Research Article https://doi.org/10.12973/eu-jer.12.2.1153

European Journal of Educational Research

Volume 12, Issue 2, 1153 - 1169.

ISSN: 2165-8714

http://www.eu-jer.com/

Data Envelopment Analysis for the Efficiency of Higher Education Departments at Sepuluh Nopember Institute of Technology, Indonesia

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Received: November 12, 2022 ▪ Revised: February 12, 2023 ▪ Accepted: March 13, 2023

Abstract: The quality of higher education is vital for a country's future, not only in terms of transferring knowledge to younger generation but also for supporting economic development. This paper applies data envelopment analysis (DEA) to evaluate the relative efficiency of 38 academic departments at Sepuluh Nopember Institute of Technology, Surabaya, Indonesia. The input factors are the number of lecturers, the number of staff and budget allocations, whereas the output is the performance achievement level. The empirical analysis incorporates two traditional DEA models: the Charnes, Cooper and Rhodes (CCR) and the Banker, Charnes and Cooper (BCC) models with input orientation. The results indicate that the CCR model considers five departments efficient while the BCC model considers ten departments efficient, five of which are those considered efficient by the CCR model. It may seem counterintuitive that a department with an output performance achievement below 100% is deemed efficient, and vice versa. However, the underlying principle of efficiency under input-oriented DEA model is resource utilization. Finally, we provide recommendations for the departments with low efficiency scores to improve their performance.

Keywords: *Data envelopment analysis, efficiency measurement, higher education.*

To cite this article: Wildani, Z., Wibowo, W., Wulandari, S. P., & Ari Dinanti, L. A. (2023). Data envelopment analysis for the efficiency of higher education departments at Sepuluh Nopember Institute of Technology, Indonesia. *European Journal of Educational Research*, *12*(2), 1153-1169. https://doi.org/10.12973/eu-jer.12.2.1153

Introduction

Higher education (HE) contributes significantly to the development of a country's economic growth and national scientific and technological achievement by producing specialists in various fields (Johnes et al., 2017). Sustainable capacity building is a critical driver of productivity and a success factor for the implementation of a strategic plan (Johnes, 2006). Previous studies analyzing the relationship between HE and economic development have demonstrated that HE improvement promotes economic development in various aspects (Kim & Lee, 2006; Youtie & Shapira, 2008). Furthermore, as the number of students enrolled in higher education grows significantly each year, HE institutions must continue improving their quality. In other words, there is an urgent need to develop a HE system that is competitive and able to use available resources (input) efficiently to meet the growing demand for education quality (output) (Abbott & Doucouliagos, 2003).

Sepuluh Nopember Institute of Technology or widely known in Indonesia as Institut Teknologi Sepuluh Nopember (ITS), is one of the leading HE institutions in the field of science and technology located in Surabaya, Indonesia. It has been conferred the status of autonomous public legal entity by the Government of Indonesia, granting it with new responsibilities, including independent management of academic operations and the implementation of organizational, financial, student affairs, manpower, and infrastructure standards. The institution has been evolving and expanding since, and it was ranked third nationally in 2021 and 751+ internationally based on the QS World University Ranking (WUR) in 2022. The current objective of ITS is to achieve a place in the Top 500 of the QS WUR by 2025. Achieving this target would require a transformation of the departments towards greater efficiency which include increased productivity of academic staff members, attainment of international accreditation, and improvements in graduate outcomes, among other measures.

Efficiency has been a topic of interest in various research fields over the past few decades, defined as the capacity to generate maximum output from the available input. The notion of technical efficiency was first introduced by Farrell

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(1957) in the initial paper on productive efficiency. Since then, many studies have measured the efficiency of non-profit organizations, including educational institutions. In fact, research on efficiency was initially concentrated on educational institutions in the early development of efficiency research (Liu et al., 2013). Recently, research on efficiency has become more critical because HE institutions frequently compete for funding support from the government. Their responsibilities are more extensive and standardized, so effectiveness has become more important (Yang et al., 2018). However, measuring efficiency is challenging as it involves examining the interrelationships between various inputs and outputs, using approaches that manage multiple variables and constraints in HE operations (Panwar et al., 2022).

Approaches to measuring efficiency include traditional approaches such as ratio analysis and Stochastic Frontier Analysis (SFA). However, these approaches cannot measure HE institutions' efficiency as they have numerous input and output variables to consider. Data Envelopment Analysis (DEA) is a more suitable method. It measures the efficiency of Decision-Making Units (DMUs) to deal with multiple inputs and outputs in the context of linear programming. A DMU is an organizational unit that converts inputs into outputs, such as a firm, a hospital, a university, or a government agency. The efficiency of a DMU is the ratio of its outputs to its inputs. DEA compares the performance of DMUs that use similar inputs to produce similar outputs. DEA has been applied to measure efficiency in many areas, including higher education institutions (Emrouznejad & Yang, 2018; Panwar et al., 2022; Seiford, 1996). Emrouznejad and Yang reviewed over 10,000 studies that used DEA between 1978 and 2016 and found that about 1.5% of all these studies were focused on evaluating the education sector. DEA was first introduced by Charnes et al. (1978), who later used it to measure the efficiency of educational institutions (Charnes et al., 1981). Since then, many studies have been conducted, including in HE institutions in the UK (Casu & Thanassoulis, 2006; Johnes, 2006; Johnes & Johnes, 1995), China (Jiang et al., 2020; Johnes & Yu, 2008; Yang et al., 2018), South Korea (Shamohammadi & Oh, 2019), Australia (Abbott & Doucouliagos, 2003; Avkiran, 2001; Duan, 2019), Taiwan (Chen & Chang, 2021; Kao & Hung, 2008), Chile (Cossani et al., 2022). As of 2013, 184 studies were recorded using DEA to measure the efficiency of education institutions (De Witte & López-Torres, 2017; Liu et al., 2013).

This study aims to measure technical and scale efficiency in academic departments of ITS by considering certain input and output variables. Thus far, research on HE efficiency in Indonesia is rare. One of the few studies calculated the efficiency of primary schools in 34 provinces in Indonesia (Fatimah & Mahmudah, 2017). This study employed two DEA models and the result showed that 12 and 17 provinces out of 34 provinces in Indonesia are efficient and three environmental variables significantly affect the efficiency score. Another study examined efficiency at the university level (Mahmudah & Lola, 2016). This study examined the top 25 universities in Indonesia in 2015 using DEA and fuzzy DEA. The finding revealed that well-known universities tend to have lower efficiency scores. Furthermore, at the departments level at Malaikulsaleh University, a study by Abdullah et al. (2017) used DEA to evaluate the efficiency of its departments. The study found that increasing the number of research could increase the efficiency scores.

DEA has not been widely employed to measure efficiency in HE institutions in Indonesia, unlike in the banking or health management industries. Therefore, this study aims to address this gap in the literature by measuring the efficiency of HE departments in Indonesia specifically ITS. Besides, one of the limitations of previous studies that used DEA in efficiency measurement is the lack of a clear interpretation of DEA results. Although DEA is a powerful tool for measuring relative efficiency, its results can be difficult to interpret without a thorough understanding of the methodology and context of the analysis. Studies that focus solely on DEA results without providing a clear explanation of how the results were obtained or what they mean in the context of the institution being studied may not provide meaningful insights for decision-makers. Therefore, this study not only employs DEA to measure efficiency of departments but also provides a comprehensive interpretation of the DEA results, making it capable of generating quantitative recommendations. The findings of this study can help university management on identifying areas for improvement, better resource allocation and finally increase international recognition of ITS.

The paper is organized as follows. Section 2 discusses the DEA methodology. Section 3 presents the results of technical and scale efficiency measures of the 38 departments at ITS and then followed by conclusion and recommendation.

Methodology

Research Design

This research uses two DEA models to measure the efficiency of the university's departments, namely the Charnes, Cooper, and Rhodes (CCR) model based on the work of (Charnes et al., 1978) and the Banker, Charnes, and Cooper (BCC) model based on the work of (Banker et al., 1984). Efficiency is defined as the ratio of output to input, as shown below (Panwar et al., 2022)

$$Efficiency\ (e) = \frac{Output}{Input} \tag{1}$$

However, in real-life scenarios, efficiency is defined by multiple inputs and outputs. This is when DEA overcome the shortcoming of other methods by measuring efficiency as a weighted sum of outputs to the inputs, as written in Equation (2).

$$Efficiency\ (e) = \frac{Weighted\ Sum\ of\ the\ Output}{Weighted\ Sum\ of\ the\ Input} \tag{2}$$

In this paper, DEA is utilized to explore technical and scale efficiencies. Technical efficiency gives information on how well a firm processes its inputs to produce outputs in relation to its best frontier, representing its maximum capacity to accomplish it (Barros & Mascarenhas, 2005). The input-oriented DEA is concerned with how much input can be reduced proportionally without changing the output level. In other words, an efficient DMU is one that uses the minimum inputs to produce a given set of outputs. Meanwhile, output-oriented DEA focuses on how much output can be improved with the same number of inputs. The efficiency score of an inefficient DMU is less than one, while the efficiency score of an efficient DMU is one.

The CCR model under the assumption of CRS is also referred as Overall Technical Efficiency (OTE), which determines inefficiency from input/output configuration and the size of operations. OTE is divided into two components: Pure Technical Efficiency (PTE) and Scale Efficiency (SE). PTE, represented by an efficiency score from the BCC model under the assumption of VRS, and has been employed to measure managerial performance. Meanwhile, SE can be obtained by the ratio of OTE to PTE defined by the CCR and BCC models. SE shows how an institution can adjust its size to the most optimal (frontier).

Sample and Data Collection

The Decision-Making Units (DMUs) selected in this study are 38 departments at ITS, which are part of seven faculties (consisting of 39 departments): (a) the Faculty of Science and Data Analytics; (b) the Faculty of Industrial Technology and Systems Engineering; (c) the Faculty of Civil, Planning, and Geo-Engineering; (d) the Faculty of Marine Technology; (e) the Faculty of Intelligent Electrical and Informatics Technology; (f) the Faculty of Creative Design and Digital Business;(g) the Faculty of Vocational Studies and (h) School of Interdisciplinary Management and Technology. The Department of Offshore Engineering, which was recently established at the Faculty of Marine Technology, was excluded from this study. The 38 departments chosen as DMUs are listed in Table 1.

Previous studies have discussed the selection of input and output variables (Dyson et al., 2001). As we mentioned earlier, the DEA model is sensitive to the specification of the inputs and outputs. There are no specific conditions are required in choosing input and output variables, the size of the sample, or the number of DMUs (Cook et al., 2014). Therefore, in this study, we consider one output and three input variables, which are presented in Table 1.

Table 1. Input and Output Variables

Input Variables	Output Variable
Number of Lecturers	Performance Achievement (%)
Number of Staff	
Budget Allocation (in '000' rupiah)	

Budget allocation refers to the expenses disbursed by the university's management to cover the operations of departments, including procurement and maintenance of equipment and facilities, the payment of adjunct professors and part-time employees, and the settlement of telephone and travel bills. The salaries of full-time lecturers and staff are paid directly by the university's Accounting Office and are not included in a department's expenses. Performance measurement (in percentage) is used as an output variable and is carried out quarterly in all work units at ITS through a performance application system.its.ac.id. The chief of each department completes the questionnaire and attaches proofs of achievement to it. The percentage of performance achievement is calculated as follows.

$$Performance\ Achievement\ (\%) = \frac{Achievement}{Target}\ x\ 100$$

Performance achievement as output variable is considered a comprehensive and robust measurement for evaluating the efficiency of ITS based on ITS performance agreement with the Ministry of Education and Research of Indonesia in 2021. The are ten key performance indicators that were formulated based on four main ITS' strategic targets, considering a range of indicators that reflect various aspects of higher education quality including the improvement of (a) the quality of HE graduates; (b) the quality of HE lecturers; (c) the quality of curriculum and learning and (d) the governance of work units within the Directorate General of Higher Educations. Data input and output variables were obtained from ITS's Program Management and Control Unit, and we used data in the year of 2021. We had obtained permission from relevant authorities to use the data.

Findings / Results

Table 2 displays the input and output variables for each department within each faculty, while Figure 1 depicts the performance achievements of the 38 departments ranked in descending order from the highest to the lowest. For the convenience of international readers, we have also included the budget allocation figures in USD with the amounts presented in brackets.

Table 2. Input and Output Measures of the 38 Departments at ITS

Faculty	Department	Output	Input			
		Performance Achievement	Number of Lecturers	Budget Allocation n '000' rupiah	[USD]	Number of Staff
Faculty of Science and Data Analytics	Physics	101.10%	41	1656552	[108427.28]	13
	Chemistry	103.34%	33	2088060	[136671.03]	12
	Mathematics	106.21%	24	1044882	[68391.28]	9
	Biology	107.22%	43	1946934	[127433.83]	11
	Statistics	110.19%	30	2828443	[185131.76]	12
	Actuarial Science	79.23%	7	1305036	[85419.30]	4
Faculty of Industrial Technology and Systems Engineering	Mechanical Engineering	106.91%	47	5469687	[358010.67]	16
	Chemical Engineering	106.84%	37	3398160	[222421.78]	19
	Physics Engineering	88.37%	31	2764851	[180969.43]	10
	Industrial Engineering	110.47%	42	5030022	[329233.01]	14
	Materials and Metallurgical Engineering	104.64%	25	2389875	[156425.91]	12
Faculty of Civil. Planning. and Geo-Engineering	Civil Engineering	106.95%	56	5344467	[349814.57]	25
	Environmental Engineering	101.90%	27	2503556	[163866.74]	12
	Geomatics Engineering	104.20%	21	1835085	[120112.91]	10
	Geophysical Engineering	96.64%	12	1215849	[79581.69]	6
	Architecture	106.09%	36	3174534	[207784.66]	12
	Urban and Regional Planning	87.46%	23	2611218	[170913.60]	10
Faculty of Marine Technology	Naval Architecture	96.78%	27	2328701	[152421.85]	15
	Marine Engineering	92.31%	32	3229476	[211380.81]	14
	Ocean Engineering	104.27%	25	2020482	[132247.81]	16
	Marine Transportation Engineering	96.00%	14	902346	[59061.79]	5
Faculty of Intelligent Electrical and Informatics Technology	Informatics Engineering	108.50%	45	6284338	[411332.50]	17
	Information System	107.22%	36	4399637	[287972.05]	12
	Information Technology	98.25%	8	1048884	[68653.23]	5
	Electrical Engineering	104.18%	55	6116175	[400325.63]	14
	Computer Engineering	91.89%	19	1390272	[90998.30]	6
	Biomedical Engineering	105.49%	10	1177836	[77093.60]	5
Faculty of Creative Design and Digital Business	Product Design	104.64%	17	1716372	[112342.72]	8
	Interior Design	94.14%	14	1332306	[87204.22]	7
	Visual Communication Design	104.70%	16	1332306	[87204.22]	5
	Business Management	107.99%	22	2513935	164546.08	7
	Development Studies	104.50%	31	734112	[48050.27]	4
Faculty of Vocational Studies	Civil Infrastructure Engineering	95.30%	31	2189280	[143296.24]	15
	Industrial Mechanical Engineering	94.52%	20	1830240	[119795.78]	8
	Automation Electric Engineering	99.45%	14	1427856	[93458.31]	8
	Industrial Chemical Engineering	98.19%	17	863704	[56532.53]	10
	Instrumentation Engineering	99.66%	13	1188948	[77820.92]	8
	Business Statistics	93.05%	14	1127700	[73812.02]	7

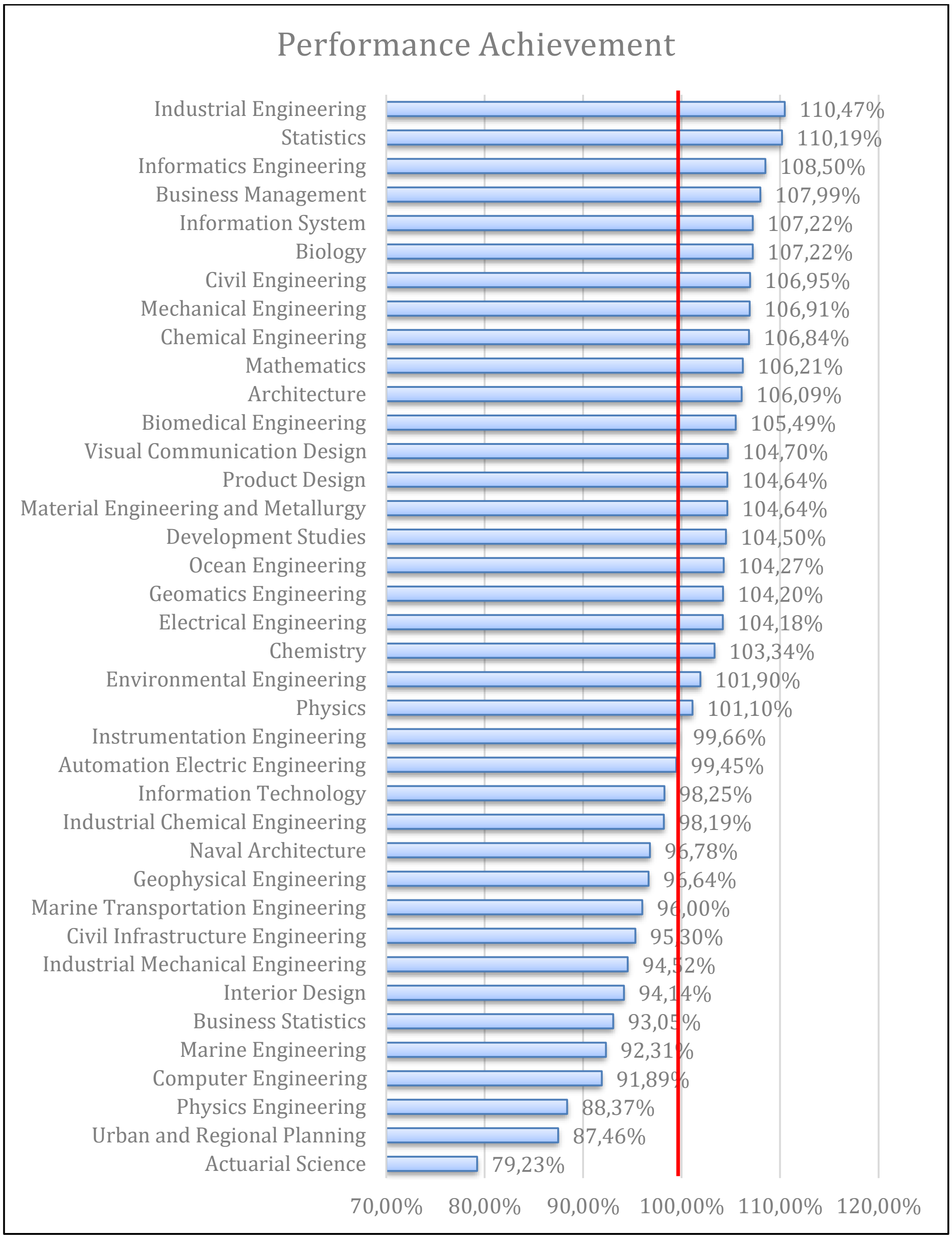

Figure 1. Performance Achievement of Departments at ITS in the Second Quarter of 2021

Overall, Figure 1 shows that there is a significant variation in performance achievements across different departments. Some departments have achieved remarkable results, while others underperformed. Out of 38 departments, there are 22 departments have achieved performance levels higher than 100% exceeding the achievement target. Meanwhile, 16 departments have underperformed with percentages below 100%. The Department of Industrial Engineering has recorded the highest performance achievement of 110.47%, while the Department of Actuarial Science has the lowest achievement of 79.23%. The top five departments with outstanding performance after the Department of Industrial Engineering were the Departments of Statistics, Informatics Engineering, Business Management, Information Systems, and Biology. The remaining 13 departments have scored greater than 90%, which could be categorized as extremely good, requiring only minor improvement to achieve 100%. Lastly, the departments with an unsatisfactory performance of below 90% were the Departments of Physic Engineering, Urban and Regional Planning, and Actuarial Science. As for the number of lecturers, the Department of civil engineering has the highest number, while the Department of Actuarial Science has the lowest. Table 3 presents the statistical analysis of the input and output variables.

Table 3. Summary Statistics of the Output and Input Variables

Variable	Mean	Variance	Min	Max
Output				
Performance Achievement (%)	100.76	50.36	79.23	110.47
Input				
Number of Lecturers	26.71	164.265	7	56
Number of Staff	10.61	21.435	4	25
Budget Allocation (in ‘000’ rupiah)	2414793	2.302e+12	734112	6284338

The table presents the mean, variance, minimum, and maximum values of input and output variables. The Performance Achievement variable has a mean of 100.76, indicating that, on average, the departments have exceeded the performance target set by the institution. The variance of 50.36 suggests that there is a considerable variation in performance across different departments. As for the number of lecturers, it has a mean of 26.71, indicating that the departments have an average of 26.71 lecturers. However, the variance of 164.265 shows that the number of lecturers varies significantly across departments, ranging from 7 to 56. The number of staff variable has a mean of 10.61, indicating that the departments have an average of 10.61 staff members. The variance of 21.435 shows that the number of staff members varies, ranging from 4 to 25. Lastly, the Budget Allocation variable (in ‘000’ rupiah) has a mean of 2,414,793, indicating that the departments have an average budget allocation of 2,414,793,000 rupiahs. The variance of 2.302e+12 suggests that there is a considerable variation in budget allocation across different departments, ranging from 734,112,000 to 6,284,338,000 rupiahs.

The CCR Model

Table 4 summarizes the results of applying an input-oriented DEA with CCR and BCC model and Scale Efficiency (SE) of the 38 departments. The result reveals that, based on the CCR model with the Constant Return to Scale (CRS) assumption, five departments are considered efficient, as shown by the scores equal to 1. These include Department of Marine Transportation Engineering (DMU_{21}), Department of Information Technology (DMU_{24}), Department of Biomedical Engineering (DMU_{27}), Department of Development Studies (DMU_{32}), and Department of Industrial Chemical Engineering (DMU_{36}). The input utilization in these departments is optimal so that they can perform best practices as efficient frontiers. These departments can set the standard for other departments to attain maximum efficiency.

Table 4. Efficiency Score of the 38 Departments at ITS

No.	DMU	CCR (OTE)	BCC (PTE)	SE = OTE/PTE
Faculty of Science and Data Analytics				
1	Physics	0.511	0.514	0.993
2	Chemistry	0.463	0.483	0.959
3	Mathematics*	0.867	**1**	0.867
4	Biology	0.478	0.818	0.584
5	Statistics*	0.426	**1**	0.426
6	Actuarial Science*	0.981	**1**	0.981
Faculty of Industrial Technology and Systems Engineering				
7	Mechanical Engineering	0.305	0.383	0.796
8	Chemical Engineering	0.318	0.469	0.677
9	Physics Engineering	0.401	0.414	0.967
10	Industrial Engineering*	0.359	**1**	0.359
11	Materials and Metallurgical Engineering	0.446	0.470	0.949
Faculty of Civil, Planning and Geo Engineering				
12	Civil Engineering	0.208	0.309	0.673
13	Environmental Engineering	0.416	0.425	0.979
14	Geomatics Engineering	0.569	0.597	0.952
15	Geophysical Engineering	0.818	0.829	0.987
16	Architecture	0.402	0.464	0.867
17	Urban and Regional Planning	0.409	0.438	0.935
Faculty of Marine Technology				
18	Naval Architecture	0.415	0.416	0.996
19	Marine Engineering	0.310	0.331	0.936
20	Ocean Engineering	0.508	0.535	0.950
21	Marine Transportation Engineering**	**1**	**1**	1

Table 5. Continued

No.	DMU	CCR (OTE)	BCC (PTE)	SE = OTE/PTE
Faculty of Intelligent Electrical and Informatics Technology				
22	Informatics Engineering	0.295	0.519	0.568
23	Information System	0.407	0.531	0.765
24	Information Technology**	**1**	**1**	1
25	Electrical Engineering	0.327	0.327	0.999
26	Computer Engineering	0.692	0.741	0.934
27	Biomedical Engineering**	1	1	1
Faculty of Creative Design and Digital Business				
28	Product Design	0.639	0.660	0.968
29	Interior Design	0.719	0.743	0.967
30	Visual Communication Design	0.946	0.946	0.999
31	Business Management*	0.698	**1**	0.698
32	Development Studies**	**1**	**1**	1
Faculty of Vocational Studies				
33	Civil Infrastructure Engineering	0.417	0.422	0.988
34	Industrial Mechanical Engineering	0.551	0.576	0.956
35	Automation Electric Engineering	0.716	0.724	0.989
36	Industrial Chemical Engineering**	**1**	**1**	1
37	Instrumentation Engineering	0.845	0.856	0.987
38	Business Statistics	0.813	0.847	0.960

* Efficient department based on BCC model; ** efficient department based on CCR and BCC model

The remaining 33 departments' performance has scored less than 1, which means they are technically inefficient. Efficiency scores among the inefficient departments range from 0.208 (the Department of Civil Engineering (DMU_{12})) to 0.981 (the Department of Actuarial Science (DMU_6)). This finding suggests that the Departments of Civil Engineering and Actuarial Science can reduce their current input levels by at least 79.2% (1-0.208 x 100) and 1.9% (1- 0.981 x 100), respectively, without jeopardizing their output. In other words, the Departments of Civil Engineering and Actuarial Science can reduce the number of lecturers and staff, as well as budget allocation by at least 79.2% and 1.9%, respectively, and achieve the same performance levels. This interpretation is also applicable to other inefficient departments or DMUs. The average aggregate efficiency score (OTE) from the CCR model is 0.597, with a standard deviation of 0.251 (see Table 5).

Based on the information provided, it appears that the evaluation of departmental efficiency is based on resource utilization, which means that departments that use fewer resources to perform their operational duties are considered more efficient, regardless of their performance achievement. The Department of Industrial Chemical Engineering (DMU_{36}) and the Department of Marine Transportation (DMU_{21}) have efficiency scores of 1, indicating that they are highly efficient in their resource utilization. Even though their overall performance may be less than 100%, they are using relatively fewer resources to achieve their outputs. In contrast, the Departments of Industrial Engineering (DMU_{10}), Statistics (DMU_5), Informatics Engineering (DMU_{22}), and Electrical Engineering (DMU_{25}) have lower efficiency scores despite performing above 100%. This indicates that they are using a larger amount of resources relative to the outputs they produce. This could be an indication that these departments could benefit from a closer look at their resource allocation and utilization to improve their overall efficiency.

The BCC Model

Table 4 also includes the efficiency scores derived from the BCC model (Pure Technical Efficiency/ PTE) under the VRS assumption. According to the PTE, inefficiency directly results from managerial underperformance in utilizing inputs. In this model, ten departments were considered efficient, five of which were the departments considered efficient by the CCR model. The five departments that became efficient under the VRS assumption but inefficient under the CRSare Mathematics (DMU_3), Statistics (DMU_5), Actuarial Science (DMU_6), Industrial Engineering (DMU_{10}), and Business Management (DMU_{31}). It is important to note that the BCC model produces efficiency scores higher or equal to those obtained by the CCR model. Since these five departments became efficient under the VRS assumption but inefficient under the CRS case, we can conclude that the inefficiency is not due to poor input utilization, i.e., managerial inefficiency, but rather due to operations with insufficient scale size (scale inefficiency). Departments scoring 1 in the CCR and BCC model are referred to as 'globally efficient' and 'locally efficient,' respectively (Kumar & Gulati, 2008).

The table also shows that 28 departments were purely technically inefficient (PTE's score was less than 1). The efficiency scores among the inefficient departments ranged from 0.309 (the Department of Civil Engineering (DMU_{12})) to 0.974 (the Department of Visual Communication Design (DMU_{30})). The exact interpretation of the efficiency score in the CCR model applies to the BCC model. Out of 28 departments, 27 departments (except for the Department of Biology) have

BCC efficiency score less than the SE score, which means that the inefficiency of input utilization in these departments is attributed more to managerial inefficiency than scale inefficiency. The average efficiency based on the BCC model is 0.679 with a standard deviation is 0.249 (see Table 5.) Scale efficiency (SE) is the ratio of CCR and BCC efficiency score.

Table 6. Summary Statistics of the Efficiency Scores (OTE, PTE, and SE)

Statistics	**CCR (OTE)**	**BCC (PTE)**	**SE**
Mean	0.597	0.679	0.885
Std. deviation	0.251	0.249	0.169
Max	1	1	1
Min	0.208	0.309	0.359
Q1	0.408	0.465	0.867
Q2	0.510	0.629	0.960
Q3	0.817	0.987	0.989

The Department's Inefficiency Levels

Categorizing the efficiency levels is an essential step in determining which department requires immediate attention. Four categories have emerged from the analysis based on quartile values of OTE and PTE scores acquired from the CCR model and BCC model (Kumar & Gulati, 2008) (refer to Table 5 for the quartile values). The least efficient departments are those with a TE score (OTE and PTE) below the first quartile (Q1), i.e., an efficiency score below 0.3. The slightly efficient departments are those with an efficiency score between the first quartile (Q1) and the second quartile (Q2), i.e., an interval efficiency score of $0.3 \le E < 0.5$. The moderately efficient category includes departments with efficiency scores between the second quartile (Q2) and third quartile (Q3), i.e., an interval efficiency score of $0.5 \le E < 0.8$. Lastly, the nearly efficient departments have efficiency scores above the third quartile, $0.8 \le E < 1$.

It is crucial to identify the departments that fall into the "least efficient" category as they require immediate attention to address their inefficiencies. The departments that fall into the "slightly efficient" category should also be monitored closely, as they are not performing optimally. The "moderately efficient" and "nearly efficient" categories indicate that the departments are performing reasonably well, but there is still room for improvement.

Table 7. The Distribution of Efficiency Scores

Efficiency Interval	**CCR (OTE)**	**BCC (PTE)**	**Categorization**
$0.2 \le E < 0.3$	2	0	Least Efficient
$0.3 \le E < 0.4$	5	4	Slightly Efficient
$0.4 \le E < 0.5$	11	9	
$0.5 \le E < 0.6$	4	6	Moderately Efficient
$0.6 \le E < 0.7$	3	1	
$0.7 \le E < 0.8$	2	3	
$0.8 \le E < 0.9$	4	4	Nearly Efficient
$0.9 \le E < 1$	2	1	
E=1	5	10	Efficient

Based on the OTE scores presented in Table 4, the Departments of Civil Engineering (DMU_{12}) and Informatics Engineering (DMU_{22}) are the most inefficient department. However, based on the PTE scores, they fall under the slightly efficient category. Although these two departments performed above 100%, for instance, the Department of Civil Engineering (DMU_{12}) achieving 106.95% and Informatics Engineering (DMU_{22}) achieving 108.5%, they achieved these scores by utilizing only 0.2 to 0.3 of their resources.

Meanwhile, based on the OTE scores, the Departments of Statistics (DMU_5), and Industrial Engineering (DMU_{10}) fall under the slightly efficient category. However, the PTE scores consider them as efficient departments. The significant differences in the efficiency scores indicate that the inefficiency is attributed more to scale than managerial inefficiency. As for the nearly efficient group (efficiency score $0.8<E<0.9$) consisting of the Departments of Geophysical Engineering (DMU_{15}), Visual Communication Design (DMU_{30}), Instrumentation Engineering (DMU_{37}), Business Statistics (DMU_{38}), and Biology (DMU_4) require special attention. It is worth noting that although these departments are not fully efficient, they operate with a high level of operational efficiency and are close to the efficient frontier. Minor improvements in the resource utilization process should help these departments achieve efficiency.

Reference Sets for Inefficient Departments

In order to improve the efficiency of inefficient departments, they can refer to efficient departments for good operating practices. The reference set is a collection of efficient DMUs that inefficient DMUs can refer to for guidance on improving their efficiency levels. The frequency at which a department appears in reference sets for inefficient departments can indicate its robustness compared to other efficient departments. Specifically, a department that appears more frequently is considered more stable. Such robustly efficient departments will remain efficient even if their inputs change significantly. On the other hand, a department may be efficient by default, meaning it does not possess the characteristics that other inefficient departments need to follow, and as a result, it may have a zero frequency in the reference set, indicating it is not a suitable reference point. Figures 2 and 3 depict the reference set for inefficient departments and the frequency of appearance of each efficient department in the reference set. The results show that the Department of Development Studies is the most robust, appearing 23 and 16 times in the reference sets for CCR and BCC models, respectively. Meanwhile, the Department of Industrial Engineering has a zero frequency in the reference set, indicating that although it is efficient, it does not have any exemplary practices that inefficient departments should emulate to improve their efficiency levels.

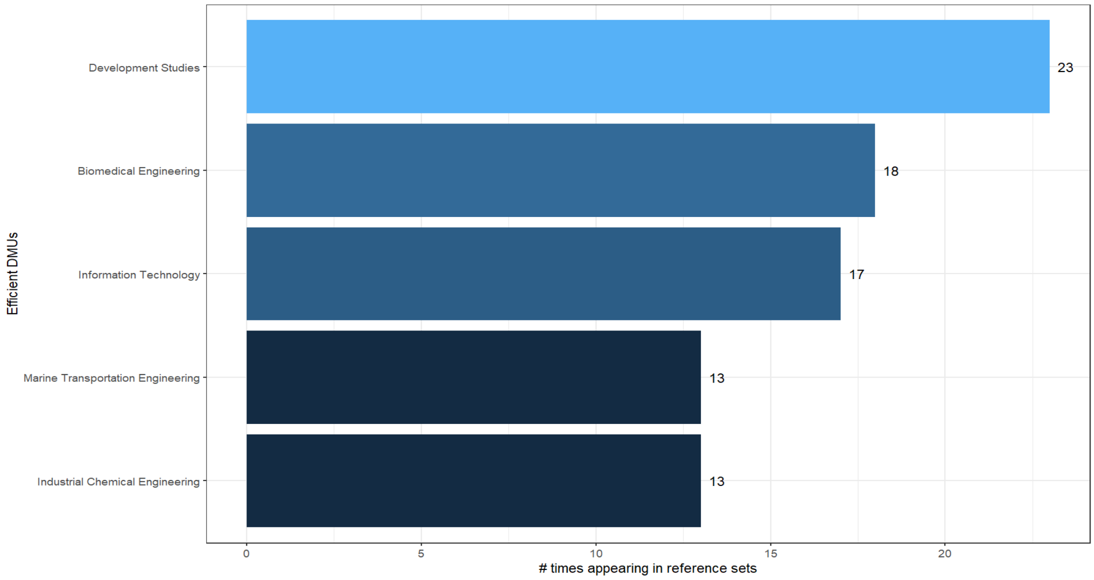

Figure 2. The Frequencies of Efficient DMUs Appearing in the Reference Set (CCR Model)

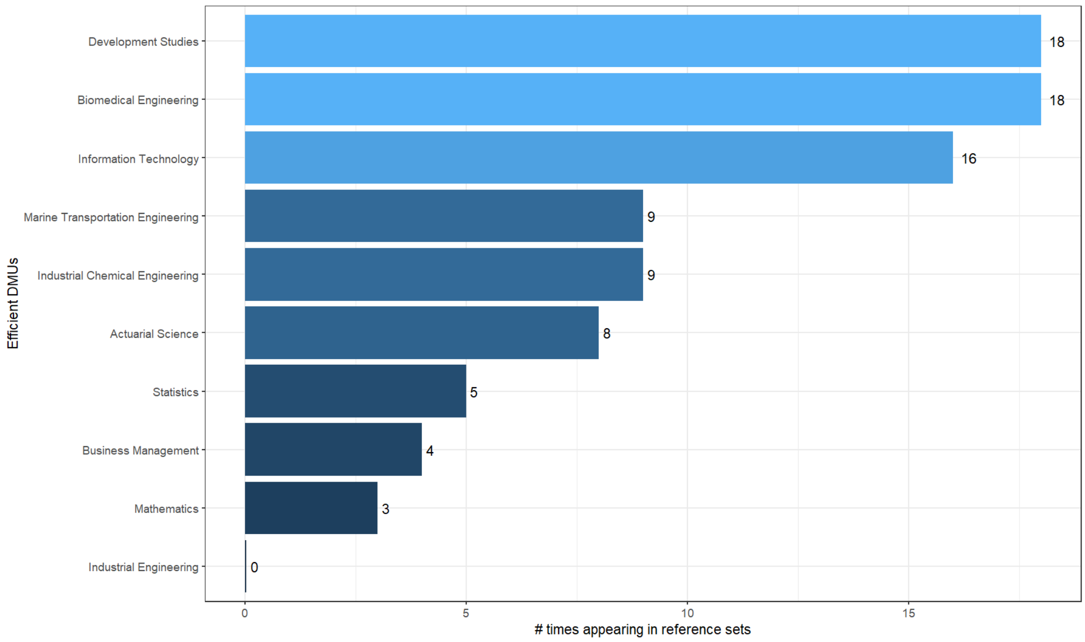

Figure. 3. The Frequencies of Efficient DMUs Appearing in the Reference Set (BCC Model)

Figures 2 and 3 only show the frequencies of efficient departments in the reference set of inefficient departments without indicating which are the ideal reference department. To identify the ideal reference department, we can examine the lambda values, which reflect the intensity level for each efficient department based on the CCR and BCC model. Table 7 shows the lambda values for each department in the sample. If the lambdas are not equal to zero, then the efficient department is in the reference set for the inefficient department. For instance, the Department of Physics (DMU_1) has lambda levels of 0.3077, 0.329, and 0.3786, from the Departments of Marine Transportation Engineering (DMU_{21}), Development Studies (DMU_{32}), and Industrial Chemical Engineering (DMU_{36}), respectively, from a solution of the CCR model. In mathematical notation, these can be written as $\lambda_j \neq 0, for\ j = 21, 32, and\ 36$, respectively, and $\lambda_j = 0$ otherwise (observing that these departments are efficient). This indicates that these efficient departments become the input utilization reference or benchmark for the Department of Physics to become efficient. Furthermore, the Department of Physics is more likely to model its practices after the Department of Industrial Chemical Engineering (DMU_{36}) than other two reference departments as observed from the respective λ weights, where the lambda weight of the Departments of Industrial Chemical Engineering (DMU_{36}) is greater than λ weights of the Departments of Marine Transportation Engineering (DMU_{21}), and Development Studies (DMU_{32}) ($\lambda_{36} = 0.3786, \lambda_{32} = 0.329, \lambda_{36} = 0.3077$). Efficient departments such as Mathematics, Statistics, and so on are considered as benchmarks for their own practices. In this case, the lambda values will be equal to 1 for themselves while the values from other departments are equal to 0.

Table 7. Lambdas Obtained from the Solutions of the CCR and BCC Models

No	DMUs	Lambdas (CCR and BCC Model)
1	Physics	$\lambda_{21} = 0.3077. \lambda_{32} = 0.329. \lambda_{36} = 0.3786$ **(CCR)** $\lambda_{24} = 0.1308. \lambda_{27} = 0.0508. \lambda_{36} = 0.4173\ \lambda_{32} = 0.4012$ **(BCC)**
2	Chemistry	$\lambda_{21} = 1.0294. \lambda_{32} = 0.0072. \lambda_{36} = 0.0383$ **(CCR)** $\lambda_{24} = 0.0622\ \lambda_{27} = 0.5141. \lambda_{32} = 0.220. \lambda_{36} = 0.2029$ **(BCC)**
3	Mathematics*	$\lambda_{21} = 0.2899. \lambda_{32} = 0.2457. \lambda_{36} = 0.5368$ **(CCR)** $\lambda_{3} = 1$ **(BCC)**
4	Biology	$\lambda_{21} = 0.7583. \lambda_{32} = 0.3074. \lambda_{36} = 0.0234$ **(CCR)** $\lambda_{3} = 0.4504. \lambda_{5} = 0.3427. \lambda_{32} = 0.2069$ **(BCC)**
5	Statistics*	$\lambda_{27} = 0.9344. \lambda_{32} = 0.1112$ **(CCR)** $\lambda_{5} = 1$ **(BCC)**
6	Actuarial Science*	$\lambda_{24} = 0.4905. \lambda_{27} = 0.2943$ **(CCR)** $\lambda_{6} = 1$ **(BCC)**
7	Mechanical Engineering	$\lambda_{27} = 0.8165. \lambda_{32} = 0.1988$ **(CCR)** $\lambda_{27} = 0.368. \lambda_{31} = 0.5862. \lambda_{32} = 0.0458$ **(BCC)**
8	Chemical Engineering	$\lambda_{21} = 0.3307. \lambda_{24} = 0.6524. \lambda_{36} = 0.112$ **(CCR)** $\lambda_{3} = 0.1481. \lambda_{5} = 0.2645. \lambda_{27} = 0.5873$ **(BCC)**
9	Physics Engineering	$\lambda_{27} = 0.6479. \lambda_{32} = 0.1916$ **(CCR)** $\lambda_{6} = 0.6244. \lambda_{24} = 0.0682. \lambda_{27} = 0.0761. \lambda_{32} = 0.2313$ **(BCC)**
10	Industrial Engineering*	$\lambda_{27} = 0.8307. \lambda_{32} = 0.2186$ **(CCR)** $\lambda_{10} = 1$**(BCC)**
11	Material Engineering and Metallurgy	$\lambda_{21} = 0.3787. \lambda_{24} = 0.6814. \lambda_{32} = 0.0128$ **(CCR)** $\lambda_{27} = 0.8435. \lambda_{32} = 0.0463. \lambda_{36} = 0.1102$ **(BCC)**
12	Civil Engineering	$\lambda_{24} = 0.6934. \lambda_{27} = 0.2546. \lambda_{32} = 0.1145$ **(CCR)** $\lambda_{3} = 0.1002. \lambda_{5} = 0.2953. \lambda_{27} = 0.6045$ **(BCC)**
13	Environmental Engineering	$\lambda_{24} = 0.8384. \lambda_{27} = 0.0591. \lambda_{32} = 0.1272$ **(CCR)** $\lambda_{24} = 0.4419. \lambda_{27} = 0.4189. \lambda_{32} = 0.0991. \lambda_{36} = 0.0401$**(BCC)**
14	Geomatics Engineering	$\lambda_{21} = 0.4629. \lambda_{24} = 0.5423. \lambda_{36} = 0.0661$ **(CCR)** $\lambda_{27} = 0.7669. \lambda_{32} = 0.0652. \lambda_{36} = 0.1679$ **(BCC)**
15	Geophysical Engineering	$\lambda_{21} = 0.2203. \lambda_{24} = 0.7406. \lambda_{32} = 0.0261$ **(CCR)** $\lambda_{6} = 0.0273. \lambda_{21} = 0.3288. \lambda_{24} = 0.644$ **(BCC)**
16	Architecture	$\lambda_{27} = 0.7977. \lambda_{32} = 0.2099$ **(CCR)** $\lambda_{5} = 0.0284. \lambda_{27} = 0.785. \lambda_{31} = 0.1866$ **(BCC)**
17	Urban and Regional Planning	$\lambda_{27} = 0.7762. \lambda_{32} = 0.0534$ **(CCR)** $\lambda_{6} = 0.562. \lambda_{21} = 0.2102. \lambda_{24} = 0.1682. \lambda_{32} = 0.0596$ **(BCC)**
18	Naval Architecture	$\lambda_{21} = 0.1648. \lambda_{24} = 0.5688. \lambda_{36} = 0.2553$ **(CCR)** $\lambda_{21} = 0.540\ \lambda_{24} = 0.4595$ **(BCC)**
19	Marine Engineering	$\lambda_{24} = 0.068. \lambda_{27} = 0.7524. \lambda_{32} = 0.0598$ **(CCR)** $\lambda_{6} = 0.3018. \lambda_{21} = 0.2551. \lambda_{24} = 0.3834. \lambda_{32} = 0.0597$ **(BCC)**
20	Ocean Engineering	$\lambda_{24} = 0.5935. \lambda_{36} = 0.468$ **(CCR)** $\lambda_{27} = 0.7377. \lambda_{32} = 0.1101. \lambda_{36} = 0.1522$ **(BCC)**
21	Marine Transportation Engineering**	$\lambda_{21} = 1$ **(CCR)** $\lambda_{21} = 1$**(BCC)**
22	Informatics Engineering	$\lambda_{27} = 0.889. \lambda_{32} = 0.1409$ **(CCR)** $\lambda_{5} = 0.4345. \lambda_{27} = 0.1783. \lambda_{31} = 0.3872$ **(BCC)**

Table 7. Continued

No	DMUs	Lambdas (CCR and BCC Model)
23	Information System	$\lambda_{27} = 0.8062. \lambda_{32} = 0.2122$ **(CCR)** $\lambda_{27} = 0.2631. \lambda_{31} = 0.7047. \lambda_{32} = 0.0322$ **(BCC)**
24	Information Technology**	$\lambda_{24} = 1$ **(CCR)** $\lambda_{24} = 1$ **(BCC)**
25	Electrical Engineering	$\lambda_{27} = 0.6078. \lambda_{32} = 0.3834$ **(CCR)** $\lambda_{6} = 0.0354. \lambda_{27} = 0.5791. \lambda_{32} = 0.3855$ **(BCC)**
26	Computer Engineering	$\lambda_{27} = 0.6623. \lambda_{32} = 0.2107$ **(CCR)** $\lambda_{6} = 0.3582\ \lambda_{21} = 0.3347. \lambda_{24} = 0.1141. \lambda_{32} = 0.193$ **(BCC)**
27	Biomedical Engineering**	$\lambda_{27} = 1$ **(CCR)** $\lambda_{27} = 1$ **(BCC)**
28	Product Design	$\lambda_{24} = 0.6916. \lambda_{27} = 0.2607. \lambda_{32} = 0.0879$ **(CCR)** $\lambda_{24} = 0.0466\ \lambda_{27} = 0.8476. \lambda_{32} = 0.0412\ \lambda_{36} = 0.0646$ **(BCC)**
29	Interior Design	$\lambda_{21} = 0.3286. \lambda_{24} = 0.5969. \lambda_{36} = 0.0402$ **(CCR)** $\lambda_{21} = 0.4008\ \lambda_{24} = 0.5992$ **(BCC)**
30	Visual Communication Design	$\lambda_{27} = 0.7482. \lambda_{32} = 0.2467$ **(CCR)** $\lambda_{6} = 0.0207\ \lambda_{27} = 0.7315. \lambda_{32} = 0.2478$ **(BCC)**
31	Business Management*	$\lambda_{27} = 0.7831. \lambda_{32} = 0.2428$ **(CCR)** $\lambda_{31} = 1$ **(BCC)**
32	Development Studies**	$\lambda_{32} = 1$ **(CCR)** $\lambda_{32} = 1$ **(BCC)**
33	Civil Infrastructure Engineering	$\lambda_{21} = 0.4415. \lambda_{24} = 0.2676. \lambda_{36} = 0.2712$ **(CCR)** $\lambda_{21} = 0.8486. \lambda_{24} = 0.1514$ **(BCC)**
34	Industrial Mechanical Engineering	$\lambda_{24} = 0.0678. \lambda_{27} = 0.7321. \lambda_{32} = 0.1017$ **(CCR)** $\lambda_{6} = 0.2389\ \lambda_{21} = 0.0543. \lambda_{24} = 0.5572\ \lambda_{32} = 0.1497$ **(BCC)**
35	Automation Electric Engineering	$\lambda_{21} = 0.1214. \lambda_{24} = 0.7628. \lambda_{36} = 0.1309$ **(CCR)** $\lambda_{24} = 0.6692\ \lambda_{27} = 0.153. \lambda_{32} = 0.0163\ \lambda_{36} = 0.1615$ **(BCC)**
36	Industrial Chemical Engineering**	$\lambda_{36} = 1$ **(CCR)** $\lambda_{36} = 1$ **(BCC)**
37	Instrumentation Engineering	$\lambda_{24} = 0.6954. \lambda_{36} = 0.3192$ **(CCR)** $\lambda_{24} = 0.4987\ \lambda_{27} = 0.1973. \lambda_{36} = 0.3041$ **(BCC)**
38	Business Statistics	$\lambda_{21} = 0.3489. \lambda_{24} = 0.4232. \lambda_{36} = 0.1831$ **(CCR)** $\lambda_{21} = 0.6422. \lambda_{24} = 0.3578$ **(BCC)**

Slacks and Target Analysis for efficiency improvement.

Non-zero slacks only relevant for inefficient DMUs. These slacks provide critical information about the areas for improvement in inefficient departments to become more efficient. Non-zero slacks are regarded as remaining values after some proportional reductions in inputs or increases in outputs have been made. However, these inefficient DMUs still cannot reach the efficiency frontier. Therefore, slacks are required to push the DMUs to the frontier. Non-zero input slack in the input-oriented DEA model denotes an excess of input, and non-zero output slack denotes output shortage (Ozcan, 2008).

Inefficient departments are characterized by efficiency score of less than 1 but greater than 0 (see Table 4). Table 8 provides information on slacks and target values obtained using the CCR and BCC models for inefficient DMUs. For example, in the Department of Civil Engineering (DMU_{12}), reducing input will allow this department to improve its efficiency or reduce its inefficiency proportionally given that an input-oriented model is used. The recommendation for the Department of Civil Engineering (DMU_{12}) is as follows: the BCC model has an efficiency score of 0.309, implying that the department need to reduce its input by 69.1% (1 - efficiency score). However, a decrease in input alone will not make it efficient. Meeting the efficiency target (at the frontier) requires some additional slack adjustments due to the presence of non-zero slack input and output. The Department of Civil Engineering (DMU_{12}) requires only small adjustments to operate at the efficient frontier as it only needs to cut the number of slack employees and budget by 0.26% and 6,45 x 10-07, respectively. Another interpretation of Table 8 from column target for Department of Civil Engineering (DMU_{12}) is that this current output level can be achieved by only 15 lectures, 7 staff and Rp. 1,651,908,000 (106,557 USD) budget allocation. Meanwhile, in reality, this DMU has 56 lecturers, 15 staff and Rp. 5,344,467,000 (344,747 USD) budget allocation.

Another example is the Department of Business Statistics (DMU_{38}). Based on Table 8, in the BCC model, this department must reduce its staff members by 5 and the number of lecturers to 12. The excess number of staff (slack value) is 0.93, however, despite this slack, the department still cannot achieve efficiency. In order to achieve efficiency, this department must also increase its performance level by 3.76%. A similar interpretation applies to other inefficient departments.

Overall, from Table 8 we can see that if we employ the CCR model, no departments have a non-zero slack in the number of lecturers, two departments have a non-zero slack in the number of staff, and 16 departments have a non-zero slack in budget allocation. However, if we apply the BCC model, two departments have non-zero slack in the number of lecturers, ten departments have non-zero slack in the number of staff, and ten departments have non-zero slack in the budget allocation. Table 8 shows the targeted levels of the input and output variables. To calculate the target values for inputs, the input value is multiplied by an optimal efficiency score, and subtracted by slack using the formula below:

$$\widehat{x_{io}} = \theta * x_{io} - s_i^{-*}, i = 1, 2, \ldots, m \tag{3}$$

where θ is the efficiency score, x_{io} is the level of input-i and s_i^{-*} is slack value. For example, the target calculations for the number of staff in the Department of Business Statistics (DMU_{38}) are calculated as follows.

$$x_{\widehat{staff,DSB}} = \theta * x_{io} - s_i^{-*},$$

$$x_{\widehat{staff,DSB}} = 0.847 * 7 - 0.93 = 4.99 \approx 5$$

where 0.847 is the efficiency score of the Department of Business Statistics (DMU_{38}) under the BCC model, 7 is the number of staff, and 0.93 is the slacks. This result means that to achieve efficiency Department of Business Statistics must reduce the number of staff from 7 people to 5 people. In an input-oriented model, efficient output targets are calculated as:

$$\widehat{y_{ro}} = y_{ro} + s_i^{+*}, r = 1, 2, \ldots, s \tag{4}$$

In our example with the Department of Business Statistics (DMU_{38}), the performance achievement target under the BCC model can be calculated as follows:

$$y_{\widehat{PA,BS}} = y_{PA,BS} + s_i^{+*},$$

$$y_{\widehat{PA,BS}} = 93.05 + 3.76 = 96.8\ \%,$$

where 3.76% is the shortage of performance level in column slack and column target, and the performance is 96.8%. Table 8 shows the confirmed calculation results for the Department of Business Statistics (DMU_{38}). The target values for other departments can be calculated in the same way.

Table 8. Slacks and Targets for Inefficient Departments at ITS

Inefficient DMUs	Slacks								Target											
	Excess Number of Lecturers		Excess Number of Staff		Excess Budget Allocation (In '000' Rupiah)		Shortage Perf. Achievement (%)		Number of Lecturers			Number of Staff			Budget Allocation (in '000' rupiah)			Performance Achievement (%)		
	CCR	BCC	CCR	BCC	CCR	BCC	CCR	BCC	Real	CCR	BCC	Real	CCR	BCC	Real	CCR	BCC	Real	CCR	BCC
Physics	0	0	0	0	0	0	0	0	41	21	21	13	7	7	1656552	846220	851880	101.1	101.1	101.1
Chemistry	0	0	0	0	0	0	0	0	33	15	16	12	6	6	2088060	967277	1008113	103.34	103.34	103.34
Biology	0	7.65	0	0	0	2,78E-07	0	0	43	21	28	11	5	9	1946934	930153	1591764	107.22	107.22	107.22
Mechanical Engineering	0	0	0	0	559840,4	153711,7	0	0	47	14	18	16	5	6	5469687	1107666	1940654	106.91	106.91	106.91
Chemical Engineering	0	0	0	1.47	0	0	0	0	37	12	17	19	6	7	3398160	1079403	1594799	106.84	106.84	106.84
Physics Engineering	0	0	0	0	203795,5	0	0	0	31	12	13	10	4	4	2764851	903790	1145837	88.37	88.37	88.37
Materials and Metallurgical Engineering	0	0	0	0.13	8,95E-08	5,95E-08	0	0	25	11	12	12	5	6	2389875	1065827	1122674	104.64	104.64	104.64
Civil Engineering	**0**	**0**	**0**	**0.26**	**6,45E-07**	**0**	**0**	**0**	**56**	**12**	**17**	**25**	**5**	**7**	**5344467**	**1111219**	**1651908**	**106.95**	**106.95**	**106.95**
Environmental Engineering	0	0	0	0	6,16E-07	0	0	0	27	11	11	12	5	5	2503556	1042375	1064287	101.9	101.9	101.9
Geomatics Engineering	0	0	0	0.20	0	5,92E-08	0	0	21	12	13	10	6	6	1835085	1043502	1096174	104.2	104.2	104.2
Geophysical Engineering	0	0	0	0	8,36E-08	0	0	0,35	12	10	10	6	5	5	1215849	994752	1007685	96.64	96.64	96.99
Architecture	0	3.91	0	0	1,84E+05	0	0	0	36	14	13	12	5	6	3174534	1093705	1474043	106.09	106.09	106.09
Urban and Regional Planning	0	0	0	0	1,16E+05	0	0	0	23	9	10	10	4	4	2611218	953417	1143284	87.46	87.46	87.46
Naval Architecture	0	0	0	1.25	0	0	0	0,25	27	11	11	15	6	**5**	2328701	965876	969682	96.78	96.78	97.03
Marine Engineering	0	0	0	0	5,57E-07	0	0	0	32	10	11	14	4	5	3229476	1001507	1070001	92.31	92.31	92.31
Ocean Engineering	0	0	0,48	2.91	0	5,92E-08	0	0	25	13	13	16	8	6	2020482	1026783	1081170	104.27	104.27	104.27
Informatics Engineering	0	0	0	0	700951,6	846581,8	0	0	45	13	23	17	5	9	6284338	1150480	2412298	108.5	108.5	108.5
Information System	0	0	0	0	683753,6	232993,8	0	0	36	15	19	12	5	6	4399637	1105355	2105161	107.22	107.22	107.22
Electrical Engineering	0	0	0	0	1000262	989213,4	0	0	55	18	18	14	5	5	6116175	997320	1011276	104.18	104.18	104.18
Computer Engineering	0	0	0	0	27849,87	0	0	0	19	13	14	6	4	4	1390272	934807	1030852	91.89	91.89	91.89
Product Design	0	0	0	0.20	6,24E-07	6,06E-08	0	0	17	11	11	8	5	5	1716372	1097027	1133244	104.64	104.64	104.64
Interior Design	0	0	0	0	0	0	0	3,21	14	10	10	7	5	5	1332306	957320	990155	94.14	94.14	97.34
Visual Communication Design	0	0	0	0	197392,8	190223,2	0	0	16	15	15	5	5	5	1332306	1062297	1070536	104.7	104.7	104.7
Civil Infrastructure Engineering	0	0	0	1.33	0	0	0	1,04	31	13	13	15	6	5	2189280	913256	924538	95.3	95.3	96.34
Industrial Mechanical Engineering	0	0	0	0	5,78E-07	0	0	0	20	11	12	8	4	5	1830240	1008094	1055014	94.52	94.52	94.52
Automation Electric Engineering	0	0	0	0	0	0	0	0	14	10	10	8	6	6	1427856	1022664	1033583	99.45	99.45	99.45
Instrumentation Engineering	0	0	0,09	0.33	0	0	0	0	13	11	11	8	7	7	1188948	1005034	1018018	99.66	99.66	99.66
Business Statistics	**0**	**0**	**0**	**0.93**	**0**	**0**	**0**	**3,76**	**14**	**11**	**12**	**7**	**6**	**5**	**1127700**	**916843**	**954777**	**93.05**	**93.05**	**96.80**

Discussion

In this study, we apply DEA models to measure the efficiency of 38 departments at Sepuluh Nopember Institute of Technology in Surabaya, Indonesia with input orientation due to deregulating the resource allocations would be more beneficial for decision-makers in HEs. Input orientation emphasizes the extent to which inputs can be lowered proportionally without affecting outputs. The inputs are the number of lecturers, the number of staff, and the budget allocation while the output is performance achievement calculated in 2021 based on key and supplementary performance indicators arranged by the Ministry of Education and Research of Indonesia. In contrast to previous studies that only focus on teaching and research as output of university (Cossani et al., 2022; Jiang et al., 2020; Kao & Hung, 2008), this study considers performance achievement that includes four main strategic targets of higher education (quality of graduates, quality of lecturers, quality of learning curriculum and quality of governance of work units within the Directorate General of Higher Education) which considered a more robust and comprehensive measure of university output.

According to the DEA analysis, only a few departments were operating efficiently and average efficiency score was relatively low. This result supports the notion that DEA efficiency score is solely related to resource utilization, and which is consistent with the findings of previous research (Chen & Chang, 2021; Kao & Hung, 2008). Some departments operate with high level of input while output value is not that high. Furthermore, the results suggest that the efficiency of departments at ITS varies, indicating a disparity between allocation of input variables among departments. The efficiency score of Department of Mechanical Engineering and Department of Informatics Engineering was relatively low despite large amount of input values and high output values. Given low efficiency score, it is necessary to objectively assess the selection indicators for financial support and productivity of lecturers and staff at those departments. On the other hand, Department of Actuarial science is smaller in terms of input and output variables than other departments. However, this department turned out to be one of efficient departments. This result is in accordance with the result from Jiang et al. (2020) which provides an insight into one of the limitations of the DEA model that identifies two or more decision-making units that operate at best practice resulting in at least some departments being given a score of one, even when the best-performing department may not be operating on the frontier (Abbott & Doucouliagos, 2003).

The outcomes of this paper provide not only relative efficiency score for the department head but also serve as a reference for the institution administration's to allocate resources and develop future strategies. Concerning budget allocation, the top administrator should verify thoroughly the use of budget allocation in department including implementing new financial policies or assessments to ensure that financial support is used correctly. In addition, to improve the quality of lecturers, universities should ensure that their lecturers and staff have access to the necessary resources and facilities to carry out their work effectively. This includes providing the latest technology, software, and equipment to help them complete their tasks efficiently. Furthermore, offering opportunities for professional development and training can help lecturers and staff improve their skills and knowledge. This can include attending workshops, seminars, and conferences. Universities also need to foster a positive work environment that can create a culture that supports and values the work of their staff and encourages collaboration, creativity, and innovation.

In terms of educational background, it is worth noting that DEA models have been widely applied in the field of education to measure the efficiency of schools and universities. However, there are some limitations and challenges in applying DEA models in this context. For instance, a study by Panwar et al. (2022) pointed out that the DEA model that we used this study may not fully capture the complex and multidimensional nature of educational institutions, and there is a need for more advanced methods to measure their efficiency.

Conclusion

Higher education institutions play a vital role in a country's development; therefore, their performance needs to be evaluated to ensure their effectiveness. This paper applies the data envelopment analysis (DEA) methodology to assess the relative efficiency of 38 departments at Sepuluh Nopember Institute of Technology in Surabaya, Indonesia. The DEA analysis focused on overall technical efficiency (CCR efficiency score), pure technical efficiency (BCC efficiency score), and scale efficiency (ratio between overall and pure technical efficiency) with the objective of improving resource allocation. Based on the findings and discussion, several conclusions are obtained: The average CCR model efficiency scores are 59.7%, and five DMUs are 100% efficient. In the meantime, the BCC model yields an average of 67.9% and ten DMUs are efficient, five of which are those considered efficient by the CCR model. The study also revealed that the efficiency of departments varied, indicating a disparity in the allocation of input variables among departments. Furthermore, the study found that some departments were operating with a high level of input while the output value was not commensurate, and the efficiency score of some departments was relatively low. This research contributes to the literature by applying DEA to evaluate the efficiency of higher education departments, a topic that has received relatively little attention in the existing literature on efficiency measurement in Indonesia. This study provides a useful framework for assessing the efficiency of academic departments, which can help higher education institutions identify areas for improvement and optimize resource utilization. Additionally, our study demonstrates the applicability of DEA as an effective tool for evaluating the performance of higher education institutions which can be applied to other higher education institutions in Indonesia and beyond.

Recommendations

The educational implications of this study suggest that HE institutions in Indonesia should focus on evaluating their departmental efficiency and improving resource allocation to ensure maximum utilization of available resources. Using DEA calculations, the top administrators of can identify the departments that are inefficient in utilizing their resources, and the department heads are able to pinpoint the areas where the greatest efficiency gains can be obtained. By incorporating value of slacks and targets, appropriate resource reallocation would enhance the total efficiency score of all inefficient departments. Department staffs are suggested to involve collaboration with targeted departments to share knowledge and expertise.

Furthermore, in this study for considered best performing departments which has output of more than 100% and high input levels, top administrators of institutions should promote departmental productivity so that available resources, particularly budgetary allocations, and the number of lecturers, are proportionate with the level of performance attained. Decision makers of institution are also encouraged to improve not only resource utilization but also managerial system as this study depicts many departments witnessing scale inefficiency Furthermore, they could encourage a culture of continuous improvement within their department by regularly evaluating practices and seeking feedback from students and faculty.

Considering our findings, we recommend that higher education institutions regularly evaluate their departmental efficiency using DEA or other appropriate methodologies. This can help identify areas for improvement and optimize resource utilization, ultimately leading to better outcomes for students and society. Additionally, further research that educational researchers could consider such as (a) using different inputs and outputs to measure the efficiency of higher education departments. For example, they could include student enrollment, graduation rates, and student satisfaction as output factors; (b) incorporating qualitative data such as survey results or interviews with students and faculty, to provide a more comprehensive understanding of the factors that influence departmental efficiency; (c) enabling comparisons between faculties or departments across different universities with international comparisons being particularly important given ITS's active pursuit of increased international exposure to achieve a Top 500 ranking by 2025; (d) conducting a dynamic analysis to identify trend over time as this study focuses on a specific point in time, therefore, future research could conduct a dynamic analysis to identify trends in departmental efficiency over time.

Limitations

This study is limited to two traditional DEA models: the CCR and BCC model, three input variables, and one output variable. Note that DEA is a highly sensitive model, therefore, different pairs of inputs and outputs will produce different results, with each variable possibly reacting differently. In addition, we used DEA approaches that cannot compare efficient departments against one another, nor does it provide information on how efficient departments might become even more efficient.

Acknowledgments

This research is supported by the Directorate of Research and Community Service of Sepuluh Nopember Institute of Technology, Surabaya, Indonesia, under contract number 1064/PKS/ITS/2022.

Authorship Contribution Statement

Wildani: Conceived and designed statistical analysis/interpretation, performed the analysis, drafting the manuscript. Wibowo: Conceptualization, editing/reviewing, supervision, drafting the manuscript, final approval. Wulandari: Conceptualization, editing/reviewing, supervision, drafting the manuscript, final approval. Ari Dinanti: Conceptualization, editing/reviewing, supervision, drafting the manuscript, final approval.

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