



# Identifying an Efficiency Productivity Model for Faculties with DEA Benchmarking Technique

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**Purpose:** Many universities in Thailand aim to raise their ranking; thus, university administrators set the target outputs for their institutions. However, the university-level targets may differ from those at the faculty levels because the inherent nature of academic fields and faculty capacity to produce outputs may not be considered. Therefore, we propose a model to determine possible target values for faculty outputs with weak efficiency by benchmarking the university under study with one of the leading universities in Thailand. As a result, the evidence-based target values allow inefficient faculties to know what outputs they need to improve under the assumption that "if each faculty improves their productivity to reach a target value, the university can rank higher." This can lead to a more realistic and achievable target instead of a single target across all faculties.

**Study design/methodology/approach:** Due to inherent differences among faculties, they are clustered by subject areas with the hierarchical cluster analysis to reduce bias. Then an efficiency score of each faculty is computed via the Data Envelopment Analysis.

**Findings:** The faculties of the university under study are clustered into three subject areas: 1) agricultural science and technology management, 2) engineering and ecology, and 3) social sciences and humanities. The DEA technique provides the slack values to be used in target settings that mitigate the bias from different capabilities on producing outputs across subject areas. For the faculties in agricultural science and technology management, social sciences, and humanities, the inadequacy of performed research and teaching operations are essential indicators, i.e., the percentage of the sum of slack values in both aspects is more than 80%. In engineering and ecology, the essential indicators (i.e., the percentage of the sum of slack values in both aspects is 91.10%) are related to teaching and international outlook operations. However, the teaching operation is the most critical aspect (i.e., the maximum value of the percentage sum of each subject area's slack values is 42.23%) that all subject areas should be focused on for improvement.

**Originality/value:** Our approach can provide a quantitative decision support tool that allows university administrators to set realistic operational policies according to evidence-based target values tailored for each subject area.

## Introduction

Higher-education institutions (also known as a university) produce advanced skills for supporting specific regional economic, social and cultural development needs that affect economic growth and sustainability and are critical to a country's competitive advantage. The rankings of world universities show the university performance across countries (Fyfe et al., 2021; Ramirez, 2015). If a university wants to raise its ranking, it needs to set productivity

targets determined by benchmarking itself with one of the leading universities (Welsh & Metcalf, 2003). Three main types of benchmarking are metric benchmarking, practice benchmarking, and policy benchmarking (OECD, 2021). We focus on policy benchmarking to determine the key output drivers for increasing university performance.

The Quacquarelli Symonds (QS) and Times Higher Education (THE) World University Rankings are the leading providers of services, analytics, and insight to global universities. There are four main outputs or metrics that reflect the performance of each university, including research, teaching, international outlook, and industry income (Heffernan & Heffernan, 2017; QS, 2020; THE, 2020). The availability of such data makes it essential to analyze and adequately evaluate them to assess the current university's performance.

A faculty (or school) is a sub-unit that supports the university's overall performance. It has a different academic discipline, one of the most important variables influencing academicians' academic activity and research productivity. Therefore, each faculty usually produces different amounts of outputs (Jung, 2012; Simpson, 2016). The university under this study specifies the target for each output, while each faculty has its different numbers. Thus, the performance target should not be one-size-fits-all, but it should consider the nature of academic disciplines and the production capacity of each faculty.

Due to 'top-down' administrative mandates, the lack of faculty involvement can be a significant obstacle to increasing successful university performance. The faculty target setting can be defined as what one wants to achieve in one's professional career. It plays a vital role in one's motivation level and the resultant performance. Since faculty responses can be reactive to university leadership's press are for raising performance, the university should be aware of alternate approaches congruent with faculty work and productivity (Agrell & Steuer, 2000; Emil & Cress, 2014).

Our work proposes a quantitative decision support tool that allows university administrators to set evidence-based operational policies on output targets varied by academic disciplines. First, the clustering technique is used for fair benchmarking to combine faculties with similar outputs as reflected by disciplinary features and transform them into a single subject area. The Data Envelopment Analysis (DEA) technique is later applied for determining each output's target values of each aggregated subject area by benchmarking the university under this study with one of the leading universities in Thailand.

## Literature Review

The analysis of the university's target setting models, such as regression methods (Broome & Darwent, 2013; Dachyar & Dewi, 2015; Dynan & Clifford, 2001), performing to explore the outputs affecting the university performance is the quantitative approach for finding the key outputs that the administrator could translate to an action plan. This approach aims to identify the issues based on significant outputs that the university should make to enhance its performance. Still, it does not specify how many improvements on each output, e.g., the number of citations or industry income, to achieve the targets. The model used in this study is similar to Kuah & Wong (2014), Ertek et al. (2015), and Ruiz et al. (2015). These works focused on evaluating the university's performance and benchmarking it relatively with the leading universities to identify the target value for enhancing their performance. Moore (2007) found that quantitative measurement helped the decision-makers make less biased judgments when provided with more apparent responses. The model assumption is that "if each faculty improves their productivity based on a slack value, their university can rank higher."

Faculties work independently to achieve their targets and give different quantities of outputs. The faculty evaluations create dynamic feedback essential to maintaining high university

performance (Askar, 2019). In operational management, universities use benchmarking to specify the performance gap with leading universities. It can identify key outputs and return each output's gap values for the target setting (Ho et al., 2006; OECD, 2021; Ruiz et al., 2015).

The target setting results in qualitative and quantitative recommendations (Dayananda et al., 2021; Kuah & Wong, 2014; Ruiz et al., 2015; Uctug & Koksal, 2010). Moreover, it is used to allocate limited resources for maximizing university productivity (Chen, 2013; Nazarko & Saparauskas, 2014). Finding information on system factors affecting university performance is an approach to setting a target to explore the strengths and weaknesses of DMUs (Dachyar & Dewi, 2015). A target setting can keep track of operations and guide where to focus the outputs, and it is necessary to plan to enhance the university's performance.

The target setting has been widely considered. A quantitative approach can be more valuable than a qualitative one for setting evidence-based operational policies on output targets. It quantifies each output's numbers that should be adjusted to achieve the targets. The benchmarking technique is a tool for target setting that its mechanism enables to identify how to raise the operational unit performance after comparing themselves with others (Achim et al., 2009). The DEA is a benchmarking technique. It is an input-process-output (IPO) analysis that computes efficiency values reflecting the university's performance (Andrejic et al., 2013; Hajiagha et al., 2019; Ruiz et al., 2015; Tchangani, 2010).

The research using DEA for benchmarking on educational management topics considers the comparative performance between internal departments of an institution or internal and external institutions within and outside of a country under the same study contexts. The study is done to monitor the progress of educational achievements (Roatamzadeh et al., 2021). For example, Rayeni & Saljooghi (2010) use DEA for benchmarking between educational departments of S and B universities to identify factors contributing to an inefficient department to an efficient one. Cook et al. (2017) apply DEA for benchmarking the research performance of Spanish public universities. The results can inform local governments to establish policies for promoting research and setting corresponding qualitative target levels. Ulucan et al. (2018) apply the DEA to benchmark the educational program quality between subdivisions of business bachelor's degree programs handled by Hacettepe University. The university administrations use the results to monitor the program based on a quality assurance system and design the improvement plan for driving the organization to best practices. Finally, Ruiz & Sirvent (2019) show an application of the proposed DEA benchmarking method to evaluate the teaching performance of Spanish public universities for setting an implementation plan on enhancing the inefficient universities into efficient ones.

The indicators reflecting the university performance are cited in four aspects, including research (i.e., academic reputation, research income, research productivity, citations per paper), teaching (i.e., employer reputation, doctorate degrees awarded to academic staff ratio, doctorate to bachelor students ratio, faculty staff to student ratio, staff with Ph.D.'s, institution income), international outlook (i.e., international collaboration, international to domestic student ratio, percentage of exchange students), and industry income (Pavel, 2015; QS, 2020; THE, 2020). For efficiency measurement, the indicators should capture both inputs and outputs (Ruiz et al., 2015). Since the university in this study does not have some data mentioned in QS and THE, only available data is used to measure the efficiency. Moreover, the faculty target setting has to accommodate the multidisciplinary aspects for fair information (Broome & Darwent, 2013; Simpson, 2016).

Taking the approach of an IPO framework classified by faculty's multidisciplinary, this study developed a faculty's target setting by applying the clustering analysis and DEA technique which will be explained in the next section.

## Methods

A model will be presented with the application of clustering and DEA techniques. Then, we explain the conceptual model based on the IPO framework under different kinds of processes (also known as multidiscipline).

### ***Clustering model for faculty's target setting***

For fairness in a multidiscipline target setting using benchmarking technique, the cluster analysis is performed. Cluster analysis is a mathematical-statistical method used to group a different set of objects into clusters, considering that the objects belonging to the same clusters are as similar as possible but also different from the objects in other clusters as much as possible. The standardized data (in the range of -1 to 1) of each object used in clustering performs better than the non-standardized ones (Nogueira & Munita, 2020). There are many approaches to cluster analysis depending on data conditions and clustering patterns. Since the data in this study are fewer than 200, the agglomerative hierarchical cluster technique is used. It assumes that each object is treated as a separate cluster in the first step (Murtagh, 2014). In step 2, the closest objects merge into the first cluster determined by distance or similarity, computed with Ward's method. In the third step, the third object is considered whether it should be merged into the same group as the first two objects or the new two objects should be integrated into another group. In each subsequent step, either a new object may be merged into an existing cluster or two new objects may be incorporated into a new cluster. These steps are iterated until all cases are in some clusters.

In the agglomerative hierarchical cluster technique, already established clusters cannot be separated later but can only be connected to other clusters (Kabok et al., 2017).

The Multivariate Analysis of Variance (MANOVA) is used to confirm the statistically significant difference of each cluster by testing the difference on the mean of each data group. The null hypothesis is  $H_0$ : There is no difference in mean values between clusters.

Since the null hypothesis is rejected, the clustering results are confirmed that our  $g$  groups are statistically different (Johnson and Wichern, 2007). The RStudio IDE is used to cluster faculties and test this hypothesis (RStudio, 2021).

### ***DEA modeling for faculty's target setting***

The DEA technique specifies a performance score resulting from DMUs benchmarking while analyzing many factors under the IPO framework. The DEA is a mathematical model which determines the weight sets to optimize the performance score of a DMU (in this study, the faculty) under evaluation by benchmarking with other DMUs. Therefore, the DEA technique is suitable for the faculty's target setting because it can provide the comparison or benchmark of operational performance with multiple inputs and outputs between faculties (Azadi & Saen, 2011; Najadat et al., 2019).

The faculty performance or efficiency score is also known as productivity. The score is calculated in terms of the weighted sum of outputs divided by the weighted sum of inputs. The set of weights comes from the DEA intending to maximize the efficiency score across all DMUs. An efficiency score of 1 represents the efficient DMU, whereas a score of less than 1 represents an inefficient DMU.

The DEA model gradually evolves into many forms. Since the objective of this study is to set evidence-based output targets, the slack-based measure (SBM) in DEA developed by Tone (2001) is chosen because it deals directly with the output shortfalls (called "slack") of the DMU. SBM can return an empirical output for setting targets. Moreover, it directly considers the input

excesses (called "surplus"). In our study, the input factors within each cluster are identical and set to the value of a leading university; therefore, there is no surplus within a cluster, and input factors are different across the cluster.

Each DMU<sub>j</sub>, ( $j = 1, 2, \dots, n$ ) uses  $m$  inputs  $x_{ij}$  ( $i = 1, 2, \dots, m$ ) to produce  $q$  outputs  $y_{rj}$  ( $r = 1, 2, \dots, q$ ). Let the surpluses be  $s_i^-$  ( $i = 1, 2, \dots, m$ ) and the output slacks be  $s_r^+$  ( $r = 1, 2, \dots, q$ ). Let the DMU<sub>j</sub> be evaluated on any trial be designated as DMU<sub>0</sub> with the objective function value  $E_0$  is found by solving the SBM model shown in Equations (1)-(2),

$$\min E_0 = \frac{1 - \frac{1}{m} \sum_{i=1}^m \frac{s_i^-}{x_{i0}}}{1 + \frac{1}{q} \sum_{r=1}^q \frac{s_r^+}{y_{r0}}} \quad (1)$$

*subject to*

$$\begin{aligned} \sum_{j=1}^n \lambda_j x_{ij} + s_i^- &= x_{i0} \\ \sum_{j=1}^n \lambda_j x_{rj} - s_r^+ &= y_{r0} \\ \sum_{j=1}^n \lambda_j &= 1 \\ \lambda_j, s_i^-, s_r^+ &\geq 0 \end{aligned} \quad (2)$$

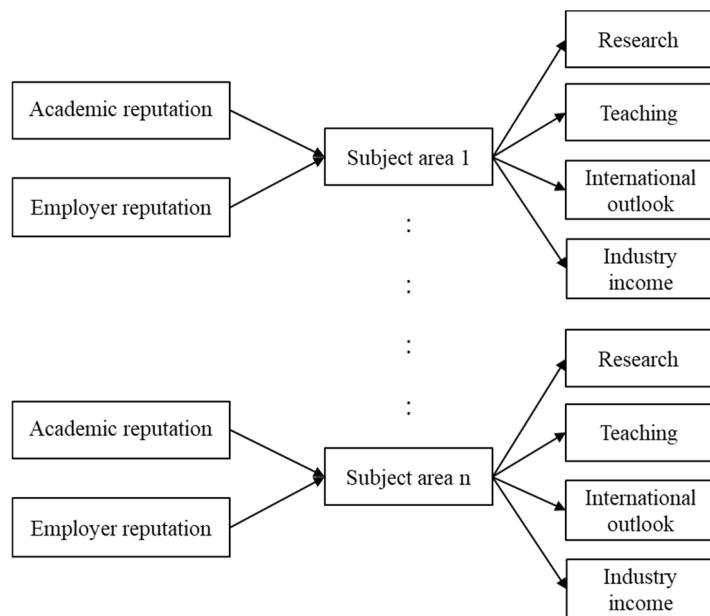
where  $\lambda_j$  is a nonnegative value of weights for the inputs and outputs. A DMU's highest score is 1, which is only achievable when all slacks are equal to zero and is defined as an efficient DMU. If the score obtained is less than 1, the DMU is defined as inefficient. The SBM results can provide feedback to the inefficient faculties on how much to improve the outputs ( $y_{r0}^*$ ) to achieve the targets by enhancing the output shortage, as shown in Equation (3). These quantitative results allow the university administrators to set an operational policy for raising the university performance compared with the benchmark university.

$$y_{r0}^* = y_{r0} + s_{r0}^+; r = 1, 2, \dots, s \quad (3)$$

The model is applied and demonstrated in an exemplifying case study section.

### ***The conceptual model for faculty's target setting***

The process or DMU is a subject area grouped by discipline similarity. Figure 1 shows the conceptual model under the IPO framework of each subject area.



**Figure 1: IPO framework of the subject areas**

The inputs and outputs used in this study are referred from QS and THE and shown in Tables 1 and 2. Under the limitation of disclosure of university information, this study uses only the publicly reported data of the university of this study and the leading university in Thailand. The definition of the indicators will be discussed next

**Table 1: Input indicators of faculty's target setting**

Symbols	Inputs	Units	Category
$x_1$	Academic reputation	%	Research
$x_2$	Employer reputation	%	Teaching

**Table 2: Output indicators of faculty's target setting**

Symbols	Outputs	Units	Category
y <sub>1</sub>	International collaboration	-	International outlook
y <sub>2</sub>	International to domestic student ratio	-	International outlook
y <sub>3</sub>	Research productivity	-	Research
y <sub>4</sub>	Research income	-	Research
y <sub>5</sub>	Doctorates awarded to academic staff ratio	-	Teaching
y <sub>6</sub>	Doctorate to bachelor's ratio	-	Teaching
y <sub>7</sub>	Faculty staff to student ratio	-	Teaching
y <sub>8</sub>	Industry income	-	Industry income
y <sub>9</sub>	Staff with a Ph.D.	%	Teaching
y <sub>10</sub>	Percentage of exchange students	%	International outlook
y <sub>11</sub>	Number of international students	Number of international students	International outlook
y <sub>12</sub>	Number of international academic staff	Number of international academic staff	International outlook

### *Input definitions*

The input  $x_1$  is the academic score associated with teaching and research quality derived from a survey from the experts. The input  $x_2$  is the university's potential score to provide the knowledge and skills to the graduates for the employment market. Setting evidence-based output targets evaluates the efficiency of producing the outputs benchmarked by using fixed inputs obtained from leading universities. Thus, the survey data used in the model is based on the leading university in Thailand derived from the QS report in 2019 (QS, 2021).

### *Output definitions*

The output  $y_1$ ,  $y_2$ ,  $y_{10}$ ,  $y_{11}$ , and  $y_{12}$  are associated with the "international outlook aspects" that demonstrate the potential of international attractiveness and competitiveness (Wachter et al., 2015). The output  $y_1$  is international collaboration shown in the ratio of the number of international publications collaborated with international institutes to all international publications. The output  $y_2$  is the international to domestic student ratio identified by the ratio of the number of international students to Thai students. The output  $y_{10}$  is the percentage of exchange students concluded from both inbound and outbound exchange students and calculated by the number of inbound and outbound exchange students divided by the total number of students. Finally, the outputs  $y_{11}$  and  $y_{12}$  are the numbers of international students and academic staff, respectively.

The output  $y_3$  and  $y_4$  are categorized in "research" aspects representing the potential to produce the high-quality academic paper and income through the research (Aydin, 2017). The output  $y_3$  is the research productivity as indicated by the ratio of the number of academic publications to academics. The output  $y_4$  is the research income shown in the ratio of external research funding to full-time faculty members.

The output  $y_5$ ,  $y_6$ ,  $y_7$ , and  $y_9$  are shown in terms of "teaching aspects" that illustrate the profile and achievements of faculty staff (Loukkola et al., 2020). The output  $y_5$  is doctorates awarded to academic staff ratio, which refers to the ratio of the number of doctoral students to full-time faculty staff. The output  $y_6$  is the doctorate to bachelor student ratio calculated by the number of doctoral students divided by the number of undergraduate students. The output  $y_7$  is the faculty staff to student ratio identified by the ratio of the number of faculty members to the total number of students. Finally, the output  $y_9$  is the staff with Ph.D. defined by the percentage of faculty members who receive doctorate degrees.

The output  $y_8$  represents the "industry income aspect" that demonstrates the knowledge transfer to an industry returning earnings to the institutions (Wachter et al., 2015).

The output data used in the model are provided by Kasetsart University and obtained from the annual report of a leading university in Thailand in 2019.

### **A case study example**

For the cluster analysis, the university under study has fifteen faculties or DMUs, including the Faculty of Agriculture, Faculty of Veterinary Technology, Faculty of Economics, Faculty of Business Administration, Faculty of Fisheries, Faculty of Humanities, Faculty of Forestry, Faculty of Science, Faculty of Engineering, Faculty of Education, Faculty of Architecture, Faculty of Social Sciences, Faculty of Veterinary Medicine, Faculty of Environment, and Faculty of Agro-Industry are considered. Therefore, the data is divided into two sets—one for clustering and the other for DEA. Table 3 shows the standardized data in 2019 for clustering.

The fifteen faculties are clustered into statistically different three groups at a 95% confidence level since the MANOVA result shows that the test statistic equal to 12.78 is more than the  $F$ -

distribution with the degree of freedom of 16 and 10 at 95% confidence level ( $12.78 > F_{16,10}(0.05) = 2.83$ ). The faculties in Cluster 1 (called agricultural science and technology management) consist of the Faculty of Agriculture (DMU1), Faculty of Veterinary Technology (DMU2), Faculty of Economics (DMU3), Faculty of Business Administration (DMU4), Faculty of Forestry (DMU7), Faculty of Science (DMU8), Faculty of Education (DMU10), Faculty of Environment (DMU14) and Faculty of Agro-Industry (DMU15). The faculties in Cluster 2 (called engineering and ecology) are the Faculty of Engineering (DMU9), Faculty of Fisheries (DMU5), and Faculty of Veterinary Medicine (DMU13). The faculties in Cluster 3 (called social sciences and humanities) are the Faculty of Humanities (DMU 6), Faculty of Architecture (DMU11), and Faculty of Social Sciences (DMU12).

Tables 4-5 show the data for DEA classified by clustering into three subject areas. Table 4 consists of the data set for DEA of cluster 1 and that of a leading university associated with the subject area in Cluster 1. Tables 5-6 are the DEA data set of Clusters 2 and 3 and the data of a leading university associated with the subject area in each cluster. The DMUs of a leading university are denoted by the U1, U2, and U3, representing a benchmarked university.

The DEA analysis in agricultural science and technology management (Cluster 1) reveals that there are 7 efficient DMUs and 3 inefficient DMUs. In addition, there are 3 efficient DMUs and 1 inefficient DMU in the subject area of engineering and ecology (Cluster 2) and social sciences and humanities (Cluster 3). The slacks of each DMU in each cluster are shown in Tables 7-9.

**Table 3: Data set as standardized values for clustering**

DMU	y <sub>2</sub>	y <sub>3</sub>	y <sub>4</sub>	y <sub>8</sub>	y <sub>9</sub>	y <sub>10</sub>	y <sub>11</sub>	y <sub>12</sub>
1	-0.23	0.05	0.10	1.27	-0.36	0.60	0.32	-0.29
2	0.74	0.14	-0.94	-1.06	-0.36	-0.81	-0.02	-0.79
3	-0.98	0.08	-0.03	1.27	-0.36	0.15	0.63	-0.48
4	-0.29	-0.01	-0.24	-0.45	-0.36	-0.72	0.53	0.14
5	0.44	0.98	0.56	-0.82	3.47	-0.56	0.36	-0.37
6	-1.34	-1.94	-1.20	0.24	-0.36	0.93	-2.11	-0.60
7	0.27	0.74	0.76	-0.34	-0.36	-0.28	0.58	-0.11
8	1.72	1.61	-0.30	-0.56	-0.36	0.22	0.57	-0.66
9	1.30	-0.72	2.80	1.38	0.51	-0.29	0.31	1.50
10	-0.87	-0.60	-0.57	-0.82	-0.36	-0.88	0.91	0.50
11	-1.26	-1.04	0.67	-0.87	0.34	-0.03	-1.83	-0.59
12	-1.32	-1.47	-0.94	-0.89	-0.36	-0.73	-1.27	-0.71
13	0.21	0.70	-0.71	0.96	-0.36	2.98	-0.72	2.93
14	0.49	0.27	-0.54	-0.89	-0.36	-0.88	0.83	-0.16
15	1.13	1.20	0.59	1.56	-0.36	0.31	0.93	-0.31

**Table 4: Data set for DEA of Cluster 1**

DMU	x <sub>1</sub>	x <sub>2</sub>	y <sub>1</sub>	y <sub>2</sub>	y <sub>3</sub>	y <sub>4</sub>	y <sub>5</sub>	y <sub>6</sub>	y <sub>7</sub>
1	62.90	58.50	0.03	0.50	1.29	561,681	0.62	0.06	0.07
2	62.90	58.50	0.00	0.55	1.48	54,762	0.10	0.00	0.03
3	62.90	58.50	0.02	0.38	2.45	371,104	0.39	0.01	0.02
4	62.90	58.50	0.00	0.38	1.50	997,392	0.94	0.02	0.02
7	62.90	58.50	0.01	0.46	1.65	746,254	0.51	0.03	0.04
8	62.90	58.50	0.02	0.38	1.61	189,811	1.02	0.10	0.08
10	62.90	58.50	0.00	0.24	1.03	1,351,447	1.91	0.22	0.05
14	62.90	58.50	0.00	0.41	1.53	696,187	1.11	0.08	0.05
15	62.90	58.50	0.02	0.28	1.61	537,229	1.01	0.06	0.05
U1	62.90	58.50	0.04	0.58	1.50	152,520	1.53	0.26	0.08

**Table 5: Data set for DEA of Cluster 2**

DMU	x <sub>1</sub>	x <sub>2</sub>	y <sub>1</sub>	y <sub>2</sub>	y <sub>3</sub>	y <sub>4</sub>	y <sub>5</sub>	y <sub>6</sub>	y <sub>7</sub>
5	46.10	55.40	0.01	0.38	1.63	479,540	0.62	0.03	0.05
9	46.10	55.40	0.01	0.28	1.32	2,365,408	0.72	0.04	0.04
13	46.10	55.40	0.07	0.56	1.49	3,807,133	0.22	0.06	0.24
U2	46.10	55.40	0.04	0.58	1.50	152,520	1.53	0.26	0.08

**Table 6: Data set for DEA of Cluster 3**

DMU	x <sub>1</sub>	x <sub>2</sub>	y <sub>1</sub>	y <sub>2</sub>	y <sub>3</sub>	y <sub>4</sub>	y <sub>5</sub>	y <sub>6</sub>	y <sub>7</sub>
6	67.70	63.80	0.03	0.00	0.53	246,251	0.36	0.02	0.06
11	67.70	63.80	0.02	0.00	0.86	254,100	0.42	0.04	0.08
12	67.70	63.80	0.00	0.33	0.86	135,690	0.02	0.00	0.03
U3	67.70	63.80	0.04	0.58	1.50	152,520	1.53	0.26	0.08

**Table 7: DEA results of agricultural science and technology management subject area (Cluster 1)**

**Table 8: DEA results of engineering and ecology subject area (Cluster 2)**

DMU	Efficiency score	$S_1^-$	$S_2^-$	$S_1^+$	$S_2^+$	$S_3^+$	$S_4^+$	$S_5^+$	$S_6^+$	$S_7^+$
5	1	0	0	0	0	0	0	0	0	0
9	0.989	0	0	0.047	0.284	0.162	0	0	0.094	0.131
13	1	0	0	0	0	0	0	0	0	0
U2	1	0	0	0	0	0	0	0	0	0

**Table 9: DEA results of social sciences and humanities subject area (Cluster 3)**

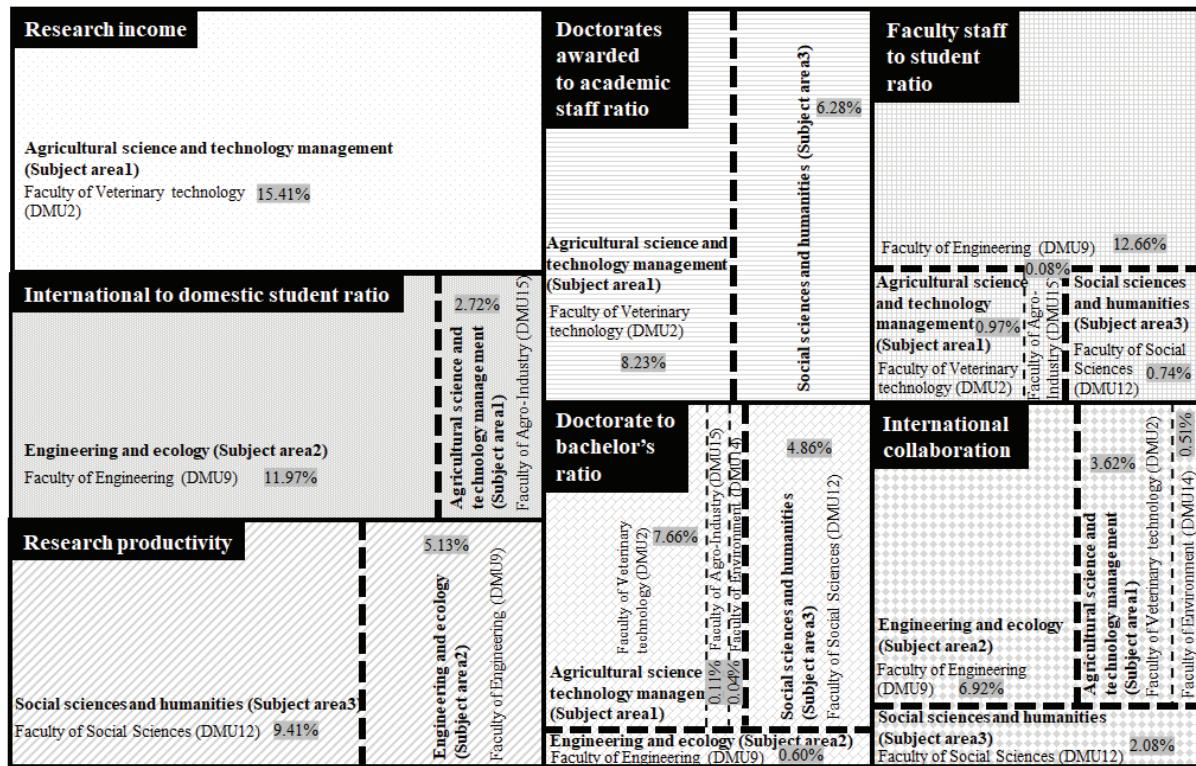
DMU	Efficiency score	$S_1^-$	$S_2^-$	$S_1^+$	$S_2^+$	$S_3^+$	$S_4^+$	$S_5^+$	$S_6^+$	$S_7^+$
6	1	0	0	0	0	0	0	0	0	0
11	1	0	0	0	0	0	0	0	0	0
12	0.763	0	0	0.029	0	0.212	0	1.231	0.201	0.041
U3	1	0	0	0	0	0	0	0	0	0

Therefore, to transform the inefficient DMUs into efficient ones, the outputs should be adjusted by increasing the output shortfalls. The slack value used as improvement targets of inefficient DMUs is set according to the result from Equation (3). For example, to encourage the Faculty of Engineering (DMU9 in Cluster 2) to become more effective (i.e., the efficiency score increases from 0.989 to 1), the number of academic publications to academics ratio of 0.162 should be increased. In 2019, the number of academic publications was 371, and the number of academics was 282 resulting in a ratio of 1.316. To improve this number to 0.162, the number of academic publications has to rise from 371 to 418 publications per year which is set for the research productivity target in the following year.

Figure 2 shows the DEA results from comparing the efficiency of each faculty in each subject area based on slack values. Among twenty slack values in three clusters, five faculties (i.e., Faculty of Veterinary Technology, Faculty of Engineering, Faculty of Social Sciences, Faculty of Environment, Faculty of Agro-Industry) have positive slack values. The faculty with the highest percentage of slack values (37.28%) is the Faculty of Engineering, followed by the Faculty of Veterinary Technology, Faculty of Social Sciences, Faculty of Agro-Industry, and Faculty of Environment with values of 35.89%, 23.37%, 2.91%, and 0.55%, respectively.

Among the slack values classified by three subject areas (i.e., agricultural science and technology management, social sciences and humanities, engineering and ecology), more than 80% of slack values in agricultural science and technology management and social sciences and humanities are research (i.e., research productivity, research income) and teaching (i.e., doctorates awarded to academic staff ratio, doctorate to bachelor's ratio, faculty staff to student ratio) aspects. However, the slack values of engineering and ecology are mostly related to teaching (i.e., doctorate to bachelor's ratio, faculty staff to student ratio) and international outlook (i.e., international collaboration, international to domestic student ratio) aspects.

These results provide essential information to define outputs that the faculties should focus on for enhancing their performance. We believe that the benchmarking technique may be one of the stimuli to increase the quality of education and good practices in university management. At the same time, one should warn against directly reading the results obtained from the DEA technique. Proper interpretation of these results requires intrinsic knowledge of the academic fields.



**Figure 2: Slack ratio of each faculty classified in each subject area of each output**

## Conclusions

We propose a quantitative decision support tool to determine possible target values. The evidence-based target values allow inefficient faculties to know what outputs they need to improve to become efficient. They assume that "if each faculty improves their productivity to reach a target value, the university can rank higher." This can lead to a more realistic target that is achievable instead of using a single target across all faculties.

For the faculties in agricultural science and technology management, social sciences, and humanities, the inadequacy of performed research and teaching operations are essential indicators, i.e., the percentage of the sum of slack values in both aspects is more than 80%. In engineering and ecology, the essential indicators (i.e., the percentage of the sum of slack values in both aspects is 91.10%) are related to teaching and international outlook operations. However, the teaching operation is the most critical aspect (i.e., the maximum value of the percentage sum of each subject area's slack values is 42.23%) that all subject areas should be focused on for improvement.

The productivity measurement in this study is deterministic, but productivity changes every year. Thus, the specified target value must change annually. For future work, the dynamic issue could also be investigated for finding the output targets that the data of outputs vary from year to year.

Finally, this research is a goal-setting based on faculty output values. We do not take into account individual-level performance within the faculty. In the future, the setting can be determined at an individual level to reflect feedback to faculty members on what outputs need to be made to increase their faculty productivity. For the cluster analysis, the fifteen faculties or DMUs including the Faculty of Agriculture, Faculty of Veterinary Technology, Faculty of Economics, Faculty of Business Administration, Faculty of Fisheries, Faculty of Humanities

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