMU_j obtained by model Ml for $j = 1,2, \dots. n$ and $l = 1,2, \dots, k$.

$$\begin{array}{ccc} M_1 & M_2 \dots & M_k \\ \downarrow & \downarrow & \downarrow \end{array}$$

$$E = \begin{pmatrix} E_{11} & E_{12} \dots & E_{1k} \\ E_{21} & E_{22} \dots & E_{2k} \\ E_{n1} & E_{n2} \dots & E_{nk} \end{pmatrix} \begin{array}{l} \leftarrow 1 \\ \leftarrow 2 \\ \leftarrow n \end{array}$$

Now to calculate the degree of the importance of each of the considered models, $M_l \in M$, it is recommended to obtain the degree of importance of models considering the information of matrix E using Shannon's entropy formula and not only based on some comparisons. The concept of Shannon's entropy (Shannon 1984; Taneja) has a central role in information theory and sometimes refers to measure of uncertainty. This concept has been extended to different scientific fields such as physics social sciences and so on. We use this formula to obtain the degree of importance of models in the following four steps:

Step 1: (Normalization) Set $\bar{E}_{jl} = \frac{E_{jl}}{\sum_{j=1}^{n} E_{jl}}$

Step 2: compute entropy e_l as

$$e_l = -e_0 + \sum_{j=1}^{n} (\bar{E}_{jl} . ln\, \bar{E}_{jl}), \qquad l = 1, \dots, k.$$

Where e_0 is the entropy constant and is considered equal to

$$e_0 = (ln\, n)^{-1}$$

Step 3: set $d_l = 1 - e_l$ as the degree of diversification for

Step 4: Set

$w_l = \frac{d_l}{\sum_{t=1}^{k} d_t}$, $l = 1, \ldots\ldots, k$ as the degree of importance of model M_l.

After calculating w_l for $l = 1,2, \ldots, k$ (using the above four steps), we calculate the following efficiency index which combines the efficiency scores (provides a weighted-sum of the efficiency score) of all of the considered models, regarding the values of $w_l s$, and is suitable to provide a full ranking:

$$B_j = \sum_{l=1}^{k} w_l \, E_{jl}, \;\; j = 1,2, \ldots\ldots, n.$$

Where $B_0 = \sum_{l=1}^{k} w_l = 1$

Applying this on research variables, the following givens will be appeared:

1. E_{33x7}: A Matrix of 33 Rows and 7 Columns(33 DMUs and 7 Variables)
2. e_l : 7 entropies come from 7 variables
3. d_l: 7 degrees of diversification come from 7 entropies.
4. w_l : 7 weights for each variable (Soleimani, 2009).

This procedure will be applied to obtain the weights of variables by replacing the efficiency scores in Matrix E with variables' values. Then, the normalized entropies of each variable will be calculated. After that, the entropies of each variable will be calculated. Then the degree of diversification for each variable will be calculated and finally the weight of each variable will be obtained.

3.5 Research Software

3.5.1 Efficiency Measurement System

Efficiency Measurement System (EMS) software version 1.3(Scheel, 2000) is used in this research to measure the technical efficiency of the departments based on both CCR and BCC input oriented models. It is also used to find out the needed potential improvements of the inefficient departments in order to become 100% efficient.

EMS is free, flexible and can deal with huge number of DMUs. In Addition to “standard” inputs and outputs, EMS can also handle “nondiscretionary” inputs and outputs (i.e., data which are not controlled by the DMUs). There are many options to use in model structure, return to scale, distance and model orientation as shown in the snapshot of EMS in Fig. 3.2.

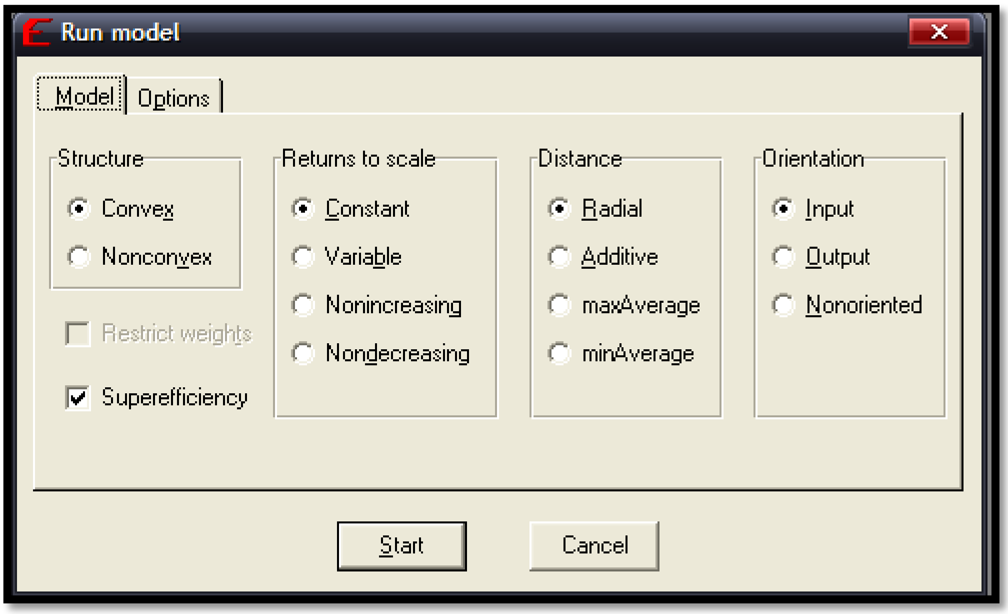

Fig. 3.2: EMS model Options

The size of the analysis is limited by the memory of the personal computer, i.e., theoretically there is no limitation on the number of DMUs, inputs and outputs in EMS. Although the code is not optimized for large scale data, the producer of EMS successfully solved problems with over 5000 DMUs and about 40 inputs and outputs.

EMS accepts data in MS Excel or in text format EMS accepts Excel 97 (and older) files (*.xls). The input output data should be collected in one worksheet and the user asked not to use formulas in this sheet, it should only contain the pure data and nothing else. Some notes about dealing with EMS are follows:

- The name of the worksheet must be "Data".
- The first line contains the input/output names. First inputs, then outputs.
- Input names contain the string "{I}".
- Output names contain the string "{O}".
- The first column contains the DMU names.

The output of EMS contains score of each DMU, weights i.e.; shadow price or virtual output/ input {V} and slacks {S} as shown in the snapshot in Fig. 3.3.

File Edit DEA Window Help

	DMU	Score	Reg{I}{V}	OE {I}{V}	LH {I}{V}	TR {I}{V}	Grad {O}{V}	Pub {O}{V}	PSA{O}{V}	Benchmarks	{S} Reg{I}	{S} OE {I}	{S} LH {I}	{S} TR {I}
1	1. General Ussoul	100.00%	0.00	0.00	0.80	0.20	0.04	0.96	0.00	2				
2	2.Islamic Shariah	100.00%	0.00	1.00	0.00	0.00	0.78	0.22	0.00	1				
3	3. Arabic	100.00%	0.00	1.00	0.00	0.00	0.00	1.00	0.00	3				
4	4.English	80.02%	0.84	0.06	0.00	0.11	0.95	0.00	0.05	2 (0.05) 11 (0.08) 12	0.00	0.00	108.66	0.00
5	5.Geography	100.00%	0.00	0.00	0.58	0.42	0.00	0.00	1.00	0				
6	6.Journalism &	58.07%	0.04	0.11	0.39	0.46	0.00	0.14	0.86	1 (0.02) 7 (0.42) 13	0.00	0.00	0.00	0.00
7	7.Public Relations and	100.00%	0.25	0.75	0.00	0.00	0.00	0.00	1.00	11				
8	8.History And	100.00%	0.00	0.00	1.00	0.00	1.00	0.00	0.00	0				
9	9.Social Work	90.10%	0.71	0.05	0.22	0.02	0.66	0.34	0.00	3 (0.38) 7 (0.02) 11	0.00	0.00	0.00	0.00
10	10.Education	100.00%	0.00	0.79	0.21	0.00	1.00	0.00	0.00	0				
11	11.Business	100.00%	0.00	0.66	0.34	0.00	0.59	0.40	0.02	4				
12	12.Economics and	100.00%	0.95	0.03	0.00	0.02	0.99	0.00	0.01	5				
13	13.Accounting	100.00%	0.20	0.62	0.00	0.18	0.00	0.05	0.95	1				

Fig. 3.3: EMS Outputs

3.5.2 MaxDEA

MaxDEA software version 5.2(Cheng G. and Qian Z., 2012) is also used in this research to measure the technical efficiency of the departments using CCR and BCC input oriented models and weighted (preference) model. MaxDEA is easy to use and powerful software for Data Envelopment Analysis; it has many features such as:

- Contained comprehensive DEA models and their possible combinations.
- There is no limitation to DMUs and variables numbers.
- Has user-friendly interface.
- Has standard database format.

Figure 3.4 shows the define data page which appears after importing the excel file of data. It has the option of identifying the column type if it is input, output or DMU name.

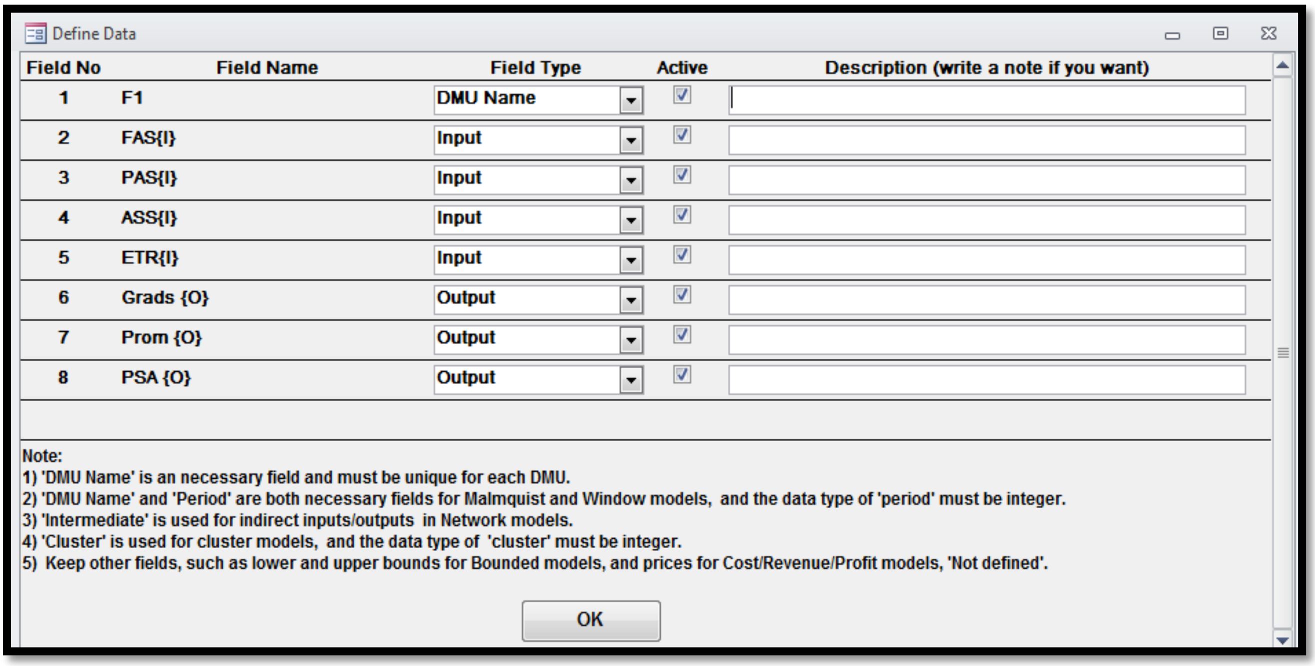

Fig. 3.4: MaxDEA Define Data interface

MaxDEA supports Excel, Access, dBase and comma delimited text file data. The data format is standard without special requirements for field names and their orders. Figure 3.5 shows the basic specifications for envelopment models include distance, orientation and returns to scale.

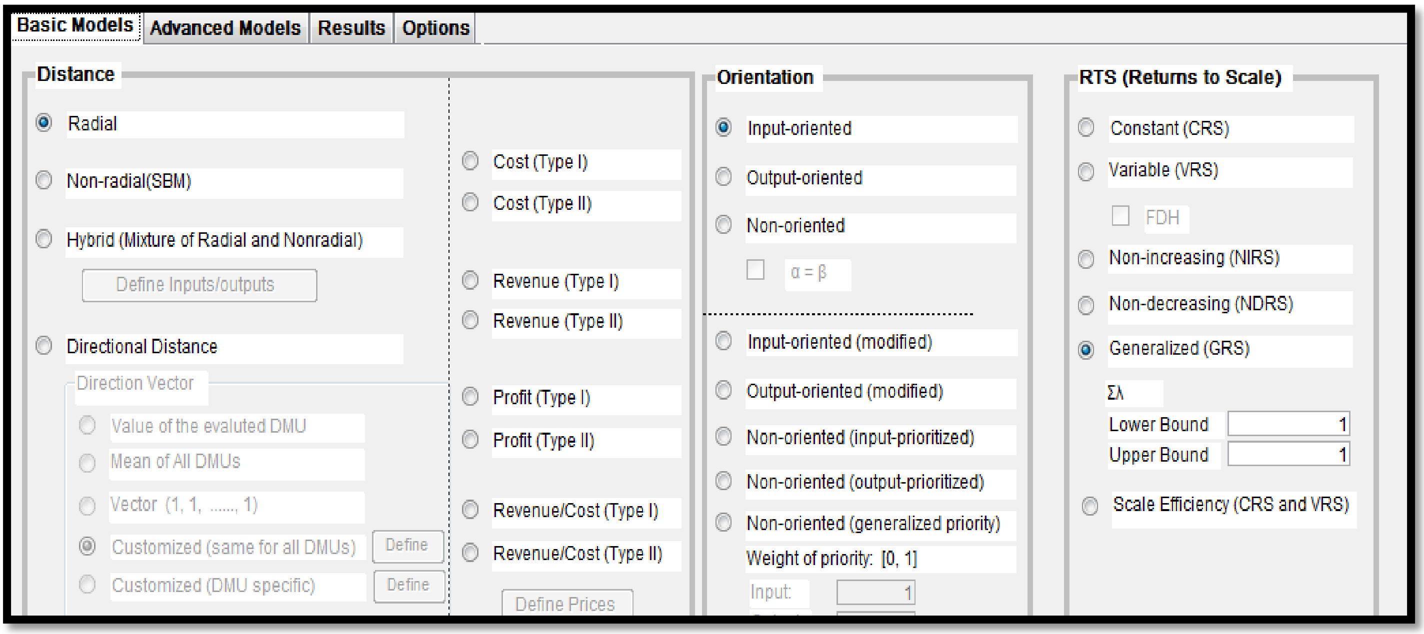

Fig. 3.5: MaxDEA Specifications page

The output of MaxDEA contains score of each DMU, benchmark, weights i.e.; shadow price or virtual output/ input {V} and slacks {S} as shown in the snapshot in fig. 3.6

N(	DMU	Score	Benchmark(Lambda)	Times as a b	Radial Move	Slack Moven	Projection (I
1	DMU1	1	DMU1(1.000)	0	0	0	37.667
2	DMU10	1	DMU10(1.000)	5	0	0	32
3	DMU11	0.725	DMU10(0.059); DMU16(0.271); DMU19(0.146)	0	-3.113	-0.619	7.601
4	DMU12	0.683	DMU10(0.006); DMU16(0.064); DMU2(0.082);	0	-4.222	-0.492	8.619
5	DMU13	1	DMU13(1.000)	2	0	0	16.667
6	DMU14	1	DMU14(1.000)	0	0	0	0.44
7	DMU15	1	DMU16(1.000); DMU8(0.000)	0	0	-0.39	0.1
8	DMU16	1	DMU16(1.000)	10	0	0	0.1
9	DMU17	0.852	DMU16(0.852); DMU3(0.097); DMU8(0.051)	0	-0.073	0	0.417
10	DMU18	1	DMU18(1.000)	1	0	0	16.667
11	DMU19	1	DMU19(1.000)	3	0	0	17.333

Fig. 3.6: MaxDEA Outputs

Chapter 4: RESULTS AND ANALYSIS

1. **CCR Results**
2. **BCC Results**
3. **CCR Vs. BCC Results**
4. **Scale Efficiency**
5. **Potential Improvements**
6. **Super Efficiency Analysis**
7. **Regression Analysis**
8. **Shannon's Entropy Analysis**

This chapter begins with describing the results obtained from EMS software for each model and then analyzing these results. Furthermore, the potential improvements in both inputs and output of the inefficient DMUs are evaluated and then, super efficiency for efficient DMUs is evaluated to rank the rest of the efficient departments. Further, Shannon's Entropy is applied to measure the weights of variables. After that, determine the effects of assigning weights for variables on efficiency scores.

4.1 CCR Results

Table 4.1 shows the CCR model average efficiency scores of the nine faculties of 33 DMUs. 12 DMUs out of 33 are considered efficient as their efficiency score is 100%.
On Faculties level, education and Shariah and Law faculties are the only efficient faculties as it is has high levels of outputs comparing with other faculties.

Faculty of Ussoul Eldeen which represented by one DMU has an average score of 68.8%. While faculty of Shariah and Law that represented by 2 DMUs has an average efficiency score of 100% and the two DMUs have 100% efficiency.

Faculty of Art which represented by six DMUs has an average efficiency score of 93.4%. Three DMUs out of six are efficient. English department has the least score in Art faculty due to relatively low outputs.

Faculty of Commerce which represented by seven DMUs has an average efficiency score of 71.1%. Three DMUs out of seven are efficient while Economics and Applied Statistics department has the least score in the faculty due to relatively low outputs.

Faculty of Science which represented seven DMUs has an average efficiency score of 63.6%. Only the mathematics department is the only efficient one while, the rest of its DMUs are considered inefficient. This comes from the relatively high inputs levels due the high cost of training labs and relatively low levels of outputs.

Faculty of Nursing is considered inefficient since the efficiency score was 93.3% because of its relatively low outputs.

Faculty of Information Technology which represented by 3 DMUs has an average efficiency score of 57.8%. One of its DMUs is considered efficient while the other two departments are inefficient due to relatively high level of inputs and low level of outputs.

Faculty of engineering which represented by five departments has an average efficiency score of 72.7% however; only the industrial department is considered efficient and the rest of its DMUs are inefficient since they have relatively large fixed cost of TR and low value of PROM.

The reference set represents the peer DMUs when compared with other DMUs and becomes its benchmark. DMUs which have benchmarks are asked to learn how to transfer their inputs to outputs, in other words, adopt their policies and techniques in the production process. For example, the reference sets of civil engineering are Social work. DMUs that have 100% efficiency score and have a reference set(s) are considered weakly efficient i.e. $\theta = 1$ and slacks $\neq 0$. For example, Journalism & Information is weakly efficient since it has 100% efficiency score and it has a reference set which is Economics and Political department. On the other hand, Islamic Shariah is considered efficient as it has 100% efficiency score and it has no reference set.

Table 4.1 shows the efficiency of each DMU and its reference sets.

In summary, the average scores of DMUs are ranging from 17.4% to 100%. 12 DMUs are efficient while 21 of DMUs are inefficient. Software development department has the least efficiency score. Moreover, faculty of education and Shariah and Law are the only efficient faculty, while the rest has scores ranging from 57.7% to 93.4%. The mean of the scores is 75.97% and the standard deviation is 0.262.

Table 4.1: CCR Results and Reference Sets

Faculty	DMU	Efficiency score	Reference set
Ussoul Eldeen	**1.** General Ussoul Eldeen	68.83%	8 (3.48) 19 (0.78) 27 (0.12)
Shariah and Law	**2.** Islamic Shariah	100.00%	
	3. Shariah and Law	100.00%	4
	Average score	**100.00%**	
Art	**4.** Arabic	100.00%	2
	5. English	77.10%	4 (0.07) 8 (2.82) 19 (0.00)
	6. Geography	86.60%	7 (0.70) 8 (0.45)
	7. Journalism & Information	100.00%	13
	8. Social Work	100.00%	10
	9. History And Archaeology	96.84%	4 (0.33) 8 (0.68) 19 (0.00)
	Average score	**93.42%**	
Education	**10.** Education	**100%**	1
Commerce	**11.** Accounting	58.49%	7 (0.19) 8 (0.98) 16 (0.80) 19 (0.05) 27 (0.06)
	12. Business Administration	59.29%	7 (0.88) 16 (0.54) 33 (0.00)
	13. Economics and Political	100.00%	
	14. Banking And Finance	100.00%	
	15. Economics And Applied Statistics	20.18%	16 (0.20)
	16. Accounting English	100.00%	9
	17. Business Admin. English	63.88%	3 (0.06) 10 (0.00) 16 (0.61)
	Average score	**71.69%**	
Science	**18.** Chemistry	95.70%	19 (0.43) 27 (0.35) 33 (1.14)
	19. Mathematics	100.00%	6
	20. Physics	74.57%	19 (0.24) 33 (1.93)
	21. Biology	42.59%	3 (0.02) 7 (0.26) 33 (0.69)
	22. Medical Technology	70.86%	7 (0.45) 8 (0.02) 16 (0.08) 27 (0.20)
	23. Environment and Earth	44.43%	3 (0.02) 7 (0.21) 33 (0.25)
	24. Optometry	17.40%	3 (0.04) 7 (0.00) 16 (0.26) 33 (0.16)
	Average score	**63.65%**	
Nursing	**25.** General Nursing	**93.32%**	7 (0.03) 8 (1.30) 27 (0.44)
Information Technology "IT"	**26.** Computer Science	57.44%	7 (0.14) 16 (0.07) 33 (0.18)
	27. Information Technology System.	100.00%	8
	28. Software Development	15.89%	7 (0.03) 16 (0.31) 33 (0.03)
	Average score	**57.78%**	
Engineering	**29.** Civil Engineering	54.55%	8 (3.00)
	30. Architecture	80.41%	7 (0.52) 8 (0.81) 27 (0.61)
	31. Electrical Engineering	54.04%	7 (0.52) 16 (0.66) 27 (0.11) 33 (0.30)
	32. Computer Engineering	74.53%	7 (0.05) 8 (1.10) 27 (0.55)
	33. Industrial Engineering	100.00%	9
	Average score	**72.71%**	
Total average score		**75.97%**	

4.2 BCC Results

Table 4.2 shows the BCC model average efficiency scores of the nine faculties of 33 DMUs. It is obvious that Ussoul Eldeen, Shariah and Law, Education and Nursing faculties are efficient faculties as they have suitable levels of outputs and inputs comparing with other faculties.

Faculty of Art has an average efficiency score of 98.1%. Four DMUs out of six are efficient. Geography department has the least score in Art faculty due to relatively low outputs.

Faculty of Commerce has an average efficiency score of 89.4%. Four DMUs out of seven are efficient while Business Administration department has the least score in the faculty due to relatively low outputs.

Faculty of Science has an average efficiency score of 64.95%. Mathematics and Chemistry are the only efficient DMU while the rest of its DMUs are considered inefficient because of the relatively high inputs levels due the high cost of training labs and relatively low levels of outputs.

Faculty of Information Technology has an average efficiency score of 63.6%. One of its DMUs is considered efficient while the other two departments are inefficient due to relatively high level of inputs (training labs) and low level of outputs.

Faculty of engineering has an average efficiency score of 86.3%. The efficient departments are Architecture and Industrial Engineering while the rest of departments are considered inefficient due to high level of inputs and low level of outputs.

In summary, the average scores of DMUs are ranging from 18.6% to 100%. 18 DMUs are efficient while 15 of DMUs are inefficient. The Optometry department has the least efficiency score. Moreover, Ussoul Eldeen, Shariah and Law, Education and Nursing faculties are efficient faculties while the rest has scores ranging from 63.6% to 98%. The mean of the scores is 84.6% and the standard deviation is 0.229.

Table 4.2: BCC Results and Reference Sets

Faculty	DMU	Efficiency score	Reference set
Ussoul Eldeen	**1.** General Ussoul Eldeen	100.00%	8 (3.48) 19 (0.78) 27 (0.12)
Shariah and Law	**2.** Islamic Shariah	100.00%	
	3. Shariah and Law	100.00%	4
	Average score	**100.00%**	
Art	**4.** Arabic	100.00%	1
	5. English	100.00%	3
	6. Geography	91.26%	5 (0.07) 7 (0.73) 8 (0.20) 25 (0.00)
	7. Journalism & Information	100.00%	10
	8. Social Work	100.00%	6
	9. History And Archaeology	97.11%	4 (0.33) 5 (0.00) 8 (0.67) 19 (0.00)
	Average score	**98.06%**	
Education	**10.** Education	100.00%	5
Commerce	**11.** Accounting	72.54%	7 (0.28) 8 (0.16) 10 (0.06) 16 (0.27) 19 (0.15) 27 (0.09)
	12. Business Administration	68.33%	2 (0.08) 7 (0.81) 10 (0.01) 16 (0.06) 33 (0.04)
	13. Economics and Political	100.00%	2
	14. Banking And Finance	100.00%	0
	15. Economics And Applied Statistics	100.00%	8 (0.00) 16 (1.00)
	16. Accounting English	100.00%	10
	17. Business Admin. English	85.18%	3 (0.10) 8 (0.05) 16 (0.85)
	Average score	**89.44%**	
Science	**18.** Chemistry	100.00%	1
	19. Mathematics	100.00%	3
	20. Physics	76.61%	19 (0.30) 33 (0.70)
	21. Biology	42.60%	3 (0.02) 7 (0.26) 16 (0.02) 33 (0.69)
	22. Medical Technology	71.38%	7 (0.45) 8 (0.02) 16 (0.33) 27 (0.21)
	23. Environment and Earth	45.43%	3 (0.00) 7 (0.24) 16 (0.53) 33 (0.22)
	24. Optometry	18.61%	3 (0.03) 7 (0.03) 16 (0.81) 33 (0.14)
	Average score	**64.95%**	
Nursing	**25.** General Nursing	100.00%	2
Information Technology "IT"	**26.** Computer Science	65.91%	13 (0.16) 16 (0.69) 33 (0.16)
	27. Information Technology System.	100.00%	4
	28. Software Development	24.79%	7 (0.02) 13 (0.02) 16 (0.94) 33 (0.02)
	Average score	**63.57%**	
Engineering	**29.** Civil Engineering	76.36%	10 (0.25) 25 (0.75)
	30. Architecture	100.00%	1
	31. Electrical Engineering	63.01%	7 (0.31) 10 (0.03) 18 (0.04) 27 (0.11) 33 (0.50)
	32. Computer Engineering	91.94%	5 (0.22) 7 (0.12) 10 (0.02) 27 (0.56) 30 (0.08)
	33. Industrial Engineering	100.00%	8
	Average score	**86.26%**	
Total average score		**84.58%**	

4.3 CCR Versus BCC Results

The difference between the two results is that CCR results are 12 efficient DMUs and 21 inefficient DMUs, the average score is 76% and the ratio of efficient DMUs to the total DMUs is 0.364 while the BCC results are 18 efficient DMUs and 15 inefficient DMUs, the average score is 84.6% the ratio of efficient DMUs to the total DMUs is 0.545. In addition, some of the CCR inefficient DMUs are efficient in BCC result as General Ussoul Eldeen, English, Economics and Applied Statistics, General Nursing, Chemistry, and Architecture.

It is obvious that BCC results are better than the CCR results because of two reasons; firstly, theoretically CCR assumes Constant Return to Scale (CRS) and BCC assumes Variable Return to Scale (VRS), CRS and VRS are ratios shared the same denominator while the numerator of VRS ratio is greater than CRS numerator ratio. Secondly, VRS relaxes the slacks variables to be greater than zero and adding lambda constraint, in other words, CRS added new constraint to the slacks variables to be zero as explained in chapter2.

Further, the values of CCR and BCC efficiencies are close to each other, which imply that either the CCR or BCC may be adopted for this research depending on the value of the correlation coefficient between DMUs size and CCR results. Full-Time Academic Staff (FAS) is considered to be the representative of DMU size because it is the most accurate gathered input that represents the DMUs and the other inputs do not fully represent the DMU size.

The correlation coefficient between DMUs size and CCR results (r) equals 0.0982 which means that there is no relation between efficiency score and DMU size. Further, even if the number of graduates is used to represent the DMU size, the correlation coefficient between the number of graduates and CCR results was still as low as 0.038. So, the results of CCR model can be adopted to be the research result (Avkiran, 2002).

Consequently, there is no relationship between efficiency scores and DMU size. Equivalently, the DMUs do not benefit from what is known in economics as economies of scale. Therefore, CCR results will be used in the analysis throughout the rest of the thesis.

Finally, the results obtained here are different than those in some of the previous studies. This could be attributed to the fact that some of these studies (Kao & Hung, 2008) only used the BCC model and it was assumed to be the one representing the academic departments' performance.

4.4 Scale Efficiency Analysis

When slacks are restricted to zero, then an assumption of constant returns to scale is imposed, and the efficiency obtained is called technical or aggregate efficiency (Chiang et al, 2006).

As mentioned in chapter 2, Technical Efficiency (TE) can be decomposed to Pure Technical Efficiency (PTE) and Scale Efficiency (SE). The ratio of technical efficiency to Pure Technical Efficiency is called Scale Efficiency (SE), which measures the inefficiency caused by inappropriate scale. In this research, PTE refers to BCC scores and TE refers to CCR scores and the SE will be TE divided by PTE. Table 4.3 compares the scale efficiency scores with technical efficiency scores and pure technical efficiency scores for each DMU. The average of TE 76%, the average of PTE is 84.6% and the average of SE is 89.8% which means that the ability to work at optimal scale is 89.8%.

Table4.3: TE, PTE, and SE Scores

Faculty	DMU	TE	PTE	SE
Ussoul Eldeen	**1.** General Ussoul Eldeen	68.83%	100.00%	68.8%
Shariah and Law	**2.** Islamic Shariah	100.00%	100.00%	100.0%
	3. Shariah and Law	100.00%	100.00%	100.0%
	Average score	**100.00%**	**100.00%**	**100.0%**
Art	**4.** Arabic	100.00%	100.00%	100.0%
	5. English	77.10%	100.00%	77.1%
	6. Geography	86.60%	91.26%	94.9%
	7. Journalism & Information	100.00%	100.00%	100.0%
	8. Social Work	100.00%	100.00%	100.0%
	9. History And Archaeology	96.84%	97.11%	99.7%
	Average score	**93.42%**	**98.06%**	**95.3%**
Education	**10.** Education	**100%**	100.00%	100.0%
Commerce	**11.** Accounting	58.49%	72.54%	80.6%
	12. Business Administration	59.29%	68.33%	86.8%
	13. Economics and Political	100.00%	100.00%	100.0%
	14. Banking And Finance	100.00%	100.00%	100.0%
	15. Economics And Applied Statistics	20.18%	100.00%	20.2%
	16. Accounting English	100.00%	100.00%	100.0%
	17. Business Admin. English	63.88%	85.18%	75.0%
	Average score	**71.69%**	**89.44%**	**80.2%**
Science	**18.** Chemistry	95.70%	100.00%	95.7%
	19. Mathematics	100.00%	100.00%	100.0%
	20. Physics	74.57%	76.61%	97.3%
	21. Biology	42.59%	42.60%	100.0%
	22. Medical Technology	70.86%	71.38%	99.3%
	23. Environment and Earth	44.43%	45.43%	97.8%
	24. Optometry	17.40%	18.61%	93.5%
	Average score	**63.65%**	**64.95%**	**98.0%**
Nursing	**25.** General Nursing	93.32%	100.00%	93.3%
Information Technology "IT"	**26.** Computer Science	57.44%	65.91%	87.1%
	27. Information Technology System.	100.00%	100.00%	100.0%
	28. Software Development	15.89%	24.79%	64.1%
	Average score	**57.78%**	**63.57%**	**90.9%**
Engineering	**29.** Civil Engineering	54.55%	76.36%	71.4%
	30. Architecture	80.41%	100.00%	80.4%
	31. Electrical Engineering	54.04%	63.01%	85.8%
	32. Computer Engineering	74.53%	91.94%	81.1%
	33. Industrial Engineering	100.00%	100.00%	100.0%
	Average score	**72.71%**	**86.26%**	**84.3%**
Total average score		**75.97%**	**84.58%**	**89.8%**

4.5 Potential Improvements

In this section, the potential improvements of each inefficient DMU for each DEA model will be discussed in the next sub-sections.

Table 4.4 shows the target levels of inputs and outputs at which each DMU will have 100% efficiency in CCR model.

Table 4.4: Target Improvements

DMU	FAS	PAS	ASS	TR	GR	Prom	PSA
1. General Ussoul Eldeen	25.93	10.10	694268.4	44738.0	246.395	4	15.374
2. Islamic Shariah	27.67	7.67	525801.9	0.1	336.667	1	5.667
3. Shariah and Law	1.67	6.67	124008.8	0.1	65.333	0	5.667
4. Arabic	22.67	5.00	512675.8	0.1	42.667	1.667	4.1
5. English	11.05	6.94	323194.3	0.4	190.909	2	9.596
6. Geography	6.64	3.85	191570.6	0.1	56.436	1	10.7
7. Journalism & Information	7.33	4.00	208275.7	0.1	38	1	13.133
8. Social Work	3.33	2.33	101397.5	0.1	66.667	0.667	3.3
9. History And Archaeology	9.68	3.23	236729.4	0.5	59.508	1	3.595
10. Education	32.00	36.00	1022039.0	110000.0	1481.667	4	16.6
11. Accounting	5.98	3.31	166666.4	19417.8	135.333	1	6.133
12. Business Administration	6.50	3.56	182747.6	9308.9	73.333	0.876	11.533
13. Economics and Political Sciences	16.67	3.67	341179.1	15700.0	13.667	0.667	12.7
14. Banking And Finance	0.44	0.44	0.4	17500.4	58.56	0	0.003
15. Economics And Applied Statistics	0.02	0.02	0.1	3168.1	15	0	0
16. Accounting English	0.10	0.10	0.1	15700.0	74.333	0	0
17. Business Administration English	0.31	0.64	12407.6	10028.8	56	0.019	0.426
18. Chemistry	15.95	1.60	329856.3	327999.6	61.584	1.333	12.9
19. Mathematics	17.33	2.33	418472.5	45000.0	11	2	4.433
20. Physics	14.39	0.75	275264.3	484680.9	69.085	0.667	17.429
21. Biology	5.68	1.28	121280.6	170892.3	35.49	0.333	9.5
22. Medical Technology	4.72	2.13	121103.8	17202.4	34.333	0.667	6.7
23. Environment and Earth Science	2.96	1.04	70680.7	62202.3	18.378	0.24	5.1
24. Optometry	0.99	0.35	20946.1	43489.9	27.667	0.02	1.667
25. General Nursing	7.47	3.73	192652.8	34589.6	109.453	1.333	6.267
26. Computer Science	1.97	0.57	45049.5	45376.6	16.667	0.155	3.333
27. Information Technology System.	6.67	1.33	125119.5	79000.0	49.667	1	3.633
28. Software Development	0.42	0.16	9205.8	12550.8	25	0.034	0.667
29. Civil Engineering	10.00	7.00	304192.6	0.3	200	2	9.9
30. Architecture	10.56	4.77	265995.4	48243.6	103.952	1.667	11.667
31. Electrical Engineering	6.28	2.34	150896.8	93847.2	85	0.667	9.867
32. Computer Engineering	7.70	3.50	190891.0	43356.3	102.508	1.333	6.3
33. Industrial Engineering	5.33	0.10	91385.9	246000.0	34.5	0.1	8.5
Average	9.0	4.0	223513.8	60605.9	121.1	1.0	7.2

Figure 4.1 shows the actual values of Full Time Academic staff versus the targeted values. It is observed that the inefficient departments such as General Ussoul Eldeen, Business Administration, Economics and Political Sciences, Physics, Biology, Medical Technology, Environment and Earth Science, Optometry, and most of engineering departments have targeted full-time academic staff less than actual values. This means that those departments are over-staffed comparing with their outputs in terms of graduates and researching outputs.

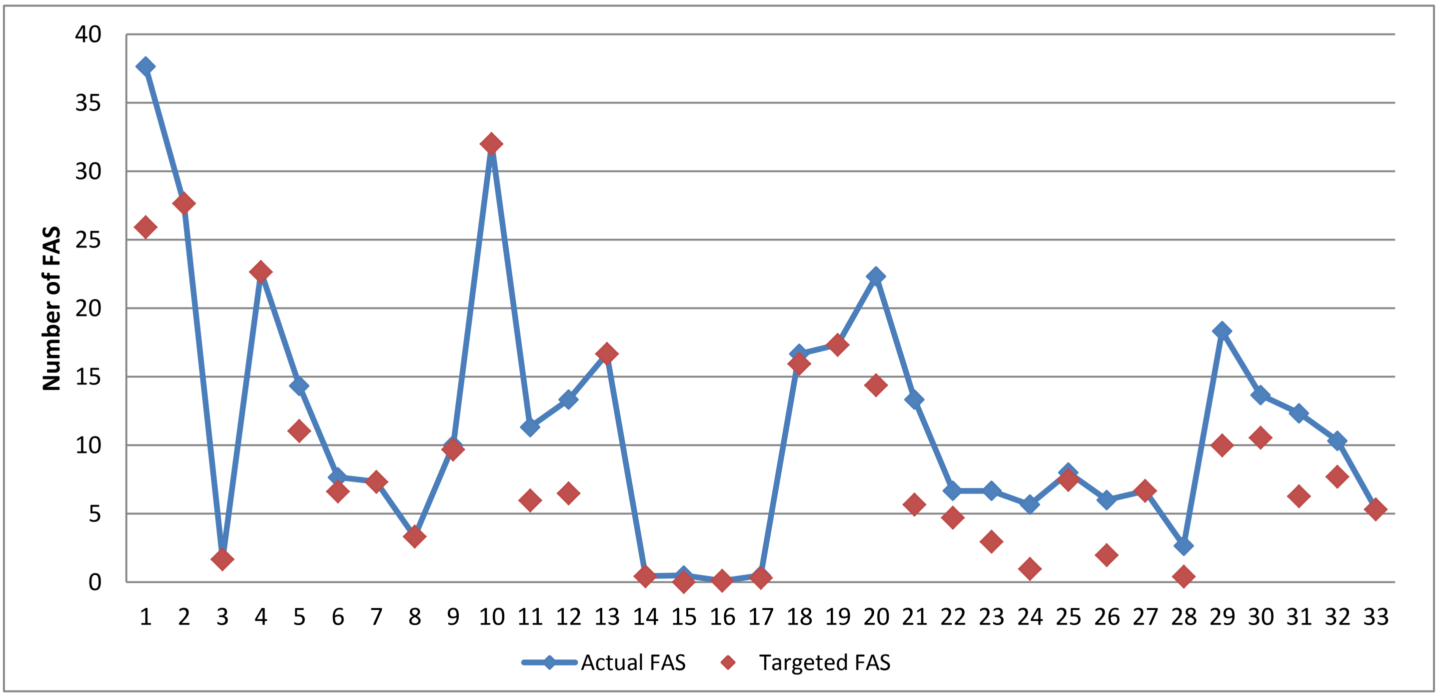

Fig 4.1: Actual FAS versus Targeted FAS

Figure 4.2 shows the actual values of Part-Time Academic staff versus the targeted values. It is observed that the inefficient departments such as General Ussoul Eldeen, Accounting, Business Administration, Economics and Political Sciences, Civil Engineering, and Electrical Engineering have targeted part-time academic staff less than actual values. The difference between actual and targeted values of this input variable is small. This means that this variable has no significant effect on the efficiency's scores.

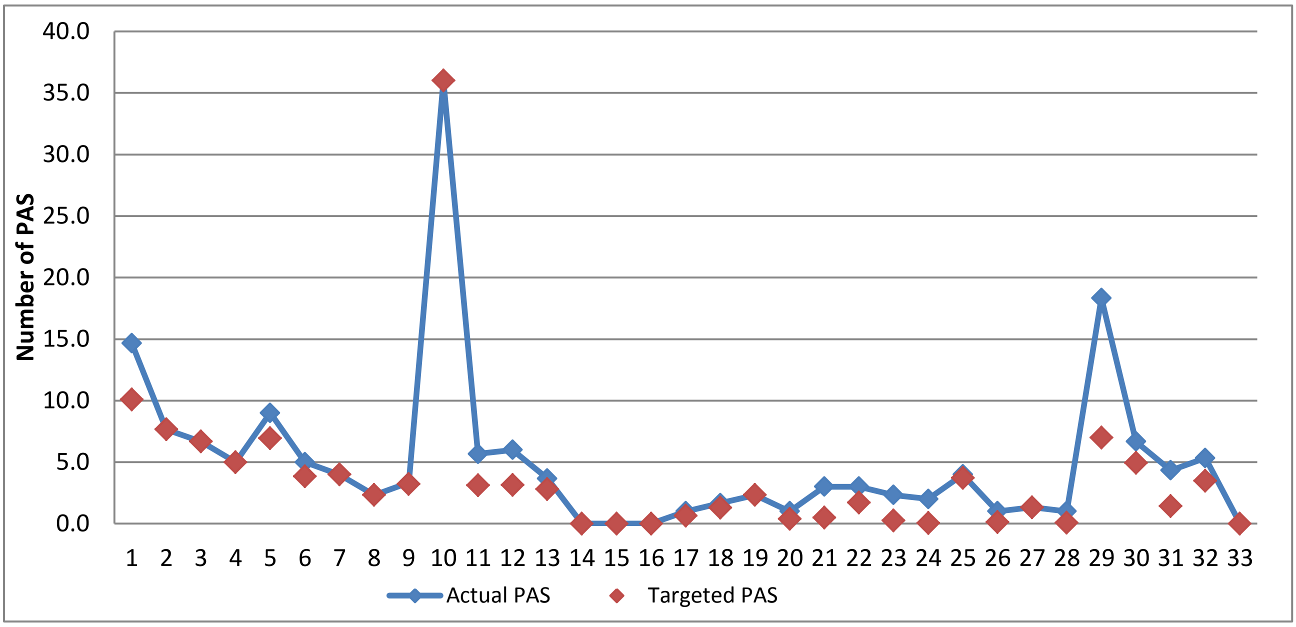

Fig 4.2: Actual PAS versus Targeted PAS

Figure 4.3 shows the actual values of Academic staff Salaries versus the targeted values. It is observed that the inefficient departments such as General Ussoul Eldeen, Business Administration, Economics and Political Sciences, Physics, Biology, Medical Technology, Environment and Earth Science, Optometry, and most of engineering departments have targeted full-time academic salaries less than actual values.

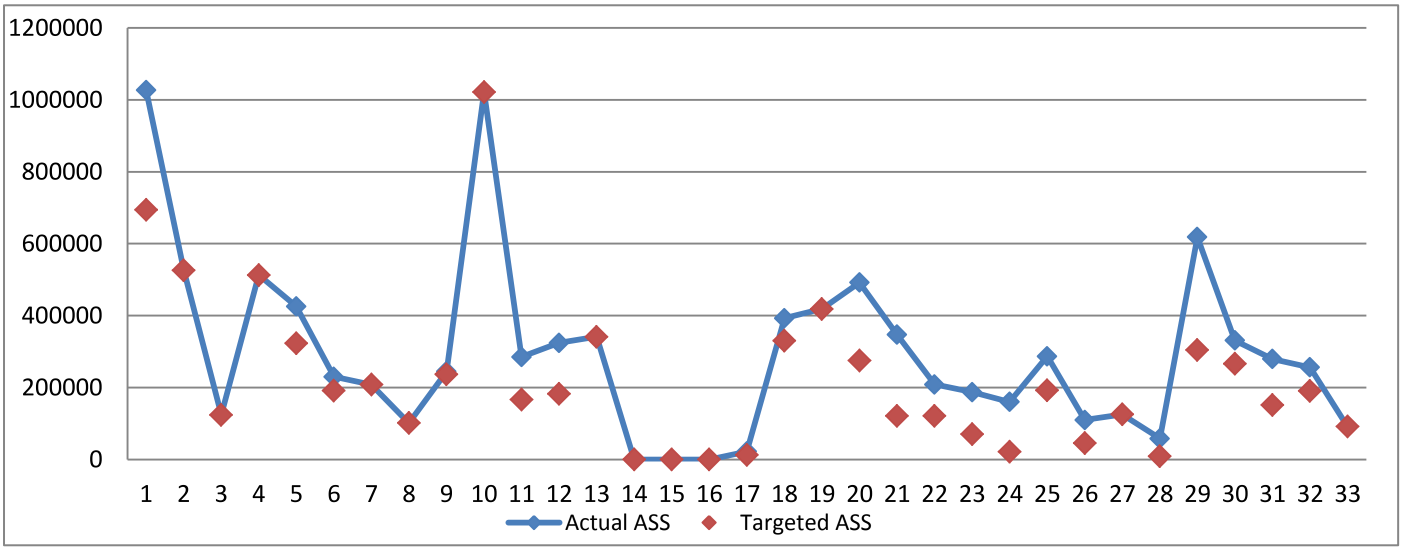

Fig 4.3: Actual AAS versus Targeted AAS

Figure 4.4 shows the actual values of Training Resources versus the targeted values. It is observed that the inefficient departments of science, Nursing, IT and engineering faculties have targeted training resources less than actual values.

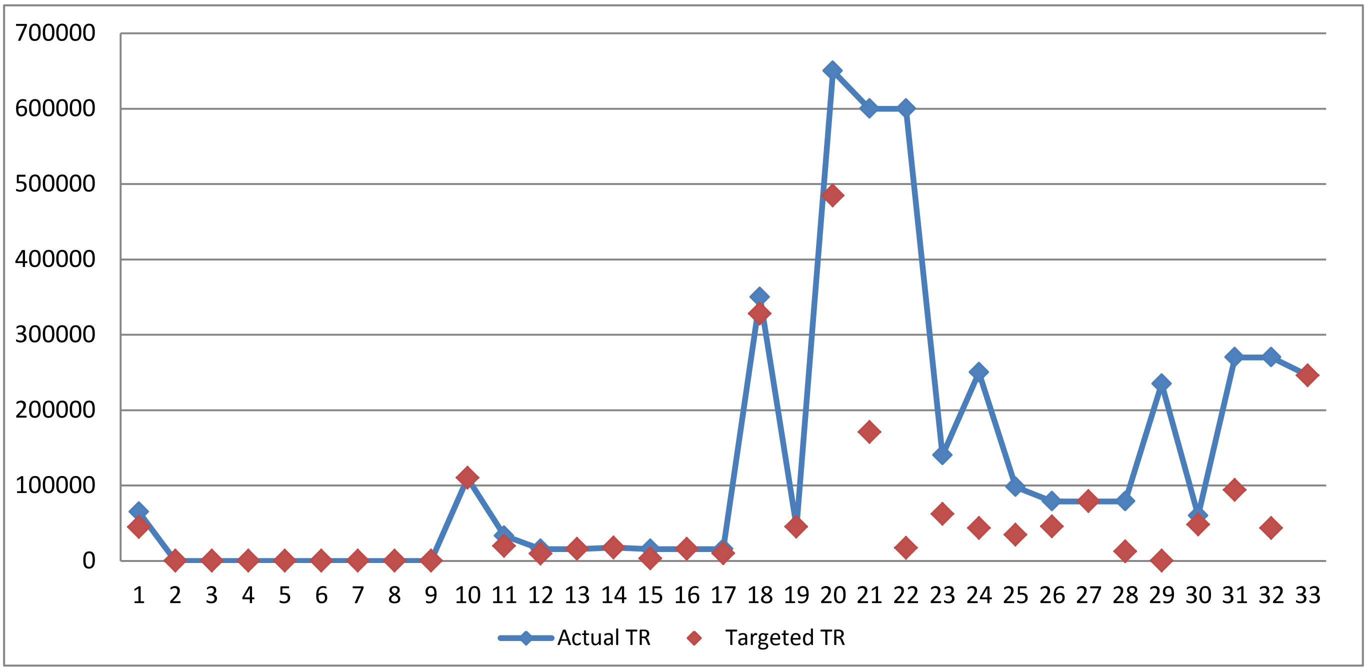

Fig 4.4: Actual TR versus Targeted TR

Figure 4.5 shows the actual values of Graduates versus the targeted values. It is observed that most of DMUs have targeted values of graduates same as actual values.

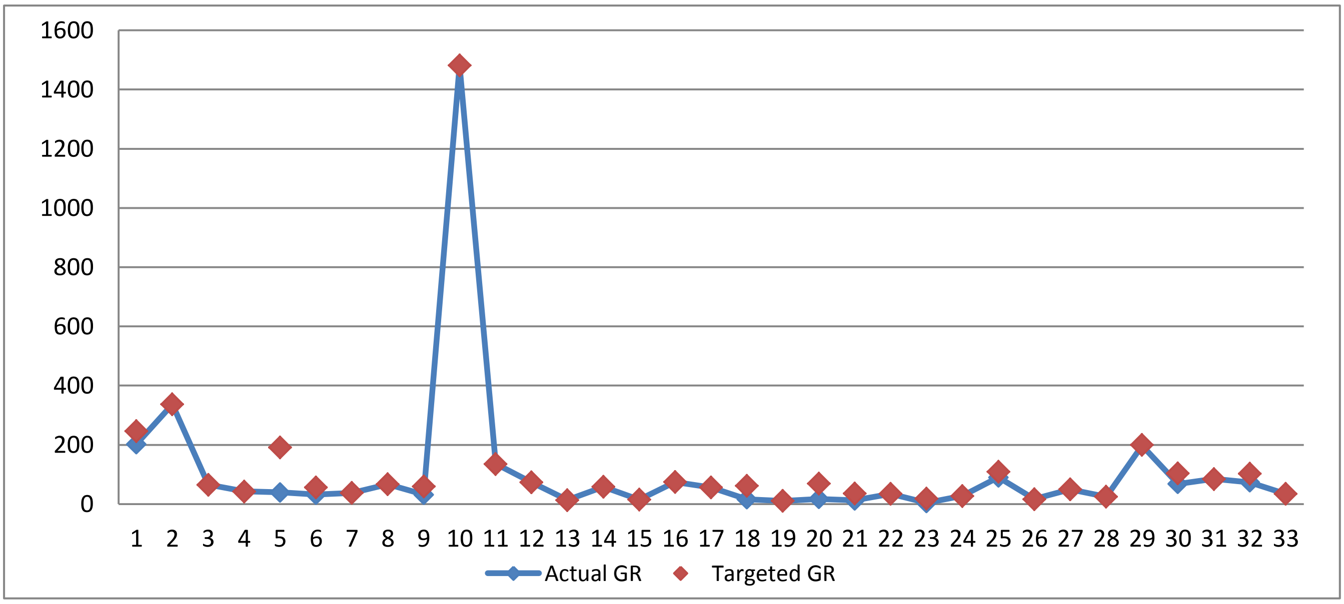

Fig 4.5: Actual GR versus Targeted GR

Figure 4.6 shows the actual values of Promotions versus the targeted values. It is observed that most of DMUs have close or same targeted values to the actual ones.

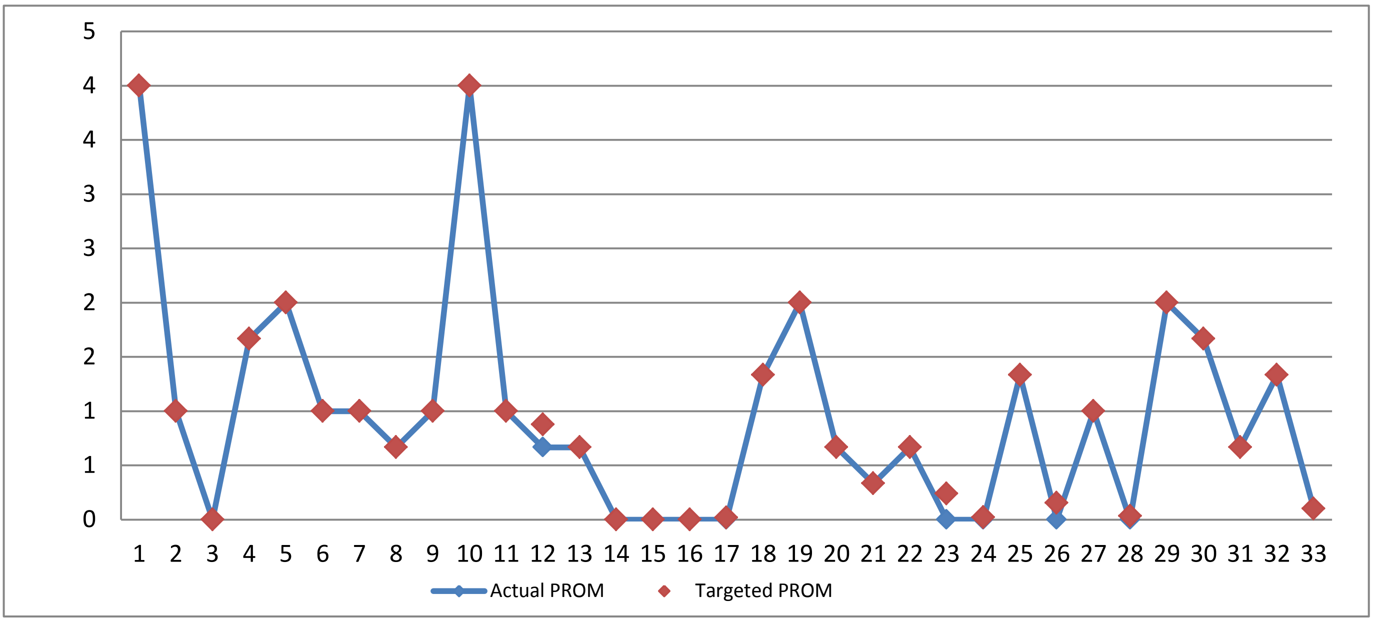

Fig 4.6: Actual PROM versus Targeted PROM

Figure 4.7 shows the actual values of PSA versus the targeted values. It is observed that most of DMUs have close or same targeted values to the actual ones. However, there are 3 DMUs with targeted values much larger than the actual ones Ussoual Eldeen, physics and Architecture. Those DMUs needs more PSA in order to be efficient departments.

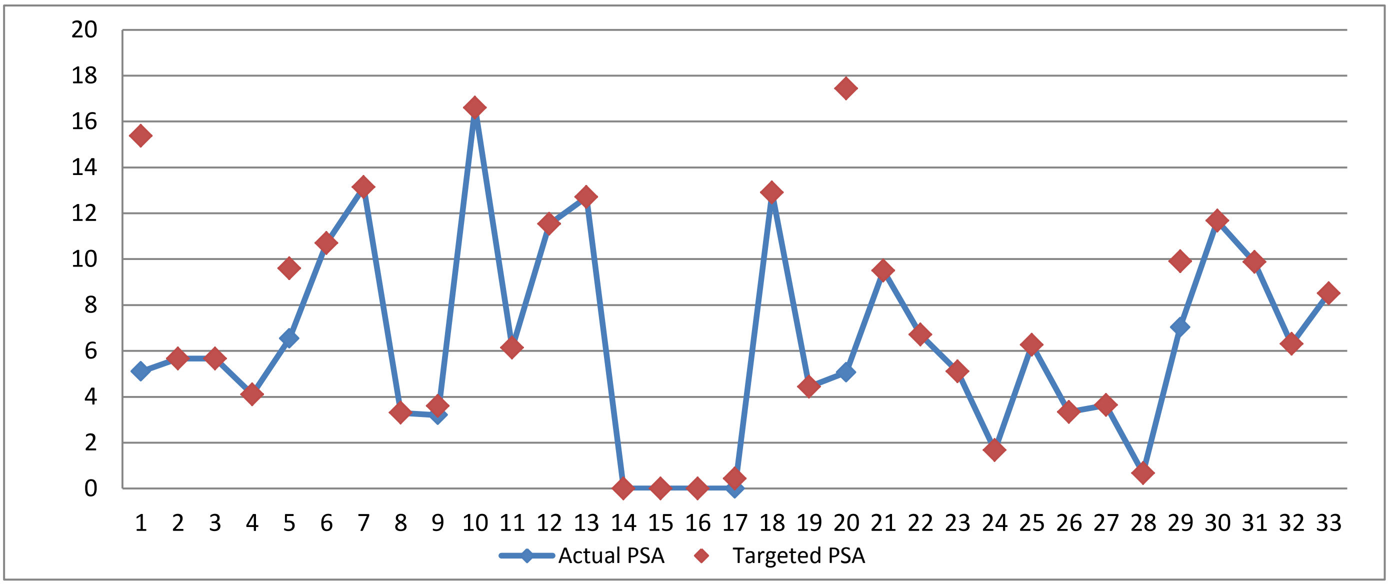

Fig 4.7: Actual PSA versus Targeted PSA

4.6 Super-Efficiency Analysis

Basic DEA models evaluate the relative efficiency of DMUs but do not allow ranking of the efficient DMUs themselves. Consequently, the super efficiency analysis is done in order to know the ranking of efficient DMUs and most efficient one. After removing the inefficient DMUs that appeared in CCR results, the super efficiency results are shown in Table 4.5.

Table 4.5: Super-efficiency scores

Department "DMU"	Super-Efficiency score%
Islamic Shariah	505.00
Shariah and Law	266.48
Arabic	166.67
Journalism & Information	311.94
Social Work	207.39
Education	125.85
Banking and Finance	7348.32
Accounting English	558.52
Mathematics	182.78
Information Technology System.	153.05
Industrial Engineering	2602.16

It is noticed that Banking and Finance department has the highest efficiency score of 7348% which is very big score while Education department has the lowest super-efficiency scores of 126%. The other efficient departments have efficiency scores ranging from 153% to 2602%. Therefore efficient departments can benefit from this study by learning from more efficient ones.

4.7 Regression Analysis

Multiple regression analysis is used in order to help departments prioritize their goals and focus on the significant variables to become efficient. This Model relates super efficiency scores to amounts of inputs, outputs and both of them. Equation (4) shows super efficiency in terms of inputs.

$$\boldsymbol{SE\ (I) = +7.41\ - 0.3527FAS\ - 0.999\ PAS\ - 1.31e - 05\ ASS\ - 0.00014144TR} \quad (\mathbf{4.1})$$

Equation 4.1 shows that PAS has the largest effect on super efficiency score in terms of inputs, followed by PAS, then TR and finally ASS as it has the smallest coefficient.

Regarding to outputs relations with super efficiency score, equation 4.2 shows the relationship between outputs and super efficiency score:

S

$$\boldsymbol{SE\ (O) = +0.113 + 0.0814\ GR + 0.895\ PROM\ +\ 1.001\ PSA} \qquad (\mathbf{4.2})$$

It is obvious that the PSA has the largest effect on super efficiency score, as indicated by its coefficient in equation (4.2), followed by PROM while GR has the least effect. Therefore; inefficient departments should set their priorities by focusing on PSA first, then PROM and finally GR.

In order to have a more sensitive prediction, both outputs and inputs were also included in the model. Super efficiency scores can be expressed as shown in equation (4.3):

$$\boldsymbol{SE\ (I, O) = +0.343\ - 0.196FAS\ - 0.201\ PAS\ - 1.67ASS\ - 0.635\ TR}$$
$$\boldsymbol{+\ 0.850GR + 0.974\ Prom +\ 1.02\ PSA} \qquad (\mathbf{4.3})$$

It is clear that PSA still has the largest contribution to super efficiency score as it was the case in equation 4.2, since it has the largest effect of 1.02 while FSS has the lowest effect on the efficiency score. Moreover, PROM and GR have a large effect on efficiency scores because their weights are between 0.85 and 0.97 and consequently they will have a dramatic effect if they are changed since the problem is an input minimizing one.

4.8 Shannon's Entropy Analysis

Shannon's Entropy methodology is used to assign weights for inputs and outputs variables. Two new constraints are added to the research model which corresponds to the weights of inputs and outputs as shown in equation (4.4).

$$min\Theta = \frac{1 - \frac{1}{m}\sum_{i=1}^{m} w_i s_i^- / x_{io}}{1 + \frac{1}{s}\sum_{r=1}^{s} w_r s_r^+ / y_{ro}}$$

Subject to: 4.4

$$\sum_{i=1}^{m} w_i = m$$

$$\sum_{r=1}^{s} w_r = s$$

Now, applying Shannon's entropy procedure yields:

1. **Entropies e_l:**

e_1	0.906	e_5	0.701
e_2	0.833	e_6	0.850
e_3	0.905	e_7	0.932
e_4	0.772		

2. **Degree of diversification d_l:**

d_1	0.906	d_5	0.701
d_2	0.833	d_6	0.850
d_3	0.905	d_7	0.932
d_4	0.772		

3. **Weights (degree of importance) w_l**

w_1	0.0856	w_5	0.2714
w_2	0.1517	w_6	0.1359
w_3	0.0859	w_7	0.0620
w_4	0.2075		

It is noticed that the weights of the variables are ranging from 0.086 to 0.271. After calculating the weight of each variable, the efficiency is again calculated by assigning each variable its corresponded weight. Table 4.11 shows the efficiency sore of each DMU.

It is clear that the results are same as CCR input oriented model results in some points and different in others. The similarities include same number of efficient DMUs, same efficient and inefficient DMUs. While, the differences include higher average efficiency score as the mean efficiency score become 87.2%, 18 out of 21 inefficient DMUs have higher efficiency scores than CCR model, whereas the remained three DMUs have lower efficiency score as shown in Fig. 4.8.

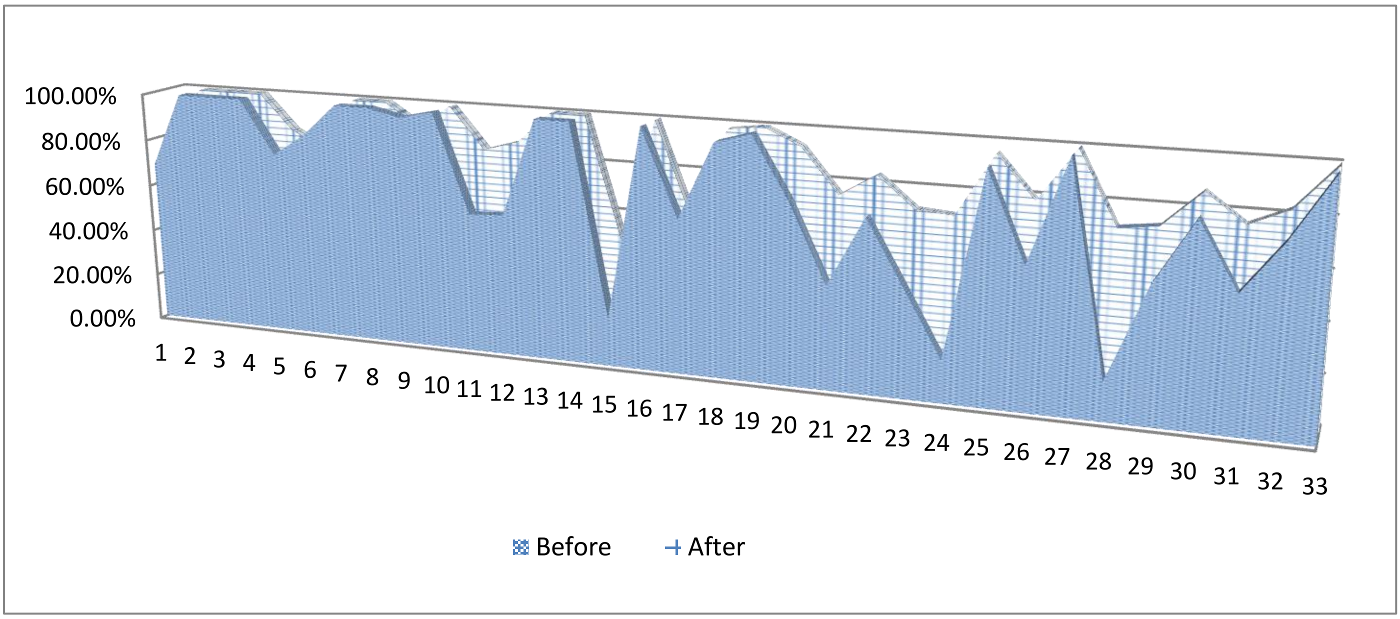

Fig 4.8: Efficiency scores before and after assigning weights

Table 4.6: Efficiency Scores before after Assigning Weights

Faculty	DMU	CCR Efficiency Scores	CCR Efficiency Scores after Assigning Weights
Ussoul Eldeen	**1.** General Ussoul Eldeen	68.83%	86.5%
Shariah and Law	**2.** Islamic Shariah	100.00%	100.0%
	3. Shariah and Law	100.00%	100.0%
	Average score	**100.00%**	**100.00%**
Art	**4.** Arabic	100.00%	100.0%
	5. English	77.10%	84.9%
	6. Geography	86.60%	78.1%
	7. Journalism & Information	100.00%	100.0%
	8. Social Work	100.00%	100.0%
	9. History And Archaeology	96.84%	90.6%
	Average score	**93.42%**	**92.27%**
Education	**10.** Education	**100%**	**100%**
Commerce	**11.** Accounting	58.49%	82.7%
	12. Business Administration	59.29%	86.9%
	13. Economics and Political	100.00%	100.0%
	14. Banking And Finance	100.00%	100.0%
	15. Economics And Applied Statistics	20.18%	48.9%
	16. Accounting English	100.00%	100.0%
	17. Business Admin. English	63.88%	60.5%
	Average score	**71.69%**	**82.71%**
Science	**18.** Chemistry	95.70%	98.2%
	19. Mathematics	100.00%	100.0%
	20. Physics	74.57%	93.2%
	21. Biology	42.59%	75.2%
	22. Medical Technology	70.86%	84.2%
	23. Environment and Earth	44.43%	71.8%
	24. Optometry	17.40%	70.7%
	Average score	**63.65%**	**84.76%**
Nursing	**25.** General Nursing	93.32%	95.9%
Information Technology "IT"	**26.** Computer Science	57.44%	78.9%
	27. Information Technology System.	100.00%	100.0%
	28. Software Development	15.89%	70.9%
	Average score	**57.78%**	**83.27%**
Engineering	**29.** Civil Engineering	54.55%	72.8%
	30. Architecture	80.41%	87.1%
	31. Electrical Engineering	54.04%	75.9%
	32. Computer Engineering	74.53%	82.7%
	33. Industrial Engineering	100.00%	100.0%
	Average score	**72.71%**	**83.70%**
Total average score		**75.97%**	**87.17%**

For Geography, History and Archaeology, and Business Administration English DMUs, the efficiency score after assigning weights for variables becomes lower while it was higher without assigning weights. For example, geography has efficiency score of 78% while it was 86.6%. This is the result of having either low value of PROM output variable or zero value of the same variable. Moreover, PROM has relatively high assigned weight (0.136) comparing with other variables. As to ensure this, the PROM value of those three DMUs was increased by one and the model is run. The results showed 100% efficiency for all of the three DMUs which confirmed what obtained about the effect of PROM variable and its weight on the efficiency score.

Now for the DMUs with higher efficiency score after assigning the weights for variables, the reasons of this are different from DMU to DMU. For example, General Ussoul Eldeen has high value of GR and PROM outputs which have high assigned weights. In addition, this DMU has high value of ASS input while this variable has low assigned weights. Those reasons are common for most of DMUs department whose efficiency score is higher when assigning weights to variables. However, the reason in case of Economics and Applied Statistics DMU is having high value of GR which has the highest assigned weights. For Environment and Earth DMU, it has high value of ASS input while it has low assigned weight.

So, there are some benefits of assigning weights for variables not limited to the below:

- Better determination of potential improvements and area of weaknesses.
- Guide for determining the variables that affect the efficiency score positively or negatively.
- Relate the efficiency score with inputs and outputs variables and the reasons behind the score.

4.9 Sensitivity Analysis

Considering regression model equation and the applied DEA input-oriented model, PAS input variable has the highest coefficient of all inputs variables which means that it will has the highest impact on efficiency score in case of change.

To illustrate this, the PAS input variable will be reduced by 20%, the average of efficiency score becomes 84.6% instead of 76%, i.e. about 15% increase. In addition, 17 DMUs become efficient instead of 11. Further, the efficiency of 19 DMUs is improved whereas 2 DMUs efficiency becomes lesser and 12 DMUs keep the same efficiency score. Table 4.7 shows the efficiency score of each DMU after reducing PAS by 20%. Figure 4.9 shows the differences between efficiency scores before and after reducing PAS by 20%.

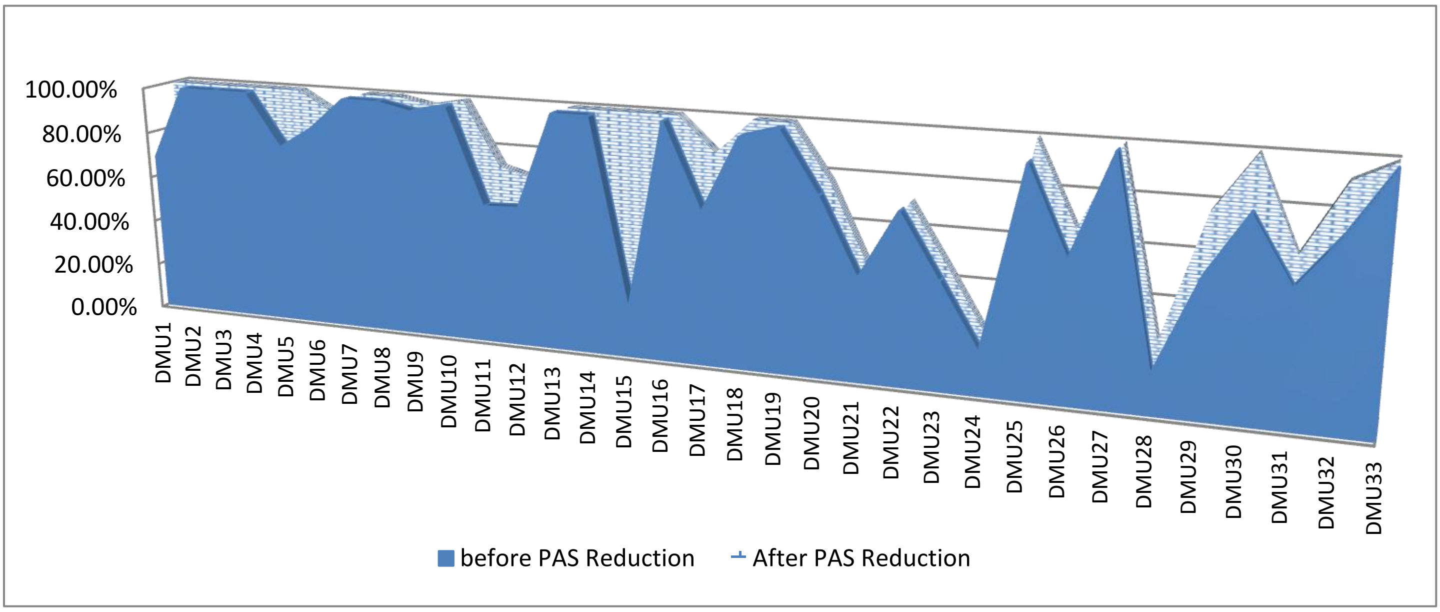

Fig 4.9: Efficiency scores before and after reducing PAS by 20%.

Table 4.7: Efficiency Scores after PAS reduced by 20%

Faculty	DMU	Efficiency Score After PAS reduced by 20%
Ussoul Eldeen	**1.** General Ussoul Eldeen	**100.0%**
Shariah and Law	**2.** Islamic Shariah	100.00%
	3. Shariah and Law	100.00%
	Average score	**100.00%**
Art	**4.** Arabic	100.0%
	5. English	100.0%
	6. Geography	91.3%
	7. Journalism & Information	100.0%
	8. Social Work	100.0%
	9. History And Archaeology	97.1%
	Average score	**98.07%**
Education	**10.** Education	100.0%
Commerce	**11.** Accounting	72.5%
	12. Business Administration	68.3%
	13. Economics and Political	100.0%
	14. Banking And Finance	100.0%
	15. Economics And Applied Statistics	100.0%
	16. Accounting English	100.0%
	17. Business Admin. English	85.2%
	Average score	**89.43%**
Science	**18.** Chemistry	100.0%
	19. Mathematics	100.0%
	20. Physics	76.6%
	21. Biology	42.6%
	22. Medical Technology	71.4%
	23. Environment and Earth	45.4%
	24. Optometry	18.6%
	Average score	**64.94%**
Nursing	**25.** General Nursing	100.0%
Information Technology "IT"	**26.** Computer Science	65.9%
	27. Information Technology System.	100.0%
	28. Software Development	24.8%
	Average score	**63.57%**
Engineering	**29.** Civil Engineering	76.4%
	30. Architecture	100.0%
	31. Electrical Engineering	63.0%
	32. Computer Engineering	91.9%
	33. Industrial Engineering	100.0%
	Average score	**86.26%**
Total average score		**84.6%**

To conclude, the DEA model is sensitive to any change in variables' values and any change in variable may affect the efficiency score. This confirmed the importance of the needed potential improvement needed for inefficient DMUs.

Chapter 5: CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

5.2 Recommendations

This chapter concludes the research with suggestions for future research. It is divided into two sections; the first section provides a conclusion or summary of the research while the second section suggests recommendations for future research.

5.1 Conclusion

This research applied DEA approach to measure the technical efficiency of IUG academic departments. The research was applied on IUG academic departments, taking a sample of 33 of IUG bachelor programs as the research sample which considered as DMUs and the study period cover the period 2008 -2010. Seven variables of inputs and outputs were selected by considering several factors such as the availability of data, and applicability of the variables on research DMUs in addition to variables taken by researchers. Eventually, Full-Time Academic Staff (FAS), Part-Time Academic Staff (PAS), Academic Staff Salaries (ASS), and Training Resources (TR) were the inputs. On other hand, Graduates (GR), Promotions (PROM), and Public Service Activities (PSA) were the outputs.

The technical efficiency of each DMU was measured by applying CCR and BCC input-oriented model without assigning weights to variables firstly and then using Shannon's Entropy to assign weights for variables. The non-weighted results of CCR model showed 12 efficient DMUS, 21 inefficient DMUs and overall average efficiency of 76% whereas the BCC results showed 18 efficient DMUs, 15 inefficient DMUs and overall average efficiency of 84.6%. This implies that BCC model gives better results than CCR model and hence generalizing the CCR results for the research. The assigned weight CCR results showed 87.2% overall average efficiency which is higher than the non- assigned weight results. This concludes that assigning weights to inputs and outputs variables results in higher the efficiency scores, better determination of potential improvements, and better determination of variables that affect the efficiency score.

The scale efficiency was determined and showed an average of 89.9%. The potential improvements were evaluated for each inefficient DMU and their targeted values varied from variable to variable. Furthermore, the super-efficiency of efficient departments is determined in order to identify the most efficient department and hence rank the rest of efficient departments. Banking and Finance has the highest super-efficiency score.

Multiple-Regression model was applied between super-efficiency score and research inputs and outputs to prioritize the variables effect on efficiency score. PROM has the largest contribution to super efficiency score.

Further, sensitivity analysis was conducted by reducing the value of one input variable (PAS) and showed enhanced efficiency. This implies that DEA model is sensitive to any change in variables.

Due to the current economic stranglehold in Palestine, research into maximizing output by using minimum inputs is of great importance. In a better economic situation, this research will add a new tool to the decision makers’ toolbox to effectively evaluate the performance of their institutions and to optimally manage their resources.

5.2 Recommendations

It is recommended to improve the Management Information System of IUG by better relating of departments activities, inputs and outputs or to establish a database center that includes all data of the university, facilities and departments. Such database will be of great help to researchers and decision makers to conduct studies in development fields since the main drawback in such studies is the lack of quantity and/or quality of data.

Second, all departments of IUG is recommended to pay attention to their respective efficiency scores particularly those departments with low efficiency scores. Such inefficient departments should pay more attention to the potential weak spots where they improvement as measured in this research. These departments should also benchmark themselves against the identified reference departments.

Third, it is recommended that university management encourage and motivate its academic staff to focus more on publications which is mainly the criteria of promotion as it was one of the weakness areas.

Further, it is recommended for decision makers to understand the DEA approach and use it as a tool for measuring the efficiency in the higher education sector.
Moreover, it is also recommended to consider other variables in future work. Such variables include, but not limited to, economic, climatic and environmental index variables.

In addition, DEA is recommended to be used in measuring the efficiency of Palestinian universities relative to each other. Also, DEA approach is recommended to be applied on other applications such as health care, banking sector, administrative sector and other sectors.

On the IUG scale, DEA could also be used to measure the technical efficiency of the different IUG units. Similarly, it can also be used to evaluate the efficiency of other Palestinian universities in order to improve the higher educational sector in general

Finally, it is recommended to apply DEA with assigned variables weights on further DEA – approached studies as the significant effects of assigning weights to variables on efficiency scores.

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Annex I: Experts and Interviewees

- Research and Development dean and director.
- Admission dean and director.
- Financial Unit
- Faculties’ Deans.
- Prof. Salah Agha
- Prof. Sanaa Abo Daqqa.
- Prof. Ellian ELhuli.
- Prof. Majid Elfarra.
- Prof. Ali Shaheen.
- Dr. Sami Abuo Al Ross
- Mr. Ahmed Abo Amsha.
- Mr. Amer Ahana
- Mr. Wasim Skaik
- Mr. Ashraf Miqdas.
- Mr. Eyad Al Zatma.
- Mr. Mohammed Aziz.
- Eng. Mohammed Shurrab
- Eng. Nader Abdelnabi