ENHANCED NETWORK SLACK-BASED MEASURE DATA ENVELOPMENT ANALYSIS MODEL WITH MIXED INTEGER VALUES AND NON-CONTROLLABLE FACTORS FOR MEASUREMENT OF PUBLIC UNIVERSITY EFFECTIVENESS

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Abstrak

Pengukuran Pengukuran keberkesanan dalam institusi pengajian tinggi menjadi semakin penting dalam persekitaran yang mencabar pada masa kini. Universiti awam berdepan dengan pelbagai cabaran berkaitan prestasi yang dipacu oleh tren global yang sentiasa berubah seperti enrolmen pelajar, kebolehpasaran graduan, dan kualiti hasil penyelidikan. Faktor-faktor ini, yang lazimnya bersifat tidak terkawal dan bernilai integer, wujud bersama pembolehubah berterusan konvensional, sekali gus merumitkan proses penilaian prestasi. Model Analisis Penyampulan Data (DEA) tradisional mempunyai keterbatasan dalam menangani kerumitan ini kerana ia menumpukan kepada kecekapan semata-mata, mengabaikan keberkesanan serta melihat universiti sebagai "kotak hitam" tanpa mengambil kira struktur dalaman dan hubungan antara fungsi teras. Universiti awam beroperasi melalui pelbagai fungsi yang saling berkait, dengan fakulti memperuntukkan sumber berdasarkan keutamaan strategik masing-masing. Oleh itu, satu pendekatan penilaian yang komprehensif diperlukan bagi menilai keberkesanan dalam satu kerangka yang bersepadu. Kajian ini membangunkan model DEA berasaskan rangkaian selari ukuran-lalai yang ditambah baik menggabungkan nilai integer bercampur dan faktor tidak terkawal untuk mengukur keberkesanan universiti. Model ini bermula dengan membentuk struktur selari yang mewakili fungsi teras universiti. Seterusnya, model ini diuji untuk mengukur keberkesanan 26 fakulti di sebuah universiti awam di Malaysia. Keputusan kajian kemudiannya dianalisis dan disahkan melalui analisis sensitiviti dengan memvariasikan spesifikasi model serta konfigurasi input–output, bagi mengenal pasti model yang stabil dan boleh dipercayai dalam mengukur keberkesanan fakulti. Dapatan kajian menunjukkan bahawa 18 fakulti beroperasi secara berkesan, manakala selebihnya didapati tidak beroperasi secara berkesan. Model rangkaian yang dibangunkan ini membolehkan pengenalpastian dan penilaian keberkesanan setiap fungsi dalaman fakulti, sekali gus membolehkan analisis prestasi yang lebih spesifik mengikut fungsi. Struktur ini memberikan pemahaman yang lebih mendalam mengenai punca ketidakberkesanan serta menyokong pembuatan keputusan yang lebih berinformasi dan berasaskan bukti di peringkat fakulti. Kajian ini berjaya membangunkan model pengukuran keberkesanan bagi universiti awam serta mencadangkan tindakan yang perlu untuk meningkatkan prestasi.

Kata Kunci: Keberkesanan, Universiti Awam, Analisis Penyampulan Data Rangkaian Selari, Data Bernilai Integer, Faktor Tidak Terkawal

Abstract

The measurement of effectiveness in higher education institutions has become increasingly critical in today’s challenging environment. Public universities face a range of performance related challenges driven by evolving global trends such as student enrolment, graduate employability, and the quality of research output. These factors, which are often non-controllable and integer-valued, coexist with conventional continuous variables, thereby complicating the performance measurement process. Traditional Data Envelopment Analysis (DEA) models are limited in capturing such complexities, as they focus on efficiency while overlooking effectiveness and treating universities as black boxes, ignoring internal structures and interrelated functions. Public universities operate through multiple interrelated functions, with faculties allocating resources based on their strategic priorities. Therefore, a comprehensive assessment approach is required to evaluate effectiveness within a unified framework. This study developed an enhanced parallel network slack-based measure DEA model that incorporates mixed-integer values and non-controllable factors to measure university effectiveness. The model began by forming a parallel structure representing the university’s core functions. It was then tested to measure the effectiveness of 26 faculties in a Malaysian public university. The results were subsequently examined and validated through sensitivity analysis by varying model specifications and input–output configurations, enabling the identification of a stable and reliable model for measuring faculty effectiveness. Findings show that 18 faculties were operating effectively, while the remaining faculties were ineffective. The developed network model enables the identification and measurement of the effectiveness of each faculty’s internal functions, thereby allowing for function-specific performance analysis. This structure provides deeper insights into the sources of ineffectiveness and supports more informed, evidence-based decision-making at the faculty level. This study has successfully developed effectiveness measurement model for a public university and proposes necessary actions to improve performance.

Keywords: Effectiveness, Public University, Parallel Network Data Envelopment Analysis, Integer-Valued Data, Non-controllable Factors

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List of Abbreviations

ADD	Additive
APD	Analisis Penyampulan Data
BCC	Banker, Charnes & Cooper Model
C	Controllable Factors
CCR	Charnes, Cooper & Rhodes Model
CRS	Constant Returns to Scale
CS	Community Service
DEA	Data Envelopment Analysis
DMU	Decision Making Unit
DRS	Decreasing Returns to Scale
FDH	Free Disposal Hull
HEI	Higher Education Institution
HSS	Humanities and Social Sciences
ILP	Integer Linear Programming
IRS	Increasing Return to Scale
KPI	Key Performance Indicator
KTP	Knowledge Transfer Programmes
LoI	Letter of Intent
LP	Linear Programming
MIDEA	Mixed Integer DEA Model
MILP	Mixed Integer Linear Programming
MoHE	Ministry of Higher Education
MRA	Multiple Regression Analysis
MyRA	Malaysian Research Assessment System
NDEA	Network Data Envelopment Analysis
No.	Number
NSBM	Network Slack-Based Measure
PhD	Doctor of Philosophy
PMS	Performance Measurement System
QS	Quacquarelli Symonds
R	Research

R&D	Research and Development
RU	Research University
SETARA	Rating System for Malaysian Higher Education
SBM	Slack-Based Measure
T	Teaching
NC	Non-controllable Factors
UiTM	Universiti Teknologi MARA
USR	University Social Responsibility
VRS	Variable Return to Scale

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CHAPTER ONE
INTRODUCTION

The measurement of organizational performance is increasingly critical in today's challenging environment, particularly for higher education institutions (HEIs). The higher education landscape has undergone substantial changes, leading to greater complexity in institutional roles and educational demands. Although university performance in Malaysia has improved considerably over the past years, it continues to face a range of challenges influenced by evolving global trends, as emphasized in the Malaysia Education Blueprint (Higher Education) 2015-2025. Consequently, there is a need for robust performance measurement frameworks that can effectively capture the multifaceted and complex nature of universities. This chapter outlines the research problem by identifying key challenges and subsequently defining the objectives of the research in accordance with the research questions. Furthermore, the chapter discusses the scope of the study and highlights its significance, thereby providing a clear understanding of its key components. Finally, this chapter presents the operational definitions relevant to the research and describes the thesis organization.

1.1 Public Universities in Malaysia

In Malaysia, HEIs can be divided into private HEIs, public universities, community colleges as well as polytechnics (Sulaiman & Ghadas, 2021). Public universities, specifically, are additionally classified into three separate categories, each with its own focus and responsibilities (Ahmad et al., 2020), namely research universities (RUs), focused universities and comprehensive universities. The first category, RUs, includes five universities recognized for their excellence in research. These universities were awarded RU status based on selection criteria that emphasize research and development activities, as well as commercialization efforts. The second category, focused universities, includes 11 universities specializing in specific academic disciplines, such as education, technical fields, management and defense studies. These universities were established with clear institutional objectives that align with their niche areas of expertise.

The third category, comprehensive universities, consists of four universities that provide a wide variety of educational courses across numerous fields. These universities have an undergraduate-to-postgraduate ratio of 70:30, while investigative and specialized universities adhere to a proportion of 50:50 between undergraduate as well as postgraduate students. Table 1.1 provides a detailed categorization of Malaysian public universities based on their respective categories.

Table 1.1

List of all Malaysian Public Universities by Category

Research Universities	Focus Universities	Comprehensive Universities
1. Universiti Malaya	1. Universiti Tun Hussein Onn Malaysia	1. Universiti Teknologi MARA
2. Universiti Sains Malaysia	2. Universiti Utara Malaysia	2. Universiti Islam Antarabangsa Malaysia
3. Universiti Kebangsaan Malaysia	3. Universiti Malaysia Terengganu	3. Universiti Malaysia Sabah
4. Universiti Putra Malaysia	4. Universiti Pendidikan Sultan Idris	4. Universiti Malaysia Sarawak
5. Universiti Teknologi Malaysia	5. Universiti Malaysia Perlis	
	6. Universiti Teknikal Malaysia Melaka	

Table 1.1 continued

Research Universities	Focus Universities	Comprehensive Universities
	7. Universiti Malaysia Pahang	
	8. Universiti Pertahanan Nasional Malaysia	
	9. Universiti Sains Islam Malaysia	
	10. Universiti Sultan Zainal Abidin	
	11. Universiti Malaysia Kelantan	

Source: MoHE, 2025

Malaysian public universities are primarily regulated by the Ministry of Higher Education (MoHE), whose main objective is to assist the government's vision of establishing Malaysia as a leading tertiary education center in the region (Mustapha et al., 2021). While significant progress has been made towards this goal, concerns regarding the quality of education offered by Malaysian HEIs have emerged (Amzat et al., 2023). Consequently, the MoHE has implemented a performance measurement system (PMS) designed to promote continuous quality improvement within HEIs (Azziz et al., 2020).

1.2 Performance Measurement System of Public Universities in Malaysia

The MoHE has introduced primary tools to measure the performance of HEIs in Malaysia, known as the Malaysian Research Assessment Instrument (MyRA), as well as the Rating System for Malaysian Higher Education (SETARA). MyRA serves as an instrument for measuring the capability to conduct research activities (Ta et al., 2021). The measurement process for MyRA is based on eight (8) criteria, which are summarized in Table 1.2.

Table 1.2

Measurement Criteria for MyRA

No.	Criteria for Research University	Weightage (in %)
1	Quantity and quality of researchers	25
2	Quantity and quality of research	30
3	Quantity of postgraduates	10
4	Quality of postgraduates	5
5	Innovation	10
6	Professional services and gifts	7
7	Networks and Linkages	8
8	Supporting Facilities	5
	Total	100

Source: Ta et al. (2021)

In addition to MyRA, the MoHE introduced the SETARA rating system in 2007 to assess the quality assurance as well as standards of university colleges and universities located in Malaysia. SETARA has continuously evolved in response to changing circumstances and educational needs, including modifications made in 2009, 2011, 2013, 2017 and 2022. Table 1.3 presents the latest measurement criteria within the SETARA 2022 framework.

Table 1.3

Measurement Criteria for SETARA 2022

General: Institutional Profile	Teaching & Learning	Research Capacity	Services & Income Generation
1. Student quality and diversity 2. Lecturer capability	1. Adequacy and Capacity of academic staff 2. Student satisfaction 3. Quality of graduates	1. Critical mass 2. Research income 3. Quantity of publications	1. Income from the commercialization of ideas 2. University's social responsibility and

Table 1.3 continued

General: Institutional Profile	Teaching & Learning	Research Capacity	Services & Income Generation
3. Academic staff recognition 4. Quality management system 5. Waqaf, Endowment and Financial sustainability 6. Institutional reputation	4. Internationalization of Academic programmes 5. Program recognition 6. Lifelong learning	4. Quality of publications	knowledge transfer program to industry, as well as the community, comprising translational research 3. Education as well as training programmes 4. Other sources of income

Sources: MoHE, 2025

Currently, SETARA measurement covers three criteria: teaching, research and services (Tham & Chong, 2023). These criteria are regarded as the three core functions of universities (Moustafa, 2024). Therefore, the SETARA rating emphasizes not only research but also teaching and services, positioning it as a more comprehensive measurement system compared to MyRA. However, despite its comprehensive framework, SETARA has its limitations. SETARA provides a single overall rating score to an HEI, rather than separate rating scores for each function. This lack of granularity limits the ability to identify specific strengths and weaknesses within teaching, research and services, thereby highlighting the need for an alternative approach that can provide deeper and more detailed functional-level insights.

In addition to MyRA and SETARA, Malaysia's public universities are also measured by various independent performance instruments like the Quacquarelli Symonds (QS) World University Rankings, Times Higher Education, and the Academic Ranking of

World Universities, at the international level (Irliana et al., 2014). However, nearly all HEIs worldwide strive to achieve performance targets established by these various ranking systems (Gokalp, 2023). For example, Doğan and Al (2019) argue that reliance on these ranking systems to measure overall university performance may yield inaccurate results. Similarly, as mentioned by Vidal and Ferreira (2020), all international ranking systems have inherent weaknesses and none are entirely perfect. Instead, universities should focus on fulfilling their institutional core missions or functions. Additionally, the distinctiveness and complexity of HEIs complicate the alignment of existing performance metrics with ranking systems (Humaira et al., 2020). Therefore, the existing measurement approach requires improvement to complement the current PMS to ensure universities' performance reflects core functions rather than merely serving as a comparative ranking tool.

Furthermore, Malaysian higher education policies continue to evolve in response to global developments. The MoHE aspires to establish a new PMS that shifts the focus from inputs and processes to outcome measures, as described in the Malaysia Education Blueprint (Higher Education) 2015–2025. Similarly, an outcome-measure approach is emphasized in Malaysia's national development agenda, particularly in the Shared Prosperity Vision 2030 (Ministry of Economic Affairs, 2019). Therefore, existing measurement approaches require enhancement to more accurately capture outcome-focused performance.

1.3 Challenges of Malaysian Public Universities Performance

Malaysia's higher education system has grown swiftly throughout the previous several decades; nevertheless, it still encounters a variety of obstacles influenced by evolving global trends, as highlighted in the Malaysia Education Blueprint (Higher Education)

2015-2025. In response to these developments, the MoHE has emphasized the need for continuous improvement to ensure that the sector remains competitive and aligned with international developments (Ahmad et al., 2024). Accordingly, the subsequent section outlines the key challenges affecting the performance of Malaysian public universities.

1.3.1 Enrolment

Among the major obstacles encountered by the MoHE is positioning Malaysia as a regional education hub (Venkatasawmy & Yeap, 2024). In response, the Malaysian higher education system has placed significant emphasis on internationalization as a strategic initiative to strengthen the country's visibility and competitiveness in the global education landscape (Munusamy & Hashim, 2021). This strategic orientation has contributed to a significant rise in international student registration. By 2023, Malaysia had emerged as a prominent higher education hub in Southeast Asia, hosting around 130,000 international students and ranking among the region's leading study destinations (ICEF Monitor, 2023).

Looking ahead, the MoHE has articulated ambitious targets for continued sectoral growth. Malaysia intends to position itself as a center of higher education excellence by enrolling 250,000 international students by 2025, as detailed in the Malaysia Education Blueprint (Higher Education) 2015-2025. Achieving this objective necessitates sustained improvements in the quality of higher education provision (Amzat et al., 2023). Consequently, Malaysian public universities must consistently deliver high-quality academic and support services to attract international students and maintain long-term enrolment growth.

1.3.2 Employability

The quality of graduates warrants focused attention within HEIs (Prosekov et al., 2020). Graduate employability, in particular, is widely employed as a marker of graduate quality (Cheng et al., 2022) and has become a key performance measure for HEIs (Pepple et al., 2025). Figure 1.1 illustrates the trend in employment rates (%) in Malaysia over the five-year period from 2020 to 2024. The data show a steady increase in employment rates, starting at approximately 86.7% in 2020 and rising each year to nearly 95% in 2024. This upward trend suggests continuous improvement in graduate employability over time. However, despite reported improvements, concerns surrounding graduate employability remain substantial (Kowang et al., 2022).

The employment landscape has been significantly reshaped by globalization, rapid technological advancements, and evolving work structures, resulting in increased demand for highly skilled labor across various sectors (Doraisamy & Rahman, 2023). Consequently, employers increasingly seek graduates who possess essential 21st-century competencies, comprising critical thinking, problem-solving, creativity, as well as decision-making skills (Kayyali, 2024).

In response, scholars continue to examine strategies to enhance graduate employability, particularly within the framework of Industry 4.0 (Suarta et al., 2020). Numerous studies indicate that university academic programs remain outdated and insufficiently aligned with current labor market requirements (Lan, 2022). Therefore, improving educational quality is crucial for producing employable graduates (Figurek et al., 2019). This requires HEIs to continuously update and innovate their curricula and teaching approaches to ensure alignment with labor market needs and effectively enhance graduate employability (Kowang et al., 2022).

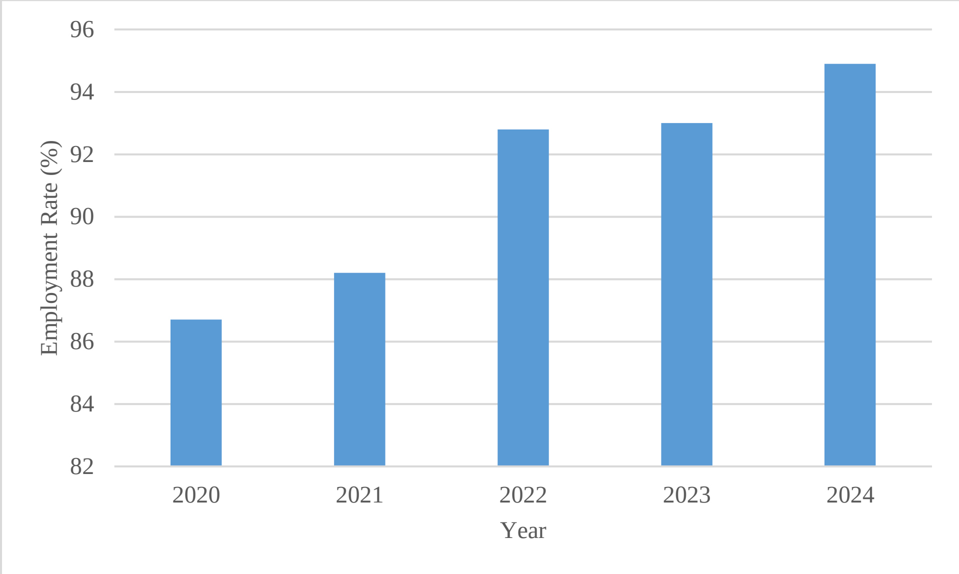


Figure 1.1. Percentage of Malaysian public university graduates based on graduate employment
Source: MoHE (2025)

1.3.3 Research Fund

Research funding performs a vital function in forming the study landscape (Chan, 2019), as it strongly influences academic outputs such as publications, patents and other forms of scientific innovation (Fu, 2023). In recent years, performance-based funding models have gained prominence globally in higher education, emphasizing research outcomes rather than inputs (Ahmad et al., 2020) to better align funding with the efficiency as well as impact of research activities.

In Malaysia, research and development funding has traditionally been dominated by the public sector. However, in line with this global trend, Malaysia has restructured the financing system for public universities to strengthen the link between institutional performance and funding allocation, as implemented by the MoHE (Ahmad, et al., 2024). For example, RUs receive approximately four times more funding than non-research universities (non-RUs). Although non-RUs continue to receive government support, their allocations remain proportionally lower than those of RUs. This funding differentiation presents significant challenges for public universities, particularly for those facing resource constraints (Chandran, 2020). Therefore, understanding the implications of these funding policies is critical, as they directly affect universities' research performance and output (Patil, Ingle, & Deshmukh, 2024).

1.3.4 Research Outputs

Research output is broadly acknowledged as a major indicator of performance, commonly measured through publications and serves as a reflection of a nation's research activity (Tabuzo et al., 2025). These publications comprise conference proceedings, journal articles, book chapters, books, as well as other academic works (Sarjidan & Kasim, 2023). They play a crucial role in translating scientific findings into accessible knowledge, significantly impacting both the research community and public understanding (Johann et al., 2024). However, the measurement of research publications must consider not only their quantity but also their quality to ensure a more reliable and comprehensive measure of performance (Lee & Worthington, 2016; Youssef & El-Bary, 2021). Therefore, researchers continuously face pressure to exhibit their research quality (Lindgreen et al., 2024). A common indicator of high-quality research output is citation count, as citations provide a measure of how widely and profoundly a publication influences subsequent scholarship (Khatoon, et al., 2024).

Over the past decade, the Malaysian higher education system has experienced a considerable increase in research output, reflected in the growing number of publications across various disciplines, particularly in science and technology (Abidin et al., 2024). Despite this growth in quantity, concerns regarding the quality of these publications have emerged (Teng et al., 2020). As a result, there exists an immediate necessity to place greater emphasis on enhancing research quality alongside quantity.

1.3.5 Income Generation

Public funding continues the primary source of financial funds for HEIs in many countries (Usman & Rahman, 2023). Similarly, in Malaysia, public HEIs rely heavily on government allocations administered through the MoHE (Jaaffar et al., 2021). However, this heavy dependence poses significant financial challenges for universities, including exposure to revenue instability and constraints arising from limited public resources (Said et al., 2023).

In response, the Malaysian government has increasingly urged public universities to diversify their income streams to ensure long-term financial sustainability (Hasbullah & Rahman, 2021). HEIs with strong financial sustainability and operational adaptability are more capable of increasing teaching and research quality, improving the overall student experience, as well as strengthening institutional reputation (Hasan et al., 2025).

In conclusion, although the performance of Malaysian public universities has shown improvement, significant challenges remain, particularly in the context of globalization. These challenges highlight the need for continuous quality enhancement across the higher education sector. Consequently, extensive research has been undertaken to measure university performance, given its critical role in sustaining improvements in educational quality (Hayati et al., 2019). In this regard, performance indicators have increasingly been employed to measure the performance and quality of HEIs (Sarrico, 2022).

A substantial body of literature has investigated public university performance and its determining factors, as reflected in studies by Duenhas et al. (2015), Duan (2019), Mojahedian et al. (2020), Mikušová (2020), Chen et al. (2021), Chen et al. (2023) and Ahmed et al. (2024), among others. However, much of this literature has primarily focused on efficiency-based indicators. While efficiency indicators remain widely used performance measures for public universities (Kashim, 2021), they do not fully capture the broader functions of universities in fulfilling the core missions of HEIs (Boyadjieva, 2022). Accordingly, effectiveness indicators have increasingly been recognized as essential measures of institutional performance, as they reflect the extent to which universities achieve their intended missions (Ghahremanloo et al., 2020) and the outcomes (Qin & Du, 2018). Additionally, this outcome-oriented emphasis is consistent with the Malaysia Education Blueprint (Higher Education) 2015–2025, which advocates performance measurement approaches that prioritize outcomes rather than inputs and processes. Accordingly, this study seeks to assess the current effectiveness level of Malaysian public universities so that necessary steps can be taken to improve their performance.

Public universities face multiple performance-related challenges, including enrolment, employability, research funding, research output and income generation. These factors have been widely recognized as outputs in measuring the performance of universities. Therefore, performance measurement in public universities is inherently complex (El Gibari et al., 2022), as these institutions produce multiple outputs (Kashim et al., 2018). Addressing these challenges requires the adoption of a comprehensive performance-based approach to measure public university performance. Moreover, several factors influencing university performance are non-controllable, as noted by

Taleb (2017). Consequently, the selection of an appropriate effectiveness measurement approach is critical to achieve more accurate measurement of public university.

1.4 Effectiveness Measurement Approaches in Universities

A wide range of approaches has been employed in previous research to measure the effectiveness of public universities. Among these approaches, Multiple Regression Analysis (MRA) has been widely used in higher education performance studies (Johnes & Taylor, 1990). MRA is categorized as a parametric approach. It models the production function by examining the relationship between multiple inputs as well as a single output (Guo, Liu, & Song, 2024). It is frequently employed to evaluate the efficiency of a Decision-Making Unit (DMU). Here, a DMU is an entity that transforms inputs into outputs (Fixler, 2008; Kuah & Wong, 2011). However, MRA has notable limitations, as negative residuals are interpreted as inefficiency while positive residuals are regarded as efficiency, which may lead to biased efficiency estimates (Sexton, 1986). Moreover, parametric approaches are often considered less suitable for measuring the performance of HEIs, as universities typically utilize various inputs to produce various outputs simultaneously (Nguyen et al., 2019). These limitations have led researchers to consider alternative, non-parametric approaches for evaluating performance.

Conversely, Data Envelopment Analysis (DEA) is a non-parametric technique established by Charnes, Cooper and Rhodes (1978), based on linear programming. In contrast to parametric techniques, DEA does not require assumptions regarding functional form or statistical distribution (Johnes, 2006a). Importantly, DEA can simultaneously measure multiple inputs and multiple outputs (Bagchi et al., 2019).

Given that universities produce a wide range of outputs such as graduate employability, research publications, citations and other academic outcomes (Kashim et al., 2018), DEA is therefore broadly acknowledged as an efficient and appropriate approach for assessing performance in the higher education sector. Nevertheless, despite its methodological advantages, DEA has received relatively limited attention in measuring public university effectiveness (Kashim, 2021).

Conventionally, DEA regards a DMU as a "black box," through which inputs are directly converted into outputs. In numerous practical scenarios, the production process of a DMU consists of multiple internal functions or stages, each defined by its individual inputs as well as outputs. As a result, the "black box" approach does not account for internal sub-functions or stages within the system. This limitation restricts the ability to measure function-specific performance and provide functional-level guidance for decision-makers seeking to improve overall organizational efficiency (Tone & Tsutsui, 2009; Taleb & Khalid, 2023). Additionally, it also does not offer insight regarding the resources of underperformance for the DMUs. Consequently, the "black-box" approach may obscure internal inefficiencies and potentially overestimate performance, leading to misleading conclusions (Kao, 2014).

To address these limitations, Network Data Envelopment Analysis (NDEA) was introduced (Färe & Grosskopf, 2000). In the context of universities, one of the most widely adopted NDEA structures is the two-stage structure. In this framework, overall performance can be decomposed into the product of the efficiencies of two stages, where inputs in the first stage generate intermediate outputs that subsequently serve as inputs to generate final outputs in the second stage (Lim & Zhu, 2019). This structure enables performance measurement at each stage of the production function (Aksoy et al., 2022). However, universities often operate through multiple parallel functions, each utilizing distinct inputs to produce different outputs simultaneously. To capture this complexity, NDEA has been extended to parallel structures, enabling a more precise measurement of the multifunctional and simultaneous characteristics of university systems (Kao, 2012; Saleh, 2024). Furthermore, DEA models that accommodate integer-valued data and non-controllable factors provide a more accurate representation of university operations.

1.5 Problem Statement

The Malaysian higher education system has undergone substantial expansion throughout the previous several decades. Nevertheless, it still confronts numerous major obstacles in adjusting to an increasingly competitive environment due to globalization. These challenges have prompted universities to enhance their quality and overall performance (Goker & Dursun, 2023). In response, the MoHE aspires to establish a new PMS that shifts the focus from inputs and processes to outcome measures, as defined in the Malaysia Education Blueprint (Higher Education) 2015–2025. Measuring outcomes enables universities to be appraised according to the degree to which they achieve the intended quality of education (Hermanu et al., 2024). Accordingly, one way to enhance the public universities' quality is by measuring their effectiveness levels. Therefore, this study seeks to assess the current effectiveness levels of Malaysian public universities so that appropriate strategies can be implemented to enhance their performance.

Additionally, many effectiveness studies in universities have overlooked the distinction between outputs and outcomes. This study focuses on the differences, where many studies have shown significant improvements, such as those by Singh et al. (2022), Qin and Du (2018), Kumar and Gulati (2009) and Keh et al. (2006). The broader academic literature consistently emphasizes the importance of clearly distinguishing between outputs and outcomes (Diewert & Fox, 2024). These studies have provided the impetus for further investigation into the differences between outputs and outcomes in university effectiveness measurement.

As mentioned in Subsection 1.3, Malaysian public universities are currently facing several performance-related challenges involving enrolment, employability, research funding, research output and income generation. These factors have been widely recognized as outputs in measuring the university's performance. Owing to the complex nature of universities (El Gibari et al., 2022), as these institutions produce multiple outputs (Kashim et al., 2018), an appropriate measurement approach is required. DEA is an approach that has been widely applied given its capacity to accommodate various inputs and multiple outputs simultaneously (Amin & Boamah, 2025). However, the capabilities of DEA have not been fully explored, especially when multiple outputs are present, as evidenced by many studies that did not consider DEA as an approach in the effectiveness measurement of universities (Kashim, 2021). Therefore, DEA is considered the most suitable approach for this study, and its capability is further extended to evaluate the effectiveness of public universities.

Subsequently, due to the disadvantage of the "black box" structure in capturing internal structure in DEA, this study focuses on the NDEA approach. Previous studies have demonstrated that NDEA provides significant improvements in measuring university performance (Kao, 2012). These studies serve as the foundation for further enhancements in NDEA formulation. Specifically, Kashim et al. (2017) developed a parallel NDEA model to measure university effectiveness. However, the developed model assumed all data to be non-integer values and controllable factors. Additionally, it omitted input and output slacks, which may result in DMUs being classified as effective despite the presence of non-zero slacks. Therefore, this study further enhances the NDEA model by adopting a non-radial slack-based measure approach, which computes input as well as output slacks to proviede a more accurate measurement of effectiveness.

The traditional DEA model assumes that all input as well as output values are non-integer valued and controllable. Nevertheless, this assumption does not fully represent real-world situations, as universities may have some factors subject to both integer-valued and non-integer variables, as well as controllable and non-controllable factors (Daraio et al., 2015; Taleb, 2017). Specifically, Taleb (2017) proposed a slack-based measure DEA model that accounts for the effect of non-integer and integer-valued elements (or simply known as mixed integer-valued data) in the existence of controllable and non-controllable factors in DEA. However, his model regards the DMU as a single "black box." Consequently, further refinement is required to extend this approach into a network DEA that captures internal university functions, thereby enabling more accurate measurement.

To address these limitations, Kao (2020) introduced a parallel NSBM approach. However, his model does not incorporate mixed integer-values and non-controllable factors into the proposed model. Building on these methodological developments, the present study further enhances the existing model by incorporating mixed integer-values and non-controllable factors into a parallel NSBM DEA model to measure the effectiveness of public universities. Additionally, this approach can assist university management in identifying weaknesses within each function. Ultimately, this refinement aligns with emerging challenges and contributes to generate more accurate and informative effectiveness scores.

In conclusion, the parallel DEA model was originally introduced by Kao (2012) to measure efficiency and was later applied by Kashim (2021) to measure university effectiveness. Kao (2020) further improved this model using the SBM approach, while Taleb (2017) developed a slack-based measure model incorporating mixed integer-valued data and non-controllable factors. This work intends to close the existing knowledge gap by incorporating mixed-integer values and non-controllable factors into a parallel NSBM DEA model, providing an enhanced approach for measuring the effectiveness of public universities.

1.6 Research Questions

This research tackles the key questions as outlined below:

1. What are the suitable variables for measuring the effectiveness of faculties in a public university, and the proper categorization of these variables?
2. How can a suitable DEA model be developed to incorporate these variables in measuring the effectiveness of faculties in a public university?
3. How can the proposed model be validated?
4. How can the performance of proposed model be evaluated?

1.7 Research Objectives

The main objective of this research is to develop an enhanced parallel NSBM model incorporating mixed integer values and non-controllable factors of DEA model to measure the effectiveness of faculties in a public university and to decompose overall effectiveness into functional components. To accomplish this main objective, several specific objectives are derived:

1. To identify suitable variables for measuring the effectiveness of faculties in a public university and to categorize them into integer and non-integer values, considering controllable and non-controllable factors.
2. To develop an enhanced parallel NSBM DEA model incorporating mixed integer values and non-controllable factors to measure the effectiveness of faculties in a public university and decompose overall effectiveness into functional components.
3. To validate the proposed model via sensitivity analysis.
4. To evaluate the proposed model by comparing its performance with existing models.

1.8 Research Scope

This study focuses on a single university, Universiti Teknologi MARA (UiTM), as a case study for the development and application of a public university effectiveness measurement model. The scope of the research is confined to a single case study due to the difficulty of achieving homogeneity among public universities, particularly arising from variations in Key Performance Indicators (KPIs) across universities. A total of 26 faculties were evaluated using data from the year 2020, which was chosen to ensure data consistency, as UiTM underwent a major faculty restructuring beginning in 2021.

This study aims to develop an enhanced parallel NSBM DEA model to measure the effectiveness of faculties within a Malaysian public university. The analysis is conducted solely under the assumption of variable returns to scale (VRS). This assumption is supported by Salleh (2012), who noted that universities within the Malaysian higher education system do not function at an optimal scale, thereby making the VRS assumption more appropriate than the constant returns to scale (CRS) assumption.

In this study, the consistency and robustness of the effectiveness scores are examined through sensitivity analysis and by comparing the proposed model with relevant exiting models. However, this study does not consider any technique to test the bias in effectiveness scores, such as the Bootstrapped method.

1.9 Significance of the Study

The study's significance is discussed in two parts: theoretical and practical.

1.9.1 Theoretical

This research is expected to contribute to the body of knowledge in a theoretical manner in the following ways:

i) The primary contribution of this research lies in the mathematical formulation of an enhanced DEA model. Specifically, a parallel NSBM DEA model is formulated to incorporate mixed integer-valued data and non-controllable factors. This enhancement extends the existing body of knowledge.

ii) This study adopts sensitivity analysis to validate the NDEA model incorporating mixed integer values and non-controllable factors. Therefore, the robustness and stability of effectiveness measures are achieved. This process also represents a methodological contribution to the NDEA literature.

iii) This study adopts DEA as an alternative method for measuring the effectiveness of public universities, thereby extending the applicability of DEA beyond its traditional use in efficiency measurement.

1.9.2 Practical

This research is expected to contribute to the body of knowledge in practice, as given below:

i) This study helps university managers identify appropriate output and outcome variables for measuring the effectiveness of public universities. It supports management in selecting relevant KPIs that accurately reflect the core missions of public universities.

ii) The proposed approach enables university management to measure public university performance by considering its three core functions of teaching, research and community service. The model provides a comprehensive and detailed measurement of the effectiveness of each function. As a result, the results obtained from applying this model can help management identify underperforming functions that require greater attention and targeted improvement strategies to enhance overall performance.

iii) This study offers an alternative framework for measuring the effectiveness of public universities. The proposed measures can contribute to enhancing the public universities' performance in accordance with the aspirations of the MoHE as presented in the Malaysia Education Blueprint (Higher Education) 2015-2025.

1.10 Operational Definition

To comprehend the methods of the DEA framework, it is essential to list the basic definitions of DEA as follows:

i) Efficient Frontier: A frontier determined by the efficient DMUs that envelops the production possibility set (all inputs and outputs). This leads to the term "data envelopment analysis" (Avkiran, 2001).

ii) Projection or Improvement: An inefficient DMU can be projected or improved its performance by removing its input excesses and/or output shortfalls (Cooper et al., 2011).

iii) Reference Set: A set consists of all efficient DMUs that can be used as a benchmark for an inefficient DMU, i.e., the efficient DMUs serve as a benchmarks for the inefficient DMU, with each inefficient DMU having one or more peers (Cooper et al., 2006; Ozcan, 2008).

iv) Slack Variable: A variable representing the difference between the efficient frontier as well as the DMU evaluated. $-$ s represents an input excess, + s represents an output shortfall, i.e., the residue portion of inefficiencies. Thus, the inefficient DMU cannot reach to the efficient frontier if all or some of its slack values are positive (Ozcan, 2008).

v) Return to Scale (RTS): A scale represents the relative change in outputs in relation to a relative change in inputs (Thanassoulis, 2001). RTS can be constant, decreasing, or increasing as follows:

a) Constant Return to Scale (CRS): A scale indicates that an increase in inputs results in a proportionate increase in outputs (Ahuja, 2006).

b) Decreasing Return to Scale (DRS): A scale represents that changes in inputs lead to a greater change in outputs (Daraio & Simar, 2007).

c) Increasing Return to Scale (IRS): A scale refers to the situation in which changes in inputs lead to smaller changes in outputs (Thanassoulis, 2001; Sherman & Zhu, 2006).

vi) Input Variable: A variable representing the amount of available resources used to produce the outputs (Avkiran, 2001).

vii) Output Variable: A variable representing an accurate measure created as an outcome of the conversion of inputs. In DEA, output refers to an indicator of the relative efficiency (Sullivan et al., 2013).

viii) Mixed Integer DEA: A DEA framework handling non-integer as well as integer valued inputs and/or outputs, i.e., the set of inputs and outputs can be categorized into a subset of integer and non-integer values.

ix) Non-controllable Factors: Factors beyond the control of a DMU's management, as certain inputs and/or outputs in a DEA model, are non-controllable.

1.11 Organization of Thesis

This research is arranged into six chapters. Chapter One sets the foundation for the study. It presents the key challenges related to the research topic and establishes the fundamental concept under investigation. Specifically, it presents the problem statements, outlines the research questions and defines the study objectives. It concludes by discussing the significance and scope of the research, along with an overview of the thesis structure.

Chapter Two reviews the overview of performance measurement, with a specific focus on effectiveness measurement within public universities. This chapter provides a comprehensive literature review on various approaches to measure university effectiveness, primarily concentrating on DEA, which is established as a superior approach in this context. The chapter includes a critical analysis of previous DEA studies in universities, categorized into three categories to identify gaps in the existing research: i) non-integer values, ii) mixed integer values, and iii) non-controllable factors.

Chapter Three explores the fundamental concepts and theories underlying the proposed methodology, examining various DEA models from previous studies. Through this process, the weaknesses of existing DEA models in the literature are identified, emphasizing aspects for enhancement. The discussion also explores the evolution of conventional DEA into NDEA. Additionally, this section offers a comprehensive examination of the mixed integer values and non-controllable DEA models. Overall, Chapter Three performs a pivotal role in establishing the foundation for the contributions of this study.

Chapter Four details the research methodology specifically designed to accomplish the objectives of the research. This chapter comprehensively explains the research structure and the specific research activities undertaken. Developing the proposed DEA model constitutes a key focus. Furthermore, in-depth discussions on the validation and evaluation processes are included to ensure the model's robustness.

Chapter Five focuses on the analysis and discussion of the research findings for the developed model. The model was tested using real data from a public university, specifically Universiti Teknologi MARA (UiTM) for the year 2020. The effectiveness measures are obtained. To ensure robust results, a validity test was conducted via sensitivity analysis and the performance of the proposed model was assessed.

The final chapter presents the study's conclusions. It begins with a summary of the research conducted and confirms the successful accomplishment of all defined objectives. Subsequently, the chapter articulates the research's theoretical as well as practical contributions. Ultimately, it recognizes its limitations and provides recommendations for forthcoming research directions.

CHAPTER TWO
LITERATURE REVIEW

This chapter provides an overview of performance measurement studies, with a particular focus on the university system. Special attention is given to DEA as an appropriate approach for measuring university effectiveness, followed by a discussion of relevant input, output and outcome variables. Subsequently, DEA models applied in the measurement of university performance are reviewed, including studies that incorporate mixed-integer variables and non-controllable factors. These models highlight their relevance to university performance measurement, forming the basis for enhancing the proposed approach.

2.1 Performance Measurement in University

Performance measurement has become increasingly important in today's dynamic and challenging organizational environment (Broccardo et al., 2024). Performance is defined as the capacity whether an entity, individual, group, or organization to accomplish specific objectives through various activities (Laitinen, 2002). According to Neely et al. (2005), performance refers to the outcomes obtained from business activities or the quantification of actions undertaken by an organization. Similarly, Ferraz and Gallardo-Vazquez (2016) view performance as the result of strategic actions taken by organizations to overcome challenges such as business competition. In another study, Bambang Gunawan (2024) further defines performance as the extent to which activities, programs, or policies successfully realize an organization's goals, missions and visions as outlined in strategic plans. Clearly, organizational performance is characterized by the achievement of targeted goals through strategic actions, enabling organizations to adapt and respond effectively to challenges in an ever-evolving environment.

Performance measurement encompasses various indicators used to assess organizational performance (Poister, 2003). Commonly employed indicators include efficiency, effectiveness and quality (Tantardini, 2023). In practice, efficiency and effectiveness are often used interchangeably and, at times, conflated (Gupta et al., 2020; Patel, 2021). Table 2.1 summarizes the key distinctions between efficiency and effectiveness as defined in the literature.

Table 2.1

Definition of Efficiency and Effectiveness

Efficiency	Effectiveness	Author
Efficiency refers to the relationship between inputs and outputs, and it should be considered alongside effectiveness.	Effectiveness in the public sector is assessed by how well a service achieves its intended goals.	Bouckaert, 1992
Efficiency is the ratio of actual output to the expected standard output, showing how effectively resources are used.	Effectiveness indicates the extent to which objectives are successfully accomplished.	Sumanth, 1994
Efficiency measures how an organization uses its resources in delivering services at a given level to ensure customer satisfaction.	Effectiveness measures how successfully customer needs are fulfilled.	Neely *et al.*, 1995
Efficiency compares the actual cost incurred with the minimum theoretical cost required to operate effectively.	How costs are used to generate results.	Jackson, 2000
"Doing things right."	"Doing the right things."	Sheth and Sisodia, 2002

Table 2.1 continued

Efficiency	Effectiveness	Author
Efficiency can be seen as the gain or benefit derived from resources.	Effectiveness reflects the ability to maximize outcomes by using resources appropriately.	Gro¨nroos and Ojasalo (2004)
Efficiency shows how resources are fully utilized in the transformation process to produce outputs.	It describes the degree to which intended outcomes are achieved.	Tangen (2005)
The focus of efficiency is on producing maximum output with minimum input.	Effectiveness emphasizes the final results, representing the achievement of organizational goals.	Israeli (2007)
The ratio between total outputs and total inputs.	Degree to which organizational goals are met.	Lengacher et al. (2014)
The ability of a system to translate inputs into outputs.	The system's ability to produce outputs that meet intended quality standards.	Qin and Du (2018)
Efficiency refers to the ratio of inputs and outputs.	Effectiveness refers to the extent to which outputs align with predetermined missions.	Ghahremanloo et al. (2020)
"How well something is done".	"How useful something is".	Singh et al. (2022)

In summary, the literature consistently distinguishes efficiency from effectiveness in organizational performance measurement. Efficiency generally refers to how well an organization uses its resources to generate outputs, whereas effectiveness emphasizes the extent to which outputs or outcomes contribute to the achievement of organizational goals or missions.

The measurement of efficiency and effectiveness is typically grounded in the relationships between inputs, outputs and outcomes (Kashim, 2021). However, the distinction between outputs and outcomes is often unclear and the two concepts are frequently used interchangeably in the literature (Mandl et al., 2008; Diewert & Fox, 2024). Table 2.2 presents an overview of output and outcome definitions.

Table 2.2

Output and Outcome Definition

Author	Output	Outcome
Kasim et al. (2017)	Outputs in the public sector as the direct products generated	Outcomes encompass broader, long-term societal impacts reflecting multiple social value dimensions
Mitchell (2013)	Outputs as the goods and services delivered by organizations	Outcomes as their intended effects on beneficiaries
Belcher and Halliwell (2021)	The direct products of research	Changes in the agency and actions of system actors when they are informed/influenced by research outputs
Hinrichs-Krapels and Grant (2016)	Production of a process	Impact (effects on society)
Kazanskaia (2025)	Immediate, tangible products of activities	Changes in knowledge, skills, behaviors, or conditions resulting from outputs
Montague (2000)	Goods and services produced by the program	The final or long-term consequences

A similar distinction between outputs and outcomes can be observed in the literature. Outputs represent the results of organizational processes, whereas outcomes capture the effects or impacts of activities or processes on these outputs. This distinction is crucial for accurately measuring organizational effectiveness.

There are numerous studies that measure the effectiveness of universities. However, most of these studies ignore the distinction between outcomes and outputs (e.g., Liu et al., 2021; Kurniawati & Noviani, 2021; Dharmarajlu et al., 2024; Hackett et al., 2023; Sanni et al., 2023; Goh et al., 2020; Al-Shoubaki, 2024; Bejinaru et al., 2023; Okofo-

Darteh & Asamoah, 2021; Qin et al., 2024; Traballo et al., 2023; Zaychikova, 2021). As this distinction is critical, it is imperative to consider these differences when determining university effectiveness in order to ensure accurate measurement.

Measuring performance in public institutions remains a major challenge for public sector management (Tiţă & Tiţă, 2023). In particular, performance measurement in public universities continues to generate debate, underscoring the need for new and more comprehensive measurement frameworks (Damjanovic & Domanovic, 2023). In Malaysia, this aligns closely with the aspirations of the MoHE, which emphasizes outcome-based performance measurement. As shown in Table 2.1, outcomes are closely associated with effectiveness, reflecting the degree to which organizational goals and missions are achieved. Accordingly, this study focuses on measuring the effectiveness of public universities, as this perspective aligns more closely with the outcome-oriented framework advocated by the MoHE.

2.2 Effectiveness Measurement Approaches in Universities

Various approaches have been employed in previous studies to measure university effectiveness. These approaches can generally be categorized into qualitative and quantitative methods. Qualitative approaches have been widely applied to measure university effectiveness (e.g., Liu et al., 2021; Kurniawati & Noviani, 2021; Dharmarajlu et al., 2024; Hackett et al., 2023; Sanni et al., 2023; Goh et al., 2020). The qualitative approach involves observing, documenting, analyzing and interpreting human experiences, meanings and behaviors (Gillis & Jackson, 2002). Its primary aim is to understand and explain phenomena rather than to predict or control outcomes (Streubert & Carpenter, 1995). Despite providing rich and in-depth insights, qualitative approaches have notable limitations. These include limited generalizability due to small sample sizes, concerns over representativeness (Xiong, 2022) and the time-consuming and cognitively demanding nature of data analysis (Berg & Lune, 2011). Consequently, while qualitative research provides deep insights, it poses limitations related to generalizability, reliability and time consumption.

In contrast, quantitative approaches have also been extensively applied and can be divided into parametric and non-parametric approaches.

2.2.1 Parametric Approaches

Two parametric approaches have been used to measure university effectiveness: Stochastic Frontier Analysis (SFA) and Multiple Regression Analysis (MRA).

2.2.1.1 Stochastic Frontier Analysis

Stochastic Frontier Analysis (SFA), developed by Aigner et al. (1977) and Meeusen and van den Broeck (1977), is an econometric method that specifies a functional form for production, cost, or profit functions while accounting for random error. In this framework, deviations from the estimated frontier are attributed to both inefficiency and statistical noise. The error term is therefore composed of two parts: a one-sided component representing inefficiency (commonly assumed to follow a half-normal distribution) and a symmetric component representing random error (typically assumed to follow a normal distribution). This distinction reflects the assumption that inefficiency cannot be negative and thus must follow a truncated distribution. However, separating inefficiency from random noise can be technically challenging, which partly explains the relatively limited application of SFA in measuring university effectiveness (e.g., Bıyıklı & Kamil, 2024).

2.2.1.2 Multiple Regression Analysis

Multiple Regression Analysis (MRA) is a commonly used parametric approach for measuring university effectiveness. Examples of studies applying this method include Al-Shoubaki (2024), Bejinaru et al. (2023), Okofo-Darteh and Asamoah (2021), Qin et al. (2024), Traballo et al. (2023), Zaychikova (2021) and Gozaly (2026). MRA is used to measure organizational effectiveness based on input and output variables (James et al., 2023). It identifies which input variables best predict a single output variable (Mayston & Jesson, 1988). The outcome of MRA is a regression equation expressed as a function of multiple input variables used to estimate the output value of a DMU (Bluman, 2013).

The regression frontier is represented by the regression line, where efficient DMUs are assumed to lie above the line, while deviations from the regression line indicate inefficiency. Inefficient DMUs are therefore located below the regression line (Sexton, 1986). In other words, the magnitude of deviation between observed data points and the regression line reflects the level of inefficiency (Cooper et al., 2006). Furthermore, the regression line serves as a benchmark for determining the performance of inefficient DMUs (Zhu, 2003).

Despite its usefulness, MRA has notable limitations. It can accommodate only a single output variable or requires multiple outputs to be aggregated into a single composite measure. Consequently, MRA is less suitable for evaluating systems characterized by multiple inputs and multiple outputs (Guo et al., 2024).

Overall, parametric approaches allow for statistical hypothesis testing but require strong assumptions about the functional form of the production frontier (Abbott &

Doucouliagos, 2003). They are also less suitable for analyzing organizations that transform multiple inputs into multiple outputs. Consequently, non-parametric methods have been developed to better evaluate such systems.

2.2.2 Non-parametric Approaches

Two non-parametric approaches that have been used to measure university effectiveness are the Free Disposal Hull (FDH) and Data Envelopment Analysis (DEA).

2.2.2.1 Free Disposal Hull

Introduced by Deprins et al. (1984), Free Disposal Hull (FDH) measures the efficiency of institutions that use multiple inputs to produce multiple outputs, such HEIs (Agasisti, 2011; Fried et al., 1996). It is based on the concept of the Production Possibility Set (PPS), where the efficient frontier is formed by efficient DMUs (Worthington, 2001). Inefficiency is measured by the distance between a DMU and this frontier. However, FDH does not impose the convexity assumption, unlike DEA (Cooper et al., 2006). This limitation has contributed to its relatively limited application in university effectiveness studies (e.g., Mayston, 2014).

2.2.2.2 DEA

DEA is a well-established non-parametric method for measuring the relative efficiency of DMUs that employ multiple inputs to generate multiple outputs. A key advantage of DEA is that it does not require assumptions about the functional form of the production frontier; efficiency is calculated solely from observed input and output data (Abbott & Doucouliagos, 2003). Each DMU’s efficiency is assessed relative to others, with all units constrained to lie on or below the efficient frontier (Seiford & Zhu, 2002).

The foundations of DEA originate from Farrell (1957) and were formalized by Charnes et al. (1978). Since then, numerous extensions and refinements have been developed, significantly advancing the study of efficiency and performance evaluation.

Data Envelopment Analysis (DEA) is especially appropriate for evaluating organizations that simultaneously utilize multiple inputs to produce multiple outputs (Orisaremi et al., 2023). This feature is particularly relevant in the context of universities, where performance is typically demonstrated through a variety of outcomes, including student graduation rates, academic performance, and graduate employability (Kashim et al., 2018). Furthermore, DEA does not require explicit price information for inputs and outputs, making it highly suitable for assessing public universities, where market prices are often unavailable or difficult to estimate (Johnes, 1996; Nakanishi & Falcocchio, 2004). In addition, DEA has been widely acknowledged as a reliable tool for performance evaluation across both profit-oriented and non-profit sectors, such as healthcare institutions, financial institutions, and educational organizations (Amézquita et al., 2018). Considering these advantages, the present study adopts DEA as a suitable and effective method for evaluating the effectiveness of public universities.

Nevertheless, despite its strengths, the use of DEA specifically to measure the effectiveness of public universities remains relatively limited (Kashim, 2021). Only a small number of studies have applied DEA models for this purpose, as outlined in Table 2.3.

Table 2.3

Previous Study on Effectiveness Measurement in Universities using DEA

Author	Period examined	DMUs	Objective	Main Finding
Firsova and Chernyshova (2019)	2015	830 universities from 80 regions of Russia	To measure the effectiveness of regional higher education systems in terms of teaching and research quality using an enhanced DEA model	The enhanced DEA model enabled a comprehensive measurement of teaching and research quality across regions and provided practical tools for improving university performance.
Mayston (2014)	2006-2007	50 Departments of Economics in UK university	To measure the relative effectiveness of individual departments using DEA and FDH approaches	The results indicated that DEA tended to overestimate the potential for improvement when compared with FDH analysis for UK economics departments.
Wang (2013)	4 years	Huanggang Normal University	To measure the cost-effectiveness of universities using DEA	The development of new DEA model allows to achieve the better result as to compared to traditional DEA.

Although substantial efforts have been made to measure university effectiveness, most existing studies measure overall performance without accounting for the internal structure of the university system. Moreover, many studies rely on conventional DEA models that do not incorporate input and output slacks when measuring effectiveness. Some researchers have attempted to model internal structures using approaches of NDEA, but applications in the context of university effectiveness remain limited.

For instance, Kashim et al. (2017) measured the effectiveness of 14 faculties within a Malaysian public university, considering both teaching and research functions. The results indicated that none of the faculties achieved relative effectiveness in terms of overall performance. However, the study employed a radial DEA model, which assumes proportional changes in all inputs and outputs, limiting its ability to capture input and output slacks. The following section will provide a more detailed discussion of DEA approaches used to measure effectiveness.

2.3 Data Envelopment Analysis and Effectiveness Measurement

DEA has been widely applied to measure efficiency across various sectors (Xu et al., 2025; Kao & Hwang, 2023; Li et al., 2020; Fenyves et al., 2018; Huang et al., 2010). In addition to efficiency measurement, DEA has also been extended to measure effectiveness. For example, Sheth and Triantis (2003) employed a fuzzy Goal DEA framework to assess effectiveness under uncertainty, measuring deviations between actual and targeted outputs. Ahn and Neumann (2014) introduced the concept of "super-effectiveness," which enables the classification and ranking of decision-making units (DMUs) based on their performance relative to predetermined targets. This approach was applied to evaluate the effectiveness of European pharmacy chains. More recently, Alhidary et al. (2025) measured efficiency, effectiveness and bed utilization across 94 Therapeutic Feeding Centers in Yemen, reporting strong clinical outcomes and high levels of effectiveness, although further improvements were needed in technical efficiency and resource utilization.

In DEA, the concept of efficiency is typically expressed in ratio form, representing the relationship between outputs and inputs, as shown in Equation (2.1) (Cooper et al., 2006; Ramanathan, 2003; Kao, 2023):

$$Efficiency = \frac{Output}{Input} \tag{2.1}$$

Effectiveness, by contrast, captures the relationship between outputs and outcomes, reflecting how well the achieved outputs align with the mission (Kashim, 2021). Accordingly, effectiveness can be conceptualized as the following ratio:

$$Effectiveness = \frac{Outcome}{Output} \tag{2.2}$$

This distinction underscores the conceptual difference between efficiency and effectiveness: efficiency focuses on how inputs are transformed into outputs, whereas effectiveness emphasizes the extent to which outputs are converted into outcomes to achieve organizational goals. Table 2.4 presents an overview of the output and outcome variables employed in DEA-based effectiveness measurement across different sectors.

Table 2.4

Output and Outcome Selections in Measuring Effectiveness in Data Envelopment Analysis

Author	Sector	Output	Outcome
Kashim et al. (2017)	HEI	1. Number of graduate students 2. Number of program offers 3. The amount of research grants	1. Percentage of graduates who are employed after 6 months of convocation 2. The number of programs accredited from professional bodies

Table 2.4 continued

Author	Sector	Output	Outcome
			3. Number of publications in SCOPUS/WOS/ERA indexed journals and indexed conference proceedings. 4. Number of publications in other journals 5. Number of research books and chapters in research books 6. Total citations of publications
Singh, Charan and Chattopadhyay, (2022)	Hotel Industry	1. Sales 2. Other Income	1. Profit before Tax
Qin and Du (2018)	R&D	1. Papers (intermediate) 2. Patents (intermediate) 3. Expenditure_Experimental 4. Personnel_Experimental	1. Technology_Income 2. Enterprise_Income
Kumar and Gulati (2009)	Banking	1. Advances 2. Investments	1. Net-interest income 2. Non-interest income
Keh, Chu and Xu (2006)	Marketing	1. Marketing expenses	1. Rooms Revenue 2.Food and beverages revenue

In the HEI sector, Kashim et al. (2017) categorized outputs as the number of graduates, the number of programs offered and the amount of research grants obtained. These variables represent the immediate results of university functions. One of the core objectives of public universities is to enhance graduate employability, both locally and internationally, in line with graduates' qualifications. In addition, universities are encouraged to strengthen research and development (R&D) activities to support national transformation agendas and innovation-driven growth. Accordingly, indicators such as graduate employability rates, program accreditation by professional bodies, research publications and citation counts are treated as outcomes, as they reflect the ultimate performance objectives of the public university.

A similar distinction between outputs and outcomes can be observed in other sectors. In the hotel industry, Singh et al. (2022) identify sales and other income as outputs because they represent immediate results, while profit before tax is considered an outcome, reflecting the final financial objective of the organization. Likewise, in the banking sector, Kumar and Gulati (2009) categorize advances and investments as outputs, whereas net interest income and non-interest income are treated as outcomes, as they represent the final financial objectives of banking operations.

In the R&D sector, Qin and Du (2018) clearly distinguish between outputs and outcomes in the measurement of system performance. They define outputs as intermediate results, such as academic papers and patents, generated from R&D activities. In contrast, outcomes reflect the ability of the R&D system to achieve broader strategic objectives. Specifically, outcomes are measured through indicators such as technological income and enterprise income, which represent the successful commercialization and practical application of research outputs.

Overall, existing studies across multiple sectors commonly measure effectiveness using both outputs and outcomes, where outputs represent intermediate results and outcomes capture the achievement of final objectives. This distinction is essential for accurately measuring organizational effectiveness and forms the conceptual basis for the output–outcome variable adopted in this study.

From the reviewed studies, it is evident that several DEA approaches have been used to define outputs and outcomes in effectiveness measurement. The following section discusses prior DEA studies in the university context.

2.4 DEA Studies in Universities

Based on existing DEA applications in universities, this study categorizes prior research into three groups. The first group includes studies that employ non-integer-valued variables, treating all inputs and outputs as continuous data. The second group addresses mixed-integer variables, combining integer-valued data (e.g., number of staff and programs) with non-integer data (e.g., expenditure and funding). The third group includes studies that incorporate non-controllable factors, which cannot be directly managed by DMUs. Ignoring mixed-integer values and non-controllable factors may lead to inaccurate efficiency estimates, as conventional DEA models assume that all inputs and outputs are non-integer and controllable. Such assumptions can result in misleading efficiency scores.

2.4.1 DEA Studies in Universities: A case of Non-Integer Valued

The following Table 2.5 summarizes recent studies that have employed DEA to measure the performance of universities.

Table 2.5

Summary of Findings from Recent Previous University Studies using DEA

Author	Period examined	DMUs	Objective	Main Finding
Maral (2023)	Five (5) years	23 research universities in Turki	To examine five years of data from 23 research universities in Turkey to evaluate their research efficiency and identify factors influencing performance	Only 8 out of the 23 universities were found to be efficient. Smaller universities demonstrated higher efficiency and regional development was found to impact efficiency. The study emphasizes the need for strategic resource allocation to enhance both the quantity and quality of research output.
Wang and Wang (2024)	2017 - 2020	Humanities and Social Sciences (HSS) across 31 provinces in China	To analyze Humanities and Social Sciences (HSS) research across 31 provinces in China between 2017 and 2020 using DEA and the Malmquist index.	HSS institutions in China exhibited high levels of static efficiency, with the Malmquist index demonstrating an overall improvement trend primarily attributed to efficiency changes.
Kangooni and Zervopoulos (2023)	2019	2014 to 2019	To measure the relative efficiency of the colleges within the University of Sharjah using an output-oriented DEA model with variable returns-to-scale	The study reported an overall improvement in efficiency during the study period, with the Colleges of Communication, Engineering, and Law serving as key benchmarks for other colleges.
Wijesundara and Prabodanie (2022)	2017 - 2019	15 state universities in Sri Lanka	To measure the relative efficiencies of state universities in Sri Lanka	Seven out of 15 universities (47%) performed efficiently.
Dimyati and Hermanu (2023)	2014 - 2018	47 universities in Mandiri group, 144 in Utama group, Indonesia	To measure the research efficiency of the Indonesian higher education system	The findings revealed that 68% of universities in the Mandiri group achieved full efficiency, compared to nearly 40% in the Utama group, and 41% when both groups were combined.

Table 2.5 continued

Author	Period examined	DMUs	Objective	Main Finding
Chao and Chen (2023)	2015-2017	40 departments in a university	To measure the research efficiency of university departments using DEA approach	The study offering insights for research policymakers, faculty and researchers to enhance research quality and international competitiveness despite limited resources.
Barahona-Urbina and Barahona-Droguett (2023)	2020	14 departments in the University of Atacama	To determine technical efficiency of departments using DEA-CCR and Data Envelopment Analysis-BCC model with variable returns to scale	The results showed that two departments within the Technological Faculty needed to significantly reduce inputs by 77.8% and 85.1%, respectively, while the Faculty of Engineering demonstrated relatively stronger performance and more efficient resource utilization.
Taleb et al. (2023)	2022	41 research and teaching universities in Taiwan	To measure the efficiency of HEIs using the Super Efficiency SBM model	25 out of the 41 universities demonstrated super efficiency status, suggesting that these institutions optimally utilized educational resources.
Qi et al. (2022)	2016 to 2020	Six (6) types of universities in China	To measure the static and dynamic trends of scientific research efficiency	Comprehensive, science and technology, and medical universities recorded the highest efficiency levels, followed by teacher training institutions, while agriculture and forestry universities showed the lowest efficiency.
Delahoz-Dominguez et al. (2022)	2012-2013	Engineering programs in Colombia	To measure academic efficiency DEA models: CCR, BCC and FDH	The study finds that the proportion of efficient engineering programs varies across the DEA models, with 14.3% efficiency in CCR, 29.8% in BCC and 88.7% in

Table 2.5 continued

Author	Period examined	DMUs	Objective	Main Finding
				FDH. Additionally, universities with high-quality accreditation achieve higher efficiency levels, with 65% in CCR, 67% in BCC and 78% in FDH.
Sun et al. (2022)	3-year	Academic disciplines within universities under China's 'Double First-Class' plan	To measure the input-output efficiency of disciplines in Chinese universities using the conventional DEA model and the super-efficiency model	The result highlighting the need for optimal resource allocation in human, financial and material aspects.
Tran et al. (2023)	2012-2016	172 Vietnamese higher education institutions	To examine the economic efficiency of Vietnamese HEIs	The findings indicated a decline in overall operational efficiency during the period. Public universities were generally less efficient than private institutions, and universities offering international programs achieved higher efficiency scores compared to those without such programs.

Despite substantial efforts devoted to DEA studies of university performance, most existing studies rely on single-stage DEA models. These models treat universities or academic departments as “black boxes,” failing to capture the internal structure of university functions, such as the transformation of inputs into intermediate outputs and, ultimately, into final outcomes (Lim & Zhu, 2019). To overcome the limitations of traditional DEA models, there has been an increasing shift toward Network DEA (NDEA), particularly two-stage structures.

Table 2.6 summarizes selected studies that have applied two-stage DEA models to measure university performance.

Table 2.6

Previous Study on Two-Stage Network DEA in University

Author-	**Period examined**	**DMUs**	**Objective**	**Main Finding**
Dogan (2023)	2023	23 Turkish research universities	to evaluate the overall, teaching and research efficiencies of Turkish research universities using shared input data using a two-stage network DEA	only 6 out of the 23 universities assessed were classified as efficient. Interestingly, some universities ranked lower in traditional metrics outperformed those with higher rankings in terms of efficiency. Additionally, there was no significant variation in efficiency among universities from different socio-economic regions.
Chen et al. (2023)	2014	52 Chinese universities	To measure the efficiency scores of Chinese universities using aggregated two-stage DEA models (teaching and research function)	53% universities operated efficiently
Chen et al. (2021)	2014	52 universities in China	To measure operational efficiency of universities using a two-stage network DEA approach, which considered shared inputs while focusing on both teaching and research functions.	It is suggested that the Chinese government enhances its financial allocation strategies and implements effective performance management techniques in budgeting processes.

Table 2.6 continued

Author-	Period examined	DMUs	Objective	Main Finding
Koçak and Örkcü (2021)	2000	State universities in Turkey	To measure and compare graduate education performance and scientific/technological research competency using independent (black box) and related (two-stage) DEA models	Their findings showed that Gebze Technical University, Hacettepe University, Istanbul Technical University, Izmir Institute of Technology, and Middle East Technical University were efficient under both models. However, Istanbul University, Ankara University, Boğaziçi University, and Gazi University were identified as efficient only under the independent model.
Shamohammadi and Oh (2019)	2010 to 2016	Korean private universities	To measure efficiency of teaching and research changes from 2010 to 2016 using a two-stage network DEA	The results indicated an overall decline in efficiency during the study period, with research-oriented universities outperforming those primarily focused on teaching.
Yadolladi and Kazemi Matin (2021)	2015	Twenty branches of Islamic Azad University	To propose a new centralized models for resource distribution within a two-stage network production system	Their model was designed to improve centralized resource distribution.

Most of these studies adopt a two-stage structure in which teaching efficiency is measured in the first stage, followed by research efficiency in the second stage. Similarly, as mentioned by Lim and Zhu (2019), in the university context, the two-stage framework represents one of the most widely adopted NDEA structures. However, the models employed in these studies can be further enhanced to allow for the simultaneous measurement of teaching and research performance. Kao (2012) introduced a parallel DEA model that concurrently measures both the overall system and functional components.

Building on this framework, several studies have applied parallel NDEA models in the university context. For example, Ding et al. (2023) developed a parallel NDEA approach to measure scientific research performance in Chinese universities by decomposing research functions into interacting subsystems. Their findings revealed substantial variations in overall and research efficiency and provided policy-relevant recommendations. Similarly, Xiong and Wu (2021) proposed centralized and decentralized DEA models for parallel systems with interdependent functions and applied them to top-tier universities in China. Their results indicated that centralized resource allocation could achieve higher outputs with fewer inputs. Additionally, Xiong et al. (2020) further extended DEA methodologies to accommodate heterogeneous subunits within multifunctional parallel systems, addressing efficiency overestimation caused by missing or zero outputs. This study successfully developed a performance framework based on a parallel system.

Despite these advances, most studies rely on radial parallel NDEA models, which impose proportional changes on inputs and outputs and fail to capture slack variables. To overcome this limitation, non-radial DEA models have been introduced. For instance, An et al. (2019) developed an additive DEA model to measure parallel interdependent process systems commonly found in competitive production environments. The model was applied to measure the efficiency of China’s “985 Project” universities and provided policy recommendations aimed at improving HEI performance. Moreover, the model is capable of measuring both overall and functional efficiencies within a parallel system.

However, despite the contributions of these studies in advancing DEA analysis for universities, several limitations remain. Most notably, these studies do not adequately address integer requirements in DEA modelling. In practice, certain inputs and outputs can only take integer values. To overcome these limitations, a growing body of research has begun to apply integer-valued DEA models to measure university performance more accurately.

2.4.2 DEA Studies in Universities: A Case of Mixed Integer Values

Subsection 2.4.1 considered various studies that used conventional DEA models (i.e., non-integer DEA models) to measure university efficiency. However, within the university context, certain input and output variables can only take integer values, such as student enrolment, academic staff, graduate numbers and published papers (Kazemi Matin & Kuosmanen, 2009), in addition to non-integer-valued inputs and outputs (e.g., teaching space, expenditures, tuition fees and grants; Taleb, 2017). Therefore, to effectively measure the efficiency of HEIs, it is necessary to incorporate mixed-integer requirements into DEA models (Kazemi Matin & Kuosmanen, 2009; Hussain et al., 2016).

The need for integer-valued DEA arises particularly when dealing with categorical or ordinal data (Banker & Morey, 1986; Rousseau & Semple, 1993). Lozano and Villa (2006) were among the first to propose an integer DEA model assuming all inputs and outputs are integers. Their findings indicated that this model could potentially overestimate efficiency measures because it relies solely on integer inputs and outputs. Subsequently, Kuosmanen and Matin (2009) expanded the framework by introducing new axioms and a Production Possibility Set (PPS) for the BCC model (Banker et al., 1984). This extended model incorporated mixed-integer inputs and outputs and was applied to measure the efficiency of university departments. However, the model did not consider the nature of returns to scale (Daraio & Simar, 2007; Thanassoulis, 2001).

Subsequently, Kuosmanen and Matin (2009) refined the model to incorporate returns to scale, including non-increasing and non-decreasing returns. To test the applicability and usefulness of this model, the efficiency of 42 scientific units was measured. The revised model produced more accurate efficiency estimates compared to the earlier integer model by Lozano and Villa (2006).

Building on the efficiency models of Kuosmanen (2005) and Kuosmanen and Podinovski (2009), Matin and Emrouznejad (2011) introduced a mixed integer-valued DEA model with bounded outputs, which was used to measure the efficiency of HEIs. The findings revealed that it produced higher efficiency values compared to the mixed-integer DEA model established by Kuosmanen and Matin (2009).

Recently, Yousef Zehi and Nana Khurizan (2024) developed a mixed-integer DEA model that excludes equality constraints. This modification enhances the robustness of the approach by avoiding restricted feasible regions or infeasible solutions. The application of this model was demonstrated through a case study of Malaysian public universities. In addition, See et al. (2023) developed a mixed-integer DEA model based on peer evaluation to measure the efficiency of regional university technology transfers in China. Their analysis, based on data from 27 provinces from 2008 to 2015, indicated that the eastern region achieved the highest average efficiency, while the western region recorded the lowest. The study concluded that the model provided more realistic results compared to conventional DEA models.

Despite these advancements, all the aforementioned integer and mixed-integer DEA studies have employed radial models. In response, Matin (2011) proposed integrating integer requirements into the non-radial model developed by Charnes et al. (1985), noting that the efficiency results from this model are stable against data perturbations. Likewise, Wu and Zhou (2011) introduced mixed-integer requirements into the efficiency model of Golany and Yu (1997), creating a mixed-objective integer DEA model that addresses slacks in both non-integer and integer inputs and outputs. The findings indicated that the efficiency scores from this model were less than or equal to those obtained by Kuosmanen and Matin's (2009) model using the same dataset, emphasizing that efficiency scores decreased when slacks of both inputs and outputs were considered simultaneously.

Hussain et al. (2016) proposed a non-radial mixed-integer DEA model based on an alternative super-efficiency SBM approach, aiming to rank both efficient and inefficient DMUs more accurately. Their study measured the efficiency of 41 academic departments at National Cheng Kung University in Taiwan, with results indicating that 51.20% of departments were classified as super-efficient, while many inefficient departments exhibited input excesses in expenses and teaching space, along with output shortfalls in publications and grants. Additionally, Moazenzadeh et al. (2022) developed a slacks-based model capable of incorporating integer-valued data, which they applied to departments within the Islamic Azad University, Karaj Branch, in Iran. Their key findings revealed that a DMU's efficiency score under the proposed model was never lower than that derived from existing models.

From the reviewed studies on university performance using DEA, it is evident that the majority focused on conventional DEA models, which overlook internal structures when measuring university performance. Moreover, most studies assumed that inputs and outputs are controllable by DMU management. However, in many real-world scenarios, certain inputs and/or outputs are non-controllable factors. Therefore, several efficiency studies in HEIs have incorporated non-controllable factors into DEA models to provide more accurate efficiency results (Agasisti, 2011; Ruggiero, 1996; Worthington, 1999).

2.4.3 DEA Studies in Universities: A Case of Non-controllable Factors

Conventional DEA models assume that all inputs and outputs are controllable by DMU management (Tavana et al., 2011). However, in real-world scenarios, certain inputs and outputs are not directly controlled by management. Examples of such non-controllable factors include student enrolment (Ghimire et al., 2021), graduate numbers (Agasisti, 2011) and employment rates (Kashim, 2021). To effectively address this issue, several studies have measured HEI efficiency using DEA models that incorporate non-controllable factors.

The basic formulation of non-controllable factors was introduced by Charnes and Cooper (1984) and Charnes et al. (1985) for both radial and non-radial DEA models.

The first radial DEA model addressing non-controllable inputs was proposed by Banker and Morey (1986). Ruggiero (1996) later expanded this model by assigning a weight of zero to completely non-controllable inputs and a weight of one to fully controllable inputs, allowing for more accurate efficiency measurement in HEIs.

Another model based on Banker and Morey's (1986) framework was introduced by Worthington (1999), who measured scale efficiency of non-controllable inputs under CRS and VRS assumptions. A comparison between pure technical efficiency scores with and without non-controllable inputs was conducted using Spearman's rank correlation, revealing that non-controllable inputs significantly influenced efficiency differences in public libraries. Similarly, Agasisti (2011) calculated scale efficiency while considering non-controllable outputs by incorporating employment rates into the CCR and BCC models. However, a major limitation of these studies is their reliance on radial models.

Farzipoor Sean (2005) introduced a slack-based measure model that accounts for non-controllable factors by assigning weights between 0 and 1 within input and output constraints. In contrast, Esmaeili (2009) proposed a model assuming that inputs and outputs are either fully controllable or fully non-controllable, integrating non-controllable factors into the SBM framework developed by Tone (2001). Applied to 23 public libraries, the results indicated that technical efficiency scores were more accurate than those obtained from Banker and Morey's (1986) radial model. This finding underscores the importance of incorporating non-controllable inputs and outputs into SBM models (Hua, Bian, & Liang, 2007; Rashidi, Shabani, & Sean, 2015).

Taleb et al. (2018) later proposed an enhanced super-efficiency SBM model that integrates mixed-integer requirements along with non-controllable factors, demonstrating its effectiveness in management scenarios where some variables are restricted to integer values.

Within the NDEA context, Kashim (2021) introduced a parallel NDEA model incorporating shared non-controllable inputs. However, the study adopted a radial modelling approach, which does not account for slack variables, thereby limiting its ability to capture input excesses and output shortfalls in detail. Additionally, the study did not consider mixed-integer values. To extend the applicability of these models, a slack-based parallel network DEA incorporating mixed-integer values and non-controllable factors is therefore necessary.

In the literature, there is no standard definition of non-controllable inputs and outputs in DEA (Hua, Bian, & Liang, 2007). Some variables may be categorized as controllable in one organisation or country but non-controllable in another. For example, Esmaeili (2009) treated floor area in Tokyo libraries as a controllable input, whereas Worthington (1999) considered the same factor as non-controllable in New South Wales public libraries. Thus, the classification of inputs and outputs as non-controllable should be based on the managerial constraints faced by DMUs. Table 2.7 presents inputs and outputs used in previous non-controllable DEA studies in universities.

Table 2.7

Inputs and Outputs using Data Envelopment Analysis in Universities

Author	Input	Categorization	Output	Categorization
Agasisti (2011)	Expenditure	Controllable	Graduation	Controllable
	Entry rate	Controllable	International students	Controllable
	Academic staff	Controllable	Public sources	Controllable
			Subsides	Controllable
			Employment rate	Non-controllable
Cordero-Ferrera et al. (2008)	Academic staff	Controllable	Graduate pursuing	Controllable
	Non-academic staff	Controllable		
	Enrolment	Non-controllable		
Daraio, Bonaccorsi and Simar (2015)	Academic staff	Controllable	Total graduates	Non-controllable
	Non-academic staff	Controllable	Factor of research	Non-controllable
	Personnel expenditures	Controllable	Total degree of doctorate	Controllable
	Non-personnel expenditures	Controllable	Published paper	Controllable
			International collaboration	Controllable
			Normalized factor	Controllable
			High quality publications	Controllable
			Excellence rate	Controllable
Esmaeili (2009)	Area	Controllable	Registered residents	Controllable
	Staff	Controllable	Borrowed books	Controllable
	Book	Controllable		
	Population	Non-controllable		
Worthington (1999)	Student population	Non-controllable	Library issues	Controllable
	Area	Non-controllable	Library expenditures	Controllable
	Population	Non-controllable	Library issue per capita	Controllable
	Non- residential borrowers	Non-controllable		
	Expenditures	Controllable		
	Aged population	Controllable		

Table 2.7 continued

Author	Input	Categorization	Output	Categorization
Taleb (2017)	Teaching space	Controllable	Tuition fees	Controllable
	Academic staff	Controllable	graduate employability	Controllable
	Non-academic staff	Controllable	Graduate pursuing	Controllable
	Enrolment students	Non-controllable	Graduate students	Non-controllable
			Unemployment of graduates	Non-controllable
Taleb et al. (2019)	Entrant student	Non-controllable	Graduates	Controllable
	Enrolment student	Controllable	Tuition fee	Controllable
	Academic staff	Controllable		
Kashim (2021)	Number of graduates from undergraduate program	Non-controllable	Graduate employability	Controllable
	Number of graduates from master and PhD program	Non-controllable	Index Journal	Controllable
	Number of programs offered	Controllable	Non-index journal	Controllable
	Research Grant	Controllable	Chapter in book	Controllable
Kashim (2021)	Number of Seminar and Training (community service)	Controllable	Cumulative Research Citation	Controllable
			Income from Seminar and Training (community service)	Controllable

2.4.4 DEA Studies in Universities: Inputs and Outputs

Before implementing DEA, it is essential to identify appropriate input and output variables to ensure accurate computation, as these variables are key factors influencing model development (Cooper et al., 2006). However, no specific guidelines exist for selecting these variables (Ramanathan, 2003). Excluding significant inputs or outputs may lead to inaccurate measurements (McMillan & Datta, 1998), yet it is also impossible to include all variables (Stern et al., 1994).

This section reviews previous DEA-based studies on universities, with particular attention to the selection of input and output variables. The findings are summarized in Table 2.8.

Table 2.8

Inputs and Outputs in Data Envelopment Analysis of Universities

Author	**Input**	**Output**
1. Avkiran (2001)	7. Full-time academic staff. 8. Full-time non-academic staff.	1. Undergraduate enrolments. 2. Postgraduate enrolments. 3. Research grants. 4. Employment rate.
2. Selim and Bursalioglu (2013)	1. Budget appropriations from government. 2. Own revenue. 3. Projects allocations. 4. Scientific research. 5. Number of academic staff.	1. Number of graduate students. 2. Number of post graduate students. 3. Number of doctoral students. 4. Number of publications. 5. Number of employments.
3. Ruiz et al. (2015)	1. Full-time academic staff. 2. Full-time non-academic staff. 3. Expenditures. 4. Teaching space (square meters).	1. Graduate rate. 2. Retention rate. 3. Progress rate.
4. Kashim et al. (2017)	1. Number of Professors. 2. Number of Associate - Professors. 3. Number of Senior Lecturers. 4. Number of graduate degree students.	1. Number of graduated degree students are employed.
5. Visbal-Cadavid et al. (2017)	1. Full-time equivalent admin staff. 2. Financial resources. 3. Physical resources. 4. Expenditure.	1. Numbers of student's enrolments. 2. Indexed journal and articles 3. Faculty mobility.

Table 2.8 continued

Author	Input	Output
6. Sagarra, Mar-Molinero and Agasisti (2017)	1. Full-time equivalent faculty. 2. Total enrolment, first joining the graduation.	1. Scopus paper. 2. Graduates.
7. Bouzouita (2019)	1. Academic staff. 2. Non-academic staff. 3. Expenditures on goods and services. 4. Surface of teaching locals.	1. Number of undergraduate students. 2. Number of graduate students. 3. Number of research masters. 4. Number of theses.
8. Işıldak, Çiçek and Köksal (2018)	1. The total amount of expenditures 2. The total amount of staff expenditures. 3. Education expenditures. 4. Number of academic staff. 5. Number Administrative staff. 6. The total number of students.	1. Number of graduates. 2. Publications. 3. Projects.
9. Moreno-Gómez, Calleja-Blanco and Moreno-Gómez (2020)	1. Number of students. 2. Numbers of full- and part-time staff.	1. Number of graduates. 2. Number of publications in the Scopus database.
10. Kosor et al. (2019)	1. Public Spending.	1. Graduates. 2. Employment rates.
11. Ma and Li (2021)	1. Number of faculty and staff of colleges. 2. Education expenditure of colleges. 3. Area of colleges. 4. Fixed asset value of colleges Year-end. 5. Number of books of colleges.	1. Number of graduates from postgraduate school. 2. Number of graduates from undergraduate school or junior college. 3. Number of academic papers published by colleges. 4. Number of scientific works published by colleges. 5. Number of patents applied by colleges.

Table 2.8 continued

Author	Input	Output
12. Ibrahim and Fadhli (2021)	1. Number of researchers/authors. 2. Number of students.	1. Publications. 2. Citations.
13. Kashim et al. (2018)	1. Number of Professors. 2. Number of Associate Professors. 3. Number of Senior Lecturers. 4. Number of lecturers. 5. Number of foreign academic staff. 6. Number of non-academic staff. 7. Expenses.	1. Number of graduates from undergraduate program. 2. Number of graduates from master program. 3. Number of graduates from PhD program. 4. Number of publications. 5. Amount of grants. 6. Number of main researchers based on different types of grants. 7. Number of expert lecturers. 8. Number of collaboration activities done under Memorandum of Understanding (MoU)/ Letter of Intent (LoI).
14. Abing et al. (2018)	1. Academic staff. 2. Non-academic staff. 3. Classrooms. 4. Laboratories. 5. Research grants. 6. Department expenditure.	1. Graduates. 2. Publications.
15. Taleb (2017)	1. Teaching space. 2. Academic staff. 3. Non-academic staff. 4. Enrolment students.	1. Tuition fees. 2. graduate employability. 3. Graduate pursuing. 4. Graduate students. 5. Unemployment of graduates.
16. Taleb et al. (2018)	1. Number of postgraduate enrolments. 2. Number of undergraduate enrolments. 3. Number of academic staff.	1. The number of graduated postgraduate students. 2. The number of graduated undergraduate students. 3. The number of graduates who furthered their studies.
17. Maral and Çetin (2024)	1. Institution budget. 2. Number of academic staff. 3. Number of academic units. 4. Development level of the region where the institution is located. 5. Students' academic 33background.	1. Number of graduates. 2. Student achievement. 3. Number of accredited programs. 4. Satisfaction score for the institution. 5. Number of publications cited in the top 10%.

Table 2.8 continued

Author	Input	Output
	6. Quality of academic staff.	6. Number of patents, models and designs finalized. 7. Number of science, incentive and art awards. 8. Number of research scholarships and support programs. 9. World ranking of the organization. 10. Number of students employed in technology development zones. 11. Number of social responsibility projects. 12. Number of activities organized for students and graduates. 13. Number of awards.
18. Letti, Bittencourt and Vila (2022)	1. Current cost. 2.Number of full-time equivalent professors. 3.Total number of employees. 4.Number of full-time equivalent undergraduate enrollments. 5.Number of postgraduate enrolments.	1. Number of full-time equivalent undergraduate degrees. 2. Number of full-time equivalent postgraduate degrees. 3. Quality index of postgraduate programs. 4. Number of professors engaged in third mission activities. 5. Number of registered patents.
19. Kashim et al. (2018)	1.Number of graduates from undergraduate program. 2.Number of graduates from master and PhD program. 3.Number of programmes offered 4.Research Grant. 5.Number of seminar and training (community service).	1. Graduate employability. 2. Index journal. 3. Non-index journal. 4. Chapter in book. 5.Cumulative Research Citation 6. Income from seminar and training (community service)
20. De La Torre et al. (2018)	1. Academic staff full time equivalent (FTE). 2. Total expenditure (excluding staff expenditure).	1. Bachelor and master graduates. 2. Publications. 3. Knowledge transfer income.

The review indicates that the most commonly used inputs and outputs are associated with the two core functions of universities: teaching and research. Teaching-related indicators typically include student enrolment, number of graduates and graduate employability rates, while research-related indicators commonly include research grants, book chapters, citations and registered patents. Beyond these two core functions, universities are increasingly expected to fulfil a "third mission" involving community engagement and social contribution (Compagnucci & Spigarelli, 2020). Examples include the number of seminars and training programmes, staff involvement in community engagement activities and university social responsibility (USR) programmes. Once relevant inputs and outputs are identified, DEA efficiency measures can be computed.

2.5 Summary

This chapter provides an overview of performance measurement in higher education institutions and highlights DEA as an appropriate method due to its ability to handle multiple inputs and outputs simultaneously. However, conventional DEA models treat universities as "black boxes," ignoring their internal functional structures, which may lead to misleading efficiency results. A university may appear efficient overall while some internal functions remain inefficient, limiting the identification of specific sources of inefficiency.

To address this limitation, researchers have decomposed university operations into multiple functional components, leading to the development of NDEA models. Among these, two-stage NDEA models are the most commonly applied, but they assume a serial production process and fail to capture simultaneous functional performance. To overcome this shortcoming, Kao (2012) proposed a parallel NDEA model reflecting the simultaneous and independent operation of multiple university functions.

Despite its contributions, the parallel NDEA model developed by Kao (2012) does not incorporate slack variables in inputs and outputs. Furthermore, conventional DEA models generally assume that all inputs and outputs are non-integer and controllable by management, which often does not reflect real-world conditions.

In response to these limitations, the present study extends the literature by examining the effects of mixed-integer variables and non-controllable factors on university effectiveness measurement. Additionally, a slack-based model is incorporated to capture inefficiencies arising from input excesses and output shortfalls, thereby providing a more accurate and informative measurement of university effectiveness.

CHAPTER THREE

A REVIEW ON CONCEPTS AND THEORIES OF DATA DEVELOPMENT ANALYSIS

This chapter reviews existing DEA models and builds upon them to enhance the proposed methodology. To establish a clear foundation, the chapter begins with an overview of the fundamental components of the DEA model, followed by a discussion of model specification and the underlying principles of linear programming (LP). Particular attention is given to the parallel NSBM model, mixed-integer variables and non-controllable factors, all of which are examined in detail. Finally, the chapter analyses the impact of incorporating mixed-integer values and non-controllable factors into DEA models, providing insights into the development of a more robust and practically applicable approach for real-world scenarios.

3.1 Data Envelopment Analysis

The measurement of organizational efficiency using a single-input, single-output framework was first introduced by Farrell (1957). This foundational work was later extended by Charnes, Cooper and Rhodes (1978), who proposed the DEA model capable of simultaneously handling multiple inputs and multiple outputs. This advancement significantly enhanced the practicality of efficiency measurement, as most organizations operate through production processes involving multiple inputs and outputs.

DEA is a non-parametric technique based on LP that measures the relative efficiency of a set of comparable entities, referred to as decision-making units (DMUs), which use multiple inputs to produce multiple outputs (Zehi & Mustafa, 2021, Dzulkarnain et al., 2024). In this context, a DMU represents an organizational unit that controls its inputs to generate outputs and whose performance is to be evaluated (Khan, 2021). A DMU is considered efficient if it utilizes its inputs optimally to maximize outputs. DEA assigns an efficiency score of one (1) to DMUs that represent best-practice performance (Cooper et al., 2011), while inefficient DMUs receive scores below one. The efficient DMUs collectively form a piecewise linear efficiency frontier, which represents the maximum attainable performance within the sample and serves as a benchmark for evaluating all other DMUs.

Based on this frontier, inefficient DMUs can improve their performance by either reducing input consumption or increasing output production. The degree of inefficiency is reflected by the distance of a DMU from the efficiency frontier. DEA identifies the necessary adjustments in inputs or outputs required for an inefficient DMU to achieve efficiency (Charnes et al., 1978). Consequently, DEA is widely used not only for efficiency measurement but also as a mechanism for setting performance targets and guiding improvement strategies for inefficient units (Kao, 2017a; Storto, 2020).

When developing DEA models, it is essential to identify several key components that play a critical role in model formulation. These components are discussed in the following subsections.

3.1.1 Components of DEA Models

Efficiency Measurement

The most commonly used measure of efficiency is expressed in ratio form, as shown in Equation (3.1) (Cooper et al., 2006; Ramanathan, 2003):

$$Efficiency = \frac{Output}{Input} \tag{3.1}$$

In this measure, the ratio of total outputs to total inputs is calculated to obtain an efficiency score. This ratio reflects how effectively an organization transforms inputs into outputs. When multiple inputs and outputs are involved, Equation (3.1) can be rewritten as Equation (3.2), where a weighted output-to-weighted input ratio is applied.

$$Efficiency = \frac{Weighted\ output}{Weighted\ input} = \frac{\sum_{s=1}^{S} v_s y_s}{\sum_{r=1}^{R} u_r x_r} \tag{3.2}$$

A key challenge of this formulation lies in selecting appropriate inputs and outputs for inclusion in the computation and assigning suitable weights to obtain a single output–input ratio (Cooper et al., 2006). DEA overcomes this limitation by not requiring users to pre-specify a set of weights for each input and output. Instead, the optimal weights for each DMU are determined through mathematical programming.

This process identifies the weights that maximize the efficiency of the evaluated DMU, subject to the condition that the efficiencies of other DMUs (calculated using the same set of weights) are restricted to values between 0 and 1 (Ramanathan, 2003). The mathematical programming model of the basic DEA formulation in fractional form is presented in Equation (3.3). In this formulation, it is assumed that there are M DMUs to be compared for efficiency. Let k denote the DMU being evaluated relative to its peers.

$$Max\ E_k = \frac{\sum_{s=1}^{S} v_{sk} y_{sk}}{\sum_{r=1}^{R} u_{rk} x_{rk}} \tag{3.3}$$

Subject to:

$$0 \leq \frac{\sum_{s=1}^{S} v_{sk} y_{sm}}{\sum_{r=1}^{R} u_{rk} x_{rm}} \leq 1; m = 1, \dots, M$$

$$v_{sk}, u_{rk} \geq 0 ; r = 1, \dots, R ; s = 1, \dots, S$$

where

v_{sk} = weight of sth output

u_{rk} = weight of rth input

x_{rk} = rth input of the kth DMU

y_{sk} = sth output of the kth DMU

x_{rm} = rth input of the mth DMU

y_{sm} = sth output of the mth DMU

Formulation (3.3) will find the optimal values of weights v_{sk} and u_{rk} to maximize the objective function value which represents the efficiency score of DMU k. Further discussion on the DEA model and its extensions can be found in Section 3.1.3.

(1) Decision Making Unit (DMU)

A DMU is the entity whose efficiency is being evaluated. Common examples include hospitals, universities, schools and banks (Purwanggono & Faruq, 2022). Two key assumptions underpin the selection of DMUs in DEA. First, DMUs must be homogeneous, meaning they perform similar functions using comparable inputs to produce comparable outputs. For example, comparing hospitals with universities would be inappropriate due to fundamental differences in their production processes.

Second, DMUs must be independent, implying that the input–output levels of one DMU do not depend on those of other DMUs (Charnes et al., 1978). The number of DMUs relative to the total number of input and output variables is also critical, as it affects the discriminatory power of the DEA model (Cooper et al., 2006). To ensure robust results, it is commonly recommended that the number of DMUs be at least three times the total number of inputs and outputs included in the analysis (Avkiran, 2001).

(2) Inputs and Outputs

Identifying appropriate input and output variables is a fundamental requirement in DEA applications. This task is challenging, as there are no universally accepted criteria for selecting these variables (Worthington, 2001). Inputs represent the resources consumed by DMUs, while outputs correspond to the goods or services produced through the utilization of these resources.

As discussed in Subsection 2.2.2.2, DEA is grounded in LP. Therefore, a sound understanding of LP concepts and formulations is essential for the effective application of DEA models.

3.1.2 Linear Programming Concept

LP employs a linear mathematical model to represent the problem under study, requiring all mathematical expressions within the model to be linear functions. The model consists of an objective function, which is either maximized or minimized and a set of constraints representing limitations or conditions that must not be violated. These components are solved simultaneously to determine the optimal solution (Eiselt & Sandblom, 2007). Additionally, LP formulation must satisfy the following assumptions:

i) Linearity: The relationships in the objective function and constraints are expressed as linear equations or inequalities (Taylor, 2012).

ii) Non-Negativity: All decision variables must take non-negative values (Hillier & Lieberman, 2001).

iii) Deterministic: The parameters of the LP model (i.e., objective function coefficients and constraint coefficients), as well as the system structure, are assumed to be constant and known with certainty (Eiselt & Sandblom, 2007).

iv) Divisibility: The level of each activity can be expressed as a real number rather than being restricted to integer values (Hillier & Lieberman, 2001).

v) Proportionality: Any change of each activity in the objective function and constraints must be proportional with the change to the value of an activity (i.e., a changing level of decision variables in the objective function and constraints must be proportional with the change in the resource of that decision variable) (Taha, 2007).

vi) Additivity: The total contribution in the objective function and constraints equals the sum of the individual contributions of each activity (Taha, 2007).

The general form of an LP model for an optimization problem is presented in Equation (3.4).

$$Max\ Z\ or\ Min\ Z = \sum_{k=1}^{K} a_k x_k \tag{3.4}$$

Subject to:

$$\sum_{k=1}^{K} b_{rk} x_k \leq OR = OR \geq c_r;\ \ r = 1, \dots, R$$

$$x_k \geq 0; \qquad\qquad k = 1, \dots, K$$

where

Z = objective function value which represents the overall performance

x_k = value of decision variable k representing level of activities

a_k = the contribution of decision variable x_k in the objective function value Z

c_r = level of available resource r allocated to activities (for $r = 1, \dots, R$)

b_{rk} = amount of resource r consumed by each unit of activity k

Over time, several advanced techniques have been developed based on the core principles of LP to address specific problem settings. These include integer linear programming (ILP), where all decision variables are restricted to integer values and mixed integer linear programming (MILP), which incorporates both integer and continuous variables. These extensions expand the applicability of LP in solving complex real-world problems.

3.1.2.1 Integer Linear Programming

In certain scenarios, decision variables must be restricted to integer values. For example, assigning individuals, students, or universities to specific activities typically requires integer quantities (Taha, 2007). When integer restrictions are imposed on all decision variables, the LP model becomes an integer linear programming (ILP) problem. ILP is a specialized category of LP in which all decision variables are constrained to take integer values (Hillier & Lieberman, 2001). Its mathematical structure is identical to that of LP, except for the additional integrality restriction imposed on the decision variables.

In many real-world situations, however, only some decision variables must be integers, while others may remain continuous (Branch, 2021). In such cases, it is necessary to incorporate both integer and continuous variables to appropriately model the problem.

3.1.2.2 Mixed Integer Programming

Mixed Integer Linear Programming (MILP) is a class of LP problems capable of modelling a wide range of real-world scenarios involving both integer and continuous decision variables (Hillier & Lieberman, 2001). The mathematical formulation of MILP is similar to that of LP, except that some decision variables are restricted to integer values. MILP is particularly valuable for measuring the efficiency of organizations in which certain input and/or output variables can only take integer values, such as in higher education institutions (Kuosmanen & Matin, 2009; Wu & Zhou, 2011). Consequently, numerous efforts have been undertaken to incorporate MILP principles into DEA modelling. A detailed discussion of these developments is presented in Section 3.5.

3.1.3 Type of Data Envelopment Analysis Model

DEA models can generally be categorized into radial and non-radial measures of efficiency (Kao, 2020). Radial models focus on the proportional reduction of inputs (input-oriented) or the proportional augmentation of outputs (output-oriented) to improve the efficiency of inefficient DMUs. These models are based on two fundamental production frontiers. The first is the CCR model, developed by Charnes et al. (1978), which assumes constant returns to scale (CRS). The second is the BCC model, introduced by Banker et al. (1984), which incorporates variable returns to scale (VRS) by adding a convexity constraint. This feature enables the BCC model to capture increasing, decreasing, or constant returns to scale, making it particularly suitable for real-world situations in which DMUs operate at different scales (Cooper et al., 2006).

Due to their reliance on proportional adjustments, radial models do not explicitly account for input and output slack variables simultaneously (Tayebi et al., 2024; Rashidi et al., 2015). To overcome this limitation, non-radial DEA models were developed. These models allow for disproportionate reductions in inputs and increases in outputs by directly incorporating input and output slacks (Du et al., 2010; Hussain et al., 2016). This capability represents a key advantage of non-radial models over radial models (Taleb, 2017). Figure 3.1 presents the categorization of radial and non-radial DEA models under both CRS and VRS assumptions.

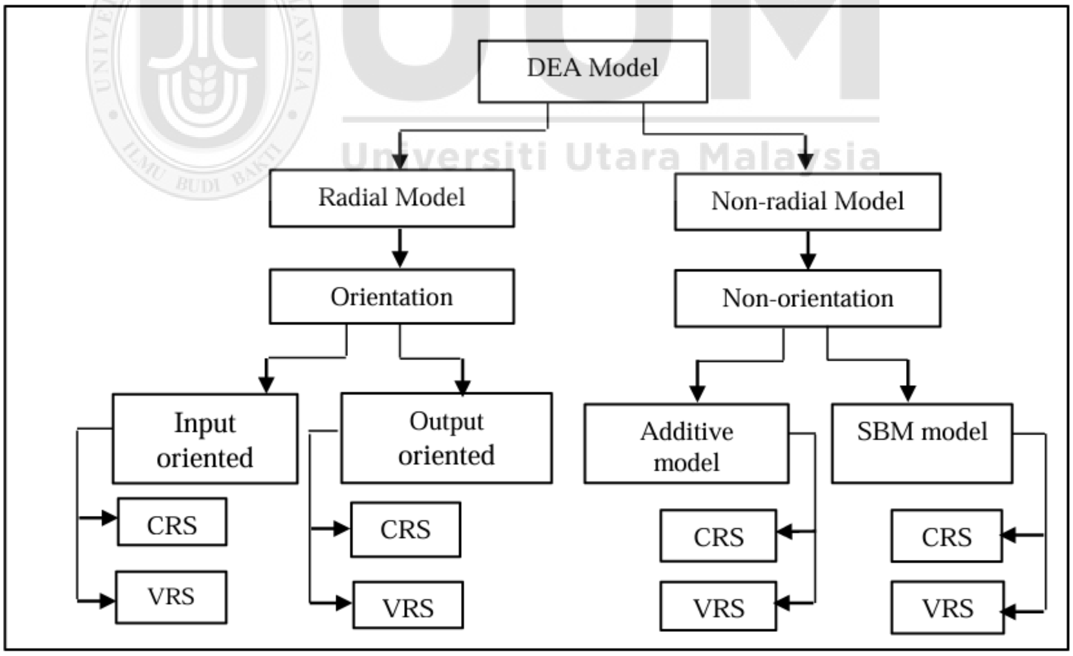


Figure 3.1. Categorization of DEA model
Source: Ozcan (2008, p.24)

The DEA approach provides three types of projections for inefficient DMUs onto the piecewise linear production frontier: input-oriented, output-oriented and non-oriented models. Figure 3.2 illustrates these three projection types.

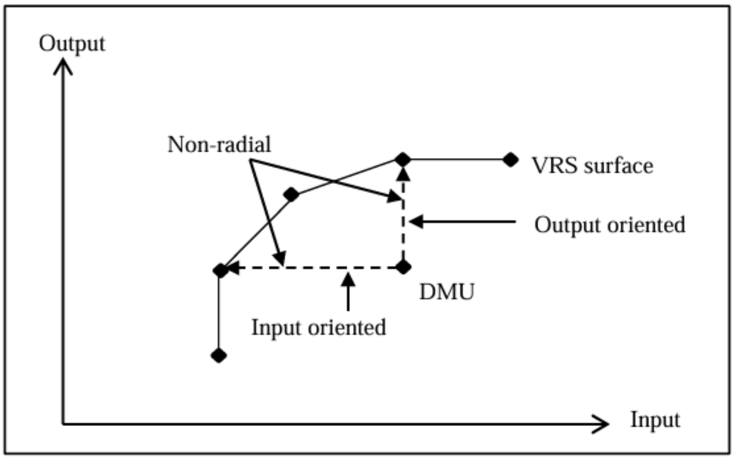


Figure 3.2. Projection of DEA models
Source: Cooper et al. (2006)

The input-oriented projection aims to proportionally reduce inputs while maintaining the current output level (Debnath et al., 2008; Ruggiero, 1996). Conversely, the output-oriented projection seeks to proportionally increase output levels while holding inputs constant. Among non-radial DEA models, two essential approaches are the additive model and the slack-based measure (SBM) model (Cooper et al., 2006).

3.1.3.1 Additive Model

The additive model (ADD), first proposed by Charnes et al. (1985), defines its objective function as the sum of all input and output slacks (Gerami et al., 2023). The basic version of the ADD model is expressed by the following formulation:

$$Max\, z_0 = \sum_{r=1}^{R} t_r^- + \sum_{s=1}^{S} t_s^+ \tag{3.5}$$

Subject to:

$$\sum_{k=1}^{K} \lambda_k x_{rk} + t_r^- = x_{r0} \qquad r = 1, \dots, R$$

$$\sum_{k=1}^{K} \lambda_k x_{sk} - t_s^- = y_{s0} \qquad s = 1, \dots, S$$

$$\lambda_k,\ t_r^-\ , t_s^+\ \geq\ 0, \forall_{r,k,s} \qquad k = 1, \dots, K$$

The ADD model determines whether a DMU is efficient or inefficient, assigning a score of zero to efficient units. However, unlike radial models, it does not provide a conventional efficiency score that reflects the magnitude of inefficiency (Cook & Seiford, 2009). To address this limitation, Tone (2001) developed the non-radial slack-based measure (SBM) model.

3.1.3.2 Slack-Based Measure

The Slack-Based Measure (SBM) is a prominent non-radial DEA model that simultaneously accounts for input excesses and output shortfalls (Hussain et al., 2016). The efficiency score produced by the SBM model ranges between zero and one and attains a value of unity if and only if the DMU under evaluation lies on the efficient frontier with all input and output slacks equal to zero (Salehzadeh, 2023). Since input reduction and output augmentation are treated independently (Tone, 2001), the SBM model allows for non-proportional reductions in inputs and non-proportional increases in outputs (Rashidi et al., 2015). The SBM model proposed by Tone (2001) is defined as follows:

Assume that there is a set of n peer DMUs, denoted as DMU_1 , DMU_2 , …, DMU_K, where $(k = 1, \ldots, K)$. These DMUs use inputs (X_r=$x_{r1}, x_{r2}, \ldots, x_{rK}$) to produce outputs ($Y_s$=$y_{s1}, y_{s2}, \ldots, y_{sK}$). To compute the efficiency score of DMU_O, the SBM model is formulated as:

$$\rho_o = min. \frac{1 - \frac{1}{R}\sum_{r=1}^{R} \frac{t_r^-}{x_{ro}}}{1 + \frac{1}{S}\sum_{s=1}^{S} \frac{t_s^+}{y_{s_o}}}, \tag{3.6}$$

Subject to:

$$\sum_{r=1}^{R} \lambda_k x_{rk} = x_{r_o} + t_{r_o}^-, \qquad ,r = 1, \ldots, R$$

$$\sum_{s=1}^{S} \lambda_k y_{sk} = y_{s_o} - t_{s_o}^+ \qquad ,s = 1, \ldots, S$$

$$\lambda_k, \qquad t_{r_o}^-, t_{s_o}^+ \geq 0 \qquad ,k = 1, \ldots, K$$

where

x_{r_o} = amount of rth of DMU

$DMU_o, r = 1, \ldots, R,$ subscript o indicating the factor which represents the DMU under evaluation.

y_{s_o} = amount of sth of

$DMU_o, s = 1, \ldots, S$

$t_{r_o}^-$ = slack of the rth input (i.e., input excees) of DMU_0

$t_{s_o}^+$ = slack of the sth output (i.e., output shortfall) of DMU_0

$\sum_{r=1}^{R} \lambda_k x_{rk}$ = reference set of the rth input for K DMUs, $k = 1, \ldots, K$

$\sum_{s=1}^{S}\lambda_k y_{sk}$ = reference set of the sth output for K DMUs, $k = 1, \ldots, K$

λ_k Positive vector denoting optimal set of weights for efficient DMUs for the of kth DMU

Based on the positive values of input and output slacks, the model improves each inefficient DMU by simultaneously reducing its inputs and augmenting its outputs. This improvement is achieved through the projection form of the SBM model. The projected values of the input and output variables are described in Equation (3.7).

$$\hat{x}_{r_o} = x_{r_o} - t_{r_o}^{-*}, (r = 1, \ldots, R) \tag{3.7}$$

$$\hat{y}_{s_o} = y_{s_o} + t_{s_o}^{+*} \; (s = 1, \ldots, S)$$

To define the efficiency measure of the SBM model, Tone (2001) introduced the following definition:

Definition 1 A DMU is said to be fully-efficient if and only if the non-radial distance of its inputs and outputs from the production frontier is equal to zero; i.e., its input excesses and output shortfalls both zero (Cooper et al., 2006).

It should be noted that the SBM model in Equation (3.6) is expressed as a fractional programming problem. To obtain the optimal solution, this fractional form must be transformed into a linear programming form.

To accomplish this, the constraints of input and output are multiplied by a non-negative scalar measure (j > 0). Since both the numerator and denominator of the objective function are fractional expressions, they are multiplied by a positive scalar (h > 0). The denominator is normalized to one and transferred into the constraints. Using the Charnes–Cooper transformation (Charnes & Cooper, 1962), the model is converted into a linear programming form by imposing $\frac{1}{j} = 1 + \frac{1}{w}\left(\sum_{s=1}^{S}\frac{t_s^+}{y_{s_o}}\right)$ (Lo & Lu, 2009). The resulting linear programming form of Model (3.6) is presented in Model (3.8).

$$\min \tau_o = j\ \frac{1}{R}\sum_{r=1}^{R}\frac{\hat{t}_r^-}{x_{ro}} \tag{3.8}$$

Subject to

$$h + \frac{1}{S}\sum_{s=1}^{S}\frac{\hat{t}_s^+}{y_{s_o}} = 1$$

$$jx_{r_o} = \sum_{r=1}^{R} x_{rk}\hat{\lambda}_k + \hat{t}_r^- \qquad r = 1, \ldots, R$$

$$jy_{s_o} = \sum_{s=1}^{S} y_{sk}\hat{\lambda}_k - \hat{t}_s^+ \qquad s = 1, \ldots, S$$

$$t_r^{+*} \geq 0, t_s^{-*} \geq 0, j > 0$$

Let the optimal solution of Model (3.7) be $(\tau_o^*, \hat{t}_r^{-*}, \hat{t}_s^{+*}, \hat{\lambda}_k^*, j^*)$, Then, the optimal solution of Model (3.5) can be defined as follow: $\rho^* = \tau_o^*$, $\lambda_k^* = \frac{\hat{\lambda}_k}{h}$, $t_r^{-*} = \hat{t}_r^-/j$, $t_s^{+*} = \hat{t}_s^+/j$.

To illustrate the SBM model graphically, Figure 3.3 depicts the simultaneous consideration of input excesses and output shortfalls (Cooper et al., 2006). Four DMUs, labelled A, B, C and D, are examined, each utilizing a single input to produce a single output. The variables t^- and t^+ represent a feasible solution for inefficient DMU D. The slacks of input excess and output shortfall are shown by dotted arrows, indicating the maximum reduction in input and maximum increase in output required for DMU D to reach the efficient reference point represented by DMU B. DMU B reflects both input reduction and output expansion for DMU D, as the SBM model simultaneously considers input contraction and output expansion to achieve efficiency on the frontier (Amirteimoori et al., 2013; Morita et al., 2005).

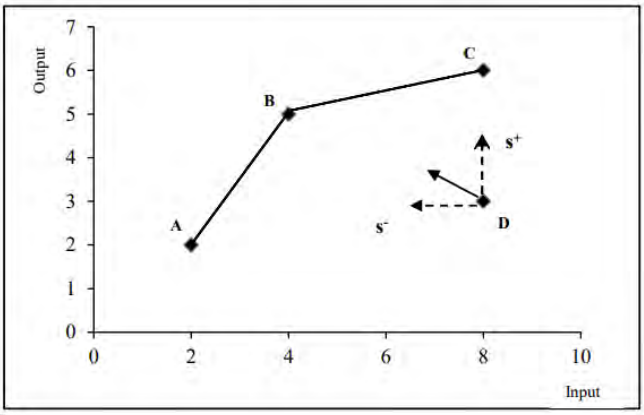


Figure 3.3. SBM model under VRS
Source: Cooper et al. (2006)

3.1.4 Single Stage Data Envelopment Analysis Model (Black Box)

Conventional DEA models treat a DMU as a single production unit governed by one production function, commonly referred to as a “black box” or single-stage system. In this setting, efficiency evaluation is based solely on the relationship between aggregated inputs and aggregated outputs. Figure 3.4 illustrates a black-box system in which R inputs, $X_r, r = 1, \ldots, R$, are used in a single-stage system to produce S outputs, $Y_s, s = 1, \ldots, S$.

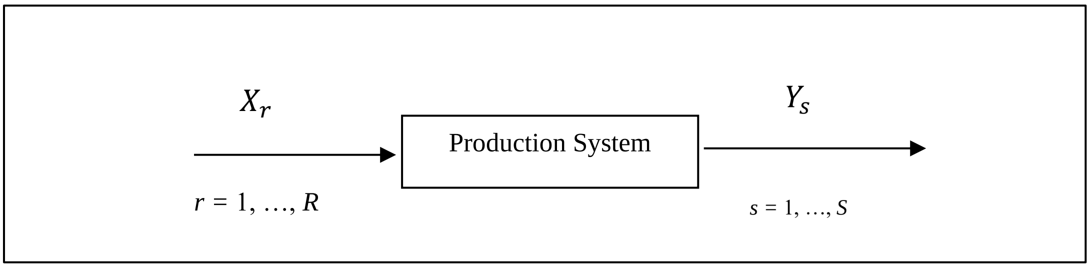


Figure 3.4. DMU represents the production system as a "black box"

In practice, however, many DMUs possess complex internal structures involving multiple interrelated functions or stages (Gan et al., 2020). These systems transform inputs into final outputs through a sequence of intermediate stages, each performing a distinct function. Conventional black-box DEA models fail to capture such internal transformation processes and therefore provide limited insight into the sources of inefficiency (Koronakos, 2019). Consequently, this approach cannot provide process-specific guidance for decision-makers seeking to improve DMU performance. The black-box DEA model is primarily appropriate when the objective is to identify inefficient DMUs (Bencová & Boháčiková, 2022) and determine their relative inefficiency levels (Taleb, 2025; Kiaei et al., 2020). To address these limitations, Network Data Envelopment Analysis (NDEA) was introduced to incorporate internal structures into efficiency evaluation (Färe & Grosskopf, 2000). The following section discusses NDEA models, which enhance performance measurement by explicitly accounting for internal processes and interconnections.

3.2 Network Data Envelopment Analysis

In response to the limitations of conventional black-box DEA models, researchers have devoted considerable effort to decomposing production systems into two-stage functional structures (Lu & Cheng, 2021). However, many real-world systems involve more than two stages. Consequently, DEA has been extended to accommodate series and parallel structures, allowing for more accurate measurement of multi-stage production systems (Despotis et al., 2016).

3.2.1 Two-stage Structure

The two-stage structure is among the most fundamental and widely applied NDEA structures (Lim & Zhu, 2019; Zhou et al., 2021). This structure decomposes overall efficiency into two sequential stages and introduces intermediate measures linking them (Aksoy et al., 2022). In the first stage, inputs are transformed into intermediate outputs, which then serve as inputs for the second stage to produce final outputs (Kao, 2014). Figure 3.5 illustrates the two-stage structure.

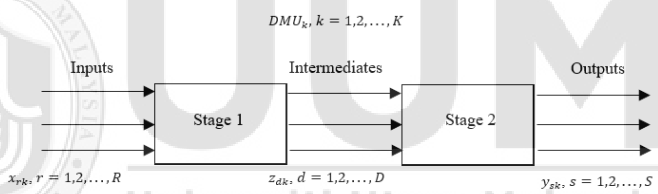


Figure 3.5. A Two-stage structure system
Source: Chen et al. (2010)

For example, Sun et al. (2024) applied a two-stage DEA model to measure the efficiency of China's agricultural water conservancy infrastructure by dividing the process into water supply and water use stages. Their findings revealed spatial disparities between the two stages, with water supply efficiency associated with resource abundance and water use efficiency linked to regional economic development. Similarly, Yin et al. (2020) decomposed hotel performance into operational and marketing stages, developing a benchmarking framework to support managerial decision-making. These studies demonstrate the effectiveness of two-stage

DEA models in capturing system complexity and identifying stage-specific improvement opportunities.

Nevertheless, many real-world systems, such as assembly-line production processes, involve more than two stages, with raw materials passing through multiple workstations before becoming final products (Kao, 2023). To address such scenarios, DEA has been extended to series structures, enabling efficiency measurement across multiple sequential stages. In recent years, substantial research attention has focused on multi-stage DEA models incorporating both series and parallel structures (Saleh, 2024).

3.2.2 Series Structure

A series structure consists of a sequence of interconnected stages, where each stage uses both external inputs and intermediate outputs generated by preceding stages. The output produced by one stage serves as the input for the subsequent stage, thereby forming a chain of production processes (Kao, 2014). Figure 3.6 illustrates a serial structure that has p functions. The first stage uses the external input x_r, (r =1, …, R) to produce intermediate outputs $Z_g^{(1)}$, which are then used as inputs in the second stage. At each subsequent stage q, intermediate outputs $Z_g^{(q-1)}$, generated by the previous stage are used to produce new intermediate outputs $Z_g^{(q)}$. The final stage p uses an intermediate product $Z_g^{(q-1)}$, to produce final outputs y_s, s = 1, ..., S.

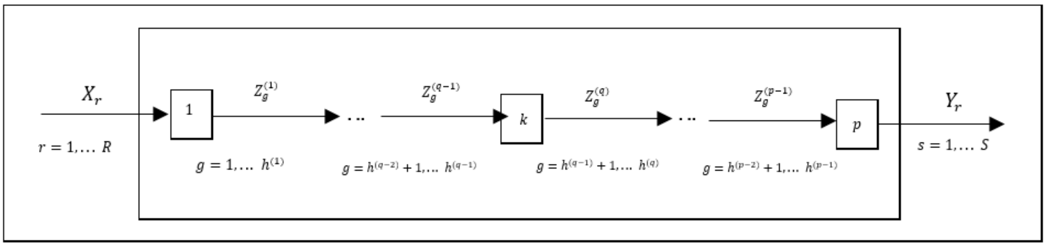


Figure 3.6. A Series structure system
Source: Kao (2017b)

However, not all systems operate sequentially. In many real-world contexts, a DMU comprises multiple independent functions operating simultaneously. For example, a company may own several factories that function independently, each using inputs to produce outputs in parallel. In such cases, the total inputs and outputs of the DMU are the aggregates of those from each parallel function (Kao, 2009).

3.2.3 Parallel Structure

To address parallel production processes, Kao (2009) developed a parallel DEA model capable of measuring both overall system efficiency and the efficiency of individual component functions. A key advantage of this model is its ability to identify inefficiencies within each function. Kao applied the model to the Taiwan National Forest Administration, enabling the identification of inefficient administrative components and facilitating more efficient resource reallocation across production functions. The parallel structure is illustrated in Figure 3.7.

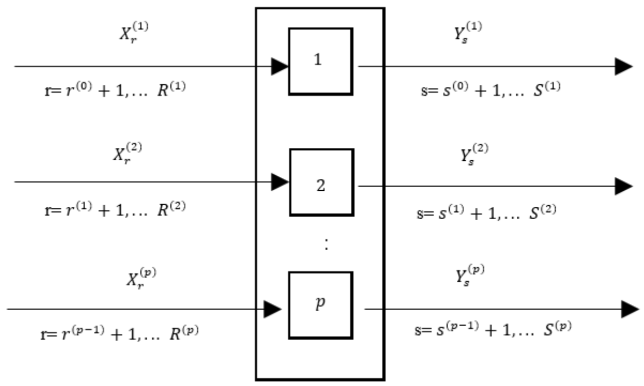


Figure 3.7. A Parallel Structure System
Source: Kao (2020)

The properties of NDEA can be summarized as follows (Tone &Tsutsui, 2009):

i) A DMU is efficient if and only if all its component functions are efficient.

ii) Under the VRS assumption, each function has at least one functionally efficient DMU.

iii) The projected DMU is overall efficient, indicated by zero slack.

However, Kao's (2009) parallel DEA model employed a radial efficiency measure, which does not simultaneously account for input and output slacks. To overcome this limitation, Kao (2020) introduced a non-radial parallel Network Slack-Based Measure (NSBM) model.

3.3 Slack Based Measure of Parallel Network Data Envelopment Analysis Model

As shown in Figure 3.7, a general parallel system consists of p functions. In this structure, each function q applies inputs $X_r^{(q)}$, $(r = r^{(q-1)},\ldots,\ R^{(q)})$ to produce outputs $Y_s^{(q)}$, $(s = s^{(q-1)} + 1,\ldots,\ S^{(q)})$ with $r^{(0)} = 0, r^{(p)} = r, s^{(0)} = 0$ and $s^{(p)} = s$. There are no intermediate products and the functions operate independently within the system. The mathematical formulation of Kao's parallel NSBM model under VRS assumption is presented as follows (3.9) and (3.10):

$$\rho^S = min. \frac{1 - \frac{1}{R}\sum_{q=1}^{p} \sum_{r=R^{(q-1)}+1}^{R^{(q)}} \frac{t_r^{(q)-}}{X_{r0}^{(q)}}}{1 + \frac{1}{S}\sum_{q=1}^{p} \sum_{s=S^{(q-1)}+1}^{S^{(q)}} \frac{t_s^{(q)+}}{Y_{s0}^{(q)}}} \tag{3.9}$$

$s.t.$

$$\sum_{k=1}^{K} \lambda_k^{(q)} X_{rk}^{(q)} + t_r^{(q)-} = X_{r0}^{(q)}, \qquad r = r^{(q-1)} + 1, \dots, R^{(q)}, \quad q = 1, \dots, p$$

$$\sum_{k=1}^{K} \lambda_k^{(q)} Y_{sk}^{(q)} - t_r^{(q)+} = Y_{s0}^{(q)}, \qquad s = s^{(q-1)} + 1, \dots, R^{(q)}, \quad q = 1, \dots, p$$

$$\sum_{k=1}^{K} \lambda_k^{(q)} = 1 \qquad q = 1, \dots, p$$

$$\lambda_k^{(q)}, t_r^{(q)-}, t_s^{(q)+} \geq 0, \qquad k = 1, \dots, K \quad q = 1, \dots, p \quad r = 1, \dots, R \quad s = 1, \dots, S$$

The efficiency of function q is:

$$\rho^{(q)} = \frac{1 - \frac{1}{R^{(q)} - R^{(q-1)}} \sum_{r=R^{(q-1)}+1}^{R^{(q)}} \frac{t_r^{(q)-}}{X_{r0}^{(q)}}}{1 + \frac{1}{S^{(q)} - S^{(q-1)}} \sum_{s=S^{(q-1)}+1}^{S^{(q)}} \frac{t_s^{(q)+}}{Y_{s0}^{(q)}}}, \qquad q = 1, \dots, p \tag{3.10}$$

Based on the positive values of input and output slacks, the model improves inefficient DMUs by simultaneously reducing inputs and augmenting outputs. This improvement is achieved through the projection form of the SBM model. Accordingly, the projected values of input and output variables onto the frontier are described in Equation (3.11).

$$x_o^{q*} \leftarrow x_o^q - t^{q-*}\ (q = 1, \ldots, p) \tag{3.11}$$

$$y_o^{q*} \leftarrow y_o^q + t^{q+*}\ (q = 1, \ldots, p)$$

However, Kao's (2020) model assumes that all inputs and outputs are fully controllable by DMU management. To enhance the applicability of DEA models to real-world scenarios, it is essential to incorporate non-controllable factors into the DEA framework.

3.4 Non-controllable Factors in DEA

Conventional DEA models assume that input and output variables are fully controllable by the DMU (Zehi & Mustafa, 2021). However, in many real-world situations, certain input or output variables lie beyond the direct control of management. Ignoring non-controllable factors may lead to inaccurate efficiency estimates, as these factors play a significant role in the production process (Amirteimoori et al., 2014). Due to the presence of such factors, DEA models incorporating non-controllable variables have been introduced. In these models, the levels of non-controllable inputs or outputs remain fixed because they cannot be adjusted by the DMU (Agasisti, 2011; Cook & Seiford, 2009). This concept has been extended to both radial and non-radial efficiency measures.

3.4.1 Non-controllable factors of radial DEA Model

There are numerous examples of non-controllable factors, including student enrollment numbers (Taleb et al., 2019), graduation rates (Daraio et al., 2015; Ruggiero, 1996), unemployment rates (Brockett et al., 2004; Ebadi & Shahraki, 2010), population size (Camanho et al., 2009) and the age of a pharmacy store (Patel & Pande, 2013). The first DEA model addressing non-controllable inputs was proposed by Banker and Morey (1986). The model allows non-controllable input constraints to reject input decrement. The rejection process is made by comparing input whose value must remain fixed with linear combination (reference sets) of other DMUs that their values are at the same level as this non-controllable input variable (Cook & Seiford, 2009).

Several researchers have explored methods for incorporating non-controllable factors into DEA. For example, Song et al. (2022) analyzed the eco-efficiency of the transportation sector in 30 Chinese provinces by applying DEA model that incorporates non-controllable inputs, demonstrating that both non-controllable factors and direction vectors significantly influence eco-efficiency outcomes. Similarly, Zadmirzaei et al. (2017) investigated forest management units and showed that ignoring external non-controllable factors may lead to overestimated efficiency scores. Long and Xia (2018) also considered non-controllable factors in operational efficiency analysis and found that some of these variables possess multiple target levels that can support efficiency improvement in practice. Collectively, these studies highlight the importance of incorporating non-controllable factors for more accurate DEA measurements.

However, these models are radial in nature, assuming that certain inputs (in input-oriented models) or outputs (in output-oriented models) are non-controllable (Patel & Pande, 2013). Due to the limitations of radial models discussed in Section 3.1.3, it is necessary to consider non-radial approaches. Therefore, extending slack-based measures to incorporate non-controllable factors becomes essential.

3.4.2 Non-controllable Factors of Non-Radial DEA Model

Given the significant role of non-radial DEA models in addressing real-world situations involving simultaneous input reduction and output augmentation (Cooper et al., 2000; Du et al., 2010; Tone, 2001), incorporating non-controllable factors into non-radial models is crucial. The first non-radial SBM model that accounted for non-controllable factors was introduced by Farzipoor Sean (2005). Subsequently, Hua et al. (2007) extended this framework by developing a non-radial output-oriented DEA model that explicitly considered non-controllable inputs and undesirable outputs.

Building on these developments, Esmaeili (2009) refined the SBM model by focusing the objective function exclusively on controllable inputs and outputs, excluding slacks associated with non-controllable variables from relevant constraints. This approach produced more accurate efficiency estimates than earlier models such as Banker and Morey (1986) and emphasized the importance of simultaneously addressing input slacks in efficiency evaluation. Further extensions of the SBM framework incorporated combinations of controllable, non-controllable, desirable and undesirable factors (Rashidi et al., 2015). More recently, Taleb et al. (2023) proposed a super-efficiency slack-based measure capable of handling non-controllable factors in supply chain management. Their approach differentiates efficient and inefficient suppliers while enabling ranking through simultaneous consideration of input excesses and output shortfalls. Given the importance of non-controllable factors in SBM models, the mathematical formulation of the SBM model with non-controllable variables is discussed below.

3.4.3 Mathematical Concepts and Notation of SBM-Non-controllable Model

Assume that there are *K* homogenous DMUs to be evaluated. Each DMU consumes *r* inputs to produce *s* outputs. Unit *k* is denoted as DMU_k, *k* =1, . . . , *K*. Let x_{rk} denote the *r*th input and y_{sk} represents the *s*th output. Both inputs and outputs are categorized into subsets of controllable and non-controllable factors of the same DMU_k. x_{rk}, y_{sk}> 0 for all possible r =1, . . . , R ; s =1, . . . , S (Farzipoor Sean, 2005; Rashidi et al., 2015). Accordingly, the fractional SBM model incorporating non-controllable factors introduced by Esmaeili (2009) is considered.

3.4.4 Efficiency Measure for SBM: Non-Controllable

To measure the efficiency of a homogeneous set of KDMUs in the presence of non-controllable variables, Esmaeili (2009) proposed the fractional SBM-NC model (3.12).

$$Min\ \rho_{NC} = \frac{1 + \frac{1}{R}\left(\sum_{\substack{r=1 \\ r\in C}}^{R} \frac{t_{r_o}^{-}}{x_{ro}}\right)}{1 - \frac{1}{S}\left(\sum_{\substack{s=1 \\ s\in C}}^{S} \frac{t_{s_o}^{+}}{y_{s_o}}\right)} \tag{3.12}$$

s.t.

$$\sum_{k=1}^{K} \lambda_k x_{r^C k} + t_{r^C o}^{-} = x_{r^C o}, \qquad r^C \in R^C$$

$$\sum_{k=1}^{K} \lambda_k x_{r^{NC} k} = x_{r^C o}, \qquad r^{NC} \in R^{NC}$$

$$\sum_{k=1}^{K} \lambda_k y_{s^C k} - t_{s^C o}^{+} = y_{s^C o}, \qquad s^C \in S^C$$

$$\sum_{k=1}^{K} \lambda_k y_{s^{NC} k} = y_{s^{NC} o} \qquad s^{NC} \in S^{NC}$$

$$x_{r^C}, y_{s^C}, \lambda_k,\ t_{r^C o}^{-}, t_{s^C o}^{+} \geq\ 0,$$

In model (3.12), the vectors $x_{r}c \in R^{r}, y_{s}c \in R^{s}$, represent positive controllable inputs and outputs respectively. $t^{-}_{r}c \in R^{r}$, $s^{+}_{s}c \in R^{s}$ represent the vector of non-radial slacks representing the amount of controllable input excesses and output shortfalls to decrease and increase the amount of their corresponding controllable inputs and outputs respectively.

Importantly, the objective function considers only controllable variables (Farzipoor Sean, 2005; Lozano & Gutiérrez, 2011), allowing the model to focus on factors that management can influence and thereby produce more accurate efficiency assessments. However, this model does not incorporate internal network structures alongside non-controllable factors.

In response, Lotfi and Hasanpour (2010) proposed a network DEA model incorporating interrelationships among functions while considering undesirable and non-controllable factors. Their framework enables simultaneous measurement of overall system efficiency and component efficiencies. Shoja et al. (2021) further extended this approach by analysing a four-stage supply chain system with non-controllable and undesirable variables, demonstrating the importance of addressing inefficiencies at different stages. Additionally, Harofteh and Harofteh (2025) focus on non-controllable in manufacturing industries with multi-stage production functions. Their model measures the economies of scope and cost-effectiveness for both two-stage and single-stage systems, helping managers optimize production processes and improve resource allocation. Their findings provide valuable insights into how these factors impact internal operational efficiency and organizational overall performance.

However, most existing studies focus primarily on radial models. To address this limitation, Vlachos et al. (2024) proposed a three-stage NSBM model incorporating non-controllable inputs and undesirable outputs within a supply chain context. Despite these advancements, the literature has not specifically addressed SBM-based network DEA in a parallel structure with non-controllable factors. Therefore, developing an enhanced parallel NSBM model incorporating non-controllable variables is necessary for more accurate efficiency measurement.

To date, the existing literature on DEA models typically assumes that all input and output values are non-integer. However, in certain cases, simply rounding inputs and/or outputs to the nearest integer values may lead to inaccuracies in efficiency measurement (Du et al., 2012; Hussain et al., 2016; Kuosmanen & Matin, 2009). Therefore, it is essential to adopt an appropriate method that can properly accommodate integer restrictions on inputs and/or outputs within the DEA framework.

3.5 Integer DEA Approach

Conventional DEA models typically assume that inputs and outputs are non-integer. However, in real-world scenarios, certain inputs and outputs must only take integer values (Noveiri & Kordrostami, 2020). Examples of integer values include some inputs, such as the number of employees, or some outputs, such as the number of transactions, which can only take integer values (Wu & Zhou, 2015).The process of rounding efficiency measures to the nearest integer can result in misleading efficiency evaluations, as it may obscure the true performance of the DMUs involved (Du et al., 2012). Let us consider an example presented by Kuosmanen and Matin (2009). Suppose a department employs three academic staff members. The reference target generated by a conventional DEA model indicates that the optimal level of academic staff should be 2.4. This result presents a dilemma: while there is no evidence to suggest that two academic staff members would be sufficient to meet the educational and scientific objectives of the department, rounding 2.4 up to three does not yield any resource savings. To address this limitation, it is necessary to formulate an integer-valued DEA model. In DEA, it is feasible to incorporate integer-valued inputs and outputs.

The pioneering integer DEA model was introduced by Lozano and Villa in 2006, considered under the assumption of Constant Returns to Scale (CRS) model (Lozano & Villa, 2006). Later, in 2007, they expanded this model to include the assumption of Variable Returns to Scale (VRS). Consequently, Kuosmanen and Matin (2009) further enhanced the model to accommodate both integer and non-integer values, distinguishing between inputs and outputs by categorizing them into respective subsets. This model is known as the mixed integer DEA Model. Each input or output in the model is categorized as either entirely integer or entirely non-integer, but not both.

Based on Kazemi Matin and Kuosmanen's (2009) model, Du et al. (2012) developed the efficiency model of mixed integer-valued DEA to consider super efficiency status of the output-oriented model. However, the model suffered from the infeasibility issue under the assumption of VRS (Andersen & Petersen, 1993). They further extended their work to propose a two-stage approach of super efficiency additive in mixed integer valued DEA. The approach consists of two models which are (i) additive in mixed integer-valued DEA model to discriminate between efficient and inefficient DMUs and (ii) additive of super efficiency in mixed integer-valued DEA model to rank efficient DMUs of the additive mixed integer model. The two models dealt with non-integer and integer inputs and outputs simultaneously.

Du et al. (2012) proposed the use of inequality for integer input-output constraints because the convex combinations of efficient frontier constructed by efficient DMUs are not always integer values. Therefore, the reference set of integer factors are not necessarily equal to their projections point on the efficient frontier, but it must be controlled by their convex combinations of efficient frontier DMUs. Consequently, the additive mixed integer-valued DEA model of Du et al. (2012) can be formulated as follows:

$$\max \varphi = \frac{1}{R+S}\left(\sum_{r_{NI}\in I^{NI}} t^{-}_{r_{NI}O} + \sum_{r_{I}\in I^{I}} t^{-}_{r_{I}O} + \sum_{s_{NI}\in O^{NI}} t^{+}_{s_{NI}O} + \sum_{s_{I}\in O^{I}} t^{+}_{s_{I}O}\right) \tag{3.13}$$

s.t. $\quad r_{NI} \in I^{NI}$

$x_{r_{NI}O} = \sum_{k=1}^{K} x_{r_{NI}k}\,\lambda_k + t^{-}_{r_{NI}O}$,

$y_{s_{NI}O} = \sum_{k=1}^{K} x_{s_{NI}k}\,\lambda_k - t^{+}_{s_{NI}O}$, $\quad s_{NI} \in O^{NI}$

$x_{r_{I}O} \geq \sum_{k=1}^{K} x_{rk}\,\lambda_k + t^{-}_{r_{I}O}$, $\quad r_{I} \in I^{I}$

$y_{s_{I}O} \geq \sum_{k=1}^{K} y_{sk}\,\lambda_k - t^{+}_{s_{I}O}$, $\quad s_{I} \in O^{I}$

$\lambda_k \geq 0$, $\quad k = 1, \ldots, K,\ k \neq 0$

$x_{r_{NI}O}, y_{s_{NI}O} > 0,\ x_{r_{I}O}, y_{s_{I}O} \in Z^{+}$

$t^{-}_{r_{NI}O}, t^{+}_{s_{NI}O} \geq 0, t^{-}_{r_{I}O}, s^{+}_{r_{I}O} \in Z^{+},\ r_{NI} \in I^{NI}$,

$s_{NI} \in O^{NI}, r_{I} \in I^{I}, s_{I} \in O^{I}$

$x_{r_{NI}O}$, $y_{s_{NI}O}$ represent the positive values of non-integer input and output variables, respectively. $x_{r_I O} \in Z^+$, $y_{s_I O} \in Z^+$, represent the integer inputs and outputs, respectively, while $s^-_{i_{NI}O}, s^+_{r_{NI}O}$, are non-radial slacks which represent the non-integer input excesses and output shortfalls. $t^-_{r_I O}$ and $t^+_{s_I O}$, reflect the non-radial slacks of integer input excesses and output shortfalls respectively. In other word, the slacks $t^-_{r_{NI}O}, t^+_{s_{NI}O}, t^-_{r_I O}, t^+_{s_I O}$,reflect the absolute difference between the actual amount of non-integer and integer input-output variables and their reference points, respectively.

Recently, Arana-Jiménez et al. (2025) developed an enhanced mixed interval slacks-based DEA model that accounts for integer and non-integer inputs and outputs while incorporating uncertainty through interval modelling. A major contribution of their study is the formulation of a super-efficiency model capable of ranking all decision-making units (DMUs), thus identifying the top-performing units for benchmarking purposes. Additionally, Ghiyasi and Cook (2024) introduced a new DEA production technology framework that incorporates resource sharing among DMUs and allows for both integer and non-integer data. By employing a mixed-integer linear programming efficiency model, they enhanced computational performance and applied their method to evaluate 15 public hospitals in Mashhad, Iran. However, their model is based on a single DEA framework and does not account for the internal structure when dealing with mixed-integer variables. To address this limitation, a network model for mixed-integer DEA is introduced.

Omrani et al. (2023) measure the efficiency of bank branches using a mixed-integer three-stage network DEA that includes shared inputs and undesirable outputs. This model is designed to evaluate the efficiency of decision-making units while incorporating integer values for certain input variables. To pinpoint inefficiency sources within these branches, projection values are computed and policy recommendations are offered. Their model can be further expanded to a parallel structure with mixed integer values to enhance efficiency analysis.

3.6 Summary

This chapter has presented a comprehensive discussion of the fundamental DEA concepts underlying the proposed model formulation. It reviewed radial and non-radial DEA models and examined network DEA structures, with particular emphasis on the parallel NSBM model proposed by Kao (2020). The treatment of non-controllable factors and mixed-integer variables was also discussed in detail. However, existing studies have not sufficiently examined the combined effects of mixed-integer variables and non-controllable factors on efficiency measurement. To address this gap, Chapter Four introduces a methodology that integrates these elements into the parallel NSBM framework, thereby enhancing its applicability to real-world university performance evaluation. The next chapter outlines the overall research methodology, including problem definition, model development and performance testing of the proposed models.

CHAPTER FOUR
METHODOLOGY

This chapter presents and explains the methodology adopted to achieve the objectives of the study. The methodology is illustrated through the development of an enhanced parallel NSBM DEA model that incorporates mixed-integer values and non-controllable factors. The validity and performance of the developed model are subsequently examined to ensure proper formulation and implementation.

4.1 Research Design

This study develops an enhanced parallel NSBM DEA model that incorporates mixed-integer values and non-controllable factors to measure the effectiveness of faculties in a Malaysian public university. Universiti Teknologi MARA (UiTM) was selected as the case study for implementing the proposed model. Accordingly, a total of 26 faculties were included in the analysis and served as decision-making units (DMUs). The development of the enhanced parallel NSBM DEA model was aligned with the internal structure of faculties and based on relevant secondary data.

The data were obtained from UiTM's annual Key Performance Indicator (KPI) reports provided by the University's Transformation Division. Following data collection, all variables were identified and categorized according to their characteristics as either integer or non-integer values, as well as controllable or non-controllable factors. Based on this categorization, the mathematical formulation of the proposed DEA model was developed.

In this study, mixed-integer values and non-controllable factors are simultaneously incorporated into a parallel NSBM DEA model. As a result, an enhanced parallel NSBM DEA model is developed. The effectiveness scores are calculated using LINGO software (Version 18). Model validity is assessed through sensitivity analysis to ensure the robustness and stability of the results, while model performance is evaluated by comparing the outcomes of the proposed model with those obtained from existing DEA models.

4.2 The Essential Research Activities

This section outlines the seven essential research activities conducted in the study. The research begins with problem identification and data collection, followed by the categorization of outputs and outcomes as either integer or non-integer variables and as controllable or non-controllable factors. To capture the internal structure of faculties, existing NDEA models are reviewed and analysed. Based on this review, an enhanced parallel NSBM model incorporating mixed-integer values and non-controllable factors is proposed.

The developed model is then solved using the initial specification of variables. Subsequently, its validity is assessed through sensitivity analysis to identify the ideal DEA model. Using this ideal model, faculty effectiveness scores are recalculated. Finally, the consistency of the results obtained from the developed model is evaluated by comparing them with those derived from existing DEA models. All essential research activities are illustrated in Figure 4.1.

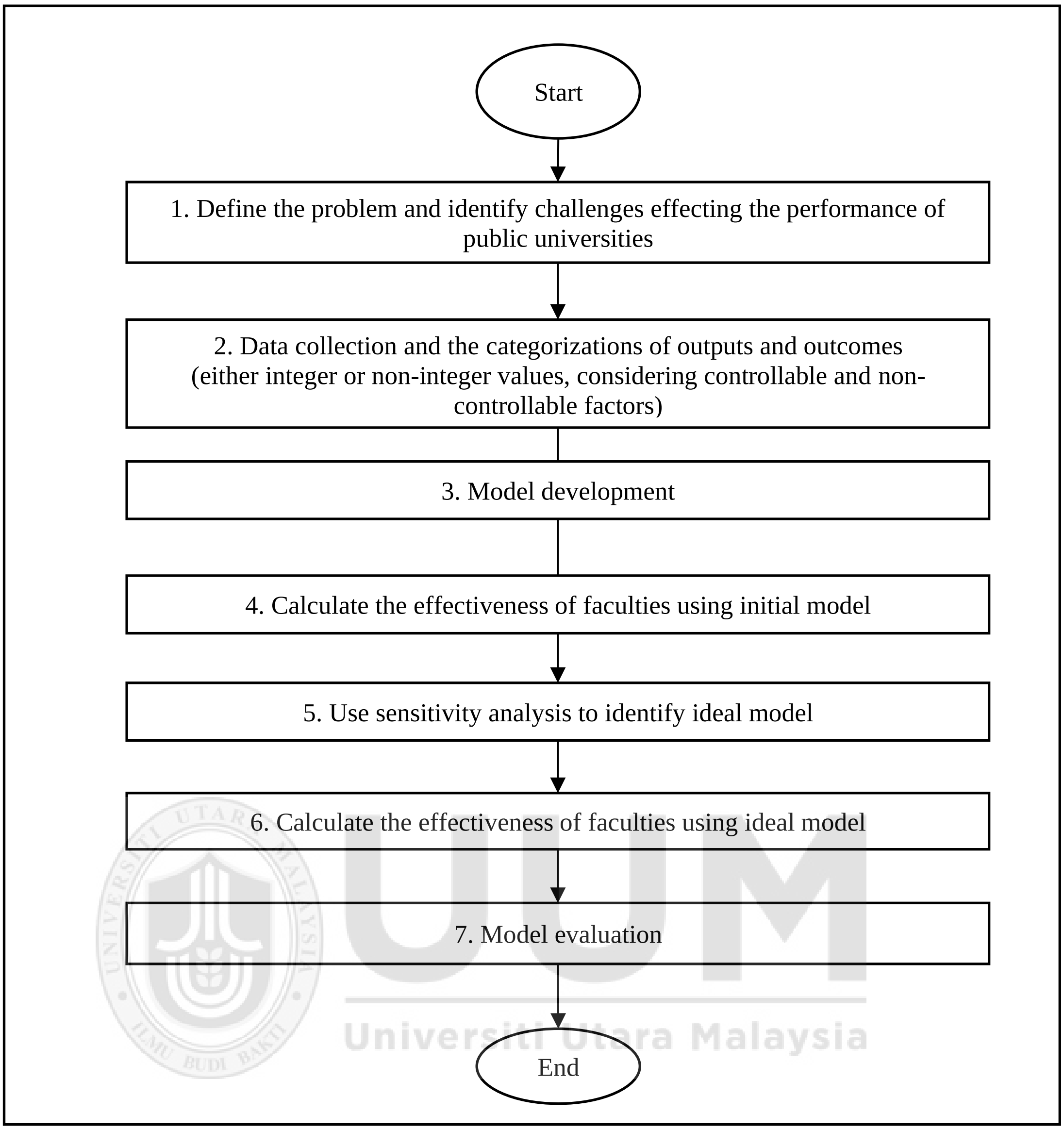
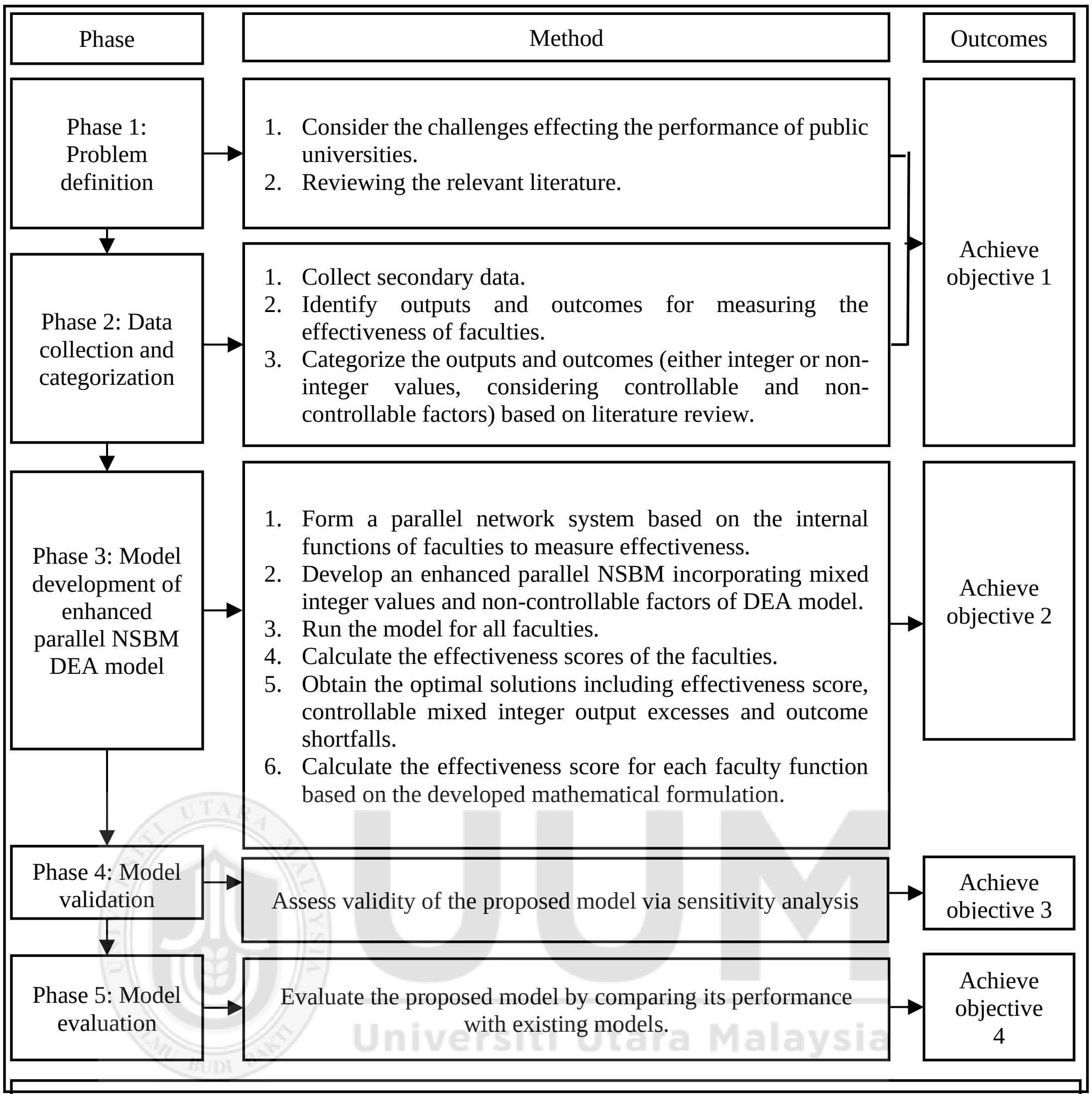


Figure 4.1. The Essential Research Activities



OBJECTIVES:
The main objective of this study is to develop an enhanced parallel NSBM DEA incorporates mixed integer values and non-controllable factors of DEA to measure the effectiveness of faculties in a public university and to decompose overall effectiveness into functional components. To achieve the main objectives, the following specific objectives are derived:

1. To identify suitable variables for measuring the effectiveness of faculties in a public university and to categorize them into integer and non-integer values, considering controllable and non-controllable factors.
2. To develop an enhanced parallel NSBM DEA model incorporating mixed integer values and non-controllable factors to measure the effectiveness of faculties in a public university and decompose overall effectiveness into functional components.
3. To validate the proposed model via sensitivity analysis.
4. To evaluate the proposed model by comparing its performance with existing models.

Figure 4.2. Main phases of the research to achieve the objectives of the study

These essential research activities are organized into five phases aligned with the research objectives of this study. As illustrated in Figure 4.2, Phases 1 and 2 focus on problem definition, literature review, data collection and variable categorization, addressing Research Objectives 1. Phase 3 involves the development of the enhanced parallel NSBM DEA model to fulfil Research Objective 2. In Phase 4, the proposed model is validated to achieve Research Objective 3. Finally, Phase 5 evaluates the performance of the developed model, thereby accomplishing Research Objective 4.

4.3 Research Framework

The research framework, illustrated in Figure 4.3, consists of three main phases: model development, validation and evaluation.

Phase 1 begins with a critical review of existing DEA models to identify their strengths and limitations, which subsequently inform the development of the proposed model. Initially, the parallel NDEA model introduced by Kao (2012) is examined. This model considers parallel internal functions and computes efficiency scores. This is followed by a review of the parallel NDEA model proposed by Kashim et al. (2017), which applies a parallel DEA framework to measure the effectiveness of DMUs. Another important model reviewed is the SBM model developed by Tone (2001), which measures DMU efficiency and distinguishes efficient from inefficient units by accounting for input excesses and output shortfalls. Subsequently, the parallel NSBM model proposed by Kao (2020) is analysed. However, these models assume that all inputs and outputs are non-integer and fully controllable by management.

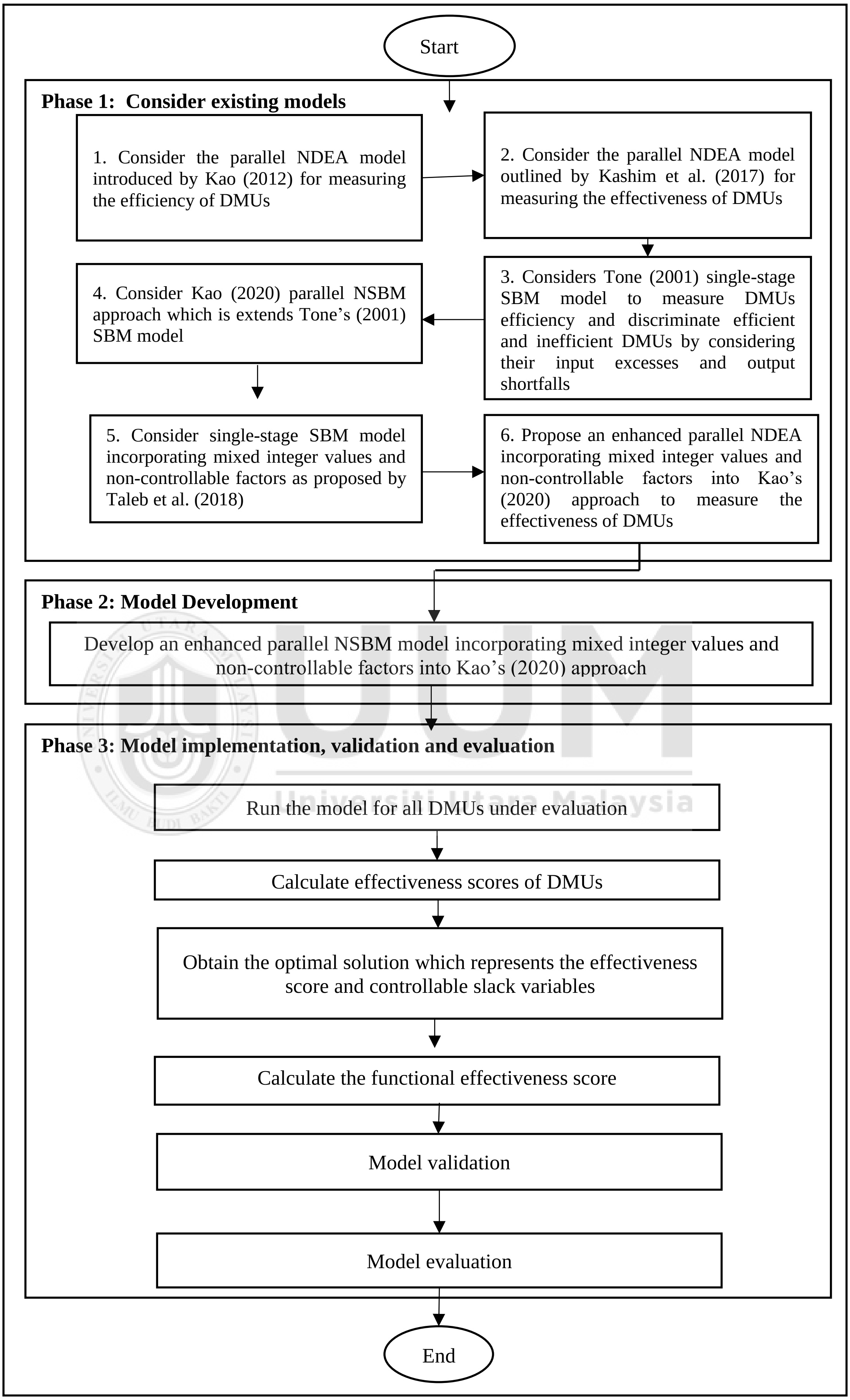


Figure 4.3. Research Framework

To address this limitation, the SBM model introduced by Taleb et al. (2018), which incorporates mixed-integer values and non-controllable factors, is also considered. Therefore, this study integrates mixed-integer values and non-controllable factors into Kao's (2020) framework to enhance effectiveness measurement of DMUs.

Phase 2 involves the development of the enhanced parallel NSBM DEA model, which is explained in detail in Section 4.6.3.

Phase 3 focuses on implementation, validation and evaluation. The process begins by running the proposed model for all DMUs under evaluation. In this study, the model is applied to a case study involving 26 faculties at Universiti Teknologi MARA (UiTM). The effectiveness scores of the faculties are then calculated based on the model formulation. Subsequently, the optimal solution is obtained, representing both the overall effectiveness score and the controllable slack variables. Functional effectiveness scores are also computed to measure the effectiveness of individual internal functions within each faculty. The model is then validated and assessed to identify the ideal DEA model. Once the ideal model is determined, the final effectiveness scores of the faculties are obtained. Finally, the performance of the developed model is evaluated by comparing its results with those generated using existing DEA models.

4.4 Problem Definition: Effectiveness of Public University in Malaysia

Public universities in Malaysia have experienced substantial growth; however, they continue to face performance challenges related to enrolment, graduate employability, research funding, research output and income generation, as discussed in Chapter One. In response, the Ministry of Higher Education's aspiration is to introduce a new performance measurement system under the Malaysia Education Blueprint (Higher Education) 2015–2025, emphasizing outcomes-based performance measurement rather than merely inputs and processes. Accordingly, this study examines the current effectiveness level of public universities in Malaysia so that necessary measures can be taken to enhance their performance.

These challenges are further complicated by the presence of multiple outputs, mixed-integer-valued data and non-controllable factors. Therefore, incorporating these elements into effectiveness measurement is essential to ensure greater accuracy. Moreover, universities operate through multiple internal functions, making it necessary to evaluate the internal components within each function. To achieve accurate effectiveness measurement, this study incorporates these requirements into the parallel NSBM model proposed by Kao (2020).

The main objective of this study is to develop an enhanced parallel NSBM DEA model that incorporates mixed-integer variables and non-controllable factors to measure faculty effectiveness while accounting for internal functions. The proposed approach builds upon the parallel NSBM DEA model of Kao (2020), the parallel DEA model by Kashim et al. (2017) and the SBM model incorporating mixed-integer values and non-controllable factors introduced by Taleb et al. (2018).

4.5 Data Source and Collection

As mentioned in Section 4.1, Universiti Teknologi MARA (UiTM) was selected as the case study. The development of the enhanced parallel NDEA model is therefore based on UiTM's organizational structure and relevant secondary data. Faculties within UiTM are identified as the DMUs for model development and validation. To ensure data consistency and homogeneity, only data from the year 2020 are used, as UiTM underwent faculty restructuring in 2021. A total of 26 faculties involved in this study are listed in Table 4.1.

Table 4.1

List of Faculties in UiTM

Programmes	**Faculties**
Academic Centre	1. Academy of Languages Studies
	2. Academy of Contemporary Islamic Studies
Science and Technology	1. Applied Sciences
	2. Architecture, Planning and Surveying
	3. Electrical Engineering
	4. Civil Engineering
	5. Mechanical Engineering
	6. Chemical Engineering
	7. Health Science
	8. Dentistry
	9. Medicine
	10. Pharmacy
	11. Plantation and Agrotechnology
	12. Computer and Mathematical Science
	13. Sports Science and Recreation
Social Science and Humanities	1. Administrative Science and Policy Studies
	2. Education
	3. Art and Design
	4. Music
	5. Communication and Media Studies
	6. Law
	7. Theatre and Animation
Business and Management	1. Accountancy
	2. Business Management
	3. Hotel and Tourism
	4. Information Management

The data were obtained from UiTM's annual KPI reports provided by the University's Transformation Division. The dataset includes mixed-integer values and non-controllable factors and the complete dataset is presented in Section 5.1.

4.6 Development of an Enhanced Parallel Network Slack-Based Measure

This study proposes an enhanced parallel NSBM DEA model that incorporates mixed-integer values and non-controllable factors to measure the effectiveness of faculties in a public university. This section outlines the selection of output and outcome variables, the conceptual structure of the model and the mathematical formulation of the developed model. The UiTM case study, involving 26 faculties, is used to demonstrate the application of the proposed model.

4.6.1 Selection of Variables in Measuring Effectiveness

The first objective of this study is to identify suitable variables for measuring the effectiveness of faculties in a Malaysian public university. The identification of appropriate variables is a critical component of DEA applications, as the selected variables must accurately represent the performance dimensions being evaluated (Abdelfattah, 2022). Accordingly, variable selection in this study is guided by previous DEA studies on universities (see Chapter 2) and by established higher education performance frameworks such as SETARA, MyRA and the QS World University Rankings. These frameworks emphasize indicators such as research grants, citations, graduate numbers, employability and university social responsibility (USR).

In addition, the variable selection is aligned with UiTM's Key Performance Indicators (KPIs). In the public sector, KPIs are measures used to assess how effectively an organization performs its functions. These KPIs are aligned with organizational goals and enable management to evaluate overall organizational performance effectively (Seitz et al., 2014). The final selection of variables is also constrained by the availability of complete and reliable data across all faculties.

Effectiveness is defined as the extent to which an organization achieves its intended outcomes in relation to its mission. These missions correspond to the organization's core functions. Accordingly, public university effectiveness is measured based on the three core functions of a university: teaching, research and community service. In this study, faculty effectiveness is defined as the relationship between outputs and outcomes, expressed as:

$$Effectiveness = \frac{Outcome}{Output} \tag{4.1}$$

In HEIs, outcomes are primarily concerned with assessing the quality and impact of institutional processes and results (Hermanu et al., 2024). These outcomes should reflect broader economic, social and cultural contributions to society, extending beyond academic outputs alone (Hermanu et al., 2022).

Therefore, in this study, the effectiveness of a public university is defined as the extent to which its core functions transform outputs into outcomes that demonstrate quality and impactful contributions. At the faculty level, outputs represent intermediate results generated through functional activities, while outcomes reflect final achievements related to quality, impact and mission fulfillment.

To measure the effectiveness of the teaching function, graduate employability is used as the outcome. Traditionally, the number of graduates produced served as the primary output of teaching performance (Lee & Johnes, 2022). However, a more meaningful measure is the extent to which graduates possess the desired qualities and values. Therefore, graduate employment rates are often used to measure the quality of university provision, as multiple studies have confirmed a significant positive relationship between teaching quality and graduate employability (Nuwabimpa, Kamukama, & Twinamatsiko, 2024; Wang et al., 2024; Qin, 2023). Improving graduate employability has a significant positive impact on society, benefiting graduates, educators, employers and the global economy as a whole (Underdahl et al., 2023). In this study, the number of graduates from undergraduate programs is treated as the immediate output of the teaching function, while the employability rate serves as the outcome.

To achieve the second research objective, this study categorizes outputs and outcomes into controllable and non-controllable factors. This categorization addresses the challenges faced by universities, as discussed in Chapter One. Through this categorization, the study aims to enhance the accuracy of public university effectiveness measurement, particularly in situations where management does not have full control over certain factors. The number of graduates from undergraduate programs and the employability rate are regarded as non-controllable outcomes because they are influenced by factors beyond university management's control.

The effectiveness of the research function is measured using research grants as the primary output and research citations as the outcome. Research grants provide essential financial resources for equipment, materials and personnel and are fundamental to the production of impactful research (Chandrasekaran, 2023). Citations, on the other hand, are widely recognized as indicators of research quality and broader scholarly and societal influence (Dougherty & Horne, 2022; Lindgreen et al., 2021; Thelwall et al., 2023). Accordingly, this study uses the amount of research grants as the output and the number of citations of indexed publications as the outcome for measuring research effectiveness.

Research grants are categorized as non-controllable outputs because they depend heavily on external funding sources such as government agencies, national and international foundations and industry partners (Laudel, 2006), rather than on direct university control. Securing research grants has been shown to enhance a scholar's research output and overall impact (Ding & Bu, 2025). Additionally, the number of citations of indexed publications is treated as a non-controllable outcome because it depends on recognition and usage by the wider academic community.

In addition to teaching and research, public universities play a critical role in community service. The effectiveness of this function can be measured by examining the extent to which university activities generate programs that produce meaningful quality and societal impact. However, measuring community service effectiveness remains challenging, as its impacts are often intangible and involve changes experienced by individuals and communities (Owen & Wright, 2025).

Knowledge Transfer (KT) programs are widely recognized as key indicators of a university's societal contribution, as they demonstrate how institutional expertise and resources are mobilized to address community needs and generate public value (Compagnucci & Spigarelli, 2020). Knowledge transfer involves the dissemination and practical application of university-generated knowledge within communities, contributing to organizational learning, regional development and social innovation

(Taufiq et al., 2021). Effective knowledge management and sharing through KT programs have been shown to contribute to higher-quality learning outcomes and the development of high-quality graduates (Ateeq, 2023).

Additionally, university social responsibility (USR) represents a critical indicator of services provided by public universities, encompassing ethical responsibility, social engagement and sustainable development outcomes (Salcedo & Núñez, 2023). USR enhances the quality of higher education by embedding social responsibility principles into teaching, research and administrative practices, thereby strengthening universities' relevance and accountability to society (Santos et al., 2020).

Through KT and USR programs, universities actively engage with society by delivering high-quality community services that promote social well-being, strengthen community capacity and support sustainable development. Therefore, in this study, KT and USR programs are employed as measurable indicators of community service effectiveness. Indicators serve as practical instruments for capturing complex phenomena when direct measurement is difficult due to constraints such as complexity, cost, or time (Meyer, 2024).

The amount of external funding received for KT and USR programs is treated as an intermediate result and a non-controllable output, as it depends primarily on external agencies, industry partners and government bodies rather than internal university control. The inclusion of this funding variable strengthens the analytical framework by accounting for the financial resources required to support impactful community service programs. The number of KT programmes and the amount of external funding received for KT and USR programmes are newly introduced variables in this analysis and constitute KPIs adopted by UiTM.

Finally, this study categorizes university outputs and outcomes into non-integer and integer-valued data, referred to as mixed-integer data. This approach facilitates more accurate performance measurement and ultimately contributes to improved decision-making within a university. Note that the data set consists of three non-integer output and outcomes which are amount of research grants, amount received (from external) for KT and USR programmes and employability rate. While the rest of the outputs and outcomes are considered as integer values. Tables 4.2 and 4.3 present the output and outcome variables used to measure faculty effectiveness, together with their definitions and respective categorizations.

Table 4.2

List and Definition of Output Variables for Measuring Effectiveness

Output variables	**Definition**
Teaching Function	
1. Number of graduates from undergraduate program (Integer and Non-controllable Factor)	The number of undergraduate students (diploma and bachelor programmes) awarded certificates upon completing their studies
Research Function	
1. Amount of Research Grants (Non-integer and Non-controllable Factor)	Total amount of national, industry and international funded grants received by faculties (in RM)
Community Service Function	
1. Amount received (from external) for KT and USR programmes. (Non-integer and Non-controllable Factor) (New Variable)	Total amount received (from external) for KT and USR programmes of faculties (in RM)

Table 4.3

List and Definition of Outcome Variables for Measuring Effectiveness

Outcome	**Definition**
Teaching Function	
1. Employability rate (Non-integer and Non-controllable Factor)	Percentage of graduates being employed, self-employed or further study by convocation year (undergraduate students)
Research Function	
1. Number of citations of indexed publications (Integer and Non-controllable Factor)	Total citation of indexed publications (SCOPUS/WoS) within 5 years cumulative
Community Service Function	
1. Number of KT programmes (Integer and Controllable Factor) (New Variable)	Number of KT programmes to benefit external community or industry
2. Number of USR programmes (Integer and Controllable Factor)	Number of USR programmes to benefit external community or industry

4.6.2 Formation of Structure for Effectiveness Measurement: Enhanced Parallel Structure

After identifying the output and outcome variables, a network structure linking the functions within the system must first be established to develop the performance measurement model. This structure serves as a conceptual framework that accurately reflects the actual operating conditions of the production system. The outcomes generated by university faculties are associated with the three core university functions which are teaching, research and community service. Each faculty allocates its resources differently across these functions. Consequently, the overall effectiveness of a faculty is the aggregate effectiveness of teaching, research and community service. From this perspective, each faculty can be modelled as a parallel production system comprising three functions, as illustrated in Figure 4.4. The selection of outputs and outcomes used to measure effectiveness is discussed in detail in Section 4.6.1.

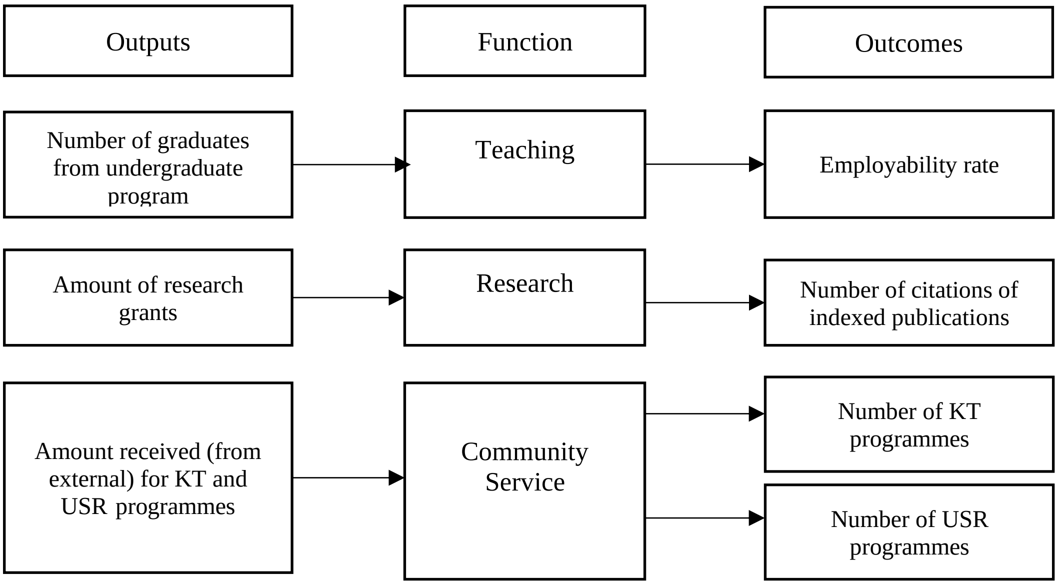


Figure 4.4. A parallel structure to measure effectiveness of a public university

4.6.3 Development of the Enhanced Parallel NSBM Model

This section addresses the second objective of the study. Section 3.3 reviewed in detail the parallel NSBM approach proposed by Kao (2020). Building on this model, the present study proposes a more accurate method for measuring the effectiveness of a public university, in which some outputs and/or outcomes are required to take integer values and are beyond the control of DMU management. By incorporating mixed-integer outputs and non-controllable output and outcome factors, this section extends the existing approach and enhances its applicability to real-world settings.

1. Enhanced Parallel Structure

Before formulating the enhanced parallel NSBM DEA model, the parallel structure must be defined to represent the actual operating conditions of the case study, which involves 26 faculties in UiTM and three university functions.

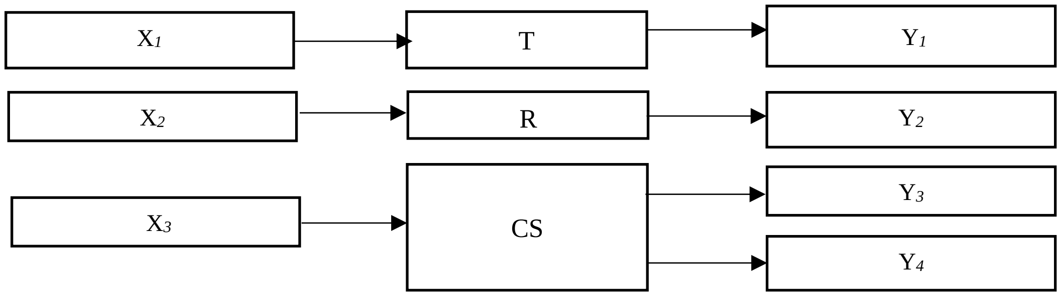


Figure 4.5. A parallel structure

The parallel production system operates simultaneously and independently with *p* functions (three functions), as illustrated in Figure 4.5. The three functions are teaching (T), research (R) and community service (CS). Each function q produces its corresponding outcomes $Y_s^{(q)}$, where $s = s^{(q-1)} + 1, \ldots, S^{(q)}$, using specific resources (outputs), $X_r^{(q)}$, where $r = r^{(q-1)} + 1, \ldots, R^{(q)}$.

Accordingly, effectiveness measurement in this study refers to the university's performance in fulfilling its functions, namely: (i) producing high-quality graduates who meet labour market demands; (ii) generating high-quality research; and (iii) delivering quality and impactful services to society through community engagement programmes. Table 4.4 summarizes the outputs and outcomes used to measure the effectiveness of 26 faculties in UiTM.

Table 4.4

List of Outputs and Outcomes Variables to Measure Effectiveness

Output	**Outcome**
Teaching Function	
1. Number of graduates from undergraduate program (X_1) (Integer and non-controllable factor)	2. Employability rate (Y_1) (Non-integer and non-controllable factor)

Table 4.4 continued

Output	Outcome
Research Function	
1. Amount of research grants (X_2) (Non-integer and non-controllable Factor)	2. Number of citations of indexed publications (Y_2) (Integer and non-controllable factor)
Community Service Function	
1. Amount received (from external) for KT and USR programmes (New variable) (X_3) (Non-integer and non-controllable factor)	1. Number of KT programmes (New variable) (Y_3) (Integer and controllable factor)
	2. Number of USR programmes (Y_4) (Integer and controllable factor)

As illustrated in Figure 4.5, four outcomes are considered: Y_1 represents the outcome of the teaching function, Y_2 represent to the outcome of the research function, while Y_3 and Y_4 represent the outcomes of the community service function. In terms of resources (outputs), X_1 is associated with teaching function, X_2 with research function and X_3 with community service function. All variables are identified and categorized according to their characteristics as either integer or non-integer values, as well as controllable or non-controllable factors.

Prior to formulating the mathematical structure of the proposed model, it is essential to define the symbols used to facilitate clearer interpretation. The symbols and their definitions are presented in Table 4.5.

Table 4.5

Notation Definition

Symbol	Definition
o	A subscript indicating a factor which represent the DMU under evaluation
$k = 1, \ldots, K$	Set of DMUs
$q = 1, \ldots, p$	Set of functions
C	Controllable factor
NC	Non-controllable factor
$r_1^{NC} = 1, \ldots, R_1^{NC(q)}$	Set of non-controllable non-integer output variables for the qth function
$r_2^{NC} = 1, \ldots, R_2^{NC(q)}$	Set of non-controllable integer output variables for the qth function
$s_2^{C} = 1, \ldots, S_2^{C(q)}$	Set of controllable integer outcome variables for the qth function
$s_1^{NC} = 1, \ldots, S_1^{NC(q)}$	Set of non-controllable non-integer outcome variables for the qth function
$s_2^{NC} = 1, \ldots, S_2^{NC(q)}$	Set of non-controllable integer outcome variables for the qth function
R_1	Number of non-integer output variables
R_2	Number of integer output variables
S_1	Number of non-integer outcome variables
S_2	Number of integer outcome variables
$x_{{r_1}^{NC}k}^{(q)}$	Non-negative amount of the rth non-controllable non-integer output for the qth function of kth DMU
$x_{{r_2}^{NC}k}^{(q)}$	Non-negative amount of the rth non-controllable integer outcome for the qth function of kth DMU
$y_{{s_2}^{C}k}^{(q)}$	Non-negative amount of the sth controllable integer outcome for the qth function of kth DMU
$y_{{s_1}^{NC}k}^{(q)}$	Non-negative amount of the sth non-controllable non-integer outcome for the qth function of kth DMU
$y_{{s_2}^{NC}k}^{(q)}$	Non-negative amount of the sth non-controllable integer outcome for the qth function of kth DMU
$\lambda_{\mathrm{k}}^{(q)}$	Positive vector denoting optimal set of weights for effective DMUs for the qth function of kth DMU
$t_{{s_2}^{C}\mathrm{o}}^{(q)+}$	Outcome shortfall of the sth controllable integer outcome variable for the qth function
E_o^{pNSBM}	Effectiveness score for the kth DMU
$E_o^{pNSBM^{(q)}}$	Effectiveness score for the kth DMU for the qth function

2. Development of the Enhanced Parallel NSBM Model: A Case of Mixed Integer Values and Non-controllable Factors

Figure 4.6 illustrates the three main phases involved in developing the enhanced parallel NSBM DEA model.

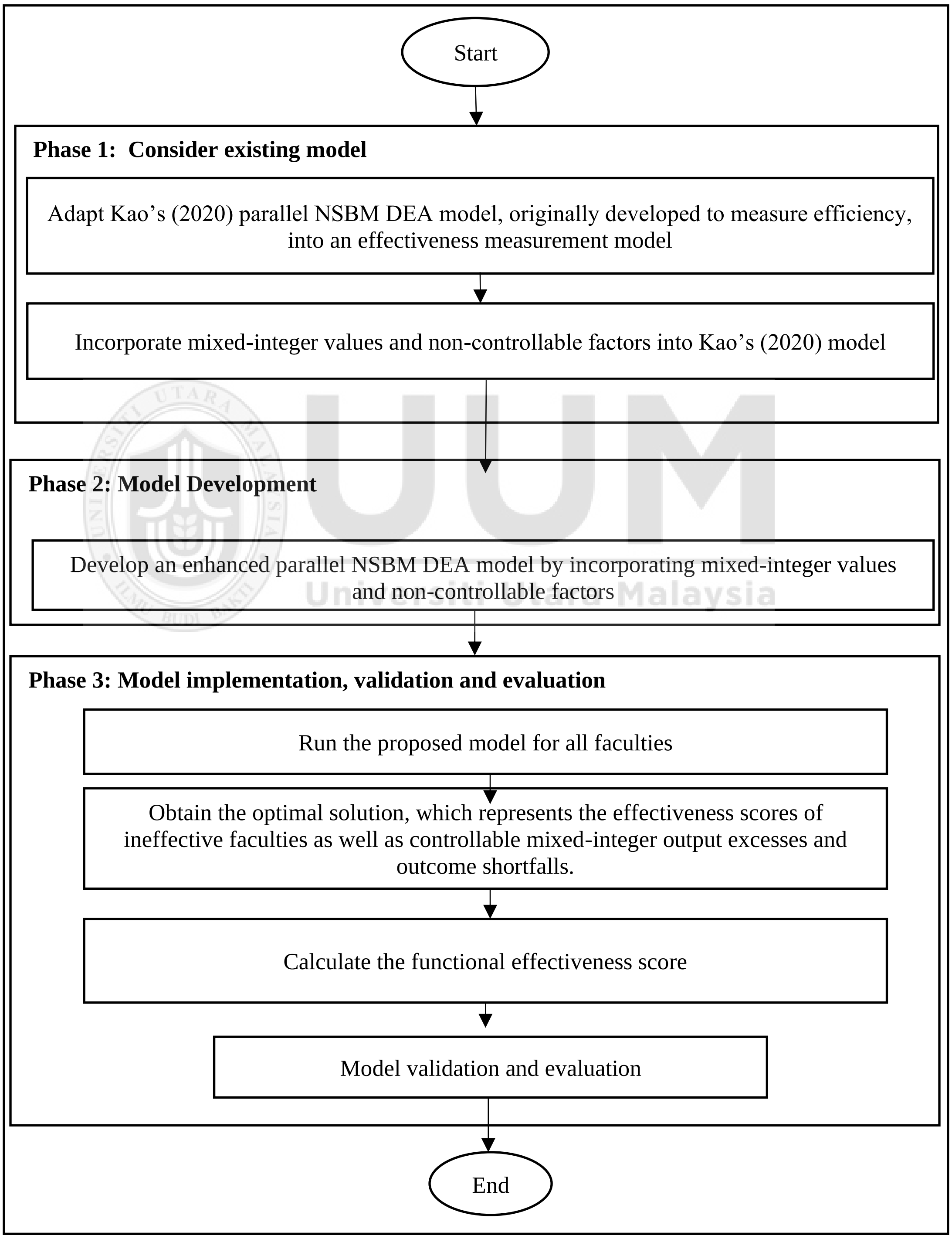


Figure 4.6. The enhanced parallel NSBM Model

Phase 1 involves enhancing the existing parallel NSBM model proposed by Kao (2020) for effectiveness measurement model. This phase incorporates mixed-integer values and non-controllable factors into the original framework.

Phase 2 focuses on integrating mixed-integer data and non-controllable factors into Kao's parallel NSBM model to develop the enhanced parallel NSBM model.

Phase 3 involves the implementation, validation and evaluation of the proposed enhanced parallel NSBM model. This phase includes: (i) running the model for all DMUs under evaluation; (ii) obtaining the optimal solution representing the effectiveness scores and the controllable mixed-integer output excesses and outcome shortfalls; (iii) calculating the effectiveness score for each function within the parallel structure based on the formulated mathematical expressions; and (iv) validating and evaluating the model, as discussed in Sections 4.6.4 and 4.6.5. The mathematical formulation of the objective function and constraints of the proposed enhanced parallel NSBM DEA model is presented in the following subsections.

4.6.3.1 Constraints

In DEA modelling, controllable constraints refer to variables whose levels can be directly influenced by DMU management. These variables are considered controllable because management has the authority to adjust their levels. Therefore, the constraints for controllable output excess and outcome shortfall are formulated by adding the controllable output excess to its reference set, while the constraints for controllable outcome shortfall are formulated by subtracting the controllable outcome shortfall from its reference set.

In contrast, non-controllable variables represent external or environmental factors that lie beyond the DMU's control. A decrease in non-controllable input values or an increase in non-controllable output values is not permitted, since these variables are assumed to be beyond the DMU's control, as suggested by Camanho et al. (2009). Accordingly, the appropriate mathematical treatment of non-controllable output and outcome variables requires preventing any increase or decrease in their values. Therefore, slack variables associated with output excesses and outcome shortfalls are removed from the relevant constraints, as they have no meaningful effect on DMU management.

This study considers the factors and elements of faculties as either fully controllable mixed integer values or fully non-controllable mixed integer values. Consequently, the mixed integer outputs and outcomes in the presence of controllable and non-controllable factors are formulated into eight (8) forms of constraints to obtain their general forms. However, only five (5) forms of constraints out of the total eight constraints are run to evaluate the effectiveness of faculties because the elements of controllable non-integer outputs and outcomes and controllable non-integer outcomes are not available in the data set.

Accordingly, two output constraints are formulated to represent non-controllable outputs whose values must remain fixed. For these non-controllable outputs, slack variables are removed from the corresponding constraints. Thus, the appropriate mathematical treatment for non-controllable mixed-integer output constraints removes outcome shortfall from Equations (4.2) and (4.3), respectively.

First, the non-controllable integer output constraint is defined as:

$$\sum_{k=1}^{K} \lambda_k^{(q)} x_{r_1{}^{NC}k}^{(q)} = x_{r_1{}^{NC}O}^{(q)}, \qquad r_1^{NC} = R_1^{NC^{(q-1)}} + 1, \ldots, R_1^{NC^{(q)}} \tag{4.2}$$

where,

$x_{r_1{}^{NC}O}^{(q)}$ denotes the current level of the number of graduates from undergraduate program for the qth function of the faculty under evaluation. Since this variable is non-controllable, the slack of the non-controllable integer output excess of number of graduates from undergraduate program is removed from the constraint.

and

$\sum_{k=1}^{K} \lambda_k^{(q)} x_{r_1{}^{NC}k}^{(q)}$ represents the reference set of the number of graduates from undergraduate program for the K faculties of the qth function under evaluation.

Second, the non-controllable non-integer output constraint is formulated as:

$$\sum_{k=1}^{K} \lambda_k^{(q)} x_{r_2{}^{NC}k}^{(q)} = x_{r_2{}^{NC}O}^{(q)}, \qquad r_2^{NC} = R_2^{NC^{(q-1)}} + 1, \ldots, R_2^{NC^{(q)}} \tag{4.3}$$

where,

$x_{r_2{}^{NC}O}^{(q)}$ denotes the current level of the amount of research grants and amount received (from external) for KT and USR programmes for the qth function of faculty under evaluation. Since this variable is non-controllable, the slack of the non-controllable non-integer output excess of amount of research grants and amount received (from external) for KT and USR programmes are removed from this constraint and

$\sum_{k=1}^{K}\lambda_k^{(q)}x_{r_2{}^{NC}{}_k}^{(q)}$ represents the reference set of the amount of research grants and amount received (from external) for KT and USR programmes for the K faculties of the qth function of DMU under evaluation.

On the other hand, the developed model includes three outcome constraints, formulated in Equations (4.4) - (4.6).

First, constraint (4.4) represents controllable integer outcomes which quantity are to be maximized. Therefore, constraint (4.4) is formulated to find the maximum increase in outcomes values for the DMU under evaluation from its reference set. The formula is as follows:

$$\sum_{k=1}^{K}\lambda_k^{(q)}y_{s_2{}^{C}{}_k}^{(q)} = y_{s_2{}^{C}{}_{\mathrm{o}}}^{(q)} + t_{s_2{}^{C}{}_{\mathrm{o}}}^{(q)+}, \qquad s_2^C = S_2^{C^{(q-1)}} + 1,\ldots,S_2^{C^{(q)}} \tag{4.4}$$

where,

$y_{s_2{}^{C}{}_{\mathrm{o}}}^{(q)} + t_{s_2{}^{C}{}_{\mathrm{o}}}^{(q)+}$ represents the projection point of number of KT and USR programmes to improve the performance of the ineffective qth function of faculties by determining the controllable integer outcome shortfalls of and number of KT and USR programmes, $t_{s_2{}^{C}{}_{\mathrm{o}}}^{(q)+}$

and

$\sum_{k=1}^{K}\lambda_k^{(q)}y_{s_2{}^{C}{}_k}^{(q)}$ represents the reference set of number of KT and USR programmes for the K faculties of the qth function under evaluation.

Second and third, constraints (4.5) and (4.6) are set of constraints to prevent an outcome augmentation in the non-controllable outcomes. The constraint compares the current level of the non-controllable outcome of a faculty under evaluation to other faculties whose reference set of the relevant non-controllable integer outcome are equal to the current level of the related outcome, i.e., the slacks of non-controllable non-integer and integer outcome shortfalls are removed from constraint (4.5) and (4.6). Therefore, the formulations are as follows:

Second:

$$\sum_{k=1}^{K} \lambda_k^{(q)} y_{{s_1}^{NC}k}^{(q)} = y_{{s_1}^{NC}\mathrm{O}}^{(q)}, \qquad s_1^{NC} = S_1^{NC(q-1)} + 1, \ldots, S_1^{NC(q)} \tag{4.5}$$

where,

$y_{{s_1}^{NC}O}^{(q)}$ is the current level of the employability rate for qth function of faculty under evaluation. The slack of the non-controllable non-integer outcome shortfalls of employability rate is removed from this constraint since its level is non-controllable,

and

$\sum_{k=1}^{K} \lambda_k^{(q)} y_{{s_1}^{NC}k}^{(q)}$ is the reference set of employability rate for the K faculties of qth function under evaluation.

Third:

$$\sum_{k=1}^{K} \lambda_k^{(q)} y_{{s_2}^{NC}k}^{(q)} = y_{{s_2}^{NC}O}^{(q)}, \qquad s_2^{NC} = S_2^{NC(q-1)} + 1, \ldots, S_2^{NC(q)} \tag{4.6}$$

where,

$y^{(q)}_{s_2{}^{NC}O}$ is the current level of the number of citations of indexed publications for qth function of faculty under evaluation. The slack of the non-controllable integer outcome shortfall of the number of citations of indexed publications is removed from this constraint since its level is non-controllable,

and

$\sum_{k=1}^{K} \lambda_k^{(q)} y^{(q)}_{s_2{}^{NC}k}$ is the reference set of the number of citations of indexed publications for the K faculties of qth function under evaluation.

Additionally, to reflect the integer values of certain variables, integer constraints are applied to the controllable outcome slack variables as below:

$$y^{(q)}_{s_2 o} \in \mathbb{Z}_+^{S^{(q)}_{C_2}}, t^{(q)+}_{s_2 o} \in \mathbb{Z}_+^{S^{(q)}_{C_2}}$$

where:

$y^{(q)}_{s_2 o}$ represent outcome variables of function qth,

$t^{(q)+}_{s_2 o}$ denote outcome slacks and

$\mathbb{Z}_+$ indicates that these variables are restricted to non-negative integer values.

4.6.3.2 Objective Function

The objective function differs from the standard parallel NSBM DEA model in terms of its objective function. The objective function is formulated to determine the effectiveness of a DMU under evaluation by computing the average of the controllable output reduction of the different functions to the average of outcome augmentation in controllable outcome of the different functions in a parallel structure. Thus, it should consider the controllable mixed integer output excesses and outcome shortfalls for faculties. It is important to note that non-controllable outputs and outcomes in mixed integer values are excluded in the objective function because these factors are beyond the control of the DMUs' management. The objective function of the model is presented in Equation (4.7).

$$E_o^{pNSBM} = \text{ min.} \frac{1}{1 + \frac{1}{S_2^{C^{(q)}}} \sum_{q=1}^{p} \left(\sum_{s_2^C = S_2^{C^{(q-1)}}+1}^{S_2^{C^{(q)}}} \frac{t_{s_2 c_o}^{(q)+}}{y_{s_2 c_o}^{(q)}} \right)} \tag{4.7}$$

4.6.3.3 Complete Model

Given that, $R_2^{NC^{(0)}} = 0$, $S_1^{NC^{(0)}} = 0$, the complete mathematical form of the proposed enhanced parallel NSBM DEA model is as given in (4.8).

$$E_o^{pNSBM} = \text{ min.} \frac{1}{1 + \frac{1}{S_2^{C^{(q)}}} \sum_{q=1}^{p} \left(\sum_{s_2^C = S_2^{C^{(q-1)}}+1}^{S_2^{C^{(q)}}} \frac{t_{s_2 c_o}^{(q)+}}{y_{s_2 c_o}^{(q)}} \right)} \tag{4.8}$$

subject to:

Teaching function constraints:

$\sum_{k=1}^{K} \lambda_k^{(q)} x_{{r_2}^{NC}k}^{(q)} = x_{{r_2}^{NC}O}^{(q)}$, $r_2^{NC} \in R_2^{NC^{(q)}}$, $r_2^{NC} = R_2^{NC^{(q-1)}} + 1, \ldots, R_2^{NC^{(q)}}$,

$\sum_{k=1}^{K} \lambda_k^{(q)} y_{{s_1}^{NC}k}^{(q)} = y_{{s_1}^{NC}O}^{(q)}$, $s_1^{NC} \in S_1^{NC^{(q)}}$, $s_1^{NC} = S_1^{NC^{(q-1)}} + 1, \ldots, S_1^{NC^{(q)}}$,

Research function constraints:

$\sum_{k=1}^{K} \lambda_k^{(q)} x_{{r_1}^{NC}k}^{(q)} = x_{{r_1}^{NC}O}^{(q)}$, $r_1^{NC} \in R_1^{NC^{(q)}}$, $r_1^{NC} = R_1^{NC^{(q-1)}} + 1, \ldots, R_1^{NC^{(q)}}$,

$\sum_{k=1}^{K} \lambda_k^{(q)} y_{s_2{}^{NC}{}_k}^{(q)} = y_{s_2{}^{NC}{}_O}^{(q)}$, $s_2^{NC} \in S_2^{NC^{(q)}}$, $s_2^{NC} = S_2^{NC^{(q-1)}} + 1, \ldots, S_2^{NC^{(q)}}$,

Community service function constraints:

$\sum_{k=1}^{K} \lambda_k^{(q)} x_{r_1{}^{NC}{}_k}^{(q)} = x_{r_1{}^{NC}{}_O}^{(q)}$, $r_1^{NC} \in R_1^{NC^{(q)}}$, $r_1^{NC} = R_1^{NC^{(q-1)}} + 1, \ldots, R_1^{NC^{(q)}}$,

$\sum_{k=1}^{K} \lambda_k^{(q)} y_{s_2{}^{C}{}_k}^{(q)} = y_{s_2{}^{C}{}_{\mathrm{o}}}^{(q)} + t_{s_2{}^{C}{}_{\mathrm{o}}}^{(q)+}$, $s_2^{C} \in S_2^{C^{(q)}}$, $s_2^{C} = S_2^{C^{(q-1)}} + 1, \ldots, S_2^{C^{(q)}}$,

$\sum_{k=1}^{K} \lambda_k^{(q)} = 1$,

$\lambda_k^{(q)} \geq 0, \ k = 1, \ldots, K, q = 1, \ldots, p$

$y_{s_2{}^{C}{}_{\mathrm{o}}}^{(q)} \in Z_+^{S_2^{C\,(q)}}, \ \ t_{s_2{}^{C}{}_{\mathrm{o}}}^{(q)+} \in Z_+^{S_2^{C\,(q)}}$

The above model assumes variable return to scale (VRS) for production. Nevertheless, if we omit the last constraint $\sum_{k=1}^{K} \lambda_k^{(q)} = 1$, we could handle the constant return to scale (CRS) assumption as well.

However, the model is a fractional program. It should be transformed into a linear programming form to obtain results as shown in Appendix C.

1. Functional score

The enhanced parallel NSBM DEA model is applied to obtain the optimal solution, which yields the effectiveness score as well as the controllable integer outcome shortfalls. Upon solving the model, the optimal values of $t_{s_2{}^{C}{}_{\mathrm{o}}}^{(q)+}$ is obtained. The effectiveness score for faculties derived from Model (4.8) can then be decomposed into the effectiveness of three individual functions, denoted as $E_o^{(q)}$. The calculations for the individual functions within the enhanced parallel DEA model are performed using Microsoft Excel. The effectiveness score for each function is calculated based on the corresponding mathematical formulations in (4.9) as follows:

$$E_o^{(q)} = \frac{1}{1 - \frac{1}{S_2^{C(q)}} \sum_{q=1}^{p} \left(\sum_{s_2^C = S_2^{C(q-1)}+1}^{S_2^{C(q)}} \frac{t_{s_2 c_o}^{(q)+}}{y_{s_2 c_o}^{(q)}} \right)} \tag{4.9}$$

4.6.4 Model Validation of the Proposed Model

To fulfill the third objective of this study, a sensitivity analysis is employed to validate the proposed DEA model. Since DEA is a non-parametric approach, its mathematical formulation does not permit the use of conventional statistical tests to analyze the obtained efficiency scores across different reduced DEA models (Johnes, 2006b; Johnes & Li, 2008). Consequently, sensitivity analysis is widely recommended to examine the robustness of DEA results (Nigam et al., 2012; Tyagi et al., 2009) by comparing results from different reduced DEA models. Previous studies suggest using sensitivity analysis to assess the robustness of DEA results to changes in model specification and variable selection. These studies advocate subjecting a DEA model to a variety of alternative variable sets and specifications to ensure stability (Hussain, 2017; Parkin & Hollingsworth, 1997). The main objective of this procedure is to test whether the formulated DEA model is sensitive to different combinations of input and output variables (Nigam et al., 2012; Rashidi et al., 2015) and to avoid misleading efficiency scores (Hussain, 2017).

Several approaches can be used to develop reduced DEA models. One common approach involves omitting selected inputs or outputs from the full model to examine their influence on efficiency scores (Johnes, 2006b; Johnes & Li, 2008). Alternatively, reduced models may be developed by replacing certain variables with relevant alternative variables to assess the sensitivity of the results to different variable specifications (Nguyen, Thenet, & Nguyen, 2015).

The effectiveness scores obtained from alternative models are then compared with those from the initial DEA model by examining the significance of their correlations. Models with high correlation coefficients are considered ideal DEA models, as they produce robust and stable efficiency scores (Hussain, 2017). The ideal DEA model represents the specification with the most appropriate combination of variables. Given the non-parametric nature of DEA, Spearman's rank correlation analysis is employed to examine the relationship between efficiency scores from the full model and those from the reduced models (Johnes, 2006a; Johnes & Li, 2008; Rashidi et al., 2015). Spearman's rank correlation coefficient is a non-parametric statistic that uses ranked data to determine the strength of association between two variables (Corder & Foreman, 2014; Schober et al., 2018; Wackerly et al., 2014). A highly correlated model indicates a more stable and robust DEA specification.

In this study, sensitivity analysis is conducted by replacing one output or outcome variable at a time, thereby generating alternative DEA models. Each relevant output or outcome variable is individually substituted within the enhanced parallel NSBM model to produce an alternative effectiveness model and a new set of effectiveness scores. Accordingly, the sensitivity analysis procedure consists of the following steps:

i) Retrieve the effectiveness scores of all DMUs obtained from the initial DEA model using the original set of output and outcome variables.
ii) Replace one output or outcome variable at a time to create different alternative DEA models with different variable combinations.
iii) Recalculate the effectiveness scores for all DMUs under each alternative model.

iv) Restore the replaced variable and repeat the process by substituting another output or outcome variable.

v) Repeat Steps (ii)–(iv) until all alternative variable combinations have been generated.

vi) Compute Spearman's rank correlation coefficients between the effectiveness scores from the initial model and each alternative model.

vii) Identify the variable combination that yields the highest correlation with the initial model. This represents the Ideal DEA model, indicating robust and stable results and confirming the validity of the proposed approach.

4.6.5 Model Evaluation of the Proposed Model

The evaluation of the proposed model is carried out to fulfill the fourth objective of this study. This evaluation aims to examine whether the developed enhanced model produces appropriate results and performs consistently compared with existing DEA models. For this purpose, the standard parallel NSBM DEA model developed by Kao (2020) is employed for comparative analysis, as the proposed model represents an enhanced version of this approach. Accordingly, the overall and functional effectiveness scores obtained from Kao's (2020) model are compared with the corresponding scores generated by the proposed enhanced NSBM model. The purpose of this comparison is to validate the impact of incorporating mixed-integer data and non-controllable factors into the standard NSBM framework, which assumes that all variables are controllable and non-integer.

To examine the association between effectiveness scores obtained from the two approaches and to validate the impact of mixed-integer data and non-controllable factors on effectiveness measures, the Mann–Whitney U test is applied (Simpson, 2007; Taleb, 2023). The Mann–Whitney U test is a non-parametric statistical test that allows two independent groups to be compared without assuming normal distribution of the data (Bluman, 2014). It is used to measure differences in both overall effectiveness scores and functional effectiveness scores derived from the two models.

The model evaluation is conducted through the following steps:

i) The effectiveness scores for each DMU are obtained using the proposed enhanced parallel NSBM model.

ii) Effectiveness scores for each DMU are calculated using the standard parallel NSBM DEA model proposed by Kao (2020).

iii) The Mann–Whitney U test is applied to measure differences in both overall effectiveness scores and functional effectiveness scores derived from the two models.

iv) Based on this analysis, the following hypotheses are tested:
a) H_0 (Null hypothesis): There is no significant difference between the effectiveness scores obtained from the proposed model and those from the standard model.
b) H_1 (Alternative hypothesis): There is a significant difference between the effectiveness scores obtained from the proposed model and those from the standard model.
Rejection of the null hypothesis (H_0) indicates that the enhanced model yields statistically different performance results, thereby demonstrating the effectiveness of the proposed approach.

All validation and evaluation results of the developed model are presented and discussed in detail in Chapter Five.

4.7 Summary

The proposed methodology addresses key challenges faced by Malaysian public universities, including number of graduates, graduate employability, research funding, and research output. These challenges involve variables that may be either integer or non-integer and may be categorized as controllable or non-controllable factors. Furthermore, this study proposes a Data Envelopment Analysis approach that accounts for the internal functions of public universities. To address these challenges and complexities, an enhanced parallel Network DEA (NDEA) model was developed, incorporating mixed-integer values and non-controllable factors. The model was applied to a case study of 26 faculties at Universiti Teknologi MARA (UiTM), using secondary data from 2020. The dataset comprised three output variables and four outcome variables, categorized as integer and non-integer in the presence of controllable and non-controllable factors.

Validation of the proposed DEA model was conducted using sensitivity analysis to assess the robustness of the effectiveness results and to identify the ideal DEA model. In this process, effectiveness scores for each faculty were recalculated using various combinations of output and outcome variables, forming several alternative DEA models. Each alternative model was generated by replacing one output or outcome variable at a time to examine how such changes affected the effectiveness scores.

The consistency between the effectiveness scores derived from the initial model and those from each alternative model was examined using correlation analysis.

Spearman's rank correlation coefficient was applied to determine the strength of association between the two sets of scores. A high correlation coefficient indicated a more stable and reliable DEA model, which was then identified as the ideal model.

Furthermore, the model evaluation included a comparative analysis between the effectiveness scores obtained from the developed DEA model and those derived from existing approaches. Specifically, the standard parallel NSBM DEA model proposed by Kao (2020) was compared with the enhanced DEA model developed in this study. This comparison assessed the consistency of the proposed model relative to the standard DEA approach using the Mann–Whitney U test. Subsequently, all effectiveness measures, along with the detailed results of the sensitivity analysis and validation procedures, are presented and discussed in the following chapter.

CHAPTER FIVE
RESULTS AND DISCUSSIONS

This study developed an enhanced parallel NSBM DEA model incorporating mixed-integer values and non-controllable factors. The enhanced model was subsequently implemented and effectiveness measures for the faculties were calculated. These effectiveness measures were calculated for a case study of 26 faculties in UiTM using data for the year 2020. The empirical findings related to the implementation, validation and evaluation of the developed model are presented in this chapter.

5.1 Descriptive Statistics

Prior to computing the effectiveness measures using the developed DEA model, a statistical analysis was conducted to examine the characteristics of the outputs and outcomes, as summarized in Table 5.2. The complete dataset used in this study is presented in Table 5.1. Note that, the dataset consists of one integer valued output, namely number of graduates from undergraduate programmes, as well as several integer-valued outcomes, namely number of citations of indexed publications, number of KT programmes and number of USR programmes. In contrast, the remaining outputs and outcomes are considered as non-integer values. Therefore, the outputs and outcomes in this dataset can be considered as mixed integer-valued data.

Table 5.1

Dataset of Outputs and Outcomes for 26 Faculties in UiTM

Faculty	***Output***			***Outcome***			
	Graduates	**Grants**	**Amounts received for USR and KTP**	**Employability**	**Citations**	**KT programmes**	**USR programmes**
	$\mathbf{X}_1$	$\mathbf{X}_2$	$\mathbf{X}_3$	$\mathbf{Y}_1$	$\mathbf{Y}_4$	$\mathbf{Y}_3$	$\mathbf{Y}_4$
FC1	317	150000.00	58750.00	74.88	25	5	10
FC2	500	209500.00	5370.00	81.09	20	12	11
FC3	189	3239198.00	8100.00	98.77	116	5	10
FC4	621	110627.00	10000.00	74.54	18	5	10
FC5	189	2583915.21	5000.00	82.84	64	20	12
FC6	613	4283434.00	16000.00	82.25	168	5	11
FC7	335	1359000.00	10000.00	74.49	67	5	10
FC8	576	2229372.00	20000.00	74	61	10	17
FC9	533	390000.00	5000.00	87.28	12	5	8
FC10	196	92000.00	5370.00	75.79	0	7	10
FC11	256	110000.00	35000.00	76.85	33	6	6
FC12	1757	1617754.70	87807.20	81.37	87	5	10
FC13	404	210000.00	6100.00	71.19	16	4	9
FC14	434	130000.00	16600.00	73.54	22	5	10
FC15	725	1093578.00	99800.00	85.09	81	13	20
FC16	46	590000.00	11000.00	93.33	58	5	5

Table 5.1 continued

Faculty	Output			Outcome			
	Graduates	Grants	Amounts received for USR and KTP	Employability	Citations	KT programmes	USR programmes
	X_1	X_2	X_3	Y_1	Y_2	Y_3	Y_4
FC17	683	343500.00	9994.00	82.52	41	4	4
FC18	865	4014957.97	7500.00	72.8	212	8	10
FC19	744	663000.00	399828.00	90.64	50	5	10
FC20	918	852573.70	10000.00	81.38	139	6	15
FC21	987	494750.00	2800.00	87.72	12	4	6
FC22	438	90000.00	83750.00	80.4	21	6	16
FC23	946	743000.00	45200.00	77.05	18	5	10
FC24	1920	889533.00	32000.00	78.73	68	6	7
FC25	356	333000.00	20000.00	94.6	13	5	10
FC26	162	3218268.00	0.00	84.91	189	6	4

It can be observed that the first output, the average number of graduates from undergraduate programmes (X_1), is 604.23, with a maximum value of 1,920 and a minimum value of 46. For the second output, the amount of research grants (X_2), the average value is RM1,155,421.60, with a maximum of RM4,283,434 and a minimum of RM90,000.00. The third output, namely the amount received (from external) for KT and USR programmes (X_3), has an average of RM38,883.43, with a maximum of RM399,828.00 and a minimum of RM0.00. It should be noted that all outputs in this study are treated as non-controllable.

Table 5.2

Descriptive Statistics of Outputs and Outcomes for 26 faculties in UiTM

Variables	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
Non-controllable integer output:				
Number of graduates from undergraduate program, X_1	604.23	447.24	46	1,920
Non-controllable non- integer outputs:				
Amount of research grants (RM), X_2	1,155,421.60	1,289,432.94	90,000	4,283,434
Amounts received (from external) for USR and KTP programmes (RM), X_3	38,883.43	78,767.33	0.00	399,828.00
Non-controllable non-integer outcome:				
Employability rate (%), Y_1	81.46	7.26	71.19	98.77
Non-controllable integer outcome:				
Number of citations of indexed publications, Y_2	61.96	58.26	0	212
Controllable integer outcomes:				
Number of KT programmes, Y_3	6.62	3.56	4	20
Number of USR programmes, Y_4	10.04	3.79	4	20

The outcome variables are categorized into non-controllable and controllable outcomes. Among the non-controllable outcomes, the employability rate (Y_1) has an average of 81.46%, with a minimum of 71.19% and a maximum of 98.77%. Additionally, the number of citations of indexed publications (Y_2) records an average of 61.96 citations, with a minimum of 0 and a maximum of 212 citations. Two controllable outcomes are also considered: the number of KT programmes (Y_3) and the number of USR programmes (Y_4). The number of KT programmes ranges from 4 to 20, with an average of 6.62 programmes, while the number of USR programmes ranges from 4 to 20, with an average of 10.04 programmes.

Significant variation is observed among the non-controllable outputs and outcomes, as these variables cannot be freely adjusted by the faculties. These include the number of graduates from undergraduate programmes (X_1), the amount of research grants (X_2), the amount received (from external) for KT and USR programmes (X_3), the employability rate (Y_1) and the number of citations of indexed publications (Y_2). Notably, one output and one outcome contain zero values, indicating that some faculties did not receive external funding for KT and USR programmes and recorded no citations of indexed publications in 2020. The presence of such zero values further suggests that these factors are beyond the direct control of university management.

5.2 Effectiveness Measures of the Enhanced parallel NSBM DEA Model: Initial Model

In this section, the proposed enhanced parallel NSBM model is applied to measure the effectiveness of the 26 faculties in UiTM. Initially, effectiveness scores of all faculties are computed using the initial specification of outputs and outcomes. The model calculates controllable mixed-integer outcome shortfalls and functional effectiveness scores for teaching, research and community service. The computation of functional effectiveness scores enables the identification of specific sources of ineffectiveness, representing a key advantage of NDEA models over conventional “black-box” DEA models. The effectiveness scores for the developed model are calculated under the VRS assumption, given that Malaysian public universities do not operate at an optimal scale (Salleh, 2012). To obtain the effectiveness scores of all the faculties, the detailed linear programming formulation (Equation 4.8) is solved. Figure 5.1 illustrates the developed enhanced parallel NSBM DEA model, with all parameter values represented in the model formulation.

$$E_o^{pNSBM} = \min \frac{1}{1+\frac{1}{2}\left(\sum_{s_2^C=1}^{2}\frac{t^{(3)+}_{s_2 c_o}}{y^{(3)}_{s_2 c_o}}\right)}$$

subject to,

Teaching function constraints:

$$\sum_{k=1}^{26}\lambda_k^{(1)} x^{(1)}_{r_2{}^{NC}k} = x^{(1)}_{r_2{}^{NC}O}, \qquad r_2^{NC} \in R_2^{NC^{(1)}}, r_2^{NC} = R_2^{NC^{(1-1)}} + 1,\ldots, R_2^{NC^{(1)}}$$

$$\sum_{k=1}^{26}\lambda_k^{(1)} y^{(1)}_{s_1{}^{NC}k} = y^{(1)}_{s_1{}^{NC}O}, \qquad s_1^{NC} \in S_1^{NC^{(1)}}, s_1^{NC} = S_1^{NC^{(1-1)}} + 1,\ldots, S_1^{NC^{(1)}}$$

Research function constraints:

$$\sum_{k=1}^{26}\lambda_k^{(2)} x^{(2)}_{r_1{}^{NC}k} = x^{(2)}_{r_1{}^{NC}O}, \qquad r_1^{NC} \in R_1^{NC^{(2)}}, r_1^{NC} = R_1^{NC^{(2-1)}} + 1,\ldots, R_1^{NC^{(2)}},$$

$$\sum_{k=1}^{26}\lambda_k^{(2)} y^{(2)}_{s_2{}^{NC}k} = y^{(2)}_{s_2{}^{NC}O}, \qquad s_2^{NC} \in S_2^{NC^{(2)}}, s_2^{NC} = S_2^{NC^{(2-1)}} + 1,\ldots, S_2^{NC^{(2)}},$$

Community service function constraints:

$$\sum_{k=1}^{26}\lambda_k^{(3)} x^{(3)}_{r_1{}^{NC}k} = x^{(3)}_{r_1{}^{NC}O}, \qquad r_1^{NC} \in R_1^{NC^{(3)}}, r_1^{NC} = R_1^{NC^{(3-1)}} + 1,\ldots, R_1^{NC^{(3)}},$$

$$\sum_{k=1}^{26}\lambda_k^{(3)} y^{(3)}_{s_2{}^{C}k} = y^{(3)}_{s_2{}^{C}o} + t^{(3)+}_{s_2{}^{C}o}, \quad s_2^{C} \in S_2^{C^{(3)}} \quad , s_2^{C} = S_2^{C^{(3-1)}} + 1,\ldots, S_2^{C^{(3)}},$$

$$\sum_{k=1}^{K}\lambda_k^{(q)} = 1,$$

$\lambda_k^{(q)} \geq 0,\ k = 1, \ldots, 26,\ q = 1,2,3$

$x_{r_1 c_o}^{(q)}, y_{s_1 c_o}^{(q)} \geq 0, \quad y_{s_2 c_o}^{(q)} \in Z_+^{S_2^C\,(q)}$

$t_{s_2 c_o}^{(q)+} \in Z_+^{S_2^C\,(q)}$

Figure 5.1. Enhanced parallel NSBM DEA model with all model parameters represented

To obtain the functional effectiveness scores (i.e., the effectiveness scores for the teaching, research and community service functions), the slacks of the controllable outcomes derived from Model (4.9) are utilised. Figure 5.2 illustrates the developed functional effectiveness component, with all parameter values represented in the formulation.

Teaching function:

$$\mathrm{E}_{\mathrm{o}}^{(1)} = \frac{1}{1 + \frac{1}{0}\left(\frac{\mathrm{t}_{\mathrm{s}_2 \mathrm{c}_{\mathrm{o}}}^{(1)+}}{\mathrm{y}_{\mathrm{s}_2 \mathrm{c}_{\mathrm{o}}}^{(1)}} + \frac{\mathrm{t}_{\mathrm{s}_2 \mathrm{c}_{\mathrm{o}}}^{(1)+}}{\mathrm{y}_{\mathrm{s}_2 \mathrm{c}_{\mathrm{o}}}^{(1)}}\right)}$$

Research function:

$$\mathrm{E}_{\mathrm{o}}^{(2)} = \frac{1}{1 + \frac{1}{0}\left(\frac{\mathrm{t}_{\mathrm{s}_2 \mathrm{c}_{\mathrm{o}}}^{(2)+}}{\mathrm{y}_{\mathrm{s}_2 \mathrm{c}_{\mathrm{o}}}^{(2)}} + \frac{\mathrm{t}_{\mathrm{s}_2 \mathrm{c}_{\mathrm{o}}}^{(2)+}}{\mathrm{y}_{\mathrm{s}_2 \mathrm{c}_{\mathrm{o}}}^{(2)}}\right)}$$

Community service function:

$$\mathrm{E}_{\mathrm{o}}^{(3)} = \frac{1}{1 + \frac{1}{2}\left(\frac{\mathrm{t}_{\mathrm{s}_2 \mathrm{c}_{\mathrm{o}}}^{(3)+}}{\mathrm{y}_{\mathrm{s}_2 \mathrm{c}_{\mathrm{o}}}^{(3)}} + \frac{\mathrm{t}_{\mathrm{s}_2 \mathrm{c}_{\mathrm{o}}}^{(3)+}}{\mathrm{y}_{\mathrm{s}_2 \mathrm{c}_{\mathrm{o}}}^{(3)}}\right)}$$

Figure 5.2. Enhanced functional effectiveness components with all model parameters represented

The solution was obtained using LINGO 18 optimization modelling software. A sample LINGO 18 code formulated to compute the effectiveness score and outcome shortfall values for Faculty 1 (using the initial model) as shown in the first row of Table 5.3 is provided in Appendix A.

Table 5.3

Effectiveness Scores of the Enhanced Parallel NSBM DEA Model for 26 Faculties in UiTM (Initial Model)

Faculty	**Overall Effectiveness**	**Teaching Function Effectiveness**	**Research Function Effectiveness**	**Community Service Function Effectiveness**	**Outcome Shortfalls**	
					No. of KT Programmes	**No. of USR Programmes**
FC1	1.0000	1.0000	1.0000	1.0000	0	0
FC2	0.8889	1.0000	1.0000	0.8889	3	0
FC3	1.0000	1.0000	1.0000	1.0000	0	0
FC4	1.0000	1.0000	1.0000	1.0000	0	0
FC5	1.0000	1.0000	1.0000	1.0000	0	0
FC6	0.8730	1.0000	1.0000	0.8730	1	1
FC7	1.0000	1.0000	1.0000	1.0000	0	0
FC8	1.0000	1.0000	1.0000	1.0000	0	0
FC9	1.0000	1.0000	1.0000	1.0000	0	0
FC10	1.0000	1.0000	1.0000	1.0000	0	0
FC11	1.0000	1.0000	1.0000	1.0000	0	0
FC12	0.9524	1.0000	1.0000	0.9524	0	1
FC13	1.0000	1.0000	1.0000	1.0000	0	0
FC14	1.0000	1.0000	1.0000	1.0000	0	0
FC15	1.0000	1.0000	1.0000	1.0000	0	0
FC16	1.0000	1.0000	1.0000	1.0000	0	0
FC17	1.0000	1.0000	1.0000	1.0000	0	0
FC18	1.0000	1.0000	1.0000	1.0000	0	0
FC19	1.0000	1.0000	1.0000	1.0000	0	0
FC20	1.0000	1.0000	1.0000	1.0000	0	0
FC21	1.0000	1.0000	1.0000	1.0000	0	0
FC22	1.0000	1.0000	1.0000	1.0000	0	0
FC23	1.0000	1.0000	1.0000	1.0000	0	0
FC24	1.0000	1.0000	1.0000	1.0000	0	0
FC25	0.8000	1.0000	1.0000	0.8000	1	3
FC26	1.0000	1.0000	1.0000	1.0000	0	0

Through the analysis, the finding shows that 22 faculties (i.e., FC1, FC3, FC4, FC5, FC7, FC8, FC9, FC10, FC11, FC13, FC14, FC15, FC16, FC17, FC18, FC19, FC20, FC21, FC22, FC23, FC24 and FC26) are overall effective across all three functions of teaching, research and community service. This indicates that these faculties perform all three functions effectively. The remaining faculties record effectiveness scores below one, indicating ineffectiveness, particularly within the community service function. It should be noted that most effectiveness scores are close to 1 because no excesses or shortfalls in the teaching and research functions. The reduced effectiveness scores in community service function are primarily due to shortfalls in the number of KT and USR programmes, as reported in Columns 6 and 7 of Table 5.3.

Faculties with higher shortfall values tend to exhibit lower effectiveness scores, as the effectiveness measure penalizes deviations from the effective frontier when shortfall values are present. For instance, Faculty FC25 records one of the lowest community service effectiveness scores (0.8000), corresponding to relatively high shortfall values, particularly outcome shortfalls of one KT program and three USR programmes. Similarly, Faculty FC6 also exhibits lower effectiveness score under the community service function, consistent with the presence of outcome shortfalls in both KT and USR programmes. These results demonstrate the strength of the enhanced parallel NSBM DEA model in identifying specific functional weaknesses that require improvement.

It should be noted that no slacks are associated with the teaching and research functions, as these outputs and outcomes are non-controllable variables and remain fixed in the optimization process. In contrast, the functional effectiveness scores for community service are computed using the slacks of the number of KT and USR programmes obtained from the model formulation. Faculties with zero slacks in their respective controllable outcomes are categorized as overall effective across the three functions: teaching, research and community service. Conversely, the presence of positive slacks in one or both outcomes indicates ineffectiveness, reflecting the additional programmes required to achieve effectiveness.

As mention above, outcome shortfalls in both KT and USR programmes are detected for ineffective faculties, specifically FC6 and FC25. In terms of the number of KT programmes, ineffectiveness is observed among FC2, FC6 and FC25 indicating that additional KT programmes are required. Notably, Faculty FC2 records the largest shortfall in KT programmes, highlighting a significant gap relative to the effective benchmark. Regarding USR programmes, shortfalls are identified for Faculties FC6, FC12 and FC25, implying that these faculties must increase their USR programmes to achieve effectiveness. Overall, these shortfalls represent the magnitude of improvement required for each ineffective faculty to reach the effective frontier in community service performance.

Up to this stage, the effectiveness of the 26 faculties has been measured based on the initial specification of outputs and outcomes. The effectiveness frontier is formed by faculties that demonstrate the best performance relative to others. However, a limitation of DEA is that it does not inherently provide statistical tests to determine the significance of results (Tyagi et al., 2009). Therefore, assessing the robustness and stability of the DEA results is essential. Sensitivity analysis is conducted to examine the effect of different combinations of outputs and outcomes on the effectiveness status.

5.3 Validation of the Proposed Model Using Sensitivity Analysis

As discussed in Subsection 4.6.4, the computed effectiveness scores may be sensitive to changes in variable specifications. Due to the non-parametric nature of DEA, conventional statistical tests cannot be directly applied to the results obtained from different reduced DEA models (Hussain, 2017; Johnes, 2006a; Johnes & Li, 2008). Therefore, sensitivity analysis is employed, as recommended in previous studies (Nigam et al., 2012; Tyagi et al., 2009), to compare results across reduced DEA models. These reduced models are generated by replacing selected outputs or outcomes one at a time, resulting in different combinations of variables, referred to as alternative models. The effectiveness scores obtained from these alternative DEA models are then analysed to assess sensitivity, as elaborated in Subsection 5.3.1.

5.3.1 Effect of Different Outputs and Outcomes Combination on the Effectiveness Score for Each Faculty

The objective of this step is to determine whether the computed effectiveness scores are sensitive to different combinations of output and outcome variables. The effectiveness scores obtained from these alternative models are tested by examining the significance of the correlation between the effectiveness scores from the initial DEA model and those from the alternative DEA models. The model with higher correlation coefficients indicates an ideal DEA model that provides robust and stable result scores (Hussain, 2017). Spearman’s rank correlation analysis is used to examine these relationships, as it has been widely adopted in prior studies (Avkiran & McCrystal, 2012; Hussain, 2017; Nigam et al., 2012; Tyagi et al., 2009).

Specifically, several alternative models are constructed by replacing selected variables as below:

i) Alternative Model 1: The number of graduates from undergraduate programmes is replaced with the number of programmes accredited by professional standard at the international level

ii) Alternative Model 2: The amount of research grants is replaced with the number of indexed publications

iii) Alternative Model 3: The number of citations of indexed publications is replaced with the number of high impact publications

iv) Alternative Model 4: The amount received (from external) for KT and USR programmes is replaced with total expenditure on KT and USR programmes

The data used for the alternative models are presented in Table 5.4.

Table 5.4

Dataset of Outputs and Outcomes for Alternative Model for Each Faculty in UiTM

Faculty	*Output*		*Outcome*	
	No. of programmes accredited at the international level	**No. of indexed publications**	**No. of high impact publications**	**Total expenditure on KT and USR programmes**
FC1	0	84	0	55000
FC2	0	119	0	2550
FC3	0	3642	47	3152
FC4	0	5	0	3110
FC5	1	1335	12	15000
FC6	0	3243	18	6000
FC7	0	2031	21	9510
FC8	0	2282	13	20800
FC9	0	6	0	2500
FC10	0	7	0	2500
FC11	0	176	0	3600
FC12	6	521	3	3000
FC13	0	65	1	1200
FC14	0	118	1	3000
FC15	4	563	1	6150
FC16	0	498	6	3000

Table 5.4 continued

Faculty	Output		Outcome	
	No. of programmes accredited at the international level	**No. of indexed publications**	**No. of high impact publications**	**Total expenditure on KT and USR programmes**
FC17	0	816	16	3110
FC18	2	3790	70	3700
FC19	0	3213	9	4000
FC20	1	1582	5	16130
FC21	0	15	1	5280
FC22	0	49	5	18848
FC23	0	125	2	4000
FC24	9	617	3	11230
FC25	0	67	1	11177
FC26	0	6813	50	1370

Table 5.5 presents the effectiveness scores obtained from the sensitivity analysis. The second column reports the effectiveness scores derived from the initial model, while the subsequent columns display the effectiveness scores generated from each alternative model. It is observed that three faculties (i.e., FC4, FC10, FC22) out of 22 effective faculties (obtained using the initial model) maintained their effectiveness status when certain outputs or outcomes were replaced, implying that changes in outputs or outcomes did not substantially influence their effectiveness scores.

Table 5.5

The Effectiveness Scores of Sensitivity Analysis for Faculties

Faculty	Initial model	Alternative Model 1	Alternative Model 2	Alternative Model 3	Alternative Model 4
FC1	1.0000	0.9524	0.0612	1.0000	0.0338
FC2	0.8889	1.0000	0.0443	1.0000	0.4727
FC3	1.0000	1.0000	0.4021	0.8333	0.8193
FC4	1.0000	1.0000	1.0000	1.0000	1.0000
FC5	1.0000	1.0000	1.0000	1.0000	0.7724
FC6	0.8730	0.8730	0.8117	0.8730	0.8397

Table 5.5 continued

Faculty	Initial model	Alternative Model 1	Alternative Model 2	Alternative Model 3	Alternative Model 4
FC7	1.0000	1.0000	0.1988	1.0000	0.1636
FC8	1.0000	1.0000	0.4541	1.0000	0.1141
FC9	1.0000	0.8333	1.0000	0.8333	1.0000
FC10	1.0000	1.0000	1.0000	1.0000	1.0000
FC11	1.0000	1.0000	0.0288	1.0000	0.6394
FC12	0.9524	0.9524	0.9331	0.9524	1.0000
FC13	1.0000	1.0000	0.0824	1.0000	1.0000
FC14	1.0000	1.0000	0.0430	1.0000	0.6938
FC15	0.8483	1.0000	0.3705	0.8483	0.3165
FC16	1.0000	0.7692	0.1149	1.0000	0.4736
FC17	1.0000	1.0000	0.0071	1.0000	0.3883
FC18	1.0000	1.0000	0.7761	1.0000	1.0000
FC19	0.8333	1.0000	0.0126	1.0000	0.3045
FC20	0.9231	1.0000	0.0916	0.9231	0.0763
FC21	1.0000	1.0000	0.8746	1.0000	0.6723
FC22	1.0000	1.0000	1.0000	1.0000	1.0000
FC23	1.0000	0.9524	0.8746	0.9524	0.8927
FC24	1.0000	1.0000	0.3101	1.0000	0.1562
FC25	0.8000	0.7692	0.0829	0.8000	0.1380
FC26	1.0000	1.0000	0.3005	1.0000	1.0000

In contrast, the remaining 19 faculties experienced a decline in effectiveness and became ineffective when certain outputs and outcomes are replaced form the analysis. These results indicate that the effectiveness level of each faculty is influenced by the replacement of particular outputs or outcomes, suggesting that these variables play a significant role in shaping performance and directly affect effectiveness scores.

5.3.2 Identifying the Ideal DEA Model Using Correlation Measures

In Section 5.3.1, the effectiveness scores for each faculty were computed using different combinations of output and outcome variables, as presented in Table 5.5. It can be observed that there is some variation in the effectiveness scores for each faculty as a result of replacing certain outputs and outcomes. While some effective faculties maintain their effectiveness status under different combinations, in most cases the effectiveness values of these faculties are also affected. Subsequently, the stability and robustness of the developed DEA model were examined using Spearman's rank correlation coefficient between the effectiveness scores of the initial model and those obtained from the alternative models, as reported in Table 5.6.

Table 5.6

Spearman's Rank Correlation Coefficient between the Initial and Alternative Model

DEA Model	**Alternative Model 1**	**Alternative Model 2**	**Alternative Model 3**	**Alternative Model 4**
Initial Model	0.234	0.238	0.512	0.319

The result shows that the correlation between the initial model and alternative model 3 is 0.512, which is higher than the correlations obtained for the other alternative models. The highest correlation coefficient leads to the identification of the Ideal DEA model (Hussain, 2017; Rashidi et al., 2015). Consequently, a new combination of outputs and outcomes is established and identified as the Ideal DEA model. Accordingly, the outcome measure "number of citations of indexed publications" is replaced with "number of high impact publications," while all other output and outcome measures are retained in the computation of effectiveness scores. In the following section, this Ideal DEA model, incorporating the identified replacement outcome, is applied to determine more accurate effectiveness scores for each faculty using the developed "Enhanced Parallel NSBM DEA Model". At this stage, the validity considered in Section 4.6.4 is assessed.

5.4 Effectiveness Measures of the Enhanced Parallel NSBM DEA Model: Ideal Model

In this section, the effectiveness measures obtained using the developed model were recalculated using the Ideal DEA model identified in Section 5.3.2. The Ideal DEA model represents the specification with the right combination of output and outcome variables, as determined through sensitivity analysis. In this model, one outcome variable was replaced; specifically, the "number of citations of indexed publications" was replaced with the "number of high-impact publications. The effectiveness of each faculty was then determined. The effectiveness results derived from the Ideal DEA model for all faculties are presented in Table 5.7.

The replacement of "number of citations of indexed publications" with "number of high-impact publications" reflects a stronger emphasis on research quality. Research quality is a complex and multidimensional concept, typically associated with methodological rigor, originality and societal or scientific impact (Langfeldt et al., 2020). Although citation counts are widely used as indicators of research quality, the relationship between citation counts and actual research quality remains weakly evidenced (Thelwall et al., 2023). In addition, citation metrics are also subject to manipulation through practices such as self-citation, citation bias, coercive citation and citation cartels (Joshi & Pandey, 2024).

In contrast, high-impact publications such as papers published in Quartile 1 (Q1) and Quartile 2 (Q2) journals indexed in Scopus (SCImago Journal Rank) provide a stronger representation of research quality, as publication in these journals requires rigorous peer review and adherence to high scientific standards (Miranda & Garcia-Carpintero, 2019). Furthermore, studies by Shehatta et al. (2023) indicate that publications in Q1 and Q2 journals demonstrate stronger impact, excellence, funding indicators and corporate interest compared to lower-quartile publications. Therefore, this Ideal model is considered to provide more accurate effectiveness measures. A sample LINGO 18 code used to compute the effectiveness score and outcome shortfall values for Faculty 1 (under the Ideal model) is provided in Appendix B.

Table 5.7

Effectiveness Score of the Enhanced Parallel NSBM DEA Model for 26 Faculties in UiTM (Ideal model)

Faculty	**Overall Effectiveness**	**Teaching Function Effectiveness**	**Research Function Effectiveness**	**Community Service Function Effectiveness**	**Outcome Shortfalls**	
					No. of KT Programmes	**No. of USR Programmes**
FC1	1.0000	1.000	1.000	1.0000	0	0
FC2	1.0000	1.000	1.000	1.0000	0	0
FC3	0.8333	1.000	1.000	0.8333	1	2
FC4	1.0000	1.000	1.000	1.0000	0	0
FC5	1.0000	1.000	1.000	1.0000	0	0
FC6	0.8730	1.000	1.000	0.8730	1	1
FC7	1.0000	1.000	1.000	1.0000	0	0
FC8	1.0000	1.000	1.000	1.0000	0	0
FC9	0.8333	1.000	1.000	0.8333	2	0
FC10	1.0000	1.000	1.000	1.0000	0	0
FC11	1.0000	1.000	1.000	1.0000	0	0
FC12	0.9524	1.000	1.000	0.9524	0	1
FC13	1.0000	1.000	1.000	1.0000	0	0
FC14	1.0000	1.000	1.000	1.0000	0	0
FC15	0.8483	1.000	1.000	0.8483	4	1
FC16	1.0000	1.000	1.000	1.0000	0	0
FC17	1.0000	1.000	1.000	1.0000	0	0
FC18	1.0000	1.000	1.000	1.0000	0	0
FC19	1.0000	1.000	1.000	1.0000	0	0
FC20	0.9231	1.000	1.000	0.9231	1	0
FC21	1.0000	1.000	1.000	1.0000	0	0
FC22	1.0000	1.000	1.000	1.0000	0	0
FC23	0.9524	1.000	1.000	0.9524	0	1
FC24	1.0000	1.000	1.000	1.0000	0	0
FC25	0.8000	1.000	1.000	0.8000	2	1
FC26	1.0000	1.000	1.000	1.0000	0	0

Table 5.7 presents the effectiveness scores for each faculty obtained using the identified Ideal model. The finding indicates that 18 faculties (FC1, FC2, FC4, FC5, FC7, FC8, FC10, FC11, FC13, FC14, FC16, FC17, FC18, FC19, FC21, FC22, FC24 and FC26) are overall effective across all three functions of teaching, research and community service. This demonstrates that these faculties perform all three functions effectively. The remaining faculties record effectiveness scores below one, indicating ineffectiveness, particularly within the community service function. It should be noted that most effectiveness scores are close to 1 because no excesses or shortfalls in the teaching and research functions. The reduced effectiveness scores in community service function are primarily due to shortfalls in the number of KT and USR programmes, as reported in Columns 6 and 7 of Table 5.7.

Faculties with higher shortfall values tend to exhibit lower effectiveness scores, as the effectiveness measure penalizes deviations from the effective frontier. For example, Faculty FC15 records are among one of the lowest effectiveness scores (0.8483), corresponding to relatively high shortfalls particularly outcome shortfalls of four KT programmes and one USR programmes. Similarly, Faculties FC3, FC6 and FC25 exhibits reduced effectiveness due to shortfalls in both KT and USR programmes. These findings demonstrate the capability of the enhanced parallel NSBM DEA model to identify specific functional weaknesses requiring improvement. To further illustrate these findings, Figure 5.3 presents the overall and functional effectiveness scores for teaching, research and community service function across the 26 faculties.

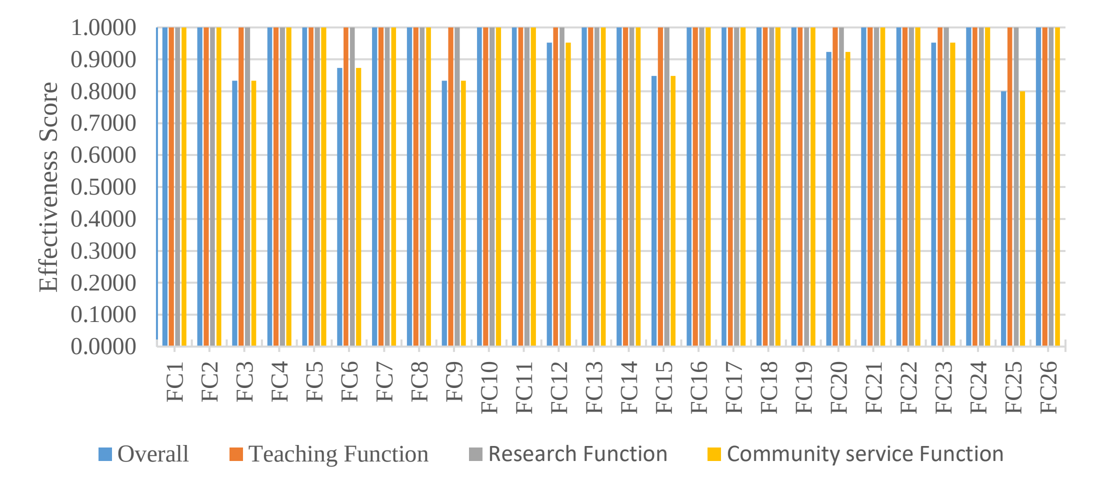


Figure 5.3. Overall and Functional Effectiveness

It should be noted that no slacks are associated with the teaching and research functions because these outputs and outcomes are non-controllable and remain fixed during optimization. In contrast, the functional effectiveness scores for community service are computed based on slacks in the controllable outcomes (KT and USR programmes). Faculties with zero slacks in controllable outcomes are categorized as overall effective across all three functions: teaching, research and community service. Conversely, positive slacks indicate ineffectiveness and represent the additional programmes required to achieve effectiveness.

Outcome shortfalls in both KT and USR programmes are observed for Faculties FC3, FC6, FC15 and FC25. For KT programmes, ineffectiveness is observed among Faculties FC3, FC6, FC9, FC15, FC20 and FC25. For USR programmes, shortfalls are identified for Faculties FC3, FC6, FC12, FC15, FC23 and FC25. Notably, Faculty FC15 records the largest shortfall in KT programmes, indicating a significant gap relative to the effective benchmark. Overall, these shortfalls represent the magnitude of improvement required for each ineffective faculty to reach the effective frontier in community service performance. These patterns are further illustrated in Figure 5.4, which visually presents the distribution of KT and USR outcome shortfalls across faculties.

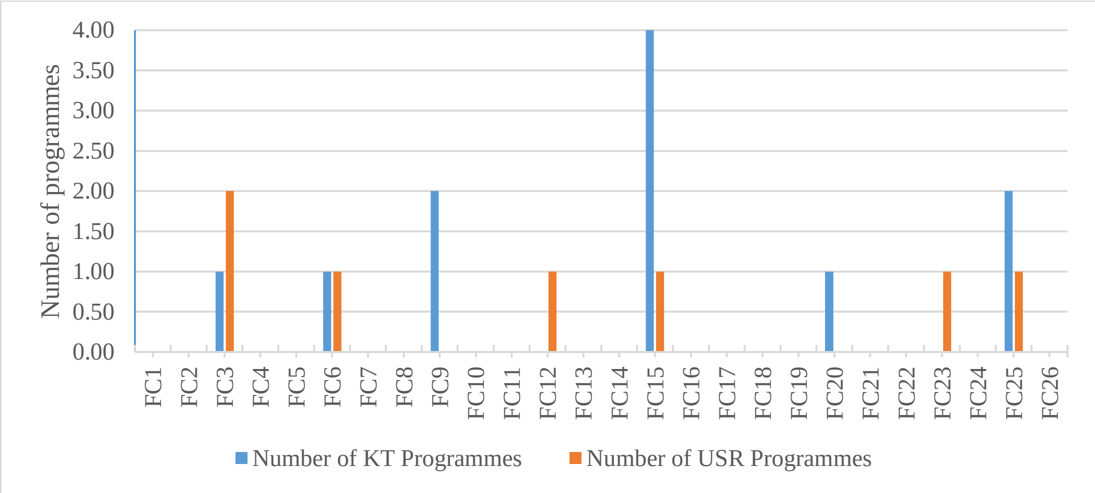


Figure 5.4. Slacks of controllable outcomes

Table 5.7 also reports the overall and functional effectiveness scores generated by the enhanced parallel NSBM DEA model, confirming that all required NDEA properties are satisfied, as discussed in Section 3.2.3. First, the model satisfies the property that a faculty is overall effective if and only if all its functions are effective. Faculties (i.e. FC1, FC2, FC4, FC5, FC7, FC8, FC10, FC11, FC13, FC14, FC16, FC17, FC18, FC19, FC21, FC22, FC24 and FC26) are identified as overall effective demonstrate effectiveness across all functional components. Second, under the Variable Returns-to-Scale (VRS) assumption, each function must have at least one functionally effective DMU. The results confirm that this condition is satisfied. Third, the projected DMU is overall effective when all associated slacks are zero. Faculties (i.e. FC1, FC2, FC4, FC5, FC7, FC8, FC10, FC11, FC13, FC14, FC16, FC17, FC18, FC19, FC21, FC22, FC24 and FC26) are identified as effective exhibit zero slack values, confirming compliance with this property. Therefore, the enhanced parallel NSBM model satisfies all required NDEA properties. A summary of the validation results is presented in Table 5.8.

Table 5.8

Validation of NDEA Model Properties under the Enhanced Parallel NSBM Model

NDEA Property	Evidenced (Faculties)	Status
A Decision-Making Unit (DMU) is effective if and only if all its functions are effective.	FC1, FC2, FC4, FC5, FC7, FC8, FC10, FC11, FC13, FC14, FC16, FC17, FC18, FC19, FC21, FC22, FC24 and FC26	Fulfilled
Under the variable returns-to-scale (VRS) assumption, every function has at least one functionally effective DMU	All faculties	Fulfilled
The projected DMU is overall effective, which is indicated by zero slack.	FC1, FC2, FC4, FC5, FC7, FC8, FC10, FC11, FC13, FC14, FC16, FC17, FC18, FC19, FC21, FC22, FC24 and FC26	Fulfilled

5.5 Evaluation of the Proposed Model

Model evaluation was conducted to assess whether the enhanced model generates appropriate results and performs consistently relative to existing DEA models. This step also verifies that all variables are correctly specified and properly incorporated (Dobos & Vörösmarty, 2021; Hussain, 2017; Muñiz et al., 2006; Ruggiero, 1996). The overall and functional effectiveness scores obtained from Kao's (2020) standard parallel NSBM model are compared with those produced by the enhanced parallel NSBM DEA model (Ideal model). The objective is to validate the integration of mixed-integer values and non-controllable factors into the standard parallel NSBM DEA model, which assumes all variables are non-integer and controllable. The overall and functional effectiveness scores produced by the standard approach and the proposed approach are presented in Table 5.9.

Table 5.9 shows that most of the overall and functional effectiveness scores produced by the standard approach of Kao (2020) are lower than those generated by the enhanced parallel NSBM model. These lower values can be attributed primarily to the presence of several non-controllable outputs and outcomes, which are not included in the objective function of the proposed model. In other words, the enhanced parallel NSBM model improves only the controllable outcomes of the 26 faculties. The improvement is achieved by increasing controllable outcomes, while non-controllable variables remain fixed at their actual observed levels, resulting in more accurate effectiveness measurements.

Table 5.9

Effectiveness Score for 26 Faculties using Kao's Standard Parallel NSBM Approach and The Enhanced Parallel NSBM Approach

	Kao's standard parallel NSBM approach				**The enhanced parallel NSBM approach**			
Faculty	**Overall Effectiveness**	**Teaching Function Effectiveness**	**Research Function Effectiveness**	**Community Service Function Effectiveness**	**Overall Effectiveness**	**Teaching Function Effectiveness**	**Research Function Effectiveness**	**Community Service Function Effectiveness**
FC1	0.8670	0.8619	1.0000	0.8696	1.0000	1.000	1.000	1.0000
FC2	0.9642	0.9102	0.9976	1.0000	1.0000	1.000	1.000	1.0000
FC3	0.7778	0.9427	0.9998	0.9084	0.8333	1.000	1.000	0.8333
FC4	0.7257	0.6632	0.9322	0.6044	1.0000	1.000	1.000	1.0000
FC5	0.9868	1.0000	0.9603	1.0000	1.0000	1.000	1.000	1.0000
FC6	0.7262	0.8223	0.6923	0.8324	0.8730	1.000	1.000	0.8730
FC7	0.8962	0.8950	0.9995	0.9993	1.0000	1.000	1.000	1.0000
FC8	0.7838	0.7965	0.4639	0.9991	1.0000	1.000	1.000	1.0000
FC9	0.8988	0.9887	1.0000	0.8600	0.8333	1.000	1.000	0.8333
FC10	0.9950	1.0000	1.0000	0.9849	1.0000	1.000	1.000	1.0000
FC11	0.3578	0.1590	0.9345	0.0497	1.0000	1.000	1.000	1.0000
FC12	0.5850	0.5805	0.9960	0.8327	0.9524	1.000	1.000	0.9524
FC13	0.6806	0.6165	0.9829	0.7953	1.0000	1.000	1.000	1.0000

Table 5.9 continued

Faculty	Kao's parallel NSBM approach				The enhanced parallel NSBM approach			
	Overall Effectiveness	**Teaching Function Effectiveness**	**Research Function Effectiveness**	**Community Service Function Effectiveness**	**Overall Effectiveness**	**Teaching Function Effectiveness**	**Research Function Effectiveness**	**Community Service Function Effectiveness**
FC14	0.7673	0.7500	0.9977	0.7683	1.0000	1.000	1.000	1.0000
FC15	0.4397	0.4254	0.9861	0.7035	0.8483	1.000	1.000	0.8483
FC16	0.9998	1.0000	0.9997	0.9998	1.0000	1.000	1.000	1.0000
FC17	0.9990	0.9971	1.0000	1.0000	1.0000	1.000	1.000	1.0000
FC18	0.5769	0.6128	0.8778	0.7431	1.0000	1.000	1.000	1.0000
FC19	0.7083	0.8885	0.5625	0.5882	1.0000	1.000	1.000	1.0000
FC20	0.6822	0.7601	0.6233	0.7981	0.9231	1.000	1.000	0.9231
FC21	0.6766	0.6312	0.9824	0.6644	1.0000	1.000	1.000	1.0000
FC22	0.9916	0.9749	1.0000	1.0000	1.0000	1.000	1.000	1.0000
FC23	0.3867	0.5790	1.0000	0.0673	0.9524	1.000	1.000	0.9524
FC24	0.6280	0.6541	0.9953	0.5630	1.0000	1.000	1.000	1.0000
FC25	0.6280	0.6245	0.9874	0.5702	0.8000	1.000	1.000	0.8000
FC26	0.6655	0.6069	0.9966	0.6667	1.0000	1.000	1.000	1.0000

To statistically assess the differences in effectiveness scores between the two approaches and to validate the integration of mixed-integer variables and non-controllable factors into the standard parallel NSBM DEA model, the Mann–Whitney U test is applied. The hypothesis testing is conducted at a one-tailed significance level of $\alpha = 0.05$ and results are presented in Table 5.10.

Table 5.10

Results of Mann-Whitney test

Statistical test	**Overall effectiveness**	**Teaching Function Effectiveness**	**Research Function Effectiveness**	**Community Service Function Effectiveness**
Mann-Whitney rank test	614	637	598	561
p-value	<0.05	<0.05	<0.05	<0.05

The test results indicate that the null hypothesis (H_0) is rejected for overall effectiveness, as the *p*-value for overall effectiveness scores is less than the $\alpha = 0.05$. This finding confirms a statistically significant difference between the overall effectiveness scores produced by the two approaches. Similarly, the *p*-values associated with the functional effectiveness scores for teaching, research and community service are all less than $\alpha = 0.05$, leading to the rejection of the null hypothesis (H_0) and confirming significant differences in functional effectiveness scores across the compared models.

The observed differences in both overall and functional effectiveness scores can be attributed to the treatment of non-controllable outputs and outcomes. The standard approach assumes that all output and outcome are controllable. In contrast, the proposed approach grants that not all outputs and outcomes are controllable, which leads to significant differences in the overall and functional effectiveness scores between the two approaches.

This distinction explains the statistically significant differences observed in both overall and functional effectiveness scores. Accordingly, there is sufficient evidence to conclude that mixed-integer variables and non-controllable factors have been appropriately incorporated into the Kao (2020) standard parallel NSBM DEA model and that the resulting effectiveness measures are correctly computed. These findings confirm that the proposed enhanced model performs effectively in determining the effectiveness of faculties in UiTM.

5.6 Summary

In summary, this chapter presents and discusses the empirical results obtained from the proposed model. The enhanced parallel NSBM DEA model, which is developed to measure DMUs effectiveness in the presence of mixed-integer values and non-controllable factors, was empirically tested and validated using data from 26 faculties of a Malaysian public university as a case study. Faculty effectiveness was evaluated at both the overall and functional levels, enabling the identification of effective and ineffective faculties. For the ineffective faculties, the model further provides the necessary outcome augmentations required to improve performance.

The model's validity was subsequently examined through sensitivity analysis to determine the most appropriate DEA specification. Spearman's rank correlation was employed to compare the effectiveness scores from the initial model with those obtained from alternative model specifications incorporating different combinations of outputs and outcomes. The model yielding the highest correlation was selected as the Ideal DEA model. Using this identified Ideal enhanced NSBM DEA model, faculty effectiveness was recalculated. Finally, the performance of the proposed model was evaluated by comparing it with existing models.

CHAPTER SIX
CONCLUSIONS

This study focuses on measuring the effectiveness of a Malaysian public university, namely Universiti Teknologi MARA (UiTM), using a NDEA model. Specifically, an enhanced parallel NSBM DEA model incorporating mixed integer values and non-controllable factors was developed and employed to achieve the objectives of this study. This enhanced model enables a more comprehensive and accurate measurement by capturing the internal structure of the university and identifying the sources contributing to overall and functional ineffectiveness at the faculty level.

As highlighted in this final chapter, the main objective of this study is to develop an enhanced parallel NSBM DEA model that incorporates mixed integer values and non-controllable factors. To achieve this main objective, several specific objectives were established: (i) to identify suitable variables for measuring the effectiveness of faculties in a public university and to categorize them into integer and non-integer values, considering controllable and non-controllable factors; (ii) to develop an enhanced parallel NSBM DEA model incorporating mixed integer values and non-controllable factors to measure the effectiveness of faculties in a public university and decompose overall effectiveness into functional components; (iii) to validate the proposed model via sensitivity analysis and (iv) to evaluate the proposed model by comparing its performance with existing models.

6.1 Summary of Effectiveness Measurement of a Public University using the Enhanced Parallel NSBM Approach

Performance measurement is a fundamental component of organizational management, particularly within the public university system. In an increasingly globalized and competitive higher education landscape, Malaysian public universities face persistent challenges, including student enrolment, graduate employability, research funding, research outputs and income generation. Although notable progress has been made in overall institutional performance, improving educational quality remains an ongoing concern.

In response, the MoHE has aspired to establish a new performance measurement system (PMS) that shifts the focus from inputs and processes to outcome-based measures, as outlined in the Malaysia Education Blueprint (Higher Education) 2015–2025. Accordingly, this study measures the effectiveness of a Malaysian public university from an outcome-based perspective, consistent with the framework advocated by the MoHE. To examine how these challenges influence university performance and to align with national aspirations, an appropriate methodological approach is required to measure university effectiveness comprehensively and accurately.

DEA is widely recognized as an appropriate approach for measuring public university effectiveness due to its ability to handle multiple inputs and outputs simultaneously. However, conventional DEA models assume a "black-box" production process, thereby ignoring the internal structure of universities. This assumption may result in inaccurate performance measurement and limits the ability to identify specific sources of ineffectiveness within internal university functions. Public universities operate through multiple functions, such as teaching, research and community service. Consequently, the overall effectiveness of a faculty is the aggregate of its teaching, research and community service effectiveness. From this perspective, each faculty can be modelled as a parallel production system comprising three functions.

Considering these characteristics, a parallel NSBM DEA is proposed, as it enables the simultaneous consideration of slacks while measuring effectiveness at both overall and functional levels. Furthermore, the proposed model incorporates mixed-integer values and non-controllable factors, which are often overlooked in conventional DEA formulations. Conventional DEA models assume that all variables are non-integer and fully controllable by DMU management. However, in public universities, certain variables take only integer values, others are non-integer and some are influenced by non-controllable factors. To better reflect real-world university operations, this study proposes an enhanced parallel NSBM DEA model that incorporates mixed-integer values and non-controllable factors.

The proposed model was empirically tested to obtain effectiveness scores for 26 faculties at UiTM. Initially, effectiveness scores were computed based on initial specification of outputs and outcomes (the Initial DEA model). However, this initial specification may lead to potentially misleading effectiveness measurements. To address this issue, a validity test using sensitivity analysis was conducted to examine different combinations of outputs and outcomes. Each combination represents an alternative DEA model. These alternative models generated different sets of effectiveness scores, which were compared with those from the initial model. Spearman's rank correlation coefficient was calculated to identify the most appropriate combination of variables. The alternative model with the highest correlation with the initial model was identified as the Ideal DEA model. Through this process, it was determined that the outcome measure “number of citations of indexed publications” should be replaced by “number of high impact publications” to produce the so-called Ideal DEA model. Thus, model validation was achieved. Once the Ideal DEA model was identified, effectiveness scores for each faculty were recalculated. Functional effectiveness measures and outcome shortfalls for each faculty were also determined.

Finally, the performance of the developed model was evaluated using the Mann–Whitney U test to examine whether statistically significant differences existed between the effectiveness scores obtained from the developed model and those derived from the standard parallel NSBM DEA model proposed by Kao (2020). The findings demonstrate that the proposed model produced significantly different effectiveness results compared with the standard parallel NSBM DEA model, indicating that mixed integer values and non-controllable factors were successfully integrated into the enhanced model.

Overall, the proposed model successfully measures the effectiveness of a public university in Malaysia. The findings highlight the importance of measuring university effectiveness through their internal structures. By decomposing effectiveness into functional components, the model provides more informative results. Consequently, university management can more accurately identify specific functions contributing to ineffectiveness and formulate targeted improvement strategies.

6.2 Accomplishment of Research Objectives

This study has successfully achieved all its research objectives. The main objective was to develop an enhanced parallel NSBM DEA model incorporating mixed integer values and non-controllable factors to measure the effectiveness of a public university. To achieve this main objective, four specific objectives were established.

The first specific objective was to identify suitable variables for measuring the effectiveness of faculties in a public university and to categorize them into integer and non-integer values, considering controllable and non-controllable factors. This objective was accomplished through data collection based on the challenges faced by public universities and a relevant literature review, as discussed in Chapter Four (Section 4.6.1).

The second specific objective was to develop an enhanced parallel NSBM DEA model incorporating mixed-integer values and non-controllable factors to measure the effectiveness of faculties in a public university and to decompose overall effectiveness into functional components. This objective was successfully achieved through the development of a DEA model capable of measuring both the overall effectiveness scores of faculties and the functional effectiveness scores within the parallel network of the university system. In addition, outcome shortfalls were identified for each ineffective faculty. The effectiveness measures obtained from the initial model are presented in Section 5.2.

The third specific objective was to validate the developed model through sensitivity analysis. This was accomplished by running several alternative DEA models using different combinations of outputs and outcomes for each faculty under evaluation. The higher correlation coefficients among the effectiveness scores across these combinations enabled the identification of the Ideal DEA model, representing the most appropriate combination of outputs and outcomes. The effectiveness scores for the various combinations, along with the corresponding correlation coefficients, are presented in Section 5.3. Subsequently, the enhanced model was implemented using the Ideal DEA model and the results are presented and discussed in detail in Section 5.4.

Finally, the fourth specific objective was to evaluate the performance of the developed model by comparing it with the standard parallel NSBM model proposed by Kao (2020). In this process, the Mann–Whitney U test was applied to examine the differences between the overall and functional effectiveness scores obtained from the standard parallel NSBM model and those generated by the proposed model. The results of this evaluation are presented in Section 5.5.

6.3 Research Contribution

This study contributes to three main areas: (i) the body of knowledge, (ii) HEI management and (iii) policymakers.

6.3.1 Contribution to The Body of Knowledge

To address the salient features of DEA, this study provides three distinct contributions to the body of knowledge. Firstly, the main theoretical contribution lies in incorporating mixed integer values and non-controllable factors into the parallel NSBM model proposed by Kao (2020) to measure university effectiveness. The proposed model considers the internal functional components of universities by dividing the overall system into multiple functions. Furthermore, the enhanced parallel network model incorporates mixed integer-valued and non-controllable elements into the measurement process, which were not examined in Kao's (2020) original approach. Therefore, this study extends the DEA literature by introducing a more accurate modelling framework that reflects practical operational conditions.

Second, the validity of the proposed enhanced parallel NSBM DEA model is assessed through sensitivity analysis. This process involves testing different combinations of outputs and outcomes to construct alternative DEA models. Each alternative model is used to assess the effect of specific variables on effectiveness scores and to identify the most appropriate or "Ideal" DEA model. By applying this Ideal model, the study confirms the robustness and consistency of the effectiveness measurements. Consequently, this process also represents a methodological contribution to the network DEA literature.

Lastly, the proposed model and its empirical application provide an alternative approach for measuring effectiveness using DEA, thereby enriching the knowledge and literature in the field of operations research.

6.3.2 Contribution to the Management of HEIs

From a practical perspective, this study offers several contributions to HEI management. First, it measures the effectiveness of a Malaysian public university using an enhanced parallel NSBM DEA approach that incorporates mixed-integer values and non-controllable factors. This approach provides a more appropriate framework for measuring university effectiveness in light of current HEI challenges.

Second, the parallel structure of the DEA model offers valuable insights by measuring effectiveness across three internal functions: teaching, research and community service. The developed model enables a detailed analysis of functional performance, allowing management to identify the sources of ineffectiveness.

Finally, the proposed model identifies outcome shortfalls for ineffective faculties. These results provide useful information for management, enabling them to determine which outcomes should be adjusted to enhance effectiveness. Such targeted recommendations support continuous quality improvement and strengthen institutional performance.

6.3.3 Contribution to Policy Makers

This research also provides important benefits for policymakers, particularly within Malaysian public universities. First, the study introduces an alternative performance measurement approach aligned with the Malaysia Education Blueprint (Higher Education) 2015–2025, offering new insights into university performance measurement.

Second, this study assists policymakers in identifying which faculties utilize their resources effectively. The resources are categorized as integer and non-integer values in the presence of controllable and non-controllable factors. This categorization of outputs and outcomes plays an important role in improving performance within the HEI sector.

Third, this research provides policymakers in determining the maximum possible increase in outcomes for each ineffective faculty, as well as to identify the sources of ineffectiveness. This enables more effective resource management and informed decision-making.

6.4 Limitation of study

Despite its contributions, this study has several limitations. First, the model assumes that all inputs and outcomes are either fully controllable or fully non-controllable. In practice, some variables may be partially controllable and the model does not currently account for this possibility. This limitation may influence the accuracy of effectiveness measurement in a Malaysian public university.

Second, the analysis is limited to data from the year 2020 due to structural changes within the university in subsequent years, which restricted the ability to track changes in performance over time.

Lastly, community service effectiveness is measured using KT and USR programmes as indicators. While these indicators provide a measurable approach to capturing universities' impact on societal engagement and quality of service, they may not fully reflect community service outcomes. Many impacts of community engagement are intangible and difficult to quantify and, therefore, may not be fully captured through programme-based indicators alone. Consequently, due to limitations related to variable selection, the results may not fully represent the actual effectiveness of public universities.

6.5 Future Research

The findings and limitations of this study suggest several directions for future research. One key limitation is the assumption that variables are either fully controllable or entirely non-controllable. In reality, many variables are only partially controllable due to external constraints or shared responsibilities. Future studies could extend the model by introducing a more flexible categorization system, such as distinguishing among controllable, partially controllable and non-controllable variables. This enhancement would allow for more accurate measurement of university performance.

Another potential avenue for future research is expanding the application of the proposed NDEA model to other complex organizations with internal functions. The developed model has strong potential for broader use in systems such as hospitals, universities, logistics centers, manufacturing networks and other multifunctional organizations. Applying the model in different contexts may help decision-makers identify ineffectiveness within specific functions and design targeted improvement strategies.

Lastly, future research is encouraged to expand the measurement of community service effectiveness by exploring additional or alternative indicators beyond KT and USR programmes. These programmes may not fully capture the effectiveness of community service in public universities. Future studies could incorporate social impact indicators so that universities can enhance their relative effectiveness by adopting appropriate effectiveness indicators aligned with community service functions. The inclusion of additional indicators in measuring the effectiveness of community service activities may lead to more comprehensive analyses.

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Appendix A

A sample LINGO 18 code to compute the effectiveness score of Faculty 1 (Initial Model)

```
min = j;

j + 1/2* (surplus1/10+surplus2/5)= 1;


!(a) Teaching;


317*u1+500*u2+189*u3+621*u4+189*u5+613*u6+335*u7+576*u8+533*u9+196*
u10+256*u11+1757*u12+404*u13+434*u14+725*u15+46*u16+683*u17+865*u18
+744*u19+918*u20+987*u21+438*u22+946*u23+1920*u24+356*u25+162*u26=(
317* j);

74.88*u1+81.09*u2+98.77*u3+74.54*u4+82.84*u5+82.85*u6+74.49*u7+74*u8+8
7.28*u9+75.79*u10+76.85*u11+81.37*u12+71.19*u13+73.54*u14+85.09*u15+93.
33*u16+82.52*u17+72.8*u18+90.64*u19+81.38*u20+87.72*u21+80.4*u22+77.05*
u23+78.73*u24+94.6*u25+84.91*u26=(74.88* j);


!(b) Research;


1500*h1+2095*h2+32391.98*h3+1106.27*h4+25839.1521*h5+42834.34*h6+1359
0*h7+22293.72*h8+3900*h9+920*h10+1100*h11+16177.547*h12+2100*h13+130
0*h14+10935.78*h15+5900*h16+3435*h17+40149.5797*h18+6630*h19+8525.737
*h20+4947.5*h21+900*h22+7430*h23+8895.33*h24+3330*h25+32182.68*h26=(1
500* j);

25*h1+20*h2+116*h3+18*h4+64*h5+168*h6+67*h7+61*h8+12*h9+0*h10+33*h1
1+87*h12+16*h13+22*h14+81*h15+58*h16+41*h17+212*h18+50*h19+139*h20+
12*h21+21*h22+18*h23+68*h24+13*h25+189*h26=(25* j);


!(c) Services ;


58750*m1+5370*m2+8100*m3+10000*m4+5000*m5+16000*m6+10000*m7+200
00*m8+5000*m9+5370*m10+35000*m11+87807.2*m12+6100*m13+16600*m14+
99800*m15+11000*m16+9994*m17+7500*m18+399828*m19+10000*m20+2800*
m21+83750*m22+45200*m23+32000*m24+20000*m25+0*m26=(58750* j);
```

```
10*m1+11*m2+10*m3+10*m4+12*m5+11*m6+10*m7+17*m8+8*m9+10*m10+6
*m11+10*m12+9*m13+10*m14+20*m15+5*m16+4*m17+10*m18+10*m19+15*
m20+6*m21+16*m22+10*m23+7*m24+10*m25+4*m26=(10* j)+ surplus1;

5*m1+12*m2+5*m3+5*m4+20*m5+5*m6+5*m7+10*m8+5*m9+7*m10+6*m11+5
*m12+4*m13+5*m14+13*m15+5*m16+4*m17+8*m18+5*m19+6*m20+4*m21+6
*m22+5*m23+6*m24+5*m25+6*m26=(5* j)+ surplus2;


u1  +u2 +u3 +u4 +u5 +u6 +u7 +u8 +u9 +u10 +u11 +u12 +u13 +u14 +u15 +u16 +u17
+u18 +u19 +u20 +u21 +u22 +u23 +u24 +u25 +u26=1;

h1  +h2 +h3 +h4 +h5 +h6 +h7 +h8 +h9 +h10 +h11 +h12 +h13 +h14 +h15 +h16 +h17
+h18 +h19 +h20 +h21 +h22+h23 +h24 +h25 +h26=1;

m1  +m2 +m3 +m4 +m5 +m6 +m7 +m8 +m9 +m10 +m11 +m12 +m13 +m14 +m15
+m16 +m17 +m18 +m19 +m20 +m21 +m22 +m23 +m24 +m25 +m26=1;


output_shortfall1 = surplus1/j;

output_shortfall2 = surplus2/j;

@gin(output_shortfall1);

@gin(output_shortfall2);
```

Appendix B

A sample LINGO 18 code to compute the effectiveness score of Faculty 1 (Ideal Model)

```
min = j;

j + 1/2* (surplus1/5+surplus2/10)= 1;


!(a) Teaching;


317*u1+500*u2+189*u3+621*u4+189*u5+613*u6+335*u7+576*u8+533*u9+196*
u10+256*u11+1757*u12+404*u13+434*u14+725*u15+46*u16+683*u17+865*u18
+744*u19+918*u20+987*u21+438*u22+946*u23+1920*u24+356*u25+162*u26=(
317* j);

74.88*u1+81.09*u2+98.77*u3+74.54*u4+82.84*u5+82.85*u6+74.49*u7+74*u8+8
7.28*u9+75.79*u10+76.85*u11+81.37*u12+71.19*u13+73.54*u14+85.09*u15+93.
33*u16+82.52*u17+72.8*u18+90.64*u19+81.38*u20+87.72*u21+80.4*u22+77.05*
u23+78.73*u24+94.6*u25+84.91*u26=(74.88* j);


!(b) Research;


1500*h1+2095*h2+32391.98*h3+1106.27*h4+25839.1521*h5+42834.34*h6+1359
0*h7+22293.72*h8+3900*h9+920*h10+1100*h11+16177.547*h12+2100*h13+130
0*h14+10935.78*h15+5900*h16+3435*h17+40149.5797*h18+6630*h19+8525.737
*h20+4947.5*h21+900*h22+7430*h23+8895.33*h24+3330*h25+32182.68*h26=(1
500* j);

0*h1+0*h2+47*h3+0*h4+12*h5+18*h6+21*h7+13*h8+0*h9+0*h10+0*h11+3*h12
+1*h13+1*h14+1*h15+6*h16+16*h17+70*h18+9*h19+5*h20+1*h21+5*h22+2*h2
3+3*h24+1*h25+50*h26=(0* j);


!(c) Services ;


58750*m1+5370*m2+8100*m3+10000*m4+5000*m5+16000*m6+10000*m7+200
00*m8+5000*m9+5370*m10+35000*m11+87807.2*m12+6100*m13+16600*m14+
99800*m15+11000*m16+9994*m17+7500*m18+399828*m19+10000*m20+2800*
m21+83750*m22+45200*m23+32000*m24+20000*m25+0*m26=(58750* j);
```

```
5*m1+12*m2+5*m3+5*m4+20*m5+5*m6+5*m7+10*m8+5*m9+7*m10+6*m11+5
*m12+4*m13+5*m14+13*m15+5*m16+4*m17+8*m18+5*m19+6*m20+4*m21+6
*m22+5*m23+6*m24+5*m25+6*m26=(5* j)+ surplus1;

10*m1+11*m2+10*m3+10*m4+12*m5+11*m6+10*m7+17*m8+8*m9+10*m10+6
*m11+10*m12+9*m13+10*m14+20*m15+5*m16+4*m17+10*m18+10*m19+15*
m20+6*m21+16*m22+10*m23+7*m24+10*m25+4*m26=(10* j)+ surplus2;


u1  +u2 +u3 +u4 +u5 +u6 +u7 +u8 +u9 +u10 +u11 +u12 +u13 +u14 +u15 +u16 +u17
+u18 +u19 +u20 +u21 +u22 +u23 +u24 +u25 +u26=1;

h1  +h2 +h3 +h4 +h5 +h6 +h7 +h8 +h9 +h10 +h11 +h12 +h13 +h14 +h15 +h16 +h17
+h18 +h19 +h20 +h21 +h22+h23 +h24 +h25 +h26=1;

m1  +m2 +m3 +m4 +m5 +m6 +m7 +m8 +m9 +m10 +m11 +m12 +m13 +m14 +m15
+m16 +m17 +m18 +m19 +m20 +m21 +m22 +m23 +m24 +m25 +m26=1;


output_shortfall1 = surplus1/j;

output_shortfall2 = surplus2/j;

@gin(output_shortfall1);

@gin(output_shortfall2);
```

Appendix C

Linear Program of the enhanced parallel NSBM DEA Model

The enhanced parallel NSBM DEA Model (4.8) is a fractional program. It can be transformed to the linear programming using the Charnes and Cooper transformation (Charnes & Cooper, 1962).

$$Let\,\frac{1}{j} = 1 + \frac{1}{S_2^{C^{(q)}}}\sum_{q=1}^{p}\left(\sum_{s_2^C=S_2^{C^{(q-1)}}+1}^{S_2^{C^{(q)}}}\frac{t_{s_2 C_O}^{(q)+}}{y_{s_2 C_O}^{(q)}}\right)$$

Therefore,

$$\min \tau_O = j - \frac{1}{R_2^{C^{(q)}}}\sum_{q=1}^{p}\left(\sum_{r_2^C=R_2^{C^{(q-1)}}+1}^{R_2^{C^{(q)}}}\frac{jt_{r_2 C_O}^{(q)-}}{x_{r_2 C_O}^{(q)}}\right) \qquad \text{(C3.1)}$$

Subject to

$$j + \frac{1}{S_2^{C^{(q)}}}\sum_{q=1}^{p}\left(\sum_{s_2^C=S_2^{C^{(q-1)}}+1}^{S_2^{C^{(q)}}}\frac{jt_{s_2 C_O}^{(q)+}}{y_{s_2 C_O}^{(q)}}\right) = 1$$

Teaching constraints:

$\sum_{k=1}^{K}\lambda_k^{(1)} x_{r_1{}^{NC}{}_k}^{(1)} = x_{r_1{}^{NC}{}_O}^{(1)} - t_{r_1{}^{NC}{}_O}^{(1)-}$, $\quad r_1^{NC} = R_1^{NC^{(0)}} + 1, \dots, R_1^{NC^{(1)}}$,

$\sum_{k=1}^{K}\lambda_k^{(1)} y_{s_1{}^{NC}{}_k}^{(1)} = y_{s_1{}^{U=NC}{}_O}^{(1)}$, $\quad s_1^{U=NC} = S_1^{U=NC^{(0)}} + 1, \dots, S_1^{NC^{(1)}}$,

Research constraints:

$\sum_{k=1}^{K} \lambda_k^{(2)} x_{r_1{}^{NC}k}^{(2)} = x_{r_1{}^{NC}o}^{(2)} - t_{r_1{}^{NC}o}^{(2)-}$, $\quad r_1^{NC} = R_1^{NC^{(1)}} + 1, \ldots, R_1^{NC^{(2)}}$,

$\sum_{k=1}^{K} \lambda_k^{(2)} y_{s_2{}^{C}k}^{(2)} = y_{s_2{}^{C}o}^{(2)} + t_{s_2{}^{C}o}^{(2)+}$, $\quad s_2^C = S_2^{C^{(1)}} + 1, \ldots, S_2^{C^{(2)}}$,

Community service constraints:

$\sum_{k=1}^{K} \lambda_k^{(3)} x_{r_1{}^{NC}k}^{(3)} = x_{r_1{}^{NC}o}^{(3)} - t_{r_1{}^{NC}o}^{(3)-}$, $\quad r_1^{NC} = R_1^{NC^{(2)}} + 1, \ldots, R_1^{NC^{(3)}}$,

$\sum_{k=1}^{K} \lambda_k^{(3)} y_{s_2{}^{C}k}^{(3)} = y_{s_2{}^{C}o}^{(3)} + t_{s_2{}^{C}o}^{(3)+}$, $\quad s_2^C = S_2^{C^{(2)}} + 1, \ldots, S_2^{C^{(3)}}$,

$\sum_{k=1}^{K} \lambda_k^{(q)} = 1$,

$\lambda_k^{(q)} \geq 0, \; k = 1, \ldots, K, q = 1, \ldots, p$

$y_{s_2{}^{C}o}^{(q)} \in Z_+^{S_2^{C\,(q)}}, \quad t_{s_2{}^{C}o}^{(q)+} \in Z_+^{S_2^{C\,(q)}}$

To transform fractional non-linear program (4.8) into linear program, we assume

$$\mathrm{j}t_{s_2{}^{C}o}^{(q)+} = \hat{t}_{s_2{}^{C}o}^{(q)+},$$

$$\mathrm{j}\lambda_k^{(q)} = \Lambda_k^{(q)}$$

Therefore,

$$\min \tau_O = \boldsymbol{j} - \frac{1}{R_2^{C(q)}} \sum_{q=1}^{p} \left(\sum_{r_2^C = R_2^{C(q-1)}+1}^{R_2^{C(q)}} \frac{\mathrm{j}t_{r_2{}^{C}o}^{(q)-}}{x_{r_2{}^{C}o}^{(q)}} \right) \text{(C3.2)}$$

Subject to

$$j + \frac{1}{S_2^{C(q)}} \sum_{q=1}^{p} \left(\sum_{s_2^C = S_2^{C(q-1)}+1}^{S_2^{C(q)}} \frac{\mathrm{j}t_{s_2{}^{C}o}^{(q)+}}{y_{s_2{}^{C}o}^{(q)}} \right) = 1$$

Teaching constraints:

$$\sum_{k=1}^{K} \lambda_k^{(1)} \Lambda_k^{(1)} = \mathrm{j}\, x_{r_2 c_{\mathrm{o}}}^{(1)} - \hat{t}_{\mathrm{r_2 c_o}}^{(1)-}, \quad r_2^C = R_2^{C^{(0)}} + 1, \ldots, R_2^{C^{(1)}},$$

$$\sum_{k=1}^{K} \lambda_k^{(1)} \Lambda_k^{(1)} = j y_{s_1{}^{NC}O}^{(1)}, \qquad s_1^{NC} = S_1^{NC^{(0)}} + 1, \ldots, S_1^{NC^{(1)}},$$

Research constraints:

$$\sum_{k=1}^{K} \lambda_k^{(2)} \Lambda_k^{(2)} = j x_{r_1{}^{NC}O}^{(2)}, \qquad r_1^{NC} = R_1^{NC^{(1)}} + 1, \ldots, R_1^{NC^{(2)}},$$

$$\sum_{k=1}^{K} \lambda_k^{(2)} \Lambda_k^{(2)} = j y_{s_2 c_{\mathrm{o}}}^{(2)} + \hat{t}_{\mathrm{s_2 c_o}}^{(2)+}, \quad s_2^C = S_2^{C^{(1)}} + 1, \ldots, S_2^{C^{(2)}},$$

Community service constraints:

$$\sum_{k=1}^{K} \lambda_k^{(3)} \Lambda_k^{(3)} = j x_{r_1{}^{NC}O}^{(3)}, \qquad r_1^{NC} = R_1^{NC^{(2)}} + 1, \ldots, R_1^{NC^{(3)}},$$

$$\sum_{k=1}^{K} \lambda_k^{(3)} \Lambda_k^{(3)} = j y_{s_2 c_{\mathrm{o}}}^{(3)} + \hat{t}_{\mathrm{s_2 c_o}}^{(3)+}, \quad s_2^C = S_2^{C^{(2)}} + 1, \ldots, S_2^{C^{(3)}},$$

$$y_{s_2 c_{\mathrm{o}}}^{(q)} \in Z_+^{S_2^C\,(q)}, \ \hat{t}_{\mathrm{s_2 c_o}}^{(q)+} \in Z_+^{S_2^C\,(q)}$$

The optimal solution to linear program (C3.2) is $\tau_O^*, j^{(q)*}, \ \hat{t}_{\mathrm{r_2 c_o}}^{(q)-*}$, $\hat{t}_{\mathrm{s_2 c_o}}^{(q)+*}, \Lambda_k^{(q)*}, j^{(q)*}$. We then have the optimal solution to model (4.8) defined by $E^{pNSBM*} = \tau_O^*, \ t_{r_2 c_{\mathrm{o}}}^{(q)-} = \hat{t}_{\mathrm{r_2 c_o}}^{(q)-*}/j$, $t_{s_2 c_{\mathrm{o}}}^{(q)+} = \hat{t}_{\mathrm{s_2 c_o}}^{(q)+*}/j, \lambda_k^{(q)*} = \Lambda_k^{(q)*}/j$. Note that all controllable integer input excesses-output shortfalls are restricted as integer values by Lingo software.