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Data Envelopment Analysis on Technical and Scale Efficiencies of Academic Departments at Universiti Teknologi Malaysia

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Abstract This paper evaluates the performance of 28 academic departments at Universiti Teknologi Malaysia using non-parametric method, namely the Data Envelopment Analysis technique. Based on the selected performance indicators, we apply input-oriented Data Envelopment Analysis models to assess the teaching and research performances for each academic department. Our results show that 10 academic departments are technically and scale efficient, and the Department of Social Education is the representative department in this sample data. For the inefficient academic departments, Data Envelopment Analysis technique identifies the amounts and sources of inefficiencies, the reference sets, and further provides the potential targets improvement.

Keywords Data envelopment analysis; Decision making unit; Technical efficiency; Pure technical efficiency; Scale efficiency.

2010 Mathematics Subject Classification 90B50, 90C05.

1 Introduction

Performance evaluation is a necessary and essential continuous improvement tool for staying competitive in the high-technology world of computers as well as telecommunications [1]. It positively forces the business unit to constantly evolve and improve in order to survive. Through performance evaluation, one can reveal the strengths and weaknesses of the business unit and further identify opportunities for future improvement. One of the frequently used techniques for performance evaluation is the Data Envelopment Analysis (DEA).

The applications of DEA at the university level have been extensively studied in the literature [2-9]. In general, there exist two types of performance evaluation at the university level, namely Type I Approach and Type II Approach. For the Type I Approach, the performances of different universities are compared and the focus is on cost efficiency, research productivity, or aggregate performance. The studies of Abbott and Doucouliagos [10] and Avkiran [11] are examples of Type I Approach. One the other hand, Type II Approach compares the teaching and research performances of the departments within a university. Typical examples include Kao and Hung [12] and Martín [13]. In the present paper, we focus on Type II Approach.

In July 2007, Universiti Teknologi Malaysia (UTM) has established Faculty of Health Science & Biomedical Engineering to champion teachings and research in biomedical sciences and engineering. This newest faculty is supported by 4 departments which are Department of Biomedical Instrumentation & Signal Processing, Department of Biomechanics & Biomedical Materials, Department of Clinical Science & Engineering, and Department of Therapy & Rehabilitation. Thus, including these 4 departments in the newest faculty, UTM has more than 50 academic departments among 12 faculties. Since the number of departments and faculties are being increased in the future, therefore UTM must be more cautious in allocating precious resources to academic departments.

The main objective of this paper is to use DEA to examine the relative efficiency of 28 selected academic departments at UTM. The input-oriented Charnes-Cooper-Rhodes (CCR) and Banker-Charnes-Cooper (BCC) models have been chosen to be the main tools for evaluating the performance of the departments. This paper is organized as follows: In Section 2, we introduce the CCR and BCC models. In Section 3, we present the data obtained from the selected academic departments as well as the input and output indicators used in our computations. In Section 4, we analyze the results obtained from the CCR and BCC models. Lastly, we conclude our paper in Section 5.

2 The CCR and BCC Models

In DEA, the organization under study is called a Decision Making Unit (DMU). The definition of DMU is rather loose to allow flexibility in its use over a wide range of possible applications [14]. In this paper, DMU refers to an academic department. Suppose there are n DMUs to be evaluated and each of them utilizes varying amounts of m different inputs to produce s different outputs. More specifically, DMU_o utilizes amount x_{io} of input i and produces amount y_{ro} of output r. As introduced by Charnes *et al.* [15], the ratio of outputs to inputs is used to measure the relative efficiency of DMU_o relative to the ratios of all of the $\mathrm{DMU}_j,\ j = 1, 2, \ldots, n$. For each DMU, the virtual input and virtual output are formed by (yet unknown) weights v_i and u_r

$$\text{Virtual input} = \sum_{i=1}^{m} v_i x_{io} \tag{1}$$

$$\text{Virtual output} = \sum_{r=1}^{s} u_r y_{ro} \tag{2}$$

where the values of v_i and u_r are obtained by solving the following fractional programming problem

$$\begin{aligned}
\max\ & \sum_{r=1}^{s} u_r y_{ro} \Big/ \sum_{i=1}^{m} v_i x_{io} \\
\text{s.t.}\ & \sum_{r=1}^{s} u_r y_{rj} \Big/ \sum_{i=1}^{m} v_i x_{ij} \le 1 \quad \text{for } j = 1, \ldots, n \\
& u_r,\ v_i \ge 0 \quad \text{for all } i \text{ and } j
\end{aligned} \tag{3}$$

However, equation (3) yields an infinite number of solutions, *i.e.* if $(u_r^*,\ v_i^*)$ is optimal, then $(\alpha u_r^*,\ \alpha v_i^*)$ is also optimal for $\alpha > 0$. In order to overcome this problem, a representative solution is selected by Charnes and Cooper [16] through transformation and hence obtained the following linear programming problem

$$\begin{aligned}
\max\ & \sum_{r=1}^{s} \mu_r y_{ro} \\
\text{s.t.}\ & \sum_{r=1}^{s} \mu_r y_{rj} \le \sum_{i=1}^{m} \nu_i x_{ij} \\
& \sum_{i=1}^{m} \nu_i x_{io} = 1 \\
& \mu_r,\ \nu_i \ge 0
\end{aligned} \tag{4}$$

where equation (4) is known as the input-oriented multiplier CCR model. It follows that the dual of equation (4) is given by

$$\begin{aligned} &\min\ \theta \\ &\text{s.t.}\ \ \theta x_{io} - \sum_{j=1}^{n} x_{ij}\lambda_j \geq 0 \\ &\quad \sum_{j=1}^{n} y_{rj}\lambda_j \geq y_{ro} \\ &\quad \lambda_j \geq 0 \end{aligned} \tag{5}$$

where equation (5) is known as the input-oriented envelopment CCR model which is built on the assumption of constant returns to scale (CRS). If the constraint

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{6}$$

is added into equation (5), the CRS assumption of the CCR model can be relaxed and modified to incorporate variable returns to scale (VRS). With this additional constraint, equations (5) and (6) are now known as input-oriented envelopment BCC model which was introduced by Banker *et al.* [17].

The CCR model measures technical efficiency (TE) of the DMU, *i.e.* how well the DMU processes inputs to achieve desired outputs. The TE measure is used to determine the inefficiency of the DMU due to input/output configuration as well as the scale size of the operations. Moreover, by utilizing the BCC model that measures the pure technical efficiency (PTE) of the DMU, it is possible to decompose TE into PTE and scale efficiency (SE). This decomposition is unique and depicts the sources of inefficiency, *i.e.* whether it is caused by inefficient operation (PTE) or by inappropriate scale of operations (SE) or by both.

3 Data, Input, and Output Indicators

The data for this paper were obtained from selected academic departments at UTM. Some departments have very close relationship with other departments within the faculty due to academic contents, hence it is difficult to separate their achievement in teaching unless aggregated departments are formed. Table 1 shows the aggregated academic departments and its components.

Consequently, the total number of academic departments being investigated in this paper is 28, with 23 of them are the original departments while the remaining are the aggregated departments as shown in Table 1.

Three input indicators were chosen to represent the resources utilized by the departments, which are total number of doctoral academic staff (x_1), total number of non-doctoral academic staff (x_2) and total number of non-academic staff (x_3). The output indicators consist of the total number of under-graduate degree graduated in year 2008 (y_1), total number of post-graduate degree graduated in year 2008 (y_2) and the total number of research grants in year 2007 (y_3). The input and output indicators for which the sample data was collected are shown in Table 2.

Table 1: Aggregated Academic Departments

Aggregated Department	Original Departments
Department of Biology	Department of Biological Sciences
	Department of Industrial Biology
Department of Civil Engineering	Department of Structure & Materials
	Department of Hydraulics & Hydrology
	Department of Geotechnics & Transportation
	Department of Environmental Engineering
Department of Microelectronics Engineering	Electronics Engineering Department
	Microelectronics & Computer Engineering Department
Department of Communication Engineering	Radio Communication Engineering Department
	Telematics & Optical Communication Engineering Department
Department of Mechatronics & Control Engineering	Mechatronics & Robotics Engineering Department
	Control & Instrumentation Engineering Department

Table 2: Data for 28 Academic Departments Under Investigation

DMU	Department	x_1	x_2	x_3	y_1	y_2	y_3
1	Department of Educational Foundation	17	21	6	85	42	9
2	Department of Educational Multimedia	4	15	11	155	24	3
3	Department of Social Education	3	6	2	351	12	1
4	Department of Science & Mathematics Education	9	10	2	154	8	2
5	Department of Technical & Engineering Education	6	22	16	521	16	2
6	Department of Geomatics Engineering	13	10	12	89	6	4
7	Department of Remote Sensing	7	8	4	47	5	5
8	Department of Land Administration & Development	6	10	2	57	42	2
9	Department of Geoinformatics	7	10	7	48	8	8
10	Department of Real Estate Management	13	14	3	119	6	2
11	Department of Physics	32	19	27	90	21	7
12	Department of Chemistry	31	22	28	147	34	26
13	Department of Mathematics	45	31	2	121	35	19
14	Department of Mechanical-Aeronautical Engineering	8	9	8	86	5	9
15	Department of Mechanical-Automotive Engineering	7	5	4	100	5	4
16	Department of Mechanical-Marine Technology	10	4	12	51	27	7
17	Department of Mechanical-Materials Engineering	5	6	16	77	2	9
18	Department of Chemical Engineering	32	22	14	134	9	22
19	Department of Petroleum Engineering	14	8	15	54	3	4
20	Department of Gas Engineering	8	11	3	70	4	9
21	Department of Polymer Engineering	10	10	7	57	4	10
22	Department of Bioprocess Engineering	10	12	6	47	11	15
23	Department of Biology	14	26	5	19	8	13
24	Department of Civil Engineering	85	70	39	488	128	45
25	Department of Electrical Power Engineering	8	16	6	277	52	5
26	Department of Microelectronics Engineering	16	40	14	131	58	19
27	Department of Communication Engineering	12	27	12	95	7	14
28	Department of Mechatronics & Control Engineering	16	27	11	163	25	14

4 Results and Analysis

In this section, we present the results obtained from the CCR and BCC models. The results for technical, pure technical and scale efficiencies are first presented in the following sub-section. Next, the returns to scale nature for each academic department is discussed in Section 4.2. In Section 4.3, the sources and amount of inefficiency for each inefficient department are presented. Finally, the potential improvements for the inefficient departments are suggested in Section 4.4.

4.1 Technical, Pure Technical and Scale Efficiencies

Table 3 shows the results of TE, PTE and SE scores for each academic department. The CRS model (CCR model) is used to calculate the TE scores for the departments. A score of 1 implies that the departments are efficient, while scores of less than 1 implies they are inefficient.

As shown in Table 3, 10 departments are technically efficient, which are the Department of Educational Multimedia (DMU_2), the Department of Social Education (DMU_3), the Department of Land Administration & Development (DMU_8), the Department of Mathematics (DMU_{13}), the Department of Mechanical-Marine Technology (DMU_{16}), the Department of Mechanical-Materials Engineering (DMU_{17}), the Department of Gas Engineering (DMU_{20}), the Department of Bioprocess Engineering (DMU_{22}), the Department of Electrical Power Engineering (DMU_{25}) and the Department of Microelectronics Engineering (DMU_{26}). They represent the best practices frontier, and no other departments generate the same output level for fewer inputs. Department with the lowest score is assumed to possess the greatest amount of inefficiency. For example, the Department of Biology (DMU_{23}) achieves a TE score of 0.8667, which means that the Department of Biology (DMU_{23}) is 86.67% efficient using its inputs and outputs. This suggests that the Department of Biology (DMU_{23}) would have to reduce its inputs by 13.33% to be considered technically efficient.

The efficiency scores assessed under the VRS model (BCC model) are referred as PTE. This technical efficiency is pure since it is net of any scale effects, *i.e.* PTE is a measure of efficiency without SE. As shown in Table 3, the PTE scores are higher than the TE scores, as expected. For example, the Department of Chemistry (DMU_{12}) is considered efficient if assuming VRS, but not if assuming CRS. This phenomenon happens is because the CRS model is more limiting than the VRS model. From Table 3, the total number of pure technically efficient departments is 16. By comparing to the technically efficient departments, there are 6 more departments considered efficient under the VRS model. These departments include the Department of Science & Mathematics Education(DMU_4), the Department of Technical & Engineering Education (DMU_5), the Department of Chemistry (DMU_{12}), the Department of Mechanical-Automotive Engineering (DMU_{15}), the Department of Chemical Engineering (DMU_{18}), and the Department of Civil Engineering (DMU_{24}). However, these results also indicate that a loss of discriminating power between the efficient and inefficient departments as evidence by a rise in the number of efficient departments.

Next, we discuss the SE scores obtained by the departments. Note that the SE score is calculated as the ratio of TE score to PTE score, and is used to measure the impact of scale size on the productivity of a DMU. The departments which are scale efficient such as the Department of Mathematics (DMU_{13}) can scale their inputs and outputs in a linear manner without increasing or decreasing efficiency. For the scale inefficient departments,

Table 3: TE, PTE, and SE Scores for 28 Academic Departments

DMU	TE Score	PTE Score	SE Score	Reference Set (Benchmarked Departments)
1	0.7257	0.8579	0.8459	{3, 8, 13, 22}
2	1	1	1	{2}
3	1	1	1	{3}
4	0.5243	1	0.5243	{3, 8, 13, 20}
5	0.7847	1	0.7847	{3, 17}
6	0.3431	0.5034	0.6816	{3, 16, 17}
7	0.5589	0.8592	0.6505	{3, 8, 16, 22}
8	1	1	1	{8}
9	0.7383	0.7539	0.9793	{17, 22, 25, 26}
10	0.3105	0.6666	0.4658	{3, 8, 13, 20, 22}
11	0.3068	0.3107	0.9874	{3, 8, 16, 22}
12	0.8025	1	0.8025	{16, 17, 22}
13	1	1	1	{13}
14	0.7314	0.7367	0.9928	{3, 16, 17, 22}
15	0.7696	1	0.7696	{3, 16, 17, 22}
16	1	1	1	{16}
17	1	1	1	{17}
18	0.7741	1	0.7741	{3, 17, 22}
19	0.3495	0.5732	0.6097	{3, 16, 17}
20	1	1	1	{20}
21	0.7426	0.7851	0.9459	{3, 17, 22}
22	1	1	1	{22}
23	0.8667	0.8890	0.9749	{8, 13, 20}
24	0.7469	1	0.7469	{3, 8, 16, 22}
25	1	1	1	{25}
26	1	1	1	{26}
27	0.6993	0.8276	0.8450	{17, 22, 26}
28	0.6727	0.8055	0.8351	{3, 17, 22, 25}

for example, the Department of Physics (DMU_{11}) has a low PTE score and a relatively high SE score among the inefficient departments. This means that the overall inefficiency (TE = 0.3068) of the Department of Physics (DMU_{11}) is caused by inefficient operations (PTE = 0.3107) rather than scale inefficiency (SE = 0.9874). On the other hand, the Department of Civil Engineering (DMU_{24}) has a fully efficient PTE score and a low SE score. This can be interpreted to mean that the inefficiency of the Department of Civil Engineering (DMU_{24}) is due to inappropriateness of scale (SE = 0.7469). By looking to the Department of Real Estate Management (DMU_{10}), it has both low PTE and SE scores, meaning that the overall inefficiency (TE = 0.3105) of the Department of Real Estate Management (DMU_{10}) is caused by technically inefficient operation (PTE = 0.6666) and at the same time by the disadvantageous scale condition (SE = 0.4658).

Observe that Table 3 also includes the reference set (benchmarked departments) for each department, which are obtained from the CCR model by

$$E_o = \left\{ j \mid \lambda_j^* > 0 \right\}, \ \text{for}\, j \in \{1, \ldots, n\} \tag{7}$$

where λ_j^* is the optimal value of λ. The benchmarked departments symbolize the departments or groups of departments to which the department should compare itself in order to become efficient. For example, the Department of Geomatics Engineering (DMU_6) can become efficient if it tries to emulate the Department of Social Education (DMU_3), the Department of Mechanical-Marine Technology (DMU_{16}) and the Department of Mechanical-Materials Engineering (DMU_{17}). Notice that the efficient departments are compared to themselves and among them the Department of Social Education (DMU_3) is the representative department because it has the highest reference frequency to other departments.

4.2 Returns to Scale

Returns to scale is very important for managerial decision making. Obviously, it makes sense for a department operating at a point where increasing returns to scale (IRS) hold to increase its scale size, as its additional inputs can produce greater output levels. On the other hand, a department operating at a point where decreasing returns to scale (DRS) hold should decrease its scale size. The ideal scale size for a department to operate at is where CRS hold. In keeping with the DEA literature, the CRS term has been used to characterize the CCR model. This is technically correct but somewhat misleading because this model can also be used to determine whether returns to scale for a DMU is increasing or decreasing, by applying the following theorem.

Theorem 1 (i) *The CRS efficiency score is equal to the VRS efficiency score if and only if CRS prevail on DMU_o. Otherwise,*

(ii) $\sum_{j=1}^{n} \lambda_j^* < 1$ *if and only if IRS prevail on DMU_o.*

(iii) $\sum_{j=1}^{n} \lambda_j^* > 1$ *if and only if DRS prevail on DMU_o.*

Table 4 shows the nature of returns to scale for each academic department. From the table, there are 10 departments belonging to CRS, 10 departments belonging to IRS, and 8 departments belonging to DRS class. Interestingly, the departments in Faculty of Science displayed three different natures of returns to scale. For the Department of Physics (DMU_{11}), its nature is IRS, which shows that it has a possibility to improve its efficiency by scaling up its activities. However, the Department of Chemistry (DMU_{12}) belongs to DRS, indicates that it is operating in a large scale size, and possible downsizing will increase its efficiency. For the Department of Mathematics (DMU_{13}), it is operates at an ideal scale size, CRS, therefore the Department of Mathematics (DMU_{13}) is free to scale its inputs and outputs in a linear manner.

4.3 Input and Output Slacks

Through DEA, it is also possible to identify the sources and amount of inefficiency for the inefficient departments. Input slack $\left(s_i^-\right)$ implies that over-utilized inputs for a department, while output slack (s_r^+) depicts outputs that are under-produced. To discover the possible input and output slacks, the following linear programming problem needs to be solved

$$
\begin{aligned}
\max\ & \sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \\
\text{s.t.}\ \ & s_i^- = \theta^* x_{io} - \sum_{j=1}^{n} x_{ij}\lambda_j \\
& s_r^+ = \sum_{j=1}^{n} y_{rj}\lambda_j - y_{ro} \\
& \lambda_j \geq 0,\ s_i^- \geq 0,\ s_r^+ \geq 0
\end{aligned}
\tag{8}
$$

where θ^* is the optimal value of the input-oriented envelopment CCR model. Table 5 shows the amounts of input and output slacks for the inefficient departments. As shown in Table 5, most of the slacks are presented in input x_1. This means that there are many departments over-utilizing the resource of doctoral staff to produce teaching and research outputs. For example, the Department of Polymer Engineering (DMU_{21}) has an input slack $\left(s_1^{-*} = 1.2459\right)$ and an output slack $\left(s_2^{+*} = 1.0964\right)$. This implies that the Department of Polymer Engineering (DMU_{21}) over-utilized approximately 2 doctoral staff and at the same time, it also under-produced approximately 2 post-graduate students. Our results also show that there is no slack for output y_3 for all inefficient departments.

4.4 Potential Improvements

For the inefficient departments, DEA helps in identifying the reference sets for them and objectively determines the productivity improvements. DEA can uses either input reduction or output increase for inefficient departments to reach the efficient frontier. The efficient frontier is composed by the departments where no input reduction and output increase are necessary. As a result, there exist input-oriented DEA models where the inputs are optimized (reduced) while the outputs are kept at least at their current levels, and output-oriented models where the outputs are optimized (increased) while the inputs are kept at most at their current levels. The potential improvements for the inefficient departments under input-oriented CCR model are computed as follows

$$
\hat{x}_{io} = \theta^* x_{io} - s_i^{-*} \tag{9}
$$

Table 4: Returns to Scale Nature for the Departments

DMU	$\sum_{j=1}^{n} \lambda_j^*$	Returns to Scale
1	1.3405	DRS
2	1	CRS
3	1	CRS
4	0.5134	IRS
5	1.5302	DRS
6	0.6278	IRS
7	0.4240	IRS
8	1	CRS
9	0.8143	IRS
10	0.4297	IRS
11	0.9411	IRS
12	2.7814	DRS
13	1	CRS
14	0.9697	IRS
15	0.6017	IRS
16	1	CRS
17	1	CRS
18	1.8563	DRS
19	0.5789	IRS
20	1	CRS
21	0.8691	IRS
22	1	CRS
23	1.4642	DRS
24	5.5588	DRS
25	1	CRS
26	1	CRS
27	1.3493	DRS
28	1.2929	DRS

Table 5: Input and Output Slacks for the Inefficient Departments

DMU	s_1^{-*}	s_2^{-*}	s_3^{-*}	s_1^{+*}	s_2^{+*}	s_3^{+*}
1	0.6248	0	0	0	0	0
4	0	0.2005	0	0	0	0
5	0	8.0815	9.2594	0	1.7748	0
6	0.8102	0	0	0	1.0973	0
7	0.3057	0	0	0	0	0
9	0	0	0	27.6141	0	0
10	0	0	0	0	0	0
11	1.5849	0	0	0	0	0
12	3.7402	0	0	27.6334	0	0
14	0.1790	0	0	0	0	0
15	2.2666	0	0	0	0	0
18	10.7296	0	0	0	4.3018	0
19	0.4354	0	0	0	7.2996	0
21	1.2459	0	0	0	1.0964	0
23	0	6.1978	0	83.6119	0	0
24	19.3934	0	0	0	0	0
27	0	8.0419	0	3.4669	0	0
28	0	3.1009	0	0	0	0

$$\hat{y}_{ro} = y_{ro} + s_r^{+*} \tag{10}$$

where s_i^{-*} and s_r^{+*} are the optimal values of the input and output slacks. Table 6 displays the potential improvements for 18 inefficient departments.

Table 6: Potential Improvements for the Inefficient Departments

DMU	TE Score	$\hat{x}_1$	$\hat{x}_2$	$\hat{x}_3$	$\hat{y}_1$	$\hat{y}_2$	$\hat{y}_3$
1	0.7257	11.71	15.24	4.35	85	42	9
4	0.5243	4.72	5.04	1.05	154	8	2
5	0.7847	4.71	9.18	3.30	521	17.77	2
6	0.3431	3.65	3.43	4.12	89	7.10	4
7	0.5589	3.61	4.47	2.24	47	5	5
9	0.7383	5.17	7.38	5.17	75.61	8	8
10	0.3105	4.04	4.35	0.93	119	6	2
11	0.3068	8.23	5.83	8.28	90	21	7
12	0.8025	21.14	17.66	22.47	174.63	34	26
14	0.7314	5.67	6.58	5.85	86	5	9
15	0.7696	3.12	3.85	3.08	100	5	4
18	0.7741	14.04	17.03	10.84	134	13.30	22
19	0.3495	4.46	2.80	5.24	54	10.30	4
21	0.7426	6.18	7.43	5.20	57	5.10	10
23	0.8667	12.13	16.33	4.33	102.61	8	13
24	0.7469	44.10	52.29	29.13	488	128	45
27	0.6993	8.39	10.84	8.39	98.47	7	14
28	0.6727	10.76	15.06	7.40	163	25	14

By referring back to Table 5, observe that all inefficient departments have either input/output slacks or both, except for the Department of Real Estate Management (DMU_{10}). No mix inefficiencies are present in the Department of Real Estate Management (DMU_{10}) because all slacks are zero. Thus, removal of all inefficiencies is achieved by reducing all inputs by $(1 - 0.3105 = 0.6895)$ or approximately 69% of its input values.

Another type of inefficiency occurs when only some (but not all) outputs (or inputs) are identified as exhibiting inefficient behavior. This kind of inefficiency is referred to as "mix inefficiency" because its elimination will alter the proportions in which outputs are produced (or inputs are utilized). Observe that all inefficient departments having mix inefficiencies, except for the Department of Real Estate Management (DMU_{10}). For example, the Department of Chemistry (DMU_{12}) can be used to illustrate both technical and mix inefficiency. The Department of Chemistry (DMU_{12}) can be achieved technically efficient if it reduces all inputs by 19.75%. However, this improvement in TE score does not remove all of the inefficiencies. Comparison of the Department of Chemistry (DMU_{12}) with its reference set shows an excess in input x_1 and shortfall in output y_1, so a further improvement can be done by reducing 3.7402 or approximately 4 doctoral staff and producing 27.6334 or approximately 28 under-graduate students. By utilizing equations (9) and (10), the ideal amount of inputs and outputs for each department to become perfectly efficient can be calculated. However, since in reality the ideal amount of an input may not be achievable, other inputs could be reduced to a lower level than its ideal amount to replace.

5 Conclusions

This paper applies the DEA technique to evaluate the relative efficiency of 28 academic departments at UTM. The findings indicate that 10 departments in this data sample are already operating at respectable levels of technical and scale efficiency. Based on the results of returns to scale, a small number of departments were operating at DRS, and 4 of 8 DRS departments were also found technically inefficient. This suggests that administrators should focus first on removing the technical inefficiency of these departments before addressing ways to restructure the scale of operations. As conclusion, DEA is a suitable technique in measuring the efficiency of departments within a university because DEA is capable of handling the multiple inputs and multiple outputs. Moreover, DEA exceeds traditional methods of analyzing the efficiency of department using simple ratio calculations. Not only did DEA successfully determine the efficiency of university departments, but it goes beyond this task and provides potential improvements for each department separately.

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