MODIFIED DIVERGENCE MEASURES BASED ON FUZZY MEREC AND TOPSIS FOR STAFF PERFORMANCE APPRAISAL

By

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Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfillment of the Requirements for the Degree of Doctor of Philosophy

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DEDICATIONS

To my respectful mother (Musalmah binti Mat Ladzim) who always had confidence in me.
To my beloved wife (Nurul Husna binti Anwar) for all her contribution, patience, and understanding throughout my Ph.D. studies. She supported me a lot and made it possible for me.
To my sons (Muhammad Al Amin and Umar Huzaifah) who enlivened my life during my Ph.D. studies. Their love has always been my greatest inspiration.
To my brothers and sisters.

And most importantly;
To Myself
A guy who works so hard to realise his dream as a Phd graduate.

Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfillment of the requirement for the degree of Doctor of Philosophy

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Chairman : **Professor Lee Lai Soon, PhD**
Faculty : **Science**

The aim of this study is to establish a divergence measure integrated with the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) approach for crisp evaluation that can overcome limitation of previous divergence measures, as well as to describe its properties. The proposed divergence measure has been enhanced by utilising fuzzy α-cut, in which experts can identify a wide range of rankings when their levels of confidence vary since uncertainty or ambiguity is an essential feature of multi-criteria decision-making (MCDM) cases. This study also provides a modified technique, the fuzzy MEthod based on the Removal Effects of Criteria (MEREC), by modifying the normalisation technique and enhancing the logarithm function used to assess the entire performance of alternatives in the weighting process. The comparative analyses are conducted through the case studies of staff performance appraisal at Universiti Putra Malaysia (UPM) and Universiti Malaysia Perlis (UniMAP) that consist of 6 and 13 sub-criteria, respectively. The simulation-based study is used to validate the effectiveness and stability of the proposed method. Regarding correlation coefficients and central processing unit (CPU) time, the findings of this study were compared to those of other MCDM methodologies. Based on the results, the proposed technique performed in a manner consistent with the current distance measure approaches since all of the values of the correlation coefficient were greater than 0.8. Besides, the proposed technique provides the advantage of being able to assess all potential score values of alternatives, including 0 and 1. Furthermore, the simulation-based study demonstrates that even in the presence of outliers in the collection of alternatives, fuzzy MEREC is able to offer consistent weights for the criterion. Since the criteria weights significantly affect the results of rankings, the sensitivity analysis is used to reveal how the rankings change due to the variation of criteria weights, which mainly explores the influence of single criterion weight changes. The correlation coefficient values between the original rankings and the rankings with decreasing and increasing criteria weights are presented. Based on the analysis, the most affecting criterion to the ranking of staff performance in each category has been identified. In addition, it has been identified that the proposed technique has the shortest CPU time when compared to the other divergence measurement methodologies. As a result, the proposed technique provides more sensible and practicable results than the others in its category.

Keywords: correlation coefficient; criteria weights; divergence measure; fuzzy α-cut; performance appraisal

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

PENGUBAHSUAIAN PENGUKURAN PENCAPAHAN BERDASARKAN MEREC KABUR DAN TOPSIS DALAM PENILAIAN PRESTASI STAF

Oleh

MOHAMAD SHAHIIR BIN SAIDIN

Disember 2023

Pengerusi : **Profesor Lee Lai Soon, PhD**
Fakulti : **Sains**

Matlamat kajian ini adalah untuk mewujudkan ukuran pencapahan yang disepadukan dengan pendekatan Teknik untuk Susunan Keutamaan oleh Kesetaraan dengan Penyelesaian Unggul (TOPSIS) untuk penilaian yang jelas yang boleh mengatasi batasan kaedah-kaedah pencapahan sebelumnya, serta untuk menerangkan sifat-sifatnya. Pengukuran pencapahan yang dicadangkan telah dipertingkatkan dengan menggunakan potongan α kabur, di mana pakar boleh mengenal pasti pelbagai kedudukan staf apabila tahap keyakinan mereka berbeza-beza kerana ketidakpastian atau kekaburan adalah ciri penting dalam membuat keputusan berbilang kriteria (MCDM). Kajian ini juga menyediakan teknik ubah suai iaitu kaedah kabur berdasarkan kesan penyingkiran kriteria (MEREC), dengan mengubah suai teknik normalisasi dan mempertingkatkan fungsi logaritma yang digunakan untuk menilai keseluruhan prestasi alternatif dalam proses pemberat. Analisis perbandingan telah dijalankan melalui kajian kes penilaian prestasi kakitangan di Universiti Putra Malaysia (UPM) dan Universiti Malaysia Perlis (UniMAP) yang masing-masing terdiri daripada 6 dan 13 sub-kriteria. Ka-

jian berasaskan simulasi digunakan untuk mengesahkan keberkesanan dan kestabilan kaedah yang dicadangkan. Berhubung pekali korelasi dan masa unit pemprosesan pusat (CPU), dapatan kajian ini dibandingkan dengan metodologi MCDM yang lain. Mengikut keputusan, teknik yang dicadangkan menghasilkan dapatan kajian yang konsisten dengan pendekatan ukuran jarak semasa kerana semua nilai pekali korelasi adalah lebih besar daripada 0.8. Selain itu, teknik yang dicadangkan memberikan kelebihan untuk dapat menilai semua nilai skor potensi alternatif, termasuk 0 dan 1. Tambahan pula, kajian berasaskan simulasi menunjukkan bahawa walaupun dengan kehadiran unsur luaran dalam koleksi alternatif, MEREC kabur mampu menawarkan pemberat yang konsisten untuk kriteria tersebut. Memandangkan wajaran kriteria memberi kesan ketara kepada keputusan kedudukan staf, analisis kepekaan digunakan untuk mendedahkan bagaimana kedudukan staf berubah disebabkan oleh variasi wajaran kriteria, yang khususnya mengkaji pengaruh perubahan berat kriteria tunggal. Nilai pekali korelasi antara kedudukan staf asal dan kedudukan staf dengan pemberat kriteria yang menurun dan meningkat dibentangkan. Berdasarkan analisis, kriteria yang paling mempengaruhi kedudukan prestasi staf bagi setiap kategori telah dikenal pasti. Di samping itu, telah dikenal pasti bahawa teknik yang dicadangkan mempunyai masa CPU yang paling singkat jika dibandingkan dengan metodologi pengukuran pencapahan yang lain. Hasilnya, teknik yang dicadangkan memberikan hasil yang lebih masuk akal dan boleh dipraktikkan daripada yang lain dalam kategorinya.

Kata Kunci: pekali korelasi; penilaian prestasi; potongan α kabur; ukuran pencapahan; wajaran kriteria

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In preparing this thesis, I share the credit for my work with my beloved family, as they have always given me the strength and support to finish this project. I wish to acknowledge the help and assistance received from my friends, who always provide helpful suggestions in the course of the project. I am also indebted to the Microsoft Visual Studio 2020 team, which has developed useful computer programming software that enables me to build my own programmings. May Allah bless all of you.

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LIST OF ABBREVIATIONS

AHP	Analytic Hierarchy Process
CPU	Central Processing Unit
CRITIC	Criteria Importance Through Inter-Criteria Correlation
ELECTRE	Elimination And Choice Expressing Reality
FJED	Fuzzy Jenson-Exponential Divergence
FSs	Fuzzy Sets
GMIR	Graded Mean Integration Representation
IF-ISF	Intuitionistic Fuzzy Improved Score Function
IFN	Intuitionistic Fuzzy Negation
IFSs	Intuitionistic Fuzzy Sets
KPI	Key Performance Indicator
K-L Divergence	Kullback-Leibler Divergence
MEREC	MEthod based on the Removal Effects of Criteria
MADM	Multi-Attribute Decision-Making
MCDM	Multi-Criteria Decision-Making
VIKOR	Multi-Criteria Optimisation And Compromise Solution
MODM	Multi-Objective Decision-Making
MCDA	Multiple Criteria Decision Analysis
NIS	Negative Ideal Solution
PIFDM	Parametric Intuitionistic Fuzzy Divergence Measure
PSNR	Peak Signal-To-Noise Ratio

PIS	Positive Ideal Solution
PROMETHEE	Preference Ranking Organisation Method For Enrichment Evaluation
PFSs	Pythagorean Fuzzy Sets
SKT	Annual Performance Target
SMART	Simple Multi-Attribute Ranking Technique
SECA	Simultaneous Evaluation Of Criteria And Alternatives
TFN	Triangular Fuzzy Number
TOPSIS	Technique For Order Preference By Similarity To An Ideal Solution
TODIM	Tomada De Decisao Interativa Multicriterio
UniMAP	Universiti Malaysia Perlis
UPM	Universiti Putra Malaysia
WDBA	Weighted Distance Based Approximation

CHAPTER 1

INTRODUCTION

1.1 Overview

All firms and organisations must have effective management and planning in order to be successful. It is well acknowledged that most businesses require good administration in their human resources division in order to grow to a higher level. Some features of successful human resource administration include the ability to qualify and quantify employees' goals or performance (Andrés et al., 2010). They would like to fully utilise employees effectively and productively for the advantage of the organisation (Burma, 2014).

Staff performance evaluation is crucial to the organisation since it is frequently regarded as an indicator of the quality of human resource management in a organisation (Aggarwal and Thakur, 2013). Job assignments, competencies, and the key performance indicator (KPI) have to be emphasised during the performance review process in order to attain the objectives and goals (Drumea, 2014). In this way, leaders can determine their employees' performance by employing a decision-making approach that can forecast their companies' future development. The approaches that will be utilised to address the performance evaluation problem must take into account the problem's aims and objectives to allow the final results to be valid for analysis.

1.2 Background of the Study

Performance evaluation is a crucial aspect of human resource management in both the private and public sectors. Due to globalisation and international competition, it has recently become an issue for both researchers and practitioners (Aksoy et al., 2010). It is also conceived as a system for determining whether an organisation is operating effectively and in accordance with its vision. In general, methods for evaluating employee performance can be classified as qualitative or quantitative evaluations (Wu et al., 2012). Organisations should develop a performance evaluation system capable of evaluating staff performance accurately and fairly in order to channel staff abilities and efforts towards organisational goals. Without an effective performance evaluation system, managers risk making bad hiring decisions and jeopardising the organization's capabilities . As a result, outstanding employees may not receive a positive response, become dissatisfied, and leave, causing the organisation to incur excessive hiring costs (Mani, 2002). A performance evaluation is a formal assessment undertaken by managers to examine the work and performance of employees over the course of a year. It involves analysing the strengths and shortcomings of the individual, providing comments, and setting goals for future performance evaluations. While the purpose of the performance evaluation is primarily to assess strengths and shortcomings and establish objectives for the upcoming period, performance appraisals primarily evaluate the actual performance of the employee during the previous year.

Previous research has demonstrated that performance appraisal is crucial for the staff in terms of self-definition, short- and long-term goal setting, and higher performance (Mowday et al., 1974; Hausdorff, 1991). It also has a high potential to enhance the organisation's operations (Gilliland and Langdon, 1998). Anisseh et al. (2009) stated that performance evaluations can provide information for decisions regarding salary and promotion, identification of development requirements and training, and verification of selection systems that may warrant termination or sanctions. As with other decision-making problems, performance evaluation is extremely complex due to the fact that it is difficult for humans to make accurate quantitative judgements, whereas they are able to make accurate qualitative forecasts. A fuzzy linguistic model is used to solve this problem because it can convert verbal expressions into numerical ones (Patel et al., 2019). Implementing a performance evaluation effectively and equitably necessitates the use of a suitable decision-making process. Decision-making is the methodical process of analysing and selecting alternatives based on specific criteria, which is carried out by a group of experts or decision-makers (Afsordegan et al., 2016).

In operations research, multi-criteria decision-making (MCDM) is described as a systematic way to make selections with several criteria or considerations. Many elements affect the result of practical decisions; therefore, one criterion cannot be used (Kumar et al., 2017). MCDM approaches allow people or organisations to assess selections and rank them according to their performance over numerous criteria simultaneously (Ertugrul Karsak, 2001). Numerous researchers propose MCDM methods to assist decision makers in analysing and developing complex decision models (Triantaphyllou, 2000). Most commonly utilised methods include the Analytic Hierarchy Process (AHP) (Irfan et al., 2022), linear programming (Rabe et al., 2022), the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) (Wang et al., 2022), the Preference Ranking Organisation Method for Enrichment Evaluation (PROMETHEE) (Feng et al., 2020), and Elimination and Choice Expressing Reality (ELECTRE) (Zahid et al., 2022). The TOPSIS method was developed by Hwang and Yoon (1981) and is a well-known MCDM method due to its concern for positive and negative ideal solutions and its fundamental programming process. Recently, a number of researchers have utilised the traditional TOPSIS method in a variety of ambiguous environments. Kumari et al. (2021) presented the Shapley-TOPSIS method with intuitionistic fuzzy sets (IFSs) to select the most suitable solution for the cloud service problem. Wang and Liao (2023) have employed fuzzy TOPSIS for reverse logistics performance measurement.

In the study of this thesis, one of the distance measures that is applied with the TOPSIS method is the divergence measure. It is often called a distance metric and defined as a mathematical function used in statistics and information theory to assess the degree to which two data sets or probability distributions differ from one another (Cha, 2007). Shannon (1948) introduce the divergence measure and define it as measuring discriminatory information. Later, researchers presented numerous entropy measures and thoroughly discussed their properties and applications (Rényi, 1961; Kailath, 1967; Hexter and Snow, 1970). Montes et al. (2002) introduced an axiomatic definition of divergence measure in a fuzzy environment and computed discrimination for fuzzy sets. In other words, divergence measures define dissimilarity and describe several intriguing axioms for approximating the discrimination between fuzzy sets (FSs). Divergence measures give a tool to analyse and quantify the differences across distributions or data sets, making them useful in numerous fields such as information theory, machine learning, and statistics (Verma and Maheshwari, 2017). Recently, Parkash and Kumar (2017) presented a modified fuzzy divergence measure to eliminate the disadvantages of previously published divergence measures, along with a discussion of its detailed properties. Following this, Joshi and Kumar (2019) presented a divergence measure based on the well-known Shannon entropy concept. In addition, a number of properties of the proposed divergence measure are discussed. Then, Rani et al. (2020a) proposed a method based on divergence measures for FSs for evaluating MCDM problems in a fuzzy environment. Rani et al. (2020b) proposed a fuzzy TOPSIS method with a divergence measure to address decision-making issues after a brief period.

There are typically four stages to the evaluation process when using MCDM approaches: (i) determining the relevant alternatives and criteria, (ii) assigning relative importance to each criterion, (iii) evaluating the alternatives' competence to meet the criteria function, and (iv) scoring the alternatives based on how well they perform across all criteria (Alfares and Duffuaa, 2016). Since the majority of researchers employ criterion weight in resolving MCDM problems, the second step of the decision-making process is undeniably essential. The potential strength of the solution can be understood more clearly if the decision-makers provide the relative significance of criteria based on various perspectives. Every aspect are unlikely to have the same amount of importance, however weighing them might be helpful in difficult judgements and is not required for the other selection methods (Baker et al., 2001). These methods may be categorised into three different categories: subjective, objective, and integrated weighing procedures. Recently, a novel objective weighting method known as MEREC (MEthod based on the Removal Effects of Criteria) was proposed in a study (Keshavarz-Ghorabaee et al., 2021). In order to calculate the weights, this procedure uses variations in the performance of each alternative for each criterion. The criterion with the most variants receives a greater weighting (Zardari et al., 2015). For calculating criteria weights, the method evaluated how removing each criterion would impact the aggregate performance of the alternatives. When the elimination of a criterion has a significant impact on the entire performance of the alternatives, that criterion is given more weight.

Numerous researchers have utilised fuzzy set theory to solve decision-making issues. This theory enables researchers to enhance human coherence when adapting with unquantifiable, deficient, and unobtainable information (El-Hossainy, 2011). Therefore, it is indisputable that they employ this method in their decision-making process. The fundamental fuzzy set theories are defined below.

Definition 1.1 *(Zadeh, 1975). Let $Z = \{z_1, z_2, ..., z_n\}$ be a finite universe of discourse and let $H \subset Z$. Then H is fuzzy set defined as:*

$$H = \{(z_i, \nu_H(z_i)) : \nu_H(z_i) \in [0,1]; \forall z_i \in Z\}, \tag{1.1}$$

where $\nu_H : Z \to [0,1]$ is membership function of H. The value $\nu_H(z_i)$ exhibits membership degree of $z_i \in Z$ to H.

Definition 1.2 *(Zadeh, 1975; Awasthi et al., 2011). A triplet (m_1, m_2, m_3) depicted in Figure 1.1 can be used to define a triangular fuzzy number, $\tilde{m}$. The definition of the* *membership function $\nu_{\tilde{m}}(z)$ is:*

$$\nu_{\tilde{m}}(z) = \begin{cases} 0 & \text{if } z < m_1, \\ \dfrac{z - m_1}{m_2 - m_1} & \text{if } m_1 \leq z < m_2, \\ \dfrac{m_3 - z}{m_3 - m_2} & \text{if } m_2 \leq z \leq m_3, \\ 0 & \text{if } z > m_3. \end{cases} \tag{1.2}$$

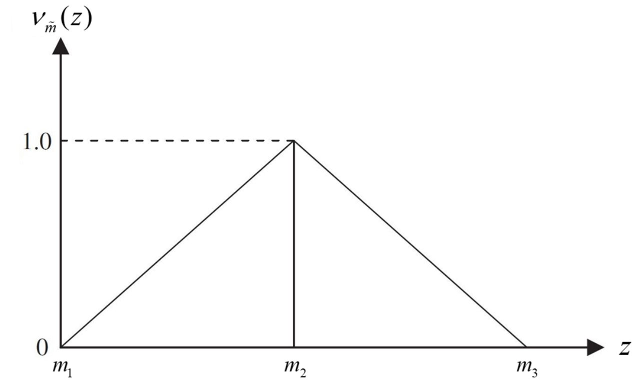

Figure 1.1: A triangular fuzzy number $\tilde{m}$.

Definition 1.3 *(Nagoor Gani and Mohamed Assarudeen, 2012). When k is a positive real number, the definitions that follow are applicable to the arithmetic operations of triangular fuzzy number, $\tilde{\Xi} = (\xi_1, \xi_2, \xi_3)$ and $\tilde{H} = (\eta_1, \eta_2, \eta_3)$:*

1. *Addition:* $\tilde{\Xi}(+)\tilde{H} = (\xi_1 + \eta_1, \xi_2 + \eta_2, \xi_3 + \eta_3)$.

2. *Subtraction:* $\tilde{\Xi}(-)\tilde{H} = (\xi_1 - \eta_3, \xi_2 - \eta_2, \xi_3 - \eta_1)$.

3. *Multiplication:* $\tilde{\Xi}(\times)\tilde{H} = (\min(\xi_1\eta_1, \xi_1\eta_3, \xi_3\eta_1, \xi_3\eta_3), \xi_2\eta_2, \max(\xi_1\eta_1, \xi_1\eta_3, \xi_3\eta_1, \xi_3\eta_3))$,

   $c(\times)\xi = (c \times \xi_1, c \times \xi_2, c \times \xi_3)$.

4. *Division:* $\tilde{\Xi}(\div)\tilde{H} = \left(\min\left(\frac{\xi_1}{\eta_1}, \frac{\xi_1}{\eta_3}, \frac{\xi_3}{\eta_1}, \frac{\xi_3}{\eta_3}\right), \frac{\xi_2}{\eta_2}, \max\left(\frac{\xi_1}{\eta_1}, \frac{\xi_1}{\eta_3}, \frac{\xi_3}{\eta_1}, \frac{\xi_3}{\eta_3}\right)\right)$.

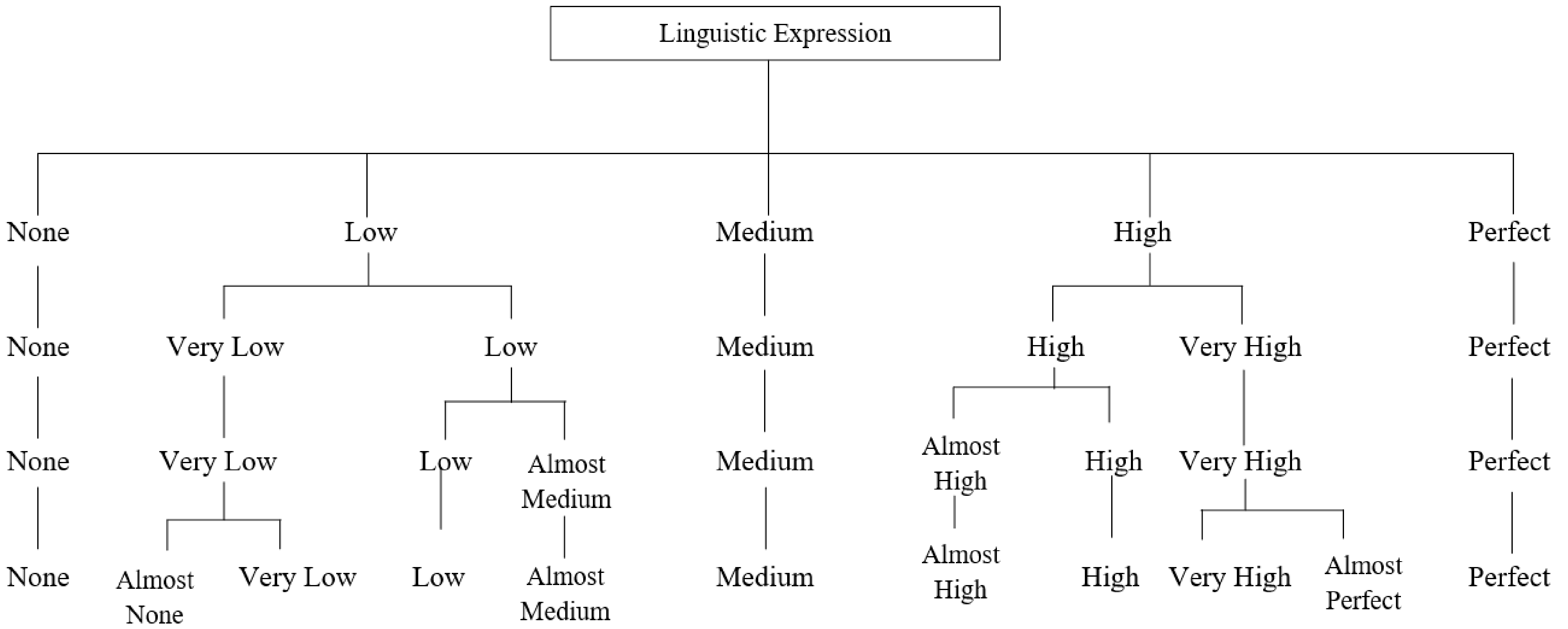

Figure 1.2: Expression domain in the form of a hierarchy (Herrera et al., 2000)**.**

The primary objective of setting linguistic classifications is to assist decision-makers with some phrases by which they may describe their thoughts naturally. In order to accomplish this goal, it is crucial to analyse the granularity of uncertainty, including the degree of discrimination between the various aspects of uncertainty and the characteristics of the linguistic phrase used when expressing the information (Herrera and Herrera-Viedma, 2000). Figure 1.2 depicts examples of various elements of uncertainty that decision-makers may employ.

It is not necessary for the constructed phrase to be infinite, but it must be readily comprehensible. Complex phrases that might be difficult for decision makers to comprehend should therefore be prevented. The linguistic attribute can be identified by the variable x in the set $A(x)$ whose value is an fuzzy number defined on X. As an example of the application of linguistic terms in real-life scenarios, consider a teacher who wishes to ascertain the weight of his or her students. Given that *weight* is the linguistic variable, the term set $A(weight) = \{light, medium, heavy\}$ corresponds to a fuzzy number defined on $X = [0, 100]$ for each term. The teacher then has to apply these terminology to estimate each student's weight in the class.

1.3 Problem Statement

When there are numerous criteria or objectives to attain, the decision-making procedure can be complex and challenging. Therefore, the decision must be made with caution, using the appropriate framework and a group of decision-makers. Using MCDM methods is one of the appropriate ways to solve this issue. Recently, many researchers have presented divergence measures for MCDM problems. Nevertheless, some of the preceding divergence measures have the limitation that they can only be used after the defuzzification procedure has been concluded. If the defuzzification procedure is disregarded, divergence measures cannot evaluate the value in the fuzzy interval when the value is either 0 or 1.

Besides, a novel objective weighting method known as MEREC (MEthod based on the Removal Effects of Criteria) was proposed in a study to determine the weights of criteria (Keshavarz-Ghorabaee et al., 2021). Nonetheless, this method is limited to a precise evaluation in which the data in the decision matrix are numerical values. Since the evaluation process is conducted in a variety of situations where it is difficult to precisely assess scores and weights, it is always difficult for decision-makers to evaluate alternatives. Additionally, decision-makers have a tendency to make accurate qualitative predictions but have trouble with quantitative problem-solving. The utilised logarithmic function is more complicated than essential, which increases the time required to complete the evaluation and necessitates a revision.

1.4 Research Questions

Based on the problems described in the previous section, some research questions can be identified as follows:

1. How could the concept of divergence measure be used to solve a decision-making problem where the data is composed of 0 and 1?
2. What is an approach for solving a decision-making problem without employing the defuzzification process and simultaneously facilitating the assessment by

experts?

3. How to improve the existing objective weighting method, which is the MEREC method, in terms of its complexity, CPU time, and integration of fuzzy concepts?

4. When the relative importance of the criterion is changed, how does that affect the outcomes of the alternative rankings?

1.5 Research Objectives

In this study, the aim of the research is to propose a general algorithm to solve multi-criteria decision making model for staff performance appraisal under fuzzy environment. The specific objectives to be achieved are as follows:

1. to propose a new divergence measure in the TOPSIS method for solving staff performance problems that can assess any potential score value of alternatives to resolve the issues with the current measures.

2. to improve the proposed method by using the fuzzy α-cut method in the performance evaluation process in which experts recognise the variety of rankings as their confidence level shifts.

3. to develop the method of evaluating the criteria weights based on fuzzy MEREC concerning the objective weight by modifying the normalisation method and introducing an improved logarithm function.

4. to identify the dependency of criteria weights on the staff performance by using sensitivity analysis to reveal how the rankings change due to the variation of criteria weights.

1.6 Scope of Study

The study is conducted using a new divergence measure based on the fuzzy TOPSIS method that incorporates the weights of the main and subcriteria. The proposed divergence measure is also improved by using the fuzzy α-cut method in the performance evaluation process. The method of evaluating the criteria weights is developed by using fuzzy MEREC concerning the objective weight by modifying the normalisation method and introducing an improved logarithm function. The proposed methods are validated using assessment reports based on the annual performance target (SKT) of academic staff at Universiti Putra Malaysia (UPM) and Universiti Malaysia Perlis (UniMAP).

1.7 Significance of the Study

This study refines and enhances the methods previously used by proposing a new divergence measure in the TOPSIS method for solving staff performance evaluation. Due to their varied backgrounds and attitudes, it is understood that the staff performance score could be any number, including 0 and 1. In the past, some researchers have presented divergence measures to solve a variety of decision-making problems. Nevertheless, the divergence measures fail to address the issue when the performance score is valued at 0 or 1. Hence, the proposed divergence measure can evaluate any conceivable score value of staff performance, thereby overcoming the deficiency of the current measures and eradicating anomalous results.

Next, this study also improves the proposed method by using the fuzzy α-cut method in the performance evaluation process. It is well known that the majority of MCDM issues pertain to the ranking procedure, which is performed by experts. Since the evaluation process is influenced by human judgement, which always deals with subjectivity, a fuzzy approach can facilitate the selection by the experts in which they can perform the evaluation based on the linguistic variables provided. In this case, the fuzzy α-cut method enables the experts to recognise the ranking variations as their confidence level shifts when making assessments. Their level of confidence reflects how well they understand the credentials and expertise of prospective alternatives based on the information presented. It is anticipated that the proposed solution for this issue will lessen the burden placed on the experts during the alternative selection process.

Furthermore, this study develops the method of evaluating the criteria weights concerning the objective weight. Since it is well-known that assessments are made by humans who are tend to be biassed due to their varied experiences and perspectives, a mathematical approach is required to reduce human preference. The determination of objective weights applied the enhanced mathematical method, which is fuzzy MEREC. The measured weights are not subject to the arbitrary decisions of experts, who occasionally make mistakes or dishonestly assign grades. This method enhances previous algorithms by modifying the normalisation method and introducing an improved logarithm function for evaluating the overall performance of alternatives. As a results, the proposed method can decrease the central processing unit (CPU) time of performing the evaluation process when involving large data. Besides, it is claimed that the criteria weights obtained by the fuzzy MEREC are the least affected by the outliers existence, then the fuzzy MEREC is the most effective method of all those that were compared. In other words, the criteria weights for the fuzzy MEREC method are consistent when there are outliers in the set of data. Hence, the fuzzy MEREC method can be the preferred method when dealing with the objective weight of criteria in various MCDM problems.

1.8 Organisation of Thesis

There are six main chapters in this thesis. The first chapter provides an overview and concise introduction to both performance evaluation and MCDM methods. In addition to identifying the problem and proposing a solution, the first chapter identifies the problem that has arisen. In addition, this chapter discusses the objectives, scope, and significance of the research.

In Chapter 2, the literature review describes previous studies pertaining to the performance appraisal procedure. In addition, detailed descriptions of the decision-making process and MCDM methodologies are provided. This research focuses primarily on the divergence measure method incorporated with TOPSIS method, which is one of the MCDM methods discussed in detail. A detailed scope is also provided for the other elements involved in the decision-making procedure.

Chapter 3 expands on the new method, which is a new divergence measure method based on the TOPSIS method for solving staff performance evaluation. Comprehensive descriptions of the decision-making process and the derivation of the generalised divergence measure, as well as its properties, are provided in this chapter for the decision-making problem. Computational studies for staff performance appraisal at UPM and UniMAP are presented to verify the efficiency of the proposed method. The results of the proposed method are then compared with those of other methods that employ crisp assessment.

Chapter 4 improves the proposed method by using the fuzzy α-cut method in the performance evaluation process. The derivation of the fuzzy $alpha$-cut method for the generalised divergence measure that is integrated with the TOPSIS method is presented in this chapter. In order to confirm the effectiveness of the proposed approach, the computational studies for staff performance evaluation at UPM and UniMAP are also given. The outcomes of the proposed method are then compared with those of different fuzzy assessment methods.

Chapter 5 develops the method of evaluating the criteria weights based on fuzzy MEREC concerning the objective weight. This approach improves on previous methods by changing the normalisation procedure and introducing a logarithmic function for evaluating alternatives. The fuzzy MEREC logarithm function is formulated in this chapter. The computational studies include comparative case studies at UPM and UniMAP and simulation-based analyses to verify the proposed method's efficiency. This chapter also employs sensitivity analysis to discover the reliance of criteria weights on staff performance. Criterion weights significantly affect ranking outcomes; hence, weight value variations should be studied. The analysis, which focuses on the impact of single criterion weight adjustments, is utilised in this study to show how the rankings vary as a result of the variation in criteria weights.

The last chapter provides the conclusion of the thesis. This chapter also recommends several potential directions for future study that might be further developed, either in a theoretical or practical manner.

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