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Analyzing the Ranking Order of the Requirements of an Information System Using Spearman's Rank Correlation Coefficient

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Various multi-criteria decision making (MCDM) methods have been developed to solve different problems in which the objective is to choose the best alternative from the set of alternatives. Among various MCDM methods, "analytic hierarchy process" (AHP) and "technique for order of preference by similarity to ideal solution" (TOPSIS) have been widely used for the solution of software requirements selection problem. The objective of this paper is to analyze the deviations in the ranking order produced by fuzzy AHP and fuzzy TOPSIS methods by considering the requirements of an institute examination system. In this paper, the Spearman's rank correlation coefficient is computed to identify the deviation in the ranking order between fuzzy AHP and fuzzy TOPSIS methods.
Keywords: Multi-criteria decision making, Software requirements, AHP, TOPSIS, and Fuzzy Logic.

1. Introduction

Over the last several decades, "multi-criteria decision making" (MCDM) methods have seen many applications in Science, Engineering, and Management. In literature, various MCDM methods have been developed to solve software requirements selection problem using "Analytic Hierarchy Process" (AHP) and "Technique for Order Preference by Similarity to Ideal Solution" (TOPSIS). In literature, following MCDM methods have been used to solve various problems like facility location selection problem, supplier selection problem, etc. (a) multi-attribute utility theory (b) Case-based reasoning, (c) Data Envelopment analysis, (d) Simple Multi-attribute rating technique, (e) goal-programming, (f) ELECTRE, and (g) PROMETHEE [1]. There are various selection problems which have been solved by MCDM methods. For example, selection of SRs is a MCDM problem because different criteria are involved in the during the selection process [2, 3]. In the field of software engineering, the NFRs are considered as criteria and FRs are refereed to as the alternatives. Fig. 1 presents a framework for the selection of SRs which includes the following steps: (a) problem definition, (b) SRs elicitation, (c) SRs evaluation by decision makers, and (d) SRs selection based on ranking order.

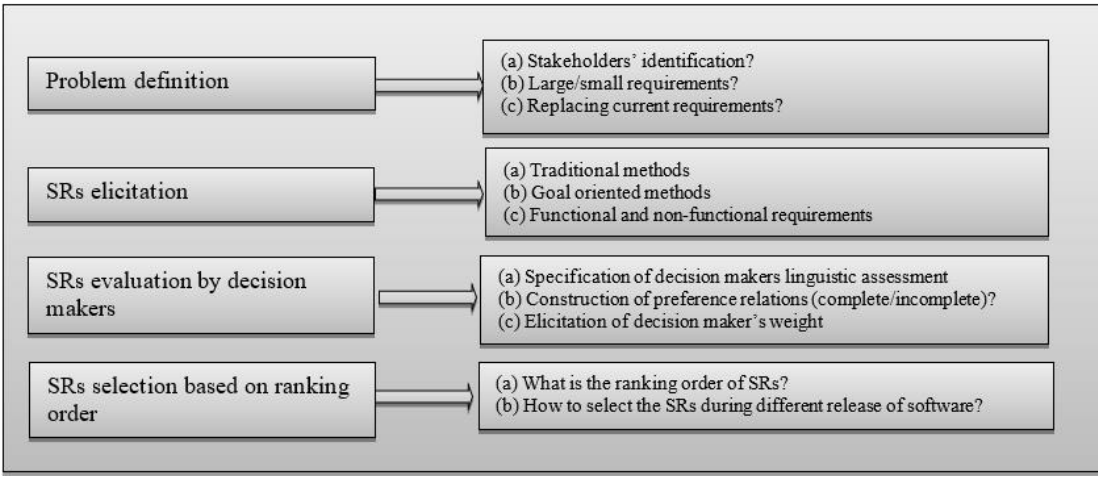

Fig. 1: The SRs selection framework [3]

The aim of the first step of SRs selection framework is to understand the problem which includes the elicitation of stakeholders, selecting FRs from the small and large set of requirements, or replacement of the requirements from the existing pool of requirements for the development of new software product. In the next step, SRs are identified based on the need of the stakeholders. Elicitation of the SRs is one of the key activities to understand the intentions and wishes of stakeholders; and different methods are used to elicit the requirements like traditional methods, goal-oriented methods, etc. The aim of this step is to identify the FRs and NFRs of software depending on the need of stakeholders [3].

Management science is the problem-solving process in which models are developed for providing guidance to the decision makers of an organization. It helps in developing the roadmaps for achieving goals of an organization and guides how resources can be used more effectively. In other words, management science can be defined as the study of problem solving and decision-making process in an organization. Research in the field of management science includes the following sub-areas like supply chain management (SCM), operations, information technology and systems, marketing, human resource management, economics, finance, strategy, and sustainability management. Among these research areas, we shall focus on SCM because it integrates operative functions of an organization for creating the general plan for satisfying the organization's service policy by maintaining the lowest possible cost in which organization operates [4]. In SCM, supply chain is a complex network which includes the following stages for producing and delivering a final product or service to the clients, i.e., order processing, purchasing, inventory control, manufacturing, and distribution. The conceptual framework for SCM is exhibited in Fig. 2. Dashed lines in Fig 1 indicates that few manufacturing companies can sell their products directly to the customers. The key stakeholders of a supply chain consist of customers, manufacturers, and suppliers. Among these stakeholders, suppliers' selection is the most important activity of purchasing department of an organization because it helps in reducing the unit price of an item and improves corporate price competitiveness [5]. A brief discussion on supplier selection problem is discussed below:

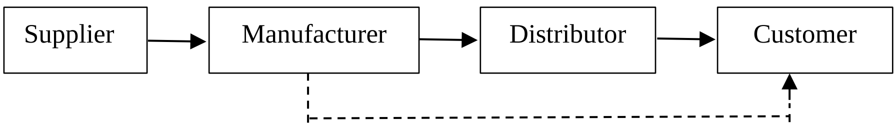

Fig. 2: The conceptual framework for SCM

Supplier selection based on various criteria creates a MCDM whose objective is to select the best supplier based on different criteria like price offered, part quality, on time delivery, supplier location, etc. Supplier selection problem is categorized into two parts, i.e., single source and multiple source [6]. Single source problems assumes that each supplier can satisfy all the requirements of the buyers in terms of demand, quality, and delivery. In this case, the aim of management of buyer is to make only one decision, i.e., which is the best supplier? On the other hand, the multiple sourcing problem assumes that there are some limitations in the suppliers' capabilities to satisfy the needs of the buyer in terms of the same factors, i.e., demand, quality, and delivery. Under this condition, the buyers look for more than one supplier who can satisfy their needs. Thus, the multiple sourcing problems focuses on two issues, i.e., (a) which suppliers should be used? (b) what is the order quantity of a part allocated to each of the selected suppliers? Various methods have been developed for the selection of supplier by using different techniques which are broadly classified into MCDM, mathematical programming techniques, and artificial intelligence (AI) techniques, see Table 1.

Table 1: Techniques used to solve supplier selection problem

S. No.	Techniques	Methods
1.	MCDM Techniques	Analytic Hierarchy Process (AHP)
		Analytic Network Process (ANP)
		Elimination and choice expression reality (ELECTRE)
		Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE)
		Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)
		VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), i.e., Multicriteria Optimization and Compromise Solution
		Decision Making Trail and Evolution Laboratory (DEMATEL)
		Simple Multi-Attribute Rating Technique (SMART)
2.		Data Envelopment Analysis (DEA)
		Linear Programming (LP)

	Mathematical Programming Techniques	Non-Linear Programming (NLP)
		Multi-Objective Programming (MOP)
		Goal Programming (GP)
		Stochastic Programming (SP)
3.	AI Techniques	Genetic Algorithm (GA)
		Grey System Theory (GST)
		Neural Network (NN)
		Rough-Set Theory (RST)
		Bayesian Network (BN)
		Decision Tree (DT)
		Case-Based Reasoning (CBR)
		Particle Swarm Optimization (PSO)
		Support Vector Machine (SVM)
		Associate Rule Mining (ARM)
		Ant Colony Algorithm (ACA)
		Dempster-Shafer Theory of Evidence (DSTE)

The aim of facility location selection problem is to choose the right location for the manufacturing facility which should have sufficient access to customers, workers, and transportation. Facility location selection is a business-critical strategic decision. There are several factors, which determines the location of facility based on various criteria. Facility location selection is a MCDM method in which best location is selected based on various criteria. Various methods have been developed for the selection of facility location. Facility location selection is the determination of a geographic site for a firm’s operations. The facility location decision involves organizations seeking to locate, relocate or expand their operations. The facility location decision process encompasses the identification, analysis, evaluation and selection among alternatives. Selecting a plant location is a very important decision for firms because they are costly and difficult to reverse, and they entail a long-term commitment. For example, Ertugrul and Karakasoglu [7] compared both AHP and TOPSIS method for the selection of best location. In their work, the authors have considered three alternatives, i.e., Alternative1, Alternative2, and Alternative3, and five criteria, i.e., (a) Favourable labour climate, Proximity to markets, Community considerations, Quality of life, Proximity to suppliers. The hierarchical structure of the problem is shown in Fig. 3.

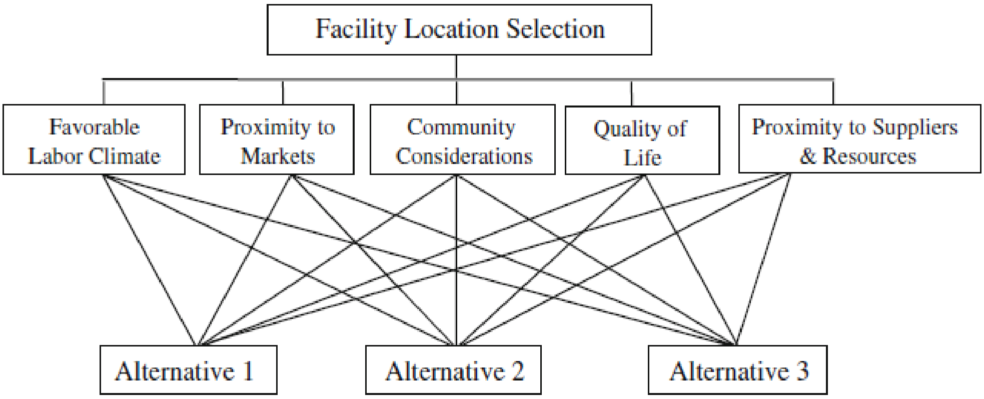

Fig. 3: Hierarchical structure of facility location selection [7]

In this study, we focused only on SRs selection problem. Based on our analysis, we found that only few MCDM methods have been employed to solve the SRs selection problem, i.e., AHP and TOPSIS. Therefore, it motivates us to analyze these two MCDM methods using Spearman's rank correlation coefficient. The contributions of our work are as follows:

1. The AHP and TOPSIS methods under fuzzy environment are analyzed using Spearman's rank correlation coefficient

2. The ranking order of the requirements of an institute examination system is calculated using fuzzy AHP and TOPSIS methods

The remaining part of this paper is structured as follows: Section 2 presents discussion on various MCDM methods which have been used to choose the best alternatives in the domain of supplier selection problem, requirements selection problem, facility location selection problem. The implementation art of our work is discussed in Section 3. Finally, the conclusion and future work are discussed in Section 4.

2. Related Work

The aim of this section is to discuss MCDM methods which have been used to compute the ranking value of the alternatives in various problem like software requirements selection problem, supplier selection problem, and facility location selection problem. Multi-Attribute Utility Theory (MAUT) is the most used MCDM method which is an extension of Multi-Attribute Value Theory (MAVT). The MAUT is a systematic methodology which focuses on "how to incorporate risk preferences" and uncertainties into MCDM methods. MAUT has been used in analyzing the risk preference in various applications. For example, Ananda and Herath [8] analyze the risk preference using MAUT in the context of forest land use in Australia. To deal with the limitations of various MCDM methods, researchers have also proposed integrated methods by combining two or more methods. For example, Konidari and Mavrakis [9] developed an integrated method for evaluating the climate change mitigation policy instruments.

The Analytic Hierarchy Process (AHP) is a widely used multi-criteria decision-making technique that uses pairwise comparison to systematically establish the weights of criteria and priorities of alternatives. Fuzzy sets have been integrated with AHP because subjective evaluations made during comparison may be inaccurate. Fuzzy AHP or FAHP is the term for this. A large number of papers have been published in the area of fuzzy AHP. Liu et al. [10] reviewed the literature of fuzzy AHP with main emphasis on subjective judgements [10].

Lai [11] examined both AHP and MAUT based on their similarities. He proved a theorem that two multi-attribute decision making techniques resulted in a consistent preference structure. The authors also provided scaling technique that was designed to incorporate both MAUT and AHP into a common logic. Both AHP and MAUT have followed the similar path in MCDM domain. The Analytic Network Process (ANP) is an extension of AHP. ANP is the general form of AHP and it is non-linear in representation as opposed to AHP, which is hierarchical and linear in representation in which goals are at the top (root node) and alternative at the lower levels (children). AHP has been combined with "Decision Making Trial and Evaluation Laboratory" (DEMTEL) technique. Wang and Tzeng [12] combined both ANP and DEMTEL technique to develop a framework of decision making to international trade practices in Taiwan. Due to certain shortcoming of AHP, ANP has been widely used in literature for developing hybrid methods with other MCDM methods. AHP is a theory of measurement in which priority scales are derived by experts based on pairwise comparisons among alternatives and criteria. There are different advantages of AHP and it is given below: (a) It is easy to use (ii) pairwise comparisons can allow the decision makers to weight coefficients and compare alternatives, (iii) it is scalable. The limitations of AHP includes the following: (a) it faces the problem of interdependence between criteria and alternatives (b) AHP is susceptible to rank reversal, etc. ANP is the general form of AHP and it focuses on network structure. ANP advantage is that it allows for dependence and include independence. It can prioritize / groups of elements. ANP can handle interdependence than AHP and can support a complex, networked decision making with various intangible criteria. ANP is often utilized in project selection, product planning, green supplying chain management, and optimal scheduling problems. [12]. Using triangular fuzzy numbers for the pairwise comparison scale of fuzzy AHP and the extent analysis method for the synthetic extent value Si of the pairwise comparison, Chang [13] developed a novel method for managing fuzzy AHP. The vectors of weight with respect to each element under a specific criterion are represented by $d(A_i) = \min V(S_i \geqslant S_k)$, $k = 1, 2, \ldots, n$; $k \neq i$, by using the fuzzy number comparison principle, which states that $V(M_1 \geqslant M_2) = 1$ iff $m_1 \geqslant m_2$, $V(M_2 \geqslant M_1) = hgt(M_1 \cap M_2) = \mu_{M_1}(d)$. An example is provided to illustrate this decision-making process. Research on multiple criteria decision-making (MCDM) has advanced quickly and is now a key field for addressing challenging decision-making issues. Examining the performance evaluation model is the aim of the paper. In order to assist industrial practitioners with performance evaluation in a fuzzy environment where subjectivity and vagueness are handled with linguistic values parameterized by triangular fuzzy numbers, Sun [14] developed an evaluation model based on the fuzzy AHP and TOPSIS. In addition to offering a more precise, efficient, and methodical decision support tool, the suggested approach helps decision analysts get a deeper understanding of the entire evaluation process. One of the main tools of artificial intelligence, fuzzy set theory, has been utilized to address imprecision and ambiguity in decision-making. Selecting software requirements is a MCDM task that is crucial for many software development firms. Few techniques have been developed to use fuzzy TOPSIS and fuzzy AHP to choose the software needs from the list of elicited requirements. Nazim et al. [15] compared the fuzzy TOPSIS and fuzzy AHP approaches in the context of the software requirements selection problem. By taking into account the small and large set of requirements of an institute examination system based on the following factors—agreement measure, time complexity, rank reversal issue, and number of judgments by decision makers—the fuzzy AHP and fuzzy TOPSIS methods have been compared.

The Case Based Reasoning (CBR) is a MCDM method that retrieves cases similar to a problem from an existing database of cases and proposes a solution to a decision-making problem based on the most similar cases. It requires little effort in terms of acquiring additional data. CBR is used in industries where a substantial number of previous cases already exist. This includes comparisons of businesses, vehicle insurance, medicines, and engineering designs. Various methods have been developed using CBR method. For example, Li and Sun [16] developed a method for predicting financial distress in companies on year prior to actual distress using CBR. The data was adopted from Shanghai and Shenzen stock exchange in China. In their work, following models were compared, i.e., Manhattan distance, Euclidian distance, and Inductive method. Finally, the results of these methods were compared to a ranking-order CBR (ROCBR) model.

Construction projects are frequently considered to be intricate and dangerous undertakings, mostly due to their susceptibility to outside factors and project-related uncertainty. For businesses in the construction sector, risk management (RM) is a vital component of success. RM is a knowledge-intensive procedure that necessitates efficient knowledge management about risks. Even while significant research has previously been done to create tools to assist knowledge-based RM processes, the majority of these systems overlook important characteristics including effective case retrieval for learning from previous projects, web-based platforms for knowledge sharing, and live knowledge capture. Furthermore, it is uncommon for a number of RM phases—including risk identification, analysis, reaction, and monitoring—to be integrated. By creating a knowledge-based RM tool (CBRisk) through case-based reasoning (CBR). Okudan et al. [17] developed a CBRisk, a web-based tool to support the cyclic RM process. It uses an efficient case retrieval mechanism that takes into account a long set of fuzzy linguistic variables that represent project similarity qualities. One of the problems of robotics and artificial intelligence is the creation of autonomous entities that carry out activities with the same dexterity as humans. Since the agent must select the optimal course of action in a dynamic environment to maximize the ultimate score, this drives research on intelligent agents. In light of this, Homem et al. [18] developed a method for Qualitative Case-Based Reasoning and Learning (QCBRL), a case-based reasoning system that retrieves and reuses instances through relationships between environmental objects using qualitative spatial representations. Without assuming a pre-processing step, QCBRL enables the agent to learn new qualitative situations at runtime when paired with reinforcement learning. QCBRL does case-base maintenance, eliminating cases that do not result in optimal performance and acquiring new (more appropriate) ones.

The Data Envelopment Analysis (DEA) uses a linear programming technique to measure the relative efficiencies of alternatives. It rates the efficiencies of alternatives against each other, with the most efficient alternatives having a rating of 1.0, with all other alternatives being a fraction of 1.0. It has several advantages. It is capable of handling multiple input and outputs. Hermans et al. [19] (2009) assessed indicators in different countries for road safety performance. DEA is used to provide policy makers of any country with a model to aid in prioritizing actions to improve the safety of their respective roadways in the most efficient ways possible. As a worldwide public health concern, infectious diseases necessitate prompt and efficient solutions. A unique model that aids in the development of such reactions is proposed [20]. The problem scenario is first structurally specified once the characteristics of infectious illness emergency scenarios are retrieved. The scenario evolution of infectious disease epidemics is analysed using a Markov model. A dynamic case-based reasoning model is then constructed. Fuzzy linguistic variables, interval numbers, crisp symbols, and crisp numbers all have different matching techniques. It is assessed how similar the goal scenario is to other historical scenarios.

Purchasing is the source of competitive advantage and plays a strategic role in supply chain management for a company. Businesses are very interested in issues like supplier evaluation, selection, and performance management because of the high buy cost to revenue ratio. Purchasing managers can assess suppliers holistically using MCDM tools. Data envelopment analysis (DEA) is one such tool that has been widely utilized for supplier selection and evaluation. Dutta et al. [21] analysed the 161 publications on the use of DEA in supplier selection that have been published since 2000.

The “Technique for Order Preference by Similarity to Ideal Solution” (TOPSIS) was proposed by Hwang and Yoon in 1981 and it was further developed by Yoon in 1987 [22]. For both individuals and businesses, making decisions is a crucial aspect of daily and professional life. Despite giving decision makers the tools they need, multi-criteria decision-making approaches differ in their underlying theories and presumptions. Therefore, choosing the appropriate approach to decision-making is just as crucial as actually making the choice. One of the most popular multi-criteria decision-making techniques, TOPSIS has drawn the attention of researchers, leading to the proposal of several enhanced variants of the method. Using a simulation tool, Çelikbilek and Tüysüz [22] examined the traditional TOPSIS method and experimentally illustrates the fundamental causes of its shortcomings. The theoretical foundations of the TOPSIS approach are revealed through in-depth experimental study based on simulation with an application in order to gain a better understanding of it and aid in its advancement. The TOPSIS is based on the concept that the selected alternative should have the shortest distance from the positive ideal solution (PIS) and the longest distance from the negative ideal solution (NIS). The TOPSIS method has been used to compute the ranking values of the alternatives. For example, Sadiq et al. [2] developed a method for the selection of SRs using fuzzy TOPSIS. In their work, the requirements of institute examination system (IES) were selected. Sustainable development requires a thorough assessment of the sustainability of communities and cities. Methodologically speaking, Multi-Criteria Decision Analysis (MCDA) techniques have demonstrated their applicability in the field of sustainability assessment. However, the traditional MCDA paradigm relies on a single set of input data to develop a model. As a result, it could result in oversimplification, particularly when it comes to sustainability. Furthermore, it is critical to understand how sustainability dynamics evolve over time in addition to the current assessment. Thus, the Data vARIability Assessment Technique for Order of Preference by Similarity to Ideal Solution (the DARIA-

TOPSIS method) is developed [23] to sustainability assessment that combines the MCDA approach with the variability of the alternatives' performance measurement.

Several earlier researchers have attempted in recent years to create, expand, suggest, and implement the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to solve decision-making problems. Zavadskas et al. [24] discussed the most recent advancements in the TOPSIS technique that have been proposed by earlier researchers. The TOPSIS approach for solving DM problems has been developed, extended, proposed, and presented in 105 reviewed publications to accomplish this goal. According to the study's findings, between 2000 and 2015, 49 academics expanded or refined the TOPSIS technique, and 56 academics suggested or introduced fresh adjustments for the technique's use in solving difficulties. The process of selecting the best choice among all viable options is known as a decision-making challenge. Jahanshahloo et al. [25] discussed the TOPSIS approach, which is one of the multicriteria models used in complicated decision-making and the multiple attribute models for the most preferred choice. Due to inadequate or unavailable information, data (attributes) are frequently less predictable in real-world scenarios, which means they are typically imprecise or fuzzy. Thus, in their work the authors applied the TOPSIS method to fuzzy data decision-making situations. Triangular fuzzy numbers were used to represent the weight of each criterion and the rating of each alternative. The idea of α-cuts was used to calculate the normalized fuzzy numbers.

3. Implementation

The aim of this section is to analyse the two fuzzy based MCDM methods, i.e., fuzzy AHP and fuzzy TOPSIS by considering the requirements of an institute examination system. The ranking order of the requirements of an IES are computed and analysed using spearman rank corelation coefficient. In this study, the dataset of the requirements of an IES are adopted from the work of Sadiq and Devi [26] and Sadiq and Jain [27]. Initially, the ranking order of the requirements of an IES are computed by applying the fuzzy AHP and fuzzy TOPSIS method. In our work, we have considered the following requirements of an IES [26, 27]:

FR1: The login module of different users of an examination system

FR2: The system should support the examination in online mode

FR3: The fee submission module for the examination form

FR4: The generate the hall ticket for end semester examination system

FR5: To generate the migration certificate from the examination department

FR6: To provide the information of the students in the institute medical center so that proper arrangement can be made during the examination time

FR7: To fill the examination form

FR8: To enter the marks of the students by the authorized faculty members

FR9: To generate the marksheet of the students

FR10: To display the examination related activities

FR11: To generate the seating arrangement of the students

The ranking order of the above FRs were computed by both fuzzy AHP and TOPSIS and the results are exhibited in Table 2. In this study, the deviation between the ranking order of the FRs of an IES are calculated by applying the Spearman's rank correlation coefficient (α) [28]. The value of α always lies between $+1$ and -1, where the value of $+1$ indicates a perfect association between fuzzy AHP and fuzzy TOPSIS methods and -1 indicates a perfect negative corelation between two ranking methods, i.e., fuzzy AHP and fuzzy TOPSIS. The value of $\alpha = 0$ indicates no association between the ranking values of fuzzy AHP and fuzzy TOPSIS. The value of α is calculated by using the Equation (1).

$$\alpha = 1 - \frac{6\sum d_i^2}{R^3 - R} \tag{1}$$

where d_i is the difference in ranking the of fuzzy AHP and fuzzy TOPSIS and R is the total number of requirements of an information system. In this study, the values of α for the ranking order produced by fuzzy AHP and fuzzy TOPSIS is shown in Table 3.

Table 2: Ranking order of the requirements of an IES using fuzzy AHP and TOPSIS

S. No.	FRs of an IES	Ranking order produced by fuzzy AHP (Rank-AHP)	Ranking order produced by fuzzy TOPSIS (Rank-TOPSIS)
1.	FR-1	1	2
2.	FR-2	8	7
3.	FR-3	6	9
4.	FR-4	5	4
5.	FR-5	10	10
6.	FR-6	11	11
7.	FR-7	4	1
8.	FR-8	7	8
9	FR-9	9	6
10.	FR-10	3	5
11.	FR-11	2	3

Table 3: Computation of Spearman's rank correlation coefficient

S. No.	FRs of an IES	Rank-AHP	Rank-TOPSIS	d_i	d_i^2
1.	FR-1	1	2	-1	1
2.	FR-2	8	7	1	1
3.	FR-3	6	9	-3	9
4.	FR-4	5	4	1	1
5.	FR-5	10	10	0	0
6.	FR-6	11	11	0	0
7.	FR-7	4	1	3	9
8.	FR-8	7	8	-1	1

9	FR-9	9	6	3	9
10.	FR-10	3	5	-2	4
11.	FR-11	2	3	-1	1

The value of α is calculated as:

$$\alpha = 1 - \frac{6\times36}{11^3-11}$$

$$\alpha = 1 - \frac{216}{1331-11}$$

$$\alpha = 1 - \frac{216}{1320}$$

$$\alpha = 1 - \frac{216}{1320}$$

$$\alpha = 0.84$$

The value of $\alpha = 0.84$ indicates a strong positive relationship between the ranks produced by fuzzy AHP and fuzzy TOPSIS methods. In order to test, if the value of $\alpha = 0.84$ is significant at 95% probability level, the value of α is compared with critical value (r_{crit}) based on the set of FRs, i.e., n, and level of significance (β). For $n = 11$ and $\beta = 0.05$, the r_{crit} is found to be 0.536 [29]. In our work, the value of Spearman's rank correlation coefficient (α) is greater than 0.536, which shows that the ranking order produced by fuzzy AHP and fuzzy TOPSIS are significant at 95% probability level.

4. Conclusion and Future Work

In this paper, the two fuzzy based MCDM methods, i.e., fuzzy AHP and fuzzy TOPSIS have been implemented and analysed using Spearman's rank correlation coefficient. For the analysis, we have considered the requirements of an institute examination system (IES). The ranking values of these requirements is calculated by using fuzzy AHP and fuzzy TOPSIS methods. To analyse the values of the ranking order of an IES, the Spearman's rank corelation coefficient (α) is computed and as a result, it is found that the ranking order produced by both the fuzzy based methods have strong positive relation with $\alpha = 0.84$. One of the limitations of this work is that only two fuzzy based MCDM methods have been used for the analysis. Thus, in future we shall focus on PROMETHEE and ELECTRE for the analysis of the requirements of an IES.

References

1. Ceballos, B., Lamata, M.T. & Pelta, D.A. (2016). A comparative analysis of multi-criteria decision-making methods. Progress of Artificial Intelligence, Vol. 5, pp. 315–322.
2. Sadiq, Mohd., Khan, S., & Mohammad, C. W. (2020). Selection of software requirements using TOPSIS under fuzzy environment. International Journal of Computers and Applications, 44(6), 503–512.
3. Nazim, M., Mohammad, C. W., & Sadiq, M. (2022). A comparison between fuzzy AHP and fuzzy TOPSIS methods to software requirements selection. Alexandria Engineering Journal, 61(12), 10851-10870.
4. Ting, S. C., & Cho, D. I. (2008). An integrated approach for supplier selection and purchasing decisions. Supply Chain Management: An International Journal, 13(2), 116-127.

5. Soni, G., & Kodali, R. (2011). A critical analysis of supply chain management content in empirical research. Business Process Management Journal, 17(2), 238-266.
6. Zou, Z., Tseng, T. L. B., Sohn, H., Song, G., & Gutierrez, R. (2011). A rough set-based approach to distributor selection in supply chain management. Expert Systems with Applications, 38(1), 106-115.
7. Ertuğrul, İ., & Karakaşoğlu, N. (2008). Comparison of fuzzy AHP and fuzzy TOPSIS methods for facility location selection. The International Journal of Advanced Manufacturing Technology, 39, 783-795.
8. Ananda, J., & Herath, G. (2005). Evaluating public risk preferences in forest land-use choices using multi-attribute utility theory. Ecological Economics, 55(3), 408-419.
9. Konidari, P., & Mavrakis, D. (2006). Multi-criteria evaluation of climate policy interactions. Journal of Multi-Criteria Decision Analysis, 14(1-3), 35-53.
10. Yan Liu Y, Eckert C. M., and Earl C. (2020). A review of fuzzy AHP methods for decision-making with subjective judgements. Expert Systems with Applications, Vol. 161.
11. Lai, S. K. (1995). A preference-based interpretation of AHP. Omega, 23(4), 453-462.
12. Wang, Y. L., & Tzeng, G. H. (2012). Brand marketing for creating brand value based on a MCDM model combining DEMATEL with ANP and VIKOR methods. Expert systems with applications, 39(5), 5600-5615.
13. Chang D. Y. (1996). Applications of the extent analysis method on fuzzy AHP, European Journal of Operational Research, 95(3), 649-655.
14. Sun C. C. (2010) A performance evaluation model by integrating fuzzy AHP and fuzzy TOPSIS methods, Expert Systems with Applications, 37 (12), 7745-7754.
15. Nazim, M., Mohammad, C. W., & Sadiq, M. (2022). A comparison between fuzzy AHP and fuzzy TOPSIS methods to software requirements selection. Alexandria Engineering Journal, 61(12), 10851-10870.
16. Li, H., & Sun, J. (2008). Ranking-order case-based reasoning for financial distress prediction. Knowledge-based systems, 21(8), 868-878.
17. Okudan O., Budayan C., Dikmen I. (2021). A knowledge-based risk management tool for construction projects using case-based reasoning, Expert Systems with Applications, 173.
18. Homem T. P. D., Santos P. E., Costa A. H. R., Bianchi R. A. D. C., Mantaras R. L. D. (2020). Qualitative case-based reasoning and learning, Artificial Intelligence, 283.
19. Hermans E., Brijs T., Wets G, Vanhoof K (2009), Benchmarking road safety: Lessons to learn from a data envelopment analysis, Accident Analysis & Prevention, Volume 41, Issue 1, 2009, Pages 174-182.
20. Duan J., Lin Z., Jiao F., Jiang Y., Chen K. (2022) A dynamic case-based reasoning system for responding to infectious disease outbreaks, Expert Systems with Applications, 204.
21. Dutta, P., Jaikumar, B. & Arora, M.S (2022). Applications of data envelopment analysis in supplier selection between 2000 and 2020: a literature review. Annals of Operations Research, 315, 1399–1454.
22. Çelikbilek, Y., & Tüysüz, F. (2020). An in-depth review of theory of the TOPSIS method: An experimental analysis. Journal of Management Analytics, 7(2), 281–300.
23. Wątróbski J., Bączkiewicz A., Ziemba E., Sałabun W. (2022) Sustainable cities and communities' assessment using the DARIA-TOPSIS method, Sustainable Cities and Society, 83.
24. Zavadskas E. K., Mardani A., Turskis Z., Jusoh A., and MD Nor K. M. (2016), Development of TOPSIS Method to Solve Complicated Decision-Making Problems — An Overview on Developments from 2000 to 2015, International Journal of Information Technology & Decision Making, 15(3), 645-682.
25. Jahanshahloo G.R., Lotfi F. H., Izadikhah M (2006). Extension of the TOPSIS method for decision-making problems with fuzzy data, Applied Mathematics and Computation, 181(2), 1544-1551.
26. Sadiq, M., & Devi, V. S. (2022). Fuzzy-soft set approach for ranking the functional requirements of software. Expert Systems with Applications, 193, 116452.
27. Sadiq, M., & Jain, S. K. (2014). Applying fuzzy preference relation for requirements prioritization in goal-oriented requirements elicitation process. International Journal of System Assurance Engineering and Management, 5, 711-723.
28. Xiao, C., Ye, J., Esteves, R. M., & Rong, C. (2016). Using Spearman's correlation coefficients for exploratory data analysis on big dataset. Concurrency and Computation: Practice and Experience, 28(14), 3866-3878.
29. Gauthier T. D. (2001). Detecting Trends using Spearman's Rank Corelation Coefficient. Environmental Forensics, 2, 359-362.