Benchmarking of Academic Departments using Data Envelopment Analysis (DEA)

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Purpose – The main objective of the paper is to develop an Investment Model using Data Envelopment Analysis (DEA) that provides a decision-making framework to allocate resources efficiently, such that the relative efficiency is improved within an available investment budget.

Design/methodology/approach – DEA models are used to evaluate the efficiency of the departments relative to their peers and providing benchmarks for the less efficient departments. Secondly, the inefficiencies in departments are identified. Finally, for the less efficient departments, a decision-support system is introduced for optimizing resource allocation to improve efficiency.

Findings – Five of the eighteen academic departments were determined to be inefficient, and benchmark departments were found for those departments. The most prevalent causes for inefficiency were the number of Undergraduate Students per Faculty and the Number of Graduate Students. Results from the Investment Model for Department 12 suggest increasing the Number of Faculty by 2 units and H-Index by 0.5 units, thereby, improving the relative efficiency of the department by 6.8% (88% to 94%), using $290,000 out of $500,000 investment budget provided.

Originality – When an investment budget is available, no study has used DEA to develop a decision-support framework for resource allocation in academic departments to maximize relative efficiency.

Keywords: Data Envelopment Analysis; Relative Efficiency; Benchmarking; Resource Allocation; Investment Model; Decision-Support System

1: Introduction

With declining resource levels and tightening budgets, university departments have looked to improve the resource utilization in their institutions. To achieve this, institutions have embraced self-evaluation strategies involving performance assessment – using results to understand where improvements are required to improve institutional performance (Bartuševičienė & Šakalytė, 2013). Higher education administrators are now more willing to adopt efficiency analyses to make educated administrative decisions. Strategic management and systematic assessment are carried out in academic departments, allowing for improved resource-allocation (Duguleana & Duguleana, 2015).

US News rankings are the most prominent assessment for university and departmental performance (Gnolek, Falciano & Kuncl, 2014). However, the rankings published by U.S. News create controversy with their models (Tsakalis & Palais, 2004), since U.S. News rankings quantify the departmental rankings through the Peer Assessment Scores. Ratings given by the departmental heads are known as Peer Assessment Score, which is often criticized as being a subjective and biased indicator of academic quality (Gnolek, Falciano & Kuncl, 2014). Also, Peer Assessment rating does not indicate how effectively resources within the departments are utilized. Although many universities have strategically established goals to improve their rankings, developing a strong understanding of what is required to move up can be challenging (Gnolek, Falciano & Kuncl, 2014). An institution is considered efficient if they are using available resources effectively. To ensure academic departments do not become inefficient, benchmarking processes are instrumental.

Benchmarking is defined as "the process of comparing practices, procedures, and performance metrics to an established standard or best practice" (Bosso, Chisholm-Burns, Nappi, Gubbins & Ross, 2010). Benchmarking involves understanding the departments' internal processes first and then identifying the peer departments' best practices. Finally, considering those best practices and implementing them to improve organizational performances.

Analyzing the efficiency of universities at the departmental level is a complicated task since universities are dynamic entities that use multiple inputs to create multiple outputs. Therefore, different methodologies are used to measure efficiency - parametric and non-parametric. Some of the most implemented methods are Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA) (Fried, Schmidt & Lovell, 2008). DEA is the non-parametric approach extensively used by academics and practitioners to assess the relative efficiencies of a set of homogeneous organizational units (Decision Making Units), capable of handling multiple inputs and outputs without assigning prior weights to inputs and outputs (Kuah, Wong & Behrouzi, 2010). DEA is a linear-programming optimization method that intends to segregate decision-making units (DMUs) into efficient and inefficient units, by comparing each DMU to its peers (Mikusova, 2015).

The main research question in this paper is: Do relative efficiency scores improve in inefficient academic departments with optimized resource-allocation the department is given an investment budget? In this article, we aim to contribute to the existing literature in the educational institutions regarding resource-allocation within a given investment budget, using DEA, by focusing on evaluating the academic departments' efficiency. We focus on the relative efficiency of the academic departments and how it can be maximized. The purpose of this study is to construct a decision-support system for decision-makers to help with resource-allocation within a given budget.

In this paper we propose three models based on DEA, which focuses on (i) evaluating the relative technical efficiency of academic departments compared to its peers; and indicate departments or sets of departments with high efficiency (efficiency = 1) to be used as a benchmark for each of the department under study; (ii) providing a slack-based benchmarking model to understand whether it is possible to attain higher outputs using the minimum level of input; (iii) an investment support model for the departmental leadership, which would help in deciding how much funds should be used to increase one or more inputs (resource allocation), so that efficiency is improved.

For the computational experiment, the DEA models are investigated empirically using data from 18 Industrial Engineering departments within the USA, containing 5 inputs and 1 output. Industrial Engineering departments were picked since it was our field of interest and data was readily available.

2: Literature Review

Organizational assessment is a common practice in high-performance organizations – continuously striving for better results – achieved through constant benchmarking and self-evaluation (Bartuševičienė & Šakalytė, 2013). An educational institution's evaluation procedures evaluate the efficiency of its educational programs to attain its stated goals. Therefore, it is imperative for educational institutions to evaluate their performance continuously and understand how efficiently they are using the resources. Relative efficiency measurements with peer departments provide less efficient departments with areas of improvement and aspiration level of where they would like themselves to be. Some examples of departmental inefficiencies include - high funding expenditures that do not result in quality publications for faculty members, and a lower faculty to student ratio with insufficient research output.

2.1: Methods of Evaluation

The methods widely used to estimate efficiency are non-parametric (DEA) and parametric (SFA). DEA is a deterministic, best practice frontier method that envelops the observations for efficiency measurements (Bates et al. 1996). Contrarily, SFA uses stochastic procedure for parametric evaluation of frontier. SFA is a useful methodology when the data contains a certain level of uncertainty, however, it is challenging to implement with multiple inputs and outputs (Kuah, Wong & Behrouzi, 2010).

DEA, developed by Charnes, Cooper & Rhodes (1978), is known as the CCR model and later extended by Banker, Charnes & Cooper (1984), known as the BCC model. The BCC method uses Variable Returns to Scale (VRS), meaning the increase/decrease in inputs does not have a proportional change in the output. DEA provides locations on the frontier acting as possible benchmarks for inefficient units while offering improvement areas for inefficient units to function efficiently (Ruiz, Segura & Sirvent, 2014).

2.2: University Rankings:

As stated by Shin & Shin (2020), "Ranking usually displays the relative ratings of universities, where weighted points are assigned to individual indicators, which contribute to the aggregated total scores (ratings) by which the relative orders of assessment are created." More importantly, rankings give information on institutional quality in the form of a single number (Kim, 2018). Besides, rankings are also used as a tool for worldwide benchmarking and associated with resource-allocation (Kim, 2018).

2.3: DEA in Education

DEA is extensively used for different applications in higher educational institutions for efficiency measurement. The paper by Gralka, Wohlrabe & Bornmann (2018) used DEA to determine whether research efficiency is based on research grants or the number of publications in German universities. Moreover, Kumar & Thakur (2019) implemented DEA to assess the relative performance of the institutions on management education in different parts of India by efficiency measurement. Conversely, Song (2018) applied DEA to evaluate relative efficiency of capital investments for higher educational institutions in China. Also, Tyagi, Yadav & Singh (2009) used DEA to evaluate the performance efficiencies of 19 academic departments in IIT Roorkee. Alternatively, Gimenez & Martinez (2006) utilized DEA for cost-efficiency for 42 departments of the Autonomous University of Barcelona, as universities look to improve quality while adhering to budgetary restrictions. Again, DEA was utilized by Johnes (2006) to measure technical and scale efficiency for 100 higher education institutions in England. Koksal & Nalcaci (2006) measured the relative efficiency of academic departments using DEA for an engineering school in Turkey. Interestingly, Bougnol & Dula (2006) used DEA as a ranking tool, comparing results from two ranking schemes. The two methods were compared, and equivalences were discovered - validating DEA as a suitable tool for ranking.

Most of the works in the literature mainly focused on two types of efficiency evaluations in universities. First, in which data is used at the institutional level. Second, in which efficiency is measured in the department-level across different universities or within the same university (Barra & Zotti, 2016). Papers by Sagarra, Mar-Molinero & Agasisti (2017), and Bayraktar *et al*. (2013) evaluates the relative efficiency between different universities of Mexico and Turkey, respectively. Whereas the studies conducted in Duguleana and Duguleana (2015), Barra and Zotti (2016) estimate the relative efficiency of academic departments within the same university.

3: Dataset and Methodology

3.1 Dataset

The data is collected from U.S. News Rankings (2019) and the American Society of Engineering Education (www.asee.org). The dataset contains data from 18 Industrial Engineering departments, with five inputs and one output. These 18 university departments were chosen to represent groupings of departments with high, mid-level, and lower-middle Peer Assessment scores, respectively. This selection procedure improves the analysis since it would be difficult for a lower- or middle-ranked department to replicate what a top-ranked university department is doing. As a result, peer university departments were chosen in groupings.

It is critical to determine the DMU that will be compared. There are a few aspects that must be considered while selecting a DMU. The main characteristics are homogeneity and the number of DMUs (Tyagi, Yadav & Singh, 2009). 18 Industrial Engineering departments in the USA were chosen, as they have similar objectives – conducting research and teaching activities. Furthermore, to distinguish between efficient and inefficient DMUs, it is ideal for the number of DMUs to be greater than the product of the number of inputs and outputs (Tyagi, Yadav & Singh, 2009). Therefore, our study comprised of 5 inputs and 1 output with 18 academic departments.

The inputs and outputs can be changed according to the study's requirements. Kumar & Thakur (2019) used faculty salaries, state research funding, total investment in physical planning, administrative overheads as inputs, while undergraduate enrollments, number of graduate enrollments, total semester credit hours, and federal and private research grants were used as outputs. Song (2018) considers faculty utilization, course offerings, and incoming student quality as inputs, while the quality of graduate students, number of journal papers, research grants, and graduate students are considered as outputs. For our paper, it was needed first to establish the inputs and outputs to be used in the models.

3.1: Selecting and defining inputs and outputs for evaluating academic departments:

Output: Efficiencies measure how well departments yield outputs from a given amount of inputs (Abbott & Doucouliagos, 2001). The following is classified as output:

- Peer Assessment Score- A score given program directors (survey). It ranges from a scale of 1-5.

Inputs: It is desired that departments produce as much output as possible with a given number of inputs; the following are classified as inputs:

- Number of Faculty- The total number of faculty in each department, indicating the department's strength (Colbert, Levary & Shaner, 2000).
- Research Expenditure per Faculty- Total research expenditure of department divided by total number of faculty in respective department. Specifies the research activity and efficiency of the faculty members (Anderson, Daim & Lavoie, 2007).
- Number of Undergraduate Students per Faculty- Total number of undergraduate students in the department divided by the total number of faculty in the respective department. Reveals the workload of faculty members outside of research (Gimenez & Martinez, 2006).
- Number of Graduate Students - Total number of graduate students in department, representing potential research capabilities (Jongbloed et al., 1994).

- Average H-index- This input indicates the quality of research conducted by the department. Google Scholar (Citations) was used in collecting the h-index of the faculty members of the respective departments (Bal & Golcukcu, 2016).

3.2 Methodology:

DEA is a non-parametric mathematical programming approach that evaluates the relative efficiency of a set of DMUs (Bayraktar, Tatoglu & Zaim, 2013). DEA estimates best practice by evaluating the performance of each DMU with every other DMU in the sample. A DMU can be defined as an entity responsible for converting input(s) into outputs(s) whose performance needs to be evaluated (Sagarra, Mar-Molinero & Agasisti, 2017).

DEA focuses on frontier tendencies rather than central tendencies - enables the identification of relationships that might otherwise go unnoticed by conventional methods (Cooper, Seiford & Zhu, 2011). DEA can measure relative efficiency without requiring explicit assumptions and variations (Cooper, Seiford & Zhu, 2011). It is specially designed for benchmarking purposes when there is a lack of absolute standards for efficiency (Gralka, Wohlrabe & Bornmann, 2018). Additionally, DEA is easy to comprehend - presents a single measure of relative efficiency.

4: DEA Models

The DEA models can be input- or output-oriented. The input-oriented models tend to reduce the input as much as possible while keeping the output constant. On the other hand, output-oriented DEA tends to grow the output to the greatest extent possible while keeping the input level constant (Bayraktar, Tatoglu & Zaim, 2013). For this paper, output-oriented DEA models are used. For each department under study, a convex linear combination is formed among the departments whose efficiencies have caused from at most the same amount of input and at least the same amount of output (Abolghasem *et al.*, 2017). The department under study is said to be inefficient if the linear combination results in larger output, and the departments selected for the convex linear combination will be considered as the benchmark departments for that respective department under study (Abolghasem *et al.*, 2017).

The Efficiency Model measures the relative efficiency of the department under study to its peers. The Benchmarking Model determines the number of inputs that are not being used efficiently in each department. The Investment Model determines the input or set of inputs to be added by the department (resource allocation) when an investment budget is allocated for the department to maximize efficiency.

4.1: Efficiency Model

For calculating relative efficiency of decision-making units (DMUs), the model proposed by Banker et al. (1978), also known as BCC, is used (Abolghasem et al., 2017). This model helps measure pure technical efficiency by comparing a DMU to a unit of a similar scale. This formulation consists of a set of DMUs (N), a set of inputs (I) and a set of outputs (O).

The parameter y_{rj} represents total output $r \in O$ produced by department $j \in N$. Alternatively, the parameter x_{ij} represents the total input $i \in I$ used by department $j \in N$. λ_j is the decision variable which represents fraction of the j-th department used in convex linear combination, projecting the department under study (j = p) into the efficiency curve. Also, the decision variable ϕ_p (growth factor) represents proportional increase in outputs of the department under study.

The proposed Efficiency Model is:

$$\max \phi_p \qquad (1)$$

Subject to,

$$\sum_{j \in N} y_{rj}\, \lambda_j \geq \phi_p y_{rp},\ \forall_r \in O \qquad (2)$$

$$\sum_{j \in N} x_{ij}\, \lambda_j \leq x_{ip},\ \forall_i \in I \qquad (3)$$

$$\sum_{j \in N} \lambda_j = 1 \qquad (4)$$

$$\lambda_j \geq 0, \ \forall_j \in N \qquad (5)$$

$$\phi_p \text{ free of sign} \qquad (6)$$

Objective function in (1) maximizes the proportional increase of output for the academic department under study. The larger the value is, the greater would be the potential for the department under study to grow. The efficiency is calculated using $1/\phi_p$, which scales the value between 0 to 1. In (2) it is ensured that the proposed level of output should be at least equal to the current value of the department under study times the growth factor (ϕ_p). Constraints (3) ensures that the amount of input in the convex combination must be equal or less than the total input consumed by the department under study. Additionally, (4) takes into account the convexity of the linear combination, whereas the nature of the decision variables is defined by (5) and (6).

4.2: Benchmarking Model

Based on the model proposed by Goksen, Dogan & Ozkarabacak (2015), the Benchmarking Model determines a set of benchmark departments (reference set) for the department under study. The optimal growth factor (ϕ_p^*) is used from the Efficiency Model by the Benchmarking Model to validate whether it is possible for the department under study to increase the output levels using the minimum amount of input. The extension in the Efficiency Model leads to the Benchmarking Model by adding slacks (s_r^+ for output r $\in O$ and s_i^- for input i$\in I$):

$$\max \textstyle\sum_{r\in O} s_r^+ + \sum_{i\in I} s_i^- \qquad (7)$$

Subject to,

$$\textstyle\sum_{j\in N} y_{rj}\,\lambda_j - s_r^+ = \phi_p^* y_{rp}, \ \forall_r \in O \qquad (8)$$

$$\textstyle\sum_{j\in N} x_{ij}\,\lambda_j + s_i^- = x_{ip}, \ \forall_i \in I \qquad (9)$$

$$\textstyle\sum_{j\in N} \lambda_j = 1 \qquad (10)$$

$$\lambda_j \geq 0,\ \forall_j \in N \tag{11}$$

$$s_r^+ \geq 0,\ \forall_r \in O \tag{12}$$

$$s_i^- \geq 0,\ \forall_i \in I \tag{13}$$

Objective function in (7) maximizes the difference between proposed inputs and outputs levels of the benchmark departments against the inputs and outputs of the department under study, by using the surpluses $s_r^+$and s_i^- slacks in the set of constraints (8) and (9), respectively. Constraints 9 uses the optimal growth factor (ϕ_p^*) from the Efficiency Model as a parameter, therefore the set of constraints (2) and (3) from the Efficiency Model are equivalent to set of constraints (8) and (9) of the Benchmarking Model. Likewise, the set of constraints (10) is equivalent to constraints (4). Lastly, constraints (11), (12), and (13) define the nature of the decision variables.

4.3: Investment Model

The Investment Model helps departments determine which inputs to add and by what amount when an investment budget is specified.

$$\max \phi_p \tag{14}$$

Subject to,

$$\sum_{j \in N} y_{rj}\, \lambda_j \geq \phi_p y_{rp},\ \forall_r \in O \tag{15}$$

$$\sum_{j \in N} x_{ij}\, \lambda_j \leq x_{ip} + \sum_{l \in I*} z_{lp} \alpha_{lip}\ ,\ \forall_i \in I \tag{16}$$

$$\sum_{i \in I} w_{ip} * z_{ip} \leq c \tag{17}$$

$$\sum_{j \in N} \lambda_j = 1 \tag{18}$$

$$\lambda_j \geq 0,\ \forall_j \in N \tag{19}$$

$$\phi_p \text{ free of sign} \tag{20}$$

$$z_{ip} \in \mathbb{Z}^{+} \tag{21}$$

Objective function in (14) maximizes the growth factor of outputs for each of the departments under study. Constraints (15) is equivalent to constraints (2) of the Efficiency Model. In constraints (16), z_{lp} is the decision variable, which tells the model the number of inputs to be added. z_{ip} can take integer values only. Also, α_{lip} is a matrix that represents the linear effect of adding one input $l \in I*$ to other inputs $i \in I$ of the department under study (p). In constraints (17), w_{ip} is a parameter, which is the amount of money needed to add 1 unit of each input, respectively. Additionally, c is the budget given to the department, which should not be exceeded. Constraints (18), (19), and (20) are equivalent to constraints (4), (5), and (6) of the Efficiency Model. Constraints (21) indicates the nature of the decision variable.

4.3.1: Estimation of Parameter values of the Investment Model:

4.3.1.1 Estimating w_{ip} values:

Based on discussions with the departmental head and the Associate Dean of the College of Engineering, several input parameter assumptions were made. The cost of adding one additional unit of each input for Department 12 was displayed in Appendix A. Furthermore, Appendix A shows the average H-Index and funding brought to Department 12 by each kind of faculty members.

Department 12's research expenditure per faculty is about $280,000, with 19 faculty members. Total research expenditure is $5,320,000 (19*$280,000). A new faculty member must contribute $299,00 (20*$281,000-19*$280,000) to raise the Research Expenditure per Faculty by $1,000 (1 unit). This amount of money could be brought to the department by an Associate Professor (Appendix A), costing $102,000 (hiring an Associate Professor).

Increasing the ratio of undergraduate students to faculty is an income for the department; while the number of professors in the department stays constant, increasing the ratio means the department will have a larger intake of undergraduate students in the class. Department 12 requires 19 (19*27.53-19*26.53) more students to increase the Undergraduate Students per Faculty by one unit. Given that Department 12's tuition fees is around $22,000, total cost is $418,000 ($22,000*19). This accounts as a negative value in the Investment Model.

Adding one graduate student would cost around $35,000 (monthly stipend with tuition waiver) for Department 12. In the same way, if Department 12 wants to raise its average H-index by one unit, it must employ a faculty member with an H-index of 35.29 (20*16.29 – 19*15.29), where 19 and 15.29 are the department's existing faculty numbers and average H-index, respectively. Therefore, costing $150,000 (hiring a Chair Professor with an H-index of approximately 40).

4.3.1.2 Matrix (α_{lip}):

As shown in Appendix B, a matrix α_{lip} is constructed to present the effects of increasing one input on other inputs at Department 12. It is critical to recognize that it will vary from one department to the next, depending on the current input values for each department.

Add an Assistant Professor has no influence on the number of Associate Professor, Professor, and Chair Professor, hence a value of 0 is used. The effect is identical when adding an Associate Professor, Professor, and Chair Professor on the other faculty members. However, adding a new faculty member impacts other inputs.

Total research expenditure of Department 12 is $5,320,000 (number of faculty (18) * Research Expenditure per Faculty ($280,009.63)). The overall Research Expenditure per Faculty member would be $273,500, with an Assistant Professor contributing $150,000. To compute the effect, the drop in Research Expenditure per Faculty will be $6,500 ($273,500-$280,009.63). A negative change implies a decrease by $6,500. In addition, Associate Professor, Professor, and Chair Professor are expected to have effects of $1,000, $11,000, and $36,000, respectively.

To assess the influence of adding a new faculty member on the Number of Undergraduate Students per Faculty, we must determine the total number of undergraduate students in the department, which is 504 (Number of Faculty (19) * Undergraduate Students per Faculty (26.53)). So, when an additional faculty member is added to the department, the new undergraduate students per faculty is 25.2 (504/20). Thus, the change in Undergraduate Students per faculty is -1.33 (25.2-26.53).

The effect of adding a new faculty member to the Number of Graduate Students in the department is estimated. 2, 4, 5, and 6 are given in the matrix when an Assistant Professor, Associate Professor, Professor, and Chair Professor is added, respectively. Furthermore, to determine the effect of an additional faculty member on the Average H-index of the department; first, the total H-index of the department is measured, which is 290.51 (Total H-index = 19*15.29). From Appendix A, the average H-index of different faculty members is used. The new average H-index, when an Assistant Professor is hired, is calculated to be 14.95 ((Total H-index of the Department + Average H-index of Assistant Professors)/New Total Number of Faculty] = (290.51 + 8.4)/20). The effect is -0.34 (14.95-15.29). Likewise, for Associate Professor, Professor, and Chair Professor, the effects are 0.08, 0.77, and 1.24, respectively.

When we consider increasing Research Expenditure per Faculty by $1,000 (one unit), it is beyond the scope of this article to estimate the likely effect on other inputs. As a result, all those effects have the value 0 assigned to them. Likewise, when increasing the number of Undergraduate Students per Faculty, Graduate Students, and H-index by one unit, 0 is given in the matrix.

5: Empirical Illustration:

The DEA models are used to evaluate 18 Industrial Engineering departments in the USA. To remain anonymous, these departments in Table I are assigned names ranging from Department 1 to Department 18. Table I shows the inputs and output selected for the study.

Table I: Inputs and the Output for the Case Study

5.1: Results from the Efficiency Model

Table II shows the results of the evaluation of the academic departments. The Efficiency column shows the efficiency of each department, indicating how well they are currently performing with the current amount of inputs. The Reference Set shows the departments it should benchmark to increase its efficiency. λ column of the Reference Set gives the fraction of respective departments a particular department should benchmark to reach the efficiency frontier. For example, Department 11 should use 68% of Department 9, 17% of Department 8, 10% of Department 5, and 5% of Department 2 as references for optimal efficiency (to reach relative efficiency of 1). According to Table II, Department 2 and Department 9 were used as benchmark departments/referents most times, followed by Department 3 and Department 8.

Table II: Summary of the results from the Efficiency Model

5.2: Results from the Benchmarking Model:

Slack input and output data are evaluated to determine what adjustments need to be done or which input/s might be used more efficiently in the academic department to increase its relative efficiency to 1. Benchmarking Model finds the least amount of input required to increase the output levels for the department under study. The slack is computed by comparing the inputs and output of the department under study with the efficient reference set, and the corresponding values indicate changes in the inputs and outputs necessary to make an academic department efficient.

Table III is the summary of the Benchmarking Model of inefficient departments. Department 11 to have a relative efficiency score of 1, it would need to reduce its Undergraduate Students per Faculty from 32.13 to 22.3 and lessen the Number of Graduate Students from 221 to 105, while maintaining similar output from the department to become efficient; otherwise with the current input levels, it must improve its Peer Assessment Score to be efficient. Also, for Department 12, it cannot be said that they have an excess Research Expenditure per Faculty, or they need to reduce the Research Expenditure per

Faculty for the department to be efficient; instead, Department 12 would need to allocate these funds efficiently to conduct cutting edge research that could lead to more visibility for the department, and in turn improve its Peer Assessment Score.

Table III: Summary of the results from the Benchmarking Model

In a real scenario, it may not be possible for the department to become efficient as some of the inputs may not be in control of the decision-makers of the department (Palocsay & Wood, 2014). For example, faculty members can be encouraged or trained to write more proposals for grants; however, whether they will get funding or not is out of their control.

5.3: Results from the Investment Model:

The Investment Model is evaluated with data from Department 12, with an availability of $500,000 investment budget. The decision-makers must decide what they want to accomplish with the allotted investment funds, i.e., give the model a lower and upper bounds for the decision variables that are aligned with departmental goals. For example, in our case study, we have limited the overall hiring of professors in the department to no more than two. Recruitment for each type of faculty members were limited to at most two. The increase in research expenditure per faculty was limited to a maximum of two units. Undergraduate Students per Faculty were limited to a maximum of two units, implying that no more than 38 (19*2) new undergraduate students may be admitted to the department. The Number of Graduate students hired was limited to a maximum of 5, and the rise in the Average H-index was limited to a maximum of 0.5. These limitations are necessary to make the model more realistic, as the model might suggest adding 30 additional graduate students or increasing the number of undergraduate students per faculty by 10 units.

Table V: Summary of the Investment Model for Department 12

The optimal values from the EXCEL SOLVER would differ depending on the investment amount and the department chosen. The model determines which inputs to add for Department 12. It proposes hiring one Assistant Professor, one Professor, and increasing the Average H-index by 0.5. With a $500,000 investment budget, the model optimizes to provide enhanced efficiency of 94 percent for Department 12, up from 88 percent previously (calculated from the Efficiency Model). Department 12 needed to spend $290,000 (1*$95,000 + 1*$120,000 + 0.5*150,000) out of the $500,000 to achieve a 6.8 percent improvement in relative efficiency.

Table V presents the effects on the inputs before and after the investments, considering the impact of adding one or more inputs on the others. Practically, to increase the average H-index of the department by 0.5 (Table V), the $150,000 allocated for that purpose (Appendix A) could be used to set up workshops for faculty members in the department, where they could be trained to write papers to attract more audience. Also, funds could be allocated to attend more conferences to improve the chances for collaborations with senior researchers. Furthermore, increasing opportunities to publish papers in well-known journals leading to improved average H-index of the department in the long run.

6: Discussion:

The principal research question grounded in this study - do relative efficiency scores improve with optimized resource-allocation in inefficient academic departments when an investment budget is provided to the department? Accordingly, in this paper, we aim to undertake this using output-oriented DEA models for optimal resource allocation, by focusing on evaluating relative efficiency of academic departments.

The Efficiency Model identified 5 departments as inefficient and provided potential benchmarks for the inefficient units. 13 departments were deemed efficient; however, with additional peer departments, that number would likely to decrease depicted in the study by Munoz (2015), where they have utilized 39 universities as DMUs and found 6 efficient institutions. The Benchmarking Model revealed that 5 inefficient departments had an excess of Undergraduate Students per Faculty, 4 inefficient departments had under-utilized Graduate Students, and 3 departments did not allocate Research Expenditure per Faculty effectively. With effective use of these inputs – departmental efficiency would rise – potentially increasing Peer Assessment Score. More importantly, the Benchmarking Model provides sources of inefficiencies for each inefficient department.

The main contribution to existing DEA research is development of the framework for the Investment Model, which would provide a system of support to departmental leadership in deciding where to allocate resources and providing directions for improving efficiency when an investment budget is allocated for academic departments. However, decision-makers must establish boundary restrictions in the Investment Model's decision variables, incorporating what is desirable and technically possible. Setting limits aids in making value judgments - avoids unsatisfactory outcomes (Ruiz, Segura & Sirvent, 2015). Examining the changes is necessary since some of the suggestions might not be practical to implement. Also, it must be understood that DEA is sensitive to outliers, which can affect the efficiency ratings. In a nutshell, effective efficiency evaluation, benchmarking, and resource allocations can assist departments to improve relative efficiency, and potentially achieve higher rankings over time.

DEA offers great benefits for benchmarking and efficiency assessments. DEA weightings are optimized in the methodology rather than any prior weightings. It allows for the processing of multiple inputs and outputs and offers an efficiency score for each department individually and identifying causes of inefficiency that provide directions for improvements of lower performing departments. Homogeneous DMUs are a critical component of DEA. However, given the diversity of academic disciplines, this may not always be the case. Science, technology, engineering, and mathematics (STEM) departments at US universities spend far more money on research than other departments. To put it into perspective - the combined research expenditure of science and engineering is more than 30 times that of the arts, humanities, and social sciences (profession.mla.org). Therefore, Research Expenditure per Faculty could be a more valuable input for STEM departments for efficiency assessment than non-STEM departments like Philosophy or Communication. Hadad, Friedman, Rybalkin, & Sinuany-Stern (2013) demonstrated that the degree of homogeneity has the most significant influence on efficiency. This problem of non-homogeneity in DEA has been tackled by Chen, Cook, Imanirad & Zhu (2020), providing fairness in performance evaluation across multiple products and organizations.

6.1 Implications for Practice:

Aside from theoretical implications, we anticipate that our findings will inspire departmental decision-makers and managerial leaders to set strategic plans by applying DEA for efficiency assessment, benchmarking, and effective resource allocation. From an administrative standpoint, with tightening budgets and continuous evaluation in departments, this study provides a structured approach and objectivity to resource allocation utilizing DEA, such that efficiency could be maximized, and potentially higher rankings could be attained. Apart from academics, the proposed framework based on output-oriented DEA models might be utilized as a decision-support system for managers in other industries such as banking (Appiahene, Missah, & Najim, 2020), manufacturing (Kwon, Lee, & Roh, 2016), and healthcare (Ulengin & Sahin, 2007).

6.2 *Directions for Future Research:*

In the future, we hope to analyze with more departments, which would allow measuring more realistic relative efficiency values of departments, making newer benchmarks more attainable for inefficient departments. In addition, accounting for non-homogeneity in the academic departments could make the DEA models more realistic. Furthermore, with more departments, machine learning could be implemented to predict efficiency using different algorithms, so that repetition of computation is not required, which could be time-consuming for large datasets. Moreover, including new inputs such as the number of faculty members in the National Academy of Engineering (NAE) and fellows of different academic societies like the American Society of Mechanical Engineers (ASME) - can help to address the subjectivity to some extent. Finally, considering the non-linear effects of adding input/s in the department under study to the other inputs, could enhance the model further.

7: Conclusion:

For continuous improvement, the university departments need to benchmark their performances by identifying areas requiring significant consideration to achieve higher departmental performance. The departmental administrators need to identify an approach that not only compares all university departments but also find ways in which the efficiency of the department could be improved. It is vital to have good practices within the department so that efficient resource allocation can be applied. How well the departments are utilizing their resources can be identified by conducting efficiency analyses. For benchmarking purposes in an academic setting, DEA is a practical approach.

The results from all three DEA models were recorded and discussed in detail in Section 5.1-5.3. The experimental case study presented that the DEA models can help to create a decision-making support system for the academic departments for effective resource allocation. Starting from finding the relative efficiency of the department to identifying what improvements an inefficient department needs to make to reach an efficiency of 1; finally, improving relative efficiency with proper resource allocation within a given investment budget**.**

Appendix A: Cost of adding one extra unit of inputs; Average H-Index and Average funding brought by faculty members

	Assistant Professor	Associate Professor	Professor	Chair Professor	Research Expenditure /Faculty	Undergraduate Students /Faculty	Graduate Students	H-Index
Approximate cost of hiring/adding one unit	$95,000	$102,000	$120,000	$150,000	$102,000	-$418,000	$35,000	$150,000
Average H-index	8.40	16.87	30.78	40	-	-	-	-
Average Research Funding brought to the Department	$150,000	$300,000	$500,000	$1,000,000	-	-	-	-

Appendix B: α_{lip} (Matrix) - the linear effect of adding one unit of each input to the other inputs of Department 12

	Assistant Professor	Associate Professor	Professor	Chair Professor	Research Expenditure /Faculty	Undergraduate Students /Faculty	Number of Graduate Students	H-Index
Assistant Professor	1	0	0	0	-6.50	-1.33	2	-0.34
Associate Professor	0	1	0	0	1	-1.33	4	0.08
Professor	0	0	1	0	11	-1.33	5	0.77
Chair Professor	0	0	0	1	36	-1.33	6	1.24
Research Expenditure /Faculty	0	0	0	0	1	0	0	0
Undergraduate Students /Faculty	0	0	0	0	0	1	0	0
Number of Graduate Students	0	0	0	0	0	0	1	0
H-Index	0	0	0	0	0	0	0	1

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Table 1: Inputs and the Output for the Case Study

	Inputs					Output
Department (DMUs)	**Number of Faculty**	**Research Expenditure/Faculty**	**Undergraduate Students/Faculty**	**Number of Graduate Students**	**H-Index**	**Peer Assessment Score**
Department 1	61	$173,339.21	21.72	244	33.40	4.8
Department 2	28	$259,818.25	15.11	192	24.18	4.6
Department 3	30	$803,591.83	19.00	146	14.75	4.1
Department 4	27	$333,101	28.70	281	22.90	4
Department 5	25	$106,837.72	17.52	156	20.90	4
Department 6	30	$471,900	21.33	330	16	3.8
Department 7	27	$102,499.96	10.04	96	17.47	3.6
Department 8	10	$82,800	48.10	147	22.82	3.2
Department 9	14	$161,428.57	16.86	80	13.38	3.2
Department 10	11	$103,000	19.45	105	27.38	3.1
Department 11	15	$147,025.60	32.13	221	16.25	3
Department 12	19	$280,009.63	26.53	91	15.29	3
Department 13	14	$76,986.36	21.79	107	14.20	3
Department 14	18	$668,817.56	9.11	253	14.57	2.9
Department 15	15	$100,567.20	14.73	49	14.33	2.7
Department 16	11	$127,578.18	16.91	40	13.33	2.7
Department 17	13	$289,758.92	36.38	142	18.86	2.7
Department 18	10	$87,937.50	31.10	52	18.57	2.5

Table II: Summary of the results from the Efficiency Model

Department (DMU)	Efficiency	Reference Set	λ for each Department in the Reference Set
Department 1	1	1	1
Department 2	1	2	1
Department 3	1	3	1
Department 5	1	5	1
Department 7	1	7	1
Department 8	1	8	1
Department 9	1	9	1
Department 10	1	10	1
Department 13	1	13	1
Department 14	1	14	1
Department 15	1	15	1
Department 16	1	16	1
Department 18	1	18	1
Department 6	0.98	3, 9, 2	0.46, 0.36, 0.18
Department 11	0.90	9, 8, 5, 2	0.68, 0.17, 0.10, 0.05
Department 4	0.90	2, 9, 3	0.88, 0.08, 0.04
Department 12	0.88	9, 7, 2	0.62, 0.33, 0.05
Department 17	0.82	8, 9, 2	0.50, 0.43, 0.07

Table III: Summary of the results from the Benchmarking Model

DMU	Number of Faculty	Research Expenditure/Faculty	Undergraduate Students/Faculty	Number of Graduate Students	H-index
Department 6	6	$0	3.82	199	0
Department 11	0	$0	9.83	116	0
Department 4	0	$66,630	13.3	100	0
Department 12	0	$153,390	11.48	0	0
Department 17	0	$202,490	15.54	39.92	1.19

Table IV: Summary of the Investment Model for Department 12

	Total Number of Faculty		Research Expenditure /Faculty	Undergraduate Students /Faculty	Number of Graduate Students	H-Index
Before the Investment	19		280.01	26.53	91	15.29
Optimized Resource Allocation from the solver	Assistant Professor 1	Professor 1	0	0	0	0.5
The effect of adding an input or the set of inputs on other inputs	0		4.5	-2.66	7	0.43
After the investment	21		284.51	23.87	103	16.32