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EXAMINING THE EFFICIENCY OF MALAYSIAN PUBLIC RESEARCH UNIVERSITIES IN SECURING WORLD UNIVERSITY RANKING

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Abstract

University ranking is crucial as it attracts prospective students and academics. The ranking of public research universities in Malaysia works as a catalyst for securing government and other corporate research funding. This study measures the technical efficiency of five public research universities in Malaysia (PRUMs). This study employs a triangular fuzzy number in the Banker, Charnes, and Cooper (BCC) Fuzzy Data Envelopment Analysis (BCC-FDEA) model. The three world ranking indicators employed as output variables are teaching and research reputations and citations, and the input variables are the number of full-time students and staff. Data gathered for the academic years from 2018/2019 to 2020/2021 are used to project the efficiency scores for 2021/2022. The BCC-FDEA model is also used to consider five public research universities in Asia (APRUs) as the decision-making units (DMUs) to solve the issue of sample size adequacy. This study projects three PRUMs as technically inefficient due to input factor issues. Two main contributions of this study are: (1) QS world ranking indicators are profound parameters that research universities should consider to attain a better position in the world ranking; (2) fuzzy efficiency scores shed light on how inefficient PRUMs can improve their operations by emulating their referent DMUs.

Keywords: *public research university, technical efficiency, fuzzy DEA, triangular fuzzy number, QS ranking.*

Introduction

The significant economic contribution of research universities has long been documented in the literature (Elnasri & Fox, 2017; Parilla & Haskins, 2023). The Malaysian government recognises the importance of research activities in contributing to national economic development, transforming five public universities into research universities (RUs) by 2010. The main targets of establishing RUs in Malaysia are increasing research and development activities, commercialisation, higher foreign student intake, and advancing the international ranking of PRUMs (Nooraini & Noordini, 2017; Komoo et al., 20008). Under the National Higher Education Strategic Plan 2007–2020, five Malaysian public universities—Universiti Malaya (UM), Universiti Sains Malaysia (USM), Universiti Kebangsaan Malaysia (UKM), Universiti Putra Malaysia (UPM), and Universiti Teknologi Malaysia (UTM) —were designated as RUs. These Malaysian public research universities (PRUMs) are intended to reinforce the research and development (R&D) culture within the public university domain (Sheriff & Abdullah, 2017). The government has a significant role in providing funds and protecting the existence of PRUMs so that they can deliver quality research and teaching services (Krull, 2005) and offer a more conducive research environment well-equipped with facilities. The PRUMs should, therefore, attract additional government funding (MOHE, 2023).

A substantial budget allocation of over RM14 billion was announced in the Malaysian 2021 Budget Report to the Higher Education Ministry. This allocation for research and management activities encompasses various forms of support and specialised research services such as incentive grants, patenting, intellectual property rights (IPR) and repositories (MOHE, 2023). This indicates the seriousness of the Malaysian government in not allowing any interruptions to the research and innovation activities of PRUMs. These initiatives aim to help PRUMs improve their research output, enhance their quality, and strengthen their international ranking and reputation by realigning their activities and priorities (MOHE, 2023). However, for the past decade, the PRUMs have experienced a decline in government funding allocated to their operational and research expenditures (Faridah Anum et al.,2014). Many public universities abroad have channelled funds at only necessary levels (Cooper et al., 2011). The allocation of public resources lacks efficiency and fails to meet the established goals of the higher education sector. In addition, the return on investment in higher education operations often lags by decades (Zafiropoulos & Vrana, 2008). There are also demands from society, media, and other stakeholders for universities to be transparent in using state and national funding (Zafiropoulos & Vrana, 2008; Gajda, 2009).

Growing pressures have also been placed on public universities in many countries across the world to improve their service quality and student activities, hence increasing their level of efficiency (Zafiropoulos & Vrana, 2008). Despite funding constraints, the PRUMs still need to develop human capital and increase their quality of research output. These two can improve the international reputation and the ranking of Malaysian universities. This can, in turn, attract quality students from abroad to pursue higher education in Malaysia (Nooraini & Noordini, 2017; Komoo et al., 20008) and boost the country's international stature and competitiveness. Similarly, the corporate sector seeks competent and well-prepared human resources who have received an excellent education from top-tier universities (TopUniversities, 2023). Information on university rankings also plays a role in influencing external stakeholders, other corporate institutions and potential international partners to collaborate in research and provide research funding for the universities, thus impacting the quality of research output (Jowkar et al., 2011).

Hence, the PRUMs' principal challenge is to achieve good university rankings. These rankings are the standard performance measurement derived from several predetermined factors like research excellence, teaching quality, and graduate employability. Therefore, the decision-makers (DMs) of PRUMs need to be informed about the current year's efficiency levels, the expected efficiency scores for the succeeding year, and the whole higher educational system in the country (Cooper et al., 2011) as the PRUMs' performance measurement is crucial for their accountability and resource allocation (Nooraini & Noordini, 2017).

Literature Review

University efficiency measurement is relevant to highlighting possible improvements for universities to achieve their potential based on best practices in resource utilisation among group members under evaluation. Technical efficiency is an alternative approach to measuring the PRUMs performance at the global level while providing valid data and information for long-term planning. Data envelopment analysis (DEA) methodology is frequently employed to gauge the efficiency of economic entities'—also termed decision-making units (DMUs) — operations and uses numerous inputs and outputs. DEA utilises linear programming optimisation to establish efficiency via the 'production frontier' concept.

DEA measures a DMU's efficiency scores relative to other DMUs or their peers. DMUs with maximum scores of 100%, or 1.00, will be the referent units and locate themselves on the frontier. Any DMUs scoring less than 100% or 1.00 are deemed inefficient, with their scores determined based on their distance from the reference units. Thus, greater efficiency is measured against closer proximity (Cooper et al., 2007). Inefficient DMUs can learn by benchmarking against best-practice DMUs, thus promoting progress toward the production frontier (Ozcan, 2014). Conventional DEA aids in identifying top performers among DMUs and provides alternative avenues for enhancing operations (Färe et al., 1994). Comparing a DMU's production plan to an efficient frontier counterpart is an exercise in benchmarking, or establishing a 'standard of excellence' (Färe et al., 1994). These standards guide achievable technical efficiency through either input-reducing efficiency (minimal inputs for constant outputs) or output-increasing efficiency (maximum output from constant input) analysis (Fried et al., 2008).

DEA is popular for non-profits such as universities and is capable of handling multiple inputs and outputs without prior value assumptions (Johnes & Yu, 2008; Miragaia et al., 2023). Technical efficiency is central in university DEA efficiency measurement literature (Johnes, 1993; Abbott & Doucouliagos, 2003; Flegg et al., 2004; Kutlar & Babacan, 2008; Gökşen et al., 2015; Ahmed et al., 2022). Although there is a lack of strict guidelines on the selection of variables under this technique (Niranjan & Andrew, 2011), higher education institutions (HEIs) can opt for inputs and outputs aligned with their objectives, such as key critical variables (Gökşen et al., 2015; Avkiran, 2001). The common variables for HEIs are academic and non-academic staff numbers and enrolments but rarely profit-related outputs. Other factors comprise accredited programs, rankings, student counts, employment, and funding (Gökşen et al., 2015; Mahmudah & Lola, 2016; Olariu & Brad, 2017; Mojahedian et al., 2020; Ahmed et al., 2022). However, conventional DEA approaches have limitations, such as sensitivity to outliers and initial data (Guo & Tanaka, 2008; Ebrahimnejad & Amani, 2021; Shero et al., 2021). Empirical data from practical situations is often imprecise and unclear. This prompts the combining of DEA with fuzzy elements by introducing fuzzy linear programming models (Hatami-Marbini et al., 2010; Peykani et al., 2019).

Fuzzy DEA employs fuzzy logic, which addresses imprecise problems through algorithmic solutions (Wen & Li, 2009; Zhang et al., 2014). Fuzzy DEA applications in HEIs are limited (Mahmudah & Lola, 2016), particularly those exploring the role of international rankings (Mahmudah & Lola, 2016). Motivated by international university ranking goals but uncontrollable international indicators, this research utilises non-parametric fuzzy data envelope analysis (FDEA) to measure PRUMs' technical efficiency. This novel application aims to estimate efficiency, forecast scores, and emulate efficient DMUs. Fuzzy DEA helps inefficient PRUMs identify improvement areas, enhancing standards and ranking (Rey & Racionero, 2010; Mahmudah & Lola, 2016). This study progresses with the proposed BCC-DEA framework, elaborates on DMUs, on input/output variables by reviewing the Malaysian PRUMs and QS World University Ranking, followed by discussing fuzzy arithmetic and then examining fuzzy DEA results and analysis before concluding remarks.

Methodology

The BCC-FDEA Conceptual Framework

While DEA models necessitate exact input and output data, real-world data is often imprecise, uncontrollable, or qualitative. For HEIs, for instance, the number of graduates keeps changing each academic year, and the level of expenses fluctuates unexpectedly, as does the number of publications (Tavana M. et al., 2021). By encoding imprecise and ambiguous data into fuzzy sets, FDEA merges fuzzy set theory with classic DEA. FDEA is in linear programming, known as 'fuzzy linear programming' (FLP) models (Hatami-Marbini et al., 2017; Peykani et al., 2019). The most potent DEA fuzzy set theory applications are the tolerance technique with the type-2 method (Hatami-Marbini et al., 2017) applied for this study. This FDEA model combines data envelopment analysis with fuzzy set theory to allow the handling of uncertain and incomplete data (Wu & Liang, 2015). The core of fuzzy logic in the DEA model is the combination of a genetic algorithm, hybrid intelligence algorithm and fuzzy simulations. The key path to this study is extending the Banker, Charnes, Cooper (BCC) DEA model of Banker et al. (1984) to fuzzy data variables by adopting the proposed FDEA model. The notion of fuzziness in the DEA model defining the tolerance levels for constraint violations is applicable and suits the objective of this study because all output variables of FDEA are considered crisps and are not controlled by DMs. The research metrics for DMUs are externally determined world ranking indicators , whereas the input variables, such as the number of international students for each academic session, are within the DMU's control. This was particularly true during the COVID-19 outbreak when there were limits on the number of students from abroad. Malaysia's Movement Control Orders (MCOs)—the procedures for travelling within and entering Malaysia from other countries in 2020 and 2021—restricted the international student ratio. The model explains the fixed number of input variables set by decision-makers (DM) from the universities. Different determinations and limitations behind the flexible tolerance approach relate to a DEA model designed with an objective function characterised by fuzziness and constraints that incorporate fuzziness.

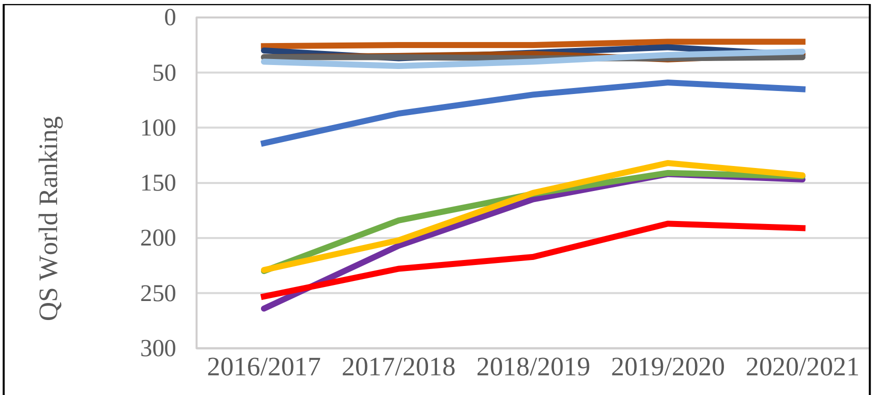
DMUs, Input and Output Variables

This study adopts the FDEA framework of Ahmed et al. (2022) to estimate the technical efficiency of five public research universities in Malaysia (PRUMs) with several QS world ranking indicators employed as the output variables. The world ranking indicators are certainly beyond the control of the PRUMs and, hence, suit the fuzzy DEA applications. The present study selects five Asian public research universities added to the list as DMUs, making a total of ten DMUs in the FDEA model. More DMUs (relative to input and output variables) would reduce the possibility of biased efficiency scores (Alirezaee et al., 1998; Farrell, 1957; Banker et al., 1993). The APRUs are the leading institutions of higher education and research in Asia, randomly selected based on the World University Research Ranking (WURR) for 2020 (https://worldresearchranking.com/ accessed: 28th January 2022). The WURR index is designed from the QS, Times Higher Education, and the Academic Ranking of World Universities (ARWU). It evaluates three critical elements: interdisciplinary research, impact, and collaboration. The study assumes the homogeneity of the DMUs based on the nature of operations and the conditions under which they operate as public research universities. Benchmarking the performance of PRUMs against APRUs can help PRUMs identify areas for improvement against international standards and provide valuable insights into the state of higher education and research and their performance in the region.

Table 1 lists the ten DMUs comprising five PRUMs and five APRUs. This study analyses input and output data of four consecutive academic cohorts from 2017/2018 to 2020/2021. The following elements comprise the input data gathered from the annual reports of the Ministry of Education in Malaysia (Higher Education Department) and the respective official websites of the selected Asian universities. (1) Number of full-time equivalent staff (No. of FTE Staff), including all academic and research staff. All staff numbers are pre-fixed or determined by each DMU (the university). (2) Number of full-time equivalent students (No. of FTE Students), including all local and international/overseas (FTE) students, all controlled and determined by the university (DMU). (3) Percentage (%) of FTE international students/total FTE students. Human (students and staff) and physical capital are the agreed inputs for university efficiency measurement (Tomkins & Green, 1988; Flegg et al., 2004; Goksen et al., 2015; Mahmudah & Lola, 2016). Because teaching and research are the main activities of HEIs, the selected output variables are teaching reputation, research reputation, and research influence.

Table 1: List of DMUs

DMU	University Name	Country	Code
1	Universiti Malaya	Malaysia	UM
2	Universiti Sains Malaysia	Malaysia	USM
3	Universiti Kebangsaan Malaysia	Malaysia	UKM
4	Universiti Putra Malaysia	Malaysia	UPM
5	Universiti Teknologi Malaysia	Malaysia	UTM
6	University of Hong Kong	Hong Kong	HUK
7	Hong Kong University of Science & Technology	Hong Kong	HKUST
8	Kyoto University	Japan	KU
9	Seoul National University	Korea	SNU
10	Fudan University China	China	FDU

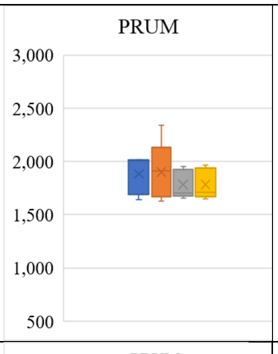
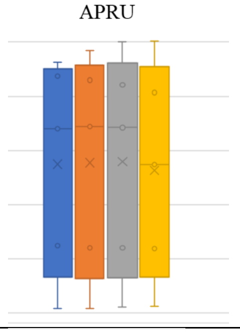
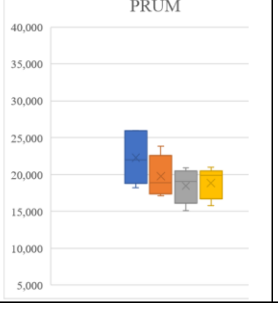
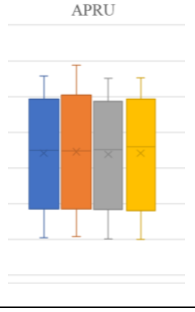


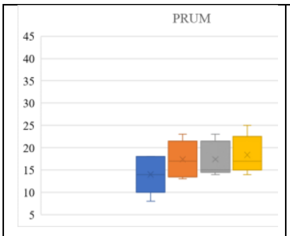
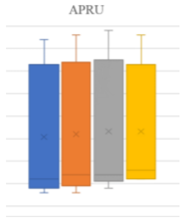
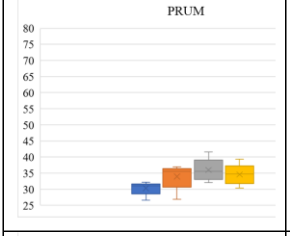
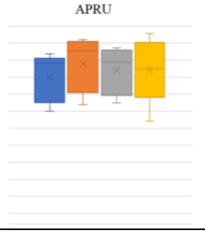
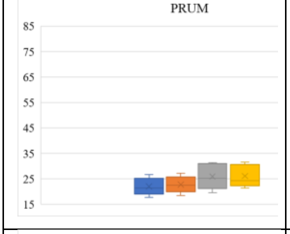
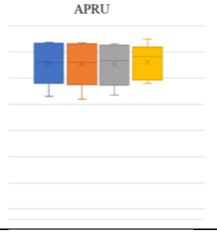
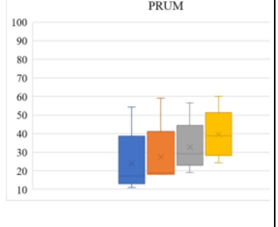
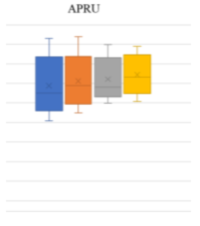
	2016/2017	2017/2018	2018/2019	2019/2020	2020/2021
UM	114	87	70	59	65
USM	264	207	165	142	147
UKM	230	184	160	141	144
UPM	229	202	159	132	143
UTM	253	228	217	187	191
HKU	26	25	25	22	22
HKUST	30	37	32	27	34
KU	36	35	33	38	33
SNU	36	36	37	37	36
FDU	40	44	40	34	31

Figure 1: QS World Ranking of PRUMs and selected APRU (2017–2021) (Source: TopUniversities [2023].)

Figure 1 presents the QS world ranking of PRUMs and APRU for 2017–2021. All data retrieved from the World University Rankings website (2023) and QS Top Universities (2023) website are consistent with both sources. Table 2 presents the mean value for each input and output variable for each PRUM and APRU category for all academic years. Table 2 reports that PRUMs are operating with more staff over the period of the study (overall mean = 1,837) although with relatively fewer students (overall mean = 19,856) than APRUs (staff overall mean of 1,767 but students averaging 22,092). Notably, the number of FTE staff and students for APRUs is more varied than that of PRUMs. The percentage of international students in the PRUMs (16.8%) is much lower relative to the APRUs (21.2%). Table 2 also shows the three QS indicators of APRUs being far above that of the PRUMs over the four academic sessions (Teaching reputation: PRUMs = 33.7; APRUs = 67.0; Research reputation: PRUMs = 24.2; APRUs = 70.6; Research influence: PRUMs = 31.0; APRUs = 71.6).

Table 2: Descriptive Statistics of Input/Output Variables: 5 PRUMs and 5 APRUs (2017/2018 – 2020/2021)

		**FTE Staff** PRUMs Overall Mean: 1,837 Std Dev: 184.83 Minimum: 1,627 Maximum: 2,339	APRUs Overall Mean: 1,767 Std Dev: 931.86 Minimum: 440 Maximum: 2,910
		**FTE Student** PRUMs Overall Mean: 19,856 Std Dev: 2,967.92 Minimum: 18,214 Maximum: 25,975	APRUs Overall Mean: 22,093 Std Dev: 10,563.20 Minimum: 9,976 Maximum: 34,393

		**% International Students** PRUMs Overall Mean: 17 Std Dev: 4.17 Minimum: 8 Maximum: 25	APRUs Overall Mean: 21 Std Dev: Minimum: 8 Maximum: 44
		**Teaching Reputation** PRUMs Overall Mean: 34 Std Dev: 3.73 Minimum: 27 Maximum: 42	APRUs Overall Mean: 67 Std Dev: 7.53 Minimum: 52 Maximum: 78
		**Research Reputation** PRUMs Overall Mean: 24 Std Dev: 4.08 Minimum: 18 Maximum: 32	APRUs Overall Mean: 71 Std Dev: 7.41 Minimum: 57 Maximum: 80
		**Influence Ratio** PRUMs Overall Mean: 31 Standard deviation: 15.30 Minimum: 11 Maximum: 60	APRUs Overall Mean: 72 Standard deviation: 12.41 Minimum: 51 Maximum: 94

Estimating PRUMs' Technical Efficiency with Fuzzy DEA

The FDEA model of Ahmed et al. (2022) proposes a tolerance approach which offers flexibility by loosening the DEA relationships while maintaining the input and output coefficients as deterministic (Hatami-Marbini et al., 2011). Although universities have more influence on their attained outcomes than the quantity of their resources (Gökşen et al., 2015; Avkiran, 2001), in this study, world ranking indicators as the output variables are beyond the control of DMUs. Henceforth, reducing the input will be the best way to improve efficiency, and being input-oriented is better than output-oriented for this study. The input-oriented model measures the ineffectiveness of PRUMs from the input perspectives and focuses on how much the inputs need to be decreased without reducing outputs. This input minimisation approach presupposes a variable return to scale that estimates the FDEA efficiency scores. This study employs three input variables with three fuzzy output variables articulated above. The basic formation of the fuzzy inference system specifies Type-2 (Karnik et al., 2001), which is the extension for ordinary fuzzy sets characterised in [0,1], allowing the handling of linguistic uncertainties or increased ability to handle inexact information logically.

Figure 2 presents the detailed processes for computing triangular fuzzy numbers (TFNs) (Zimmermann, 2001) for crisp output data using the R-Soft application. Fuzzy numbers are widely applied to obtain better results where decision-making and analysis are involved (Clement & Janani, 2017). Fuzzy number theory extends the domain of the characteristic function from the discrete set {0, 1} to the closed real interval [0, 1]. Zadeh (1965) described a fuzzy set as a class of items with gradations of membership along a continuum. Based on this, many researchers have reformed the fuzzy theory sets, including 'triangular fuzzy theory' (Zimmermann, 2001). Nine TFN concepts and definitions are described by Clement and Janani (2017), and this study employs their ninth definition to derive and redefine definitions 1–8. Ahmed et al. (2022) give details of the triangular fuzzy number definitions and the algorithm of fuzzy numbers with TFN employed in this study. Table 3 shows the TFNs generated from the crisp output data.

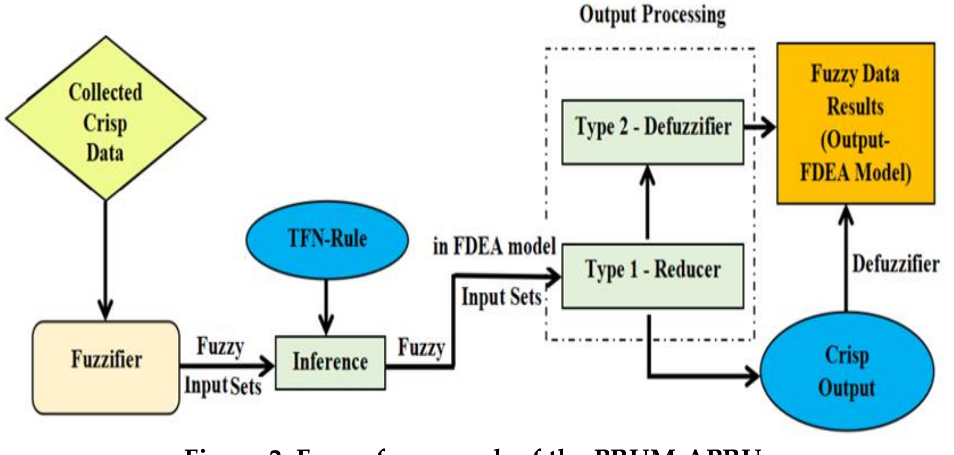


Figure 2: Fuzzy framework of the PRUM-APRU case
(Source: Authors.)

Table 3: Fuzzifying: Converting data to TFNs.

DMU	Input			Output (Fuzzy)		
	No of FTE Staff	No of FTE Students	International Students %	Teaching Reputation % (y_{1L}, y_{1M}, y_{1U})	Research Reputation % (y_{2L}, y_{2M}, y_{2U})	Citations % (y_{3L}, y_{3M}, y_{3U})
DMU1	(1903, 1903, 1903)	(15794, 15794, 15794)	(20, 20, 20)	(31.2, 37.35, 41.6)	(26.6, 28.93, 31.5)	(54.4, 57.53, 60)
DMU2	(1967, 1967, 1967)	(21039, 21039, 21039)	(14, 14, 14)	(32.2, 34.53, 35.6)	(17.7, 21.53, 23.3)	(15, 23.18 , 32.2)
DMU3	(1709, 1709, 1709)	(17601, 17601, 17601)	(16, 16, 16)	(30.5, 33.58, 35.3)	(19.6, 20.95, 21.4)	(11, 26.05, 42.5)
DMU4	(1648, 1648, 1648)	(19937, 19937, 19937)	(25, 25, 25)	(26.6, 29.7, 33.3)	(18.5, 25.8 , 31.4)	(17.2, 19.7, 24.4)
DMU5	(1694, 1694, 1694)	(19988, 19988, 19988)	(17, 17, 17)	(30.4, 33.45, 36.4)	(20.4, 23.58, 25.2)	(22.7, 28.5, 38.8)
DMU6	(996, 996, 996)	(18135, 18135, 18135)	(43, 43, 43)	(67.5, 69.65, 72.6)	(73.3, 76.73, 78.4)	(73.7, 76.15, 80.3)
DMU7	(462, 462, 462)	(9976, 9976, 9976)	(30, 30, 30)	(52.1, 55.38, 57.4)	(63, 66.28, 68)	(88.9, 91.43, 94)
DMU8	(2434, 2434, 2434)	(22935, 22935, 22935)	(11, 11, 11)	(71.8, 74.85, 77.9)	(78, 78.65, 79.9)	(50.9, 56.65, 60.8)
DMU9	(1772, 1772, 1772)	(26757, 26757, 26757)	(11, 11, 11)	(69.3, 72.25, 75)	(71, 71.85, 73.8)	(61, 65.08, 68.8)
DMU10	(2910, 2910, 2910)	(32597, 32597, 32597)	(13, 13, 13)	(59.9, 61.45, 64)	(57, 59.8, 65.6)	(65, 68.85, 73.3)

Note: All input data are in TFN form and are similar to values based on Definition 1.

Expanding the FDEA Model for the PRUM–APRU Case

Since technical efficiency is expressed as the ratio of overall output weight to total input weight, this ratio must be between 1 and 0. If we examine the p^{th} DMU (DMUp), the BCC-RCC (as a non-linear) model for relative efficiency is as follows (Charnes et al., 1978):

$$\theta_p{}^* = \quad \max \frac{\sum_{r=1}^{s} u_r y_{rp}}{\sum_{i=1}^{m} v_i x_{ip}}$$

$$s.t.$$

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1, \quad \forall j$$

Model 1
$$u_r, v_i \geq 0 \qquad \forall r, i.$$

In the above model, $n = 10$ DMUs (PRUM and APRU) with $m = 3$ inputs x_{ij} ($i = 1, 2, \ldots, m$), to obtain s =3 outputs y_{rj} ($r = 1, 2, \ldots, s$). Here u_r ($r = 1, 2, \ldots, s$) and v_i ($i = 1, 2, \ldots, m$) are the weights of the i^{th} input and r^{th} output. This fractional program is computed for each DMU in order to determine the appropriate input and output weights. The above model is a nonlinear program; to simplify the calculations, the model is converted into a linear program (LP) denoted as below, where $\theta_p{}^*$, the objective function for both models, is defined for the PRUM–APRU case.

$$\theta_P^* = Max \sum_{r=1}^{s} u_r\, y_{rp} + \mu_0$$

s.t :

$$\sum_{i=1}^{m} v_i\, x_{ip} = 1$$

$$\sum_{r=1}^{s} u_r\, y_{ij} - \sum_{i=1}^{m} v_i\, x_{ij} + \mu_0 \le 0, \forall\, j$$

$$u_r, v_i \ge 0 \qquad \forall\, r, i,\ \mu_0 \in R$$

Model 2

For both models, the objective function of the optimisation problem maximises the ratio of weighted output to weighted input. The constraints specify that the weights of each DMU must not offer an efficiency score of more than 1 compared to any other DMU, which is the benchmarking of DMU. The highest efficiency score (the full score or the optimal objective value) is equal to 1.
Before expanding Model 2 and defining the FDEA model, the BCC efficiency definition should be considered as follows.

1) DMU_P is BCC-efficient if θ_p^* =1, and there exists at least one optimal a^*, b^* with $a^* > 0$, $b^* > 0$.
2) Otherwise, DMU_p is BCC-inefficient

Additionally, if θ_{p^*} =1, then DMU_p is efficient; otherwise it is inefficient. Thus, by using the above definition, the technical efficiency score can be estimated for the academic year 2021/2022 by developing Model 3 below as a fuzzy DEA model for PRUM-APRU as follows:

$$\theta_P^* = Max \sum_{r=1}^{s} u_r\, \tilde{y}_{rp} + \mu_0$$

s.t:

$$\sum_{i=1}^{m} v_i\, \tilde{x}_{ip} = 1$$

$$\sum_{r=1}^{s} u_r\, \tilde{y}_{ij} - \sum_{i=1}^{m} v_i\, \tilde{x}_{ij} + \mu_0 \le 0,\ \forall\, j$$

$$u_r, v_i \ge 0 \qquad \forall\, r, i,\ \mu_0 \in R$$

Model 3

where, $\tilde{x}_{ij}$ (i = 1, 2, 3) are not fuzzy inputs but are converted into fuzzy form, and $\tilde{y}_{rj}$ (r = 1, 2, 3) and fuzzy outputs variables for the jth DMU (DMU_j). The other parameters have the same definition as in the previous models. The fuzzy BCC of

Model 3 is known to be a robust technique for assessing the efficiency of DMUs with any inaccurate information (Peykani et al., 2019). By expanding the Banker, Charnes and Cooper transformation model using TFNs' triangular fuzzy definition, the form $\tilde{x}_{ij}$ and $\tilde{y}_{rj}$ could be defined as the following, such that $\tilde{x}_{ij} = (x_{ij}^L, x_{ij}^M, x_{ij}^U)$ and $\tilde{y}_{ij} = (y_{rj}^L, y_{rj}^M, y_{rj}^U)$; Model 3 can thus be re-written as:

$$\theta_P^* = \text{Max} \sum_{r=1}^{s} u_r \otimes \left(y_{rp}^L, y_{rp}^M, y_{rp}^U\right) + \mu_0$$

$$s.t$$

$$\sum_{i=1}^{m} v_i \otimes (x_{ip}^L, x_{ip}^M, x_{ip}^U) = (1,1,1)$$

$$\sum_{r=1}^{s} u_r \otimes (y_{rj}^L, y_{rj}^M, y_{rj}^U) - \sum_{i=1}^{m} v_i \otimes (x_{ij}^L, x_{ij}^M, x_{ij}^U) + \mu_0 \leq (0,0,0),\ \forall j$$

$$u_r, v_i \geq 0 \qquad \forall\, r, i,\ \mu_0 \in R$$

Model 4

where, $\tilde{x}_{ij}$ *(i = 1, 2, . . ., m)* and for PRUM-APRU case *m =3*; also, $\tilde{y}_{rj}$ *(r = 1, 2, . . ., s)* and *s =3* inputs are in fuzzy form, and the real fuzzy outputs are for the *j^th^* DMU (DMU_j). This study utilises Solver-365 and Win4Deap2 software for the technical efficiency measurement of the next academic year, 2021/2022. Two sub-components of technical efficiency are pure technical and scale efficiency (Diacon et al., 2002). Pure technical efficiency assesses the degree to which a firm can reduce its inputs (while maintaining fixed proportions) and still operate at the efficiency frontier. In simpler terms, it gauges the overall effectiveness of a DMU in utilising its inputs. On the other hand, scale efficiency pertains to the degree to which a DMU operates along the variable return-to-scale efficiency frontier while further reducing its inputs (and maintaining fixed proportions) but still operating within the constant return-to-scale frontier. In this context, scale efficiency quantifies a DMU's ability to minimise inputs by transitioning to the frontier characterised by more favourable returns to scale attributes (Diacon et al., 2002).

FDEA Results and Findings

By utilising the 2017/2018–2020/2021 dataset, this study's FDEA model projects the technical efficiency scores of all PRUMs and selected APRUs for the academic year 2021/2022. Table 4 reports the projected technical efficiency scores for constant return to scale (CRS) DEA decomposed into 'pure' technical efficiency for variable-return-to-scale (VRS) DEA and scale efficiency scores. Technical efficiency reflects the ability to obtain minimum inputs based on a given set of outputs. Table 4 reports a technical efficiency of 51.4% for PRUMs, suggesting there is still room to improve efficiency for the academic year 2021/2022. This can be done by reducing

48.6% of the input factors. By doing this, PRUMs can maintain the same QS world ranking indicators (teaching reputation, research reputation, and research influence). The estimated mean scale efficiency (53.9%) is slightly higher than technical efficiency, indicating the potential for substantial input reduction and better scale management. A pure technical efficiency of 94.6% suggests that suboptimal input factor settings or PRUMs are relatively efficient in converting inputs to output when scale is not considered. Nonetheless, there is still room for optimising the input usage.

By contrast, all selected APRUs, are projected to achieve full efficiency (SD = 0.087) for the same academic year. This implies that APRUs effectively utilise their input resources to achieve optimal output levels.

Table 4: Projected Technical, Pure Technical, and Scale Efficiency of PRUM and selected APRU for 2021/2022 academic sessions

	Technical Efficiency	Pure Technical Efficiency	Scale Efficiency
<u>PRUMs</u>			
Mean	0.514	0.946	0.539
Standard Deviation	0.154	0.084	0.132
Minimum	0.359	0.801	0.449
Maximum	0.772	1.000	0.772
<u>APRUs</u>			
Mean	0.941	1.000	0.941
Standard Deviation	0.087	1.000	0.087
Minimum	0.805	1.000	0.805
Maximum	1.000	1.000	1.000

Table 4 shows that APRUs achieve much higher technical, pure technical and scale efficiency. This indicates that APRUs are better at converting their inputs into desirable outputs for the 2021/2022 academic year. Benchmarking against the five APRUs reveals that the PRUMs would not achieve full technical efficiency. However, DMU1 and DMU3 are projected to achieve full technical efficiency. In simple terms, both these DMUs have the potential to effectively utilise their input factors for the 2021/2022 academic session. Despite this, DMU1 and DMU3 seem unable to operate at optimal scale efficiency. In other words, when scale is not considered, PRUMs are relatively efficient in managing their resources. Table 5 outlines the detailed CRS, VRS, and scale efficiency scores of all DMUs.

Table 5: Summary of Technical Efficiency Constant Returns to Scale (TE -CRS); Pure Technical Efficiency Variable Returns to Scale (PTE - VRS) and Scale Efficiency (SE) of PRUMs and APRU

	TE - CRS	PTE – VRS	SE = TE/PTE	Returns to Scale
DMU1	0.772	1.000	0.772	Increasing
DMU2	0.480	0.981	0.489	Increasing
DMU3	0.497	1.000	0.497	Increasing
DMU4	0.359	0.801	0.449	Increasing
DMU5	0.462	0.950	0.487	Increasing
DMU6	0.805	1.000	0.805	Decreasing
DMU7	1.000	1.000	1.000	-
DMU8	1.000	1.000	1.000	-
DMU9	1.000	1.000	1.000	-
DMU10	0.902	1.000	0.902	Decreasing

Table 5 shows that DMUs 2, 4, and 5 are projected to be technically inefficient under CRS and VRS (all scores are less than 1.00). Such results support the conclusion of Khoshnevis & Teirlinck (2018) that R&D firms normally face challenges related to both technical inefficiency and suboptimal scale size, with the average scale efficiency being modest. In DEA methodology, there is a reference group known as 'peers' for the inefficient DMU to refer to as a reference for improvement. These peers may include at least one efficient DMU, achieving a 100% 'pure' efficiency score or more. Inefficient DMUs should aim to emulate their more efficient peers to 'move towards the efficiency frontier' by benchmarking against their peer DMU(s) and adjusting their inputs or outputs accordingly. Peers (or DMUs) that are relatively close to the efficiency frontier share similar characteristics with inefficient DMUs as indicated by the weight or lambda (λ) value assigned to each referent peer (Sung & Daecheol, 2019).

Lambda values are the weights assigned to each peer DMU, with a higher value indicating a more prominent referent for the inefficient DMU to emulate (Ozcan, 2014). Tables 6, 7, and 8 below summarise the projected inefficiency analysis of DMUs 2, 4 and 5, respectively, for the 2021/2022 academic session.

Table 6: Projected DMU2 inefficiency analysis

DMU2
Technical efficiency = 0.981
Scale efficiency = 0.489 (increasing returns to scale)
List of peers (lambda weight): DMU8 (0.290), DMU9 (0.163), DMU3 (0.547)

Variables	Original value	Radial	Slack	Projected value
Output				
Teach reputation	32.2	0.000	16.6	48.806
Research reputation	17.7	17.7	0.00	44.921
Research influence	15.0	15.0	0.00	30.723
Input				
FTE staff	1,967	-37.296	0.00	1,629.704
FTE students	21,039	-398.918	0.00	20,640.082
International student ratio	14.0	-0.265	0.00	13.735

Table 6 reports the projection that DMU2 will achieve 98.1% 'pure' technical efficiency and only 48.9% scale efficiency for the 2021/2022 academic session. By operating at increasing returns-to-scale (IRS), DMU2 can make further enhancements and achieve full efficiency by decreasing FTE staff to 1,930, taking in only 20,640 FTE students, and setting the international student ratio to 13.7%. Reductions by 1.9% (100 - 98.1) are equivalent to around 1.9% of the original values for each input factor: FTE staff (- 37.296 /1967) x 100, FTE students (-398.918 / 21039) x 100, and international student ratio (-0.265/14) x 100. It is also important to note that DMU2 needs to boost its teaching reputation by 16.6% as shown by the value of slack movement. In progressing toward full efficiency, DMU2 must emulate the practice of its peers DMUs 3, 8, and 9. Ideally, DMU2 should emulate best practices from a composite based on lambda weight: 54.7% of DMU3, 29% of DMU8, and 16.3% of DMU9. Alternatively, DMU2 could only focus on DMU3, the peer referent with the highest lambda weight. In short, DMU2 should reduce its FTE staff, FTE students, and the international student ratio to achieve full efficiency.

Table 7: Projected DMU4 inefficiency analysis for the 2021/2022 academic session

DMU4
Technical efficiency = 0.801
Scale efficiency = 0.449 (increasing returns to scale)
List of peers (lambda weight): DMU3 (0.599), DMU7 (0.317), DMU9 (0.085)

Variables	Original value	Radial	Slack	Projected value
Output				
Teach reputation	26.6	0.000	16.6	48.806
Research	18.5	0.000	0.00	44.921
Reputation	17.2	0.000	0.00	30.723
Research influence				
Input				
FTE staff	1,648	-328.763	0.00	1,319.237
FTE student	19,937	-3,977.278	0.00	15,959.722
International student ratio	25	-4.987	0.00	20.013

Table 7 shows that DMU4 is projected to operate at 80.1% 'pure' technical efficiency relative to the best practice frontier. However, its scale efficiency is only 44.9%, indicating that DMU4 is not operating at an optimal scale. DMU4, which operates at IRS, suggests that it could achieve greater efficiency by expanding its scale of operation. To achieve full efficiency, DMU4 should adjust its input to 1,319 full-time staff, 15,959 full-time enrolled students, and an international-student ratio of 20%. By making these changes, DMU4 could potentially achieve a teaching reputation of 48.8%, a 44.9% research reputation, and a research influence of 30.7%. For further improvement, DMU4 should emulate the practices of its peer institutions, DMUs 3, 7, and 9. Among these, DMU3 is ideal for DMU 4 because it has the highest influence, with a lambda weight of 59.9%.

Table 8: DMU5 inefficiency projection analysis for the 2021/2022 academic session

DMU5
Technical efficiency = 0.950
Scale efficiency = 0.487 (increasing returns to scale)
List of peers (lambda weight): DMU3 (0.681), DMU7 (0.092), DMU9 (0.227)

Variables	Original value	Radial	Slack	Projected value
Output				
Teach reputation	30.4	0.000	10.908	41.308
Research reputation	20.4	0.000	14.874	35.274
Research influence	22.7	0.000	6.82	29.520
Input				
FTE staff	1694	-85.04	0.00	1608.96
FTE student	19988	-1003.416	0.00	18984.584
International student ratio	17	-0.853	0.00	16.147

Table 8 shows DMU5 as projected to achieve 95% technical efficiency and 48.7% scale efficiency under IRS. To improve this, DMU5 must reduce its input factors by 5% (100% - 95%). This reduction is equivalent to 5 % of the original inputs: (-85.04/1694) x 100 for FTE staff, (-1003.416/19988) x 100 for FTE students and (-0.853/17) x 100 for international students ratio. For benchmarking, DMU5 must examine the practices of DMU 3 (68.1%), DMU 7 (22.7%), and DMU 9 (9.2%) for its best practice analysis. All projected inefficiency analyses of DMUs 2, 4 and 5 suggest that the DMUs should improve scale efficiency by optimising size and reallocating resources more effectively. The analyses also show that DMU3 is the most frequently referenced peer for inefficient DMUs, based on DMU3's highest lambda weight. This is despite DMU1 scoring the highest relative technical efficiency compared to DMU3.

Table 9 summarises the input/output data and operation scales of DMU3 and DMU1. Typically, DMU1 employs more staff to serve fewer students than DMU3. Earlier analysis in Table 2 shows that APRUs (ranked higher) generally operate with fewer staff but higher student enrolments over the study period. APRUs also have a higher ratio of international students. Earlier, Table 5 reported that, apart from DMU1 and DMU3 being the only two technically efficient DMUs, DMU3 is the common peer referent for other inefficient PRUMs. Technically, this is because of its proximity to the efficiency frontiers and similar operational scale (Sung & Daecheol, 2019). Additionally, DMU3 has shown good progress in its QS world ranking over the period under study, reinforcing its role as an efficient benchmark for the other inefficient PRUMs.

Table 9: DMU3 and DMU1 Input/Output Comparison

Input/ Output Variables		Academic Session				
		2017/ 2018	2018/2019	2019/2020	2020/2021	Mean
FTE staff	DMU3	1,641	1,704	1,701	1,709	1,688.75
	DMU1	2,018	1,921	1,893	1,903	1,933.75
FTE student	DMU3	19,353	18,904	17,180	17,601	18,259.50
	DMU1	21,990	17,095	15,140	15,794	17,504.75
% International student	DMU3	12	14	15	16	14.25
	DMU1	18	23	20	20	20.25
Teaching reputation	DMU3	30.5	34.3	34.2	35.3	33.58
	DMU1	31.2	37	41.6	39.3	37.28
Research reputation	DMU3	21.4	21.4	19.6	21.4	20.95
	DMU1	26.6	27.1	30.5	31.5	28.93
Research influence	DMU3	11	18.4	32.3	42.5	26.05
	DMU1	54.4	59.1	56.6	60	57.53
		2017/ 2018	2018/2019	2019/2020	2020/2021	2021/2022
QS world ranking	DMU1	184	160	141	144	129
	DMU3	87	70	59	65	70

For the period under study, the operational differences between DMU1 and DMU3, as shown in Table 9, can be summarised by their scale of operation, efficiency, internalisation, and output quality. DMU1 has more staff and slightly fewer students than DMU3. This suggests that DMU1 adopts a more resource-intensive approach and operates on a larger scale. In contrast, DMU3, has fewer staff and more students and this efficiency is likely to contribute to its improvement in QS world ranking for 2021/2022. DMU1 reveals its higher teaching and research reputations, thus positively impacting its global reputation and ranking for the same period.

Discussion

Overall, the fuzzy DEA (FDEA) model in this study identifies three PRUMs as being technically inefficient for the academic year 2021/2022: DMU2 (PTE=0.981), DMU4 (PTE=0.801), and DMU5 (PTE=0.950) along with other DMUs with a scale efficiency (SE) of less than 0.5. These findings are consistent with Khoshnevis and Teirlinck (2018), who found that firms engaged in R&D often face technical inefficiencies and scale challenges despite scoring an average scale efficiency. The scale inefficiency suggests a need for a proportional reduction in these input factors. Therefore, these PRUMs should reduce their input factors, including FTE staff, FTE students, and international student ratio, to improve efficiency. However, this study does not differentiate between undergraduate and postgraduate FTE students. Postgraduate students, particularly those in PhD or post-doc training, are crucial to research (Philips, 2012). Additionally, the FTE staff variable combines academic and administrative staff. Academic staff involved in research activities, especially professors working with PhDs, are more relevant to a DMU's research reputation (Bucheli, 2019), but they are not analysed separately. These two limitations in input data selection could result in an inaccurate representation of resource use and hence the output of research universities. Consequently, this distorts the efficiency scores, thus making it harder to identify and address the true sources of inefficiency.

DMU3's strategy of maintaining a stable staff and managing a higher number of students and its gradual improvements in its output metric have positively impacted its QS world ranking. While DMU1 also showed significant improvement in QS ranking, the number of staff and students is more varied; therefore, a strong emphasis on internationalisation and higher output quality is needed. Despite both institutions achieving positive outcomes, DMU3's more balanced approach appears to have had more impact on efficiency scores. This study illustrates how DEA model variables reflect changing means–ends relationships (Epstein & Henderson, 1989). The DEA models, also known as 'control system models', can potentially evaluate the ability of a DMU to allocate resources to achieve its objectives (Anthony, 1965).

Conclusion

Improving international ranking is a crucial issue for most universities worldwide, and this study has made several contributions in that respect for public research universities. Firstly, it demonstrates the application of QS world ranking indicators as output variables of a fuzzy BCC DEA approach to examine the technical efficiency of five public research universities in Malaysia (PRUMs). This was done for the academic year 2021/2022, using data from 2017/2018 to 2020/2021. The proposed FDEA in this study is suitable because it effectively handles vague, uncertain, and imprecise output data like the QS world university ranking indicators, which are often beyond a university's direct control.

Secondly, by benchmarking the public research universities in Malaysia (PRUMs) against five selected public research universities in Asia (APRU) within the same model, the PRUMs can identify gaps in international student enrolment, research reputation, and overall technical efficiency. Analysis of the inefficiency scores of PRUMs suggests reductions in the scale of input factors in fixed proportions and an increase in operation scale. The larger-scale research university (DMU1) with a higher number of staff operates in a different league, while a smaller scale research university with gradual improvements in output metric (DMU3) demonstrates consistent improvement in the world ranking, highlighting its effective operational strategies. This suggests that other inefficient public research universities could emulate these strategies. Notably, a university's scale of operations significantly affects its ability to improve world ranking. For instance, the PRUMs can leverage many staff members to enhance academic staff composition, support extensive research projects, and offer a wide range of academic programs.

The final contribution lies in the policy implications that this study proposes. PRUM decision-makers can use the insights from this study to create supportive policies that foster an environment conducive to promoting higher efficiency and global competitiveness. Funding for international partnerships, grants for impactful R&D, and incentives for high-quality teaching can increase global appeal, attracting more talent from abroad. As this study suggests, benchmarking against the excellent performance of APRUs guides PRUMs towards achieving higher international standards, contributing to the global knowledge economy, and providing valuable insights into the state of higher education and research and their performance in the region.

Good world rankings significantly influence external stakeholders and corporate institutions to provide research funding, directly reducing the government's financial burdens. Increased collaboration between universities, government, and the private sector maximises their potential for global, national, and local development. This evidence highlights the crucial role of research universities in national development. Additionally, practices within these statutory bodies (public universities) should support academic independence and organisational self-governance, fully realising the potential of higher education in Malaysia and contributing to economic and societal development.

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